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RECENT ADVANCES IN AUTOMATED DETECTION AND CLASSIFICATION OF DIABETIC RETINOPATHY USING DEEP LEARNING

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ABSTRACT

Diabetes is a very common disease worldwide. It is primary cause of blindness for people having age less than 50 years. Diabetic retinopathy is a common retinal complication associated with diabetes. Screening and classifying malignancies in diabetic retinopathy is a challenging task because it is symptomatic. Several techniques are available for the identification of abnormality. In this paper algorithms based on deep learning and convolution neural networks are reviewed for diagnosis of Diabetic Retinopathy. A comparison of all methods based on preprocessing techniques, types of feature extraction, convolution neural network architectures and performance metrics is presented. It is observed that Accuracy of any technique depends upon various factors like number of preprocessing steps, number of features used, and number of convolution layers, number and type of data sets used for training the model at the cost of complexity.

Index Terms—Diabetic Retinopathy; Deep Learning; Convolution Neural Network; Microneurysms; Hemorrhages; Exudates.

INTRODUCTION

Diabetes is one of the main reasons for the rapid progression of diabetes current health care challenges. Number of people suffering from this disease are growing into a dangerous state Rate. The World Health Organization (WHO) expects the number of people with diabetics to increase from 130 million to 350 million over the next 25 years [1]. Diabetes is a disorder affecting the body's metabolism wherein the body cannot store and use the energy it contains in food. More precisely, this is a condition that impedes the body's ability to use glucose as a fuel. As a result, blood sugar levels gradually increase. When the blood glucose level is high, many complications like macro and micro vascular changes that result in heart disease, Kidney, retinal problems, and Retinopathy.

Diabetic Retinopathy (DR) is a silent disease and fatal illness. It occurs at last stage where treatment is difficult and in few cases impossible to treat, this can be effectively treated only in its early stages and therefore it is important to find it out at its earliest through regular screening. DR is a prominent example of diabetic eye illness. It comes about due to variations in the blood vessel of the retina. It affects sight seriously and in few occurrences causes blindness. The retinais the tissues that are sensitive to light and are positioned at the backward portion of the eye. For a good vision robust retina is essential. No symptoms are present in the former stages of DR. Some may observe variations in vision like the difficulty of reading or seeing far away objects. These changes may come and go. Blood starts to flow into the membranes (liquid-like gel in the center of the eye) in the retina. If this takes place, one can see dark floating spots [2].

When the disease progresses, various retinal abnormalities begin to appear inside the retina such as Microneurysms (MA), Hemorrhages (HEM), Hard Exudates (HE), Soft Exudates (SE). Microneurysms are the earliest clinically see able changes of DR. They are small, circle and dark spots. MA is small usually less than 125 micrometers. Hemorrhages occurs due to blood leaks from the retinal vessels. Caused by hypertension, blockage of arterial vein. HM is similar to MA but larger and has not regular size. Hard exudates are yellowish dark spots that can be developed into rings known as circinates. Soft exudates are small, yellow-white spots. Multiple soft exudates more than six in one eye indicate generalized ischemia [3]. Fig. 1. Shows a sample input image affected by DR.

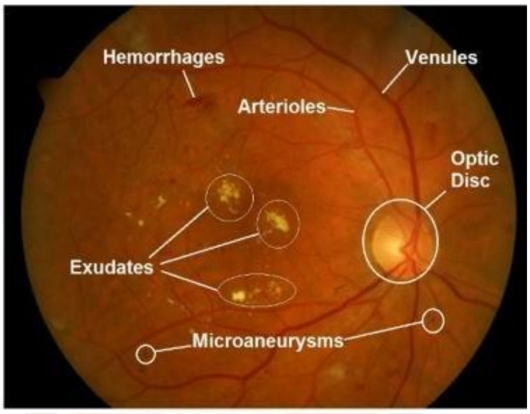

Fig. 1. DR Affected Sample Retinal Image [2]

DR is classified as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR): NPDR is the initial stage of DR. In this symptoms will be mild and non-existent and microscopic changes occur in the blood vessel of the eye. It is initially characterized by microneurysms that fall from the eyes and burst. PDR is a developing form by which new but weak blood vessels commence to restore blood supply [3].

DR can damage retina without showing any signs at the primary stage, successful early stage detection of DR can reduce the risk of progression to the advanced stages of DR. Automated analysis of retina color images has advantages that include efficiency and coverage of screening programs, reduced barriers to access, and early detection and treatment. In recent years, most problems for the computer vision have been solved more precisely with the help of Deep Learning (DL) algorithms, such as Convolutional Neural Network (CNN). CNN has proven to be revolutionary in terms of computer detection of tracking and object detection, image and medical disease classification and localization, pedestrian detection, action recognition, and more. CNNs main feature is that it extracts features depending upon the application in automated way.

This paper is organized as follows: Section II gives a brief description about deep Learning and commonly used convolutional neural network architectures in the field of fundus retinal image processing. Section III details the fundus retinal image databases available for the DR classification. Section IV discusses the several deep learning based techniques used to detect and classify DR. Section V concludes the paper.

DEEP LEARNING

DL is a part of machine learning. DL methods have wide applications within different research analysis viz. graphical modeling of data, neural networks, parameters optimization, image analysis, and signal processing. DL method is the most important technology with many ophthalmology applications. DL has become a major research area in image processing and computer vision domain owing to the achievement in different applications. The DL is made up of multiple processing layers that learn the data representation; each level learns different aspects of the data.

CNN is also known as ConvNet, It is a deep learning algorithm that was initiated by Kunihiko Fukushima [4]. ConvNet is specializing in data processing that uses many layers such as convolution layers, pooling layers, and fully connected layers. Fig. 2. Shows a simple CNN architecture for MNIST classification [5].

Input Layer: The input layer holds the pixel values of the image.

Convolution Layer: This layer is very important in deter- mining the operation on CNN. The convolution layer applies the filter to extract features. The most important parameters in this layer are the number of kernels and the size of the kernels. A filter (or kernel) is an integral component of the layered architecture.

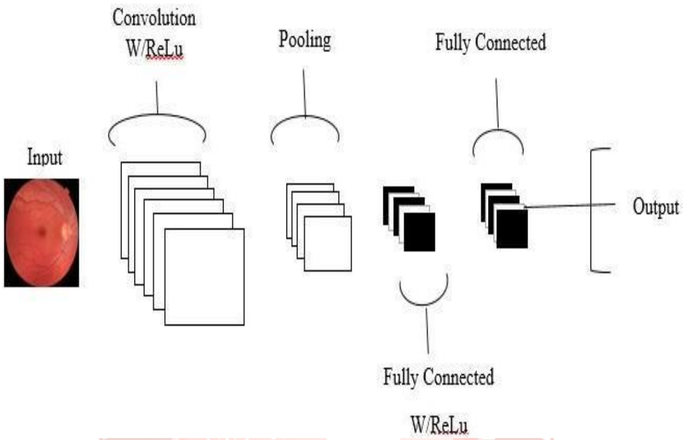

Fig. 2. CNN example [5]

Activation function layer: After applying convolution function nonlinearity is added to the output. Most common types of activation functions are Sigmoid, Rectified Linear Unit (ReLU), tanh, Leaky ReLU, Softmax etc.

Pooling Layer: To reduce the dimensionality of the net- work, pooling is done. It operates on each feature map independently. The most common approach used in pooling is max pooling.

Fully Connected layer: Fully connected layers are used at the end of the CNN after the convolution layers and the pooling layers. This layer take the results of the convolution/pooling process and use them to classify the image into a label. There are different types of CNN architecture they are described as follows:

A. GoogLeNet / Inception:

The Inception micro-architecture was first started by Szegedy [5]. This network architecture is very complex and deep. It introduced a new layer called Inception. Each inception layer has 6 convolutions and 1 pooling layer. GoogLe Net has recently monetized Popularity due to network architecture and use in many data science challenges. Several versions of GoogLeNet are available and can be used for image classification. Googlenet trains faster than VGG. Fig. 3. Shows inception module used in GoogLeNet.

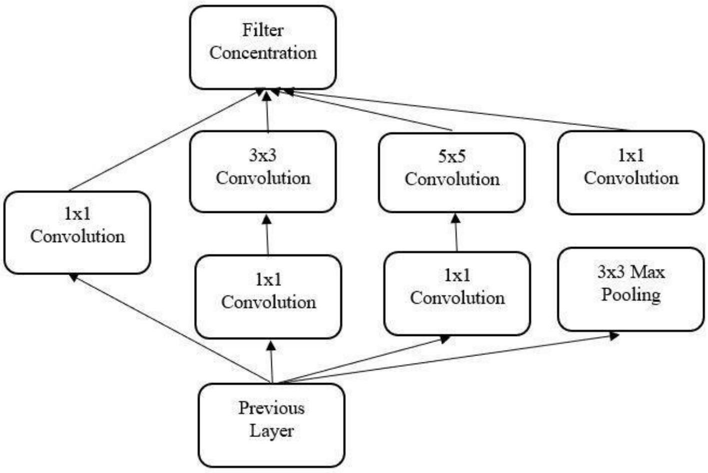

Fig. 3. Inception module used in GoogLeNet [6]

B. AlexNet:

The AlexNet network architecture was introduced by Alex Krizhevsky [7]. AlexNet consists of 8 layers: 5 convolution layers, 2 hidden layers and 1 output layer. AlexNet used ReLU as its activation function instead of Sigmoid. Fig.4. shows AlexNet architecture.

TABLE I

DATASETS FOR DR DETECTION

Datasets	Images	Format	Resolution	Tasks
DIARET DB1 [22]	5 Normal 84 with at least one NPDR sign	Images, Masks, GT: PNG	1500*1152	Microneurysms Hemorrhages Hard Exudates Soft Exudates
Kaggle [23]	80,000	JPEG	—	No DR Mild Moderate Severe PDR
DRIVE [24]	33 Normal 7 Mild to early DR Stage	Images:TIFF GT, masks:GIF	768*584	Vessels Extraction
STARE [25]	40	PPM	605*700	13 retinal diseases Vessels Extraction Optic Nerve
MESSIDOR [26]	1200	Images:TIFF Diagnosis: excel file	1440*960, 2240*1488, 23048*1536	DR grading Risk of DME
EyePACS [27]	9963	—	—	Referable DR Microneurysms

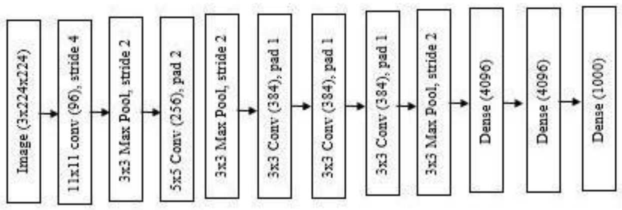

Fig. 4. AlexNet architecture [8]

C. VGGNet:

The VGG network architecture was first started by Simonyan [8]. VGG stands for Visual Geometry Group, the structure was designed to find how the intensity of a network influences its accuracy. Like Lennet and AlexNet, the VGG network can be segregate into two parts: the first part is usually the convolution and pooling layers, and the second is fully connected layers. This network could be used for image localization and classification tasks. VGG-M and VGG-VD- 16 are products of this research group. Fig. 5. Shows VGG architecture.

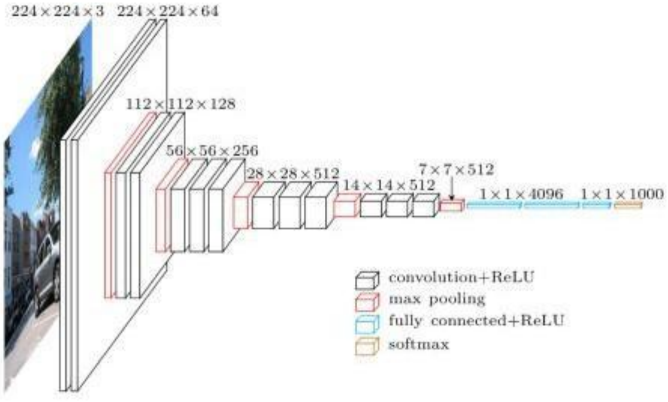

Fig. 5. VGG architecture [9]

I. AVAILABLE DATASETS

There are various datasets available publicly with fundus images used for validating automatic DR detection models. In deep learning methods, the image dataset is split into validation and training. Test dataset is used to assess network performance after training the network. The datasets available for DR research are shown in Table I.

II. RELATED WORK IN DR

In the last few years, many research work have been carried out and many effective methodologies, features and algorithms have been suggested by researchers. Fig. 6. Shows Generalized Block Diagram of Detection of DR and Classification using DL and CNN.

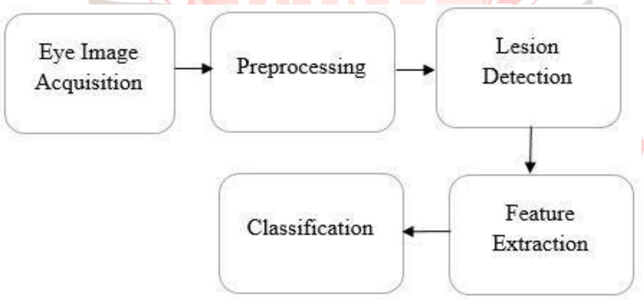

Fig. 6. Generalized Block Diagram of Detection of DR and Classification

- Step 1: Acquisition of image from publicly available data- sets and real time data.
- Step 2: Pre-processing operation on the data to remove noise and improve the quality of image.
- Step 3: Detection of various lesions such as Exudates, Microneurysms and Hemorrhages.
- Step 4: Extraction of features such as microneurysms counts, perimeter, area and exudate count, the area and perimeter of blood vessels and so on.
- Step 5: Classification based on combination of features using deep learning algorithm.

The performance of any algorithm for DR detection is measured in terms of various parameters such as Accuracy (AC), Sensitivity (SN) and Specificity (SP).

Let, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

Accuracy: It is defined as the ratio of the events correctly classified to the total number of instances $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$

- Sensitivity: It measures the degree of positively classified Positive events.

TP network. In this process, the analysis and training of algorithm is performed by Kaggle data set. The steps involved are translation, stretching, rotation and flipping to the labeled data set. Then convolution neural network is used for the automatic classification of diabetic retinopathy using color fundus image and achieved an accuracy of 94.5%.

Sensitivity = *TP* + *FN*

Jaun Shan et al., 2016 [17] have developed for

Microneurysms detection using CNN. In this approach Stacked

- Specificity: It measures the portion of correctly classified Negative instances.

$$\text{Specificity} = \frac{TN}{TN+FP}$$

Pavle Prentasi et al., 2015 [10] have investigated a technique for the exudates detection using CNN. The last segmentation result improved by enhancing the network by adding some preprocessing and post processing steps because grouping detected pixels in clusters and added some high level features. Darshit Doshi et al., 2016 [11] have proposed an approach for DR detection using deep CNN. The design and implementation of Graphics Processor Unit (GPU) increased deep convolution neural networks to automatically detect has been presented hence classifying retinal images into 5 stages of the disease based on severity. Three major CNN models were designed their architectures constructed and the corresponding quadratic kappa was found. The single model achieved an accuracy of 0.386 on a quadratic weighted kappa metric and the combination of the three types of models resulted in
0.3996.

Harry Pratta et al., 2016 [12] have developed a method for DR using CNN. Kaggle data set is used for testing and contains roughly 6m pixels per image and more than 80,000 images of retinopathy scales and they achieved an accuracy of 75%.

Lin at al., 2018 [13] have proposed deep learning method to compare the performance of detection for severe diabetic retinopathy between entropy images and original fundus images. In this paper authors achieved an accuracy of 86.10%, sensitivity of 73.24% and specificity of 93.81% using entropy images.

Sairaj Burewar et al., 2018 [14] have suggested method to detect DR through retinal segmentation by merging regions using CNN. Here U-Net segmentation with merging regions & Convolution Neural Network is used to detect various stages of DR. They achieved an accuracy of up to 93.33%.

Chandrakumar et al., 2016 [15] have advised deep convolution neural network solution that find better way to classifying the retinal images with little preprocessing techniques and might give high accuracy in DR classification. In this work authors used publicly available data sets such as Kaggle, DRIVE and STARE achieved around 94% of accuracy for classifying DR stages.

Kele Xu et al., 2017 [16] have presented an automated detection of diabetic retinopathy using deep convolution neural

Sparse auto encoder is used to detect MA. The stacked sparse auto encoder learns features from pixel intensity to identify specific features of the MA. Extracted features are given to the classifier to categories each image patch as MA or NON- MA. In this works authors measured the performance in terms of F-Measure 91.3% and average area under the ROC curve (AUC) 96.2%. F measure, is a measure of a tests accuracy. It is defined as the weighted harmonic mean of the tests precision and recall.

S. N. Sangeethaa and P. Uma Maheswari, 2018 [18] have developed a method for blood vessel segmentation in diagnosing diabetic retinopathy using CNN. Here morphological processing, thresholding, adaptive histogram equalization and edge detection are used for extraction of blood vessels and retinal image segmentation. Here CNN architecture is used for accurately classifying its severity. They achieved an accuracy of 96.7%, a sensitivity of 98%, and a specificity of 93%.

Maya K V and Adarsh K S, 2019 [19] used a DL algorithm in their work to detect the lesions in diabetic retinopathy. Here various preprocessing steps like, Optic disc is detected using morphological operation and the blood vessels are extracted using kernel fuzzy c-means algorithm. The Recognition of Diabetic features, involves two steps, first is to recognize HE, which is based on recursive region growing algorithm. Second recognition of HM and MA by using Matched Filtering and Mutual Information Maximization using differential evolution. Various features such as MA counts margin, area, and exudate count, the area and margin of BV are extracted. Then extracted features are assigned to CNN for classification purposes. 98% accuracy is achieved due to exhaustive feature extraction technique.

Hazim Johari et al., 2018 [20] used Alexnet deep learning neural network on retinal images for diabetic retinopathy detection by using availability public MESSIDOR data set. It is demonstrated that Alexnet layers is the perfect layer for deep learning. They achieved an accuracy of 99.3% for training and 88.3% for the testing set.

Carson Lam et al., 2019 [21] have developed a method for automatic diabetic retinopathy detection. Various preprocessing steps are used, cropped images using Otsu's method. The number of real-time images is increased to improve the efficiency of network localization.

In all these work, it has been observed that by changing preprocessing steps, feature extraction method, number of convolution layers Accuracy, sensitivity and specificity can be improved

TABLE II

COMPARATIVE ANALYSIS OF DEEP LEARNING METHODS

Authors	**Year**	**Purpose**	**Dataset**	**Preprocessing**	**Method**	**Performance Metrics**
Prentasic et al., [9]	2015	Detection of exudates in fundus images using CNN for early diagnosis of DR.	DRiDB	Total variation regularization denoising	Deep Neural Network or CNN	Sensitivity=0.78%, Ppv=0.78%, F-score=0.77%.
Doshi et al., [10]	2016	DR detection using deep CNNs.	EyePACS	Resized Image Green channel extraction Image enhancement	Deep CNN design, architecture and implementation for DR detection and quadratic kappa metric for	Accuracy=0.386 using single model and accuracy=0.3996 using Ensemble of three models.

					evaluation	
Carson Lam et al., [20]	2019	Automated Detection of Diabetic Retinopathy using Deep Learning.	MESSIDOR	Cropped Image Normalized Image Image Enhancement	Network with CNN architecture and data augmentation	Transfer learning on pretrained GoogLeNet and AlexNet models from ImageNet improved peak test set accuracies to 74.5%, 68.8%, and 57.2% on 2-ary, 3-ary, and 4-ary classification models, respectively.
Pratt, et al., [11]	2016	Diagnose DR from digital fundus images and Classifying its severity.	Kaggle	Image Resized Normalized Image	Network with CNN architecture and data augmentation	Sensitivity= 95%, Accuracy= 75%.
G. Lin et al., [12]	2018	Transforming Retinal Photographs to Entropy Images in DL to improve Automated detection for DR.	Kaggle	Image Rescaling Rotating Flipping	CNN	Sensitivity = 73.24%, Specificity= 93.81% , Accuracy= 86.10%.
Sairaj Burewar et al., [13]	2018	Diabetic Retinopathy Detection by Retinal segmentation with Region merging using CNN.	DRIVE	Black box removal & Image Resizing Green channel extraction Image Enhancement	U-Net segmentation with region merging & CNN	Accuracy=93.33 %.
Chandrakumar et al.,[14]	2016	Classifying Diabetic Retinopathy Using Deep Learning Architecture.	Kaggle, DRIVE,	Resizing Image Convert to gray scale then convert into the L-model	Deep CNN	Accuracy= 94%.

			STARE			
Xu et al., [15]	2017	Deep Convolutional Neural Network Based Early Automated Detection of Diabetic Retinopathy using Fundus Image.	Kaggle	Rotation Flipping Shearing Rescaling Translation	Deep CNN	Accuracy= 94.5%.
Shan et al., [16]	2016	Detection of microneurysms for early detection of DR.	DiaretDB	Image Rescaling Green channel extraction	2-layered stacked sparse autoencoder framework	F-measure=91.3%, Accuracy=96.2%.
Sangeethaa et al.,[17]	2018	Blood Vessel Segmentation in Diagnosing DR using CNN.	DRIVE, DiaretDB	Green channel extraction Image enhancement	Morphological Operation and CNN	Sensitivity =0.98 %, Specificity= 0.93% , Accuracy= 0.96%.
Maya K V et al., [18]	2019	Detection of Retinal Lesions Based on Deep Learning for Diabetic Retinopathy.	MESSIDOR	Green channel extraction	Recursive Region Growing Segmentation , Principle Component Analysis and CNN	Accuracy=\98% .
Hazim Johari et al., [19]	2018	Early Detection of DR by using Deep Learning Neural Network	MESSIDOR	Image Filtering Image Resizing	Alexnet Convolution Neural Network	Accuracy of the CNN for training 99.3 % and testing set 88.3%.

CONCLUSION

DR is a form of diabetes that worsens the retina, causing vision problems. Early detection of diabetic retinopathy is very important as it allows timely treatment to curtail the burden of disease on patients and their families. In this paper DR detection and classification based on DL techniques are reviewed. Table II shows the comparative analysis of various method described in this paper. From this survey it is concluded that the accuracy of the model can be improved by the combination of preprocessing and suitable number of convolution layers. It is also observed that alexnet convolution neural network achieves the higher detection accuracy

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