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Analysis of Human Skin Texture by using Machine Learning Approaches

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Abstract: The production and improvement of cosmetic, skin texture modelling, facial recognition in security application, as well as computer-assisted dermatology diagnostic, all benefit greatly from an understanding of skin texture analysis. Several types of skin condition that affect human will increasing the problem in daily life. Own research shows that the methods have significant limitations such as lack of accuracy and also the methods for texture analysis can't be in specific category. So, to overcome the problem, the method and technique was improved to solve the problem about the human skin texture. The Gray Level Co-Occurrence Matrix features method and Decision Tree methods as a classifier to analyze the human skin texture was used in this project. The features will be used to train a machine learning algorithm that will learn and analyze the skin features extracted in the previous process. Using this data, the machine learning algorithm can easily categorize the skin texture based on its level of dryness. The experiment result shows that the overall framework achieved a satisfactory result in recognizing and categorizing the skin dryness based on the skin texture.

Keywords: Machine Learning, Skin Texture Analysis, Gray Level Co-Occurrence Matrix, Decision Tree Classifier

1. Introduction

The human skin texture is the appearance of the skin smooth surface. A person's health and skin texture are intimately associated [1]. Numerous variables contribute to the characteristics of this texture, including food and hydration, the amount of collagen, hormones, and skincare products [2]. The location of the skin on the body also affects its texture. Images processing tools are used in the arena of texture analysis, since it is considered as a scanned image [3]. In order to determine whether there are any images in a set of many pictures that are closed to any essentially random previously encountered, a number of algorithms have been devised to categorize the images and determine statistical distance among them [4].

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Skin texture analysis makes it simple to determine how healthy the skin is. By selecting a set of texture qualities that consider the spatial arrangement of the images, texture discrimination can be achieved [2]. Texture analysis is regarded as a method of determining the spatial variation in pixel intensities (grey value), which is useful for a variety of purposes. The most important visual cue for differentiating between standardized portions is texture. Prior to that, independent requirement reports evaluate the photos to separate the components of the hemoglobin and melanin. The description has been artificially created for comparisons, and the texture elements also corrupted, separating the representation of layers of skin into the initial solution along with the extracted features, which is based on which the pixel variation is observed to find patterns and structure [5]. A non-linear approach is used in the filtering technique that was first developed and is actually used on dermoscopic skin recognition [6].

2. Methods

This section presents the methodology that used for the software development and technique that will support to complete the project. The subsection presents the overall block diagram for the overall of the project as in Figure 1.

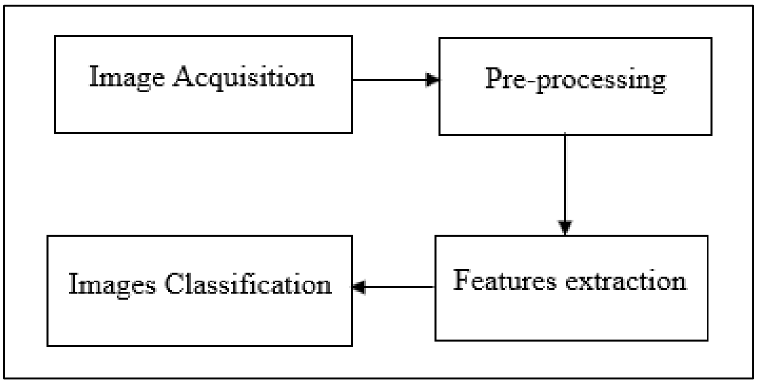

Figure 1: Block diagram for overall of the project

2.1 Data acquisition

The images were taken from the Freepik.com website and it represent three different variations of human skin textures. The three sets of images that are namely normal skin condition, mildly dryness skin condition and severely dryness skin condition problems are taken into consideration and the dataset consists of 300 skin images where each skin condition consisting of 100 images. Further processing are not possible if there are no images.

2.2 Pre-processing

The pre-processing method is used to remove and eliminated unwanted distortion from the images data. The image is resized to a uniform scale 128x128 to ensure that all of the images in dataset are the same size and easy to train due to their small size and then it transforms to grayscale by using the rgb2gray () method. Jpeg files are used to store the captured images. Histogram method is used for image enhancement to obtain the better-quality images.

2.3 Features extraction

Differentiate the input patterns is used in this process. The Gray-Level Co-Occurrence Matrix (GLCM) is used in texture analysis to extract its characteristics. GLCM is a powerful tool for image features extraction that maps the Gray-Level Co-Occurrence probabilities based on spatial relations of pixels in different angular directions. This technique uses the grey comatrix function to generate a GLCM. The grey comatrix function determines how frequently a pixel with the intensity (grey level) value i appear in a particular spatial connection to a pixel with the value j to produce a Gray-Level Co-Occurrence Matrix (GLCM). The default definition of the spatial relationship is the pixel of interest and the pixel immediately to its right (horizontally adjacent).

The features of the GLCM contrast, correlation, energy and homogeneity as in Eq. (1)-(4). Energy returns the sum of the squared elements in the GLCM, and it ranges from 0 to 1. For constant images energy is equal to 1. Correlation ranges from -1 to 1 for a perfectly positively or negatively correlated images. Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image while homogeneity measures how well the GLCM diagonal and element distribution match. In this case, the values go from 0 to 1. For the diagonal GLCM, homogeneity is 1.

$$E = \sum_{i,j=1}^{n} P(i,j)^2 \qquad \text{Eq. 1}$$

$$Cr = \sum_{i,j=0}^{n} Pij(i-\mu)(j-\mu)/\sigma 2 \qquad \text{Eq. 2}$$

$$C = \sum_{i,j=1}^{n} Pi,j(i-j)^2 \qquad \text{Eq. 3}$$

$$H = \sum_{i,j=0}^{n} \frac{P(i,j)}{1+(i-j)^2} \qquad \text{Eq. 4}$$

2.4 Images classification

The experiment has been carried out by implementing machine learning technique by using Python Software and use Google Collab as a main platform. The model is trained and tested by using two different samples like training set and testing set. For training dataset, 80% of the dataset which equal to 240 images and 20% dataset which equal to 60 images are used for testing. One of the most common and simple categorization techniques is the Decision Tree. Decision Tree is a supervised learning method used for constructing prediction model from the dataset. The tree is constructed in top-down recursive manner by partitioning the data space based on some splitting criteria. It splits a dataset into smaller subsets while at the same time connected decision tree is incrementally developed.

3. Results and Discussion

The result indicate that Decision Tree Classifier yield a better performance for classification and prediction compared to the other methods. It includes images processing result, features extraction result and images classification result.

3.1 Images processing result

Images were chosen from the dataset and used as input images. Three types of human skin texture which are normal skin, mildly dryness skin condition and severely dryness skin condition were considered for the skin texture classification system. Table 1 shows the sample images used as input images.

Table 1: Sample of human skin condition

Normal skin condition		
Mildly dryness skin condition		
Severely dryness skin condition		

The brightness, contrast enhancement and saturation of the sample images was randomly adjusted. Histogram equalization and resized images was used to enhance the contrast of the images. Table 2 presented as output images.

Table 2: Pre-process sample images

Input images	
Brightness	
Contrast	
Saturation	

3.2 Features extraction result

Feature extraction process used GLCM features to analyze the skin condition and neural network. After pre-processing, GLCM features was extracted for each sample image as Table 3. The Decision Tree's input level is represented by the features contrast, correlation, energy, and homogeneity.

Table 3: Extracted features of skin condition samples

Skin condition \ Features	Contrast	Correlation	Energy	Homogeneity
Normal skin	6.907428	0.675319	0.136039	0.468466
Mildly dryness	8.174113	0.603945	0.125975	0.432948
Severely dryness	9.680391	0.529896	0.11894	0.404606

3.3 Image classification result

The extracted features are separated into training and testing dataset, where 80% of the images from each group are used to train the system and the remaining of the images serves as the testing set.

3.3.1 Training

The training dataset was trained based on the Decision Tree Classifier to predict the human skin texture as an output. 80% of the dataset, which are 240 images has been separated for training the performance method. For training the dataset, it just takes only below two minutes to get the output. The purpose for the training is to ensure that the performance is according to our standard requirements.

A confusion matric is a technique for summarizing the performance of a classification algorithms. It can give a better idea of what are the classification model is getting right and what types of errors it is making. The output '0' shows severely dryness skin condition, output '1' shows mildly dryness skin condition and output '2' for normal skin condition. The classification of the skin texture condition sample was showed in confusion matrix as given in Figure 2, whereby 240 images was correctly classified while Table 4 shows the training result.

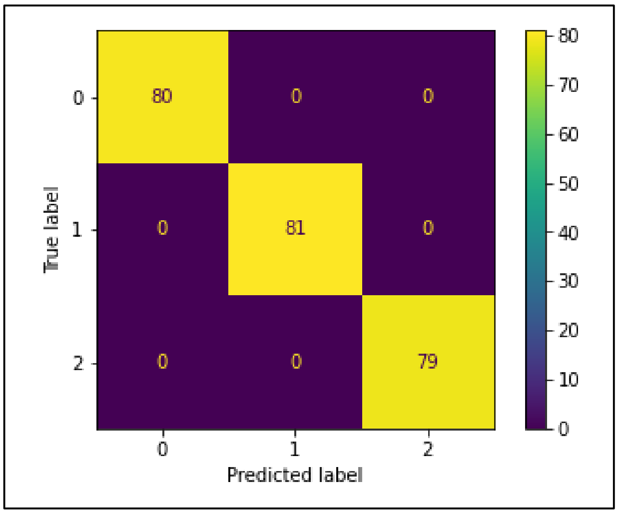

Figure 2: Confusion matrix for training dataset

Table 4: Result for the training dataset

Skin condition / Model	Normal skin condition	Mildly dryness skin condition	Severe dryness skin condition
Precision	0.65	0.75	0.78
Recall	0.94	0.91	0.74
F1-score	0.77	0.82	0.76
Macro average	0.79	0.80	0.79
Weighted average	0.79	0.79	0.79
Accuracy	72.13%	77.05%	78.69%

3.3.2 Testing

In the testing performance method, 20% of the dataset, which are 60 images has been separated. For testing the dataset, it just takes only below one minutes to get the output. The purposes for the testing dataset are to verify how well our standard requirement and real applications requirement works. The classification of the human skin texture condition sample was showed in confusion matrix as given in Figure 3, whereby 46 images was correctly classified and 14 images misclassified. There is data that is not classified due to the lack of its accuracy. Table 5 shows the result for testing dataset.

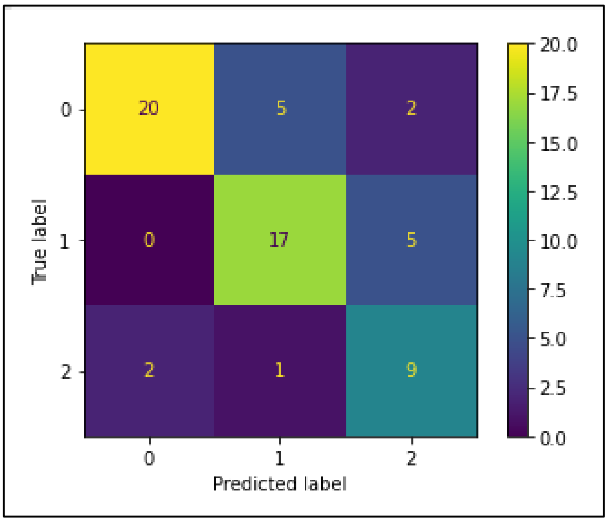

Figure 3: Confusion matrix for testing dataset

Table 5: Result for the testing dataset

Skin condition / Model	Normal skin condition	Mildly dryness skin condition	Severe dryness skin condition
Precision	0.78	0.72	0.70
Recall	0.82	0.72	0.74
F1-score	0.80	0.72	0.72
Macro average	0.79	0.77	0.78
Weighted average	0.79	0.79	0.78
Accuracy	78.69%	68.85%	73.77%

4. Conclusion

The main focus of this research is to use machine learning techniques to analyze the texture of human skin. To categorize the various forms of skin texture, the machine algorithms Decision Tree (DT) classifier are used. The system has been successfully implemented for the identification of correct classification algorithms. Result accuracy will increase with images quality and features combinations.

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