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DEEP LEARNING TECHNIQUES FOR DIABETIC RETINOPATHY: A SURVEY

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Abstract: Diabetes is a common type of constantly recurring illness observed with various people with varying age segments resulting from low insulin generation, resulting in generating high glucose content in the body. If Diabetes is not treated in proper manner, it will lead to several diseases affecting different organs of the body. One such organ which gets affected with diabetes, if not treated properly is the Eye. Diabetes Retinopathy (DR) is one kind of Eye disease which is caused by overtime diabetes. Lots of people around the world suffer from this disease that would result in blindness if not cured on time. Many automated diagnostic systems is observed from literature that makes use of traditional extracted features. With the advent of Deep Learning, more precisely in the field of medical imaging, very specific and excellent results are obtained as the model learns to extract features by itself. Convolutional Neural Networks (CNN's) are prominent methods in deep learning in detection of DR through large datasets. In this paper, various traditional and deep learning based DR detection and classification methodologies are analyzed.

***Index Terms* - Convolutional Neural Networks (CNN), NPDR, PDR, Deep Learning, DR.**

I. INTRODUCTION

Diabetes mellitus, also known as Diabetes, is caused by high blood glucose level over the prolonged duration of time. As per the epidemic estimation over 370 million people worldwide will be affected by Diabetes by the end of 2030. People suffering from the above disease has high chances of DR occurrence because of damage occurred to retinal blood vessels due to high insulin level as mentioned above. With systematic screening and medical check-up around 85% of the people can be diagnosed and future trouble can be avoided. The only trouble with DR is it is almost asymptomatic eye disease where it will not show unique symptoms until the end stage is reached. Manual inspection of retinal image features is a tedious task. Hence many automated diagnostics systems have been developed which in turn helps optomologists in examining retinal abnormalities. The structure of the paper is as follows: section 2 gives insight on Diabetic retinopathy and its classifications. Section 3 gives the insight on Deep learning and different pretrained convolutional Neural Networks (CNN) Techniques used, section 4 gives the literature review and section 5 draws the conclusion remarks and inferences.

II. INSIGHT TO DR

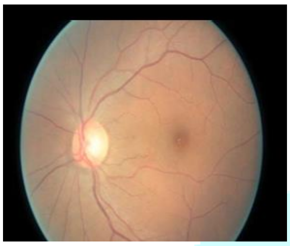
DR can be classified into two stages, one proliferative DR (NPDR) and proliferative DR (PDR).NPDR is early stage of DR which also has mild, moderate and severe phases.

The following table shows the different features of DR Classifications

Table 1. DR Classification Features

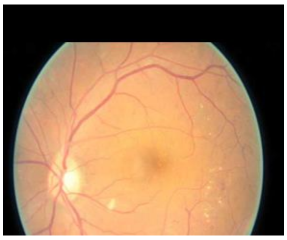
Stage	Observable findings	Class
I	No abnormalities	No DR
II	Micro-aneurysms only	Mild NPDR
III	Any of the following: - micro-aneurysms - retinal dot and blot haemorrhages - hard exudates	Moderate NPDR
IV	Any of the following: - > 20 intra-retinal hemorrhages in each of 4 quadrants - definite venous beading in 2 or more quadrants	Severe NPDR

	- prominent intra-retinal microvascular abnormality (IRMA) in 1 or more quadrants	
V	One or both of the following: - Neovascularization -Vitreous hemorrhage	PDR

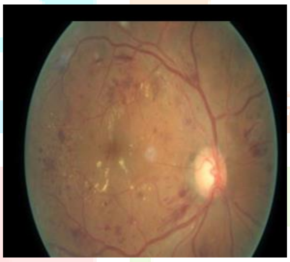


a)No DR

b)Mild DR



c)Moderate DR



d) Severe DR

e) PDR

Fig1.Stages of DR with increasing severity.

III.DEEP LEARNING

Deep learning is a powerful subset of ML which itself spans within AI[16]. Deep learning is the advancement on ANN after the introduction of convolution through CNN.Most of the detection and classification problems in medical domain are carried out with Deep learning techniques like convolutional Neural Networks (CNN), since the model doesn't require any separate classifier. The model will get trained with large image data sets and with more number of epochs training and validation losses will be minimized.

As shown in fig 2 the image will produce feature maps depending upon number of filters used to convolve in each layer.

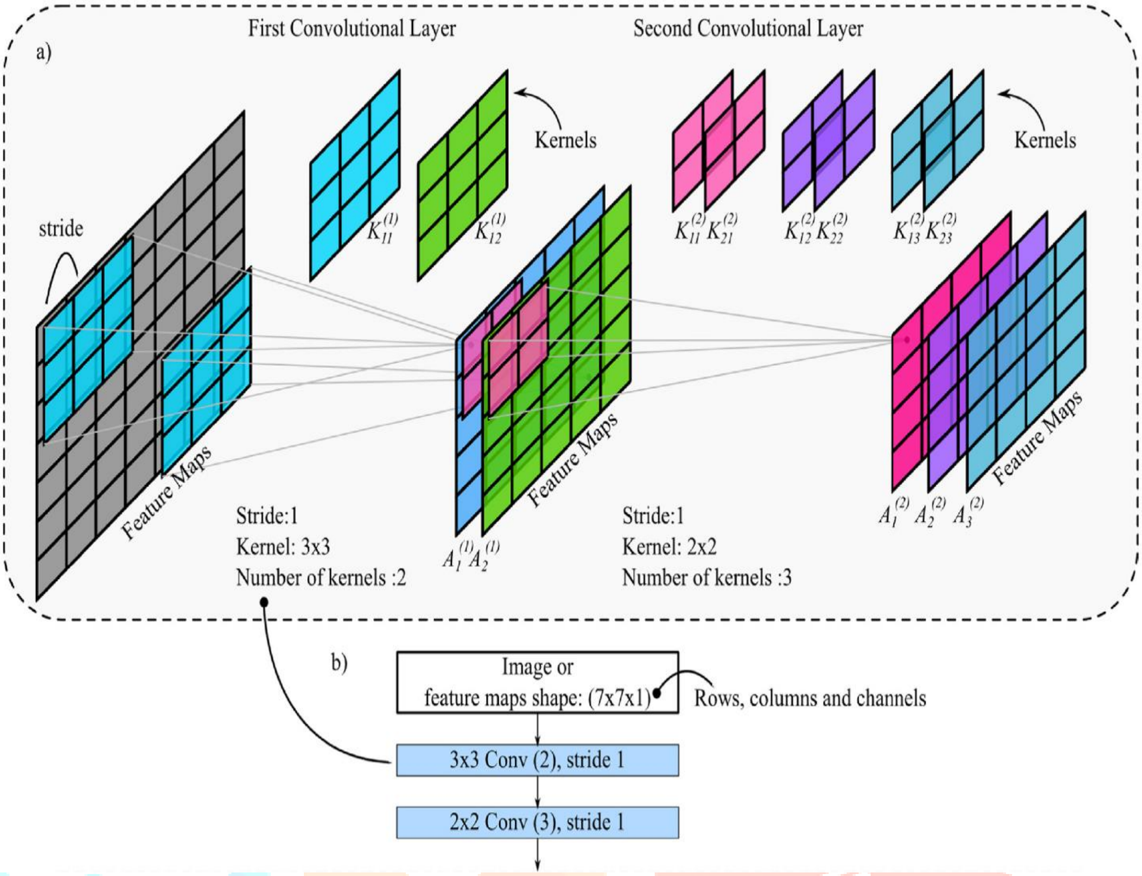


Fig2. Description of a two-layer convolutional neural network with 2 and 3 filters,

Different pretrained Architectures under CNN is described below

i)AlexNet

AlexNet is Pretrained CNN, which constitutes around 640,000 neurons and 60 million parameters. Developed in 2012 by Alex Krizhevsky and his co-authors in [2]. AlexNet consists of 5 convolution layers, some of them are succeeded with max-pooling layers and at the end with 3 fully connected layers with a softmax layer .There are many activation functions like hyperbolic tangent(tanh),sigmoid functions used in CNN ,but AlexNet salient feature is the implementation of the ReLu nonlinearity activation function into the training process.of neurons. Another salient feature is “dropout”, the process of enabling output of each hidden neurons to zero with a probability of 50%, for the last few fully connected layers to overcome over fitting problem. AlexNet architecture is shown below

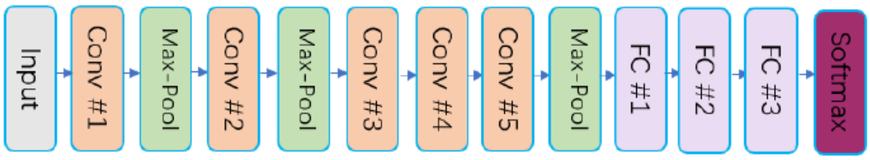


Fig 3.AlexNet Architecture

ii) VGG16

VGG16 is a variant of VGG model with 16 convolution layers. In this model we use kernel (filter) of size 3X3 with stride 1 to run over all convolution layers and with same padding to extract information. Different set of these filters are capable of extracting the information as that equivalent of AlexNet big filters, thereby enhancing the efficiency and advantage of lower number of parameters to be estimated during training. The max pooling layers uses 2x2 filters with stride 2 which decimates the activation maps. The output from the 13 convolution layers is then fed to three fully connected layers with 4,096, 4,096 and 1,000 channels respectively. A soft-max layer is applied at the end to obtain results in form of probabilities which makes characterization easier. The architecture of VGG 1 is shown below

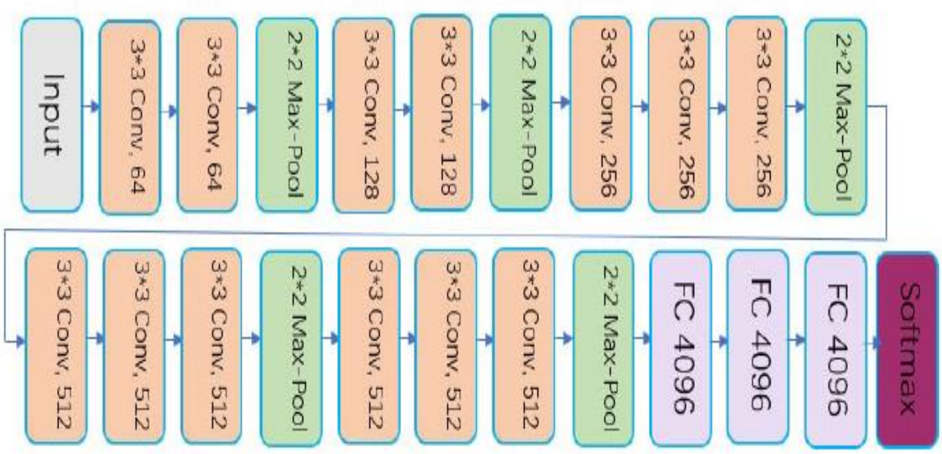


Fig 4.VGG16 Architecture

IV.LITERATURE REVIEW

Before diving into DL based DR detection methodologies, we will first look into the studies that rely on classical image processing techniques for detecting, segmenting, and analysing lesions in images depending on their precise characteristics and use of classifiers are discussed first.

DR classification into Normal, NPDR and PDR is carried out by using Neural network. Features once entered into neural Network it will classify into the subsequent classes. The results obtained are validated with by Comparing with grading from expert ophthalmologists. The outcome provided a classification accuracy of 93%, sensitivity of 90% and specificity of 100%. Dataset of 14 images was used here .Feature extraction was done using traditional method which is time consuming [4].

Gardner et al aim was to identify whether neural network can be used to identify DR in retinal images. A small dataset of 200 images were used. Features extracted were fed to network and the model was trained. The model provided sensitivity and specificity results of 88.4% and 83.5% when compared with ophthalmologist respectively for binary classification of DR.

Acharya et al have created an automated method for identifying the five classes ie Normal, Mild DR,Moderate DR,Severe DR,PDR. Features, which are extracted from the raw data using a higher-order spectra method, are fed in to the SVM classifier to generate the output. A small data set of 300 images was used .This method reported average accuracy of 82%, specificity of 86% and sensitivity of 82%.

Acharya et al[4] proposed a 5 class classification methodology by localizing features, like haemorrhages, micro-aneurysms, exudate and blood vessel. These extracted features are then fed to the SVM classifier. A sensitivity of 82%, specificity of 86% and accuracy of 85.9% was achieved by this model. A small dataset of 331 images were used in this method.

Adarsh et al also used image processing techniques to produce an automated diagnosis for DR through the detection of retinal blood vessels, exudate, micro- aneurysms and texture features. The area of lesions and texture features were used to construct the feature vector for the multiclass SVM. This achieved accuracies of 96% and 94.6% on the public 89 and 130 image databases DIARETDB0 and DIARETDB1 respectively [4].

From all the above methods we found that required features needs to be extracted well in advance before feeding it to the classifier. Also we observed th the data set used are maximum up to the range of 30 images. Thus these methods are fewer real times applicable.

We would discuss different methodologies under deep learning

Dorizz.B et al. [1] proposed a model in which 2 CNNs were used to diagnose DR, in accordance with statistical parameters of lesion patches. DIARETDB1 dataset was utilized for training purpose. IDRiD, Messidor, Messidor-2 DIARETDB0 Kaggle dataset were utilized for testing. The best outcome with sensitivity of 0.94 and an AUC of 0.912 was derived from Messidor.

Zhang et al. [2] proposed a system which uses Three CNNs to categorize the fundus image set as referable/ non-referable DR. Ahead to CNN training, preprocessing of images, augmentation is carried out , later Adaboost technique was applied to integrate. Network weights Updation is carried out by Adam optimizer. The model provided 88.21% of accuracy and AUC of 0.946while compared to individual deep learning models.

Chen.WB et al. in [3] proposed 3 different CNNs to determine the 5 stage DR making use of Kaggle fundus dataset .Performance measure of each CNN was carried out. The images were resized as preprocessing step as it is required individually by 3 pre-trained models and produced accuracy of 63.23%,for Inception –v3 50.03% for VGG16 , and 37.43% for AlexNet.

Coenen.F et al. [4] proposed a model where CNN was customized with following specification. The architecture is built up with 10 convolutional layers, 8 max-pooling layers, 3 FCL, and a softmax classifier to categorize Kaggle fundus images into 5 classes depending upon DR severity levels. The model has produced 95% specificity, 75% accuracy on data set of 8000 images and 5000 validation images.

Michael David et al.[5]developed a method where device IDX-DR X2.1 is incorporated with CNN.The analysis software in the device provided four results Negative,rDR,vtDR,low quality. Messidor -2(1748 images)dataset was used for analysis. Provided the sensitivity of 96.8%, specificity of 87%.A drawback in this method was it treats mild DR images as No-DR.

Mobeen-Ur-Rehaman et al.[6]developed a method which used customized 5 layer CNN model .Messidor dataset(1200 images) was used. The model was compared with pretrained AlexNet, VGG-16 and Squeeze Net which gave promising result of 97.87%Specificity, 98.94% of Sensitivity.

Yan Liang et .al[7] developed a method where transfer learning and hyper parameter tuning was coupled to pretrained models like AlexNet, VGGNet, GoogleNet, ResNet and made the comparison on DR image classification. Kaggle (35535 images) data set was used.VGG Net gave promising results with Specificity of 97.43% and Sensitivity of 97.43%.

Wang wt.al [9] developed a method that uses R-FCN .Feature pyramid network is used for modifying R-FCN.Two data set Messidor and hospital data set is used. Sensitivity of 92.59% for Messidor and Sensitivity of 99.3% is obtained.

Harangi et.al[8] developed a model where AlexNet is integrated with Handcrafted feature set. Kaggle data set was used for training and IDRiD for testing .Accuracy of 90.07% is obtained.

V.CONCLUSION

Automated DR detection systems are cost reliable, it will help in reduction of time for doctors in diagnosing retinal disorders and with on time treatment can be provided to prevent further complications. These systems impart a vital role in diagnosing diseases more precisely. Beginning of this paper, DR and its 5 stage classification with symptoms are discussed. In the literature survey, Traditional approach with feature extraction, SVM classifiers, ANN were discussed. With deep learning in this domain more promising results that can outstand traditional approaches can be achieved.

Through the Literature review some peer observation could be noticed that better performance can be attained with customized models and also with combination of Handcrafted features with CNN could be explored further.

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