Identification of Retinoblastoma Using the Extreme Learning Machine

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Abstract. Retinoblastoma is cancer on the retina that often occurs in infants and children that can cause blindness and even death. The cause of retinoblastoma is due to the mutation of the RB1 gene which keeps retinal cells reproducing until the tumor grows on the retina. In general, to identify a retinoblastoma the doctor uses an ophthalmoscope that shines brightly through the pupil to examine the back of the eye and see the presence of white or yellowish white tumor lesions in the eye. In addition, the examination is also done by analyzing the retinal fundus image from the fundus camera. The image of the fundus camera is re-analyzed by a doctor or expert to determine whether or not there is retinoblastoma. Therefore, a system is needed to help the expert to diagnose retinoblastoma. The method used in this study is the extreme learning machine. Retinal fundus images are used as input images to identify retinoblastoma. Before being identified, pre-processing of the image is carried out, it consists of scaling, green channel, contrast stretching, thresholding, and feature extraction using the zoning method. From this study, it was concluded that the proposed method had the ability to identify retinoblastoma with an accuracy of 92%.

1. Introduction

The retina is a thin layer of nerve tissue that lines the inside of the back of the eye that is sensitive to light and is responsible for human visual abilities. The retina is the only place in the body where blood vessels can be directly observed and evaluated for pathological abnormalities, including disease like retinoblastoma or eye cancer. Retinoblastoma (RB) is a cancer of the retina that often occurs in infants and children which can cause blindness and even death. Retinoblastoma cancer can attack either side of the eye or both eyeballs. The typical symptoms of retinoblastoma are the child's eyes look like cat's eyes and the presence of leukocoria with the drug [1].

According to the 2013 Basic Health Research Results, retinoblastoma occurs because of a genetic mutation that keeps the retinoblast reproducing. When retinoblastoma occurs, eye cells called retinoblasts do not turn into mature cells, but continue to divide to form cancer in the retina. This cancer can grow to all parts of the eye and spread to other body parts, such as the brain and spine. The frequency of retinoblastoma growth has increased over the past 60 years. Now it occurs in 1 in every 15,000 births. 250 to 350 new cases are diagnosed each year in the US with more than 90% of cases occurring before 5 years of age [2].

Based on the 2013 Basic Health Research Results, the prevalence of cancer in children aged 0-14 years old was around 16,291 cases. The types of cancer that most children suffer from in Indonesia are leukemia and eye cancer (retinoblastoma). Retinoblastoma (eye cancer) is cancer that attacks the back of the eye that consists of special nerve cells that are sensitive to light. In general, identification is done...
manually by experts (doctors) through the results of the retinal fundus image. The examination is carried out to see the presence of white or yellowish white tumors that require a long time. Therefore, a method is needed that can facilitate the ophthalmologists in identifying retinoblastoma through retinal images.

Several studies using the retinal fundus image have previously been used to identify retinoblastoma using image enhancement, segmentation using canny edge detection to distinguish objects from the background. The resulting pixels are applied to the apriori algorithm [3]. It was then utilizing fundus cameras to identify retinoblastoma through analysis of fundus images using the Gaussian filter, fast Fourier transform, then log transform was applied to compress light pixels in the image [4].

Extreme Learning Machine (ELM). The new ELM method is part of artificial neural networks. The ELM learning method was created to overcome the weaknesses of feedforward artificial neural networks especially in terms of learning speed [5]. Previous ELM has been used for the classification of parkinson's disease by using particle swarm optimization as feature extraction to improve performance in classification [6].

The next research was conducted by Nurrahmadayeni about the identification of hypertensive retinopathy through retinal fundus images. The stages before identification are the preprocessing process of the image and feature extraction using two methods, fractal dimension and invariant moments. Then it used the Probabilistic Neural Network (PNN) method for the identification of normal retina or hypertensive retinopathy. This study resulted in a very good level of identification of 100% accuracy [7].

The next study conducted by Sandri was identification of retinoblastoma through retinal fundus images. The input image was carried out in the stages of image processing, then the extraction of image features was using gray level co-occurrence (GLCM). The backpropagation neural network method was used to identify retinoblastoma or normal retina. This study resulted in an identification level of 90% accuracy [8].

The research conducted by Amalia was the identification of retinopathy hypertension through retinal fundus images. Image processing was done on the image, the extraction of image features was using the zoning method. Then the Backpropagation neural network method was used to identify retinopathy or normal retinal hypertension. This study resulted in an identification level of 95% accuracy [9].

The treatment for retinoblastoma involves many parties where the most important goal is to save the lives of the sufferers while maintaining the eyeball and vision function. The earlier the retinoblastoma is detected, the better the treatment can be given so that the number of deaths from retinoblastoma can be suppressed. Early detection of this disease can be done by physical examination and further examination using Lactic Acid Dehydrogenase (LDH), Magnetic Resonance Imaging (MRI), Ultrasound Orbita, Computerized Tomography Scan (CT Scan), and Biopsy.

In general, to identify retinoblastoma, doctors use an ophthalmoscope that shines brightly through the pupil to examine the back of the eye and see the presence of white or yellowish white tumor lesions in the eye. In addition, the examination is also carried out by analyzing the retinal fundus image from the fundus camera. The image of the fundus camera is re-analyzed manually by the doctor (expert) as the basis for diagnosing RB disease.

2. Method

At this research, we use Extreme Learning Machine as the algorithm to identify retinoblastoma from the image of fundus camera. Figure 1 show general architecture from this research.
Figure 1. General Architecture to Identify Retinoblastoma

a. Preprocessing

Scaling

Scaling is used to change the size of pixels to the size of M x N. This is done because each image processed does not necessarily have the same size. Scaling is used to change the resolution of an image, whether it reduces or enlarges image resolution [10]. Scaling can also be used to normalize the size of all images so they have the same size. It can be calculated with the following equation:

\[
\text{Scale value} = \begin{cases} 
> 1 & \text{enlarge the original image} \\
< 1 & \text{reduce the original image} 
\end{cases}
\]

Formula used:
\[
x' = S_h x \\
y' = S_v y
\] (1)
Green Channel

Green channel is one type of grayscaling that replaces the value of each pixel in an image only with the green value of the pixel image [11]. Green channel is chosen because it produces the best image compared to the red channel and blue channel [12]. Fundus images sometimes experience oversaturated saturation, especially in the central region and optic nerve. Whereas the blue channel can experience undersaturated saturation and there is a lot of noise. Green channel is done by equation 2. It can be calculated with the following equation:

\[ I(x, y) = 0.\, R + 1.\, G + 0.\, B = G \]  

Contrast Stretching

The next step is image repair, it is a process carried out to improve image quality by manipulating parameters in the image so that the characteristics of the image can be highlighted. Image improvement allows information to be displayed or taken from an image to be better and clearer. Image repair done is a contrast improvement using contrast stretching method. Contrast Stretching is able to overcome the lack of light or excess light in the image by expanding the distribution of gray values of pixels [13]. Contrast stretching is a method of improving the image that is point processing, it means processing only depends on the gray intensity value of each pixel, regardless of the other pixels around it. Contrast stretching is done by equation 3.

\[ CS'(x, y) = \frac{CS(xy) - c}{d - c} \, (G - 1) \]  

b. Segmentation

Thresholding

The next stage is the thresholding stage to obtain a binary image that has a value of 0 and 1 (Black and White). It can be calculated by equation:

\[ g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases} \]  

c. Feature Extraction:

Zoning

This study used the zoning method which is a feature extraction method that is done by dividing the character image into a specific area. In the next stage, a probability value between the bits in the character zone will be searched with a bit pattern stored in the system template [14]. At this stage, 380 x 300 pixels image will be divided into 38 columns and 30 rows so that 1140 zones will represent 1140 features.

d. Identification

The next step, the results of feature extraction will be used as input to the identification process. The method used for the identification process is the Extreme Learning Machine (ELM). The architecture that will be used in this network consists of 3 layers: input layer, hidden layer, and output layer. In ELM, input weight parameters are randomly selected so that ELM has a fast and capable learning speed to produce a good performance. This method has a mathematical model that is simpler and more effective than feedforward artificial neural networks [15]. The training steps that will be processed are as follows:
Step 1: Initialize all weights and bias with small random numbers [0 - 1].
Step 2: If the termination has not been fulfilled, then do step 3 through step 7.

Phase 1 feedforward

Step 3: Each input unit \( X_i \) (\( i = 1, 2, ..., n \)) receives a signal and passes the signal to all hidden layers.
Step 4: Calculate each layer of the hidden unit \( Z_j \) (\( j = 1, 2, ..., m \)) by summing the weighted input signals.

\[
z_{\text{net}} = b_j + \sum_{i=1}^{n} x_i w_{ji}
\]

Then calculate the output in the hidden layer with the sigmoid binner activation function.

\[
g(z_{\text{net}}) = \frac{1}{1-e^{z_{\text{net}}}}
\]

After getting the output on the hidden layer, then the next step is,

Step 5: Calculate the matrix \( H \) with size \( n \times m \)

\[
H = \begin{pmatrix}
g(w_{11} \cdot x_1 + b_{10}) & g(w_{12} \cdot x_1 + b_{20}) & g(w_{13} \cdot x_1 + b_{30}) & g(w_{14} \cdot x_1 + b_{40}) \\
g(w_{21} \cdot x_2 + b_{10}) & g(w_{22} \cdot x_2 + b_{20}) & g(w_{23} \cdot x_2 + b_{30}) & g(w_{24} \cdot x_2 + b_{40}) \\
g(w_{31} \cdot x_3 + b_{10}) & g(w_{32} \cdot x_3 + b_{20}) & g(w_{33} \cdot x_3 + b_{30}) & g(w_{34} \cdot x_3 + b_{40}) \\
g(w_{41} \cdot x_4 + b_{10}) & g(w_{42} \cdot x_4 + b_{20}) & g(w_{43} \cdot x_4 + b_{30}) & g(w_{44} \cdot x_4 + b_{40}) \\
g(w_{51} \cdot x_5 + b_{10}) & g(w_{52} \cdot x_5 + b_{20}) & g(w_{53} \cdot x_5 + b_{30}) & g(w_{54} \cdot x_5 + b_{40})
\end{pmatrix}
\]

After getting the \( H \) matrix with size \( n \times m \), then calculate \( H^+ \) which is the pseudo inverse matrix of the \( H \) matrix that will be used to find the weights between the hidden layer and the output layer.

The equation \( H^+ \) is as follows:

\[
H^+ = (HTH)^{-1} HT
\]

Then look for the weights to output layer (\( \beta \))

\[
\beta = H^+ t_i
\]

\( t_i \) is the target of the training process

Step 6: Calculate the output value using the equation:

\[
\sum_{j=1}^{m} \beta_j g \left( z_{\text{net}_j} \right) = y
\]

Step 7: Calculate the error value in the output unit

\[
E = \| y - t_j \|
\]

Phase II: Changes to weights and biases update

Step 8: Calculate all changes in weight and bias connected to hidden layer units

\[
W_{ij}^{\text{(new)}} = W_{ij}^{\text{old}} + \alpha \delta_j x_i
\]

Step 9: Check the termination, the iteration in the training process will stop if the epoch < epoch max that has been determined.

Step 10: Save the optimal or appropriate bias weight.

From the results of the calculation of new weights, then the calculation starts from steps 3 - 7 until the termination condition is fulfilled. The iteration in the training process will stop if the epoch < epoch max that has been determined. After that, save the optimal or appropriate bias
weight. Then enter the testing stage to test the accuracy of the system in identifying retinoblastoma and the steps are:

1. Enter the data tested.
2. Enter the optimal value of the hidden node weight from the training data.
3. Perform a feedforward process with 1 iteration, which is to calculate the output.
4. Analysis of output results.
5. Draw conclusions from the output.

The data used in this study are retinal fundus images consisting of normal images and retinoblastoma images. The image data in this study are images obtained from the site http://imagebank.asrs.org. Retina Image Bank is a project of the American Society of Retina Specialists which contains a collection of retinal images with various conditions and is a source of centralized access to retinal specialists, doctors, researchers and independent students.

The image data obtained were 60 images, 30 normal images and 30 retinoblastoma images. The collected image data was divided into two datasets, namely for training datasets and testing datasets which would be used to determine the accuracy of the identification process. Normal training datasets were 24 images and retinoblastoma datasets were 24 images. While for the testing dataset, 6 images will be used for normal and 6 images for retinoblastoma. Image samples can be seen in Figure 2.

![Figure 2. (a) Retinoblastoma Image (b) Normal Image](image)

### 3. Results and Discussions

At this stage, data and system tests were carried out in identifying retinoblastoma in fundal images. The tests were carried out on data and systems to determine the ability of the system built in identifying retinoblastoma disease. Data testing was performed on 6 retinal retinoblastoma images and 6 normal retinal images. Before the test was carried out the data was trained in 48 images consisting of 24 normal images and 24 retinoblastoma images.

Extreme Learning Machine parameters used were epoch value = 1000, learning rate = 0.2 and hidden node = 30. The parameters of the epoch tested also varied, starting from 150, 300, 550, 700, 850 and 1000. The testing with different epoch values aimed to obtain epoch values which were able to identify retinoblastoma diseases with high accuracy. The graph of test results from different epochs on test data from Retinoblastoma and Normal can be seen in Figure 3.

![Figure 3. The Epoch Test Result](image)

Based on the test results as shown in the graph of the test results in Figure 4.16. The hidden node value = 30 and epoch = 1000 get high accuracy compared to the others. However, the magnitude of the hidden
node value and epoch will prolong the training process. So the best accuracy was obtained from the hidden node value ≥ 30 and epoch = 1000. The results of the test data on the test data that have been carried out can be seen in Table 1.

Table 1. Retina Fundus Image Data Test Results

| No | Image     | Desired Output | Actual Output | Status |
|----|-----------|----------------|---------------|--------|
| 1  | tnm(1).jpg | Normal         | Normal        | Succeeded |
| 2  | tnm(2).jpg | Normal         | Normal        | Succeeded |
| 3  | tnm(3).jpg | Normal         | Normal        | Succeeded |
| 4  | tnm(4).jpg | Normal         | Normal        | Succeeded |
| 5  | tnm(5).jpg | Normal         | Normal        | Succeeded |
| 6  | tnm(6).jpg | Normal         | RB            | Failed   |
| 7  | trb(1).jpg | RB             | RB            | Succeeded |
| 8  | trb(2).jpg | RB             | RB            | Succeeded |
| 9  | trb(3).jpg | RB             | RB            | Succeeded |
| 10 | trb(4).jpg | RB             | RB            | Succeeded |
| 11 | trb(5).jpg | RB             | RB            | Succeeded |
| 12 | trb(6).jpg | RB             | RB            | Succeeded |

Accuracy calculations are carried out using equation 12:

\[
\text{Accuracy Percentage} = \frac{\text{The number of correct test data}}{\text{Total number of test data}} 
\] (12)

Overall accuracy is obtained by using equation 4.1, namely by adding the desired number of outputs according to the actual output divided by the number of all test image data used as follows.

\[
\text{Accuracy} = \frac{11}{12} \times 100\% = 92\%
\]

From the above calculation, it can be seen that the accuracy of the Extreme Learning Machine method in identifying retinoblastoma through the retinal fundus image can reach 92%. Based on the test results in table 2 the normal image tnm(6).jpg failed to be identified as a normal image. Image identification failure was caused by data that had high noise so that at the thresholding step the non-tumor part was in the segmentation area so that an identification error occurred in the image.

4. Conclusions
The conclusions that can be taken based on the results of the system testing for identification of retinoblastoma using the extreme learning machine are as follows:

a. In the preprocessing process, the determination of contrast stretching and thresholding values in the image must be appropriate because it will affect the accuracy of the system.
b. The Extreme Learning Machine (ELM) method is able to identify retinoblastoma through the retinal fundus image properly. So the results of the process of identifying retinoblastoma through fundal images have an accuracy rate of 92%.

c. The fundus images that have high noise is one of the obstacles in the thresholding stage that the non-tumor part is in the segmentation area so that the identification error occurs in the image.

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