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Optic Disc Detection on Retina Image using Extreme Learning Machine

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Abstract: Optic disk detection on retina image has become one of many initial steps in evaluation of Diabetic Macular Edema (DME) severity. As much as early the step is, the result of the step is extremely essential. This article discusses the optic disk detection on retina image based on the color histogram value. The detection is done by using color histogram value which is taken from window sliding process with the size of 50x50 pixels. First, the candidates of optic disc were detected using Extreme Learning Machine towards the histogram value. Then the optic disc was selected form the candidates of optic which has highest average intensity. 4 retina image datasets were employed in the evaluation, including Drions dataset, DRIVE dataset, DiaretDB1 dataset, and Messidor dataset. The result of evaluation then validated by medical expert. The model outcome reaches the accuracy as much as 85,39 % for DiaretDB1 dataset, 95% for DRIVE dataset, 98,18% for Drions and 99% for Messidor dataset.

Keywords: Retina image; optic disk detection; ELM; histogram; Diabetic Macular Edema (DME)

INTRODUCTION

Diabetes mellitus (DM) becomes one disease with the most prevalent rate in the world. There are 171 million people diabetes infected and it is expected to increase rapidly to the rate of 366 million people in 2030 (Wild et al., 2004)(Verma et al., 2002)(Rama et al., 2013). This has come to realization by taking notes that diabetes not only affect the organ performance but also affect the important organs in human body, such as heart, liver, feet, and eyes (Verma et al., 2002) (Al., 2015)(Alghadyan, 2015)(S. Zheng et al., 2014). Early detection of diabetic retinopathy might help to avoid blindness or other seizures. The early detection of the disease has become important to provide a bigger chance in avoiding any worse condition.

One problem that can happen to diabetic retinopathy is Edema Makula or which is familiarly known as Diabetic Macular Edema (DME)/ Edema Makula (Ciulla et al., 2003). Optic Disk, MF and the blood vessel on retina are top tree of the most important structural anatomy which can be used in DME examination. In common retina image, optic disk can be recognized as a part with the shape of ellipse, and it has the brightest color. In addition, the optic disk is the center of blood vessel in retina (Tobin et al., 2007).

Although Optic Disk has a distinct characteristic other than other components in the retina, finding the method which can be used to locate the optic disk automatically, exactly and accurately is not simple. This is caused by the appearance of optic disk in retina is various in general. Thus, several methods has been developed to be able to detect the optic disk effectively for every possibility of various sizes and appearances (Youssif et al., 2008).

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Many research on optic disk detection have been much established (Nija et al., 2019)(Listyalina & Dharmawan, 2019)(Kakade et al., 2021)(J & B, 2022)(Martinez-Perez et al., 2019)(Al Shalchi & Rahebi, 2022)(Zhou et al., 2020). One of them is the approach of relative position towards vascular curve (Tobin et al., 2007) (Fleming et al., 2007)(Niemeijer et al., 2007)(Niemeijer et al., 2009). The result obtained from the previous research has reached high rate of accuracy. However, on the previous research, the vascular curve should be first seen and detected in order to detect the optic disk location.

In other research, Lalonde et al (Lalonde et al., 2001) suggest the method to detect the area of optic disk in the green canal by using pyramidal decomposition number which is Wavelet Haar Transformation. Meanwhile, Sopharak et al (Sopharak et al., 2008) propose optic disk detection technic by using entropy filter. The true image in RGB color space is converted into HIS color space. Ravishankar et al (Ravishankar et al., 2009) suggest the search of optic disk by combining the early convergence in the first blood vessel and high intensity rate from a disk by applying Hough transformation.

Meanwhile, the Extreme Learning Machine (ELM) has shown that the best performance in several application are text recognition (W. Zheng et al., 2013), hand writing character recognition (Chacko et al., 2012), face recognition (Mohammed et al., 2011), pattern recognition of electromyography (Anam & Al-Jumaily, 2017). Furthermore, ELM also has an important role in cancer detection (Saraswathi et al., 2011) and determining severity level of diabetes (Punithavathi & Kumar, 2017). As a singgle hidden layer feedforward network (SLFN), ELM has a shorter time than the other SLFN, this is affected by the use of projection in hidden layer to count the outer weight of ELM. Therefore, it is not necessary to do an iteration process (G. Bin Huang et al., 2006)(G.-B. Huang et al., 2012).

This article will deliver the method to detect the optic disk location on the retina image without depending on the availability of the vascular curve information. This method uses Extreme Learning Machine as the classifier. It is also combined with the comparison of the average image intensity. These two steps are done by applying color histogram value as the feature.

LITERATURE REVIEW

There have been various approaches to detect and locate the optic disc, which involve a combination of features and techniques such as edges, shapes of the disc, blood vessels, color spaces, and operations like template matching and morphological operations (Almazroa, A., Burman, R., Raahemifar, K., Lakshminarayanan, 2015). Algorithms that already exist for detecting and locating the optic disc have taken advantage of the fact that it is the brightest area in a fundus image. Previous works, such as those cited in references (Walter, T., Klein, 2001) , have proposed algorithms that utilize this property. In addition, Giraddi et al. have achieved optic disc segmentation through the use of P-tile thresholding, connected component analysis, and the gradient vector field (Giraddi, S., Pujari, J., Hiremath, 2017).

Another technique involves using multiple fuzzy segments of vessels to obtain an image that is then thresholded to find the strongest point(s) for localization, as proposed by Hoover and Goldbaum in 2003. Welfer et al. proposed an adaptive method that uses mathematical morphology and can be applied to images captured under different illumination and acquisition conditions for automatic optic disc segmentation (Welfer, D., Scharcanski, J., Kitamura, C.M., DalPizzol, M.M., Ludwig, L.W., Marinho, 2010). Additionally, Hashim et al. suggested using morphological operators, contrast enhancement techniques, and the difference of Gaussian filter to detect the boundary of the optic disc (Hashim, F., Salem, N., Seddik, 2015).

Alternatively, the optic disc can be detected by using a geometric model that is based on the directional pattern of retinal vessels, as suggested by Foracchia et al. in 2004 (Foracchia, M., Grisan, E., Ruggeri, 2004). Furthermore, Mahfouz and Fahmy proposed a fast technique that involves analyzing two projections of an image in 2010. Lu used a circular transformation method to detect the circular shape of the optic disc in 2011 (Mahfouz, A.E., Fahmy, 2010).

Another approach for optic disk localization is to use template matching, and then apply global elliptical locally deformable models for segmentation (Lowell, J., Hunter, A., Steel, D., Basu, A., Ryder, R., Fletcher, E., Kennedy, 2004). Another option is to detect the optic disc by matching the anticipated directional pattern of retinal blood vessels (Youssif et al., 2008). Additionally, edges in CIE Lab* color

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space can be obtained by calculating color gradients of fundus images (Fondon et al., 2013). To detect the optic disc, a method based on Hough transformation has been proposed (Zhang, D., Zhao, 2016).

In another work, vessel-based method employs a vessel convergence approach that relies on high vasculature convergence to localize the optic disc (Soares, I., Castelo-Branco, M., Pinheiro, 2016). The initial disc candidates can also be detected by analyzing the features of intensity, edges, vessel direction, and size of bright regions (Xiong & Li, 2016). Furthermore, optic disc localization can be achieved by utilizing the statistics of salient visual cues of retinal vasculature.

Various optic disc localization methods that employ machine learning and optimization techniques have been proposed. Some of these methods use feature vectors and a kNN-classifier, as in (Staal et al., 2004) and (Niemeijer et al., 2009). Additionally, Qureshi et al. modeled the problem as an energy minimization problem to localize the optic disc center (Qureshi, R.J., Kovacs, L., Harangi, B., Nagy, B., Peto, T., Hajdu, 2012).

Lately, popular models like Deep Convolutional Neural Network (DCNN), encoder-decoder network, and Region-based Convolutional Neural Networks (R-CNN) have been utilized for detecting and locating optical discs, as reported by (Mirhassani & Ahmadi, n.d.), (Bajwa, M.N., Malik, M.I., Siddiqui, S.A., Dengel, A., Shafait, F., Neumeier, W., Ahmed, 2019), and (Hasan, M.K., Alam, M.A., Elahi, M.T.E., Roy, S., Martí, 2021). Despite providing satisfactory accuracy, these deep learning-based techniques necessitate a vast amount of training data and a significant amount of time for learning a model. Moreover, to achieve an efficient model, they also require adjusting various parameters, such as the depth of the network and the number of convolutions.

METHOD

Extreme Learning Machine (ELM)

ELM is a feed-forward JST (feed-forward neural network - FFNN) which has one hidden layer or known as single hidden layer feed-forward neural network (SLFN). As a part of FFNN, ELM does not establish iteration process in the search of net weight but it does establish the projection from input value to output value. Therefore, ELM has shorter time range than any conventional feed-forward method such as Backpropagation (G. Bin Huang et al., 2006)(G.-B. Huang et al., 2012). The main purpose of the training process is to earn weight values. The steps of training process can be seen as follows (G. Bin Huang et al., 2006):

Initialization

The variables started in the first time are input weight (w), bias (b), and amount of hidden neuron (j). Input weight and bias are initialized randomly with the range (-1,1) for input weight and range (0,1) for bias. While the amount of hidden neuron used is 2/3 of input neuron and output neuron combined.
Calculating the hidden layer matrix output:

By using sigmoid activation function (g(x)) to calculate hidden layer matrix output (H_ij) with the equation 1 and 2.

$$g(x) = \frac{1}{1+e^{-H}} \qquad (1)$$

$$H_{ij} = g\left(\sum_{i=1}^{n} w_i \cdot X_j + b_i\right) \quad (2)$$

where:
$g(x)$ = Sigmoid activation function
H = Hidden layer matrix output
i = [1, 2, ……, N] in which N is the amount of hidden neuron
j = [1, 2, ……, Ñ] in which N is data amount
n = Amount of neuron input
w = Weight input
X = Input data
b = Bias

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Calculating the moore-penrose matrix:

The moore-penrose matrix is obtained by multiplying inverse matrix and hidden layer output transpose with the equation 3.

$$H^{+} = (H^{T}.H)^{-1}.H^{T} \quad (3)$$

where:
H^{+} = Moore-penrose pseudo inverse matrix
H = Hidden layer output matrix
H^{T} = Hidden layer output transpose matrix

Calculating output weight:

Output weight is resulted from multiplication of moore-penrosed hidden layer and output layer with the equation 4.

$$\beta = H^{+}.T \quad (4)$$

where:
β =Weight output matrix
H^{+} =Moore-penrose generalized inverse matrix of H matrix
T =Target matrix or output class

Testing process use weight input, weight output, and bias which is obtained from the training process. The result can be calculated with the equation 5.

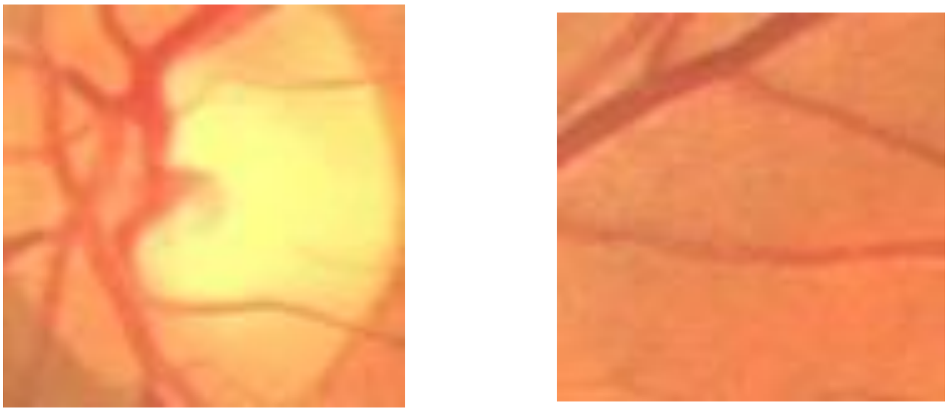
$$Y = H.\beta \quad (5)$$

where:
Y = Result of classification/ recognition
H = Hidden layer output matrix
β = Weight output matrix

Feature Specification

Optic disc on retina image is often used as a reference to detect other objects existed on the retina image. Optic disk is a place where the blood vessel converged; thus, there is a knot pattern seen on this object. In addition, optic disk is also known as an object which is commonly seen as an ellipse and has bright color (Tobin et al., 2007). The color in every lesion can be functioned to differentiate the lesions on a retina image. There have been many researches done to detect abnormality on a retina image by using the color information (Sopharak et al., 2008).

features which can be used to expect whether or not an object on the retina image is an optic disk. On this research, the color histogram value is used as a distinctive feature whether or not the object is an optic disk. This is concluded due to the fact that most retina images appeared to be the main distinction between optic disk and another object. The main distinction is the color intensity rate. Optic disk has a brighter color than other objects. Thus, it can be concluded that histogram pattern in one area on optic disk has a different histogram pattern from another object as seen on Fig. 1.



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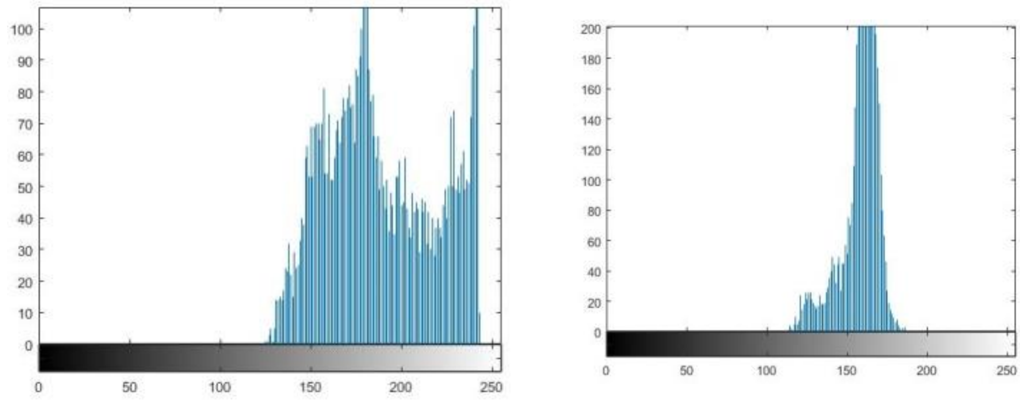

Optic disk Non-optic disk

Fig. 1 Histogram Pattern Comparison between Optic Disk and Non-Optic Disk

In this study, the histogram is obtained from the gray scale value of the image with RGB color space which may produce more optimal results in classification process. Gray scale value of an image can be acquired from the average value of R, G, and B channels or directly from one of the channels. The gray scale value that is applied in this study is the one that is obtained from the Green channel which has better contrast in RGB color space (Wiharto et al., 2018). Besides color histogram, the color average of an examination area is also taken into consideration in order to define the optic disk. The color average is gathered from the average value of the R, G, and B channels. This color average will be incredibly helpful as a filter in a condition where the histogram pattern of the optic disk area and its surroundings have proximity. The histogram value is used in the process of training and determining while the color average acts only as a subsidiary when detection is in progress.

ELM for optic disk detection

A network has 257 input neurons that will be used to collect input values that include histogram value of images and refraction. Meanwhile, the number of neuron in the hidden layer is as much as 170 neurons. On the other hand, output network layer uses two neurons to determine the output. These two neurons act as the representation of optic and non-optic neuron class. The architecture of the artificial ELM tissue that is applied in this study is shown in Fig. 2. The output is produced by evaluating the output value of both neurons. The neuron with the highest value becomes the result class from the entered data. Output of this ELM may still be the assumed area of optic disk.

Detection process for optic disk location is exercised by using the sliding window method. By implementing this method, there will be a scanning process on images. A window will be run overlapping the image beginning from the top left image to the image on the lower right. The window size applied in this optic disk detection study is 50x50 pixels.

When this process is run, a 50x50 pixel window will move and take histogram value from the area inside the window. From that area, two kinds of value will be extracted, which are the histogram value of green channel image and the average brightness of the area that are measured based on the gray channel. The obtained histogram value will be transformed into a 256 sized array. This value becomes the input in the formed ELM model. Thus, by using the β value that is acquired from the training process, an output will also be obtained in the form of input class determining whether or not it is an optic disk.

If the output is evidently an optic disk class, then the average brightness will be compared with the average brightness in the previous process. Otherwise, if the brightness in the new window area turns out to be higher than the previous one, the update process of optic disk candidates will be conducted. The coordinates of window position with higher brightness is the position of the expected optic disk.

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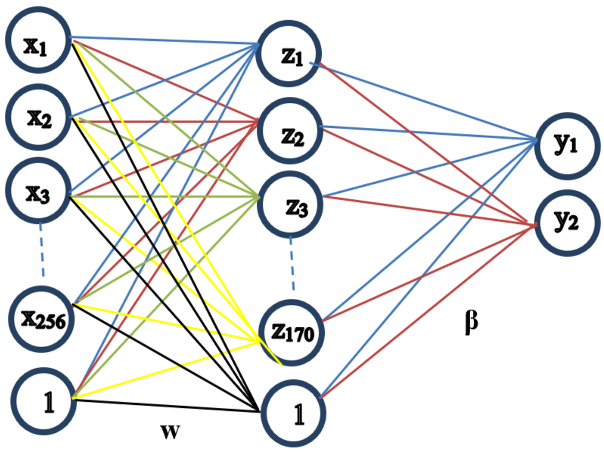

Fig. 2 The architecture of ELM for optic disk detector

RESULT

Optic disk detection is implemented on four retinal image datasets that taken by ophthamologist, consisting of DRIVE (Staal et al., 2004), DRIONS (Carmona et al., 2008), DIARETDB1 (Kauppi, 2007), and MESSIDOR (Decencière, 2014). MESSIDOR dataset is collected from base31 dataset. The test results of the propose method validated by medical expert can be seen in Table 1.

Table 1
Accuracy of Optic Disk Detection Results using ELM

No.	Dataset	Number of images	Image Size (pixels)	Result Accuracy
1	DRIVE	40	584X565	95,00%
2	DIARETDB1	89	1152X1500	85,39%
3	DRIONS	110	400X600	98,18%
4	MESIDOR	100	960X1440	99,00%

From the results seen in table 1, the proposed method is found to be successful in presenting the performance of optic disk detection well. The combination of color histogram pattern processed with ELM and the average color intensity is able to distinguish optic and non-optic disk. Color histogram has been helpful in providing patterns that characterize a color distribution of an optic disk area. By using several parts of optic and non-optic disk from several retinal images, ELM gives a final weight that may contribute in distinguishing the histogram pattern of an area. ELM with a final weight may determine whether a window is included in the optic disk. However, the deviation of several windows with identical label is very small and random. Therefore, when it is used in optic disk detection with sliding window method, the application of ELM in the detection will face difficulties as shown in Fig. 3. In Fig. 3, it can be seen that a window located under the coordination of the optic location is considered as the optic disk location.

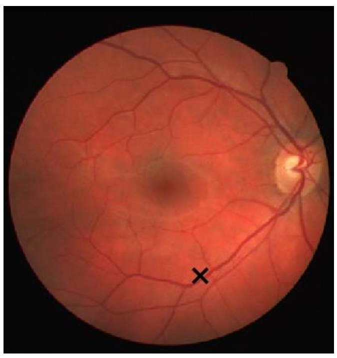

Fig. 3 Optic disk detection only uses color histogram ELM

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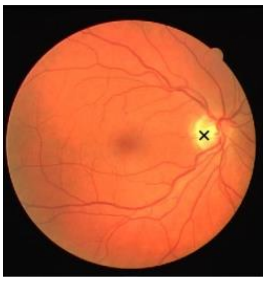
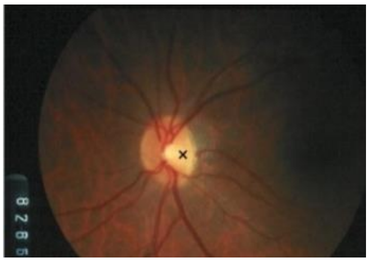
Therefore, in this proposed method, additional examination is incorporated, such as examination on the average color intensity in moving windows. When a location of a window is detected as an optic disk by ELM process, then the value comparison between the average window color intensity rate and the previous windows is conducted. If it is found that the window candidate has higher average intensity, then the location will be moved to the new window location. Meanwhile, if the average intensity is lower that the chosen location coordinates are the old window coordinates. The results of this addition are shown in Fig. 4. Examples of the detection results on the four datasets by implementing the proposed method can be seen in Fig. 5.

Fig. 4 The results of ELM implementation along with the comparison of average color intensity

DIARETDB1



DRIVE



DRIONS

MESIDOR

Fig. 5 Examples of optic disk detection results

DISCUSSIONS

The results of this proposed method have a high accuracy. If compared to the study done by Muhammed (Muhammed, 2018), this study has a slightly lower result for the DIARETDB1 dataset, which is 85% against 89%, whereas on DRIVE dataset, the resulted accuracy is identical at 95%. However, this study is able to outperform the previous study with significant differences when it is applied on DRIONS dataset, which produces an accuracy of 98,18%, compared to Muhammed's which only has an accuracy of 77%.

Moreover, the resulted method has similar performance to the method constructed by (Cirneanu et al., 2017) which produces an accuracy of 99% for MESIDOR dataset. The results on MESIDOR dataset are better than the ones resulted by L Xiong (Xiong & Li, 2016) which is of 97,9% and Rahebi (Rahebi & Hardalaç, 2016) which produces an accuracy of 96,5% .

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CONCLUSION

This study that aims to detect the optic disk location in eye retinal image has successfully created a method with high accuracy. The determination of histogram value as object features and Extreme Learning Machine as classifier incorporated with value comparison of average color intensity is able to detect the optic disk location in retinal image with different surroundings. The method constructed in this study may produce accuracy of 85,39 % for DIARETDB1 dataset, 95% for DRIVE dataset, 98,18% for DRIONS dataset, and 99% for MESIDOR dataset.

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