ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail
editor.ijmece@gmail.com
editor@ijmece.com

www.ijmece.com

ISSN2321-2152

www.ijmece .com

Vol 12, Issue.2, 2024

Classification Of Diabetic Walking Through Machine Learning: Survey Targeting Senior Citizens

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ABSTRACT:

A Convolutional Neural Networks (CNNs) approach is proposed to automate the method of Diabetic Retinopathy(DR) screening using color fundus retinal photography as input. Our network uses CNN along with denoising to identify features like micro-aneurysms and haemorrhages on the retina. Our models were developed leveraging Theano, an open source numerical computation library for Python. We trained this network using a high-end GPU on the publicly available Kaggle dataset. On the data set of over 30,000 images our proposed model achieves around 95% accuracy for the two class classification and around 85% accuracy for the five class classification on around 3,000 validation images

Keywords: CNN, Haemorrhages, kaggle dataset, python.

1. INTRODUCTION:

Diabetic Retinopathy (DR) is an eye disease that damages the retina of patients with long-standing diabetes. This is an ocular complication of the eye that affects 75% of diabetic patients leading to blindness in the age group of 20-64 [1]. There are different ways to diagnose DR. The World Health Organization reports that about 347 million people in the world are affected by DR. About 366 million adults with diabetes is estimated by International Diabetes Federation. This figure is expected to rise to 552 million by 2030. Estimated occurrence of type 2 diabetes mellitus and diabetic retinopathy is quite high in India, according to the studies that have been conducted so far. Based on a survey in 2000, the top three countries with highest number of diabetes mellitus are India (31.7 million), China (20.8 million) and USA (17.7 million) [2]. Trained clinicians are required to examine the color fundus photographs of retina and detect DR.

The process of identifying DR involves detection of lesions with vascular abnormalities. This is an effective way of detection but requires the service of experienced clinicians for analysis of the photographs manually, which is time-consuming. Rural areas, where the rate of diabetes is usually high, lack the expertise of well-trained clinicians and sophisticated equipment that are necessary for detection of DR. Better infrastructure with automated detection techniques are now required to tackle the growing number of individuals with diabetes. An early detection can help to avert or decrease the spread of DR which otherwise might cause blindness [3]. Previous research work for identification of the stages of DR using automated techniques includes support vector machines [4] and k-NN classifiers [5]. Most of the methods treat this as a two-class classification problem for detection of DR.

2. EXISTING SYSTEM:

Numerous techniques are tested by researchers in the area for DR classification with encouraging results. Recent work for addressing blood vessel segmentation includes the application of CNN (LeNet-5 architecture) as feature extractor .Three heads are used in this model at different layers of the convnent which are then fed into three random forests. The final classifier achieved an accuracy of 0.97 and 0.98 on the DRIVE and STARE dataset. An automatic segmentation of blood vessels in color fundus images is implemented by M.Melinscak et al using deep max-pooling convnet to separate the blood vessels. The model contains a deep max-pooling convolutional neural networks to segment blood vessels. It deployed 10-layer architecture for achieving a maximum accuracy of around 0.94. It was carried around 4-convolutional and 4-max pooling layer with 2 additional fully connected layers for vessel segmentation. Automated analysis of DR using images processing techniques are introduced by Adarsh et al. In this approach, extraction of retinal blood vessels, exudate, micro-aneurysms, haemorrhages and texture features takes place, followed by construction of Multiclass SVM using area of lesions and texture features. Impressive results are reported using the publicly available datasets DIARETDB0 and DIARETDB1 with accuracy of 0.96 and 0.946 respectively.

PROPOSED SYSTEM:

A. Overview

ISSN2321-2152

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Data is collected from the dataset provide by the Kaggle coding website and maintained by EyePacs. The dataset consists of colour fundus photographs collected from various sources. The images are classified based on the severity of DR, where each image was assigned to a class by a trained clinician1. The figure below shows the various stages of diabetic retinopathy(DR)

B. Class Imbalance:

The class labels of the dataset are highly imbalanced i.e more than 73% of the class are negative, which makes our model difficult to train. Table I below shows the class proportion statistics, where PDR and NPDR refers to proliferative and Non-proliferative DR respectively.

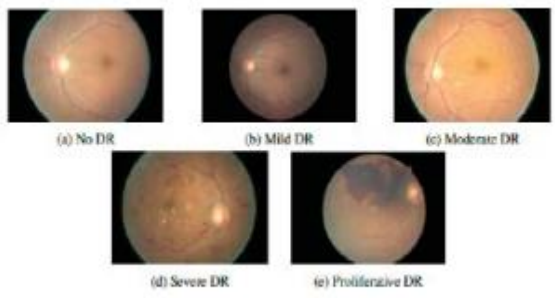

Fig. 1. Diabetic Retinopathy(DR) stages

Class	Number	Percentage
Negative	25810	73.5%
Mild NPDR	2443	6.90%
Moderate NPDR	5292	15.10%
Severe NPDR	873	2.50%
PDR	708	2.00%

TABLE I. CLASS IMBALANCE.

FEATURES SELECTION:

A. Pre-processing:

The dimension of images in the dataset is 3000x2000 pixels. For convenient use of the CNN using the resources at our disposal, the images are cropped and resized to squares of 512 pixels.

B. Data Augmentation:

Augmented images were created to increase the class size as there was limited number of training samples for some of the classes. Brightness of each of the images created after pre-processing were adjusted by converting the RGB image to float representation followed by converting into the original data type. This is done by adding a delta value to all the components of the image. The images are scaled appropriately and both the image and delta are converted to float prior to addition. As the addition to the image is

ISSN2321-2152
www.ijmece .com
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performed in floating point representation, the delta must be in the range [0,1) whereas the pixel values are in [0,1). The original and the brightness adjusted images are then rotated by 90 and 180 degree which inherently increase the class size 6 times. This makes our mod del immune to different orientations and lighting conditions.

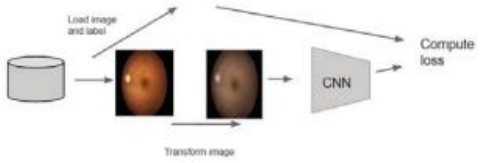


Fig. 2. Data Augmentation

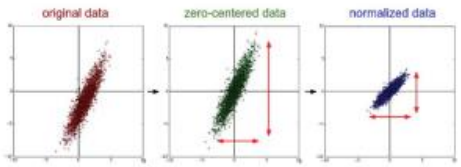
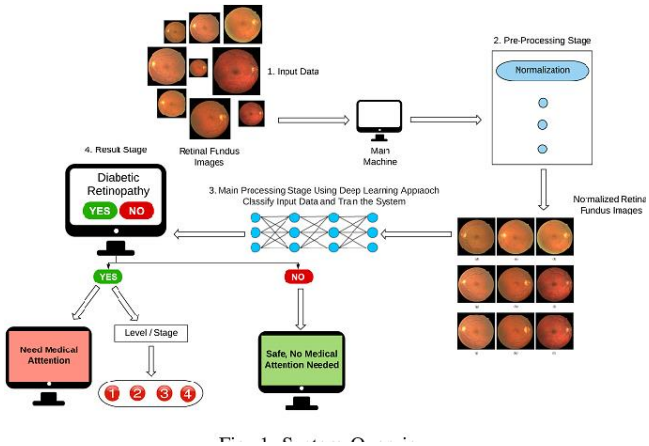


Fig. 3. Normalizing

In this approach, extraction of retinal blood vessels, exudate, micro-aneurysms, haemorrhages and texture features takes place, followed by construction of Multiclass SVM using area of lesions and texture features. Impressive results are reported using the publicly available datasets DIARETDB0 and DIARETDB1 with accuracy of 0.96 and 0.946 respectively. Considering the heterogeneity of the dataset, the performance of the proposed model is satisfactory. The accuracy of the model can be increased by using other complex denoising techniques.



3. METHODOLOGY

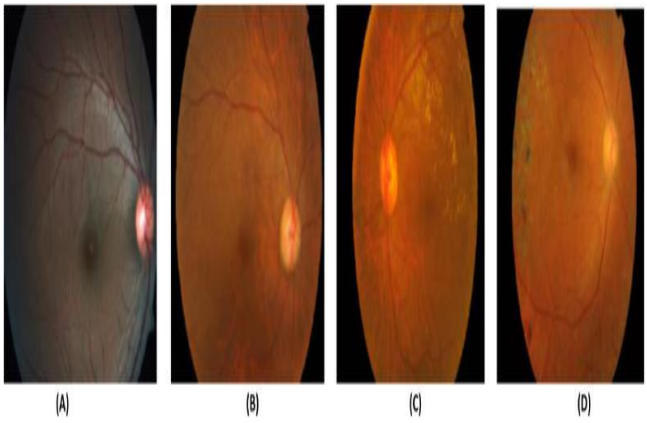
Upload MRI images dataset: use this button to get upload images.

Generate images train & test model: use this button to get generate images train & test model.

Generate deep learning CNN model: use this button to get deep learning CNN model.

Get drive HQ images: using this button to get open drive HQ

Predict tumor: use this button to get predict tumor.



CONCLUSION

A model is presented for classification of DR stages based on the severity using color fundus images. The performance of the model is assessed using different metrics. Considering the heterogeneity of the dataset, the performance of the proposed model is satisfactory. The accuracy of the model can be increased by using other complex denoising techniques. Incorporating experimental errors during image capture will be helpful in developing more efficient normalization methods.

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