Identification of Diabetic Retinopathy from Color Fundus Images using Deep Convolutional Neural Network

Bansode Balhim Narhari, Bakwad K.M., Ajij Dildar Sayyad

Abstract: Existing methods on retinal disease detection are mostly depends on lesion detection techniques or multiple instance learning framework. However extensive research efforts fail to address effective representations of the different lesions from fundus images. In this paper, a innovative techniques is offered built on pre-examined entirely convolutional neural network (CNN) over and done with transfer learning. The proposed method utilizes the effective learning from recent deep CNN models with use of SVM classifier at the end. Meanwhile, additional retinal image pre-processing technique is applied for the better classification results. The improved result has contributed to the area of computer aided diagnosis for retinal screening system. Extensive experiments have been conducted on Messidor and IDRiD database with desired obtained accuracy of 96.29 % and 94.82 %. The proposed method supports retinal disease screening effectively by deep learning methods.

Keywords :Diabetic retinopathy (DR), Deep convolutional neural network, deep learning, transfer learning, pre-trained model.

I. INTRODUCTION

Complications of diabetes that affect the eyes and the minor blood pots at the retina are known as diabetic retinopathy (DR). DR is unique form of common retinal disorders in addition to the leading cause of human blindness [1]. Occurrence of lesions like microaneuruysms in retinal pictures is one and only of the early signs of DR. It is very difficult to develop dedicated method for the detection of microaneuruysms lesion [7]. However, ophthalmologist manually could not able to manage every patient at screening, although possible, but it is a time consuming and repetitive work [2].

In addition to increasing the cases of diabetic patients and the nonexistence of resources causes

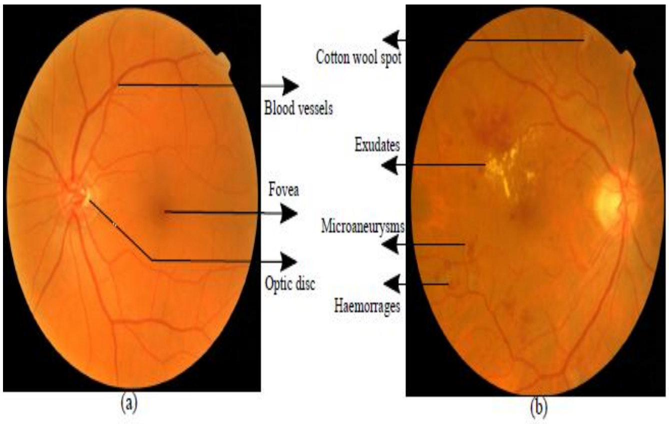

Fig.1.1 Retinal anatomical structures and lesions a) Normal b) Disease Eyes

many patients left untreated leads to severe DR conditions. The automated diagnosis of goal pathology existing in the patient or not, have confirmed an efficient second expert opinion while DR mass screening. In order to reduce the workload of ophthalmologist, there is a need of automatic and correct analysis of retinal pathology [2]. The ultimate goal is to classify the cases with similar pathologies by designing an effective image representation method with advanced CNN techniques.

The performance of a DR classification depends on the domain specific feature extraction step and accurate disease classification step, which have been widely studied by many researchers [1], [14]. The challenge with fundus image analysis lies in various lesion representation with high-level pathological concepts perceived only by clinician. However, previous studies tried to handle these challenges using computer vision and machine learning techniques [5]. Nowadays, advanced CNN technique has been evolved that can addresses the issue of accurate detection of many retinal diseases [13]. In Gardner et al. [4], first the neural network with back propagation is used for exercise of the system. Furthermore, the optic disc is detached by masking using green channel of spitting image and manual division is completed. They have achieved the accuracy of 91.7% for DR screening. Varun Gulshan et al. [6] has reported an sensitivity of 97% using a single Inception network with several two estimates. Furthermore, the image is categorized into normal and abnormal retinopathy lesson. Joel [8] proposed a hybrid technique using color fundus images for screening retinopathy. The fundus images were preprocessed followed by feature extraction using morlet wavelet.

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These structures are providing for the unsystematic forest classifier for sorting. The technique splits, retinal image into normal images and abnormal images like DR(Diabetic retinopathy) images and NPDR(Non proliferative diabetic Retinopathy) images. Quellec et al. [13] proposed a method with CNN and hyper-parameter tuning using ResNet for DR image grouping. They used freely accessible Kaggle platform for exercise these models with an grouping good accurateness. Sisodiaetal. [16] used the multi-class,instance learning (MIL) context for DR arrangement job by means of the shade autocorrelation plot. Finally, used SVM for the classification using 14 directional features of hemorrhages and micro aneurysms.

The aim of our method lies in the interplay of disease classification for diabetic retinopathy. Over the past decades, a variety of conventional DR detection approaches has been proposed based on hand crafted feature extraction techniques lesions such as hemorrhages and[6]. Recently, deep knowledge framework on behalf of image arrangement is widely accepted since, this one is capable to learn features directly from images without domain knowledge. The greatest commonly applied type are Deep are known Convolutional Neural Networks(CNNs). Several CNN models created very decent results, namely AlexNet (2012) [9],consist of 5 convolutional layers, 3 pooling layers and 3 fully connected layers(FCLs), VggNet (2014) [15], which proved that deeper networks improve classification by adding more convolution and pooling layers, GoogLeNet [17] that introduced inception modules (i.e., a mini network within a network) to minimize the figure of factors and increase calculated efficiency, Beginning-V3 (2016) [18] that combined the idea of Google Net and VggNet (using only 3x3 filter size for convolution).Quellec et al. [13] proposed method detecting referable and non-referable DR with achieved 94.5 % accuracy in performance. They have done the image-level predictions by creating heat maps after trained ConvNet model. Furthermore, a CNN trained for image-level arrangement can be used to identify injuries as well. Although many approaches previously studied the retinal disease analysis research, still the performances of many of them needs better improvement. However, the accuracy can still improve by exploiting the new approach of different CNN models with transfer learning.

II. SUMMARY OF CONTRIBUTION

This paper gives us new techniques for automatic screening of diabetic retinopathy using classifying disease and normal images. The proposed method uses transfer learning with CNN model with advanced classifier at the end to characterize the different retinal lesions for better feature representation. The offered technique is efficient, in terms of accurateness and computational complexity. Furthermore, the use of CNN effectively able to represents the retinal lesions.

1. We announce a deep learning framework on behalf of classifying DR in addition to normal images using advanced CNN pre-trained models for effective representations of pathology

in retinal images.

2. Multiple deep learning models including Alexnet, Vgg16 and Google Net were investigated for improving performance of automatic diabetic retinopathy detection.

3. Transfer learning with hyper-factors tuning are approved with SVM classifier and the investigational results have confirmed the improved performance than the existing methods for DR disease classification. The remaining paper is organized as follows. In second sector, present the offered approach and database intended for retinal disease exposure depends on deep learning approach. Now Section III and IV, presents the experimental results and discussion in comparison of the up-to-date techniques. Finally, in Section V, we summarized the conclusions with future work.

III. METHODS AND MATERIAL

3.1 Database Used

3.1.1 MESSIDOR data [3]

The assessment of offered method has been approved on widely existing MESSIDOR

Data sets consisting 1200 retinal images. The images were obtained from 3ophthalmology departments using Topcon TRC NW6 non mydriatic camera per 45degree FOV having three distinctive resolutions as 1440 x 960, 2240 x 1488 or 2304 x 1536pixels. Specifications of retinopathy for MESSIDOR database is shown in Table 1.from 1200 images 800 were captured with mydriasis and 400 without mydriasis.The images are stored in TIFF file setup and a file through medicinal opinion for each image related to DR grading is provided. Moreover, we performed our method on512 x 512 rescaled retinal images as their size change in database.

Table 3.1.1 Specifications of retinopathy for MESSIDOR database

DR .Grading	Detailed specification	Total Images
0	Normal	546
1	(0<µA<= 5) AND (H=0)	155
2	((5µA<15) OR (0<H<5) AND (NV=0)	247
3	(µA >=15)OR (H>=5) OR (NV=1)	252

μA - Micro aneurysms, H- Hemorrhages, NV-Neovascularization

3.1.2 IDRiD data [12]

The fundus images used in IDRiD database were recently publish in ISBI-2018 [11].The database consist of total 516 images were accomplished employing a Kowa advanced fundus camera with 50 point field of see (FOV) and completely stay centred at the macula.The pictures have resolution of 4288x2848 pixels and are kept with jpg file arrangement. Scope of each one image is near to 1 MB. The FOV of every image is circular having diameter of 1500 pixels. Severity Grading based on standards of International Diabetes Federation (IDF).In total 516 color fundus images all variation of extreme situations of DR and DME were present. The diabetic retinal photos were separated into diverse sets agreeing to the universal restorative diabetic retinopathy degree comparative to (absence of DR, 0; mild, 1; moderate, 2; severe, 3; and proliferative DR, 4) shown in Table 2. Where, NV =0: No signs of Neovascularization absent, and NV = 1: Signs of Neovascularization are present.

3.2 Pre-processing with retinal patches extraction

The architecture of the proposed retinal disease classification system is shown inFig.3.2.1. The offered framework is classified into three main parts namely, the retinal field of view (FOV) extraction with image normalization. Secondly, use of transfer

Table 3.1.2. Specifications of retinopathy for IDRiD database

DR.Greding	Detailed Specification	Total Images
0	Normal	151
1	(0<μA< =5) AND (H=0)	182
2	((5<μA<15) OR (0<H<5))	115
3	((μA>=15) OR (HE>=5)) AND (NV=0)	47
4	((μA>=15) OR (HE>=5) AND (NV=1)	28

μA - Micro aneurysms, HE- Hard Exudates, NV-Neovascularization

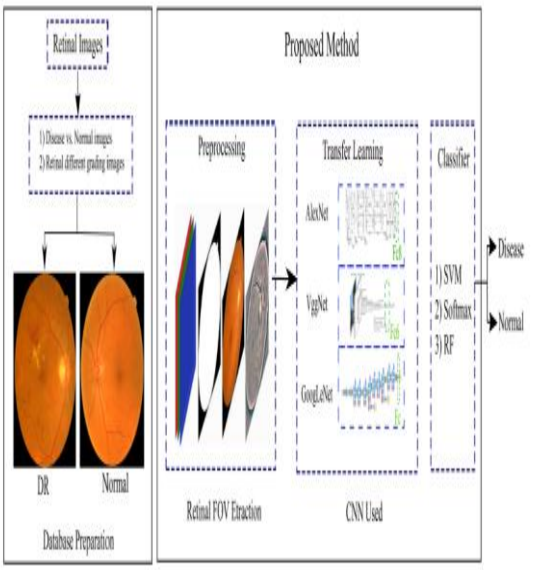

Fig. 3.2.1 Proposed Method of DR vs Normal images Classification using different CNNs.

learning techniques with different CNN models and finally, classification step for disease vs. normal images.

The method start by preprocessing of retinal images, as the image quality varies throughout the whole datasets. Many of retinal images had excess dark-space on the side of the eye, therefore preprocessing is essential for retinal ROI extraction. As the images present in varying sizes, so standardized it by downsizing all images to 370-by-370 after ROI extraction [10]. The proposed method is utilized as simple and computerized field of see (FOV) expulsion strategy utilizing thresholding as appeared inFig.3.2.1 The red channel from the color fundus image is used for the FOV extraction. Furthermore, an automatic extraction of retinal patches from images is proposed after FOV detection. During training the input images are normalized for illumination equalization and contrast enhancement is performed. At long last, the pictures were resized made on the necessities of each pre-examined framework (i.e., (1) Alexei's 227×227×3; (2) Vgg-16 and Google Net is 224×224×3; Once its prepared, the pictures are fed into distinctive CNNs for DR(Diabetic Retinopathy) vs typical distinguishing proof.

3.3 Transference learning using pre-accomplished CNN architectures Transfer learning of pre-trained CNN architectures leverages the pre-trained weights of a CNN trained from a very large dataset to remove features for our DR dataset [19]. In general, transferal learning shapes on accomplished information from one dataset to increase book learning in extra dataset. Further definitely, it can be defined as a technique which aims to expand learning the goal analytical function. Through the development of profound learning, the CNN utilize transference learning frameworks, frequently upgrade the adjustment layers to proficiently diminish the contrast among the domestic space and objective space [13].Features are extracted at different depths of

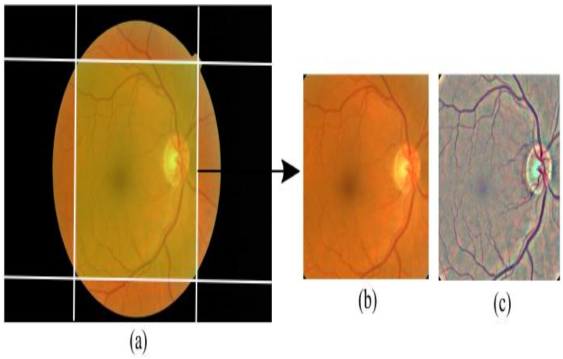

Fig. 3.3.1 Retinal patch extraction using preprocessing. (a) Original Messidor database image (b) Cropped ROI retinal patch (c) Color normalized retinal patch.

a CNN later the FCLs were used for sorting. The pre-qualified CNNs in this study are used as Alex Net, VggNet and GoogLeNet. A CNN comprises of numerous covered up layers counting convolutional layers, pooling layers, fully connected (fc) layers that are combined to create a feed forward network that can be characterized in Eq.(1).

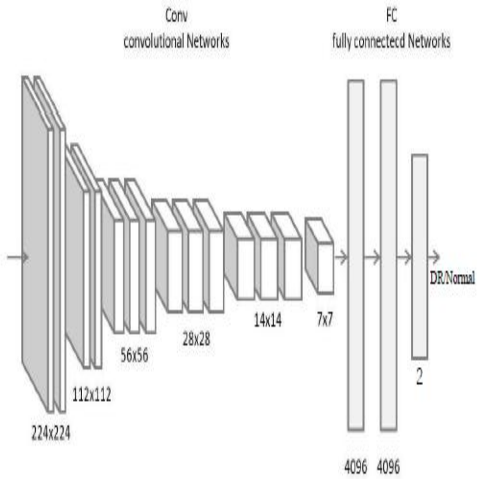

Fig. 3.3.2 Vgg16 CNN module with transfer learning for two classes DR vs. Normal.

$C(x) = cN(cN{-}1\,(....\,(c_i(x))))$ ---------------(1)

N shows the number of covered up layers and ci demonstrates the work within the identical layer i.A building block of a CNN is the convolutional layer where c consists of multiple convolution kernels(

(y1…..,yk-1,yk) each yk represents a linear function in the k-th kernel. The fractious entropy damage function was used as in Eq. (2). It calculates the compatibility between a expectation (e.g., the course scores in a classification issue) and the ground-truth name by minimizing the mistake.

$$\text{Loss}=\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{c} yi^{*(k)} \log yi^{(k)} \quad \text{--- (2)}$$

where $y_i^{*(k)}$ and y_i^{k} are separately the ground-truth name and the anticipated yield of the ith picture at the kth lesson with n work out pictures. The complete sum of sessions signified by c. The misfortune is at that point back-transmitted to advise the organize components utilizing the optimizer.

The precision was calculated for all classifier to compare the concert of the classification calculation and found that the greatest accurateness with SVM and RBF part. Highlights extricated from all FCLs of 3 pre-trained CNN models prepared the chosen classifiers through exchange learning. In this work VGG16 [15], Alex net [9]and Google net [17] were chosen for fine tuning and feature extraction. The benefits of fine-tuned CNNs, as opposed to training a new CNN, are that they require less computational power and less data. The errors are back-transmitted to the previously. Replaced covers of the network during training. The experiments were performed on two datasets as a different number of DR classes are present to fine tune the CNNs.

3.4 Inception module fine-tuned with DR lesions

The offered technique includes adjustment a Google net pre-trained model to identify DR in fundus images. Google Net presents the initiation structure, which keeps up computational sanctioning with strong networks as well as intensives the sparsity of CNNs structure. The procedure to make strides the rightness of the show is to development the complexity of show. The incomparable straight way to make strides the concert of the organize is to development the profundity and thickness of the organize, which shows a colossal sum expanding of variables. The components within the final fully-connected layer can adjust superior to the DR information. The ultimate 3 layers of each pre-trained CNN is supplanted to tune DME vs typical

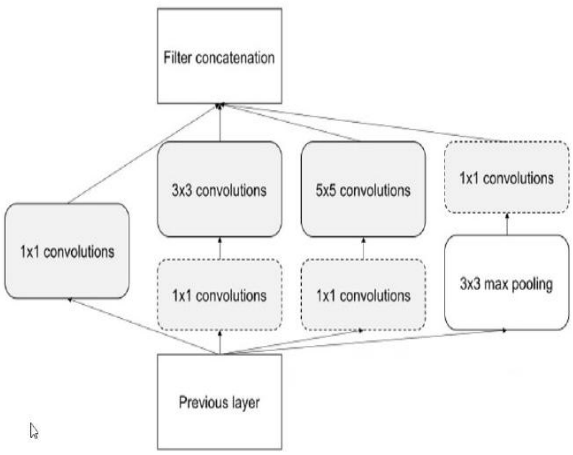

Fig.3.4.1 Inception module of Google Net CNN

The initiation layer is the center concept of a softly connected engineering. Beginning module could be a concoction of all those layers (specifically, 1x1 Convolutional layer, 3x3 Convolutional layer, 5x5 Convolutional layer) with their yield channel banks concatenated into a single yield course making the input of the another arrange. Gulshanet al. utilized this Initiation arrange for programmed recognizable proof of diabetic retinopathy and diabetic macular edema disease in retinal fundus images. Moreover, the weights of Inception module has been tune with DR pathological images. The utilization of Google net allows us to explore more on DR classification with SVM.

3.5 Use of SVM as classifier

We are investigating ways to scale up classification execution by combining the classification comes about from the exchange learning of each person pre-trained CNN systems (Alex Net, VggNet and Google Net). After FC layer, at last we used SVM as classifier which gives good results. A arrangement of combinations were tested to recognize the most excellent gathering as a choice show. The prediction is based on plurality rule, whereby a color fundus image is predicted as a disease or normal if the majority between Alex Net, VggNet and Google Net is DR or normal, respectively.

IV. EXPRIMENTAL RESULTS

In the experimental result section, the image level classification displays the report on both the dataset. Each image is labeled as per the grading standards, in increasing order of DR severity: {NoDR, Mild, Moderate, Severe, And Proliferative}. An image is deemed abnormal if it is of severity scale Mild and above, and normal if the severity scale is No DR. Table 4.1 shows the summary of the experimental outcomes about the classification performance of each proposed model. Each line compares the cumulative effect on the various contributing factors of each technique. To guarantee that exchange learning was completely optimized, highlights were extricated employing a pre-trained Alex Net, VggNet-16,and Google Net and prepared with diverse classifiers i.e. SVM and arbitrary forests.SVMs speak to the piece courses in a bit space over a polynomials of the first factors, allowing instruction of non-linear models. Finally, we used RBF kernel of SVM with hinge loss for better classification. For training the different CNNs experimentation 70% of images are used and remaining 30% for testing. The test subset folder contained 360 images from the messidor dataset. Data augmentation is used while training for better accuracy. The evaluation results presented in Table 4.2 shows that the method gives an average sensitivity of 95.45%, specificity of 97.20% and accuracy of 96.29% of referred DR on Messidor dataset. Figure 7 summarizes the generally precision of each classifier in each pre-trained CNN demonstrate. In general, it can be seen that the GoogLeNet had the most noteworthy generally exactness for all three classifiers. The presentation of beginning modules provides benefits over the Alex Net and VggNet architectures. Evaluation measures were the same as most other publications.

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The picture classification execution of the distinctive organizes was assessed based on the taking after parameters of sensitivity, specificity and accuracy:

Sensitivity (SE):- Measures the capability of the framework to accurately decide a DME lesson in terms of genuine positives (Tp) and untrue negatives (Fn)

SE= $\frac{Tp}{Tp+Fn}$ ---------------------(3)

Specificity (SP) ;- It measures the capability of the framework to accurately recognize a Normal lesson in terms of genuine negative (Tn) and wrong positive (Fp) value.

SP= $\frac{Tn}{Tn+Fp}$ ----------------------------------(4)

Accuracy (ACC) – It measure the accuracy of the classification

ACC= $\frac{Tp+Tn}{Tp+Tn+Fn+Fp}$ ---------------- (5)

Table 4.1 Confusion matrix of the SVM classifier for DR grading on test set of Messidor

True class		Predicted class			
	R0	R0	R1	R2	R3
	R1	161	2	0	1
	R2	4	41	1	0
	R3	3	2	67	2
	R4	0	0	1	75

Database. Columns and rows represent predicted and true class label, respectively

Table 4.1 shows advanced visualization monitoring and confusion matrix statistical analysis provided important insights. The highest performance was obtained for features with different fully connected layers of AlexNet, VggNet and Google Net and trained with a cubic SVM, softmax and random forest classifiers. The best obtained results ware with the Google Net FC layer gives 94.75% accuracy with trained model. Finally, the highest accuracy is a fine tuned Googlenet with 96.29% on Messidor and 94.82% on IDRiD database using a SVM classifier with mini-batch estimate of 16 over 10 ages. The fine-tuned CNN models are prepared over a mini-size of the group is 16 utilizing Stochastic Slope Plummet with Force (SGDM) having the energy run of 0.9 and learning rate of 0.0001. The SGDM calculation upgrades the weights and inclinations of the arrange employing a subsection of the preparing pictures. The strategies were executed totally in MATLAB-2018a on a Quadra P5000 GPU ard from NVIDIA with an Intel Xeon 2.1GHzx16 CPU with 24 GB DDR2 RAM. The time taken to prepare a show over one dataset is an normal of 5 hours.As the fully

Table 4.2 Experimental results on Messidor database

Method	SE	SP	ACC
Alex net	91.67%	87.50%	93.75%
Vgg 16	93.75%	87.50%	90.63%
Google Net	94.89%	87.50%	94.75%
Transfer Learning (Alex net)	93.74%	93.75%	93.48%
Tranfer Learning Vgg 16	96.64%	93.75%	94.88%
Transfer Learning (Google Net)	95.45%	97.20%	96.29%

connected layers are randomly initialized, the training model performance is also partly random.

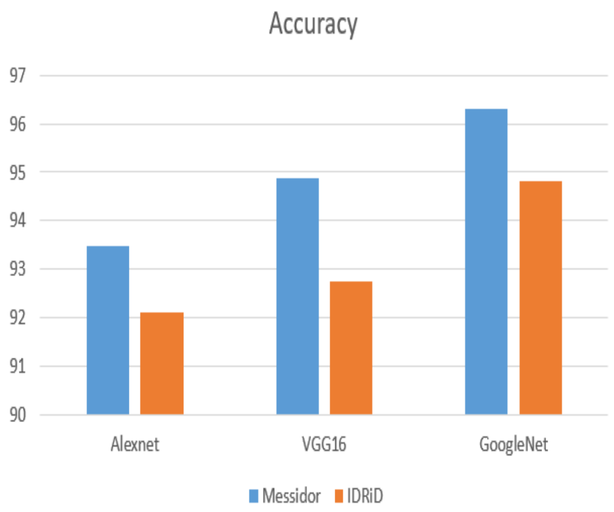

Fig.4.1 Comparison of CNNs model on different databases

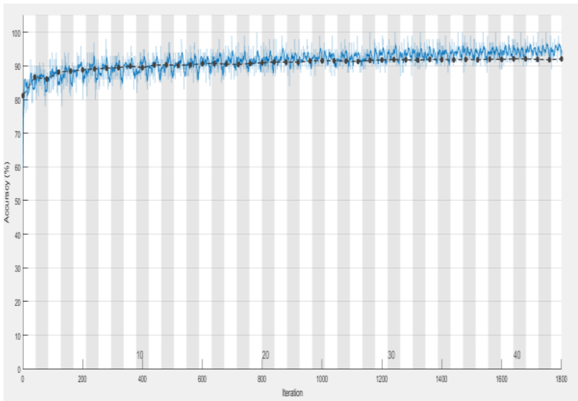

Fig. 4.2 Training accuracy of pre-trained GoogleNet CNN with transfer learning on Messidor database.

V. DISCUSSION

We observe that with transfer learning GoogLeNet performed well in terms of sensitivity compared to Vgg-16 and Alex Net. Since, the DR images gas interclass abnormalities very close to each other. Subsequently, amid preparing, the classifier might come up short to measure the DR vs. typical cases. However, with the very deep architectures and inception module is able to detect the DR lesions and obtains highest accuracy. It is watched that fine tuning GoogLeNet beats other strategies. It implies that the demonstrate is utilized to precisely identify a DR or typical case for both the dataset. The fine tuning of GoogLeNet has an made strides classification execution compared to other CNN organize. For future work, more later and vigorous CNN models can be investigated as well, i.e. Inception-V3 [18], which has the interesting highlight of a split-transform and it combines beginning modules and leftover mapping.From the confusion matrix, we see that for grading of DR the mis-classification is relatively more in between classes 0 (normal) and 1. It also observed that the CNN model has liberally predict normal (class 0) vs. not-normal (remaining all classes) DR images. Also, we notice one interesting result that the CNN model is relatively good at identifying images of class 4 compared to the other classes. This leads to referral decision while mass screening of DR. The limitation of this offered method is extraction of features using CNN model. As the deep learning training process is the most time consuming process because of these heavy network. Fortunately, we only need to train the model of once and the operation can be done off-line. The next steps of this study include use of multiple instances learning (MIL) and deep learning techniques.

VI. CONCLUSION

In this term paper, we have offered a novel convolutional neural organize strategy for diabetic retinopathy discovery utilizing transfer learning approach. The method consists of preprocessing including automatic extraction of retinal patches for improvement in results. Furthermore, the proposed technique outperformed for various CNN model including Alex net, VGG16 and Google net for DR classification. Our experiments show that a Inception CNN model shows a better classification performance and succeeded retinal pathological feature representation. The best results achieved for referral DR with an accuracy of 96.29% on Messidor database. In future work, we will investigate some advanced deep learning techniques for multi-modality of the retinal images.

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