Diagnosis of Diabetic Retinopathy Disease Based on Edge Detection of Spiking Neural Network Based on Percolation Theory

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Abstract

Today, one of the problems that medical science is struggling with is the lack of systems for identifying, detecting and predicting various diseases that work accurately and practically. Diabetes is one of the diseases that has embroiled people in today’s world because of failing to regard the biological issues. Diabetes has different types, one of which is diabetic retinopathy, one of the main dangers of which is loss of vision. Micro-aneryums, which are red spots, are the first symptoms of the disease that occur in the retina. The most important issue in this area is the early diagnosis of retinopathy for person to keep his sight and postpone the consequences of this disease for a while. This research presents a new approach to detect and diagnose diabetic retinopathy by using mixed methods. The proposed approach has four stages. In the first step, pre-processing is done with the aim of eliminating the probabilistic noise and standardizing the input dataset. Afterwards, segmentation and edge detection operations are performed based on spiking neural network. In the following, the percolation method is used to reduce the dimensions, the selection and extraction of the characteristic, which in fact features, are the edges of the blood vessels and the intensity of the brightness at the edge. Diagnosis of retinopathy areas is also done based on the combination of two methods of spiking neural network and percolation.

Keywords: Retinopathy, Image segmentation, Edge detection, Spiking neural network, percolation theory.

1. Introduction

Nowadays, diabetes is recognized as an unavoidable disease in the early stages, that one of the most dangerous diabetes is related to retinopathy, which occurs due to changes in blood vessels. Diabetic retinopathy is a general term used to express vascular problems in the retina of diabetic patients, and is divided into two types of proliferative and non-proliferative. The first sign of changes in the vascular wall in diabetic retinopathy is micro-aneryums, which appear as small red spots on the retina surface. Micro-aneryums alone do not cause blindness, but the lack of attention to the disease and its development leads to the formation of new vessels and also other complications and finally leads to visual impairments. Therefore, early diagnosis of micro-aneryums in the retina image is a diagnosis of diabetic retinopathy in its early stages and an action to prevent, treat and prevent blindness. Therefore,
the necessity of accurate extraction of blood vessels from retina images requires the use of algorithms and tools that reduce the dependence of this action on the user and eliminate the error factors and allow the early detection of micro-aneurysms. The most important tool for medical diagnosis in pictures is image processing and machine vision, which operates on the basis of a series of machine learning methods. The study also uses a series of tools and algorithms from a visual image data collection to detect micro-aneurysms in eye retinopathy. In the following, at first, a series of research and methods are mentioned in this area. Then, the proposed approach is propounded and a simulation will be done based on it. In the following, the simulation results are posed along with comparing with other studies.

2. Research background

Several methods and approaches have been introduced to reveal the vessels in the retina, each with its own positive and negative features. In the research [1], the methods of vascular diagnosis are introduced and compared. In this study, conducted in 2004, methods are divided into categories of; Model-based methods, Pixel Classification-Based Methods, Vessel Tracking-based Methods, Multi-Scalable Analysis-based Methods. In model-based methods, the structure is considered for the vessels and then, according to it, they extract the similar patterns in the image. Secondary-based Gaussian models, primitive-based Gaussian models, and groove models which are presented in [2], are models used for the veins. Of course, this kind of methods are also called window-based methods. In a study which was conducted in [3], the veins models in the image are assumed as a Gaussian curve and improve the contrast of the vein or the background using filters matching the Gaussian model, and then by apply a thresholding the veins are zoned. The primitive-based method, presented in [2], performs the zoning of the vessels by extracting the grooves in the image, which are very good approximation of the veins. Then, a classifier of K-nearest neighbor (KNN) is used. Of course, this method can be set in classifying Pixel Classification-Based Methods. In Pixel Classification-Based Methods, an observer classification technique is used to assign pixels to the class of vessels and non-vessel class, and the feature vector is formed of different properties such as the brightness of the pixels or Conversion factors such as Wavelet Transform, or Morelet Wavelet according to [4] or Steerable Wavelet according to [5]. In [4] identifies the veins through changing the scale and rotation angle parameters in the two-dimensional wavelet transform using Morelet Wavelet. In Vessel Tracking-based methods, Tracking is used to access the structure of the vessels. The first method of this category was proposed by [6], that is the curvature, the central line, the thickness and density of the vein, is continuous, and each vessel is composed of a set of pieces of the veins. Each piece of vessel is characterized by three parameters. These three parameters are: direction, central line and width. With these three parameters for the current vessel piece and all the previous pieces of vessel, the next piece of vessel is estimated with the Kalman filter. Then, using the Gaussian filter, the actual location of the estimated vessel piece is obtained. In Multi-Scalable Analysis-based Methods, multi-scalable analysis is used, which, in contrast to other methods, have the advantage of detecting veins in each diameter and length. In [7], a method is proposed based on the extraction of multi-scalable features that local maximum actions on gradient range scales and the maximum of main curvature of Hessian Tensor in a two-step process of region development are used in this method. In method [8], a Hessian and Gaussian combination filter has been used. In [9], the mixed method of Gabor mixed filters is used to reduce background noise and increase the quality of blood vessels and then detect blood vessels using thresholding based on the attached pixel matrix in order to extract blood vessels. In [10], an observer approach for detecting blood vessels in digital retina images is presented, which is based on categorizing by neural network and extracting blood vessels. In [11], the ant colony optimization method has been used to identify the vessels. One similar research has also used an ant colony optimization algorithm with the aim of selecting the characteristics of piece-based retinopathy images [12]. Generally, vascular demonstration algorithms for diagnosis are encountered with problems such as the presence of noise, low contrast between the veins and the image background, and the variability in width, intensity of lighting, and shape of the vessels. In the extraction of vessels, there are challenges that make it hard to perform an accurate diagnosis. Among them, the low contrast of the capillaries, the optical disk border and the borderline of the retinal image and pathological spots can be mentioned. An ideal zone is the one which solves all the problems and challenges above.
3. Method presented

The proposed approach has three stages. Initially, the pre-processing is performed on the image. Then the segmentation operations based on the image edge-detection is done. Then the feature extraction operations, as well as the reduction of dimensions and feature selection are performed. At the end, the diagnosis of retinopathy and its areas is done. Initially, it is necessary to normalize the input images which are the diabetic retinopathy images. This normalization is done with the aim of reducing noise, resizing all the images to a certain size and adjusting its brightness to the same amount. A segmentation method is then used to segment an image into regions or objects forming it. The proposed approach is to use the Spiking Neural Network in this section. In order to apply this network, it is necessary to determine the spikes, that there are three general methods for doing this, including thresholding wavelet coefficients, matching filters and thresholding the range of action potentials. The approach of this research for segmentation based on edge-detection is to use the thresholding of the range of action potentials. The value of this threshold is determined by the relation (1).

\[
\begin{align*}
\sigma_n &= \text{median}\{|x| \cdot 0.6745 \\
\text{Threshold} &= 3.5 \sigma_n
\end{align*}
\] (1)

In relation (1), \(x\) is the signal recorded by the microelectrode (raw signal) and \(\sigma_n\) is an estimation of noise deviation. It is important to note that in case of using the standard deviation of the signal, a higher value will be obtained for the threshold, and as a result, some of the spikes will be deleted by mistake.

After selecting the threshold value, spikes are also aligned based on their maximum values. The precise alignment of spikes is a very important and decisive factor in the segmentation based on edge detection with spikes. This neural network, like networks, needs training that the purpose of this tutorial is to find a mapping such as \(f: R^n \rightarrow R\) as the relation (2).

\[
f(v) = \sum_i w_i \phi(||v - C_i||)
\] (2)

In accordance with equation (2), \(v \in R^n\) is a 32-point vector for input, and the Gaussian basis function \(\phi(0)\) is determined as (3).

\[
\phi(v) = \exp\left(-\frac{v^2}{2\sigma^2}\right)
\] (3)

Then, it is necessary to calculate the corresponding error for each sample from the gradient Descent for random values for weights, for each training sample, as (4).

\[
e_i = t_i - y_i = t_i \sum_{j=1}^{N} w_j \phi(||v_i - C_j||)
\] (4)

Therefore, the total network error for all vector of training input or \(P\) of image data is equal to \(E = \frac{1}{2} \sum_{i=1}^{P} |e_i|^2\). If the error \(E\) reaches less than threshold error, the training ends. This amount is set manually at the beginning of the task. Otherwise weights will be updated using gradient Descent. After completion of the training course with the Spiking Neural Network, the ability to amount of each spike attachment to a class belongs to the segmentation and then the edges, is obtained.

Then there is a need for a section of dimension reduction, feature selection, and feature extraction that percolation theory will be used. This theory, which is used most often in graphs, works in extracting image properties, as if a fluid has been poured in a porous body, and the goal is whether this liquid by transmitted through the pores of the image edges, can reach the low level. This method works based on Kolmogorov’s law. In order to improve the extraction of features, the relation (5) is used.

\[
\eta^* = \frac{P(\frac{\nu}{\text{SelectedFeatures}})}{P(\frac{\nu}{\text{TotalFeatures}})}
\] (5)

Which according to equation (5), \(P(\frac{\nu}{\text{SelectedFeatures}})\), and \(P(\frac{\nu}{\text{TotalFeatures}})\) represent the selected properties and the sum of the properties, which generally expresses as the probability of the specific value \(\nu\) for the chosen characteristic and all the characteristics. With the same relation, a dimensional reduction operation is also performed. It is necessary to have a threshold here, which is set to 0.01 by...
default. It should be noted that the selected features include color and contrast on the edges as well as fragments resulted from edge-based segmentation operations. It is clear that as the number of attributes is lower, if the results have a high operational accuracy than other methods, it will show the strength and power of the proposed method. After the processes mentioned till here, the mixed method of the spiking neural network and the percolation theory, which received its results from the previous three steps, is used here.

4. Simulation

This research uses the DIARETDB1 data set. We give one of the images as an input to the program. Then the preprocessing operation is done with the aim of eliminating possible noise and converting to a gray level. Segmentation operations are performed based on edge-detection using the Spiking Neural Network. Then, the percolation model is used to reduce the size, selection and extraction of features based on the segmentation and edge detection resulted from the spiking neural network. At the end, the mixed approach of the two mentioned methods begins to work, and performs the correct region detection and determines in which part the diabetes is located and shows the extent of influence of diabetic retinopathy. All operations mentioned are shown from left to right in figure 1, respectively.

![Figure 1: the output results of the proposed method.](image)

According to figure (1), the top left is the main input. After applying the proposed approach, the exact region with retinopathy can be observed, which is same as in figure (2).

![Figure 2. Retinopathic area](image)

1 http://www.it.lut.fi/project/imageret/diaretdb1/
The size of area is also 7.18 in millimeters. Based on the data training based on the proposed approach, 8 forms of diabetic retinopathy have been proposed, that figure 2 has complete diabetic retinopathies, which is 8. The explanation of these 8 steps is given in Table (1).

**Table 1**: General Diagnosis of Retinopathy

<table>
<thead>
<tr>
<th>No.</th>
<th>Diabetic retinopathy stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None</td>
</tr>
<tr>
<td>2</td>
<td>Suspected</td>
</tr>
<tr>
<td>3</td>
<td>In primary stages</td>
</tr>
<tr>
<td>4</td>
<td>Annual progression</td>
</tr>
<tr>
<td>5</td>
<td>Biennial progression</td>
</tr>
<tr>
<td>6</td>
<td>Triennial progression</td>
</tr>
<tr>
<td>7</td>
<td>Complete progression</td>
</tr>
<tr>
<td>8</td>
<td>Severe</td>
</tr>
</tbody>
</table>

5. Evaluation and comparison

In this research, several evaluation methods have been used that include mean square error, signal to noise ratio peak, signal to noise ratio, and accuracy criteria. Table (2) shows the results obtained from each evaluator. The results shown in this table are used for the image, the output results of figure (1).

**Table 2**: the evaluation results are used for the image

<table>
<thead>
<tr>
<th>Process</th>
<th>Duration (sec)</th>
<th>MSE</th>
<th>PSNR (dB)</th>
<th>SNR (dB)</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Process Duration (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.1253</td>
<td>13.1818</td>
<td>34.9490</td>
<td>98.2471</td>
<td>84.0000</td>
<td>88.9655</td>
<td>2.4748</td>
</tr>
</tbody>
</table>

Now, 7 images have been used. By summing up the results of the evaluation values and dividing them into numbers, these values are obtained, and the results are presented in Table (3). The method presented in several other methods, which are both general and general methods, is compared in several criteria, as shown in Table (4).
Table 3: Evaluation Results 7 Images

<table>
<thead>
<tr>
<th>MSE</th>
<th>PSNR (dB)</th>
<th>SNR (dB)</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Process Duration (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0189</td>
<td>13.0871</td>
<td>34.5631</td>
<td>98.1745</td>
<td>86.3210</td>
<td>88.8236</td>
<td>2.3598</td>
</tr>
</tbody>
</table>

Table 4: Comparison of the proposed method with other methods

<table>
<thead>
<tr>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
<th>Research</th>
</tr>
</thead>
<tbody>
<tr>
<td>86.47</td>
<td>96.00</td>
<td>95.41</td>
<td>Siddalingaswamy P. C., and Gopalakrishna Prabhu K., 2010 [9]</td>
</tr>
<tr>
<td>69.44</td>
<td>98.19</td>
<td>95.26</td>
<td>Diego Marín et al, 2011 [10]</td>
</tr>
<tr>
<td>86.3210</td>
<td>88.8236</td>
<td>98.1745</td>
<td>presented method of this project</td>
</tr>
</tbody>
</table>

The results obtained from comparison with other methods indicate that the accuracy criterion of the proposed method is superior to other methods. But in the criteria of sensitivity and rate of features, there are also methods that are better.

6. Conclusion

Diabetic retinopathy is recognized as an important disease in today’s world that its dangers can cause loss of vision. Therefore, the existence of automated systems that can detect and diagnose this disease is very important. Microanurysms, which are red spots, are the first symptoms of the disease that occur in the retina. The most important issue in this area is the early diagnosis of retinopathy to keep a person in sight. This research presents a novel approach to detect diabetic retinopathy using hybrid methods. The proposed approach has four stages. In the first step, pre-processing is done with the aim of eliminating the probability noise and standardizing the input dataset. Subsequent fragmentation operations are then performed with the spiking neural network. In the following, the leakage model is used to reduce the size, selection and extraction of the characteristic. Finally, in order to detect the area and size, as well as the rate of growth of diabetic retinopathy, the combination of the spiky neural network and the leakage model is used. Results show that the accuracy of the proposed method is better than other methods.
7. References


