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A Deep Learning Approach for Detecting Diabetic Retinopathy

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***Abstract*—The World Health Organization (WHO) reports that diabetic retinopathy affects one-third of diabetics, regardless of their stage of the disease. Several research efforts are focused on its automated detection and diagnosis. Identifying diabetic retinopathy is crucial due to the damage that occurs to the blood vessels of the eye retina, leading to vision blur or even complete blindness. Thus, an annual checkup is needed for people with diabetes. Moreover, uncontrolled sugar levels for diabetes patients could worsen the current stage of diabetic retinopathy. Consequently, automated detection can greatly contribute to the treatment of disease. This can be carried out through several algorithms, including deep learning models and support vector machines, in addition to transfer learning. This contribution proposes a new approach for diabetic retinopathy automated detection based on convolutional neural network (CNN) models. The proposed model provides both binary and multi-class detection. Both scenarios have shown promising results, where the training accuracies of both the binary classification and the multi-class are 92% and 94%, respectively.**

Keywords—Diabetic Retinopathy; Convolutional Neural Network

I. Introduction

Diabetic retinopathy is considered a major global cause of blindness, according to the World Health Organization (WHO) [1]. Early detection and treatment of diabetic retinopathy are indispensable in order to prevent its adverse effects. In the United States, statistics reveal that an approximate 9.6 million people suffer from it. This represents around 26% of those who are diabetic [2]. Meanwhile, people suffering from the late stage of diabetic retinopathy (vision-threatening stage) represent 5.1 % of those with diabetes [3]. Furthermore, it is believed that the disease severity can be categorized into four main stages. The initial stage is mild diabetic retinopathy, where microaneurysms occur in this stage due to small swelling in the blood vessels, as shown in Fig. 1(a). Although the human vision is not affected in this stage, it is considered the initial stage of diabetic retinopathy. Accordingly, it is highly recommended to do a screening test within 12 months [4].

The second disease stage is moderate diabetic retinopathy, where blood vessels are significantly damaged, causing blood supply to significantly increase, as clearly illustrated in Fig. 1(b). If this stage is left without treatment, it can cause blindness due to the high blood sugar that damages the back of the eye retina [5]. The next stage is the severe diabetic retinopathy stage, where the blood is not flowing in a normal way due to partial blocking in the retina of the eye due to the progress of diabetic retinopathy, as shown in Fig. 1(c). As the retinal hemorrhage in the eye is increasing [6], the vision starts to get affected in specific lighting conditions. This leads to the worst stage, which is severe diabetic retinopathy, illustrated in Fig. 1(d). In such a stage, the new blood vessels formed from the previous stage have become worse, leading to blood leaks as they are weak blood vessels. The leaked blood is poured on vitreous humor that can lead to blindness [7], in a condition known as neovascularization where new abnormal blood vessels start to form.

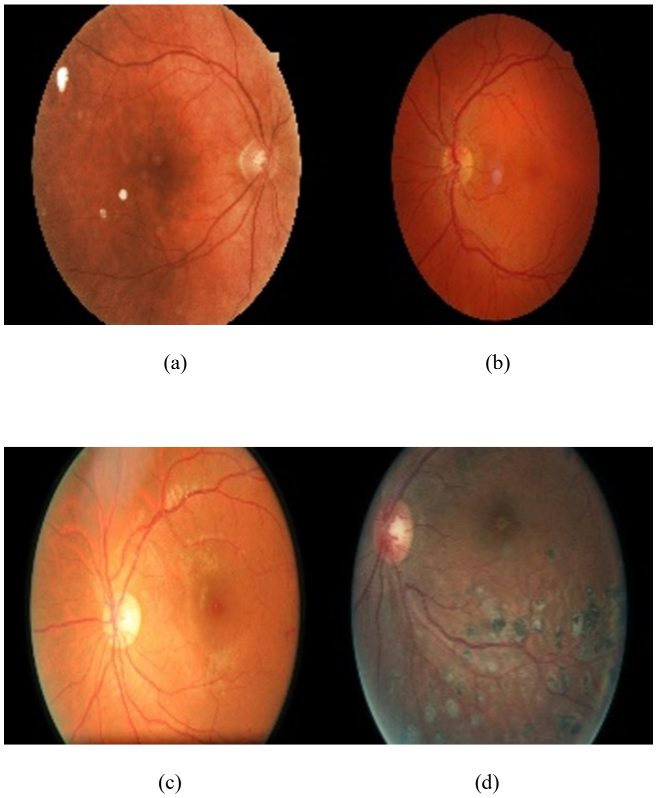

Fig. 1. The Four Diabetic Retinopathy classes, (a) Mild, (b) Moderate, (c) Severe, and (d) Proliferative

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Such disease can cause lesions on the retina, leading to blindness if not detected at its early stages [8]. Consequently, after disease detection, early treatment is crucial in order to prevent vision loss. Essentially, diabetic retinopathy is induced by persistently elevated blood sugar levels resulting from diabetes, making its detection imperative for individuals with diabetes, regardless of the stage of their condition.

The traditional standard fundus photography is used for screening diabetic retinopathy. However, in some cases it does not show the fine details [9]. Other screening techniques are utilized for the diagnosis of diabetic retinopathy, such as MRI and fluorescein angiography. Fluorescein angiography was introduced in 1967 for diagnosing and checking the retinal vasculature, which is the part of the eye affected by diabetes [10]. It simply uses a special camera that captures the blood flow in the retina due to its light sensitivity [11]. Screening is conducted by an experienced ophthalmologist using dilated fundus examination, which is also known as retinal photography, and it is important to note that screening could be difficult for certain stages in addition to detection of certain stages being difficult as well [11]. Ophthalmologists usually diagnose diabetic retinopathy manually using certain methodologies that could be a trade-off among time, consumption, effort, and cost. Starting with the traditional screening, it is considered the main standard form of retina screening. It can capture 30 degrees from the posterior pole of the eye. Its simplicity makes it available to most ophthalmologists. Going further on to Optical Coherence Tomography (OCT), which was introduced firstly in 1991 by Huang et. al. [12], where imaging is done by the echo time delay measurement of the reflected light using low-coherence interferometry and mainly depends on the correlation of such delay time with the light traveling in the reference path.

The current challenge is to build and develop a suitable algorithm for the automated detection of diabetic retinopathy with its different classifications. Previous studies have introduced several and various machine learning and CNN models along with different preprocessing approaches [13]. However, some had shown promising results, while others focused on only binary classification instead of the detection of all stages of diabetic retinopathy [14], [15]. Accordingly, there have been several research efforts that adopt various approaches such as deep learning, support vector machines (SVMs), transfer learning, and K-nearest neighbor to automate the detection process.

Among efficient techniques, deep learning models, specifically convolutional neural networks (CNNs), are widely utilized for detecting different types of diseases including diabetic retinopathy. CNNs can be used at various disease stages, starting from the healthy stage till reaching proliferative stage [16]. Different perspectives and research were recently conducted in order to address this matter. Some research efforts focused on the preprocessing for obtaining the best detailed definition while others perform a normal level of preprocessing while using complex algorithms. Some researchers tend to use better approaches, in which they use a detailed preprocessing of the dataset along with an efficient algorithm, which is based on resizing the dataset, transferring to the grayscale color model, a Gaussian high-pass filter, and adaptive histogram equalization using the green channel of the dataset. Additionally, the algorithm could be simple, however, with using the hyperparameters, the results could be affected positively. Concerning the data preprocessing, several studies focused on the image green channel as it contains the most relevant information of the training process [17]. Also, some research utilized CLAHE and ESRGAN as preprocessing techniques with the aim of merging them as one technique, then comparing each one of them separately [18].

It is believed that effective detection techniques are directed towards automatic detection of diabetic retinopathy through retina images using CNN models. Recently, several CNN architectures have been utilized for the automated detection of diseases using pre-trained CNN models such as VGG16, ResNet50, AlexNet, Inception v2, Inception v4, or even Xception. In addition, there is a wide range of datasets used in the detection of diabetic retinopathy, such as IDRiD (Indian diabetic retinopathy Image Dataset) [19], Kaggle diabetic retinopathy detection [20], Messidor [21], and Digital Retinal Images for Vessel Extraction (DRIVE) [22].

Alghazo et al. [23] developed a detailed study for diabetic retinopathy detection based on modified CNN using Fundus images at Sindh Institute of Ophthalmology. Their main focus was on using a custom-built dataset of 57,625 diabetic retinopathy images. Their work represents the binary classification of diabetic retinopathy. This enabled them to achieve a validation accuracy of 93.40%, where they also considered other statistical metrics such as sensitivity and specificity depending mainly on the evaluation of their model performance in terms of the percentage of true positive, false positive, true negative, and false negative findings.

In another study conducted by Lin et al. [24], the SUS-Tech-SYSU dataset was used for the automated exudate detection in diabetic retinopathy grading by recognizing the lesions along with a dataset of 1,234 fundus images, which required pixel annotations and segmentation.Their main goal was to describe the fundus of diabetic retinopathy in terms of the diabetes stages. Additionally, they expressed the absence of diabetic retinopathy fundus as predicted in the diabetes of stage zero and for the fundus dataset of certain laser spots as late stage of diabetes, either stage three or stage four, which is equivalent to severe non-proliferative diabetic retinopathy or proliferative diabetic retinopathy.

Berbar et al. [25] presented a deep learning approach for diabetic retinopathy detection. Their preprocessing technique was built upon histogram matching for the red and blue channels of the fundus dataset with respect to a reference image. Hence, the resulting dataset brightness is almost the same or even similarly parallel to that of the reference image. They used the dataset Messidor-1 [26], which is used to evaluate segmentation and indexing techniques in the field of retinal ophthalmology. Additionally, Messidor-2 [27], which is an extension for the Messidor-1 dataset, has been tested as well and found to have better performance than that of Messidor-1. They also used the DR2Net model [29]. In the utilized dataset, the training percentage to the testing percentage split ratio was 70% to 30% respectively.

Pratt et al. adopted the idea of preprocessing then augmentation for the purpose of improving the localization ability of the network [30]. They used a dataset that contains 80,000 high-quality images obtained from Kaggle for diabetic retinopathy. They avoided the problem of overfitting by updating the weights with a ratio that is proportional to the number of images in the training batch of healthy individuals [30]. However, other researchers had a different point of view and did not adopt such methodology as it affects the results in

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a negative way. Dai et. al. built their model for detecting diabetic retinopathy using the dataset for both eyes and also for different disease stages; their dataset had 666,383 fundus images for better diagnosis [31].

Reguant et al. [32] developed research in order to understand the feature extraction nature of the CNN for detection of diabetic retinopathy. The utilized datasets were EyePACS27 [32] and DIARETDB1 [33], where EyePACS27 is the largest available dataset. They tested the dimensionality of the dataset to have the best overall accuracy and concluded that 512 × 512 was the best image size to use. Additionally, Reguant et al. adopted various augmentation techniques using an image data generator from Tensorflow with different scaling and rotation factors. They used several architectures, such as Inception v3, ResNet50, InceptionResNet50, and Xception. Consequently, the best model was trained for hundred epochs along with epoch patience (20 epochs) for the early stop callback, enabling them to reach an area under the curve of approximately 0.96.

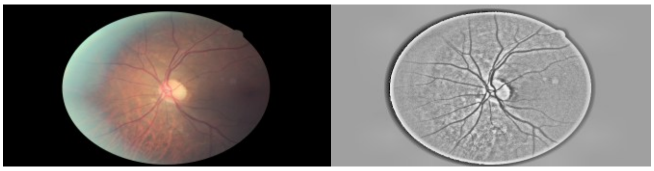
In this contribution, a methodology is proposed that is based on the approach of deep learning, specifically the utilization of convolutional neural networks, due to their promising results in disease detection. They are mainly used for screening and diagnosis. The results of the proposed architecture are based on adopting the VGG16 CNN model as a multi-classifier and another hierarchy using VGG16 CNN as a binary-classifier, followed by a multi-classifier that is built using VGG16 CNN. Finally, a 3-layer CNN model was proposed in this contribution as a binary classifier for the healthy and early-stage positive diabetic retinopathy that reached a training accuracy of 99.98% and a validation accuracy of 95.83%. On the other hand, the multi-classifier model reached a training accuracy of 99.93% for different disease stages and a validation accuracy of 90.00%. This research opens up the door for the utilization of convolutional neural networks in different applications in the medical field, focusing on diabetic retinal imaging and highlighting its transformative potential in clinical practice and research. The rest of this paper is organized as follows: Section II presents the related work. Section III presents the design of the CNN model adopted in the proposed approach. Section III provides details about the experimental results of the conducted experiments and is followed by the conclusion in Section IV.

II. Convolutional Neural Network Design

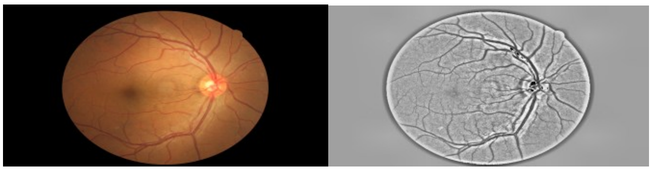
In this section, an effective solution for diabetic retinopathy early detection is proposed. It starts with a preprocessing stage that has been developed with the aim of emphasizing the relevant details in the retina to prepare for the training process. These relevant details include blood vessels and lesions, where the lesions are more involved in the later stages of diabetic retinopathy and changes occur to the blood vessels when grading through its stages. During the training process, several approaches are conducted on the chosen dataset. The dataset was acquired from the Kaggle dataset [34], consisting of five classes of diabetic retinopathy depending on severity.

Upon this, the chosen CNN architecture models are trained on the five preprocessed classes. The utilized preprocessing technique focuses mainly on defining the relevant details in the retina dataset and extracting them through resizing the dataset to an appropriate size. The Gaussian high-pass filter is applied next on the dataset, followed by contrast-limited adaptive histogram equalization (CLAHE). The preprocessing is applied to the entire dataset, and Fig. 1 shows samples from the five classes in the dataset of diabetic retinopathy after the preprocessing. Moreover, although this preprocessing showed quite satisfying results; it was further enhanced by applying it on the green channel for the whole dataset, and the results were very promising. A sample of applying the improved preprocessing technique is represented below.

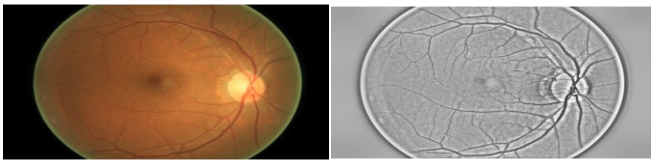
The improved preprocessing was applied through observing the histograms of the three image channels, then performing histogram equalization to spread the intensities. It has been proven that the most accurate results were obtained from the green channel [17]. Fig. 3 shows the three channels of a sample from the dataset where a histogram equalization was applied to the three channels for contrast enhancement, and it can be noted that the green channel has the most relevant information.



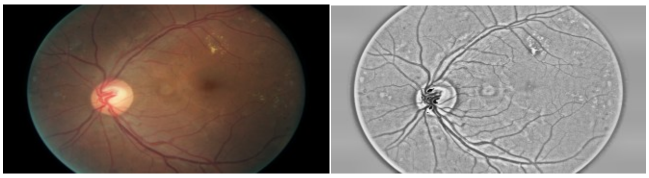
(a)



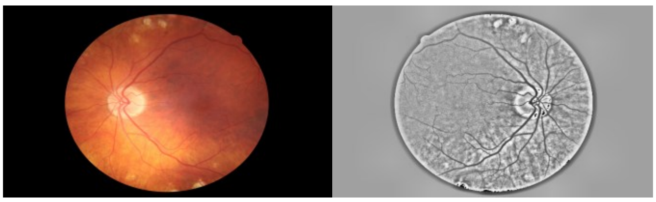
(b)



(c)



(d)



(e)

Fig. 2. Diabetic Retinopathy after preprocessing, (a) Healthy, (b) Mild, (c) Moderate, (d) Severe, and (e) Proliferative

This hints that the architecture of the convolutional neural networks can be selected for having a better deep learning process for a preprocessed dataset. However, an obstacle was encountered due to the different number of images in each class. The healthy class had more than 25,000 images, which creates a vast gap due to its contrasting classification that ends up with a biasing problem. Consequently, the first

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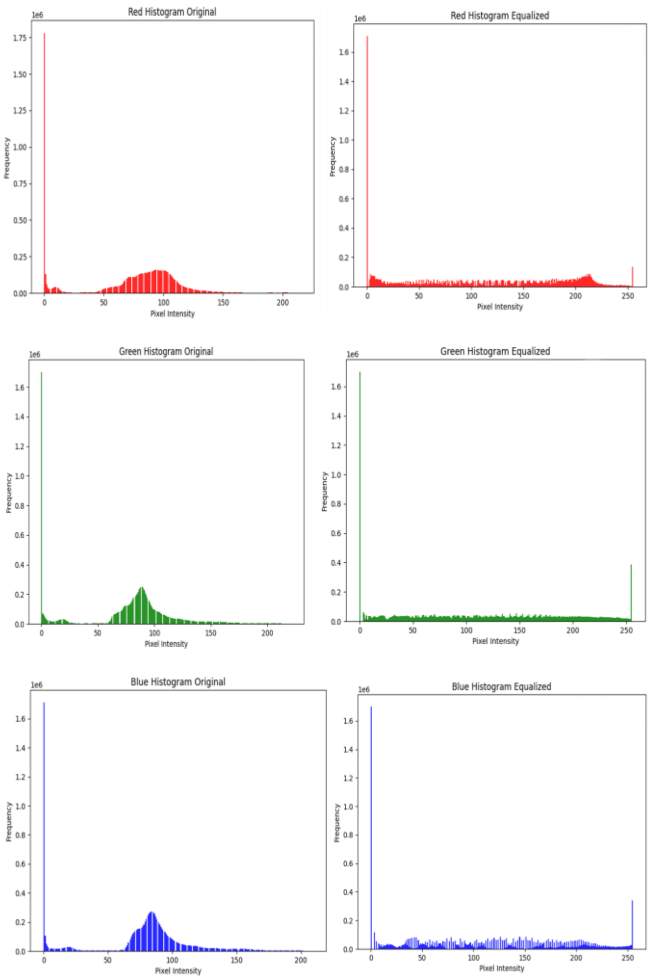
classification data number was limited to cope with the other classes, given that the split was around 30% for validation and 70% for training.

This paper tested several CNN architectures to achieve the desired performance. First, the VGG16 CNN model was employed to classify the image directly by tuning the hyperparameters to cope with the large size of the dataset. Although this approach succeeded in effectively distinguishing between the different classes, an alternative approach based on 2-stage classification as depicted in Fig. 4 has shown much better results. In the alternative approach, the VGG16 model was used as a binary classifier for healthy and diseased images, and then the diseased images were processed by another VGG16 CNN model to decide its severity level based on the four progressive stages of diabetic retinopathy depicted in Fig. 1.

III. Detection and Classification Results

Several experiments are performed for the purpose of testing the proposed model, followed by a complete study of the collected results.



(a) (b)

Fig. 3. Histogram distribution, (a) Before equalization, and (b) After equalization

VGG16 CNN model is trained with the preprocessed dataset. A small batch size of 64 was used in order to better handle the large image size in the chosen dataset. Additionally, the learning rate is set to 0.01 along with the Adam optimizer to make the model converge faster. Adoption of these hyper-parameters has led to achieving an accuracy of 84.5% using the first preprocessing technique (considering all three channels).

In this work, the EyePACS Kaggle dataset [34] was used for multi-stage hierarchy. The classification process started with a binary classifier in order to differentiate between healthy and diseased images. As a second step, if the image was classified as a diseased image, the multi-class stage will be then applied. Additionally, it has been observed that the loss in the multi-class stage increased more than that of the optimized VGG16. Moreover, to have an effective comparison between both architectures, the first architecture simply used the VGG16 model with default hyperparameters [35] on the five classes of diabetic retinopathy, while the second architecture is a binary classifier followed by a multi-class stage for effectively detecting the severity stage of diabetic retinopathy. The VGG16 model needed to be trained on the second preprocessing of the dataset, as such preprocessing has shown much better and more promising results in the multi-stage hierarchy. This can be observed from Table I, where it shows the comparison of using VGG16 directly on the five classes of diabetic retinopathy versus the multi-class hierarchy, which consists of a binary classification followed by a multi-classification stage as mentioned earlier. The metric of comparison is the training and the validation accuracy.

TABLE I. A comparison between 1-stage and 2-stage VGG16

Hierarchy	1-stage VGG16 (5 o/p classes)	2-stage VGG16	
		Binary Classification (2 o/p classes)	Multi-Classification (4 o/p classes)
Training Accuracy	89%	92% “37th epoch”	94.5% “54th epoch”
Testing Accuracy	65%	75%	71%

Our proposed approach involves designing a customized three-layer CNN model for a two-stage binary classification process, followed by a multi-classifier process for the diseased images to determine the disease severity level. The implemented model consists of three convolutional layers; each layer is followed by a Max pooling layer, followed by two fully connected dense layers. For each layer, it accepts an RGB input image of size 256×256, along with 16 kernels each of size 3×3. Similarly, the second and third layers are of the same structure, except that the second layer has 32 kernels instead of 16. Increasing the number of filters is usually beneficial for the purpose of learning more image features with improved generalization. The developed approach had achieved promising results. The validation accuracy of the implemented model was 95.83% as a binary classifier. On the other hand, the model as a multi-classifier achieved a validation accuracy of 90%. These results proved the applicability of detecting both diseased and healthy classes using a deep CNN architecture with a small number of layers (3 convolutional layers) along with the advanced preprocessing technique adopted in this contribution. This opens the possibility of embedded hardware implementation of the proposed scheme due to the affordability of computational resources and memory usage.

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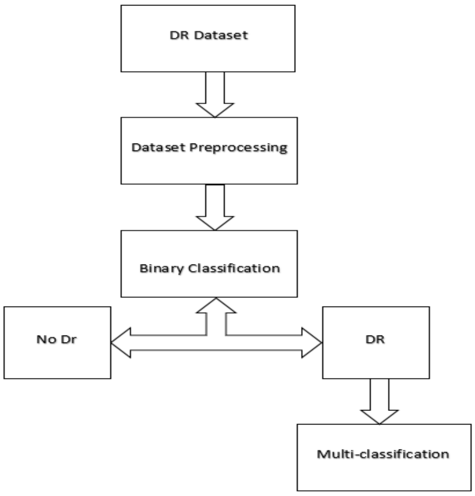

Fig. 4. Flowchart of the proposed classification algorithm

TABLE II. PROPOSED ARCHITECUTRE RESULTS

Hierarchy	Binary Classification	Multi-Classification
Training Accuracy	99.98%	99.93%
Testing Accuracy	95.83%	90.00%

IV. CONCLUSION AND FUTURE WORK

In this paper, a new approach for automatic detection of diabetic retinopathy is proposed. Several VGG16 CNN architectures were tested either in single-stage classification or multi-stage classification along with two preprocessing techniques for the diabetic retinopathy. The multi-stage classification architecture was able to achieve a testing accuracy of 75% in detecting the presence of diabetic retinopathy and 71% in deciding its progressive severity level. Compared to the VGG16 model, the developed proposed three-layer CNN model, with its simple structure and minimum number of convolutional layers, was able to achieve a testing accuracy of 95% in detecting the presence of diabetic retinopathy and 91% in classifying its progressive severity level. In future work, it is desired to implement the proposed CNN structure on an embedded AI platform for real-time disease detection.

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