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Article Title: Detection Classification of Diabetic Retinopathy Using Deep Learning Neural Network

Detection Classification of Diabetic Retinopathy Using Deep Learning Neural Network

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ABSTRACT

Diabetic Retinopathy (DR) is an eye condition that mainly affects individuals who have diabetes and is one of the important causes of blindness in adults. As the infection progresses, it may lead to permanent loss of vision. Diagnosing diabetic retinopathy manuallywith the help of an ophthalmologist has been a tedious and a very laborious procedure. This paper not only focuses on diabetic retinopathy detection but also on the analysis of different DR stages, which is performed with the help of Deep Learning (DL) and transfer learning algorithms. Diabetic Retinopathy (DR) is one of the leading causes of blindness for people who have diabetes in the world. Early detection of this disease can essentially decrease its effects on the patient. Dense Net are used on a huge dataset with around 3662 train images toautomatically detect which stage DR has progressed. Five DR stages, which are 0 (No DR), 1 (Mild DR), 2 (Moderate), 3 (Severe) and 4 (Proliferative DR) are processed in the proposed work. It presented an AI based smart tele ophthalmology application for diagnosis of diabetic retinopathy. The app has the ability to facilitate the analyses of eye fundus images via deep learning from the Kaggle database using Tensor Flow mathematical library. The app would be useful in promoting health and timely treatment of diabetic retinopathy by clinicians.

Keywords: Diabetic Retinopathy, Algorithms.

1 Introduction

Diabetic retinopathy is an eye condition that can cause vision loss and blindness in people who have diabetes. It affects blood vessels in the retina (the light-sensitive layer of tissue in the back of your eye). If you have diabetes, it's important to get a comprehensive dilated eye exam at least once a year.

Over time, too much sugar in your blood can lead to the blockage of the tiny blood vessels that nourish the retina, cutting off its blood supply. As a result, the eye attempts to grow new blood vessels. But these new blood vessels don't develop properly and can leak easily.

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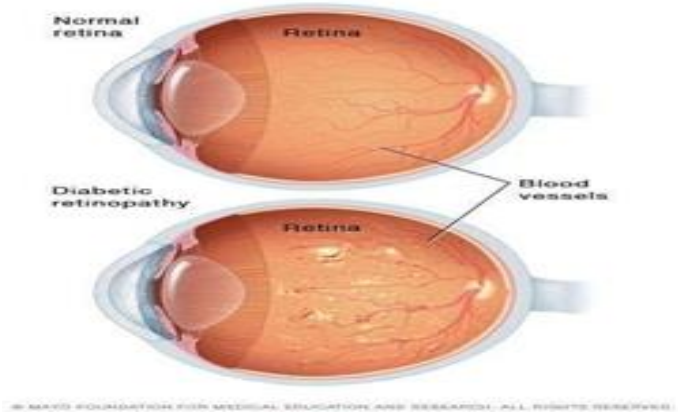

Figure 1: *Difference between Normal Retina and Diabetic Retinopathy*

People with diabetes are prone to an eye disease called "Diabetic retinopathy". Diabetic retinopathy is considered as a deadly eye condition as it can cause a loss of vision and blindness in people who have diabetes. The very high blood sugar levels cause significant damage to the blood vessels in the retina. Blood vessels in the eye begin to leak fluid causing the macula to swell or thicken, preventing blood from passing through. Sometimes, there is an abnormal growth of new blood vessels on the retina. All of the mentioned conditions can cause permanent loss of vision. Diabetic retinopathy doesn't show up with symptoms at first but eventually can worsen things up by causing vision loss. Diagnosing at an early stage can help oneself save their vision. One might not experience symptoms in the early stages of diabetic retinopathy. It might cause trouble reading or seeing faraway objects. As the infection becomes worse or progresses, the symptoms include: Spots floating in your vision floaters, an increased number of floaters, cloudy vision, Poor night vision, fluctuating vision, Impaired color vision unable to distinguish colors, Dark or empty areas in your vision shadows cast by specks floating in the eye and Vision loss complete loss of vision.

2 Related Works

[1] Brain Tumor Detection in MRI Images Using PNN and GRNN, Thara, K. S., and Jasmine, K [2016]. Brain tumor detection is the most significant method to describe the early tumor. Enlarging the tumor is being a huge challenge due to the complex characteristics of the MRI Images which gives highly intensive, divergent and uncertain boundaries. To address this problem, tumor segmentation method for MRI images which separates tumorous cells from healthy tissues has been carried out by the use of two types of clustering methods. In the proposed method input Image is pre-processed, followed by which the segmentation is done using K Means clustering method and Fuzzy C Means clustering method. While comparing these two techniques, it is seen that Fuzzy C Means clustering produces better segmentation. Further the features like magnitude, direction and the area are extracted from the tumorous part of Fuzzy Means segmented Image. Based on the features extracted, the MRI image is classified as

tumorous or non-tumorous. Classification is done by using the supervised neural network called the Radial Basis Function (RBF), Generalized Regression neural network (GRNN), Probabilisticneural network (PNN). In the proposed method the classification is done by using the Fuzzy probabilistic neural network classifier (FPNNC) has been used to classify the MRI Image as normal or abnormal and the classifiers are compared in terms of accuracy, specificity and sensitivity. This proves that the proposed method produces better accuracy compared to the existingclassifiers.

[2] Handbook of Retinal Screening in Diabetes Diagnosis and Management, Taylor R and Batey D [2012]. Beginning with chapters summarizing the basics of diabetic retinopathy, this updated volume outlines the need for screening, how to screen safely and correctly, and the normal condition of the retina without diabetic retinopathy, all using excellent line and halftone illustrations. The core focus then moves on to examining each different form of retinopathy, all supported by outstanding color retinal photographs illustrating the appearance of the retina at various stages of retinopathy, plus an analysis on the best treatment for each stage. The book ends with chapters providing self-assessment questions of the type that screeners will encounter when gaining their now mandatory retinal screening qualifications, as well as a background information chapter offering advice on related UK, European, and US. Organizations.

[3] Causes of Vision Loss Worldwide, 1990-2010: A Systematic Analysis, Bourne RR [2013]. Background: Data on causes of vision impairment and blindness are important for development of public health policies, but comprehensive analysis of change in prevalence over time is lacking. We did a systematic analysis of published and unpublished data on the causes of blindness (visual acuity in the better eye less than 3/60) and moderate and severe vision impairment ([MSVI] visual acuity in the better eye less than 6/18 but at least 3/60) from 1980 to 2012. We estimated the proportions of overall vision impairment attributable to cataract, glaucoma, macular degeneration, diabetic retinopathy, trachoma, and uncorrected refractive error in 1990-2010 by age, geographical region, and year. In 2010, 65% (95% uncertainty interval [UI] 61-68) of 32·4 million blind people and 76% (73-79) of 191 million people with MSVI worldwide had a preventable or treatable cause, compared with 68% (95% UI 65-70) of 31·8 million and 80% (78-83) of 172 million in 1990. Leading causes worldwide in 1990 and 2010 for blindness were cataract (39% and 33%, respectively), uncorrected refractive error (20% and 21%), and macular degeneration (5% and 7%), and for MSVI were uncorrected refractive error (51% and 53%), cataract (26% and 18%), and macular degeneration (2% and 3%). Causes of blindness varied substantially by region. Worldwide and in all regions more women than men were blind or had MSVI due to cataract and macular degeneration. The differences and temporal changes we found in causes of blindness and MSVI have implications for planning and resource allocation in eye care.

[4] Grading Diabetic Retinopathy from Stereoscopic Color Fundus Photographs- An Extension of the Modified Airlie House Classification, E. T. D. R. S. R. GROUP [2014]. The modified Airlie House classification of diabetic retinopathy has been extended for use in

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the Early Treatment Diabetic Retinopathy Study (ETDRS). Televised classification provides additional steps in the grading scale for some characteristics, separates other characteristics previously combined, expands the section on macular edema, and adds several characteristics not previously graded. The classification is described and illustrated and its reproducibility between graders is assessed by calculating percentages of agreement and kappa statistics for duplicate grading of baseline color no simultaneous stereoscopic fundus photographs. For retinal hemorrhages and/or micro aneurysms, hard exudates, new vessels, fibrous proliferations, and macular edema, agreement was substantial (weighted kappa, 0.61to 0.80). For soft exudates, intraregional microvascular abnormalities, and venous beading, agreement was moderate (weighted kappa, 0.41 to 0.60). A double grading system, with adjudication of disagreements of two or more steps between duplicate grading, led to some improvement in reproducibility for most characteristics.

[5] Big Data Deep Learning: Challenges and Perspectives, Chen XW and Lin X [2014]. Deep learning is currently an extremely active research area in machine learning and pattern recognition society. It has gained huge successes in a broad area of applications such as speech recognition, computer vision, and natural language processing. With the sheer size of data available today, big data brings big opportunities and transformative potential for various sectors; on the other hand, it also presents unprecedented challenges to harnessing data and information. As the data keeps getting bigger, deep learning is coming to play a key role in providing big data predictive analytics solutions. In this paper, we provide a brief overview of deep learning, and highlight current research efforts and the challenges to big data, as well as the future trends.

3 Proposed Work

Using a publicly available Kaggle dataset, this study detected diabetic retinopathy. The database was built using images from publicly available records to detect retinopathy. There are 1000 images in the Kaggle dataset. 300 diabetic retinopathy images and 700 normal images are chosen from the total number of images. Exudate, bleeding, and micro aneurysms were among the abnormal images chosen. Appearance, number, distribution and size, exudate area, Micro aneurysms and bleeding are all the factors present in DR a. Exudate is a bright area of yellowish appearance that is slightly different in color from the nipple. The ruptured blood vessels contain lipids and exudate appears.

3.1 Advantages

High accuracy score, Found better model, Detection speed is high.

3.2 Modules

Load Dataset: We can read and store images on our machines, Machine can identify the retinal image in pixel value, After Training the images 2 class in normal image and abnormal images

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(example 300 images).

Pre-processing the Retinal image is increasing brightness and contrast adjustments, Size Normalization, Shape Normalization, Color Normalization.

Feature Extraction: Flip the image horizontally, Flip the image vertically, randomly rotate the image in the range of [-25, 25] degrees, Randomly zoom in or out in the range of [0.85, 1.15], Randomly distort the image.

CNN Models: The first layer might learn edges while the deepest layer learns to interpret hard exudate, a DR classification feature. The network contains convolution blocks with activation on the top layer that defines complex functional mappings between inputs and response variables. Followed by batch normalization after each convolution layer. As the number of feature maps increases, one batch normalization per block is introduced in succession. Dense Net 201 model we applied.

4 Result and Discussion

The evaluation results (averaged over five datasets) for each model are listed in TABLE 4. The Inception-V3 model and the adapted Inception@4 model surpass all other models. It is notable that by classifying more Normal samples(together with samples with Mild DR) as Mild DR, the recall rate of VGG-19 is 0.6% higher than that of Inception-V3, however this is at the cost of 2.51% of precision and 2.85% overall accuracy. By a similar reason, the Inception@4 model has a lower precision rate than the Inception-V3 model, however, the increase in accuracy and recall is more significant and preferable.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
densenet121 (Functional)     (None, 7, 7, 1024)        7037504
_________________________________________________________________
global_average_pooling2d (Gl (None, 1024)              0
_________________________________________________________________
dropout (Dropout)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 5)                 5125
=================================================================
Total params: 7,042,629
Trainable params: 6,958,981
Non-trainable params: 83,648
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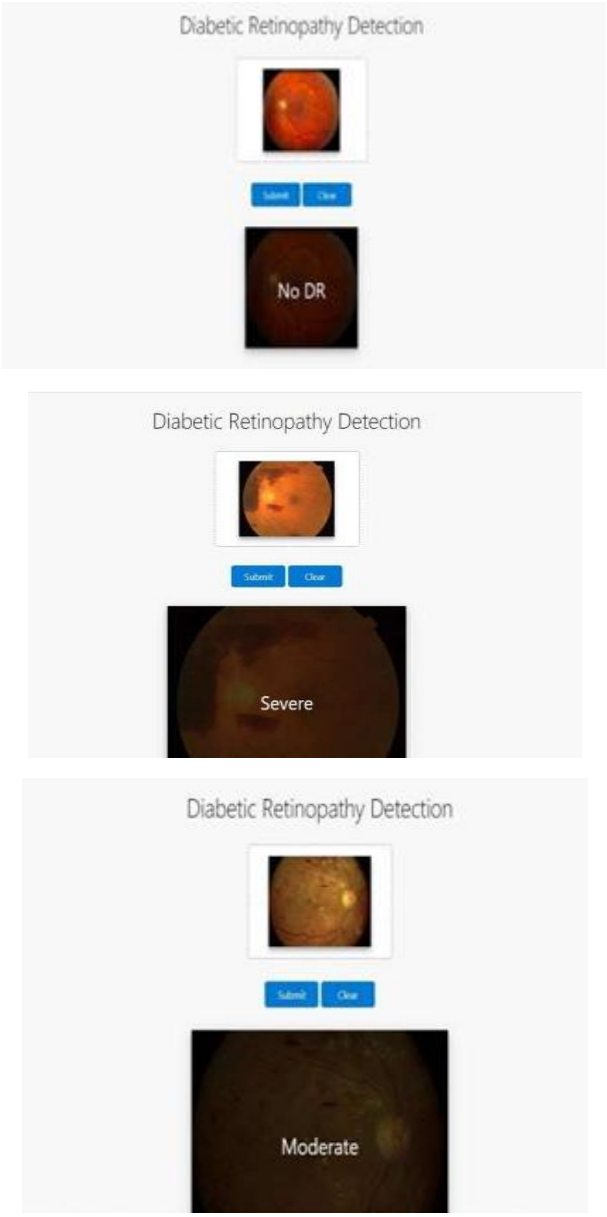

Figure 2: *Result Prediction*

5 Conclusion

Diabetes is the fastest growing illnesses in recent years. According to studies, diabetics have a 30% risk of developing diabetic retinopathy. If the disease is not diagnosed early, it can lead to floater, blurred vision, and ultimately blindness. Manual diagnosis of these photographs is time consuming, complex and requires highly qualified professionals. A convolutional neural network model has been successfully created using the VGG19 framework that detects diabetic retinopathy and provides information on the severity of the disease. The accuracy of the model achieved is 92%. This model helps doctors diagnose the disease more quickly. Similar models

can be developed to diagnose other diseases, especially those that affect the eye. This helps identify such illnesses early and avoid permanent blindness.

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