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Diagnosis and Grading of Diabetic Retinopathy using Deep Learning

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Abstract

Diabetic retinopathy (DR), which causes tissue on the eye that damages visibility, is a common complication of type-2 diabetes. If it is not discovered in time, total blindness might occur. DR is irreversible. DR is primarily among adults who are of working age. More than 150 million people are affected by diabetic retinopathy (DR), which accounts for 2.6% of blindness worldwide. Different indications of DR are vision distortion, bulging of the eye, and formation of irregular blood vessels. The traditional way is to use Computer-aided Diagnosis (CAD) systems during treatment. The dataset used is the APTOS blindness detection dataset that is accessible in Kaggle. The Convolutional Neural Networks (CNN) is the most effective way for classifying images. In this paper, the MobileNet architecture, a deep learning technique is utilized to automate the diagnosis of the disease and estimate the severity of the eye into several stages through which the accuracy obtained for training is 95% and validation is 82%.

Keywords: Diabetic Retinoapthy(DR), Convolutional Neural Networks(CNN), MobileNet architecture, Computer-aided Diagnosis (CAD).

Introduction

Diabetic retinopathy (DR) occurs when damage to the retina is caused by diabetes. Blindness may result from it. It is a vascular complication of diabetes. Despite these alarming numbers, according to the study, if the eyes were treated and monitored properly and diligently, at least 90% of these new occurrences might be decreased.

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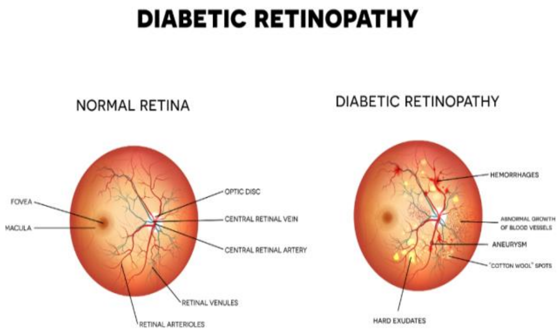

Fig.1: Comparison between normal and DR eye

A person has a greater risk of getting diabetic retinopathy the longer they have diabetes. Microaneurysms, ruptured blood vessels, eye bruising and the development of unusual and injured vascular are only a few of the signs and indications of diabetic retinopathy. Five stages are described in below picture:

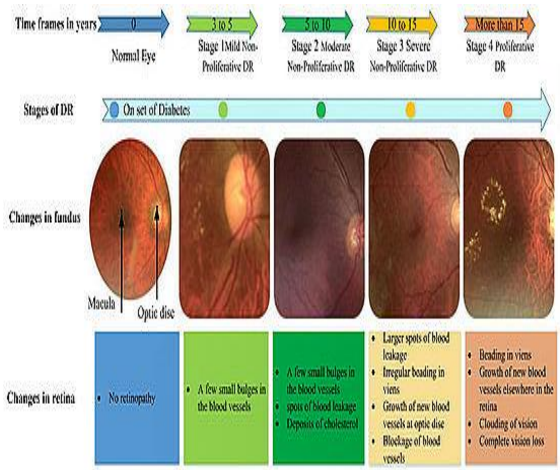

Fig.2:Different stages and their symptoms

In this paper, the proposed system is to develop a digitalized screening using a pretrained architecture called MobileNet which is developed in deep learning using Keras and designed a website for giving input using Flask in python and obtain the DR grading as output and the graph with percentage of prediction belonging to each class.

Literature survey

The issue of detecting diabetic retinopathy has been addressed by a number of machine learning strategies and deep learning methods.

- In this study, the algorithms used are ResNet 18 with two contrast enhancement techniques, Gaussian and CLAHE filters. The image is preproces into 256 X 256. The Gaussian filter achieved more specifity than the CLAHE filter [1].
- In this research paper, the classifiers used are Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor which are machine learning techniques for

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diagnosing. The dataset explored is UCI Diabetic Retinopathy, which is derived from Messidor database using various approaches to image processing [2].

- Nine commonly used categorization methods were compared throughout the research. This study makes use of the UCI Diabetic Retinopathy dataset. The algorithms are Naive Bayes, Decision Tree (DT), Adaptive Boosting, Random Forest (RF), Gaussian Process, Multi-Layer Perceptron Neural Network, Quadratic Discriminant Analysis (QDA) and Support Vector Machine (SVM). According to the findings, the best results come from the Gaussian process classifier at identifying diabetic retinopathy instance [3].
- In this paper Convolutional Neural Network is used. The Sequential model, which enables building the model layer by layer in Keras. Input size is resized and balanced for the MESSIDOR dataset. Both No-DR and DR exist. Afterwards, probability values were generated to divide the photos into other categories [4].
- In this paper The Kaggle APTOS dataset is used in the experiment. The model is trained using a step-size of 0.002 with total of 75 cycles using transfer learning. Two models, SEResNeXt32x4d and EfficientNetb3 were used [5].

Problem Identification

Diabetic Retinopathy presence will be performed through scanning the eye. In rural areas there will be lack of doctors and equipment for medical monitoring.

There may be some who cannot afford for checkup of the disease. By looking for lesions connected to the vascular anomalies brought on by the disease, clinicians can recognize DR. Patients lose time between having their eyes scanned, having their images examined by medical professionals, and setting up a follow-up visit. [7-15]

By using automated systems, the proposed method can solve the above mentioned problems. Previous attempts have used image classification, pattern recognition, and machine learning to make quick progress in developing a thorough and automated approach of DR screening.

Here the proposed solution is the MobileNet architecture which will make it possible for patients to request and schedule therapy on the same day by processing images in real-time. Long-running projects have advanced the development of a thorough and automated DR screening method by using image categorization, pattern recognition, and machine learning.

Methodology

The primary goal of the proposed method is to label the retinal fundus picture to any of the five categories listed below.

- Class 0:No DR
- Class 1: Mild DR
- Class 2: Moderate DR

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- Class 3: Severe DR
- Class 4: Proliferative DR (PDR)

Every retinal fundus picture will go through data augmentation in this stage to be classified. The DR level of the patient will then be classified using the CNN architecture.

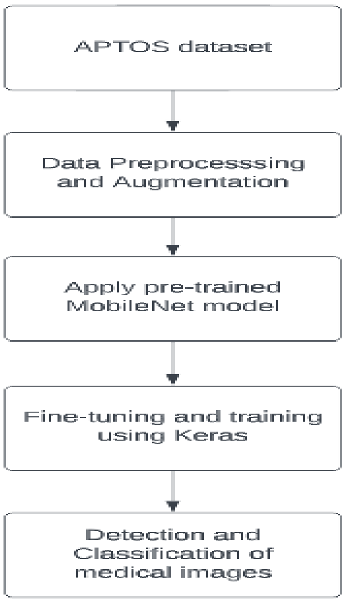

Fig.3: Flowchart for classification of DR images for MobileNet model

The proposed methodology is to design a deep learning model using Convolutional Neural Networks (CNN). MobileNet is a pretrained model used by means of transfer learning when inadequate data is present in original data to fully train a model from foundation. The process of developing is described in the above flowchart which is Fig.2.

Implementation

A. Dataset

The data-source utilized throughout this research article is the Kaggle APTOS competition. Pictures are identified using a 12 digit code that includes both alphabetic and numeric characters. For instance, the 025a169a0bb0.png picture is an example of a random sample.

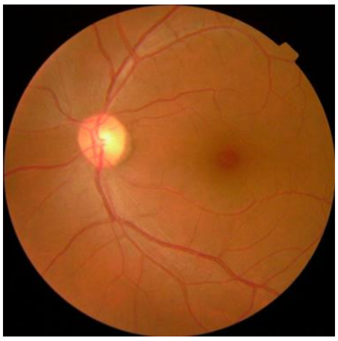

Fig.4: Sample image

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This dataset is a sizable collection of retina pictures in high quality that were captured by the Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium [6] under various imaging circumstances.

According to medical experts, there are 3662 training photos in the dataset which are rated from 0 to 4, as shown in Table 1. The data were noisy and dirty. The collection includes coloured images that vary in dimensions.

DR Grade	Class name of DR	Count of Images
0	No DR	1805
1	Mild DR	370
2	Moderate DR	999
3	Severe DR	193
4	Proliferative DR	295

Table I. Distribution of Data

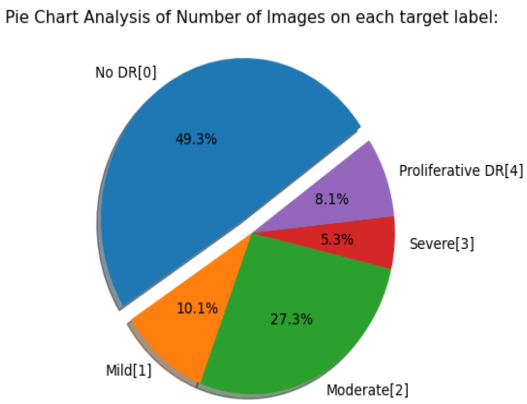

Fig.5: The percentage of images present in each class

B. Pre-processing

Here the fundus images are taken as input. The dataset contains many files and directories such as training and test images, and csv files for training and test images.

The train images are splitted into training and validation directories and create a folder for every class and the images belonging to the class.

C. Data Augmentation

From the Table I, there are a large number of class-0 images in the dataset. The data were very imbalanced. The data is augmented by rotation, zooming, flipping etc.. except class-0 images by making use of ImageDataGenerator.

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D. MobileNet Architecture

In this paper, the MobileNet architecture is used. As MobileNet is a lightweight architecture . It employs depth-wise separable convolutions, which essentially implies that just one convolution is performed on each colour channel rather than merging all three and flattening the image. Because it requires extremely little maintenance, it operates well at high speeds.

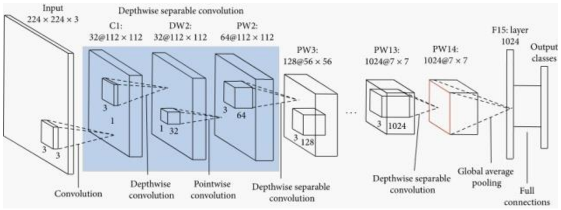

Fig.6: Architecture of MobileNet

E. Building and Training model

The APTOS dataset was trained using the Mobilenet architecture. The dataset is splitted into 80% training and 20% validation images.

The input image is of size 128 X 128 and has three channels RGB. It is passed through convolutional layers and it uses "batch normalization" for standardizing the input layer and "ReLu" activation layer for adding non-linearity to the network.

The pretrained model which is modeled from the imaganet database from which initial weights are taken into consideration. The fully connected layers are removed from the trained model,then freeze the top 16 layers as they are already trained as add layers such as convolutional, max pooling layer and dense layers and train them. The adam optimizer is used and the learning rate is 0.001 with epochs=20. Categorical crossentropy is used for multi-class grading.

F.Categorical Cross-Entropy loss function:

The categorical-crossentropy is used as loss function. The formula is

$$\text{Categorical Cross-Entropy} = \frac{\text{Sum of Cross-Entropy for N data}}{\text{N}}$$

G. Evaluation metrics

The accuracy is taken into consideration while measuring the performance of the prediaction. The accuracy is evaluated from confusion matrix.

The formula for accaurcy is

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$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Results

In this paper, the proposed MobileNet model used augmentation to balance the dataset through the over-fiiting is eliminated and the performance is increased during the prediction.

DR Grade	Class name of DR	Count of Images
0	No DR	1805
1	Mild DR	1804
2	Moderate DR	1948
3	Severe DR	1421
4	Proliferative DR	1711

Table II: After augmentation of the dataset, the distrubution of class images

The obtained training and validation accuracies are 95% and 82% respectively.

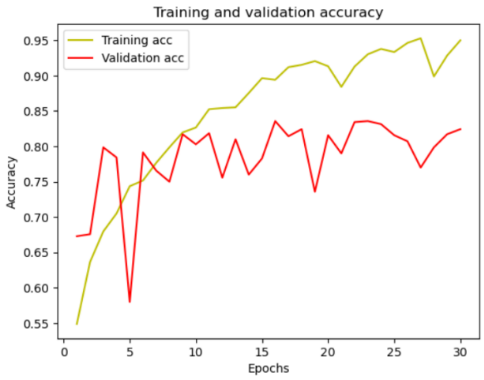

Fig.7: Accuracy curve for training and validation images

The losses for the both images are:

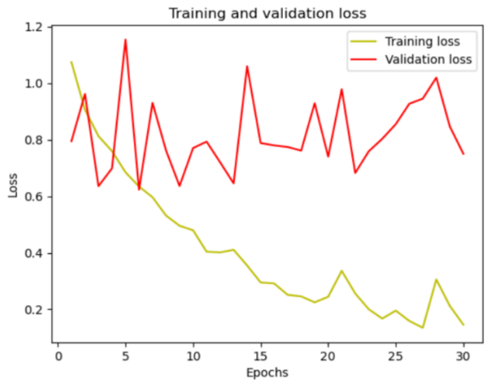

Fig.8: Loss curve

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Percentage	Accuracy	Loss
Training	95	14
Validation	82	75

Table III: Accuracy and Loss percentages

The evaluation metrics like precision, recall, f1-score which are also illustrated for the diabetic retinopathy disease. The validation set has a total of 733 images and the metrics got better results for class-0 when compared to other classes.

	precision	recall	f1-score	support
No DR	0.93	0.99	0.96	361
Mild DR	0.73	0.50	0.59	74
Moderate DR	0.69	0.80	0.74	200
Severe DR	0.39	0.33	0.36	39
Proliferative DR	0.60	0.36	0.45	59
accuracy			0.80	733
macro avg	0.67	0.60	0.62	733
weighted avg	0.79	0.80	0.79	733

Fig.9: Precision, recall and f1-score

Conclusion

In this paper, the proposed MobileNet model produced promising results. The model accuractely predicts the illness in the input image. It achieved the training accuracy of 95% and validation accuracy of 82% with the loss of 14% and 75% respectively.

Future scope

Fundus photography is currently employed for DR detection, in the future work by using new imaging modalities such as Optical Coherence Tomography (OCT) and Fluorescein Angiography (FA), can provide additional information about the structure and function of the retina which improve both accuracy and reliability. As MobileNet has the potential to be used in real-time detection to assist patients in taking quick action to combat the crippling disease debilitating illness since it is a lightweight CNN that operates very effectively.

References

[1] M. S. Sallam, A. L. Asnawi and R. F. Olanrewaju, "Diabetic Retinopathy Grading Using ResNet Convolutional Neural Network," 2020 IEEE Conference on Big Data and Analytics (ICBDA), Kota Kinabalu, Malaysia, 2020, pp. 73-78, doi: 10.1109/ICBDA50157.2020.9289822.

[2] Anushree Vartak , Sagar Kataria , Zeal Vala , Dr. Swapna Borde, 2021, Detection of Diabetic Retinopathy using Deep Learning, INTERNATIONAL JOURNAL OF

ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 10, Issue 05 (May 2021),

[3] S. Mohammadian, A. Karsaz and Y. M. Roshan, "A comparative analysis of classification algorithms in diabetic retinopathy screening," 2017 7th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, Iran, 2017, pp. 84-89, doi: 10.1109/ICCKE.2017.8167934.

[4] C. Jayakumari, V. Lavanya and E. P. Sumesh, "Automated Diabetic Retinopathy Detection and classification using ImageNet Convolution Neural Network using Fundus Images," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 577-582, doi: 10.1109/ICOSEC49089.2020.9215270.

[5] S. Ramchandre, B. Patil, S. Pharande, K. Javali and H. Pande, "A Deep Learning Approach for Diabetic Retinopathy detection using Transfer Learning," 2020 IEEE International Conference for Innovation in Technology (INOCON), Bangluru, India, 2020, pp. 1-5, doi: 10.1109/INOCON50539.2020.9298201.

[6] Kaggle APTOS competition dataset: https://www.kaggle.com/c/aptos2019-blindness-detection/data

[7] Sri Hari Nallamala, et al., "A Literature Survey on Data Mining Approach to Effectively Handle Cancer Treatment", (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 729 – 732, March 2018.

[8] Sri Hari Nallamala, et.al., "An Appraisal on Recurrent Pattern Analysis Algorithm from the Net Monitor Records", (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 542 – 545, March 2018.

[9] Sri Hari Nallamala, et.al, "Qualitative Metrics on Breast Cancer Diagnosis with Neuro Fuzzy Inference Systems", International Journal of Advanced Trends in Computer Science and Engineering, (IJATCSE), ISSN (ONLINE): 2278 – 3091, Vol. 8 No. 2, Page No: 259 – 264, March / April 2019.

[10] Sri Hari Nallamala, et.al, "Breast Cancer Detection using Machine Learning Way", International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8, Issue-2S3, Page No: 1402 – 1405, July 2019.

[11] Sri Hari Nallamala, et.al, "Pedagogy and Reduction of K-nn Algorithm for Filtering Samples in the Breast Cancer Treatment", International Journal of Scientific and Technology Research, (IJSTR), ISSN: 2277-8616, Vol. 8, Issue 11, Page No: 2168 – 2173, November 2019.

[12] Kolla Bhanu Prakash, Sri Hari Nallamala, et al., "Accurate Hand Gesture Recognition using CNN and RNN Approaches" International Journal of Advanced Trends in Computer Science and Engineering, 9(3), May – June 2020, 3216 – 3222.

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

[13] Sri Hari Nallamala, et al., "A Review on 'Applications, Early Successes & Challenges of Big Data in Modern Healthcare Management'", Vol.83, May - June 2020 ISSN: 0193-4120 Page No. 11117 – 11121.

[14] Nallamala, S.H., et al., "A Brief Analysis of Collaborative and Content Based Filtering Algorithms used in Recommender Systems", IOP Conference Series: Materials Science and Engineering, 2020, 981(2), 022008.

[15] Nallamala, S.H., Mishra, P., Koneru, S.V., "Breast cancer detection using machine learning approaches", International Journal of Recent Technology and Engineering, 2019, 7(5), pp. 478–481.