Detection of Diabetic Retinopathy Using CNN

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Abstract. Diabetic retinopathy is one of the most common diseases for diabetic patients around the world. Moreover, this disease causes lesions on the retina which affect the vision of the patient. Hence, diabetic retinopathy may lead to blindness in some cases if not detected earlier. Therefore, early detection of this disease is required to prevent vision loss. In this paper, deep learning techniques were used to produce a good performance in detecting and classifying fundus images. The proposed method is an implementation of CNN algorithm that detects and classifies fundus images based on the stage of the disease. As a result, the accuracy we obtained in our approach has reached 92.26% and MSE of 0.0628.

Keywords: CNN · Deep learning · Diabetic retinopathy · Median filter · Morphology · Interpolation

1 Introduction

Diabetes is a serious chronic disease that affects the lives of individuals, their families and society. It does not only affect adults, but children likewise. Moreover, it may occur in three situations: when the pancreas does not produce insulin, does not produce it properly or when the body cannot use the insulin produced by the pancreas [1]. Additionally, insulin is a hormone that allows glucose absorbed from food to pass from the blood flow into the cells to produce energy. According to the International Diabetes Federation, 463 million people around the world are diabetics. Moreover, 55 million of them are in the MENA region, 33.8 million in North America, 59 million are in Europe and 87.6 million are in the South East of Asia [1].

There are three types of diabetes: Type 1 Diabetes (T1D), Type 2 Diabetes (T2D) and Gestational Diabetes Mellitus (GDM) [2]. The first one occurs when the pancreas produces little to no insulin. Consequently, the patient needs a daily insulin injection to control the glucose level in the blood. As for the second, it occurs when the body does not use the insulin produced by the pancreas. Thus, it has various treatments such as: healthy lifestyle, oral drugs and insulin injection. Whereas, the third occurs during pregnancy when the mother has high level of glucose in her blood. Also, this type affects both the mother and the child. Even though glucose level decreases back to normal after pregnancy, some cases have shown that it evolves into type 2 diabetes [1].

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Diabetic retinopathy is one of the complications of diabetes that requires an annual examination for early detection. Whereas, it occurs in type 1 and type 2 diabetes and is the most recurrent cause for blindness among adults [3]. As a definition, diabetic retinopathy is a diabetes complication that damages the blood vessels inside the retina causing blood and fluid leakage. Additionally, this leakage creates microaneurysms, exudates and hemorrhages [4]. Figure 1 shows how microaneurysms, exudates and hemorrhages look inside the eye using fundus photography [5]. Whereas, microaneurysms appear as small red dots inside blood vessels, exudates appear as yellow spots on the retina and hemorrhages appears as red spots which are usually larger than microaneurysms.

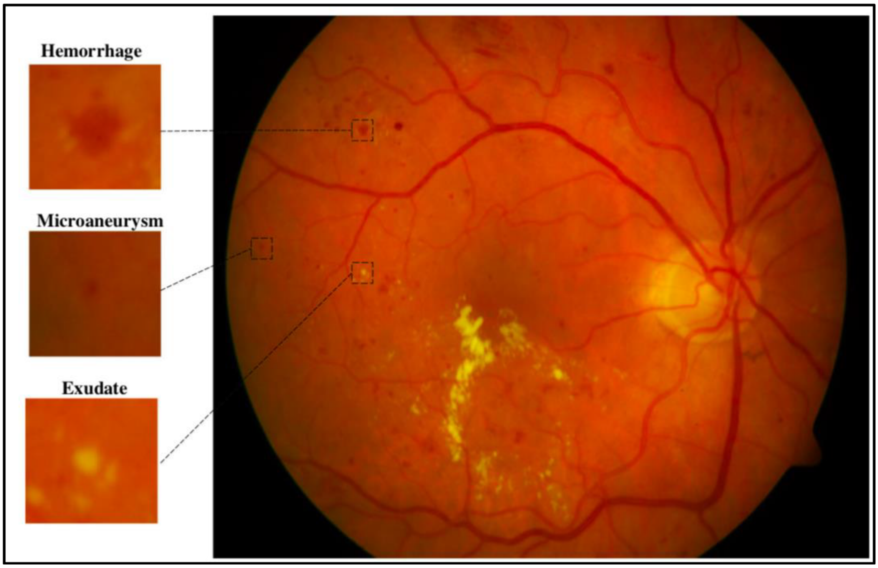

Fig. 1. Exudates, hemorrhages and microaneurysms inside the eye tissue [6].

The process of extracting retina blood vessels to determine the diseases is a time-consuming process. Therefore, automating the extraction process will help simplifying and accelerate the process. Also, detecting the diseases early will decrease the blindness risk by 95% [6, 7]. Hence, the proposed system aims to identify diabetic retinopathy using image processing and deep learning techniques. Thus, fundus photography images of the retina with different cases of diabetic retinopathy were used as a dataset [8]. As for the deep learning technique, Convolutional Neural Network (CNN) was used to classify the stage of the disease. Further, the four stages used for classification are: not detected, low, mild and severe.

The rest of the paper is organized as follows. Section 2 provides a background about the diabetic retinopathy disease and some basic information about deep learning, image processing and how they are combined. In Sect. 3, we provided some literature review on the previous image processing techniques that have been proposed by different researchers. In Sect. 4, we proposed the methodology we used to develop our method.

Section 5 discusses the results that we obtained. Whereas Sect. 6 provides the conclusion of our paper.

2 Background

2.1 Diabetic Retinopathy

One of the senses our body has is our eyes. They allow us to see and differentiate everything around us. Specifically, the light gets into the pupil-along with the iris and cornea's help-upon the retina. Then, the retina helps to convert the image so the brain can process the environment with the help of rods and cones. Thus, a healthy retina plays an important role in human vision. However, the retina can be affected by many diseases leading to blindness. Diabetic eye disease is the most common retina disease which includes: Diabetic Retinopathy, Glaucoma, and Cataract [9].

Diabetic Retinopathy is an eye disease that affects diabetic patients. In addition, it is considered to be the most popular one and it is the cause of visual weakness for adults. However, it is a consequence of an alteration in the retina blood vessels. In consequence, the retina is located in the eye rear and is described as the sensitive tissue. Moreover, the retina blood vessels in some cases of diabetic retinopathy tend to swell and leak fluid, while the growth of new blood vessels on the retina surface is the abnormal case.

Proliferative Diabetic Retinopathy (P.D.R) and Non-Proliferative Diabetic Retinopathy (NPDR) are the two stages of diabetic retinopathy [10]. NPDR is considered to be the early stage of diabetic retinopathy. Whereas, it happens when the blood vessels in the retina start to leak blood and fluids. Sometimes, these blood vessels might close off, causing what is called exudates. PDR on the other hand, is a more advanced and serious stage. Consequently, it occurs when new blood vessels start to grow. Accordingly, these blood vessels are fragile, so they bleed through the retina. If the vessels bleed a little, it causes dark floaters. And if they bleed a lot, it blocks the vision causing blindness [10].

2.2 Deep Learning Techniques

Deep learning methods have a huge impact on different fields, especially on medical image analysis which is considered a huge research area that has been developed in the last decade and is still improving. The reason for that is it helps us not only to identify the different diseases found by images, but it helps also to construct new features, measure predictive targets and provides actionable prediction models [11].

Deep learning uses artificial intelligence to process large information and extract meaningful patterns based on domain knowledge. It processes the data in hierarchical architectures like the human brain for classification, feature extraction or representational learning without the need for human intervention [11]. Regarding that, it still has some issues including unavailability of the dataset, privacy and legal issues, dedicated medical experts, data interoperability, data standards and others more [12].

Convolutional Neural Network (CNN) is one of the outbreaks in the evolution of deep learning. It is a method that is based on a sliding filter that scans over the image and creates a layer that consists of image features [13]. Then, an activation function is performed on each filter to produce an output between 0 and 1 which indicates the activation state. Simply, the activation function in a neural network is used to change the state or the activation level of a neuron into an output signal [11, 13]. After that, the results from each filter are passed to the second layer where it groups multiple filters to one neuron. Hence, the number of inputs in each neuron is fixed for all neurons. This process is repeated until the whole image is covered.

There are many activation functions developed and used in deep learning such as Rectified Linear Unit (ReLU), sigmoid and softmax. Moreover, Rectified Linear Unit (ReLU) is an activation function usually combines with other activation functions in order to get rid of negative numbers and exchange them with zeros [13]. Also, it helps retaining converged values instead of having a clog at a certain edge [13]. In fact, the ReLU function gained its reputation for that reason. That is, having converged values helps the machine to differentiate different values and classify data. The ReLU function can be represented with the following function [13]:

$$f(x) = \max(x, 0) \tag{1}$$

Where x is the number of inputs.

Sigmoid function is a non-linear function that is mostly used for the purpose of training data. Hence, it provides and output of either 0 or 1 [12]. Consequently, it is very useful in designing and understanding neural activity. It can be represented with the following function [12]:

$$f(s) = \frac{1}{(1 + e^{-x})} \tag{2}$$

Where x is the number of inputs.

Softmax is another popular activation function used for developing neural network models. Simply, it maps each output in a way that the total sum of a neuron is 1. Hence, the output is a probability distribution [13]. Consequently, the softmax function is mostly used in CNN. Softmax can be represented with the following function [13]:

$$\partial(z)_j = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} \text{for j} = 1, \ldots, \text{k} \tag{2}$$

Where z is a vector of inputs to outputs layer and j is the output units from 1 to k.

2.3 Image Processing

When talking about image processing, it is concerned with different techniques that generate a new array of numbers where it represents an enhanced image or classification of an image [13]. Whereas, image classification is a product of feature extraction techniques implemented using deep learning approaches. Although, some images can be difficult to analyze due to haziness or having a low resolution. Thus, preprocessing techniques can be applied to enhance image quality and remove any distortion or noises [14]. See Fig. 2.

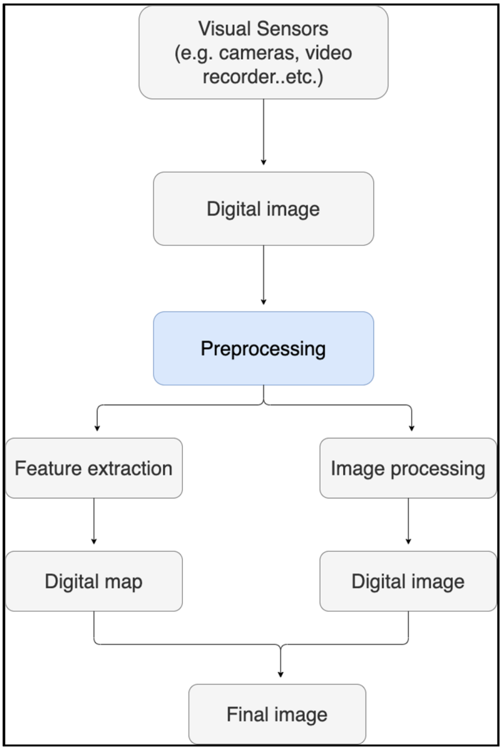

Fig. 2. Processes of image processing

The only way to detect diabetic retinopathy is through fundus images. That is, its complications are inside the retina tissue and cannot be visible by the naked eye. As mentioned before, these complications are exudates, microaneurysms and hemorrhages. Thus, many solutions have been developed using artificial intelligence and deep learning to process images and detect diabetic retinopathy for better classification and higher accuracy. And to diagnose diabetic retinopathy, its symptoms have to be detected and classified.

3 Related Work

In the past several years, the number of diabetic patients has increased in the world with an estimation of 463 million adults. Along with this chronic disease comes the possibility of being diagnosed with diabetic retinopathy. Since it can be early detected, there is a possibility of preventing or treating it. Therefore, many image processing techniques have been developed to detect and classify this disease in the early stages.

In [15], the authors used deep neural networks in the medical image to extract the information using the Siamese convolutional neural network (SCNN). Particularly, the method trains a pair of binary images that require less supervision. Also, they used a diabetic retinopathy fundus image dataset to evaluate their method. The researchers have provided a comparison between their state-of-the-art approach and a single supervised CNN approach which showed that their method required less supervision for training. Yet, they need to do more experiments on different metrics for evaluation like recall on top-N.

Where researchers in [11] have developed a deep learning approach using Convolutional Neural Network (CNN) for detecting diabetic retinopathy and fundus images as a dataset. Also, their approach has scored 97% sensitivity. As for [12], they used smartphone-based fundus photography and artificial intelligence to detect diabetic retinopathy. For the dataset, they used retinal photography of type 2 diabetes only. Furthermore, they used a software called EyeArtTM for detecting diabetic retinopathy. Consequently, the software scored a sensitivity of 95.8% and specificity of 80.2%.

As for in [16], a combination of fractal analysis and K-nearest neighbor (KNN) components have been used. This approach has scored an accuracy of 98.17%. Additionally, they used a Support Vector Machine (SVM) approach which separates blood vessels, exudates and microaneurysms for feature extraction and then, it detects the existence of diabetic retinopathy. This approach has scored 95% as maximum sensitivity.

4 Methodology

In the proposed approach, a deep learning technique was developed to detect diabetic retinopathy disease based on image processing using Python. On that account, our method is based on the Convolution Neural Networks (CNN) approach using fundus images. Thus, we used a MacOS operating system that uses a 1.8 GHz Intel Core i-5 processor, 8 GB memory.

CNN is known to be a supervised neural network. Hence, images were labeled based on the severity of the disease for classification. So first, the model takes fundus images as an input. Then, these images are pre-processed by being resized, padded, filtered and dilated. Hence, these operations are used to enhance images and improve feature extraction and classification. After that, images are segmented to locate boundaries and objects of each image. Thus, these segmentations are used for blood vessels, exudates, hemorrhage and microaneurysms detection. Then, the features of each label are extracted and images are classified based on disease severity. See Fig. 3.

4.1 Data Collection

In this study, a publicly available high-quality dataset from two databases were used. For the first dataset, the same dataset tested in [17] from GitHub was used. While the second dataset was taken from Kaggle [18]. Consequently, the dataset contained 600 fundus images for healthy patients and patients with diabetic retinopathy. Then, images were labeled based on the diabetic retinopathy stage whether it was not detected, low, mild or severe.

4.2 Preprocessing

For the preprocessing stage, re-sizing, interpolation, filtering and morphological operations were used to have a better visual of exudates, hemorrhage and microaneurysms.

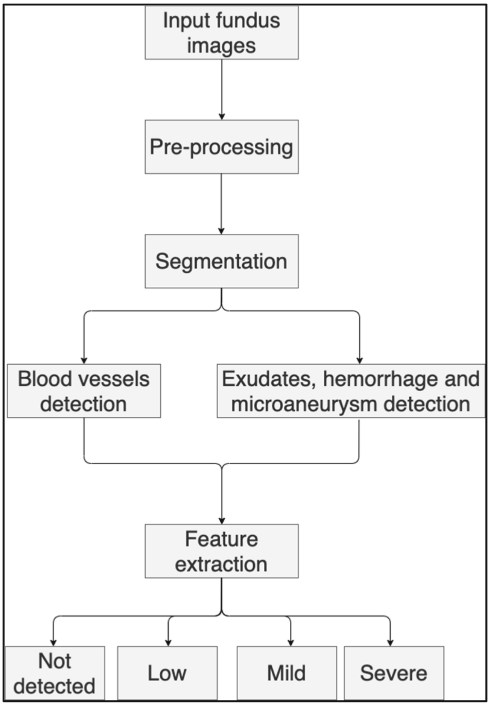

Fig. 3. Processes of the proposed model.

First, all images were re-sized to 90 × 90 pixels since images differed in size. Then, a bicubic interpolation was performed which takes 4 × 4 pixels to fill the neighboring pixels. After that, a median filter is performed to enhance the image. Finally, we used a morphological operation called dilation which adds pixels to the boundaries of an object in the image. Moreover, Fig. 4 shows a preprocessed image of a healthy eye where boundaries of the eye and retina veins are more visible but no sign of diabetic retinopathy was detected. As in Fig. 5, hemorrhage and exudates are much clearer and easier to detect.

4.3 Feature Extraction and Classification Using Deep Learning

After preprocessing, CNN was applied along with a window size of 3 × 3. Also, ReLU activation function was used for feature learning. While sigmoid function was used for feature extraction. In addition, the ReLU function was performed on each filter to produce an output between 0 and 1 at each neuron which finally provided the activation state and produced features of each label [19]. For the sigmoid function, it was used to provide an output of either 0 or 1 as well [20]. However, the final result of sigmoid function is the feature extraction for images. After that, we specified the input size to be 32 at each layer. Further, 90% of the dataset was used for training and 10% for validation.

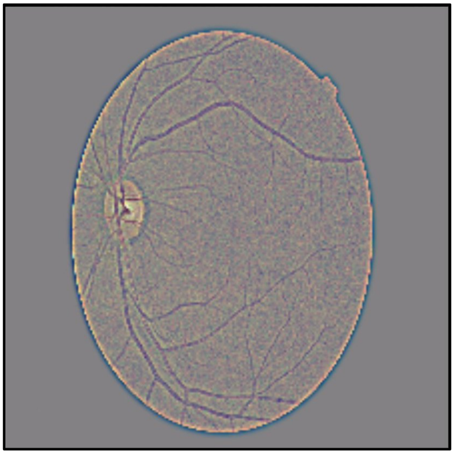

Fig. 4. Preprocessed fundus image of a healthy eye.

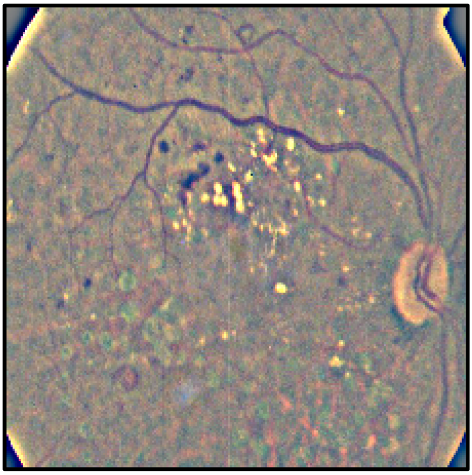

Fig. 5. Preprocessed fundus images of a diabetic retinopathy patient.

5 Results and Discussion

In preprocessing, resizing and applying gaussian filters on images were first applied. However, it produced a very low accuracy. Using different metrices, the processing of the images hit accuracy of 48% at best. Thus, the preprocessing technique was changed to median filter, morphology and interpolation. Thus, the resulted accuracy was much better.

During the testing phase, multiple parameters were experimented to increase the accuracy of the proposed method. Thus, a various types of activation functions were used along with manipulations of input size and validation dataset percentage. Hence, an experimentation of using softmax activation function in the feature extraction layer was done. However, the accuracy ranged from 40–50%. After experimenting with the sigmoid function, accuracy results have increased the by 50–80%. Further, using a large input size provided very poor outcomes. After multiple trials, an input size of 32 suited the proposed method. Also, an experimentation of varying the validation dataset from 10% to 30% was performed but it did not affect the accuracy rate.

With an input size of 32 and setting the epoch to 50, the highest accuracy achieved was 92.26% with MSE of 0.0628. See Fig. 6. Hence, it shows that the proposed method was successful in identifying diabetic retinopathy. Nonetheless, diabetic retinopathy is a serious disease that cannot be diagnosed at early stages. For that reason, more experimentation on enhancing this method could possibly done to obtain a higher accuracy. For example, Asymmetric CNN (ACNN) can be used to see its effect on the diagnosis of diabetic retinopathy since it is a promising method in image processing.

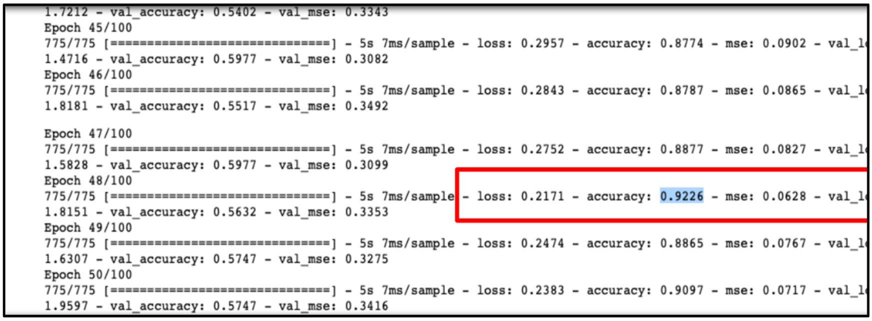

Fig. 6. Highest accuracy obtained.

Table 1 shows a comparison of the proposed technique and other techniques discussed in Sect. 3. Whereas, the proposed system scored higher accuracy than EyeArtTM system. However, the system proposed in [11] provided a better accuracy. Although, the method was not clearly explained in the preprocessing and classification. Thus, it is difficult to compare between the two approaches. KNN has also scored higher accuracy. According to the authors, using SVM has drastically changed accuracy for their technique. Hence, it can be used in the future to test it with the proposed system and test its potentials.

Table 1. A comparison between the proposed system and other diabetic retinopathy detection techniques.

Technique	Classification	Accuracy
Proposed system	CNN	92.26%
Razzak, M. I., Naz, S., Zaib, A. [11]	CNN	97%
Chung Y.A., Weng, W.H. [12]	EyeArtTM	80.02%
Schowengerdt, R. A. [16]	KNN	98.17%

6 Conclusion

Diabetic retinopathy is a serious disease that affects people with diabetes. Consequently, it is considered to be the most common cause of blindness among adults. Therefore, diabetic patients are required to do an annual check since it does not have any early symptoms. To assess the diagnosis of this disease, an image processing technique was proposed which uses CNN to detect diabetic retinopathy using fundus images. Additionally, a dataset from Kaggle and GitHub were used for the fundus images. To preprocess and enhance fundus image, morphological operations and normalization techniques were performed. Thus, the morphological operations used were: opening, closing, erosion and dilation. After that, the CNN technique was applied for image classification. As a result, the best accuracy obtained was of 92.26% with MSE of 0.0628. Hence, the results show promising results in detecting such serious disease with a prospect of improving.

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