OPEN ACCESS
International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-2, December, 2019

Classification among Microaneurysms, Exudates, and Lesion free Retinal Regions in the Eye Images using Transfer Learned CNNs

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Abstract: ***When pancreas fails to secrete sufficient insulin in the human body, the glucose level in blood either becomes too high or too low. This fluctuation in glucose level affects different body organs such as kidney, brain, and eye. When the complications start appearing in the eyes due to Diabetic Mellitus (DM), it is called Diabetic Retinopathy (DR). DR can be categorized in several classes based on the severity, it can be Microaneurysms (ME), Haemorrhages (HE), Hard and Soft Exudates (EX and SE). DR is a slow start process that starts with very mild symptoms, becomes moderate with the time and results in complete vision loss, if not detected on time. Early-stage detection may greatly bolster in vision loss. However, it is impassable to detect the symptoms of DR with naked eyes. Ophthalmologist harbor to the several approaches and algorithm which makes use of different Machine Learning (ML) methods and classifiers to overcome this disease. The burgeoning insistence of Convolutional Neural Network (CNN) and their advancement in extracting features from different fundus images captivate several researchers to strive on it. Transfer Learning (TL) techniques help to use pre-trained CNN on a dataset that has finite training data, especially that in under developing countries. In this work, we propose several CNN architecture along with distinct classifiers which segregate the different lesions (ME and EX) in DR images with very eye-catching accuracies.***

Keywords**:** ***Deep Learning, Hardexudates Logistic Regression, Random Forest, Machine Learning, Soft exudates.***

I. INTRODUCTION

Diabetic Retinopathy is one among many diseases which are not curable and caused by the fluctuation of glucose level in blood. DR is one of the major disorder which starts with normal symptoms, grows to moderate with the time and finally results in complete myopia. 126.6 million people were detected with DR worldwide and it will become 191 million in the end of 2030 [1]. If the necessary steps will not be taken the rate of Vision Threatening Diabetic Retinopathy (VTDR) will be 56.3 million from 37.3 million.

Revised Manuscript Received on December 30, 2019.
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Based on severity, DR is classified in several categories: 1) The early stage is called Mild Non-Proliferative Retinopathy. Sometime due to leaking of fluid in retina results in swelling the surface of the retina which is called Microaneurysms. Finally, this ME weakens the blood vessels of the retina. 2) Moderate Non-Proliferative Retinopathy [2] results in damaging the blood vessels which provide nourishment to the retina. Some spots may be detected which ensures the presence of hemorrhages, hard exudates. 3) The third stage is called Severe Non-proliferative Retinopathy in which the blood vessels for providing the nourishment to retina were very badly blocked due to which a signal is passed growing more new blood vessels and 4) The most severe and final is Proliferative Retinopathy in which new blood vessels are grown which are very weak. If these weak blood vessels anyhow leak the blood, it will result in complete or permanent blindness [2].

A lot of research is carried out in the past to overcome these diseases. If DR is detected at an early stage, it can be controlled from further damage. Also, classifying the stage of DR may help ophthalmologists to provide the best solution to stop DR from enhancing [3]. Image classification is the ongoing technique for detecting or classifying the severity and stage of DR. ML based models and classifiers are used to classify the images according to the stage of the disease. The transfer learning technique is used to feed the dataset with fewer images to the CNN model which classifies the images with very high accuracy. Several applications of Deep Learning (DL)show the promising results in classifying the fundus images [4].

II. LITERATURE REVIEW

Detection of lesions with the help of TL and DL methods in the DR fundus images has gained the attention of many researchers and a lot of work has been done in this direction. Recently, in [5], the authors proposed CNN model to detect RDR based on deep learning. The model proposed has a Siamese like architecture which accepts binocular fundus images as input. The Area Under the ROC Curve (AUC) value of 0.951 is obtained. The sensitivity (Se) and specificity (Sp) for proposed model is 82.2% and 70.7%. Proposed model outperforms the Inception V3 and state of art algorithms. In [6], the authors proposed an approach to detect hard exudates (EX). These EX leaks the lipoprotein in the retina and causes permanent blindness therefore their accurate detection is foremost important. DIARETDB1 and DRIVE datasets are used as input, and after preprocessing the input images feature extracting algorithms are applied and finally with the help of classifiers 99.34% accuracy is obtained

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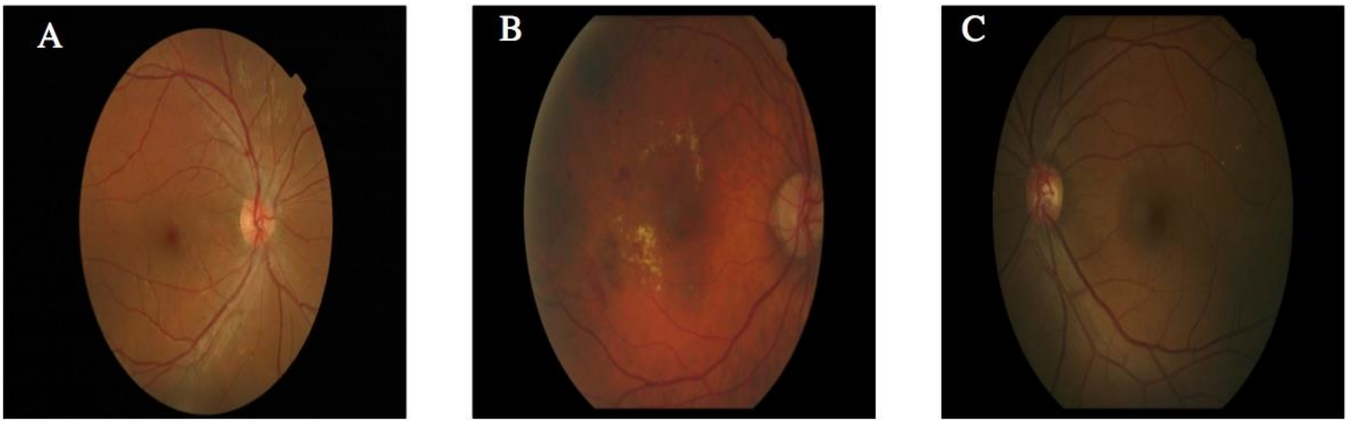

Fig. 1 Typical fundus and Normal photographs from O-ophtha dataset. (A) Photograph of healthy fundus (B) Photograph of fundus with Exudates (C) Photograph of fundus with Microaneurysms

In [7], the authors performed classification of fundus images by using Deep Neural Network (DNN).For this several techniques are combined together such as Gaussian Mixture Model (GMM), VGGNet, Singular Value Decomposition (SVD), Principle Component Analysis (PCA) and softmax for obtaining features and classifying fundus images. A dataset from KAGGLE containing 35,126 images is used. In terms of accuracy, proposed model outperforms AlexNet and Spatial Invariant Feature Transform (SIFT) models. In [8], the authors presented the methodology for detection of Diabetic Macular Edema (DME) in fundus images. Authors use several image processing algorithms after which features are extracted and supervised classification techniques were used. The experiment is done taking 1058 retina graphics of 529 diabetic patients. The sensitivity of 90% is achieved in this work. In [9], the authors used deep learning-based approach to detect the red lesions in fundus images. They have used DIARETDBI and MESSIDOR datasets. Several features are trained using CNN network and very high accuracy is obtained by using the Random Forest (RF) classifier.In [10] the authors proposed the model for detection of both HE and MA in color fundus images. Six different datasets are applied on a new set of shape features called dynamic shape features. The advantage of using this technique is that it do not require precise segmentation. For messidor dataset, 0.899 is the obtained ROC value. The obtained results out performed the state of art approaches. In [11], authors have proposed an ensemble-based ME detector. This detector has gained 1st position in an open online challenge and proved its efficiency. A search algorithm is used to select an optimal combination. Authors have used MESSIDOR dataset with 1200 images and achieved 90% AUC value which outperforms the previous result on the same dataset.Authors in [12], proposed a new supervised method for detection of blood vessels in digital retinal images. Pixel classification is done by using the neural network and computes a 7D vector composed of a gray level. The dataset used are DRIVE and STARE. These methods perform well and outperform several other methods. Hence this proposes a suitable method for early detection of lesions in retinal images.

III. PROPOSED METHODOLOGY

In the following work, an efficient framework is proposed which uses CNN for detection of ME and EX. ME is generally the initial stage of DR and detection of ME is of utmost important by making use of ML classifiers. The method used in our work helps us to classify the ME and exudates present in E-ophtha dataset [13]. The target for classifying the lesions in fundus images is accomplished by the following steps. 1) The E-ophtha dataset is used for classification and images are pre-processed. 2) Several models such as Inception V3, VGG16, and VGG19 are trained using images present in e-ophtha dataset. 3) Extracted features from previous steps are classified by using different classifiers. Finally, the best classification accuracy is extracted. Fig. 1 shows fundus and normal images.

A. Dataset Description and Pre-processing

To carry forward the scientific research, e-ophtha dataset is designed. This dataset comprises of two sub dataset: 1) e-ophtha-MA and e-ophtha-EX [13]. Each sub data comprises of several folders, each containing data related to visit of patient to hospital. The folder contains one or more fundus images and related binary mask made up of lesions. The data of patients with no lesions sign is also present. E-ophtha-MA comprises of 148 images with Microaneurysms or small hemorrhages and 233 normal images, which do not show any sign of lesions. E-ophtha-EX comprises of 47 images with exudates and 35 images which do not show any sign of lesions. Table 1 shows the E-ophtha dataset description[13].

Table- I: Dataset Description

Type	Dataset		
	Training set	Testing set	Total
Microaneurysms (MA)	97	51	148
Exudates	31	16	47
Normal Images	176	92	268

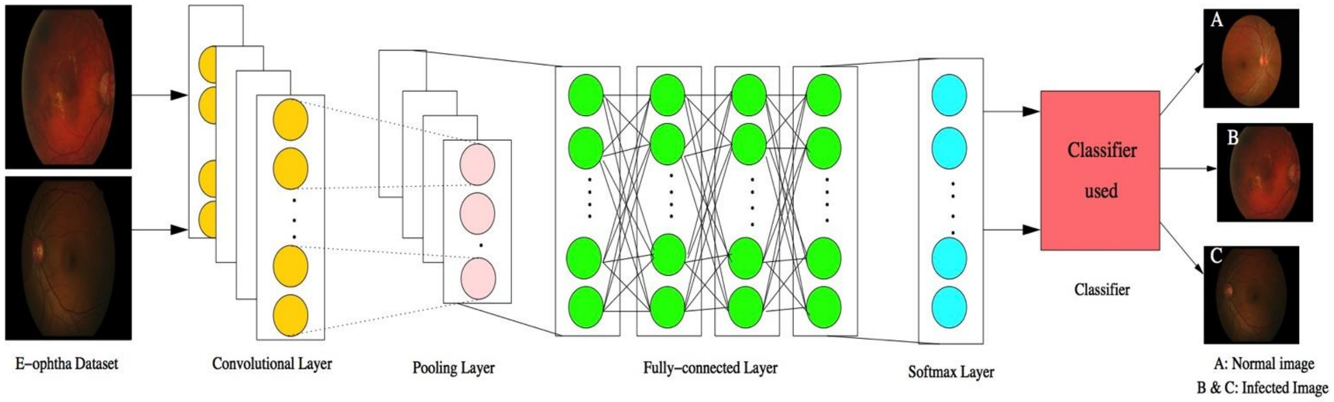

Fig. 2 Block Diagram of the proposed scheme using convolutional neural network (VGG19 model) along with several classifiers detecting images as (A) Normal image (B & C) Diabetic image

B. Training the CNN

The deep learning models which we have used for training and learning of features are VGG16 [14] and VGG19 [14]. These models are very deep learning models with 16 and 19 trainable layers respectively. VGG16 has 13 convolution layers and VGG19 has 16 convolution layers. Both of these networks have 3 fully connected layers each. Both the networks have 5 maxpool layers which are non trainable. The activation used in the networks are RELU. RELU offers simplicity in derivation and lowering the chances of vanishing gradients as these networks are very deep and thus back propagation algorithms run too deep on the network to update the successive weights of the filters used to extract the features. We have used dropout layer as well with a dropout of 0.4. This layer has been added after feature extraction part in the fully connected layers to reduce the over fitting. Total number of features learned are 138 and 144 million respectively. Thus our classifiers were fed with so much features to weigh upon and this is the reason for such a high accuracy. The size of the filters are kept uniform in each successive layers with a fix of 3 X 3. The number of filters used in each layer varies from 64, 128, 256 upto 512 in the last few layers. These last layers were used to capture abstract features as compared to the primitives of image signals captured by lower convolution filters. Fig. 2 shows the proposed architecture where the different fundus images of e-ophtha dataset are feed to CNN network which comprises of VGG19 model and final trained images are feed in several classifier (KNN, AdaBoost) and different classes of lesions is obtained as the result [14].

Classifiers used are KNN (K nearest neighbors) [15], NN (Artificial Neural Networks) [16], Naïve Bayes [17], Logistic Regression (LR) [18] and Random Forest (RF) [19].

IV. RESULT AND DISCUSSIONS

In the current work, E-ophtha dataset is used to evaluate the results after applying proposed model (VGG19). The accuracies obtained after applying several classifiers proves itself to be one of the beneficial approach to detect DR from fundus images. The test bed is composed by using 463 images from e-ophtha dataset. 66% images are used for testing. The images present in the dataset are labeled as ME, exudates, and normal. Out of total images, 148 are labeled as ME, 47 as exudates and 268 are normal images. VGG16, VGG19, Inception V3 models are used to train the images and several classifiers such as KNN (K-Nearest Neighbor) [15], Artificial Neural Network (NN) [16], Naïve Bayes [17], Logistic Regression (LR) [18], Random Forest (RF) [19], AdaBoost are used to detect the ME and exudates from E-ophtha dataset.

The result obtained after classification of ME and exudates were superimposed with the original database images and thereby the different lesions can easily be categorized in different diseases. This will help the ophthalmologists to examine the lesions more accurately and provide the quick treatment. The proposed method and classifiers classifies and able to distinguish between normal and diabetic fundus images. To more precisely measure the accuracy of our algorithm, we have used several energy functions such as CA (Cumulative Accuracy), Recall. The values obtained through these functions will prove how accurately our model is detecting the images into right lesion class [20].

Accuracy is defined as the number of correct predictions made by model to the total number of samples taken. Accuracy determines how well the model is at classifying the lesions in our case. Accuracy may be improved by increasing the number of input samples. Results in Table II. shows that for classifying exudates and ME, the KNN classifier gives the highest accuracy of 89% and 68.7%, for classifying normal images AdaBoost classifier gives 69.5%. The accuracy may be calculated by using the equation (1).

$$Accuracy\;\square\square\square\;TP+TN/TP+FP+FN+TN \qquad (1)$$

Table- II: Accuracy on Test dataset on four lesions

Table	**CA**				
	KNN	**NN**	**Naïve**	**LR**	**Ada**
Microaneurysms	**0.687**	0.585	0.678	0.609	0.648
Exudates	**0.890**	0.827	0.566	0.832	0.857
Normal	0.624	0.659	0.581	0.652	**0.695**

Recall [21] also known as sensitivity is defined as the technique for classifying the abnormal fundus images as the abnormal by using detection methods. The best value for sensitivity is 1 and the worst value of sensitivity is 0. Table III shows by using LR classifier the accuracy of 37.8% is obtained, Naïve bayes gives 66% accuracy for classifying the exudates and KNN classifies normal images with the accuracy of 88.1%. The sensitivity can be calculated by using the equation (3). The specificity or the true negative rate and according to our work, specificity is defined as the test done to find out how many people are diagnosed with no diabetes and in real also they are not having any disease. The values of specificity can be found by using the equation (4).

Sensitivity/Recall□□□TP/TP+FN (3)

Specificity = TN/TN+FP (4)

Table- III: Recall on Test dataset on four lesions

Table	Recall				
	KNN	NN	Naive	LR	Ada
Microaneurysms	0.284	0.358	0.142	**0.378**	0.324
Hemorrhage	0.142	0.043	**0.660**	0.043	0.043
Red Small dots	**0.881**	0.720	0.519	0.728	0.858

Receiver Operating Characteristic (ROC) [21] curve provides a graphical representation of how the proposed model is able to deal with the detection of lesions in all images of dataset. ROC provides one of the easiest way to measure the performance of algorithm to detect image as normal or infected. The ROC graph includes (sensitivity) on Y coordinate and (1 - specificity) or false positive rate on X coordinate. We have used ROC curve to measure the performance of several classifier. The AUC value for ROC is best at 1 or nearby. Fig. 4 shows the ROC curve for ME using VGG19 model.

Microaneurysms [22] shows the early symptoms for DR. They appear as red and round dots that are often appear in clusters. ME do not show any affect on vision loss. They appear as early symptoms and if not treated on time, will lead to severe stage of DR. Fig. 3 shows the ROC curve for ME using VGG19 model and several classifiers such as KNN, NN, Naïve bayes, LR, RF, AdaBoost.

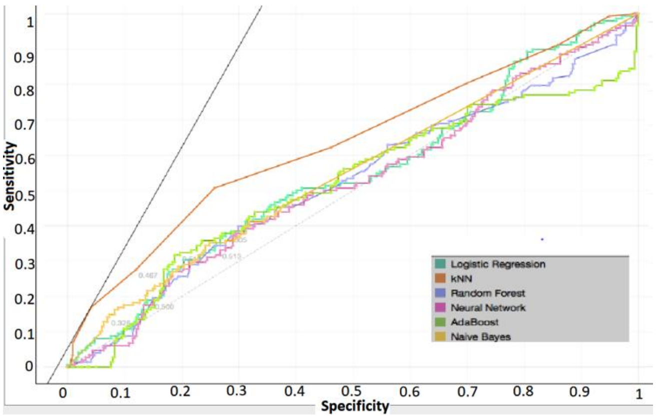

Fig. 3 ROC curve for microaneurysms using VGG19

An exudate [23] is protein that percolate from the circulatory system towards the lesions. This fluid during injury leakes out from the blood vessels into nearby tissues. Exudates can be categorised as hard exudates and soft exudates. Hard exudates are formed by chronic localised retinal edema. They are formed between the retinal swelling and normal retina. They are composed of lipid protein and lipid filled macrophages. They are small white yellowish flex found in outer plexiform layer. Soft exudates are also called as cotton wool spots which are pre-capillary arterial occlusions appear in the form of white patches in the retina. They are primarily caused by damaging of nerve fibres [23]. The ROC for exudates can be seen in Fig. 4.

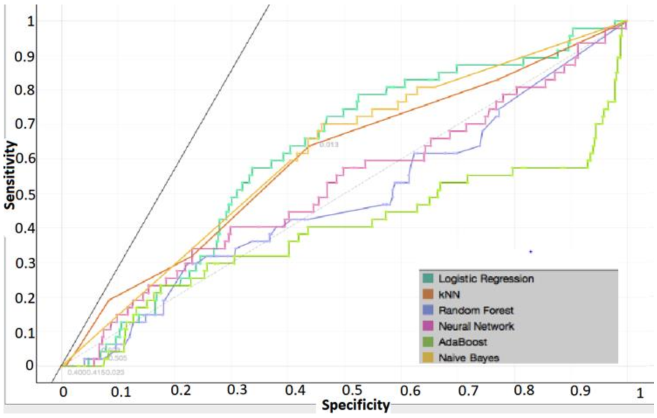

Fig. 4ROC curve for exudates using VGG19

Normal Images are those which do not show any sign of lesions. During the patient visit to hospital, several tests are peformed to detect the stage of DR in the retina. If there is no sign of DR in the retinal fundus image then it is classified as the normal image. The ROC curve for classifying image as normal by several classifier can be seen in Fig. 5.

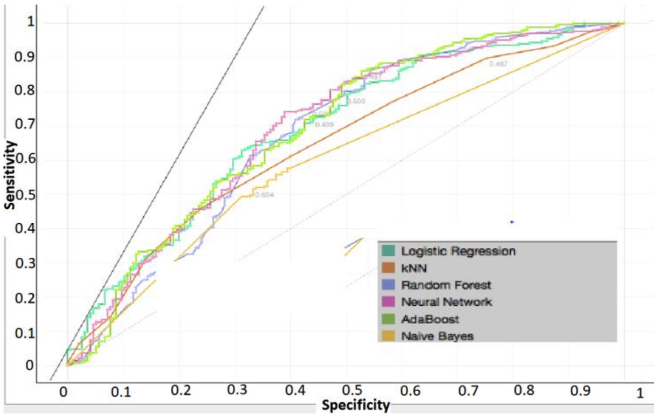

Fig. 5ROC curve for Haemorrhages using VGG19

V. CONCLUSION

Diabetic Retinopathy is one of the major diseases which starts with no symptoms and with the time results in vision loss. However, the diagnosis of DR at an early stage can control the damage. In this work, an adequate model for the classification of lesions in DR images is proposed. A novel technique is proposed which classifies the lesions with very high accuracy. The advantage of using machine learning along with transfer learning is that it classifies the image as ME, exudates and normal which is very useful for the ophthalmologist to provide the right treatment at the right time which will help in detecting DR at a very early or initial stage. The detection of lesions present in the dataset by deploying CNN is executed in the current work.

E-ophtha dataset is used with a total of 463 images out of which 66% of the images are used for the purpose of training and rest 34% of the images are used for testing the model. We have used cumulative accuracy, sensitivity, specificity measures to evaluate the performance of our proposed model (VGG19). The accuracy of 89% is obtained to classify exudates using the KNN classifier, 68.7% for classifying ME using the KNN classifier and 69.5% for normal images using the AdaBoost classifier.

In future we will try to enhance the results either by increasing the number of images in dataset or by using different CNN network.

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