Diabetic Retinopathy Identification using Deep Believe Network

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Abstract. Diabetic retinopathy is an eye disease caused by swelling in blood vessels. If it gets worse the blood vessels will rupture and this is the main factor of blindness. This disease is rarely found in children and symptoms can be seen during puberty. One way to find out this disease is a wide and comprehensive pupil jerky eye examination performed by an ophthalmologist manually. Manual examination takes a long time and can cause misidentification because the similarity of characteristics of diabetic retinopathy is difficult to see directly. Because of this problem a method is needed that can facilitate the eye doctor in identifying diabetic retinopathy by simply inserting a retinal image into the system. The method proposed in this study is Deep Belief Network (DBN). The steps taken before identification are the image of the retina undergoing pre-processing in the form of grayscale, median filter, contrast stretching, morphological close operation and feature extraction using the Grey level Counselling Matrix (GLCM). In this study it was shown that the proposed method was able to identify diabetic retinopathy with 84% accuracy, sensitivity 93%, and specificity 70%.

1. Introduction

Diabetic retinopathy (DR) is a long-term diabetic microvascular complication and is a major cause of vision loss due to changes in retinal blood vessels. The main visual loss due to DR can be prevented by routine checks and timely intervention at the initial stage [1].

Damage to small blood vessels in the retina is the cause of DR. The retina is a light sensitive network that blocks the inside of the eye. DR can range from minor to severe. During the initial stages, changes in blood vessels occur, but there may be no symptoms. Over time, loss of vision can occur if a damaged blood vessel such as liquid or bleeding leaks.

Based on WHO data (2016), diabetic retinopathy ranks 4th as a cause of global blindness after cataracts, glaucoma and macular degeneration. DR caused 1.9% of severe visual impairments globally and 2.6% of blindness in 2010. The prevalence of retinopathy in patients with DM in the world in 2012 was 35% and 7% among them were the prevalence of proliferative retinopathy.

DR is also known as diabetes which causes damage to the retina of the eye and can eventually cause blindness. This is a manifestation of ocular diabetes. Apart from alarming statistics, research shows that at least 90% of new cases can be reduced if there is proper care, alertness and eye monitoring. DR can
be diagnosed in 5 stages: mild, moderate, severe, proliferative or no disease. The characteristics of this disease include microaneurysms, leakage of blood vessels, swelling of the retina, abnormal growth of new blood vessels and damaged nerve tissue [2].

Diabetic retinopathy is a microvascular complication of diabetes mellitus that attacks blood vessels in the retina. To identify this disease is still done manually through the retinal image that is examined by an ophthalmologist and requires a long time. Therefore, we need a method to make it easier for ophthalmologists to identify DR through retinal images so that accurate and fast examination results can be obtained.

Several studies have been done before, including: In 2016 Purandare & Noronha through fundus image analysis to classify diabetic retinopathy. At the pre-processing stage, use the adaptive histogram equalizer (AHE) to remove the inappropriate part of the background. Using 2-D Gabor Wavelet for segmentation of blood vessels. In the feature extraction stage using grey level coefficient. For classification SVM is used to classify normal retina or diabetic retinopathy. Accuracy achieved is 92.55% [3]. Quinn, E. A. E. and Krishnan, K. G conducted a study aimed at blood vessel therapy in diabetic retinopathy and hypertensive retinopathy. At the pre-processing stage, use a green channel because it can bring up vessels brighter than the background [4]. Another research conducted by Febriani in 2014, namely the identification of diabetic retinopathy using Modified k-Nearest Neighbor can identify diabetic retinopathy through retinal images with 86.4% accuracy, 91.6% sensitivity, and 80% specificity. The stages before identification are cutting the image, reducing the size of the image (scaling), forming a green channel image, improving image quality, feature extraction image processing using the Gray Level Cooccurrence Matrix (GLCM) [5]. The other research in 2015 was carried out by Abdel-Zaher & Eldeib to classify breast cancer using the Deep Belief Network (DBN) which in the pre-training process uses backpropagation. The overall accuracy of DBN reaches 99.68% with 100% sensitivity and 99.47% specificity [6]. Our previous research which related diabetic retinopathy is in classifying hypertensive retinopathy using Backpropagation [7] and Probabilistic Neural Network [8].
2. Methodology

2.1. Pre-processing

2.1.1. Resizing
In the initial stage of the pre-processing process, it is resized to change the image size by reducing the size of the image in the horizontal and/or vertical direction to 350x302. This aims to uniformize the size of each image used during the training and testing process.

2.1.2. Grayscale
The retinal image received is a colour image, so the grayscale process needs to be done first to get an image with grey level. Can be calculated by the following equation:

\[ I(x, y) = \alpha \cdot R + \beta \cdot G + \gamma \cdot B \]

2.1.3. Median Filter
This filter is used to eliminate salt & pepper type noise which is often found in retinal images. The median filter works by replacing the value of a pixel with the median value of all pixels in a window.

2.1.4. Contrast Stretching
The next process is to improve image quality using stretching. Contrast stretching is used to improve image contrast so that features in the retinal image can be seen more clearly.

2.1.5. Thresholding
The next step uses thresholding technique to obtain binary images with values 0 and 1 (Black and White).

2.1.6. Morphological Close
The next step is extracting (separating) the background and optical disk by using morphological close because the object is not included in the feature to be extracted. Morphological close used is dilation and erosion. The process of dilation (thickening of the object image) then continued the process of erosion (separation of image objects). The dilation process can be calculated by the following equation:

\[ D(A, B) = A \bigoplus B = \{ x : Bx \cap A \neq \emptyset \} \]

The erosion process can be calculated by the following equation:

\[ E(A, B) = A \bigtriangleup B = \{ x : Bx \cap X \} \]

2.2. Feature Extraction
After the pre-processing stage, the next step is feature extraction. In this study, feature extraction used is the Grey Level Co-occurrence Matrix (GLCM) method. To take part of the retina in the image, use masking. Masking is a binary image that is used to take certain parts. Masking must have the same dimensions as the image you want to take the image. The masking used is shown in Figure 2.

![Figure 2. Image masking.](image)
Figure 2 is a masking image that is used only to separate the retina from the background. The feature extraction steps using GLCM is as follows:

- Determine the grey level value to form the matrix framework. Grey level used is 256. Diagnosis 0 is normal image, diagnosis code number 7 and 8 is the image of diabetic retinopathy. The total number of normal images and diabetic retinopathy are 122 images sample.
- Determine the direction and distance between reference pixels can be seen in Figure 3. with neighbouring pixels. Distance used is 1 and the direction used is 0 °, 45 °, 90 °, and 135 °.
- Calculate concurrency value based on direction and the specified distance. Value concurrency calculated using the concept masking.
- Adding a concurrency matrix with the transpose matrix so that the concurrency matrix becomes symmetrical.
- Normalize the concurrency matrix which is already in symmetrical form by dividing the concurrency value by the sum of all existing concurrency values, so that the sum of all concurrency values is 1.
- Calculate statistical features. Statistics feature is used in number 6, namely contrast, homogeneity, energy, entropy, variance, and correlation.

2.3. Classification

After obtaining the value of 24 features in the feature extraction process using GLCM, the next process is the image classification process using the Deep Belief Network method. The initial stage of the classification process is the process of training data input training or training data. In this study researchers used 97 input data to be trained. The Restricted Boltzmann Machine (RBM) algorithm is used the number of codes used during the training process, in this method will also use the Contrastive Divergence (CD) algorithm to determine the best value of the weight.

2.4. Output

The output obtained is the result of identification of normal retinal images and retinal diabetic retinopathy images.

The data used in this study are retinal images consisting of normal images and images of diabetic retinopathy. This data is obtained through Structure Analysis of the Retina (STARE). STARE is a project that was compiled and started in 1957 by Michael Goldblum, M.D., at the University of California, San Diego. Images and clinical data are provided by the Shiley Eye Centre at the University of California, San Diego, and by the Veterans Administration Medical Centre, San Diego. All data amounted to 400 images, to determine the normal image and image of diabetic retinopathy can be seen with the diagnosis code number.

![Figure 3. Hypertensive image retinopathy.](image1)

![Figure 4. Normal image.](image2)

3. Result and discussion

At this stage, data testing and systems were conducted to identify diabetic retinopathy. In determining the parameters used in the identification process using deep belief network, prior experiments were conducted on the selection of decay, momentum, learning rate, supervised epoch and unsupervised epoch parameters in the training process with several tests.
Previously, there were 28 data testing of diabetic retinopathy and 20 normal images with different epoch parameters with a duration of 10 minutes to 1 hour. The results of testing 48 images with epoch parameters can be seen in Figure 4.

Figure 5. SE and UE graphic.

The experiment was carried out using different parameter values. The higher the epoch value, the longer the training process, but the higher the learning value, the duration of training is uncertain. The best test results obtained 84% accuracy with parameter values that can be seen in Table 1.

| Type               | Value          |
|--------------------|----------------|
| Decay              | 0.001          |
| Learning Rate      | 0.1            |
| Momentum           | 0.5            |
| Unsupervised epoch | 50             |
| Supervised epoch   | 200            |

4. Conclusion

The conclusions that can be drawn based on the results of testing the system for identification of diabetic retinopathy by using DBN are as follows:

- The use of the DBN method can identify diabetic retinopathy through retinal images with 84% accuracy, 93% sensitivity and 70% specificity.
- The selection of DBN parameter values influences the accuracy. The parameters used were supervised epoch 200, unsupervised epoch 50 and learning rate 0.1 on contrast divergence learning and backpropagation.
- The difference in values used in the parameters also affects the duration of time. The higher the unsupervised epoch value, the more time the training data increases, this also happens if the learning rate used is different.

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