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CLASSIFICATION OF FACIAL SKIN TYPE USING DISCRETE WAVELET TRANSFORM, CONTRAST, LOCAL BINARY PATTERN AND SUPPORT VECTOR MACHINE

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ABSTRACT

There are two effects cosmetics on the skin, namely positive and negative effects. The use of cosmetics in accordance with the skin type will have a positive impact on the skin while the use of cosmetics that do not fit the skin type will negatively affect the skin. Each person's skin type is not the same, therefore it is important to know the type of skin before deciding to buy suitable cosmetics. This research will build an intelligent system that can classify facial skin types by utilizing the concept of data mining. This research uses Discrete Wavelet Transform (DWT), contrast, and Local Binary Pattern (LBP) for extracting the features contained in the face image and use Support Vector Machine (SVM) as the classifier to determine the facial skin type. Based on the experimental results, it is proven that the proposed method able to properly classify facial skin types. The proposed method gives the average classification accuracy of 91.66% with the average running time of 31.571 seconds.

Keywords: *Classification, Facial Skin Type, Discrete Wavelet Transform, Local Binary Pattern, Support Vector Machine*

1. INTRODUCTION

Smooth, bright and healthy skin is everyone's dream to maintain self-confidence[1]. Beautiful skin reflects that the owner is very concerned about his personal health because skin health is a useful marker of a person's current health condition[2]. Skin is a "blanket" that covers the surface of the body and has main function as the protector of various kinds of interference and external stimulation[3]. Skin is human body organ that is very important because it is located on the outside of the body that serves to receive stimuli such as touch, pain, and other influences from the outside[4]. Facial skin is a very important part of the body to be taken care of. In daily activities, facial skin can not be free from dirt, dust, ultraviolet exposure, or cosmetics that stick to the skin, especially for someone who is traveling. This condition, if left unchecked, will cause some skin disorders, such as blackheads, acnes or pimples, pigmentation, small wrinkles, and so on[5]. To overcome this, it is necessary to do regular and periodic maintenance.

Regular skin care can be done with the right technique and using appropriate cosmetics. According to the Regulation of the Minister of Health of the Republic of Indonesia No. 220 in 1976, "Cosmetics are materials or mixtures of ingredients to be rubbed, placed, poured, sprinkled, or sprayed on, inserted in, used on the body or parts of the human body in order to clean, maintain, increase attraction or change shape and not belong to the class of drugs". The explanation above explains that cosmetics is a mixture of ingredients used in the outer body with various ways to treat and beautify themselves so that it can add attraction and increase the self-confidence of the user and not to treat or cure a particular disease. Now there are many cosmetic products on the market with various brands and forms[6].

Cosmetics or facial skin care products for women now become a special need and an important item. Today, many types of skin care products are offered, both at expensive and even very cheap prices. In addition, there are several contents of the skin care product that are not guaranteed to be used[7]. This is compounded by the lack of the women knowledge about these skin care products. There are only a few women who use cosmetics who also do facial skin care, because women do not have sufficient knowledge about the types of cosmetics for skin care[8]. In addition, some women do not understand the importance of skin analysis and the use of cosmetics that suit their skin type, and prefer the same cosmetics as their friends even though they have different skin types [9].

The effect of cosmetics on the skin is the main target in receiving various influences from the use of cosmetics. There are two effects of cosmetics on the skin, namely positive and negative effects. Of course what is expected is the positive effect, while the negative effects are not desirable because it can cause skin abnormalities[10].The use of cosmetics in accordance with the skin type will have a positive impact on the skin while the use of cosmetics that do not fit the skin type will negatively affect the skin. Each person's skin type is not the same, therefore it is important to know the type of skin before deciding to buy suitable cosmetics. Based on the problems that have been described, it is necessary to analyze facial skin that aims to determine the type of skin, as well as abnormalities or skin problems experienced by a person. After knowing the type of facial skin that is owned, the right treatment can be given and the level of error in choosing cosmetics can be minimized to obtain beautiful and healthy skin, especially facial skin.

Meanwhile, the rapid development of technology now supports the existence of intelligent systems that can help in analyzing human needs. One of them is the need for the knowledge of the type of facial skin type that a person has. This will certainly becomes very helpful for women who want to know the type of their facial skin. In addition, this technology can save the costs that must be spent on the consultation process and can improve time and energy efficiency. Based on this explanation, this study will build an intelligent system that can classify facial skin types by utilizing the concept of data mining. Data mining is a series of processes to explore the added value of a data collection in the form of knowledge that has not been known manually[11]. This research will use Discrete Wavelet Transform (DWT), contrast, and Local Binary Pattern (LBP) for extracting the features contained in the face image and use Support Vector Machine (SVM) as the classifier to determine the facial skin type.

2. RELATED WORKS

The process of determining the type of facial skin is usually done manually by an expert (dermatologist) by measuring the level of oil production on facial skin. However, the process of determining manually has the potential of inter-observer error and intra-observer error. Inter-observer error is the difference in measurement results between two observers. This can be influenced by the level of experience of the observers. Intra-observer error is the difference in the results of measurements made by one observer but at different times. This can be influenced by various factors, both internal and external.

Therefore, several studies have been developed to determine the type of facial skin by using computer aids. The computer has advantages because it can provide consistent results, thereby reducing errors that occur due to observer errors. Wahyuningtyas, et al. (2015) developed an expert system to determine the type of facial skin of women using the Naïve Bayes method [12]. The expert will enter information related to the determination of skin type into the system which will then be used to determine the skin type of the user through a series of question and answer process. Using 30 training data and 10 test data, the system obtained 100% accuracy.

Santi &Andari (2019) developed an expert system to identify the type of facial skin by using certainty factor method [13]. The study uses data collected from 40 female respondents. This study categorized the type of facial skin into 5 types: normal, oily, dry, combination, and sensitive skin. By using information provided by the experts, the system categorizes the facial skin types by using its characteristics. For example, the sensitive skin type has thin texture, prone to allergy, irritation, and injury, and easily looks reddish. According to the data provides by the experts, the system will generates treatment solution that is suitable for the user's skin type. This research did not explain the accuracy of the system in classifying the facial skin types. However, this study measures the satisfaction rate of the user in using the system.

Sokibi, et al. (2019) implemented an expert system for determining the type of facial skin care by using the forward chaining method [14]. Based on the data of risk factors and symptoms, the appropriate skin treatmentfor the user can be determined. The relationship between risk factors and skin type is such as: working in a room with air conditioner, having wrinkles, having allergies, and following a family planning program (*keluargaberencana*/ KB) will result in high risk of having dry skin type. While oily skin is the risk of liking spicy foods, often touches the face, often eats high protein foods, and has skin with large pores. Based on these risk factors, it can be determined the user's skin type where each skin type has specific symptoms. For example, dry skin is usually marked by black spots on the face and fine lines around the eyes or mouth. Oily skin is characterized by red spots on the face, pus, black spots around the nose or cheeks, and hard white spots. Based on these symptom data, the system will determine the right facial skin care for the user.

Expert system is very helpful for users in recognizing their own skin type. However, to answer the questions raised by the system, the user must conduct a self-assessment that can be inaccurate if the user lacks knowledge of skin conditions. Therefore, an automatic determination of facial skin types without user intervention in the assessment process is needed.

Arabi, et al. (2017) categorized three skin types (normal, oily, and dry) images by using 4-connectivity and 8-connectivity region properties to measure its texture [15]. This research resulted in the texture difference between those three skin types. The normal skin type has the lowest texture value, while dry skin has the highest texture value both by using 4-connectivity and 8-connectivity region properties. High value in the dry skin images is the result of wrinkles, while the high value in the oily skin images is the result of skin pores. This research informs that the characteristics of each skin type can be identified by using the image processing methods. The result from this research is then developed to classify the texture features by using Fuzzy C-Means (FCM) clustering method[16]. The accuracy in classifying 15 test data into three skin types (normal, oily, and dry) by using 4-connectivity and 8-connectivity region properties is 58.33%.

Indriyani, et al. (2016) proposed automatic detection of T-zone area on facial images by using Canny edge detection and Hough transformation [17]. The experimental results on 60 input image show that the average classification accuracy of the system is 90,38% with the average running time of 16.734 seconds. However, the detection of the T-area is influenced by many factors such as the presence of hair and uneven lighting on the face. In addition, there are many other parameters that must be tuned so that an optimal accurate detection of facial skin type is obtained. For example, to determine the location of face, it is also necessary to determine the optimal Hough transformation parameters (such as the range of the circle radius) based on experiments.

Nusantara, et al. (2018) classified men's facial skin types based on facial image textures using the Gray Level Co-occurance Matrix (GLCM) method and Support Vector Machine (SVM)[18]. This study classify facial skin types into dry, oily and combination skin type. A sample of 100 facial images from 9 men was used. This study manually taking region of interest at 5 points, namely forehead, nose, upper chin, right cheek, and left cheek. Texture features were extracted from the five points using the GLCM method, then the features were classified using SVM whether the area was dry or oily skin type. The next process is the voting of the result of the classification process of the five areas to determine the final type of the patient's facial skin. If three of the five parts are dry or oily skin types, the patient has a combination skin type. This research resulted in an accuracy of 88.89% with an average running time of 4 seconds. However, the number of respondents involved in this study is still small so it needs to be added.

Farhan, et al. (2019) classified the facial skin type into oily and non-oily by using Haar wavelet and Support Vector Machine (SVM) [19]. This research uses 112 facial images which categorized as oily (58 images) and non-oily (54 images). The accuracy of this research in detecting the oily facial skin type is 90%. Amelia, et al. (2019) classified the facial skin type by using Discrete Wavelet Transform (DWT) and Backpropagation Neural Network [20]. This research used 40 facial images as the test data and obtained 95% accuracy with the average running time of 0.75 seconds. However, this research only classify the facial skin into dry and oily type.

3. RESEARCH METHOD

There are three main processes for creating intelligent systems for the classification of facial skin types, which are preprocessing, feature extraction, and classification. The methodology of the proposed research method is shown in Figure 1. The purpose of preprocessing in this research is to eliminate noise and clarify data features. The preprocessing method used in this research is the median filter method. After the preprocessing is complete, the data of face images will be ready to be extracted. Features extraction is the process of retrieving unique features from the data to be processed. In this research, Discrete Wavelet

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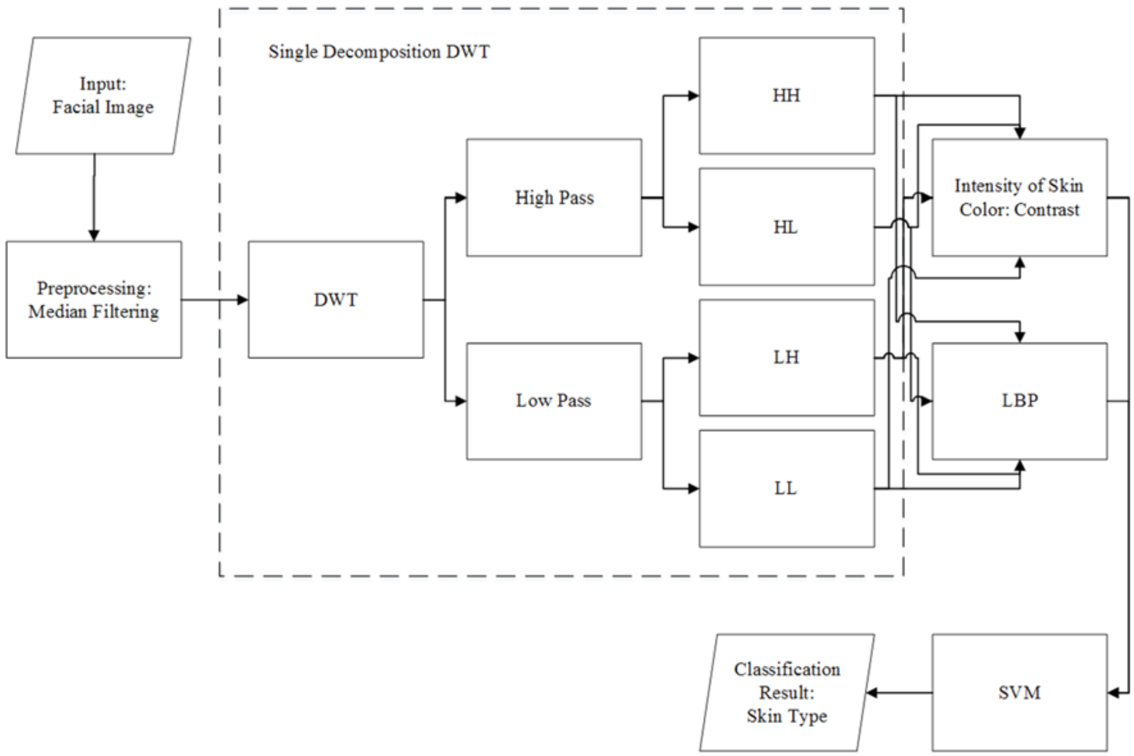

Figure 1: The Methodology of Facial Skin Type Classification

Transform (DWT), 'Contrast' property from Gray-level Co-Occurrence Matrix (GLCM) method, and Local Binary Patterns (LBP) are used in the extraction feature process. The last process is classification using Support Vector Machine (SVM) method. As a statistical based method, SVM has a theoretical basis that can be analyzed clearly, and is not a black box method like neural network. Explanation of each component is described in the following sections.

3.1. Skin Types

The skin is the largest organ of the human body and it has a very important role, therefore skin should always be kept healthy[21]. Not only the facial skin, but the skin throughout the body must be maintained. Understanding the structure and function of the skin can be the first step in the overall series of efforts to treat and maintain healthy skin [22].

Human skin types vary depending on environmental conditions and offspring[23]. Therefore, skin care activities will be tailored to the type of skin. Because different skin types also have different treatments too. The use of skin products that are not right with the classification of skin types will cause damage to the skin. The types of skin used in making the system in this study are as follows[23]:

a. Normal
   Normal skin is a type of skin that tends to be easily treated. Oil glands (sebaceous gland) on normal skin are usually not too much a problem, because the oil (sebum) that is released is balanced, not excessive or lacking.
b. Dry
   Dry skin is a type of skin that lacks sebum. Because the amount of sebum is limited, dry skin often lacks sebum and the skin moisture decreases rapidly.
c. Oily
   Oily skin is a type of skin caused by the sebaceous gland that is very active at puberty when stimulated by the male hormone (androgen).
d. Combination
   Combination skin is a combination of more than one type of skin, such as dry skin and oily skin. The oily part is generally found in the chin, nose and forehead area.

3.2. Gray-level Co-Occurrence Matrix (GLCM)

Gray-level Co-occurrence Matrix (GLCM) is a common method for texture analysis. GLCM uses co-occurrence matrix to describe the frequency of a gray level appearing in a specific spatial position with another gray level[24]. By using GLCM method, several statistical value (property) can be extracted, such as the energy, contrast, variance, correlation, entropy, and inverse difference moment from the analyzed texture.

The 'Energy' value measures the uniformity of the texture. If the texture is homogenous, the 'Energy' will gives 1 value. If the texture is heterogeneous, the 'Energy' will gives 0 value. The 'Entropy' value measures the disorder of an image. 'Entropy' property is strongly but inversely correlated to the 'Energy' property. If the texture is uniform, then the 'Entropy' will gives 0 value. The 'Contrast' value measures the difference between the highest and lowest value of a set of pixels. A low-contrast image will result in low GLCM 'Contrast' value. A high-contrast image will result in high GLCM 'Contrast' value.

The 'Variance' value measures the heterogeneity of the texture and strongly correlated with standard deviation value. The 'Variance' value increases when the gray level values differ from their mean value. The 'Correlation' value measures the gray level linear-dependencies in the image. High 'Correlation' value means there is linear relationship between the gray levels of pixel pairs. The 'Inverse Difference Moment' measures image homogeneity, which gives larger values for smaller gray level differences in pixel pair element.

3.3. Discrete Wavelet Transform (DWT)

In the feature extraction process, image transformation is carried out to get clearer information that is contained in the image. The transformation in this process is the change of image domain. Through the transformation process, images can be expressed as the linear combinations of basic signals which are often referred to as base functions[25]. Wavelets are defined as small waves. The wavelet transform will convert a signal into a series of waves. These short waves are functions that are located at different times. Wavelet transforms are able to provide frequency information that appears and provide information about the scale or duration or time. Wavelets can be used to analyze a waveform (signal) as a combination of time (scale) and frequency.

The transformation process in wavelet can be exemplified as follows: the image that was originally transformed is divided (decomposed) into four new sub-images to replace it[26]. The size of each sub-image is ¼ times of the original size. The three sub-images on the upper right, lower right and lower left positions will look like the rough versions of the original image because they contain high frequency components from the original image. While the sub-image in the upper left position will looks like the finer version of the original image, because it contains low frequency components from the original image. The sub-image in the upper left (low frequency) is further divided into four new sub-images. The process is repeated according to the level of transformation used. The level of transformation used in this research is 1, namely single decomposition, so that 1 input facial image will produce 4 facial images. The process of single decomposition in Discrete Wavelet Transform can be seen in Figure 2.

3.4. Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is a method for describing textures that can be used to represent a person's face, because facial images can be seen as a micro-texture-pattern composition, which is a non-parametric operator that describes the local spatial image[27]. LBP is defined as a comparison of the binary values of pixels in the center of the image with 8 pixel values around it in which each of these pixels has a different value. For example, in an image with 3x3 pixels, the binary value at the center of the image is compared with the value of the surrounding pixels[28]. The value of the surrounding pixel will be 1 if the value of the center pixel is smaller and 0 if the value of the center pixel is bigger. After that, the obtained 8 binary values will be arranged clockwise or vice versa, and then it will be converted into decimal values to replace the value of the center pixel[29].

LBP was originally designed for texture descriptors. The LBP operator will label each pixel of an image based on the thresholding of the 8-neighbor value of the central pixel and change the result as a binary number. Then the histogram from

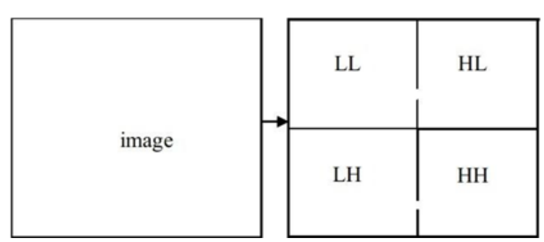

Figure 2. Single Decomposition of Wavelet

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the label can be used as a texture descriptor. From the computational results it will produce a value that shows the Local Binary Pattern code[30]. The LBP codes will be represented through histograms. The histogram will show the frequency of occurrences of various LBP values.

3.5. Support Vector Machine (SVM)

Support Vector Machine (SVM) was developed by Boser, Guyon, and Vapnik[31]. SVM was first introduced in 1992 at the Annual Workshop on Computational Learning Theory. The basic concept of the SVM is actually a combination of the existing computational theories, such as the margin of the hyperplane, kernel, Lagrange Multiplier, and other supporting concepts[32].

SVM is a supervised learning method that is used to perform the classification of the two classes. The SVM technique is used to get the optimal separator (hyperplane) function to separate observations that have different target variable values[33]. Looking for the best hyperplane equal to maximize the margins or the distance between the collections of data object from two different classes.This hyperplane can be a line on two dimensions (linear function) and can be a flat plane in multiple dimensions by using kernel function. There are various forms of the kernel, such as radial basis function (RBF), polynomial, etc. The characteristics of SVM are generally summarized as follows[34]:

1. In principle, SVM is a linear classifier.
2. Pattern recognition is done by transforming data in the input space into a higher dimension space (feature space), and optimization is done in the new vector space. This distinguishes SVM from the pattern recognition solution in general, which optimizes the parameters of the transformation results that are lower than the input space dimension[35].
3. Implement a Structural Risk Minimization (SRM) strategy.
4. The working principle of SVM is basically only able to handle the classification of two classes, but has been developed for the classification of more than two classes in the presence of pattern recognition.

The Support Vector Machine method has several advantages, such as:

1. Generalization
   Generalization is defined as the ability of a method to classify a pattern that is not included in the data used in the learning phase of the method[36].
2. Curse of dimensionality
   Curse of dimensionality is defined as the problem faced by a pattern recognition method in estimating parameters because the number of sample data is relatively less than the dimensional space of the vector[37].
3. Feasibility
   SVM can be implemented relatively easily, because the process of determining support vectors can be formulated in Quadratic Programing (QP) problems[34].

The development of SVM method has been made to do classification process of many classes, which is called Multiclass Support Vector Machine (Multiclass SVM) [38]. In the training process, multiclass SVM build the model of each class gradually. If the data is divided into *k* class, then the SVM classification process will be done *k* times. In the first process, the data in the first class is labeled as 1 while the data in other classes are labeled as 0; and then SVM model for the first class is built. In the second process, the data in the second class is labeled as 1 while the data on other classes are labeled as 0; and then SVM model for the second class is built. The process is repeated until the model of *k*-th class is built. In the testing processing of multiclass SVM, the classification of each data is done using each SVM models that have been built. The model that gives label or classification result 1 for the test data is the class of the test data.

3. RESULT AND ANALYSIS

The system testing is based on several parameters obtained during the system programming process. The result of each experiment is presented in the form of tables and conclusions in graphical form. To validate the results of the experiments from the classification process, the *k*-fold cross validation method is used to distribute the training and testing data that is used in the classification process.

3.1. Dataset

The experiments on the classification system of facial skin types uses a total of 60 facial images as the data. The data used are photos of the faces of Indonesian people from Sifra Skin Care (Pati, JawaTengah), GriyaAyuClarista (Sidoarjo, JawaTimur), Rossi Skin Care & Spa (Denpasar, Bali), and RumahCantikAssyva (Kediri, JawaTimur) using cell phone's camera and DSLR camera[17]. The dataset is divided into 4 classes, which are normal skin, dry skin, oily skin, and

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combination skin. For normal skin types there are 17 images, for dry skin types there are 12 images, for oily skin types there are 17 images, and for combination skin types there are 16 images. All of the facial images have size of 400 pixels x 600 pixels.

3.2. Preprocessing

Preprocessing is a step to improve image quality, eliminate noise in the image, and determine the part of the image that will be used in the next stage[39]. In this research, this process is done so that the image is clear of noise. Noise is signal that disrupts the brightness of the image in the form of spots on the image so that it disturbs the beauty or clarity of the image[40]. Noise removal at this preprocessing stage uses the median filtering method. Median filtering is done by looking for the median value of the neighboring pixel value that affects the center pixel[41]. This technique works by filling in the values of each pixel with the neighbor's median value. The median selection process begins with sorting the values of neighboring pixels, then selecting the median value. Comparison of images before and after median filtering can be seen in Figure 3. By using median filtering in the preprocessing step, the noise pixels whose values are too high or too low compared to neighboring pixels will be eliminated. This causes the value of the extracted features to become more homogeneous.

Figure 3: Comparison of the Preprocessing

3.3. Feature Extraction

There are two types of feature extracted from the data, which are the intensity of skin color and the skin texture. The skin intensity feature is extracted using the Gray-level Co-Occurrence Matrix (GLCM) method, while the skin texture is extracted using a combination of Discrete Wavelet Transform (DWT) and Local Binary Pattern (LBP). This is based on several researches that use GLCM, wavelet transform, or LBP to extract the skin features [27][42][43][44].

The skin intensity feature is used to detect the presence or absence of shiny parts on the face. If there are shiny parts, the facial skin tends to be oily. GLCM method uses co-occurrence matrix to calculate the statistical property of the image, such as the energy, moment, entropy, probability, contrast, etc[45]. GLCM 'Contrast' will give a value of 0 to an image whose color intensity is constant so that if there is a shiny part of the face the value of the feature intensity is greater than 0. Table 1 shows the minimum value, maximum value, and average skin color intensity feature. From the Table 1, it shows that the average contrast value is highest in the combination skin type and lowest in the oily skin type. This is because the oily (shiny) part of the image is often appear on combination skin types (because combination skin consist of both oily and dry skin). Meanwhile, the oily skin type gives the lowest average contrast value because there is many pimples in the oily skin images that have low intensity. Therefore, the oily skin images tends to give low contrast value.

After the intensity of skin color feature is obtained using contrast, the next step is extracting skin texture feature from the facial images. Texture feature extraction is done in two stages. First, the image will be decomposed using DWT so that 1 image will produce 4 new images. DWT is effective to analysis texture with different scales, therefore the texture of skin can be captured by using DWT[46]. The process of discrete wavelet decomposition can be seen in Figure 4. From Figure 4(c), it can be seen that the decomposition of

Table 1: The Intensity of Skin Color Feature

Skin Type	Minimum Value	Maximum Value	Average Value
Normal skin	5.7×10^{-6}	537.1×10^{-6}	45.50×10^{-6}
Dry skin	7.5×10^{-6}	326.3×10^{-6}	51.06×10^{-6}
Oily skin	5.7×10^{-6}	168.6×10^{-6}	31.86×10^{-6}
Combination skin	7.43×10^{-6}	152.1×10^{-6}	141.10×10^{-6}

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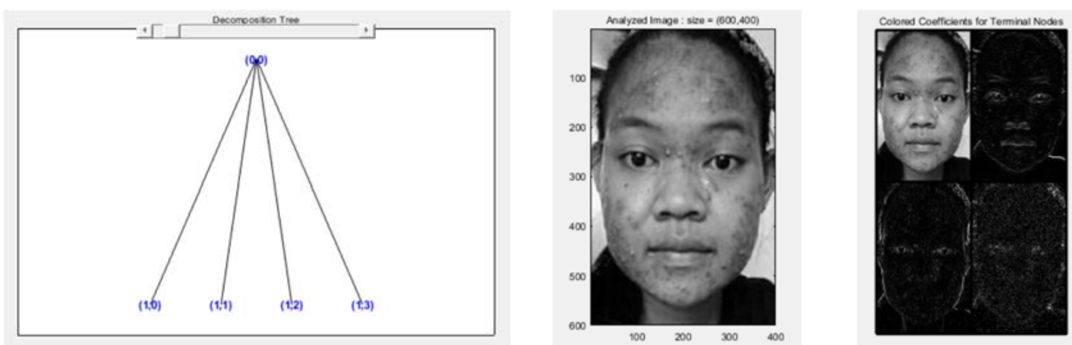
wavelet transform can obtain the lines, pimples, and pores (fine-grained texture) in the face image, separately. The wrinkles that characterized the dry skin type and pimples that characterized the oily skin type can be captured by using wavelet decomposition.

After the image is successfully decomposed, each image will be extracted using the LBP method. The LBP method produces a texture image from the image, then histogram is made from the texture image. The histogram shows the number of pixels in the texture image that has a certain graylevel value. Examples of texture images (from the low frequency component of the DWT transform) and its LBP histograms for each type of skin are shown in Figure 5 - Figure 8. The value of 256 graylevel on the histogram of 4 texture images is then used as the texture feature.

3.4. Experiment Using SVM as Classifier

To validate the results of the accuracy measurement from the system in classifying the skin types, the *k*-fold cross validation method is used. The used *k* values are 2, 5 and 10. In each experiment, data randomization is performed, but the amount of data in each class at each fold remains the same. For example, in the value of $k = 2$ then the amount data in the first and second fold is 30 images each, with the number of normal class data on each fold is 9 images and 8 images respectively, the number of dry class data on each fold is 6 images, the number of oily class data on each fold is 9 images and 8 images respectively, and the number of combination class data on each fold is 7 images. The accuracy of the proposed method is calculated by using one fold, alternately, as the testing set and the remaining folds as the training set[47]. Accuracy measures the percentage of the testing data that were correctly classified [47]. The results of the system accuracy measurement can be seen on Table 2.



(a) (b) (c)

Figure 4:Single Decomposition of DWT. a) Decomposition Tree. b) Analyzed Image. c) DWT result

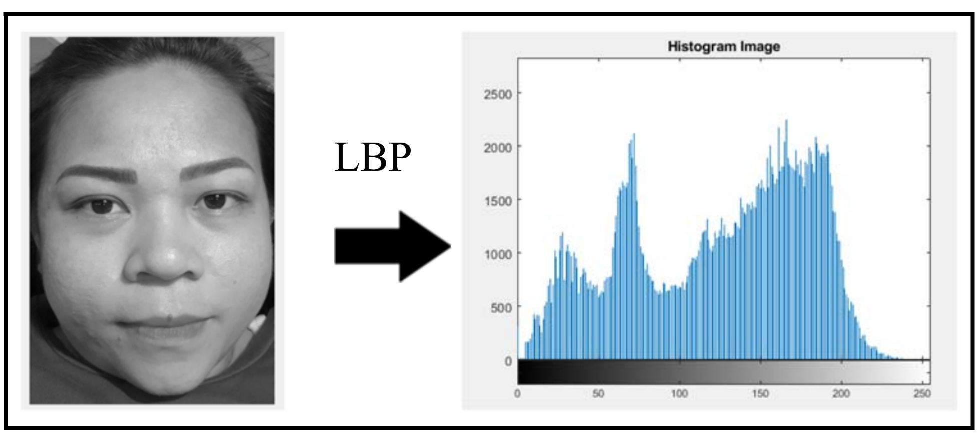


Figure 5:Histogram of Normal Skin Type

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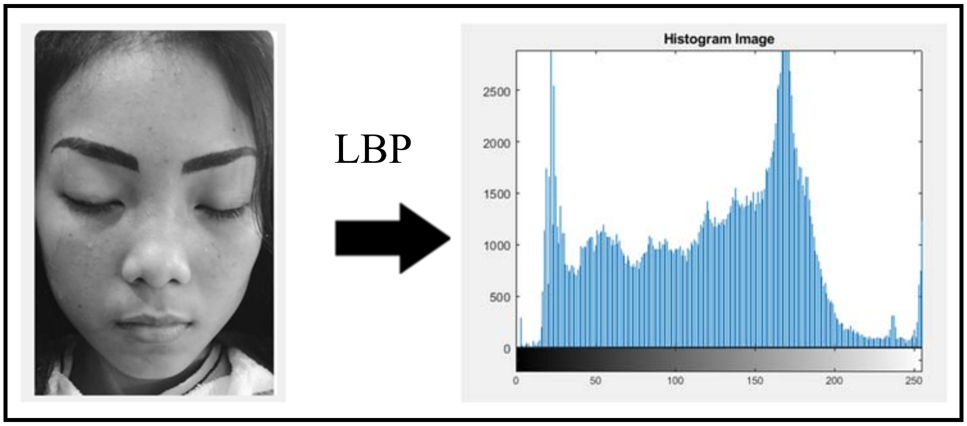

Figure 6:Histogram of Dry Skin Type

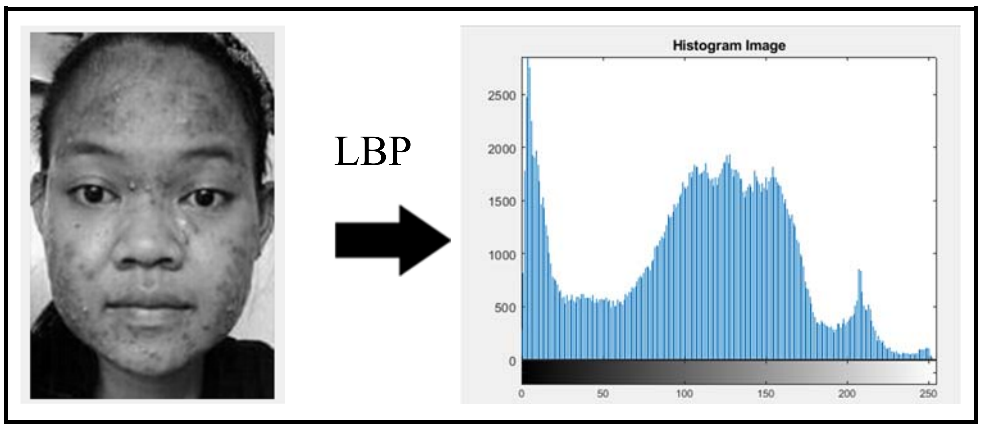

Figure 7:Histogram of Oily Skin Type

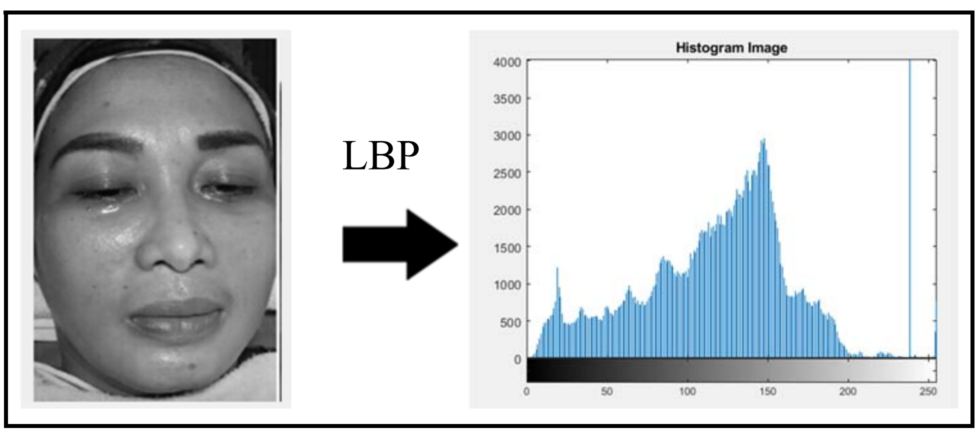

Figure 8:Histogram of Combination Skin Type

The proposed system uses 60 facial images and classify it into 4 class (normal, dry, oily, and combination skin type). The proposed system obtained the average accuracy of 91.66% with the average running time of 31.571 seconds. The proposed system gives higher accuracy than the previous studies, such as in [16],[17], [18], and [19]. The research in [20] has higher accuracy, which is 95%,than the proposed method. However, the research in [20] only use 40 facial images and only classify the facial skin into dry and oily type.

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Table 2: Accuracy Measurement

k	Accuracy (%)	Running Time (s)
2	91.67	25.143
5	90.00	34.225
10	93.33	35.347
Average	**91.66**	**31.571**

Compared to the previous studies, the proposed method in this study provides a much longer running time. This is mainly because the feature extraction process by using LBP method has high computation. Although 31.571 seconds is not long, for real-time application use it is necessary to reduce the running time. There are several more efficient development of the methods that were used in this research, such as for median filtering in the preprocessing step [48], GLCM method [49], DWT method [50], and multiclass SVM method [51]. By using a more efficient methods, it is expected that the proposed system can be developed so that it is better for real-time application.Therefore, the proposed system can classify facial skin types effectively and efficiently.

4. CONCLUSION

Based on the experiments, it is proven that the proposed method is able to properly classify facial skin types. Detection of facial skin types using the DWT, Contrast, LBP and SVM methods gives an average classification result of 91.66% with an average running time of 31.571 seconds. The level of transformation used in this study is one level, namely single decomposition, so that one facial image will produce four new facial images. For future work, to increase the system's accuracy it is necessary to try to increase the level of decomposition carried out in the DWT process. Using more efficient development of the methods in the proposed system, such as median filtering, GLCM, DWT, and multiclass SVM can improve the system's efficiency and suitability for real-time application.

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