Diabetic Retinopathy Detection Using Deep Learning

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Abstract Diabetes sickness upsurges the quantity of glucose in the blood triggered by a deficiency of insulin. Diabetes affects retina, heart, nerves and kidney. One important complication is Diabetic Retinopathy. The mechanized methods for Diabetic Retinopathy recognition are flexible for cost and time reduction and are more competent over manual analysis. Deep Learning technique performs computer aided medical diagnosis. This paper is an attempt toward finding an automatic solution for Diabetic Retinopathy disease in initial stage. Using Artificial Intelligence and Deep Learning, doctors can find blindness before it happens. In this project we are using supervised learning approach to perform classification on fundus images. For this task we are employing several image processing procedures and filters to improve many significant features like microaneurysm, hemorrhages, exudates, swollen blood vessels which are the features of fundus image that imply that particular person has Diabetic Retinopathy and then using neural networks for classification. This classifies the fundus images with an accuracy of 82% by using ResNet architecture.

Keywords Deep learning · Diabetic Retinopathy · ResNet

1 Introduction

Blindness or Diabetic Retinopathy is a problem with diabetes that reasons blood vessels of the retina to swell and to leak fluids and blood. It is a condition because of Type 1 and Type 2 diabetes and can progress if blood sugar levels are not controlled

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for a longer duration. These problems affect vision of eye. So, dealing of diseases at prior stage is vital. Diabetic Retinopathy is perceived by the presence of different types of lesions on a retina image.

Providing a user-friendly interface to detect whether the patient has Diabetic Retinopathy. The user has to upload the fundus image, this image undergoes preprocessing and the trained model predicts the results. Using ResNet architecture significantly enhanced the performance of neural networks with more layers. ResNet architecture is used to train the model for classification of fundus images into 5 categories as: No_DR, Mild, Moderate, Proliferate and Severe.

2 Literature Survey

Abràmoff et al. [1], considered two fundus images from each eye which was analyzed by a retinal expert. Author applied two algorithms separately on the dataset. The result of applying the Eye Check algorithm gave an AUC of 0.839 and applying the Challenge 2009 algorithm gave an AUC of 0.821. Gargey et al. [2], developed a device for automatic discovery of Diabetic Retinopathy and classified the images into healthy or having DR. Author tested model using the public MESSIDOR 2 and E-Ophtha databases for external evaluation and resulted 0.94 and 0.95 AUC values. Wilfred Franklin and Edward Rajan [3] proposed automated tool with high accuracy of the detection of blood vessels. Author worked on automatic segmentation algorithm on images of the DRIVE database and noticed 95.03% accuracy.

Antal and Hajdu et al. [4], used image level, lesion-specific and anatomical components. Author worked on classifiers and tested on the publicly available dataset Messidor, where resultant AUC is observed 0.989. Liskowski et al. [5], used supervised approach along with deep neural networks on image datasets also proposed a supervised method which makes use of deep neural networks on raw images data. But they can work more efficiently on preprocessed images. Author performs structured prediction with classification and produced result with AUC greater than 0.99, accuracy greater than 0.97. Results also derived sensitivity greater than 0.87 in fine vessels. Revathy et al. [6], used an SVM-based training approach to data and classified them into three classes as mild, moderate non-proliferative Diabetic Retinopathy and proliferative Diabetic Retinopathy. Approach used various classification algorithms and noted good accuracy with 82%.

3 Proposed System

The goal of the proposed system is to increase screening ability for disease with severity condition. We are proposing model based on a ResNet which mechanically traces patient's fundus image collected from technician and helps to guess the severity of blindness. Architecture of proposed work is given in Fig. 1.

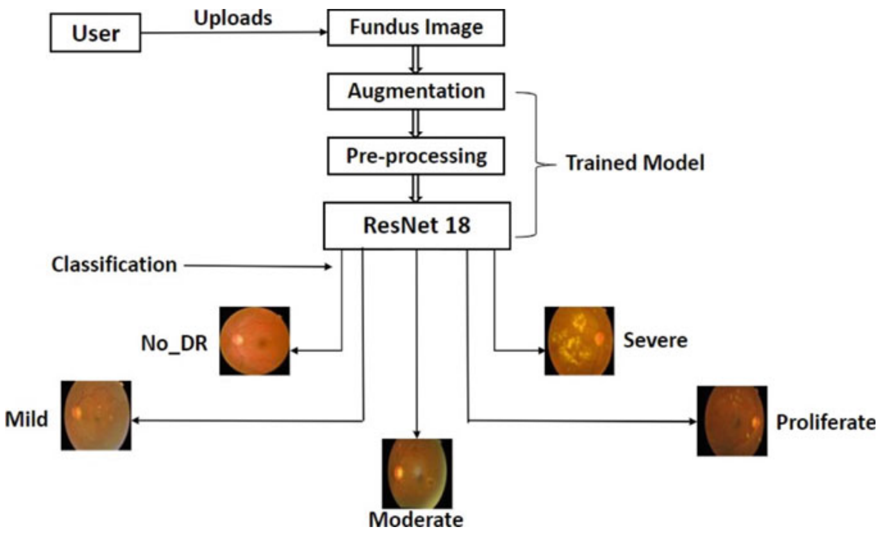

Fig. 1 Architecture diagram

The image is taken in the form of an array of pixels. The images are labeled with their classnames (No_DR, Mild, Moderate, Proliferate, Severe). The dataset is rescaled and preprocessed with certain filters to extract the important features.

The preprocessing stage includes rescaling, grey_scale, horizontal_flip, vertical_flip, shear_angle etc. performing data augmentation and shuffling the dataset and splitting it into train and test. Creating a data generator for training, testing and validation datasets. Building ResNet-based deep learning model which has 18 layers. The Res-block has an identity block and convolutional block. The Res-block has an identity block and convolutional block followed by Compiling and training the model. To prevent the overfitting issue we performed early stopping to exit training if validation loss is not declining even after certain epochs. We assessed the performance of the trained model and visualized the results and plotted the confusion matrix to analyze the classification. The result, which is the diagnosis of the patient, is displayed on the user interface.

4 Implementation

We have used the following software tools for model training and deployment: Anaconda-Jupyter for Training and Anaconda—Spyder for Deployment. For front end development Sublime text editor is used along with Programming languages Python, HTML, CSS, JavaScript, Flask app.

The dataset is taken from the Kaggle source which has fundus images taken by technicians. The fundus image is taken from the back side of the retina while the pupil is dilated. Obtained Graph and Pie-Chart of Dataset is given in Fig. 2

Figure 2 depicts the number of fundus images under different classes i.e., No_DR, Mild, Moderate, Proliferate, Severe.

We have used the ResNet architecture to train the model with 18 layers. Below is the sample table which depicts the layers of the trained model (Table 1).

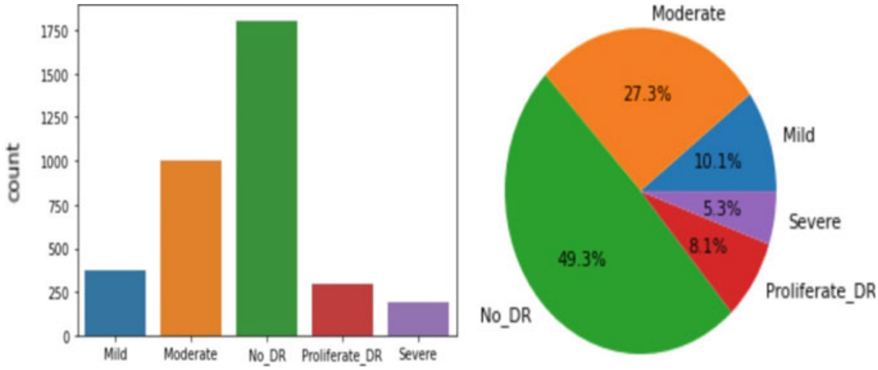

Fig. 2 Graph and Pie-chart of dataset

Table 1 Layers of trained model

Model: "Resnet18"			
Layer (type)	Output Shape	Param#	Connected to
input_1 (InputLayer)	(None, 256, 256, 3)	0	
zero_padding2d (ZeroPadding2D)	(None, 262, 262, 3)	0	Input_1[0][0]
conv1 (Conv2D)	(None, 128, 128, 64)	9472	zero_padding2d[0][0]
bn_conv1 (BatchNormalization)	(None, 128, 128, 64)	256	Conv1[0][0]
activation (Activation)	(None, 128, 128, 64)	0	bn_conv1[0][0]
max_pooling2d (MaxPooling2D)	(None, 63, 63, 64)	0	activation [0][0]
res_2_conv_a (Conv2D)	(None, 63, 63, 64)	4160	max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 31, 31, 64)	0	res_2_conv_a[0][0]
bn_2_conv_a (BatchNormalization)	(None, 31, 31, 64)	256	max_pooling2d_1[0][0]
activation_1 (Activation)	(None, 31, 31, 64)	0	bn_2_conv_a[0][0]

(continued)

Table 1 (continued)

Model: "Resnet18"			
Layer (type)	Output Shape	Param#	Connected to
res_2_conv_b (Conv2D)	(None, 31, 31, 64)	36,928	activation_1[0][0]
bn_2_conv_b (BatchNormalization)	(None, 31, 31, 64)	256	res_2_conv_b[0][0]
activation_2 (Activation)	(None, 31, 31, 64)	0	bn_2_conv_b[0][0]
res_2_conv_copy (Conv2D)	(None, 63, 63, 256)	16,640	max_pooling2d[0][0]
res_2_conv_c (Conv2D)	(None, 31, 31, 256)	16,640	activation_2[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 31, 31, 256)	0	res_2_conv_copy[0][0]
bn_2_conv_c (BatchNormalization)	(None, 31, 31, 64)	1024	res_2_conv_c[0][0]
bn_2_conv_copy (BatchNormalization)	(None, 31, 31, 256)	1024	max_pooling2d_2[0][0]
add(Add)	(None, 31, 31, 256)	0	bn_2_conv_c[0][0] bn_2_conv_copy[0][0]
activation_3 (Activation)	(None, 31, 31, 256)	0	add[0][0]
res_2_identity_1_a (Conv2D)	(None, 31, 31, 64)	16,448	activation_3[0][0]
bn_2_identity_1_a (BatchNormalization)	(None, 31, 31, 64)	256	res_2_identity_1_a[0][0]
activation_4 (Activation)	(None, 31, 31, 64)	0	bn_2_identity_1_a[0][0]
res_2_identity_1_b (Conv2D)	(None, 31, 31, 64)	36,928	activation_4[0][0]
bn_2_identity_1_b (BatchNormalization)	(None, 31, 31, 64)	256	res_2_identity_1_b[0][0]
activation_5 (Activation)	(None, 31, 31, 64)	0	bn_2_identity_1_b[0][0]
res_2_identity_1_c (Conv2D)	(None, 31, 31, 256)	16,440	activation_5[0][0]
bn_2_identity_1_c (BatchNormalization)	(None, 31, 31, 256)	1024	res_2_identity_1_c[0][0]
Add_1(Add)	(None, 31, 31, 256)	0	bn_2_identity_1_c[0][0] activation_3[0][0]
activation_6 (Activation)	(None, 31, 31, 256)	0	add_1[0][0]
res_2_identity_2_a (Conv2D)	(None, 31, 31, 64)	16,448	activation_6[0][0]
bn_2_identity_2_a (BatchNormalization)	(None, 31, 31, 64)	256	res_2_identity_2_a[0][0]
activation_7 (Activation)	(None, 31, 31, 64)	0	bn_2_identity_2_a[0][0]

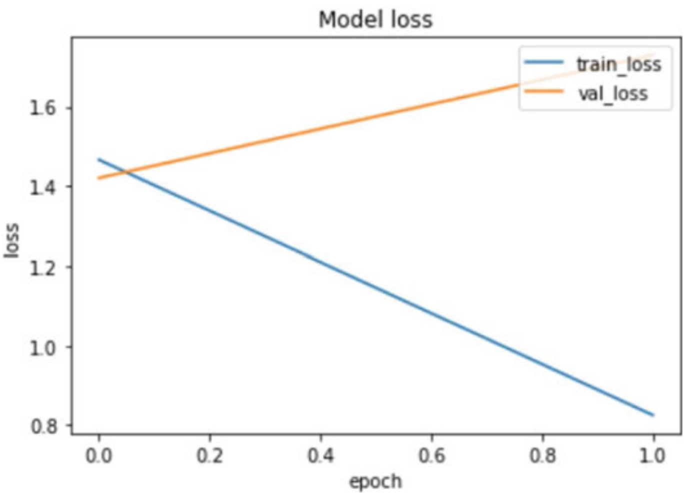

Fig. 3 Graph depicting validation loss

	precision	recall	f1-score	support
Mild	0.71	0.51	0.59	73
Moderate	0.71	0.83	0.76	196
No_DR	0.94	0.97	0.95	371
Proliferate_DR	0.65	0.54	0.59	56
Severe	0.65	0.41	0.50	37
accuracy			0.82	733
macro avg	0.73	0.65	0.68	733
weighted avg	0.82	0.82	0.82	733

Fig. 4 Classification report

The validation loss of the trained model is shown below as a graph with X-axis as Epoch and-axis as Loss in Fig. 3.

Classification report is shown in Fig. 4.

5 Conclusion

In manual scenario images are directed to clinicians for scaling does not perform accurate grade and classification. The trained model using ResNet architecture performs fast diagnosis and immediate reply. We received classification of the fundus images with an accuracy of 82% by using ResNet architecture.

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