Design and Development of Deep Learning Based Fundus ImageDiabetic Retinopathy

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Abstract—**The healthcare industry is completely different from other industries. It is a high-priority department where people expect the highest levels of care and service, regardless of cost. Even if it consumes a lot of budget, it does not meet social expectations. Most medical data is interpreted by medical experts. In the image interpretation of human experts, it is very limited due to its subjectivity, complexity of images, wide differences between different interpreters and fatigue. After deep learning in other practical applications, it also provides an exciting solution with good medical imaging accuracy and is considered a key method for future health sector applications. In this chapter, we discuss the most advanced deep learning architecture and its optimization for medical image segmentation and classification. In the previous section, we discussed the challenges of medical imaging and open research based on deep learning.**

Automated detection of diabetic retinopathy is critical because it is the leading cause of irreversible vision loss in working-age populations in developed countries. The early detection of the occurrence of diabetic retinopathy is very helpful for clinical treatment; although several different feature extraction methods have been proposed, even for those trained clinicians, the classification task of retinal images is still tedious. Recently, deep convolutional neural networks have shown superior performance in image classification compared to previous feature-based image classification methods based on handcrafting. Therefore, in this study, we explored the use of deep convolutional neural network methods to automatically classify diabetic retinopathy using color fundus images to obtain high precision in our datasets, superior to those obtained using classical methods.

***Keywords*—Orthogonal frequency division multiplexing (OFDM), Peak-to-average power ratio (PAPR), constant modulus algorithm (CMA).Complementary cumulative distribution function (CCDF).**

I. INTRODUCTION

Diabetes can be characterized as a chronic increase in glucose in the blood and has become one of the fastest growing health threats in the world [19,19]. An estimated 150 to 200 million people are diagnosed with diabetes, of which about 50 million are in Europe alone [23]. In addition, many people are still unsatisfied. In Finland, which has a population of about 5 million, 280,000 people are treated for diabetes, insulin production in islets causes permanent damage to 40,000 people (type 1 diabetes), and insulin resistance increases in 240,000 people (type 2 diabetes) [18]. In addition, the current estimate predicts that there are 200,000 undiagnosed patients, and the number of people receiving diabetes care will double every 12 years. These shocking facts promote prevention strategies and screening for large populations because proper and early treatment of diabetes is cost-effective [15].

Digital imaging technology has evolved into a versatile, non-invasive measurement tool for a wide range of applications in medical science. Imaging the fundus with modern technology is the current practice in many eye clinics, and it becomes more important as life expectancy and healthcare costs increase. Because the retina is susceptible to microvascular changes in diabetes, diabetic retinopathy is the most common complication of diabetes, so fundus imaging is considered a non-invasive and painless route to screen and monitor diabetic eyes [17].

As the diagnostic procedure requires the attention of an ophthalmologist and regular monitoring of the disease, the workload and staff shortage will eventually exceed the current screening capacity. In response to these challenges, digital imaging of the fundus and automated or semi-automated image analysis algorithms based on image processing and computer vision technology offer great potential [11,127]. By automating the analysis process, more patients can be screened and further examined, and ophthalmologists have more time to pay attention because most fundus images do not cause any medical behavior.

II. DIABETIC RETINOPATHY

In the past few decades, the number of people diagnosed with diabetes has increased dramatically, and diabetes has increased the risk of a series of eye diseases, among which diabetic retinopathy is one of the most serious diseases. In addition, diabetic retinopathy is the leading cause of blindness in middle-aged people. Despite ongoing efforts, early detection of diabetic retinopathy is a time-consuming process, even for trained clinicians, which can lead to delays in treatment and poor communication. The importance of automated methods for detecting diabetic retinopathy has been recognized. . In our study, we focused on the classification of retinal images into normal images and diabetic retinopathy images (sample frameworks for our classification problems. Previous efforts to use image feature extraction and machine learning methods have made good progress. The classifier features hard exudates, red lesions, microaneurysms, and vascular detection, while the classifier for tasks includes neural networks, sparse representation classifiers, linear discriminant analysis (LDA), and support vector machines (SVM).), k-nearest neighbor (KNN) algorithm, etc. However, none of the manual features can cover all symptoms of diabetic retinopathy in the image, and a large proportion of cases become normal, and many times are used to diagnose normal cases. The actual clinical application of the system islimited.

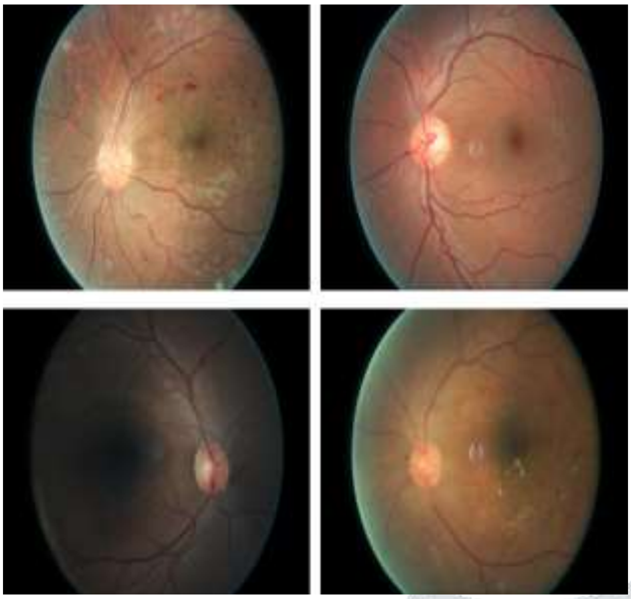
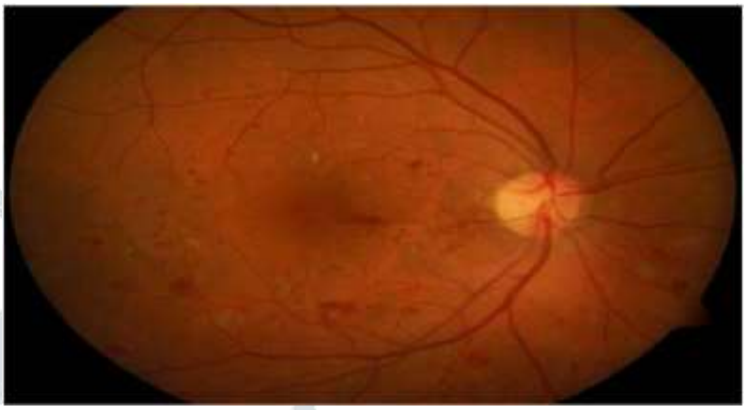


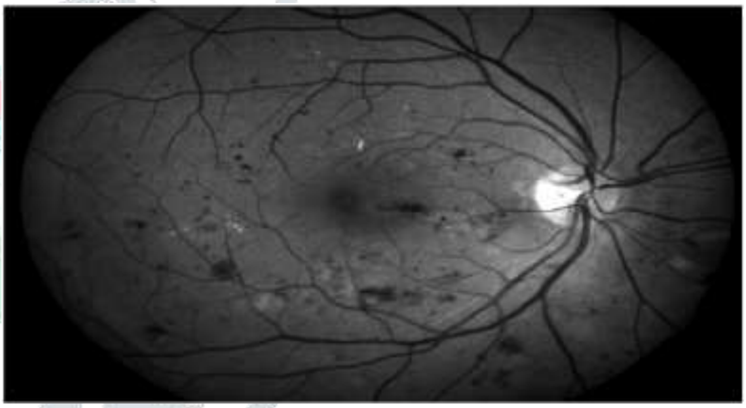
Figure 1.Sample frames of the retina images.

The first two frames of the top row are from normal subjects, while the two frames of the bottom row are from patients with diabetic retinopathy. Recent advances in Convolutional Neural Networks (CNN) have made it the most advanced technology in image classification tasks, and variants have begun to dominate in many areas of computer vision, such as object detection, image classification, object tracking, and edge detection. CNN can learn a range of functions, rather than making the necessary use of hand-made functions, which can be used for image classification. Because hierarchical methods can be used to learn more complex features, as well as translation and distortion features in higher layers, the accuracy of CNN-based image classification methods can be higher. Based on this hypothesis, we explored the use of CNN-based methods for diabetic retinopathy trials in this work. In addition, a specific multi-layer CNN architecture was designed and experiments were performed on real retina data.

Diabetic retinopathy is a microvascular complication of diabetes that causes abnormalities in the retina. There are usually no significant symptoms at an early stage, but the amount and severity are mainly increased in time. In the following, the progression of the disease is described in detail. Diabetic retinopathy usually begins with small changes in the retinal capillaries. The smallest detectable abnormal microaneurysm (MA) appears as a small red dot in the retina and is a localized dilation of the weakened retinal capillaries. Due to these damaged capillary walls, small blood vessels may rupture and cause intraretinal hemorrhage (HA). In the retina, the bleeding can be a small red dot that is different from a microaneurysm, or it can be a large circular footprint of an irregular contour. Diabetic retinopathy also increases the permeability of the capillary wall, leading to retinal edema and hard exudate (HE). Hard exudate is a lipid former that oozes out from weakened blood vessels and appears yellow with good boundaries. If local capillary circulation and oxygen support fail due to vascular occlusion, a pale area with blurred edges appears in the retina. These areas are small microinfarcts called soft exudates (Se). Intraretinal micro vascular abnormalities (IRMA) and venous diseases are signs of severe changes in diabetic retinopathy, in which micro vascular abnormalities in the region are characterized by capillary system dilatation and venous lesions, and changes in arterial and venous shape. A large number of hypoxia and capillary blockages in the retina lead to the formation of new fragile blood vessels. These new blood vessels attempt to grow in a tissue-filled direction to provide nutrients and oxygen. However, new blood vessels are fragile and tend to grow into the space between the retina and vitreous humor, or directly into the vitreous humor, which can lead to pre-retinal hemorrhage and sudden blindness. The growth of these new blood vessels is called neovascularization.



(a)



(b)

Figure 2: Examples of eye fundus images: (a) colour image of an eye fundus; (b) corre- sponding red-free image.

As mentioned above, fundus photography is considered the preferred method of diagnosis because it is reliable, non-invasive and easy to use [29]. Compared with traditional ophthalmoscopes, it can record diagnostic data and then conduct expert consultations. More importantly, fundus photography can improve sensitivity, that is, the detection rate of abnormal fundus is higher [39]. Due to the rapid development of digital imaging, fundus cameras also provide easy-to-file images in portable formats, using image analysis algorithms to automatically diagnose diabetic retinopathy.

The fundus camera is divided into two groups: dilated and non-mydriatic cameras, where the front photograph indicates that the pupil needs to be dilated with eye drops. Since expansion is used in practice for both fundus camera types, the pre-setting is misleading. The non-mydriatic fundus camera is small and suitable for screening purposes, but at the same time the image quality is worse and the field of view is smaller. Therefore, when a more accurate diagnosis is required, a dilated camera is used. The patient sits in front of the fundus camera with the head in the headrest of the instrument. The generated light is emitted into the patient's eye using an optical mirror and a lens, and the reflected light is captured by the camera sensor. The captured image is typically the color image of Figure 1.7, but since the retina is transparent and the depth of penetration of the emitted light depends on the wavelength, an optical filter can be used to emphasize the desired retinal structure. A typical alternative to color images for diagnosing diabetic retinopathy is a red-eye fundus-free image. The recommendation for the diagnosis of diabetic retinopathy is to use no red and color images. [17] Two images were taken by focusing a 45° field fundus camera to the macula and optic disc (two field of view 45° fundus photography) [14]. For long-term diabetic patients, two-dimensional photography is recommended because even if the central region of the retina changes little, it is necessary to find new blood vessel changes that need to be treated in the periphery [45].

III. METHODOLOGIES

The Convolutional Neural Network (CNN) is a feedforward artificial neural network (ANN) that is very similar to a normal neural network. CNN is a well-known deep learning architecture in which individual neurons are tiled in such a way that they respond to overlapping regions in the field of view. CNN is an important class of learnable representations that are inspired by biological neural networks. Many variations have been proposed in the past few years. However, the basic components are very similar. CNN consists of alternating convolution and pooling operations. Typically, convolutional layers are interspersed with collection layers to reduce computation time and create further spatial and configuration invariance; the last few layers (near the output) will be fully connected to the one-dimensional layer. In more detail, the feedforward neural network can be viewed as a function f of the mapping data x:

$$f(x)=f_L(...f_2(f_1(x_1,w_1),w_2)...,w_L).$$

The parameters can be learned differently from the example data such that the resulting function f implements a useful mapping. Formally, in the CNN, each x1 will be an M x N x C array. Because our problem can be reduced to a binary classification problem. The results of these sets are then tiled so that they overlap to obtain a better representation of the original image (eg, edges in the image). The convolution layer consists of a rectangular neuron grid that takes the rectangular area of the previous layer as input. In addition, each convolution layer may have several meshes, using filters that may be different. Typically, there is a pooling layer after each convolutional layer that is subsampled from the previous convolutional layer. This collection can be done in a variety of ways, such as averages, maxima, and the like. Finally, after several convolutional layers and maximum collection layers, a fully connected layer (or layers) (possibly a fully connected, aggregated or convolved layer) will be constructed using the output of the previous layer, used to describe the entire input image. Compact features. Optimize the network by backpropagation and stochastic gradient descent. Note that the forward and backward propagation can vary depending on the type of layer.C.

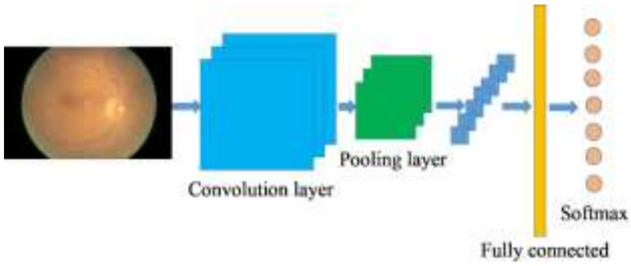


Figure.3 AnExemplary Architecture of The Convolutional Neural Network.

IV. SIMULATION

The data set contains images from different patient populations with extremely different illumination levels in the fundus photography. Illumination affects pixel intensity values in the image and produces unrelated unnecessary changes classification level. A multi-layer convolution neural network has been implemented to detect and match the input images with targets. Simulation was carried out on mathematical modeling tool MATLAB and algorithm was tested on given images to test execution time and accuracy.

V. RESULTS

The performance of proposed network was tested on 10 subjects and it was found to have good accuracy and fast execution for achieving the gradient error. The accuracy and error threshold was achieved in 15 epochs where one epoch was processed in 05 seconds. The number of epochs and execution time depends on number of samples in dataset, with increase in size of dataset the execution time and number of epochs required to achieve error gradient and desired accuracy will also increase significantly. The proposed algorithm can work both on real time as well as offline dataset.

Table-6.1(Analysis of Accuracy and Execution Time)

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Epoch	Iteration	Time Elapsed	Batch Accuracy
1	1	05 Second	0 %
15	15	38 Second	100 %

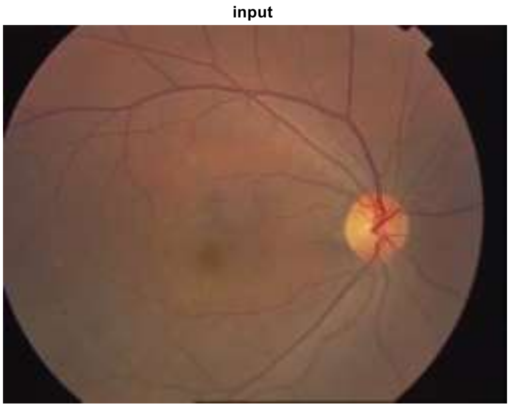

Figure.4Sample Data Set

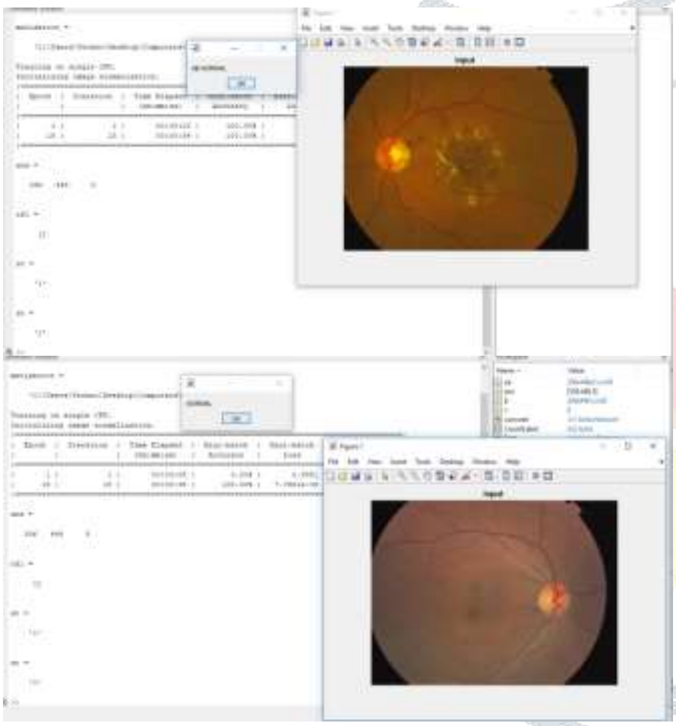

Figure.5Detection of Normal and Abnormal Input Image Using Deep Learning CNN

Figures 4 and figure 5 show the sample dataset and execution of algorithm with respect to input data of different sets.

VI. CONCLUSION

Automated detection and screening provide us with a unique opportunity to prevent most vision losspopulation. In recent years, researchers have added CNN to the set of algorithms used to screen for diabetes.CNN is committed to using doctors to screen and learn from a large number of images that have been accumulated.From the original pixel. The high and low deviations of these models allow CNN to diagnose a wider range of non-diabetic patientsThe same is true for diseases.

However, although we use binary classifiers to achieve the most advanced performance of CNN, the model performance is degraded.As the number of courses increases. Although it's easy to guess that more data might be better, the previous work is still in progress.The field has confirmed that CNN's ability to tolerate scale changes is limited, others recommend in this casethe distinction between mild and normal disease is less than 1% of the total pixel volume, which is a subtle degree human interpreters are often difficult to find.

VII. REFERENCES

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