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Procedia Computer Science 116 (2017) 166–173

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2nd International Conference on Computer Science and Computational Intelligence 2017, ICCSCI 2017, 13-14 October 2017, Bali, Indonesia

The Classification of Hypertensive Retinopathy using Convolutional Neural Network

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Abstract

Changes in the retina of the eyes may occur due to high blood pressure, hypertensive retinopathy (HR) is a type of eye disease in which there is a change of the blood vessels of the eyes in the eye retina caused by arterial hypertension. HR signs occur because of narrowing of the arteries in the retina, bleeding in the retina of the eye and cotton wool spots. The diagnosis is conventionally performed by an ophthalmologist by performing fundus image analysis to determine the phases of HR disease symptoms. This paper proposes an early detection system of hypertensive retinopathy disease. We propose to use Fundus image as a Convolutional Neural Network (CNN) input to determine whether there are any HR symptoms or not. The proposed system is tested by DRIVE image dataset and base on experiment, the accuracy of proposed method is 98.6%, where the more the number of iterations the higher the accuracy level of the training

Keywords: Hypertensive retinopathy; Classification; Convolutional Neural Network.

1. Introduction

The majority of heart attack patients occur because of the absence of signs of known high blood pressure. Hypertension retinopathy (HR) is a sign of high blood pressure. The main signs of HR include the narrowing of arteries

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Peer-review under responsibility of the scientific committee of the 2nd International Conference on Computer Science and Computational Intelligence 2017.
10.1016/j.procs.2017.10.066

in the retina of the eye, the occurrence of bleeding in the retina of the eye and cotton wool spots. Figure 1 shows retinal image of the eyes without HR and retinal image of the eyes that have signs of HR disease. Therefore, it is important to know accurately the early signs of HR symptoms for preventive and treatment measures. In general, the usual action is to perform a fundus image analysis by the doctor whether there is a sign of HR disease, this action is done because the retina of the eye is an object that can be used by doctors to conduct examination of the blood vessels of the retina of the eye directly without surgery.

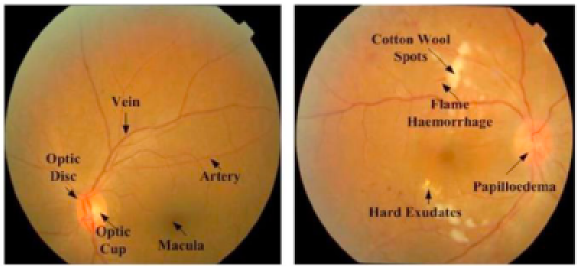

Fig. 1. Fundus images a) Normal, b) Symptoms of hypertensive retinopathy [1].

The majority of heart attacks occur in people with unknown or detectable high blood pressure. HR is one indication in patients with high blood pressure that can cause acute damage to the patient's vision. Stroke attacks occur as a result of HR which is a symptom of hypertension that is not detected early. Stroke risk assessment can be performed by analyzing the patient's retinal image to determine the early signs of HR symptoms [2]. Early diagnosis of HR symptoms is very important as a precaution and treatment of stroke patients more accurately.

A computer-based system is needed to facilitate ophthalmologists detect retinal diseases, diagnosis and treatment more accurately. This paper proposed a model to classify whether a patient is exposed to HR symptoms or not as an initial measure to anticipate the risk of stroke and heart attack using Convolutional Neural Network (CNN).

2. Related work

There have been many previous studies to recognize HR symptoms through retinal photos of the eyes, each of the researchers using a variety of techniques and methods to perform HR symptom detection automatically. [3] Detects HR using vascular segmentation methods on the retina of the eye using Radon transformation, as well as optical disk detection using Hough transformation, then calculates the ratio of arterial vein and Vein from the retina of the eye (AVR), [3] use test data from Digital Retinal Images for Vessel Extraction (DRIVE) database with an accuracy of 92%. Other HR detection systems are also proposed by [4] they segmented vessel using Gabor wavelet, gradients, morphological operations and Niblack and measuring the vessel caliber as classification feature with an accuracy of 92%. Methods of HR symptom detection are also proposed by [5] to estimate the vessel width using skeleton method, this system was tested in DRIVE with an accuracy of 93.7% and also tested in Structured Analysis of the Retina (STARE) database with an accuracy of 93.1%.

Researchers [6] proposed HR disease detection methods with ship segmentation techniques on retinas in gray scale, and uses support vector machines (SVM) for classification. Information from the intensity and color of retinal imagery is used for classification as arterial and venous blood vessels then performs the ratio of the width of vessels and arterial and venous blood vessels. The system has been tested on VICAVR database with 93% accuracy rate. [7] Propose a method of HR classification by measuring the ratio of arteries and veins (AVR) automatically. Vein segmentation and feature extraction based on color intensity are used for classification such as arteries and veins using SVM and discriminant analysis. The proposed algorithm has been tested on a DRIVE database with 96% accuracy. An HR disease detection method is automatically proposed by [8] they were classified the segmented image into arteries and veins by using the linear discriminant analysis with an accuracy of 88.2%, while the HR disease classification method using artificial neural networks has been proposed by [9], which uses a combination of Neural network and Decision Tree (DT) to determine the area of the vein or arterial in the retina and using the naïve Bayes method and Support

Vector Machine (SVM) for HR classification with an accuracy using ANN is 76%, using Naive Bayes is 75%, using Decision Tree is 68% and using Support Vector machines is 81%. Several previous research studies that we have done make reference in this study and for further research.

From a number of previous studies using the Artificial Neural Network method for medical image classification, only a few researchers have used the Deep Learning approach for HR disease classification, Such as [10] to detection of diabetic retinopathy. They use a Stacked Sparse Auto Encoder (SSAE) to extract the high level feature directly from raw images by Deep Learning strategy with an accuracy of 96.2% , so this is still open area of research to continue.

3. Theoretical Background

3.1. Convolutional Neural Network (CNN)

One of the Deep Learning architecture models is the Convolutional Neural Network (CNN) which is the development of the Multilayer Neural Network model designed to be able to process two-dimensional data. CNN is one type of Deep Neural Network (DNN) with a high layer depth on the network and is most widely used for image or video data Multilayer Perceptron (MLP) is less suitable for image classification, because it cannot store spatial information from images. MLP reads each pixel as an independent feature and therefore the result is not good. CNN is a good alternative to image classification. CNN was originally developed by [11] under the name Neo-Cognitron. The CNN model is perfected by [12] under the name LeNet which was developed by LeCun to recognize numerical and handwritten images MLP has a similar way of working with CNN, but on CNN neurons are arranged in two-dimensional format whereas neurons in MLP are in one-dimensional format which is neuro-biologically motivated by sensitive nerve findings and local selective orientation cells in the visual cortex [13]. The construct structures implicitly extract the relevant features, with the weight of the nerve weights one layer into the local receptive on the layer is in front of it, so the second layer map feature on the convolutional layer experiences a spatial scale descent [13]. Besides that there is a decrease in the number of parameters by using the same weight for the overall feature on feature map [14]. Figure 2 shows organization of layers in the CNN of the proposed by [15] where S is stride, P is zero padding and n is number of hidden units in penultimate affine layer variable in different CNN.

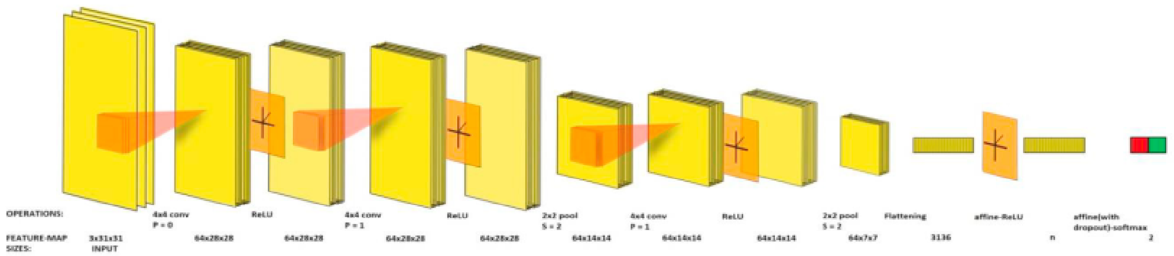

Fig. 2. The architecture of the CNN [14].

3.1.1. Convolutional Layer

This is the first and foremost layer laid after the input images which want to be classified. The backbone of the convolutional neural network is local receptive fields and shared weights. These are making deep convolutional neural network for image recognition. In the process of recognizing images in the convolution layer there are several layers, where each layer consists of several neurons that extract a small part of the input image and invoke certain receptive fields. Each feature map of the convolutional neural network shared the same weights and bias values [16], this share values will represent the same feature all over the image. Depends on the application, the feature map generation is varied.

In the convolution layer there are several kernels or local receptive fields (set filters), where each filter is combined with an input image. Further features of the input image are extracted on a new layer or activation map. Each input image produces an activation map that represents some special characteristic or important feature, the layer of N x N input neuron multiplied by the filter m x m. Then, (S) is the output size of the convolution layer, where S is derived from:

$$S = (N - n + 1) \times (N - m + 1) \tag{1}$$

It applied non- linearity through neural activation function.

3.1.2. Pooling Layer

Pooling layer is one of the most significant layers which help the network from avoiding over-fitting by reduce Some parameters and computing within the network. The workings of the pooling layer is a non-linear down sampling process, which divides the activation map into specific sizes as well as collects the maximum value in the sub-region. Pooling partition a down size the pixels with features. For instance, if N x N input layer, that will give output layer of (N/K) x (N/K) layer. The main significance of pooling layer selecting the generated feature can be found in the image area section, further removing the information in the appropriate positions.

3.1.3. Rectified Linear Unit (ReLU) Layer

The ReLU layer is an activation function obtained through the equation.

$$f(x) = \max(0,\ x) \tag{2}$$

Where x is the input to the neuron and the transfer function is finely approximated to the rectifier into an analytic function.

$$f(x) = \ln(1 + e^{x}) \tag{3}$$

This activation function induces the sparsity in the hidden units. Also, It has been shown that the deep neural networks can be trained efficiently compared than *sigmoid* and logistic regression activation function. The transfer function of ReLU has a section that can normalize the input to avoid saturation conditions in the training process. Some training algorithms generate positive feedback to the ReLU transfer function so that training will be performed on the neuron [17].

3.1.4. Fully Connected Layer

Fully connected layer is a CNN layer whose position is after the convolutional layer and the pooling layer. The reasoning process occurs in the fully connected layer during classification. The fully connected layer takes all neurons in the previous layer of the pooling layer and connects with all neurons in the fully connected layer where it is no longer spatially connected, but visualizes it in a one-dimensional layer.

3.1.5. Classification layer

After the stacked or deep multiple layers, the final layer is a *softmax* layer which stacked at the end for classifying the image followed by the fully connected layer output. Here, the deciding as a single-class classification or multi-class classification.

3.2. Training CNN

CNN is a special form of multilayer perceptron where its training method uses backpropagation [12]. In each CNN convolution layer, a single filter generates one feature map by being applied at different spatial positions. This means the set of weights the filter consists of are shared. A different feature map is then generated by a different filter and thus different weights, so that the number of parameters can be further reduced compared to the multilayer perceptron in which each neuron is interconnected, resulting in an implicit reduction of the test data and training data In the subsampling layer there is a weight and bias that can be trained using the local average coefficient [12], which causes the independent parameters of the subsampling layer to be less than the convolution layer. In the CNN training process requires less computation time compared to multilayer perceptron training, this is because at least the number of free parameters. Another thing is that CNN does extraction of implicit and invariant features of distortion to some degree, so CNN is appropriate for the classification process especially pattern recognition. In artificial neural network problems, the network architecture must be trained repeatedly. If training data is not available then it can use the new data available [18-20].

3.3. Proposed Method

The Convolutional Neural Network (CNN) is applied on the task of HR Classification, and firstly, we have presented a fundus image in grayscale to reduce computational complexity by changing from three channel imagery to one channel image without losing feature information in image, we use dataset from Digital Retinal Images for Vessel Extraction (DRIVE) and then resize image to 32 X 32 pixels. Secondly, we convert image to CSV file format as a input of CNN. Finally, the training procedure of CNN until convergence, and the classification process of HR will be tested to calculate the accuracy of the classification result. The proposed method of HR classification shows on Figure 3.

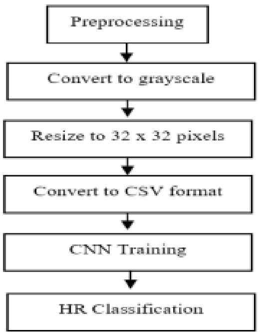

Fig. 3. The diagram of the proposed method.

To test the system prototype, we used 40 images of 768 x 584 pixels in JPEG file format retrieved from the Digital Retinal Images for Vessel Extraction (DRIVE) database. The DRIVE dataset contains 40 images consisting of 20 normal retinas and 20 retinal images with HR symptoms. The first step is preprocessing to convert color fundus image into grayscale. Then, linear The initial stage is preprocessing in the form of a process of changing the colored retinal image into a grayscale form. The calculation of grayscale change uses the weighted sum of the three intensity channels of Red (R), Green (G) and Blue (B) channels based on the 1931 Y CIE formula [21], which is based on

$$Y = 0.2126R + 0.7152G + 0.0722B \quad (4)$$

We resize each image to 32×32 pixel to reduce the complexity of image dimensions in order to accelerate the learning process, although with the limitations of some of the details the information will be lost. Next we convert each image into the matrix into the CSV format numeric matrix, in which the first column is the label for each image. The signals that the images are grayscale, they have only ones channel. For testing we use the ReLU activation function, 2 convolution layers and 2 pooling layers, 2 fully-connected layers and softmax output. Each convolutional layer uses a 5 x 5 kernel with a number of filters with certain coefficient values. The pooling layer uses max pooling. Table 1 presents the proposed CNN architecture.

Table 1. Proposed architecture of CNN for HR classification.

Layer	Type	Maps and neurons	Kernel
0	Input	1 map of 32 X 32 neurons	
1	Convolutional	20 maps of 32 X 32 neurons	5 X 5
2	ReLu	20 maps of 32 X 32 neurons	
3	Max pooling	20 maps of 16 X 16 neurons	2 X 2
4	Convolutional	50 maps of 16 X 16 neurons	5 X 5
5	ReLu	50 maps of 16 X 16 neurons	
6	Max pooling	50 maps of 8 X 8 neurons	2 X 2
7	Fully connected	500 neurons	1 X 1
8	ReLu	500 neurons	
9	Fully connected	1 neuron	1 X 1
10	Output softmax	1 neuron	

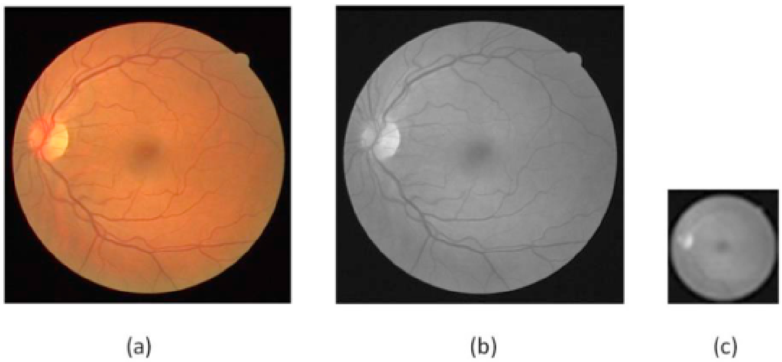

Fig. 4. Image Pre-processing: a) normal image, b) grayscale image, c) Resized image.

The implementation of CNN model has been implemented in R utilize the MxNet package, we use the value of learning rate 0.001 and cross-entropy learning criteria, with the number of iterations or epoch 8000, momentum 0.9 and the initiation value of all the weights in the full connected layer is 0.0005, meaning to initialize all the weights with the same value in the first iteration of the learning process, then the weight will be updated during the learning process. We do test scenarios, first using the number of training image objects of 20, 200 and 1000 each with 1000 iterations or epoch, and second we use 20 training image objects with a total of 10000 iterations. We duplicate from 20 training data in the DRIVE database to get the number of objects 200 and 1000 objects.

4. Result

To test our method, we use R to implement the method and run in machine with hardware specification Pentium Core i7 3.5 GHz and memory 8GB. Based on experiment the accuracy of classification hypertensive retinopathy is 98,6 %. This result can be due to the simplicity in the complexity of the dimensions of the input image, although its weakness will remove some information from the original image, so this method may be less suitable for other image types which are more concerned with the details of the original image information. However, we have not done comparison with the system without pre-processing, so in the follow-up research we will develop by reading the input image without pre-processing. Figure 5 show graph of learning process until 1000 iterations, where the results show that the more the number of training objects the accuracy of training is increasing, and figure 6 shows the accuracy of the training process using 20 objects up to 10000 iterations, where the more the number of iterations the higher the accuracy level of the training. The comparison of previous related work shows on table 2.

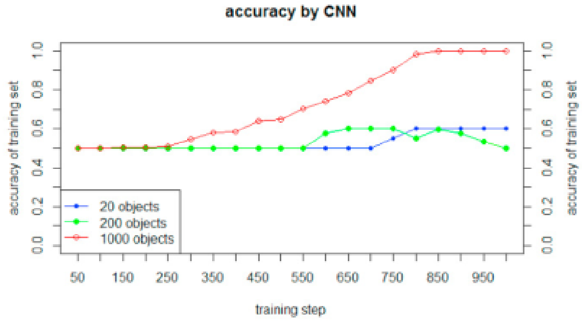

Fig. 5. Graph of learning process based on number of object

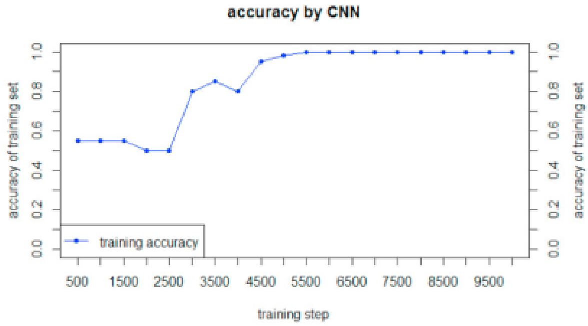

Fig. 6. Graph of learning process based on epoch.

Table 2. Comparison with others method.

Method	Classification	Dataset	Accuracy
Noronha et al. [3]	Bayesian classifier	DRIVE	92%
Manikis et al [5]	Statistical measure	DRIVE,	93.7%
		STARE	93.1%
Narasimhan et al [6]	Support Vector Machines	VICAVR	93%
Mirsharif et al [7]	Statistical measure	DRIVE	96%
Proposed method	Convolutional Neural Network	DRIVE	98.6%

The proposed method relatively have higher accuracy than others method, however in our future work, we will improve the accuracy with include a blood vessel of retina as a input feature of CNN and the classification not only two class which is normal and symptoms of HR but also the classification of HR grade base on four grades of HR.

5. Conclusion

The proposed of classification of hypertensive retinopathy has been presented. Base on experiment the accuracy of proposed method is 98.6 %, where the more the number of iterations the higher the accuracy level of the training the degree of accuracy of the training is pertinent to the number of training objects and the number of iterations. Our next research will make an early detection model of hypertensive retinopathy disease. Then perform the analysis of the effectiveness and accuracy of the use of major features of HR disease, such as retinal vessels, optic disks for the classification of hypertensive retinopathy symptoms using Deep Learning and Boltzmann machine approaches on fully connected layers.

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