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An artificial neural network approach for detecting skin cancer

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Abstract

This study aims to present diagnose of melanoma skin cancer at an early stage. It applies feature extraction method of the first order for feature extraction based on texture in order to get high degree of accuracy with method of classification using artificial neural network (ANN). The method used is training and testing phases with classification of Multilayer Perceptron (MLP) neural network. The results showed that the accuracy of test image with 4 sets of training for image not suspected of melanoma and melanoma with the lowest accuracy of 80% and the highest accuracy of 88,88%, respectively. The 4 sets of training used consisted of 23 images. Of the 23 images used as a training consisted of 6 as not suspected of melanoma images and 17 as suspected melanoma images.

***Keywords**: artificial neural network, first-order feature extraction, melanoma, multilayer perceptron*

1. Introduction

Melanoma is one type of skin cancer which serious enough and could not be handled perfectly, so it can be lead to death, disability and requires large medical expenses [1]. There are many method used in detecting Melanoma and one of the successful one is based on image processing, where it can be used to help the process of diagnosing skin cancer [2-5]. Now is done dermatologist to diagnose wounds skin cancer using two imaging techniques that are macroscopic with accuracy of 65%-80% and dermatocopic with accuracy of 75%-97% [6]. Boundary detection for skin cancer image is early stage and very important for diagnose support system for skin diseases based on computer [7]. Accuracy of diagnosis is determined by accuracy of boundary detection of the skin cancer lesions. So that the image that experience impaired become easier at the interpretation, then the image need to be done image manipulation process known as image processing [8-12]. Early detection of skin cancer will be easier in handling and treatment based on types of the cancer suffered. Experience for dermatological expert showed the difficult to distinguish melanoma from other pigment wound on the skin, such as typical wound and not typical (harmless) [10]. One of the solutions in detecting skin cancer is based on computational intelligence techniques.

Numerous computational intelligence (CI) techniques have emerged motivated for solving many real world problems by real biological systems, namely, artificial neural networks (NNs) [13-22] , evolutional computation, simulated annealing and swarm intelligence, which were enthused by biological nervous systems, natural selection, the principle of thermodynamics and insect behavior, respectively. Despite the limitations associated with each of these mentioned techniques, they are robust and have been applied in solving real life problems in the areas of science, technology, business and commerce including the works of [23-25].

Based on the above explanation, this study aims to present diagnose of melanoma skin cancer at an early stage. It applies feature extraction method of the first order for feature extraction based on texture in order to get high degree of accuracy with method of classification using artificial neural network (ANN). The method used is training and testing phases with classification of Multilayer Perceptron (MLP) neural network.

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2. Research Method

In this section, the system design for skin cancer detection program using artificial neural network (ANN) with input data in the form of color image dermatoscopic is presented. The diagram for whole the process mentioned above can be illustrated in Figure 1 as follows:

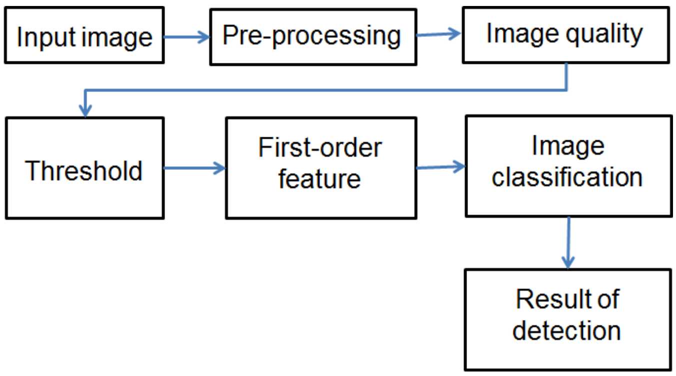

Figure 1. The diagram for skin cancer detection

With this program expected to help in the early detection of melanoma. System design stages are described as follows:

1) Select image Input
2) Preprocessing by changing RGB original image into gray image.
3) Possibility distribution image quality improvement with distribution possibility algorithm.
4) Segmentation with threshold method to separate object with the background..
5) Feature extraction based on texture by using first-order characteristic extraction method.
6) Image classification with Artificial Neural Networks.
7) The final result of diagnose type of melanoma skin cancer and non-melanoma.

3. Results and Discussion

Gray scaling is a technique used to change color image i.e. RGB into grey level (from black to white) with this modification then matrix to compose the image that previous 3 matrix will change to just 1 matrix [10]. Preprocessing to improve the quality of the image using Distribution Possibility Algorithm (DPA) aims to improve image quality using fuzzy logic approach using 5 parameters i.e. α, β1, γ, β2 and max. Distribution Possibility Algorithm described as follows :

1) Step-1 : Initialization Parameter
   Set β1 = (min + mean)/2
   Set β2 = (max + mean)/2
2) Step-2 : Fuzzification
   For all pixels (i,j) in the image

a) if (data(i,j)>= min) && (data(i,j) <β1)
   new-grey(i,j) = 2*(((data(i,j)-min)/(means-min))^2)
b) if (data(i,j)>= b1) && (data(i,j) < means)
   new-grey(i,j) = 1-(2*(((data(i,j)-means)/(means-min))^2))
c) if (data(i,j)>= means) && (data(i,j) < b2)
   new-grey(i,j)=1-(2*(((data(i,j)-means)/(maks-means))^2))
d) if (data(i,j)>= b2) && (data(i,j) < maks)
   new-grey(i,j)=2*(((data(i,j)-means)/(maks-means))^2)

3) Step-3 : Modification
   Fuzzy-data2(i,j) = new-grey(i,j)^2
4) Step-4: Defuzzification
   For all pixels (i, j) in the quality image (i,j) = fuzzydata2(i,j)*data(i,j)

Next, thresholding process to grayscale image that aim to produce binary image that mathematically can be written as follows:

$$g_{(x,y)} = \begin{cases} 0, & (\mathrm{x,y}) \geq T \\ 1, & (x,y) < T \end{cases} \quad (1)$$

The purpose of Otsu Thresholding algorithm using to perform image segmentation with a differentiated way into 2 classes, that is background (the value is set by 0) and the object (the value is set by 1) use certain level as a boundary. The steps to perform thresholding Otsu is [13]:

1) From the image that have increased its image, taken number of pixels at i level, which is represented by n total of the number of pixels defined by N = n1 + n2 + ... + nn. Then obtained a p-value of the number of pixels divided by the total of the number of pixels.

$$p_i = \frac{n_i}{N},\ p_i \geq 0\ ,\ \sum_{i=1}^{L} p_i = 1 \quad (2)$$

2) Afterwards performed division pixels into 2 classes, that is C0 as background and C1 as object.

$$\omega_0 = \Pr(C_0) = \sum_{i=1}^{k} \quad \mathrm{Pi}{=}\omega(\mathrm{k}) \quad (3)$$

$$\omega_1 = \Pr(C_1) = \sum_{i=k+1}^{k} \quad \mathrm{Pi}{=}1 - \omega(\mathrm{k}) \quad (4)$$

3) Then to get mean value is represented by formula as follows:

$$\mu\,(\mathrm{k}) = \sum_{i=1}^{L}\ ip_i \quad (5)$$

$$\mu\ \ _T = \mu(L) \sum_{i=1}^{L}\ ip_i \quad (6)$$

4) To get class variance is defined by formula as follows:

$$\sigma_W^2 = \omega_0\sigma_0^2 + \omega_0\sigma_1^2 \quad (7)$$

$$\sigma\ _B^2 = \omega_0(\mu_0 - \mu_T)^2 +\ \omega_1(\mu_1 - \mu_T)^2 = \omega_0\,\omega_1(\mu_1 - \mu_0)^2 \quad (8)$$

$$\sigma_T^2 = \sum_{i=1}^{L} (\mathrm{i} - \mu_T)^2\, P_i \quad (9)$$

5) Afterwards the search is done for maximum value from all values visible, and threshold value is determined using the average of the discovery of variance values. If not found then threshold value is equal to zero (0.0).

$$\sigma_B^2(k^*) = \max \sigma_B^2 \quad (k),\ \text{for } 1 \leq k < \mathrm{L} \quad (10)$$

$$S^* = \{k; \omega_0\,\omega_1 = \omega(k)[1 - \omega(k)] > 0, or\ 0 <\ \omega(k) < 1\} \quad (11)$$

The first-order feature extraction is the characteristic collection methods which are based on characteristic of image histogram. The histogram is shows probability the emergence of value from the degree of gray pixels in an image. For the values in the histogram is generated then it can be counted several parameters on the first-order characteristic, among other things: mean, skewness, variance, kurtosis, and entropy [14].

1) *Mean* (μ) shows the dispersion size of an image.

$$\mu = \sum_n \mathrm{fn}\ \mathrm{p(fn)} \quad (12)$$

2) *Variance* (σ2) shows the elements variance in the histogram in an image.

$$\sigma^{2=}(f_n-\mu)^2\, p\,(f_n) \quad (13)$$

3) *Skewness* (σ^3) shows the level relative skewness on histogram curve in an image.

$$a_3 = \frac{1}{a_3}\sum_n (f_n - \mu)^3\, p(f_n) \quad (14)$$

4) *Kurtosis* (σ^4) shows the level of skewness relative on histogram curve in an image.

$$a_4 = \frac{1}{a_4}\sum_n (f_n - \mu)^4\, p(f_n) - 3 \quad (15)$$

5) *Contrast* shows the size of the deployment (moment of inertia) elements of the image matrix.

$$Contrast = \sum_{i,i=0}^{G=1} (i-j)^2\, p(i,j) \quad (16)$$

6) *Standard* Deviation is used to measure the average contrast of image intensity [26].

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(\mathrm{i} - \mu_i)^2 \quad (17)$$

7) *Smoothness* is used to measure the relative smoothness of the intensity of the image. *R* Value = 0 for image with a constant intensity, while R Value that approaching 1 for image with the scattered intensity.

$$R= 1-1/(1+ \sigma^2) \quad (18)$$

8) *Entropy* (*H*) shows the size of irregularity shape in an image.

$$\mathrm{H} = -\sum_n p(f_n)^4 \log p(f_n) \quad (19)$$

Artificial neural network is an information processing paradigm that is inspired by biological neural cell system, just like the brain that processes information. In this study, we are using a classification method Artificial Neural Networks (ANN) Multilayer Perceptron (MLP). The ANN-PB training algorithm that formulated by Rumelhart in 1986, briefly as follows:
1) Initialization of weights, which can be done at random.
2) The calculation of activation value, each neural calculates activation value from input that it receives. Activation value input layer is identity function. In the hidden layer and the output of value activation is calculated by activation function.
3) Adjustment of weights, where in adjustment of weights is affected by magnitude of error value output targets and the output value of the current network
4) Iterations will continue to be done until certain minimum error criteria are fulfilled.

In feature extraction stage, image based on texture with first-order characteristic extraction method using 6 parameters i.e. contrast, variance, standard deviation, kurtosis, mean and smoothness obtained varying parameter values. Next process is stages of identification that it performed with training, testing and system performance. Images used 23 images, that they were ordinary wounds image are not cancer and melanoma image.

The training process with Artificial Neural Network (ANN) with the image of the train is a combination of the image is non melanoma and melanoma that generates parameter values. Testing on test image with 4 sets of testing with combination training image and test image as shown in Tables 1-4. From Table 1, the combination of set I (50%) equals to 50%; from Table 2 the combination of set II (60%) equals to 40%; from Table 3 the combination of set III (70%) equals to 30%; and from Table 4 the combination of set IV (80%) equals to 20%.

Table 5 presents the comparison of accuracy obtained from Tables 1-4. Table 5 based on the testing have been done with 4 times set testing. It can be obtained that the accuracy of the test image non melanoma and melanoma images. Results of detection had the low accuracy of 80% and the highest accuracy of 88.88%.

Table 1. Testing Set I

Image	Recognition	Result of Testing
Non_03.JPG	Non-Melanoma	TRUE
Non_04.JPG	Non-Melanoma	TRUE
melanoma_01.JPEG	Melanoma	TRUE
melanoma_02.JPEG	Melanoma	TRUE
melanoma_03.JPEG	Melanoma	TRUE
melanoma_06.JPEG	Non-Melanoma	FALSE
melanoma_08.JPEG	Melanoma	TRUE

Table 2. Testing Set II

Image	Recognition	Result of Testing
Non_01.JPG	Non-Melanoma	TRUE
Non_04.JPG	Melanoma	FALSE
Non_06.JPG	Melanoma	FALSE
Non_07.JPG	Non-Melanoma	TRUE
melanoma_01.JPEG	Melanoma	TRUE
melanoma_03.JPEG	Melanoma	TRUE
melanoma_04.JPEG	Melanoma	TRUE
melanoma_05.JPEG	Melanoma	TRUE
melanoma_06.JPEG	Melanoma	TRUE
melanoma_08.JPEG	Melanoma	TRUE
melanoma_12.JPEG	Melanoma	TRUE

Table 3. Testing Set III

Image	Recognition	Result of Testing
Non_07.JPG	Non-Melanoma	TRUE
Non_08.JPG	Non-Melanoma	TRUE
melanoma_13.JPEG	Melanoma	TRUE
melanoma_14.JPEG	Non-Melanoma	FALSE
melanoma_15.JPEG	Melanoma	TRUE

Table 4. Testing Set IV

Image	Recognition	Result of Testing
Non_01.JPG	Non-Melanoma	TRUE
Non_03.JPG	Non-Melanoma	TRUE
Non_06.JPG	Melanoma	FALSE
melanoma_1.JPEG	Melanoma	TRUE
melanoma_3.JPEG	Melanoma	TRUE
melanoma_4.JPEG	Melanoma	TRUE
melanoma_8.JPEG	Melanoma	TRUE
melanoma_11.JPEG	Melanoma	TRUE
melanoma_15.JPEG	Melanoma	TRUE

Table 5. Comparison of the Accuracy

Set	Comparison (%)	Accuracy (%)
I	50 : 50	85,71
II	60 : 40	81.81
III	70 : 30	88.88
IV	80 : 20	80.00

4. Conclusion

In the system of skin cancer detection, performed feature extraction based on texture with first-order feature extraction that produces varying parameters value so we need an appropriate classification method. The development of future studies should use samples with higher numbers so can be used as a comparison in order to produce a better accuracy.

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