First-order Feature Extraction Methods for Image Texture and Melanoma Skin Cancer Detection

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Abstract. Skin cancer is a disease characterized by the growth of uncontrolled skin cells, which can damage surrounding tissue and spread to other body parts. The purpose of this study was to facilitate early recognition of skin cancer by applying the first-order extraction method using 6 parameters i.e. contrast, variance, standard deviation, kurtosis, mean and smoothness, for feature extraction based on texture to obtain a good level of accuracy and classification methods using Multilayer Perceptron Neural Network (MLP NN). The results of diagnostic identification consist of 2 outputs, i.e. melanoma and not melanoma. From the research, accuracy measurements were obtained through 4 sets of test images using melanoma and non-melanoma images and the results showed that the lowest level of accuracy was 81.81% and the highest level of accuracy was 85.71% so that the overall accuracy rate is 83.86%.

1. Introduction
Melanoma is a type of skin cancer that is quite serious, which until now cannot be handled perfectly so that it can cause death, disability and requires large medical costs. Image processing can be used to help diagnose skin cancer. Currently, dermatologists recognize skin cancer lesions using macroscopic and dermoscopic imaging techniques. Macroscopic is an imaging technique using an enlargement lens and light source, coupled with immersion fluid [1]. Meanwhile, the dermoscopic technique is a non-invasive imaging technique using immersion oil. The images produced from the dermoscopic technique provide a more detailed picture than the images produced from macroscopic techniques. Furthermore, a comparison of the segmentation method was reviewed for skin lesions, both in macroscopic and dermoscopic images found in [2].

Detecting the image boundary of skin cancer is the initial stage and is very important for systems that support the diagnosis of skin diseases with the help of computers [3]. The accuracy of the diagnosis results is determined by the accuracy of the detection of the limits of skin cancer lesions. Early detection of skin cancer will facilitate handling and treatment based on the type of cancer suffered, so the possibility of healing is greater.

One way taken is a biopsy process. A biopsy is the removal of tissue for the body of a laboratory examination [4], examination of the tissue aims to detect a suspected diagnosis or to determine the degree of malignancy of abnormal tissue. However, removal of tissue from the biopsy process also has risks such as infection or bleeding, so many people do not want to do it. This process also uses advanced and expensive technology, making it difficult to do in areas with inadequate facilities.
addition, the experience of dermatologists shows the difficulty of distinguishing melanoma from other pigmented lesions on the skin, such as typical and non-malicious (which is harmless) [5]. Accordingly, it motivates the authors to examine how to diagnose melanoma automatically based on dermatoscopic color image interpretation using a computer, which can help dermatologists take analytical decision steps in detecting wound margins and classification of various types of injuries. Therefore, the authors tried to apply first-order extraction methods to extract based on skin color texture and to detect skin cancer using the Multilayer Perceptron Neural Network classification method to design a system that can detect wounds whether melanoma skin cancer or non-melanoma skin cancer.

2. Methodology and Related Work

2.1. Grayscale
Gray-scaling is a technique used to extract image rough (RGB) by converting the RGB-formatted image into a Grayscale format [6]. With this conversion, the matrix of the previous image will change to one matrix. Grayscale images are stored in the 8-bit format for each sample pixel, allowing as many as 256 intensities. This format is very helpful in programming because there is not too much bit manipulation.

2.2. Fuzzy Possibility
Preprocessing for image quality improvement using Possibility Distribution Algorithm [7], aiming to improve image quality using a fuzzy logic approach using 5 parameters, i.e. $\alpha$, $\beta_1$, $\gamma$, $\beta_2$ and max. The purpose of using the possibility distribution algorithm in improving image quality is to decrease gray pixel level, which has a gray value between $\beta_1$ and $\beta_2$. Fuzzy rules and stage of the possibility distribution algorithm used to perform image contrast enhancement refer to [7].

2.3. Image Threshold
In general, the threshold is the grayscale image process to produce a binary image, mathematically using the equation refer to [8]. The purpose of the Otsu Threshold algorithm [8], is to segment the image by differentiating it into two classes, the background (value set to 0) and the object (value set to 1) using a certain level as a delimiter. The steps taken to conduct the Otsu threshold in this study refers to [7].

2.4. Statistical Feature Extraction
The study used statistical methods that use the statistical calculation of the gray degree distribution (histogram) by measuring the contrast, granularity, and roughness of a region of the inter-pixel interconnection within the image. This statistical paradigm uses unlimited, making it suitable for unstructured natural textures of sub-patterns and set rules (microstructures).

2.5. First-order Feature Extraction
First-order characteristic extraction is a characteristic retrieval method based on the histogram characteristic of the image. The histogram shows the probability of occurrence of the pixel gray degree value in an image. From the values on the resulting histogram, it can be calculated with some first-order characteristic parameters, including mean, skewness, variance, kurtosis and an entropy.

3. Results and Discussion
3.1. System Design
Skin cancer detection program using Artificial Neural Network (ANN) with input data in the form of dermatoscopic color images. This program is expected to help in detecting melanoma early. Stages of system design as follows:

1. Selecting Input Image, the first process in this software is to select an input image in the form of dermatoscopic color imagery.

![Non-Melanoma](image1.jpg) ![The Melanoma](image2.jpg)

**Figure 1.** The dermatoscopic color imagery.

2. Preprocessing by converting the original image of RGB into Gray image.

![Figure 2. Converting the original image of RGB into Gray image](image3.jpg)

Figure 2, the pre-processing by changing the original RGB image into a Gray image uses the Grayscaling technique to change the color image (RGB) to a grayscale or gray level (from black to white). With this change, the previous three (3) matrix compiler matrix will change to 1 matrix.

3. Improved image quality with Possibility Distribution Algorithm.

![Figure 3. Improved image quality with Possibility Distribution Algorithm](image4.jpg)

The Possibility Distribution algorithm aims to improve image quality using the fuzzy logic approach using 5 parameters, i.e. \( \alpha, \beta_1, \gamma, \beta_2 \) and max. From the parameters needed, \( \alpha \) represents the minimum value of distribution, \( \gamma \) represents the average value of distribution and max represents the maximum value of distribution. The fuzzy transformation function to get the overall value is defined (\( \alpha = \min, \beta_1 = (\alpha + \gamma) / 2, \gamma = \text{mean}, \beta_2 = (\max + \gamma) / 2, \max = \max \)).
The possibility distribution algorithm process in Figure 3 with the following stages:

1. Step 1: Parameter Initialization
   - Set $\beta_1 = (\text{min} + \text{mean}) / 2$
   - Set $\beta_2 = (\text{max} + \text{mean}) / 2$

2. Step 2: Fuzzification
   - For all pixels $(i, j)$ in the image:
     1. if $(\text{data}(i, j) \geq \text{min}) \&& (\text{data}(i, j) < \beta_1)$
        $$\text{graybaru}(i, j) = 2 \times (\frac{\text{data}(i, j) - \text{min}}{(\text{mean} - \text{min})})^2$$
     2. if $(\text{data}(i, j) \geq \beta_1) \&& (\text{data}(i, j) < \text{mean})$
        $$\text{graybaru}(i, j) = 1 - (2 \times (\frac{\text{data}(i, j) - \text{mean}}{(\text{mean} - \text{min})})^2)$$
     3. if $(\text{data}(i, j) \geq \text{mean}) \&& (\text{data}(i, j) < \beta_2)$
        $$\text{graybaru}(i, j) = 2 \times (\frac{\text{data}(i, j) - \text{mean}}{(\text{max} - \text{mean})})^2$$
     4. if $(\text{data}(i, j) \geq \beta_2) \&& (\text{data}(i, j) < \text{max})$
        $$\text{graybaru}(i, j) = 2 \times (\frac{\text{data}(i, j) - \text{mean}}{(\text{max} - \text{mean})})^2$$

3. Step 3: Modification
   $$\text{fuzzydata2}(i, j) = \text{graybaru}(i, j)^2$$

4. Step 4: Defuzzification
   - For all pixels $(i, j)$ in the image:
     $$\text{quality}(i, j) = \text{fuzzydata2}(i, j) \times \text{data}(i, j)$$

4. Segmentation with the threshold method to separate the object from the background.

![Figure 4. Separate the object from the background](image)

The thresholding process of grayscale images in Figure 4 aims to produce binary images, mathematically can be written as follows:

$$g(x, y) = \begin{cases} 1 & (x, y) \geq T \\ 0 & (x, y) < T \end{cases}$$  \hspace{1cm} (1)$$

With $g(x, y)$ is a binary image of the grayscale image $f(x, y)$, and $T$ states the threshold value of the $T$ value is determined using the global thresholding method and local thresholding. The Otsu Thresholding algorithm segments images by distinguishing them into two classes, namely the background (value set to 0) and object (value set to 1) using a certain level as a delimiter.

5. Feature-based extraction using the first-order feature extraction method.
   - The process of taking characteristics based on the characteristics of the image histogram. The histogram shows the probability of the occurrence of the value of the gray degree of pixels in an image. From the values in the resulting histogram, we can calculate several first-order characteristic parameters, including contrast, variance, standard deviation, kurtosis, mean and smoothness.

6. Image classification with Artificial Neural Network.
   - This process uses the Back Propagation ANN learning algorithm, the stages:
     1. Initialize weights, which can be done randomly.
2. Calculation of activation values, each neuron calculates the activation value of the input it receives. In the input layer the activation value is an identity function. In the hidden layer and output the activation value is calculated through the activation function.

3. Weight adjustment, weight adjustment is influenced by the magnitude of the error value of the target output and the current value of the network output.

4. Iterations will continue until certain minimum error criteria are met. From the test results, obtained the decision whether the image input including melanoma or not melanoma.

7. Its final result is skin cancer type diagnosis of the input as melanoma skin cancer or non-melanoma skin cancer.

3.2. Image Feature Extraction Stage

At feature extraction step of non-melanoma and melanoma image, based on texture with first-order feature extraction method using 6 parameters i.e. contrast, variance, standard deviation, kurtosis, mean and smoothness. The figure 5 and table 1 represent a summary of the value of the first-order feature extraction parameter.

| Image       | Contrast | Variance | STD    | Kurtosis | Mean   | Smoothness |
|-------------|----------|----------|--------|----------|--------|------------|
| not_01.JPG  | 0.072137 | 0.02897  | 0.147733 | 5,372,769 | 0.428971 | 0.028617  |
| not_02.JPG  | 0.060268 | 0.053701 | 0.219048 | 2,822,850 | 0.580094 | 0.051871  |
| not_03.JPG  | 0.214989 | 0.033305 | 0.162659 | 2,729,729 | 0.36305 | 0.032774  |
| not_04.JPG  | 0.426667 | 0.07181  | 0.258617 | 2,233,231 | 0.512081 | 0.068212  |
| not_05.JPG  | 1.018485 | 0.066762 | 0.248249 | 2,006,239 | 0.459617 | 0.063714  |
| not_06.JPG  | 0.761461 | 0.040903 | 0.185794 | 3,677,541 | 0.541939 | 0.039977  |
| not_07.JPG  | 0.202533 | 0.03851  | 0.17885  | 2,316,822 | 0.360219 | 0.03772  |
| not_08.JPG  | 0.299541 | 0.023343 | 0.125512 | 8,380,091 | 0.758819 | 0.023167  |
| melanoma-01.JPG | 0.505189 | 0.095978 | 0.303219 | 1,583,199 | 0.462179 | 0.089171  |
| melanoma-02.JPG | 0.135743 | 0.104988 | 0.318201 | 2,826,594 | 0.640383 | 0.096748  |
| melanoma-03.JPG | 0.186456 | 0.125222 | 0.349443 | 1,609,507 | 0.522289 | 0.113317  |
| melanoma-04.JPG | 0.650304 | 0.084934 | 0.28374 | 1,588,458 | 0.40846 | 0.07971  |
| melanoma-05.JPG | 0.904733 | 0.094009 | 0.299844 | 1,763,396 | 0.404746 | 0.087499  |
| melanoma-06.JPG | 0.310173 | 0.085284 | 0.284379 | 2,167,014 | 0.550386 | 0.080013  |
| melanoma-07.JPG | 0.922503 | 0.053805 | 0.219295 | 3,283,494 | 0.588641 | 0.051966  |
| melanoma-08.JPG | 1.010136 | 0.091415 | 0.295333 | 1,529,410 | 0.434551 | 0.085285  |
| melanoma-09.JPG | 1.42912 | 0.067932 | 0.25069 | 2,101,570 | 0.452014 | 0.064759  |
| melanoma-10.JPG | 0.455617 | 0.084993 | 0.283848 | 3,690,294 | 0.630769 | 0.079761  |
| melanoma-11.JPG | 1.032816 | 0.109409 | 0.325292 | 1,448,126 | 0.481374 | 0.10042  |
| melanoma-12.JPG | 0.426207 | 0.037577 | 0.176064 | 5,228,502 | 0.497799 | 0.036837  |
| melanoma-13.JPG | 0.154543 | 0.106788 | 0.321109 | 2,765,981 | 0.636789 | 0.098247  |
| melanoma-14.JPG | 0.073016 | 0.053826 | 0.219346 | 2,876,890 | 0.463091 | 0.051986  |
| melanoma-15.JPG | 0.434079 | 0.110672 | 0.327288 | 1,386,944 | 0.349315 | 0.101464  |

From table 1, Contrast indicates the size of the spread (moment of inertia) of the image matrix elements. If it is far from the main diagonal, the contrast value is large. In visualization, the value of the contrast value is the measure of variation between the gray degrees of the image area is stated by the following equation (1):
The Variance ($\sigma^2$) shows the variation of elements in the histogram of an image using the equation (2):

$$\sigma^2 = \sum_{i,j=0}^{N-1} (i-j)^2 p(i,j)$$

(1)

Standard Deviation is used to measure the contrast average of the image intensity using the equation (3):

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} p_{ij} (i-\mu_i)^2$$

(2)

Kurtosis ($\sigma_4$) shows the level of the relative curve of the histogram curve of the Image is stated as equation (4):

$$\alpha_4 = \frac{1}{\sigma_4} \sum_{n} (f_n - \mu)^4 p(f_n) - 3$$

(3)

Mean value ($\mu$) shows the dispersion size of an image. The $f_n$ is a gray intensity value and the $p(f_n)$ shows the value of the histogram (probability of occurrence of that intensity in the image) through the equation (5):

$$\mu = \sum_{n} f_n p(fn)$$

(4)

and the Smoothness is used to measure the relative smoothness of the image intensity. $R$-value = 0 for images with a constant intensity and the value of $R$ is close to 1 for images with scattered intensity, is stated by the equation (6):

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

(5)

The parameter values of first-order feature extraction in Table 1, is obtained by implementation of the equation (1)-(6) be depicted by a diagram in the figure 5 follow:

Figure 5. The value of the first-order feature extraction parameter

3.3. Identification Stages

The identification phase is carried out by training, testing and system performance. The training images used were 23 images, consisting of 8 non-melanoma images and 15 melanoma images. The classification process in the system for detecting melanoma skin cancer is described in figure 6.
In figure 6, there are two parts of the involved process, namely the training on Artificial Neural Networks and the identification of Artificial Neural Networks.

1. Training on Artificial Neural Networks
   The training process with Artificial Neural Networks (ANN) with training images is a combination of non-melanoma and melanoma images that produce values from the six parameters used, i.e. contrast, variance, standard deviation, kurtosis, mean and smoothness. The training was conducted in 4 sets of tests by combining non-melanoma images and melanoma images.

2. Identification of Artificial Neural Networks
   After the system is trained, then the test image is tested with 4 sets of tests with a combination of training images and test images, is presented in table 2.

### Table 2. Combination of training images and test images.

| Combination | Percentage | Information          |
|-------------|------------|----------------------|
| set I       | 50%:50%    | 8 melanoma, 4 non melanoma |
| set II      | 60%: 40%   | 9 melanoma, 3 non melanoma |
| set III     | 70%: 30%   | 10 melanoma, 2 non melanoma |
| set IV      | 80%: 20%   | 12 melanoma, 1 non melanoma |

3.4. System Accuracy
   The accuracy rate of the neural network in recognizing the image of melanoma and non-melanoma that has been tested using 23 data images that have been trained. The results of the image test consist of 8 images of non-melanoma and 15 images of melanoma. Where previously been trained and then tested again. And the results can be recognized as a whole so get 100% accuracy. Example of calculating accuracy for combining set I is presented in table 3.
Table 3. The results of the combination set I.

| Num. | Input Image       | Recognized as | Test Results | Point |
|------|-------------------|---------------|--------------|-------|
| 1    | not_01.JPG        | Non Melanoma  | succeeded    | 9,091 |
| 2    | not_04.JPG        | Melanoma      | failed       | 0,000 |
| 3    | not_06.JPG        | Melanoma      | failed       | 0,000 |
| 4    | not_07.JPG        | Non Melanoma  | succeeded    | 9,091 |
| 5    | melanoma_01.JPG   | Melanoma      | succeeded    | 9,091 |
| 6    | melanoma_03.JPG   | Melanoma      | succeeded    | 9,091 |
| 7    | melanoma_04.JPG   | Melanoma      | succeeded    | 9,091 |
| 8    | melanoma_05.JPG   | Melanoma      | succeeded    | 9,091 |
| 9    | melanoma_06.JPG   | Melanoma      | succeeded    | 9,091 |
| 10   | melanoma_08.JPG   | Melanoma      | succeeded    | 9,091 |
| 11   | melanoma_12.JPG   | Melanoma      | succeeded    | 9,091 |
|      | Total             |               |              | 81,818|

The accuracy rate of ANN in recognizing the image of melanoma and non-melanoma obtained by performing 4 sets of testing that is combining images of non-melanoma and melanoma images. Test result the comparison of accuracy can be seen in table 4.

Table 4. The comparison accuracy 4 sets of testing.

| Set  | Comparison | Total image testing | Succeeded | Failed | Accuracy (%) |
|------|------------|---------------------|-----------|--------|--------------|
| I    | 50% : 50%  | 11                  | 9         | 2      | 81.81        |
| II   | 60% : 40%  | 12                  | 10        | 2      | 83.33        |
| III  | 70% : 30%  | 12                  | 9         | 3      | 85.71        |
| IV   | 80% : 20%  | 13                  | 11        | 2      | 84.61        |
|      | Average    |                     |           |        | 83.86        |

Based on the test that has been done with 4 times the test set obtained the accuracy rate of testing of non-melanoma image and melanoma image obtained the lowest accuracy rate is 81.81% and the highest accuracy rate is 85.71% so that the overall accuracy rate is 83.86%.

4. Conclusion
From the results of the study, it was concluded that in the skin cancer detection system is used the texture-based feature extraction by first-order feature extraction using 6 parameters i.e. contrast, variance, standard deviation, kurtosis, mean and smoothness, so that the right classification method is needed. The classification process with ANN takes measurements of accuracy rate for test images with four sets of tests in obtaining accuracy for non-melanoma images. The training images used were 23 images, consisting of 8 non-melanoma images and 15 melanoma images. The images of melanoma obtained the lowest accuracy rate is 81.81% and the highest accuracy rate is 85.71% so that overall is obtained average accuracy rate is 83.86%. Based on the tests conducted, the level of accuracy is still far from expected. For the development of further research, you should use a sample of data with more and varied amounts. This can be used as a comparison to produce better accuracy and to improve image quality can use other methods to produce better accuracy.
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