Diabetic Retinopathy Detection Using Deep Learning

Ms.S.Devisri,Ms B.Sangamitra, Mr.Y.Sakthivel, Ms.K.Sujitha
Department Of Computer Science And Engineering ,Velalar College Of Engineering And Technology, Erode
Assistant Professor, Student

ABSTRACT- Digital retina fundus images were used with computer vision technique to automatically detect diabetic retinopathy in different stages, and more recently, by using deep learning image processing method. Deep learning is a proven methodology that automatically extracts features from images processed by a layer stack of a convolutional neural network. These features can determine what is present in the image, and therefore it is useful for classification purposes. Deep learning models showed a higher capability in recognizing objects than the human eye. However, this methodology still requires considerable data and computational resources to optimize the model's parameters. In this work, we proposed a Deep learning model to classify retina fundus images. These fundus images are pre-processed, augmented and trained to detect the presence of DR in its different stages. The model was optimized using transfer-learning from DenseNet121 to differentiate between a healthy eyeball and a proliferated one. Our proposal was tested over the APTOS dataset for each phase in predicting diabetic retinopathy presence in fundus oculi images.

Keywords---Diabetic Retinopathy (DR), Deep Learning, DenseNet121 Architecture

I. INTRODUCTION

In recent times, India and other parts of the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey, 8% of the country population has been diagnosed of diabetes disease alone and it had been recognized and accepted as one of the main causes of blindness in the country if not properly treated and managed. The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is a disease that affects the blood vessels present in the retina, which is damaged due to multiple alterations by a set of metabolic disorders. It causes progressive damage to the retina, the light-sensitive lining at the back of the eye. Diabetic retinopathy is a serious sight-threatening complication of diabetes.

Depending on the stage of diabetic retinopathy, it can be classified into different classes, from the earliest to the most advanced. This classification depends on the condition of the retina in its fundus oculi evaluation, divided into two main categories, Non-proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is subdivided into slight, medium, and severe, and the changes it produces are limited to the retina and do not go beyond the inner retinal limiting membrane. PDR can be subdivided into early, high-risk, and advanced, with alterations produced by ischemia, result in blood vessels which proliferate beyond the retina. No DR: Patient without retinal alterations due to diabetes.

Mild DR: In this case, microaneurysms, exudates, cotton-wool spots, and retinal hemorrhages are considered. Moderate DR: The fundus oculi present hemorrhages, severe microaneurysms, or venous rosaries in some retina quadrants. Severe DR: Two of three criteria from the medium NPDR exist in the fundus oculi. Proliferative DR: Proliferative retinal neovessels appear in the retina's image.

II. RELATED WORKS

[1] Diabetic retinopathy detection using deep learning

In this paper, training is done using the model called DenseNet on an enormous dataset including around 3662 images to automatically detect the DR stage and these are classified into high resolution fundus images. The Dataset used in this project is available on Kaggle (APTOS). There are five DR stages, which are 0, 1, 2, 3, and 4. In this paper patient's fundus eye images are used as the input parameters. A trained model (DenseNet Architecture) will further extract the feature of fundus images of eye and after that activation function gives the output. This architecture gave an accuracy of 0.9611 (quadratic weighted kappa score of 0.8981) to DR detection. The comparison between two CNN architectures, which are VGG16 architecture and DenseNet121 architecture is done. The two architectures are VGG16 and DenseNet121 and the accuracies are 0.7326 and 0.9611 respectively. The QWK scores are obtained from the model.

[2]Diabetic retinopathy detection using deep Convolutional neural network

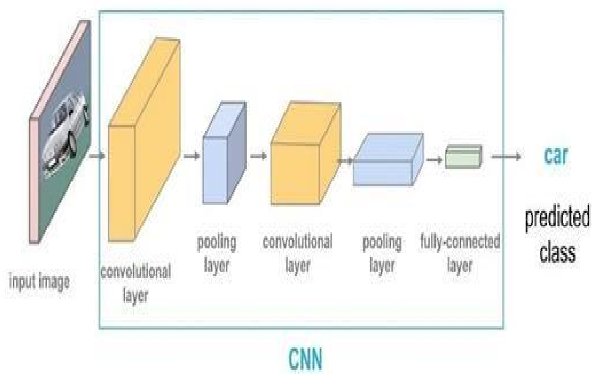
This paper presents the design and implementation of GPU accelerated deep convolutional neural networks to automatically diagnose and thereby classify highresolution retinal images into 5 stages of the disease based on severity. The single model accuracy of the convolutional neural networks presented in this paper is 0.386 on a quadratic weighted kappa metric and ensembling of three such similar models resulted in a score of 0.3996. This paper presents the design, architecture and implementation of deep convolutional neural networks for automatic detection and classification of diabetic retinopathy from color fundus retinal images. It also discusses the quadratic kappa metric used to evaluate the prediction results. This research involves three major CNN models, designing their architectures and finding the corresponding quadratic kappa scores..

[3]Convolutional neural networks for diabetic retinopathy

In this experiment, convolution neural network approach is used for detecting diabetic retinopathy. The publicly accessible Aptos Blindness Detection dataset is used to train a convolution neural network, where the image is processed at an early stage, primarily involving image resizing, pixel rescaling, and label encoder. After that, an image is given to the convolution neural network model, to decide whether the patient has diabetic retinopathy or not. About 3789 color retinal images are used in experiments to train the proposed model and about 948 images are collected to test its efficiency in classification. Accuracy of 96.15%, Sensitivity 79%, Precision 89%, and F1-Score 84.1% is achieved using the Convolution Neural Network-based method.

[4] Automatic Detection of Diabetic Retinopathy using Neural Networks and Support Vector Machine

In image pre-processing, segmentation techniques involves processing of fundus images to detect features. The proposed techniques have been tested on the images of IDRiD database for DR. So, a total of 516 images were tested and classified into normal, abnormal and microaneurysm. The detection results were judged by some expert ophthalmologists and a classification sensitivity, specificity and accuracy of 98%, 67% and 96%, are respectively obtained.



[5]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% were scored on the Messidor-2, consecutively.

III.DATASETS

APTOS: APTOS stands for Asia pacific Tele-Ophthalmology Society dataset which consists of 3662 labelled high-resolution colour fundus retinal images belonging to five classes corresponding to the five stages of the disease. The test set consists of 1928 images and fully have been utilized for this paper. The images have been open-sourced by Kaggle, a free platform for retinopathy screening. A trained clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4. The images in the dataset come from different models and types of cameras, which can affect the visual appearance of left and right retinas. Some images are shown as one would see the retina anatomically (macula on the left, optic nerve on the right for the right eye). Others are shown as one would see through a microscope condensing lens (i.e. inverted, as one sees in a typical live eye exam). There is also noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed, or overexposed and are of different resolutions.

Number of images in APTOS Dataset:

LABEL	VALUE COUNT
No DR	1805
MILD DR	370
MODERATE DR	999
SEVERE	193
PROLIFERATIVE DR	295

IV.METHODOLOGIES

DENSENET121 – ARCHITECTURE

In a traditional feed-forward Convolutional Neural Network (CNN), each convolutional layer except the first one (which takes in the input), receives the output of the previous convolutional layer and produces an output feature map that is then passed on to the next convolutional layer. Therefore, for 'L' layers, there are 'L' direct connections; one between each layer and the next layer. However, as the number of layers in the CNN increase, i.e. as they get deeper, the 'vanishing gradient' problem arises. This means that as the path for information from the input to the output layers increases, it can cause certain information to 'vanish' or get lost which reduces the ability of the network to train effectively. DenseNets resolve this problem by modifying the standard CNN architecture and simplifying the connectivity pattern between layers. In a DenseNet architecture, each layer is connected directly with every other layer, hence the name Densely Connected Convolutional Network. For 'L' layers, there are L(L+1)/2 direct connections.

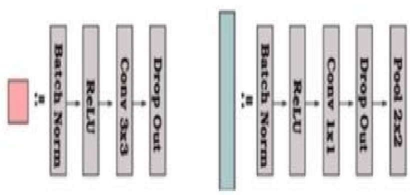
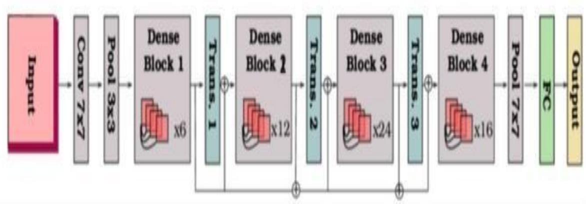


Fig 2: DenseNet-121 Architecture



Connectivity

In each layer, the feature maps of all the previous layers are not summed, but concatenated and used as inputs. Consequently, DenseNets require fewer parameters than an equivalent traditional CNN, and this allows for feature reuse as redundant feature maps are discarded. So, the lth layer receives the feature-maps of all preceding layers, x0,...,xl-1, as input:

DenseBlocks

The use of the concatenation operation is not feasible when the size of feature maps changes. However, an essential part of CNNs is the down-sampling of layers which reduces the size of feature-maps through dimensionality reduction to gain higher 12 computation speeds. To enable this, DenseNets are divided into DenseBlocks, where the dimensions of the feature maps remains constant within a block, but the number of filters between them is changed. The layers between the blocks are called Transition Layers which reduce the number of channels to half of that of the existing channels.For each layer, from the connectivity formula, Hl is defined as a composite function which applies three consecutive operations: batch normalization (BN), a rectified linear unit (ReLU) and a convolution (Conv). In the Fig 3, a deep DenseNet with four dense blocks is shown. The layers between two adjacent blocks are the transition layers which perform downsampling (i.e. change the size of the feature-maps) via convolution and pooling operations, whilst within the dense block the size of the feature maps is the same to enable feature concatenation.

Growth Rate

The size of the feature map grows after a pass through each dense layer with each layer adding 'K' features on top of the

Although each layer only produces k output feature-maps, the number of inputs can be quite high, especially for further layers. Thus, a 1x1 convolution layer can be introduced as a bottleneck layer before each 3x3 convolution to improve the efficiency and speed of computations.

PROJECT WORKFLOW

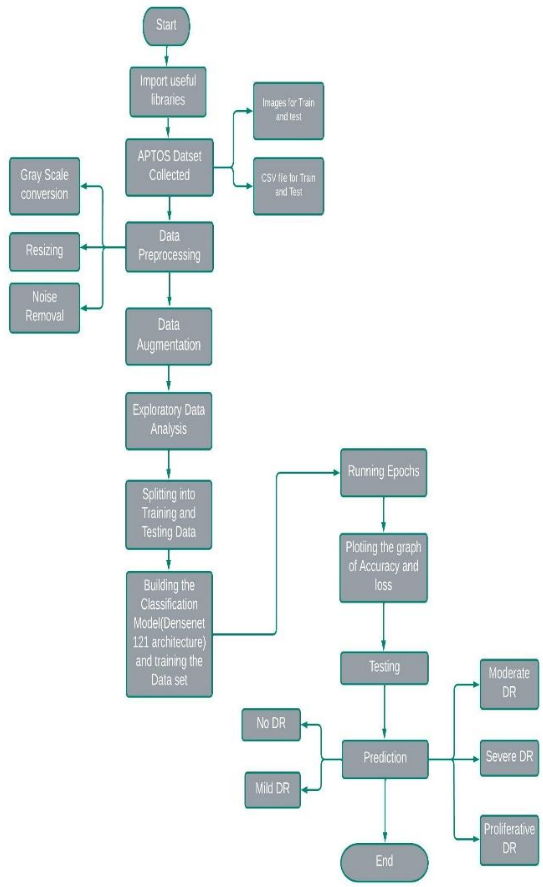


Fig 4. Project workflow

VII.CONCLUSION

In this project, deep learning is implemented to classify Diabetic Retinopathy into 5 classes with a much-reduced training data than other previous DR classification techniques employed. This was done to design a way to train a DL model that performs well on unseen data by efficiently learning from small dataset because training data is limited in healthcare. Our model has reached at an accuracy that is comparatively higher than other techniques that have used transfer learning on the whole Kaggle DR 29 challenge dataset for multi-class classification. Deep learning techniques that can learn from small dataset to categorize medical images should be utilized to classify DR, as this can be transferred to other medical image classification problems facing the challenge of insufficient training data. Experiments should be done to compare performances of other pre-trained deep convolutional Networks.

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