Face Skin Disease Detection with Textural Feature Extraction

Wirdayanti
Department of Informatics, Faculty of Engineering
Tadulako University
Palu, Indonesia
wirda.ida28@gmail.com

Irwan Mahmudi
Department of Electrical, Faculty of Engineering
Tadulako University
Palu, Indonesia
irwan.mahmudi@untad.ac.id

Andi Chairul Ahsan
Department of Architecture, Faculty of Engineering
Tadulako University
Palu, Indonesia
andichairulachsan@gmail.com

Anita Ahmad Kasim
Department of Informatics, Faculty of Engineering
Tadulako University
Palu, Indonesia
nita.kasim@gmail.com

Rosmala Nur
Department of Public Health
Tadulako University
Palu, Indonesia
nurrosmala09@gmail.com

Rafifah Basalamah
Study Program of Informatics, Faculty of Engineering
Tadulako University
Palu, Indonesia
rafifah.b13@gmail.com

Anindita Septiarini
Department of Informatics, Faculty of Engineering, Mulawarman University,
Samarinda, Indonesia
anindita.septiarini@gmail.com

2020 6th International Conference on Science in Information Technology (ICSITech) | 978-1-7281-7349-8/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICSITech49800.2020.9392030

***Abstract*— This study aims to build a model for the detection of facial skin diseases by utilizing the texture features in digital images of facial skin. The model is an automatic initial screening system for facial skin that can be used before carrying out further diagnosis processes by utilizing relatively expensive medical technology. Characteristics in facial images are obtained by extracting the textural features of the face digital image. Texture characteristics will distinguish the class of each facial problem based on their respective severity. The method used to extract textural features is the Gray Level Co-Occurrence Matrices (GLCM) method with the K-Nearest Neighbor classification method. The facial image data used were 150 digital images of problematic faces which were divided into 70% training data and 30% test data. This study produces a model accuracy of 80% accuracy with an error rate of 20%.**

Keywords—face skin, disease, GLCM Texture, feature extraction,

I. Introduction

The skin is the largest organ in the human body and covers the entire human body [1]. One part of the skin that needs important handling is the facial skin. Facial skin often gets diseases in certain facial conditions. Facial skin disease is one of the most common disorders in humans [2]. Unhealthy facial skin is characterized by abnormalities (disorders or diseases) in the skin. Cases of facial skin disorders that often occur are oil gland cases such as acne. Handling of facial skin diseases should be done as early as possible to avoid the severity of the disease. Medical technology can diagnose facial skin diseases, but the price is still relatively expensive. Another alternative that can be used to detect types of facial skin diseases is to use digital images [3], [4]. The use of digital images in the object classification process has been implemented in various medical and non-medical fields [5]–[7]. A digital image of the problem skin is extracted to obtain its characteristics. Feature extraction is very important because features will represent images and be used as input for machine learning or content-based retrieval methods. Most feature extraction methods operate on a single channel 8-bit image, the equivalent of a gray scale image. Even the color feature extraction method is often applied in 8-bit images [8].

Previous research on the classification of facial skin diseases was carried out by capturing digital images of faces with a camera and processing them using the classification method [9]. The approach used in detecting face digital images utilizes color face images. Then the feature extraction used is the Convolution Neural Network (CNN). The final results obtained were the type of skin disease, its distribution, and the classification of the disease. Besides, facial skin detection has also been carried out using deep learning methods. This method can attach a skin label to each pixel of the face image. The size of the image resolution used uses a gray scale image with low resolution (64x32 pixels) [10]. However, previous studies have not focused on the problem of the detection of facial skin diseases based on their severity. In this study, the detection of acne-prone skin disease was carried out by grouping the image based on its severity. The severity of acne consists of levels I, II, and III. The facial image data used are from adolescents, adults, and the elderly, both women and men.

II. Material and Methods

The facial image used and observed involves all areas of the face. The area of observation on the face is limited to the front of the head, from the upper forehead to the chin and between one ear and the other. Image acquisition is carried out in this study by capturing the facial image of an individual detected by facial skin disease, namely acne through a cellphone camera as an object to be examined. Position the face towards the camera. The image of the facial skin is obtained by looking forward. Obtaining image data consists of 150 facial images detected by acne. The results of the acquisition of image afterward will be divided into 2 parts, namely 70% training data, and 30% test data. This data will be used for testing with a confusion matrix. In this study, the facial images tested and trained were image data without filters. Observed facial image data is expressionless or flat data. The proposed method in this study can be seen in Figure 1.

978-1-7281-7349-8/20/$31.00 ©2020 IEEE

Authorized licensed use limited to: C. V. Raman Global University - Bhubaneswar. Downloaded on August 11,2023 at 07:50:58 UTC from IEEE Xplore. Restrictions apply.

Image acquisition is the process of retrieving data where the data will be stored in a database. The image is processed in the form of a matrix so that a series of matrices will be obtained which is ready to be trained. Preprocessing, at this stage image processing is carried out to produce a better image to be processed to the next stage which consists of several parts including resizing, cropping, transformation to gray scale.

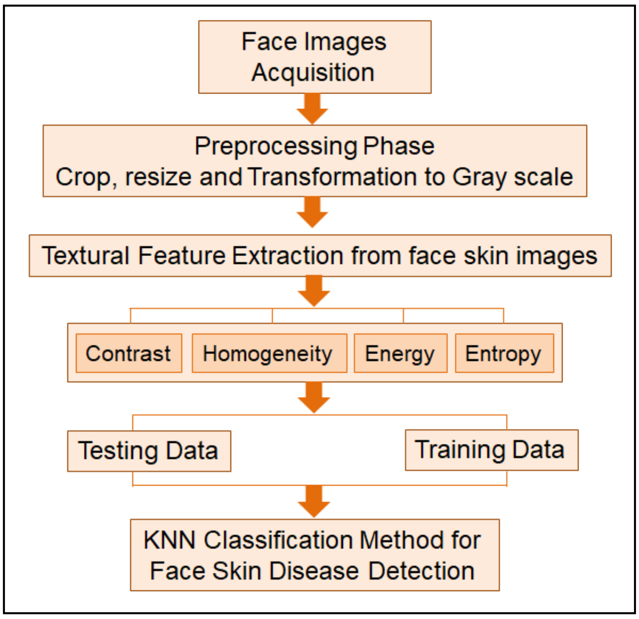

Fig. 1. The proposed Methods

Cropping is an image cutting process, to remove unnecessary parts of the image while improving image quality is used to improve image quality. Resize is used to normalize the image size so that it is the same size. Transforming an RGB image into gray scale, this process aims to simplify the pixel value in an image where initially each pixel has three values, namely RGB to only 1 gray value. The pre-processing stage of facial skin digital images can be seen in Figure 2.

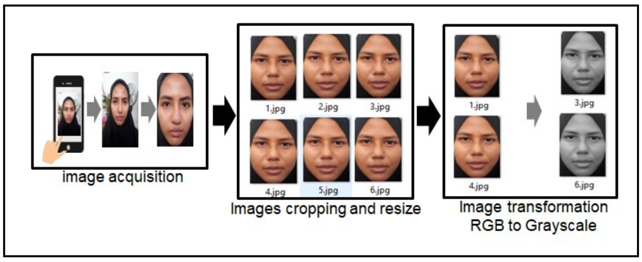

Fig. 2. Face skin image preprocessing process

In general, four directions are commonly used to make a GLCM matrix, namely the 0 °, 90 °, 45 ° and 135 ° directions. The measurement of texture values is based on the Harralick equation which is defined as follows:

A. Contrast

Contrast is a measure of the difference between the degrees of the grayness of an area in the image. In the histogram, contrast shows the size of the spread of the image intensity value. The contrast calculation can be seen in equation (1)

$$Contrast = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-j)^2\, P(i,j) \qquad (1)$$

With:

P(i,j) = the values in row i and column j of the normalization matrix.

B. Homogeneity

Homogeneity shows the homogeneity of the intensity variation in the image. The homogeneity calculation can be seen in equation (2)

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{P(i,j)}{1+(i-j)^2} \qquad (2)$$

C. Energy

Energy is a feature of GLCM which is used to measure the concentration of intensity pairs on the GLCM matrix. The energy calculation can be seen in equation (3)

$$Energy = \sum_{j=0}^{G-1} \sum_{i=0}^{G-1} (P(i,j))^2 \qquad (3)$$

D. Entropy

Entropy shows a measure of irregularity in the shape of image texture. If the image structure is regular, then the entropy value is large, conversely, if the entropy value is small, it means that the image structure is irregular (varies). The entropy calculation can be seen in equation (4)

$$Entropy = \sum_{j=0}^{G-1} \sum_{i=0}^{G-1} P(i,j), \log(P(i,j)) \qquad (4)$$

The extraction process of facial skin texture features can be seen in Figure 3.

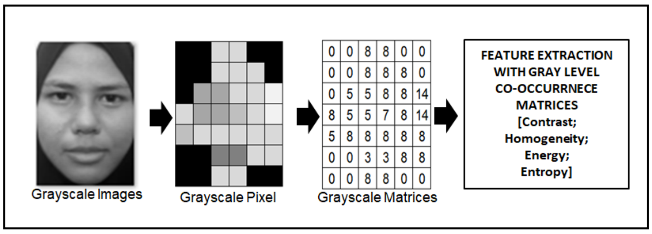

Fig. 3. Feature Extraction Process of facial image texture features

The classification method used is a K-nearest Neighbor (K-NN). The k value used in the K-NN method is 5. The K-nearest neighbor (KNN) algorithm is one of the algorithms used to classify data based on attributes and samples from training data. The KNN algorithm uses neighborhood classification as the predictive value of the new instance. New instance classification is carried out based on the majority of the nearest neighbors. Meanwhile, the proximity of neighbors is usually calculated based on the Euclidean distance (d) or formula for finding the distance between 2 points in dimensional space represented in the equation (5)

$$d = \sqrt{(x_2-x_1)^2 + (y_2-y_1)^2} \qquad (5)$$

With

d = Euclidean distance
x_2 = feature the first object of the test data
x_1 = feature of the first object from the training data
y_2 = the second object characteristic of the test data

Authorized licensed use limited to: C. V. Raman Global University - Bhubaneswar. Downloaded on August 11,2023 at 07:50:58 UTC from IEEE Xplore. Restrictions apply.

y_1 = the second object characteristic of the training data

The KNN algorithm is described as follows:

1. Define the K Value
2. Determine the testing data class based on the majority classification results
3. Calculate the distance between training data and testing data
4. Sort by data that has the smallest distance

The object of this research is the image of areas on facial skin that are classified into acne levels first-class, second-class, and third-class. The American Academy of Dermatology Acne Consensus Conference (ACC) classifies acne based on its severity, calculated from the number and type of lesions that appear. The severity of acne can be seen in Table 1

a. Mild I (comedo blackheads (open comedones)/ whiteheads (closed comedones))

b. Mild II (papule / pustule + / ++, nodule 0)

c. Moderate III (papules / pustules ++ / +++, nodules +/ ++)

TABLE I. ACNE SEVERITY [11]

Acne level	Qualitative description	Quantitative description
First-class	Comedonal acne	Only blackheads, number <10 on the face, were not found on any part of the body, without scarring, only non-inflammatory lesions.
Second-class	acne papules	Total 10-25 papules on the face and body parts, there is light scarring, the diameter of inflammatory lesions <5 mm.
Third-class	acne pustules	The number of pustules is more than 25 pieces, scarring is a little severe. It is similar in size to a papule but is more visible to the eye

System testing is divided into several parts consisting of testing the implementation of the K-NN algorithm using training data and testing facial image test data. Testing is done by comparing the results of the system implementation and the test results from the clinic. In this study, a confusion matrix was used. The confusion matrix is a table that records the classification results. This study analyzes facial skin problems with a total of 3 classes so that a multi-class confusion matrix performance measure is needed.

Performance measures that are also used in this study are accuracy and error rate. The calculation of the accuracy of the proposed model based on the multi-class confusion matrix is done by comparing the amount of data that is on the main diagonal of the matrix with the total amount of data used and its error rate value can be used to measure the performance of a classification model [12].

III. RESULT AN DISCUSSION

Facial image data with acne level based on the I, II, and III severity levels will be used as training data and testing data. The stages in data collection were divided into three parts, namely facial image data with acne levels I, II, and III. Acquisition of facial data for acne level is facial image data of beauty clinic patients whose data has been validated by skin specialists. The capture of face image data is done using a smartphone camera, taking facial images for each individual is carried out 10 times a face capture using the rear camera with the camera screen position that is landscape. There were 5 individuals from each category of acne levels. The process of taking facial images is assisted by using a tripod so that the position of the face remains symmetrical, the distance between the object to be captured and the position of the camera remains the same, namely 10 to 15 cm.

In the training process, the facial images were taken using a smartphone camera. After that, the cropping process is carried out which only takes the focus of the face image object. Furthermore, the resizing process will be carried out to uniform the image size. After that, the RGB to gray scale image transformation process is carried out and then quantized with a value range of 0-63 to save on the computation process. The quantized gray scale image results will be entered into the Gray level co-occurrence matrix which aims to facilitate the extraction of textural features from the Haralick equation. Extraction of texture features consisting of contrast features, homogeneity features, entropy features, and energy features in facial skin images where acne levels are found based on equation 1, equation 2, equation 3 and equation 4 produce facial skin texture feature values with acne levels. After feature extraction is carried out, it will proceed to the calculation phase of the K-NN algorithm.

The range of values for facial skin image contrast features where the level of acne at an angle of 0 ° ranges from a minimum value of 235841 to a maximum value of 2943530. The value of the extraction results for homogeneity features is in the range of 0.00000699612 to 0.0304149. The energy feature values range from 0.00554694 to 0.0212534. The value of the entropy feature extraction results in the range 4.40538 to 5.6833. The range of values resulting from the extraction of facial skin features can be seen in Table 2 and the range of values for the overall level of acne.

TABLE II. THE RANGE OF VALUES FOR EACH TEXTURE FEATURE

The Feature Extraction value	Min	Max
Contrast	235841	2943530
Homogeneity	0,00000699612	0,0304149
Energy	0,00554694	0,0212534
Entropy	4,40538	5,6833

Detection of facial skin problems based on the texture characteristics of digital images consists of two stages, namely the training stage and the testing phase. Data on facial skin image features with acne levels first-class, second-class, and third-class that have been obtained in the extraction process are divided into two parts, namely training data and testing data. The data sharing ratio is divided into 70% training data and 30% test data. The training data amounted to 105 training data from 150 data and test data

Authorized licensed use limited to: C. V. Raman Global University - Bhubaneswar. Downloaded on August 11,2023 at 07:50:58 UTC from IEEE Xplore. Restrictions apply.

amounted to 45 data from 150 data. One hundred five training data and forty-five test data for facial skin with acne consist of 3 severity levels including severity level first-class, second-class, and third-class. Training is conducted on datasets involving texture features.

The use of Multiclass confusion matrices in the detection of facial skin problems based on the texture features of digital images using GLCM is shown in Table 3. The configuration matrix consists of 3 output class columns and 3 target class rows.

TABLE III. THE RANGE OF VALUES FOR EACH TEXTURE FEATURE

T = TRUE *F = FALSE*		Output Class		
		First-class	**Second-Class**	**Third-Class**
Target Class	first-class	$T_{first\text{-}class}$	$F_{first\text{-}class}$	$F_{first\text{-}class}$
	second-class	$F_{second\text{-}class}$	$T_{second\text{-}class}$	$F_{second\text{-}class}$
	third-class	$F_{third\text{-}class}$	$F_{third\text{-}class}$	$T_{third\text{-}class}$

Each column and row represents each class. Columns and Rows are stated as follows:

- Column / Row 1: first-class acne level
- Column / Row 2: second class acne level
- Column / Row 3: third-class acne level

This training uses the K-Nearest Neighbor algorithm to detect facial skin problems, while the k value on the K-NN used is 5. The training with a dataset uses 105 image data for facial skin with acne, each class of acne levels consisting of thirty-five facial skin images. First-class acne level is targeted to detect fifteen images of the first-class acne, but there are two first-class acne level images detected in the second-level acne class and two first-class acne grade images detected at the third-grade acne level. The second-level acne class has a target number of fifteen images, but two first-level acne class images are classified in the second-level acne class image output class so that the output class which should be fifteen images turns into seventeen second-class acne grade images. Similar to the third-grade acne level image class, there are three third-class acne level images detected into the first-class acne level so that the first-class acne level output increases to eighteen images. An example of an image that misclassification can be seen in Figure 4.

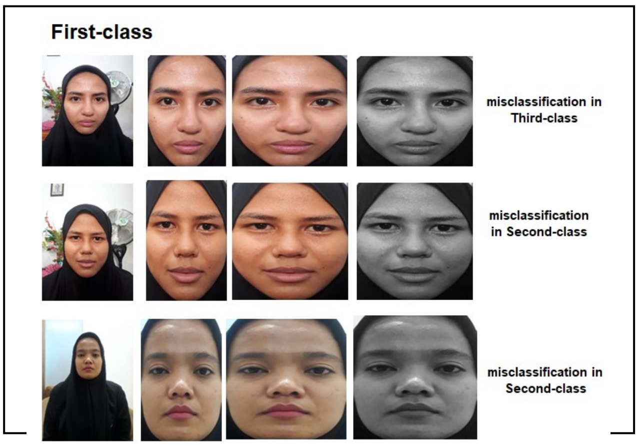

Fig. 4. Misclassification image of Face Skin Disease Detection

The image of facial skin with acne that is not recognized for the level of acne is influenced by several factors, namely the value of the resulting texture features is similar to the features of the image of facial skin with other acne classes so that there is an error in its classification. Multiclass confusion matrices for testing the k value on a K-NN of 5 can be seen in Table 4.

TABLE IV. THE RANGE OF VALUES FOR EACH TEXTURE FEATURE

T = TRUE *F = FALSE*		Output Class		
		First-class	**Second-Class**	**Third-Class**
Target Class	first-class	11	2	2
	second-class	0	13	2
	third-class	3	0	23

$$\text{Pccuracy} = \frac{11+13+12}{45} \; X\ 100\% \; = \; 80\%$$

The confusion matrix testing phase is carried out to determine the recall, precision, accuracy and error rate which are used as parameters for the success and accuracy of the K-NN algorithm in detecting facial skin problems. The testing phase was carried out on 45 test data. The results of the testing phase showed that an accuracy of 80%, that is, the image of facial skin with acne was predicted to be the category I, II and III severity levels of the entire facial skin image tested. The precision, namely the image data of facial skin with acne which is taken based on information that is less or wrong or not accurate by 80%, while the recall is the image data of facial skin with acne that cannot be predicted correctly by 80% and the error rate is the result of incorrect predictions of 20 %. The test results showed no significant difference between the accuracy value, precision value and recall value. This means that the detection process for facial skin problems based on the texture features of digital images is able to detect facial skin with acne prone skin precisely according to the target specified in the target class proposed in the detection of facial skin problems based on the texture characteristics of the digital image. If there is a difference in the accuracy value, precision value and recall value, this indicates that the detection process has not been able to detect facial skin problems with acne with accuracy.

$$Error\ rate = 100 - 80\% = 20\%$$

The results of the testing phase showed that an accuracy of 80%, that is, the image of facial skin with acne was predicted to be the first-level, second-level and third-level of severity levels of the entire facial skin image tested.

IV. CONCLUSION

The accuracy, namely the image data of facial skin with acne taken based on information that is insufficient or wrong or incorrect by 80%, the error rate is the result of an incorrect prediction of 20%. This means that the detection process for facial skin problems based on the texture features of digital images can detect facial skin with acne prone skin precisely according to the target specified in the target class proposed in the detection of facial skin problems based on the texture characteristics of the digital image

Authorized licensed use limited to: C. V. Raman Global University - Bhubaneswar. Downloaded on August 11,2023 at 07:50:58 UTC from IEEE Xplore. Restrictions apply.

ACKNOWLEDGMENT

This work supported and funding by DIPA BLU Fakultas Teknik Universitas Tadulako in scheme Penelitian Pembinaan in 2020 (Grant No. 646.m/UN28.2/PL/2020)

REFERENCES

[1] V. R. Balaji, S. T. Suganthi, R. Rajadevi, V. Krishna Kumar, B. Saravana Balaji, and S. Pandiyan, "Skin disease detection and segmentation using dynamic graph cut algorithm and classification through Naive Bayes classifier," *Meas. J. Int. Meas. Confed.*, vol. 163, p. 107922, 2020, doi: 10.1016/j.measurement.2020.107922.

[2] A. Lumini and L. Nanni, "Fair comparison of skin detection approaches on publicly available datasets," *Expert Syst. Appl.*, vol. 160, p. 113677, 2020, doi: 10.1016/j.eswa.2020.113677.

[3] Dong ping Tian, "A Review on Image Feature Extraction and Representation Techniques," *Int. J. Multimed. Ubiquitous Eng.*, vol. 8, no. 4, pp. 385–396, 2013.

[4] Gaurav Mandloi, "A Survey on Feature Extraction Techniques for Color Images," *Int. J. Comput. Sci. Inf. Technol.*, vol. 03, no. 3, pp. 14–18, 2013.

[5] A. Septiarini and A. Harjoko, "Automatic glaucoma detection based on the type of features used: A review," *J. Theor. Appl. Inf. Technol.*, vol. 72, no. 3, pp. 366–375, 2015.

[6] A. Septiarini, H. Hamdani, H. R. Hatta, and A. A. Kasim, "Image-based processing for ripeness classification of oil palm fruit," in *2019 5th International Conference on Science in Information Technology (ICSITech)*, 2019, pp. 23–26.

[7] A. A. Kasim, R. Wardoyo, and A. Harjoko, "Batik Classification with Artificial Neural Network Based on Texture-Shape Feature of Main Ornament," *I.J. Intell. Syst. Appl.*, vol. 9, no. June, pp. 55–65, 2017, doi: 10.5815/ijisa.2017.06.06.

[8] M. Ponti, T. S. Nazaré, and G. S. Thumé, "Image quantization as a dimensionality reduction procedure in color and texture feature extraction," *Neurocomputing*, vol. 173, pp. 385–396, 2016, doi: 10.1016/j.neucom.2015.04.114.

[9] N. S. Alkolifi Alenezi, "A Method of Skin Disease Detection Using Image Processing and Machine Learning," *Procedia Comput. Sci.*, vol. 163, pp. 85–92, 2019, doi: 10.1016/j.procs.2019.12.090.

[10] M. Paracchini, M. Marcon, F. Villa, and S. Tubaro, "Deep skin detection on low resolution grayscale images," *Pattern Recognit. Lett.*, vol. 131, pp. 322–328, 2020, doi: 10.1016/j.patrec.2019.12.021.

[11] J. . Billow, "Handbook of Nonprescription Drugs.pdf," 14th ed., 2004.

[12] A. A. Kasim, "Quadratic Support Vector Machine For The Bomba Traditional Textile Motif Classification," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 11, no. 3, pp. 1004–1014, 2018, doi: 10.11591/ijeecs.v11.i3.pp1004-1014.

Authorized licensed use limited to: C. V. Raman Global University - Bhubaneswar. Downloaded on August 11,2023 at 07:50:58 UTC from IEEE Xplore. Restrictions apply.