Detection of Hypertension Retinopathy Using Deep Learning and Boltzmann Machines

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Abstract. hypertensive retinopathy (HR) in the retina of the eye is disturbance caused by high blood pressure disease, where there is a systemic change of arterial in the blood vessels of the retina. Most heart attacks occur in patients caused by high blood pressure symptoms of undiagnosed. Hypertensive retinopathy Symptoms such as arteriolar narrowing, retinal haemorrhage and cotton wool spots. Based on this reasons, the early diagnosis of the symptoms of hypertensive retinopathy is very urgent to aim the prevention and treatment more accurate. This research aims to develop a system for early detection of hypertension retinopathy stage. The proposed method is to determine the combined features artery and vein diameter ratio (AVR) as well as changes position with Optic Disk (OD) in retinal images to review the classification of hypertensive retinopathy using Deep Neural Networks (DNN) and Boltzmann Machines approach. We choose this approach of because based on previous research DNN models were more accurate in the image pattern recognition, whereas Boltzmann machines selected because It requires speedy iteration in the process of learning neural network. The expected results from this research are designed a prototype system early detection of hypertensive retinopathy stage and analysed the effectiveness and accuracy of the proposed methods.

1. Introduction

High blood pressure can cause a lot of disturbance on the retina of the eye, one of which is hypertensive retinopathy (HR) where systemic changes produced by arterial hypertension is reflected in the blood vessels of the retina. Most heart attacks occur in patients with undiagnosed high blood pressure symptoms. Hypertensive retinopathy is a hallmark of high blood pressure. Symptoms of hypertensive retinopathy form arteriolar narrowing, while the other major signs are the presence of retinal hemorrhage and Cotton wool spots [1].

Then the diagnosis of early symptoms of hypertensive retinopathy is indispensable for the prevention and accurate treatment. The traditional way to do is through a fundus image analysis to evaluate the presence of hypertensive retinopathy disease and establish a phase of evolution, because the retina is the only place that allows the doctor to examine the blood vessels of the retina directly and by means of non-invasive and the ethics of science this is related to patient privacy [2].

The diameter of retinal blood vessels is one of the most important characteristics for the diagnosis of hypertension, health professionals have been using the ratio of arterial blood vessels of the retina (AVR) to establish the presence of high blood pressure. The diameter of retinal blood vessels is one of the most important characteristics for the diagnosis of hypertension, health professionals have been using the ratio of arterial blood vessels of the retina (AVR) to establish the presence of high blood

pressure. This paper proposed the framework to implement Deep Neural Networks and Boltzmann Machines approach to the classification of hypertensive retinopathy stages.

2. Literature Review

A computerized system to facilitate the detection of retinal disease ophthalmologists to review diagnosis and treatment of diseases accurate planning. Hypertension or high blood pressure causes Severe damage to the human eye and vision as hypertensive retinopathy, optic neuropathy and choroidopathy [3]. Retinal disorders (Network Behind the eye) caused by high blood pressure is called hypertensive retinopathy (HR) [4]. Fundus digital image analysis is used to diagnose HR review with track changes picture. The changes including tortuous arterioles, bleeding, hard exudates, cotton wool spots and papilledema.

Important Symptoms of HR abnormal vein width that leads into low ratio of the average diameter of arterial venous (AVR). Retinal diseases can be tracked by changes in blood vessels of the retina hearts. Figure 1 shows the normal fundus image and the image has symptoms of retinal from HR. Research on the identification of hypertensive retinopathy through retinal images have been done before, there are many techniques presented literature to review the automatic detection of HR. [5] proposed a support system for the review in which the HR detection blood vessels are segmented using the Radon transform and the optical disk is detected using the Hough transform and finally counting AVR.
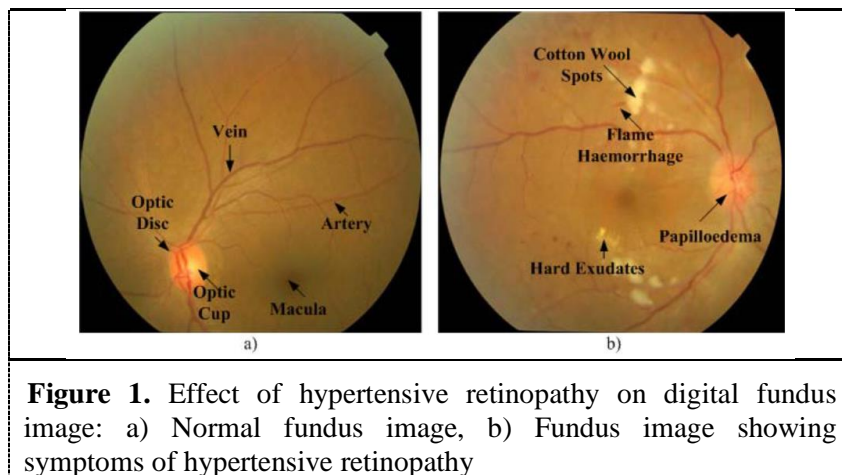

Figure 1. Effect of hypertensive retinopathy on digital fundus image: a) Normal fundus image, b) Fundus image showing symptoms of hypertensive retinopathy

The proposed algorithm was tested on a database DRIVE and showed 92% accuracy. [5]. HR other systems for diagnosis developed by [6]. [7] proposed a system for early detection of HR. Ship segmented using multiscale filtering and identification by region. The width of the vessel and AVR are calculated to find HR. This system was tested in DRIVE and STARE database had an accuracy of 93.7% and 93.1% respectively. The author [8] presents a method for the detection of HR where vessels are segmented using a torque based and features a gray level and support vector machine (SVM) for classification.

The intensity and color information used to classify the vessel as arteries and veins were then used to calculate the ratio of the width of the ship and AV. The proposed system showed 93% accuracy on VICAVR database. [9] proposed a classification method for the measurement of AVR auto ship. Ships segmented and some features based on the intensity of color is extracted for classification of vessels such as arteries and veins by using SVM and ship discriminant analysis (LDA). DRIVE database used to test algorithms and the system showed 96% accuracy. Another HR automated detection method proposed by [10]. The blood vessels of the retina that is detected by the cap and filter transformation of the double ring. Temporal region of the optical disk selected as a destination to calculate the ratio of AV. Features taken from the vessel in the ROI to classify them as arteries and veins using LDA.

2.1. Deep Learning Neural Network
Although many previous studies that utilize ANN-MLP for medical image classification, but the few studies that use Deep Learning for classification of hypertensive retinopathy. Convolutional Neural Network (CNN) is development of Multilayer Perceptron (MLP) that is designed to process two-dimensional data. CNN included in this type of Deep Neural Network for high tissue depth and widely applied to image data.

In the case of image classification, the MLP is less suitable for use because it does not store the spatial information of the image data and consider each pixel is an independent feature that produces poor results as well. CNN first developed under the name NeoCognitron by [11]. The concept is then finalized by [12]. Model CNN named Lenet successfully applied by [11] on his research on the numbers and handwriting recognition. How to work on the MLP CNN have in common, however on CNN every neuron is presented in the form of two-dimensional, unlike the MLP that each neuron is only measuring one dimension of a MLP as in Fig. 3. have the i layer (Red and blue boxes) with each layer containing neurons ji (white circles). MLP received a one-dimensional data input and propagates that data on the network to produce output. [13].

Figure 2. Simple MLP architecture.
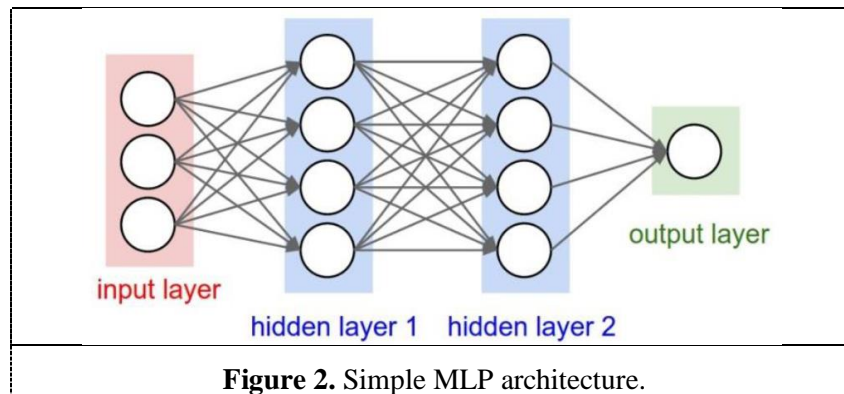
Each neuron in the relationship between two adjacent layers have a weight of one-dimensional parameter that determines the quality mode. In each of the input data on a layer linear operation performed by the weight value is, and then computing the results will be transformed using a non linear operation which is called the activation function. On CNN, the data is propagated on the network is a two-dimensional data, so that the linear operation and parameters of different weights on CNN. On CNN linear operation using convolution operation, while the weights are no longer one-dimensional, but the form is a collection of four-dimensional convolution kernel as in figure 3 Dimensional weight on CNN is: neuron input x output x height x width Due to the nature of convolution process, then it can only CNN used on data that have two-dimensional structure such as images and sounds.

Figure 3. Convolution process on CNN.
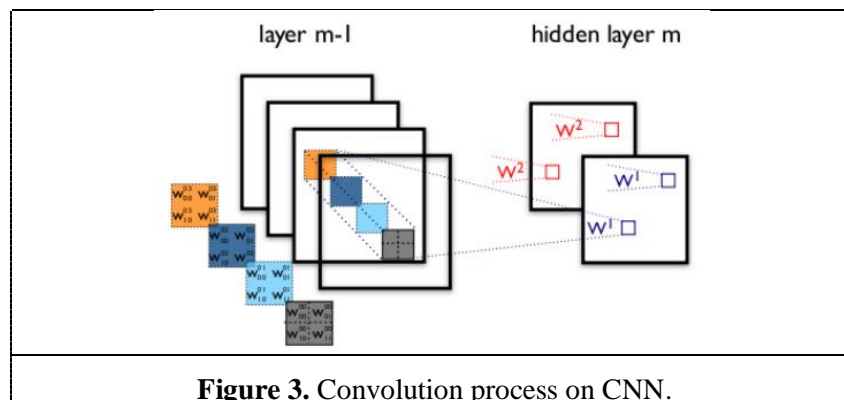
2.2. Boltzmann machine

The Boltzmann machine is a particular type of energy-based model with hidden variables, and RBMs are special forms of Boltzmann machines in which P(h|x) and P(x|h) are both tractable because they factorize. In a Boltzmann machine, the energy function is a general second-order polynomial:

$$\text{Energy}(x,h) = -b'x - c'h - h'Wx - x'Ux - h'V\,h \tag{1}$$

There are two types of parameters, which we collectively denote by θ: the offsets b_i and c_i (each associated with a single element of the vector x or of the vector h), and the weights W_{ij}, U_{ij} and V_{ij} (each associated with a pair of units). Matrices U and V are assumed to be symmetric 1, and in most models with zeros in the diagonal. Non-zeros in the diagonal can be used to obtain other variants, e.g., with Gaussian instead of binomial units. The Boltzmann machine energy function can be rewritten by putting all the parameters in a vector d and a symmetric matrix A. [14].

$$\text{Energy}(s) = -d's - s'As \tag{2}$$

Let d−i denote the vector d without the element di, A−i the matrix A without the ith row and column, and a−i the vector that is the ith row (or column) of A, without the ith element. Using this notation, we obtain that P(si|s−i) can be computed and sampled from easily in a Boltzmann machine.

One study using Neural Network for classification hypertensive retinopathy is [15], which utilizes Neural Network and Decision Tree (DT) to determine the area of the arteries or veins using a Naive Bayes classifier and Support Vector Machine (SVM). From the literature review conducted in this study are gaps (gap) that can be used as a reference to subsequent research, namely:

- Required to standardize image acquisition protocols to guarantee the same conditions, retinal images to be taken by trained personnel only.
- It takes a more objective system with the help of automated tools that can monitor disease hypertensive retinopathy.
- It takes a more accurate measurement of AVR for the classification of the arteries and veins to detect retinal disorders.
- The detection of Cotton Wool Spots CWS on the retinal image more accurate eye essential for building a computer system to analyse the symptoms of disease diagnosis at an early stage and at an advanced stage.
- Need to repair blood vessel segmentation algorithm on the image of the eye retina to obtain accurate measurement results ore.
- Keep registration fundus copy image of the same patient on a regular basis (i.e. 6 to 12 months). For comparison automatically changes as the vessel monitoring system that is more efficient and accurate in the diagnosis of hypertensive retinopathy.

The contribution of this research is a computer-based automatic aid system that can monitor disease states hypertensive retinopathy more accurately through the image of the retina.

3. Methodology

Based on the objectives of the research that has been described previously, the following is a proposed framework or approach that will be proposed as shown in figure 4 are as follows:

Figure 4. Flowchart of Proposed Methodology.
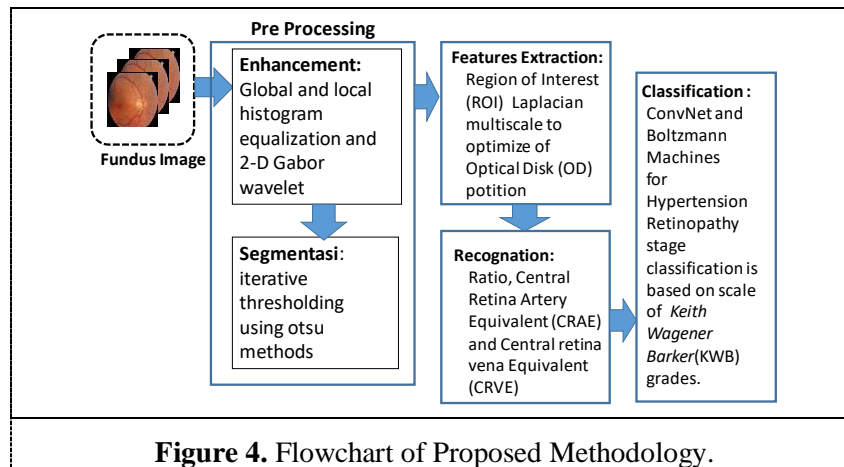
3.1. Features.

Features used is a combination of the average ratio of the width of arteriovenous (AV) and Optic Disk (OD).

3.2. Data Sets

At the initial staged will use 40 the retinal image size of 768 x 584 pixels in JPEG format on the database DRIVE well as 20 images of the fundus camera the size of 700 x 605 pixels in format PPM STARE database. While at an advanced stage will use 100 fundus-copy images of Eye Hospital, 20 patients were taken at regular intervals (6 to 12 months). to test prototype monitoring system for the diagnosis of stage symptoms of hypertensive retinopathy.

3.3. Stages of the process:
- Enhancement:
  Using Global and local histogram equalization as well as 2-D Gabor wavelet to improve the visibility of the arteries and veins.
- Segmentation:
  Using iterative Otsu thresholding method for determining the threshold value.
- Features Extraction:
  Using the Set Region of Interest (ROI) as a measurement area of arteries and veins of the retina. Optical Disk (OD) of the retina is used to find the ROI where ROI is set three times larger radius OD.
- Recognition:
  Using Multiscale Laplacian to estimate the radius Optic Disk (OD). Calculate the ratio, Central Retinal Artery Equivalent (CRAE) and Central retinal vein Equivalent (CRVE), which is determined by the measurement of the arteries and veins.
- Classification:
  Using Convolutional Neural Network and Boltzmann machines for Retinopathy Hypertension stage classification is based on a scale of Keith Wagener Barker (KWB) grades.

4. Conclusion

The proposed of computer-based automatic aid framework that can monitor disease states hypertensive retinopathy has been presented. the diagnosis of early symptoms of hypertensive retinopathy is indispensable for the prevention and accurate treatment. The diameter of retinal blood vessels is one of the most important characteristics for the diagnosis of hypertension.

This paper proposed the framework to implement Deep Neural Networks and Boltzmann Machines approach to the classification of hypertensive retinopathy stages. The future work of this this research are to design a prototype system early detection of hypertensive retinopathy stage and analyze the effectiveness and accuracy of features combined ratio of diameter arteries and veins (AVR) with a change in the position of Optic Disk (OD) in the retinal image for the classification of hypertensive retinopathy using Deep Neural Network and Boltzmann machines.

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