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A Review on Classification of Diabetic Retinopathy Using Convolution Neural Network (CNN)

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ABSTRACT: Diabetic Retinopathy (DR) is certainly a common vision disease and substantial reason behind blindness in diabetics. It is one of the problems of diabetes that affects the eyes. If not really at an early on stages, then it can cause long term blindness.DR is a medical condition where the retina is damaged because fluid leaks from blood vessels into the retina. Diabetic retinopathy based on features such as blood vessel, exudes, hemorrhages, micro aneurysms.To accurately train a deep leaning model to classify DR, an enormous number of images is required and this is an important limitation in the DR. In this paper, target task is to implement diabetic retinopathy fundus images classification using CNNs based Transfer learning. Transfer learning technique that can help in overcoming the scarcity of fundus images. The main idea that is exploited by Transfer learning is that deep leaning architecture trained on Non-medical images. This review paper that focus on Automatic DR Detection and classification by using transfer learning to present the best existing methods to address this problem.

Figure 1: Normal and Diabetic Retinopathy

Retina is a part of human eye which faces a disease commonly terminated Diabetic retinopathy (DR). Diabetic patient is undoubtedly more prone to chance of DR. In case if the disease is not cured and it keeps growing, a person might be affected with complete blindness. The under developed nations do not have enough trained ophthalmologists and people are also not aware of such disease. DR is diagnosed by evaluating the retinal images of patients captured over time. However, the manual grading of images to define the severity of DR is very time consumingtogether with resource demanding. The blood flow toward all levels of retina is performed through micro blood vessel. Any congestion in this vessel experienced prospects to a significant eyeball destruction.

The symptoms of Diabetic retinopathy comprises of microaneurysms (MAs), hemorrhages (HMs),exudates (EXs) as well as the irregular

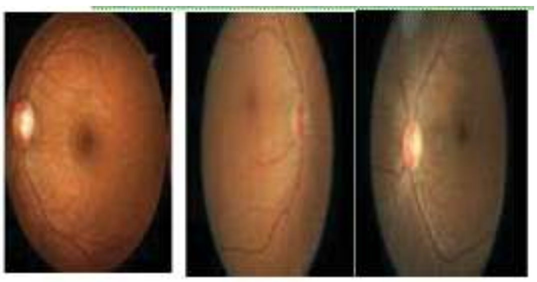
Keywords: Convolution Neural Network, Transfer learning, deep learning, Fundus images, Diabetic Retinopathy.

I. INTRODUCTION

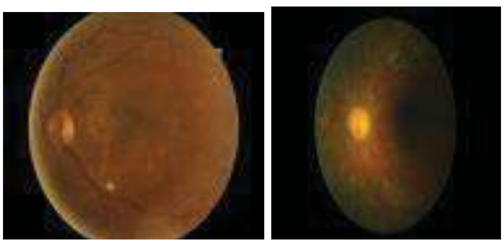
Diabetes mellitus (DM) is a chronic, metabolic, clinically heterogeneous disorder in which prevalence has been increasing steadily all over the world [1]. DM is characterized by persistenthyperglycemia, which may be due to impaired insulin secretion resistance to the peripheral action of insulin, or both, which eventually leads to pancreatic beta-cell failure [2]. People living with DM are more vulnerable to various forms of both short- and long-term complications due to metabolic aberrations that can cause damage to version organ systems, leading to the development of disablingand life-threatening health complications, the most prominent of which are micro vascular (retinopathy,nephropathy, and neuropathy) and macrovascular complication [3].

growth of blood veins. Diabetic retinopathy can be classify into five stages:

(a)No DR: Normal sign with No DR.
(b) Mild nonproliferativeretinopathy: During early stage of the disease microaneurysms occurs. Microaneurysms are small areas where balloon like swelling occurs in the blood vessel of the retina. It causes the fluid to leak into the retina.
(c)Moderatenonproliferative retinopathy:while the disease advances, the blood vessels begin to swell and distort. This completely affects their ability to transport blood. This condition incites change in the appearance of the retina.
(d) Severe nonproliferative retinopathy: During this stage blood vessels gets completely blocked. This seizes blood supply to area of the retina. These area disguise growth factors and gives signal the retina to grow new blood vessels.
(e) Proliferative diabetic retinopathy: This is highest stage of severity of diabetic retinopathy. At this stage, the growth factor triggers the retina to form new blood vessels. These new blood vessels are fragile and likely to leak and bleed. This lead to the contraction of scar tissues which causes retinal detachment.



(b) (c)



(d) (e)

Figure 2: Stages of Diabetic Retinopathy

Deep learning belongs to the broad family of machine learning methods [4]. Differently to traditional neural networks-based classifiers, deep learning builds classifiers with many hidden layers, aiming at identifying the salient low-level features of an image [5]. In the context of deep learning, transfer learning is a technique that exploits the usage of features that were learned by a network over a given problem to solve a different problem in the same domain.

Krizhevsky et al. [6], CNNs became the most popular technique for addressing the image classification problem. The authors achieved state-of-the-art performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition [7], outperforming other commonly used machine learning techniques. CNNs can be used in image classification, as well as natural language processing [8–10] and time series analysis [11, 12]. In all of these cases, training the weights of the deep network from scratch requires a substantial amount of time and huge datasets (hundreds of thousands of images). These requirements make deep learning algorithms very challenging in the context of medical images where, typically, only a limited number of images are available. A lot of time and experience are required to annotate medical images, and that is where transfer learning can play a significant role: It allows for the use of a pre-trained architecture that was previously fitted to images of the same domain.

Thus, transfer learning is particularly suitable for addressing the DR classification domain, whereThere is a lack of images to accurately train a CNN from scratch. Several studies have been done to classify DR by using CNN, either by using transfer

Learningorby introducing novel architectures but to the best of our knowledge, there have not been any reviews that survey the existing transfer learning techniques to classify DR images.

II. REVIEW PAPER

Xiaogang et al. (2017) discussed the usage of transfer learning for detecting DR by comparing differentnetwork architectures, including AlexNet, VGG-S, VGG16, and VGG19, to two datasets: the DR1 and Messidor datasets. DR1 1014 color images acquired.Images have resolution of 640x480 pixels. Messidor consists 1200 eye funds images acquired and resolution of 2240x1488 pixels. Three transfer learning techniques were analyzed: fine-tuning the entire networks,fine-tuning the networks layer-wise, and, finally the weights of network andapplying SVM as a classification layer. The authors used a stochastic gradient descent for the optimizer,and the images were pre-classified as either DR or No DR to pose a binary classification problem.The accuracy measure used was the AUC of the ROC curve. The highest AUC achieved was obtainedby fine-tuning the entire network, while the second-best performance was achieved by fine-tuninglayer-wise. The VGG-S architecture obtained the highest AUC that was achieved for the Messidordataset with an AUC of 98.34%. For the DR1 dataset, an AUC of 97.86% was obtained by using thesame network.

Shaohua wan et al. (2018) discussed compared the difference between transfer learning and learning from scratch. The author used different architecture like, AlexNet, Vggnet, Google Net, ResNet. The author experiment on the publically available Kaggle dataset they used the AUC of the ROC curve, Accuracy, Sensitivity, Specificity as evaluation criteria. The dataset contains 35,126 high resolution RGB Images with a resolution of about 3500x3000 pixels multiple varieties of imaging situations. The best experiment transfer learning did significantly increase the performance of CNN, with vgg-s producing the highest AUC 97.86% and ACC 85.86%.

Wang et al. (2018) In this paperstate-of-the-art CNN architecture used like, AlexNet, VGG16,Inception Net V3 for DR stage classification. The author experiment has been performed 166 images used from kaggle dataset. The author used for five stage classification instead of binary classification for specific dataset. Transfer learning process could be executed properly DR dataset are resized to 227x227 pixels, 224x224 pixels and 229x229 pixels respectively for AlexNet, VGG 16 and Inception Net V3. The author used K-fold validation with k=5 cross validation accuracy obtained by Inception Net V3 with best performed accuracy of 63.23%.

Harry pratt et al. (2016) CNN approach to diagnosing DR from digital fundus images and accurately classify severity. The author develops a network with CNN architecture and Data augmentation which can identify the intricate features involved in the classification task such as micro aneurysms, exudates, hemorrhages on the retina and consequently provide a diagnosis automatically and without user input. They train this network using a high end graphics processing unit (GPU) on the Kaggle dataset and impressive results particularly for a high level classification task. The author used five class classifications that has been used for support vector machine. The dataset of 80,000 used images and high resolution of 512x512 pixels. CNN achieves a sensitivity of 95% and accuracy 75% on 5,000 validation images.

S.M. Danish et al. (2019) In this paper automated tools are to detect diabetes using diabetic retinopathy images, the methodology used to detect DR images is CNN architecture. The author implemented pre-trained CNN models like, Alex Net, VGG-16, squeeze Net and also implement a customized CNN models for the specific problems of classification of DR images. Customized CNN models consists of 5 layers, 2 convolution layers and 3 fully connected layers neural network for classification. The author used MESSIDOR dataset and consists of 1200 images. These images are resized 244x244 pixel optimize the execution time.

Di Xiao et al. (2017) In this paper deep convolution neural network-based method for exudates detection and classification in the pixel level. A set of exudates first extracted with morphological ultimate opening technique and then the trained CNN deep network for classification. The author used dataset E-Ophtha EX. E-Ophtha EX contains in 82 Images used. All images size ranging from 1440x960 pixels to 2544x1696 pixels.

Chandore et al. (2017) In this paper an automated and efficient solution that could detect the symptoms of DR from a retinal image within seconds and simplify the process of reviewing images. The author implement one may split method used to detect DR into CNN architecture, Morphology or rule-based method andmachine learning. Trained CNN to classify stages of 5 DR images. The author trained a deep convolution neural network model on a large dataset consisting around 35,000 high resolution images with a resolution of 3000x3000 pixels. They used dropout layer technique to achieve higher accuracy 88%.

Carson et al. (2018) In this paper use of convolution neural network (CNN) on color fundus images for the recognition task of DR staging. The author trained a CNN architecture using transfer learning of the Alex Net, VGG 16 and Google Net. The author experiment result Google Net achieved the highest sensitivity of 95% and specificity of 96%. Transfer learning on Pretrained Google Net and Alex Net models from Image Net test set accuracy 74.5%, 68.8% and 57.2% on 2-ary, 3-ary and 4-ary classification models. DR images are acquired from a kaggle dataset of 35,000 images with 5 class labels and messidor-1 dataset of 1200 color fundus images with 4-class labels. The author tied to utilize the multiclass kaggle dataset but they stated that CNN cannot learn mild class sensitivity. The author achieved decent results for detecting mild grades when using the messiodor-1 dataset.

Shenoy et al. (2016) in this paper proposing a Diabetic retinopathy diagnosis model that automatically learn feature which are pivotal in diagnosing the stage of the disease without explicit or manual feature extraction. This paper presents

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the design and implementation of GPU accelerated deep convolution neural network to automatically diagnose and there by classify high resolution retinal images into 5 stages of the disease based on severity. The single model accuracy of the CNN presented in this paper is 0.386 on quadratic weighted kappa metric and ensemble of three such similar models result in a score of 0.3996. The author used dataset consist of 35,126 labeled high resolution color fundus retinal images. Training images of resolution 512x512 pixels to form a standardized dataset.

Sehrish et al. (2019) in this paper automatically detect DR and its different stages from retinal images. The author used deep convolution neural network model like, Resnet 50, Inception v3, Xecption, Dense 121, Dense 169. This architecture encodes the rich feature and improves the classification for different stages of DR. The authorexperiment results proposed model detect all the stages of DR and perform better to the state-of-the-art method on the Kaggle dataset. They used Kaggle dataset which contains 32,126 color fundus images and crop of image size 512x512 pixels. The accuracy measured used was the AUC of the ROC curve. The highest AUC of 97%.

Architecture and performance measure is illustrated in Table-1 given below:

Reference no	Architecture	No. of class	Dataset	Dataset size	Performance measure	Results
13	Alex Net, VGG-S, VGG 16, VGG-19	2	Messidor, DR1	1200, 1014	AUC	77.27%, 98.34% 74.37% 68.69%
14	Alex Net, VGG-S, VGG 16, VGG-19, Google Net, Resent	5	Kaggle	35,126	AUC	93.42% 97.86% 96.16% 96.84% 92.72% 93.65
15	Alex Net, VGG 16, Inception V3	5	Kaggle	166	Accuracy	63.23%
16	All Architecture	5	Kaggle	80,000	Accuracy	75%
17	Alex Net, VGG 16, Squeeze Net	5	Messidor	1200	Accuracy	98.15%
18	All architecture	5	E-optha Ex	82	Accuracy	91.92%
19	All Architecture	5	Kaggle	35,126	Kappa	88%

20	Alex Net, Google Net, VGG 16	2	Messidor Kaggle	1200 35,00	Sensitivity, Specificity, Accuracy	95% 96% 74.5%
21	All Architecture	5	Eye PAC	35,126	kappa	0.3996
22	Res Net 50, Inception V3 Xception Dense 121 Dense 169	5	kaggle	35,126	Accuracy	97%

Table-1 Architecture and performance measure

III. CONCLUSION

In this review paper Convolution Neural networks Architecture/Models for classifying Diabetic Retinopathy Fundus images. Many state-of-the-art Architecture have been solve to DR classification. While Inception V3 was most commonly used followed by the Alex Net and VGG Architecture. The author used Architecture did not depend on the size of the dataset. But author compared different architecture to determine the best performance one. Most commonly useddataset kaggle and Messidor dataset. Consider binary classification task due to the lack of a sufficient number of images for some of the classes. The unbalanced of the dataset to the difficulty (more models used) in distinguishing among more than two classes. Difficulty was caused by the low number of class as well as quality of the images.

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