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by Lukman Medriavin Silalahi

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Toucless Palm Print Recognition System Design Using Gray Level Co-occurrence Matrix Feature with K-Nearest Neighbour Classification in Matlab

Agus Dendi Rochendi[1*], Lukman Medriavin Silalahi[2*], Imelda Uli Vistalina Simanjuntak[3]
[1]Research Center for Oceanographic Physic, Badan Riset dan Inovasi Nasional, Indonesia
[2,3]Department of Electrical Engineering, Faculty of Engineering, Universitas Mercu Buana, Indonesia

Abstract
This research designs a touchless palmprint identification biometric system. Observation of the touchless palmprint recognition system is a good choice because the system works without touching the scanner so as to reduce direct physical contact, and is applied in various identity recognition applications. This research aims to implement palm image in validating identity using GLCM (Gray-Level Co-occurrence Matrix) features using K-NN classification method in MATLAB. The identification process is divided into several stages, including image acquisition, pre-processing, feature extraction with GLCM and database matching using KNN classification. System testing uses the 10-fold cross validation method with a total of 100 image samples (90 training images and 10 test images) that are tested alternately to calculate the average accuracy and analyse system performance. Furthermore, the test uses GLCM angles (0º, 45º, 90º dan 135º) and K-NN with k values of 1, 5 and 7. The research results produced the highest accuracy of 72% using an angle of 0° in GLCM and k=1 and the lowest at an angle of 90° and k=7 in K-NN. The advantage of this design is the recognition of the identity of the palm print owner in real time. Suggestions for further research development are to add training data, add feature extraction methods, and add a pre-processing stage to improve recognition accuracy as well as reduce noise and adjust brightness. In addition, the development of auto tracking in RoI (Region of Interest) Segmentation so that the position captured on the palm of the hand is uniform or the same and results in better cropping of the RoI.

Keywords:
Biometric;
Region of Interest;
Toucless;
Palmprint Recognition;
Gray Level Co-occurance Matrix;
K-Nearest Neighbor
(consist of 3-5 words, separated with semicolon, sort Ascending, 9 Italic)

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Corresponding Author:
Lukman Medriavin Silalahi
Electrical Engineering Department, Universitas Mercu Buana, Indonesia
Email:
lukman.medriavin@mercubuana.ac.id

INTRODUCTION

Biometric identification is a technique to establish a personal identity through physiological characteristics. Fingerprint and iris identification are the most widely used implementations of biometric identification. The use of fingerprints is mostly used for employee attendance systems, mobile phone screen authentication and identity cards [1]–[3]. However, it is limited due to its use as a medium for spreading the COVID-19 virus. Therefore, this research designs an identity validation system using a palm image without the need for physical contact or called touchless to prevent the spread of the COVID-19 virus [4].

Like other biometric identifiers, the palm is believed to have critical properties, including universality, uniqueness, and collectibility. Using the human hand as an identifier, the moulded patterns of principal lines, ridges, and wrinkles present in the palm are used as biometric feature matching. This is because no two people have the same palm pattern, even twins. Palm recognition has been recognised as an effective and user-friendly biometric identifier for personal authentication [1], [5], [6].

The novelty of the research is obtained from a review of a collection of previous research references so that the process of identifying problems, hypotheses, formulating methods, to conclusions has a correlation and produces excellence/improvement of research results on palm print recognition. Firstly, research conducted by [7] proposed the use of canny edge detection and GLCM (Gray Level Co-Occurance Matrix) features. The preprocessing results are classified using K-NN (K-Nearest Neighbours). (K-NN) is a method of classifying an object based on the closest distance learning data to the object. The accuracy of the KNN classifier was evaluated using k-fold cross validation with an accuracy of 98% with k = 7.

Secondly, [8] proposed a RoI (Region of Interest) generating image capture scheme, application of median filtering to remove noise and increase sharpness using texture features that have been extracted from each part of the image separately using Gabor filter orientation and SVM (Support Vector Machine) classification, resulting in a recognition percentage of about 94.5%.

Third, research conducted by [9] presents an identification system using various basic functions of the wavelet transform to extract palmprint features. RoI local features of the region of interest are extracted using ED (Euclidean Distance). The recognition percentage is 94.33% with minimum distance classification based on ED.

Fourth, based on the results of research conducted by [10] proposed a scheme to extract RoI of palm image using CHVD (Competitive Hand Valley Detection) and ED techniques, then LBP (Local Binary Patterns) feature extraction for texture extraction. The results show that CHVD-LBP produces an accuracy percentage of 96.1% while the best ED results reach 88.24%.

Fifth, research conducted by [11] built a texture-based palm line image identification application using the LDA (Linear Discriminant Analysis) method for feature extraction and the naïve Bayesian method to calculate the chances of similarity of the test image with the training image. This research produces an accuracy percentage of 95% for testing test images against training images, 93.4% for test images against salt and pepper noise 0.005 and 93.4% for testing test images with Gaussian filters.

$$f(x,y) = \begin{vmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(0,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{vmatrix} \quad (1)$$

Eq. 1 explains that a digital image is defined as a function f(x,y), of M-rows and N-columns. X-axis and Y-axis are spatial coordinates. F is the amplitude at the coordinate point (x,y) as the intensity or grey level of the image. If the x-axis, y-axis, and F (amplitude) are all finite and discrete, then the image is a digital image. Thus, a digital image is an array of real values or complex values represented in a specific array of bits, as well as a two-dimensional function [12]–[14].

Therefore, digital image processing functions improve the quality of an image to facilitate the interpretation of the human eye and process information in an image for the purposes of automatic object recognition. Figure 1 shows the stages of digital-grayscale image processing, including Image Acquisition, Preprocessing, Segmentation, Representation and Description, Recognition, and Interpretation.

Eq. 2 is a channel value equation to indicate the colour internality at each pixel, from Red = Green = Blue based on the derivative of Eq. 1. Each element in the image array is a discrete pixel value in digital image processing, N-array and grey level G are generally taken as integer powers of 2, that is, N = 2n and G = 2m. For images, N takes 256 or 512, grey G 64 to 256, which can meet the needs of image processing. Eq. 3 shows the number B to be the number of bits required to store a digital image. R is the grey scale relationship of G: G = 2k. When M = N shown in Eq. 4.

$$Gray = 0{,}2989 \times R + 0{,}5870 \times G + 0{,}1140 \times B \quad (2)$$

$$B = M \times N \times R \quad (3)$$

$$B = N^2 \times K \quad (4)$$

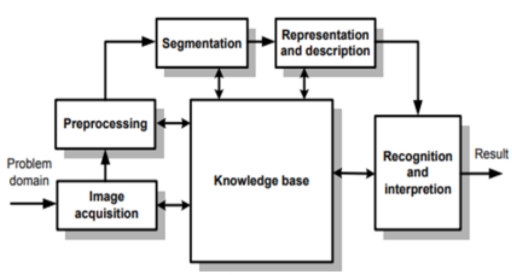

Figure 1. The steps of digital image processing

Eq. 1 to Eq.3 are grayscale image processing equations that have colour gradations starting from white to black at each pixel, then produce feature extraction. The feature extraction methods proposed in this research are RoI and GLCM.

RoI extraction in touchless palm print recognition is a pre-processing challenge due to its important role in impacting feature extraction and recognition [15], [16]. In RoI extraction, it automatically and reliably clusters small regions of the captured palm that contain a lot of information, when the user may pose in a natural way or deform in other ways, such as rotation, stretching, and scale variability [17]–[20]. Thus, RoI is an area localisation stage based on classification and masking of a selected part of the image for processing. RoI is very helpful for image segmentation because this technique allows different coding of certain areas of the digital image, making it more recognisable, divided into certain regions according to the object image, and producing better quality than the surrounding area.

To ensure accuracy, the RoIs that have been extracted from different palm images taken from the same person at different times should be at the same position to enable proper feature extraction.

$$d(H_1, H_2) = \frac{\sum_I (H_1(I) - \bar{H}_1)(H_2(I) - \bar{H}_2)}{\sqrt{\sum_I (H_1(I) - \bar{H}_1)^2 \sum_I (H_2(I) - \bar{H}_2)^2}}$$

$$\bar{H}_k = \frac{1}{N} \sum_J H_K(J) \tag{5}$$

Eq. 5 is a correlation comparison algorithm to calculate the similarity between two RoIs of the same person for evaluation. where Hi is the histogram of the RoI and N is the number of bins in the histogram. The range $d(H_1, H_2)$ is 0-1 with higher correlation indicating higher similarity between two RoIs, which means if the RoIs are extracted from the same palm position, the correlation between each other will be high. On the contrary, if the RoIs cannot be extracted from the same palm position, a low image correlation score will be given.

The next proposed palm texture feature extraction method is the GLCM algorithm [21]. GLCM is a matrix consisting of the number of rows and columns equal to the number of distant grey levels or pixels in the surface image. GLCM matrix is useful for texture recognition, image segmentation, image retrieval, colour image analysis, image classification, object recognition, etc.

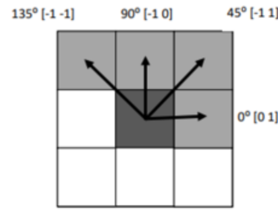

Figure 2. Illustration of GLCM angle direction

Figure 2 is a description of a simple approach using statistical moments from the intensity histogram of an image. Firstly, it extracts or calculates the GLCM feature set by converting RGB (Red, Green, Blue) image to a grayscale image. Secondly, creating a co-occurrence matrix. Thirdly, determining the spatial relationship between reference pixel and neighbour pixel based on the angle $\boldsymbol{\theta}^{o}$ to create a symmetric matrix. Finally, calculating GLCM features in four directions, namely 0°, 45°, 90°, and 135° [22]–[24].

Once the co-occurrence matrix [25] is obtained, the characteristic features representing the image can be calculated. There are several texture features that can be obtained from an image that are used to distinguish between images of a certain class and those of another class. The feature parameters in this research are as follows:

1. Contrast is a measurement of light intensity from the degree of grey between neighbouring pixels shown in Eq. 6 [26]–[28].

$$Contrast = \sum i \sum j\, (i-j)^2 C(i,j) \tag{6}$$

2. Correlation is a measure of the linear dependency of the grey degree of the image thus indicating the presence of a linear structure in the image shown in Eq. 7 [26]–[28].

$$Correlation = \sum i \sum j \frac{(i \times j)C(i,j) - (\mu_x \times \mu_y)}{\sigma_x \times \sigma_y} \tag{7}$$

3. Energy is a measurement of texture uniformity. Energy will be high when the pixel values are similar to other pixels as shown in Eq. 8 [26]–[28].

$$Energy = C^2(i,j) \tag{8}$$

4. Homogeneity is a high-value texture when all pixels have the same value and is sensitive to the diagonal values shown in Eq. 9 [26]–[28].

$$Homogenity = \sum_i \sum_j \frac{C(i,j)}{1+|i+j|} \quad (9)$$

Referring to the background, this research designs a biometric system model for identity verification through the palm of the hand. The designed system uses K-NN classification [29], [30] and GLCM texture features for feature extraction and MATLAB. Image matching based on the human palm by matching the test image taken through the smartphone's IP camera directly with the training image contained in the dataset. Contributions to this research are expected to be developed into various systems that require aspects of palm line recognition, especially authentication systems for a person's identity, so that a more reliable identification and verification system is obtained.

The goal to be achieved is to implement a verifiable palm image for identity validation by utilising GLCM features with the K-NN classification method with MATLAB software.

Research results are utilised on topics in the Information and Communication Technology Field of Excellence.

METHOD

Figure 3 is a block diagram of the touchless biometric system for palm identity verification using K-NN classification, GLCM features to extract texture features using MATLAB. Each stage is explained as follows:

1. Image Acquisition

The image data uses jpeg format (.jpg) measuring 1920 x 1080 pixels. The dataset is a collection of images of the left palm taken directly totaling 100 sample images, with details of 90 training images and 10 test images. Image acquisition uses a smartphone camera connected to MATLAB. First, the acquired images are used as training images. Secondly, the test image is taken directly in the second session. An illustration of the tool used for acquisition can be seen in Figure 4.

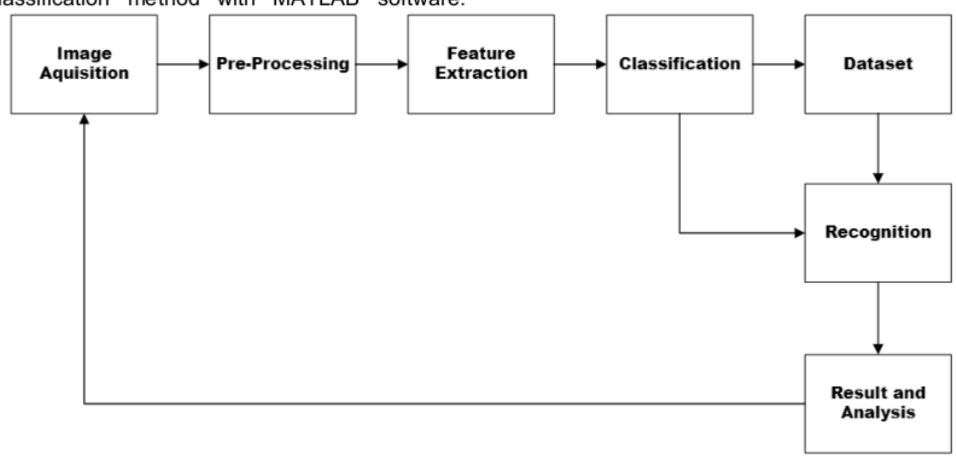

Figure 3. Illustration of GLCM angle direction

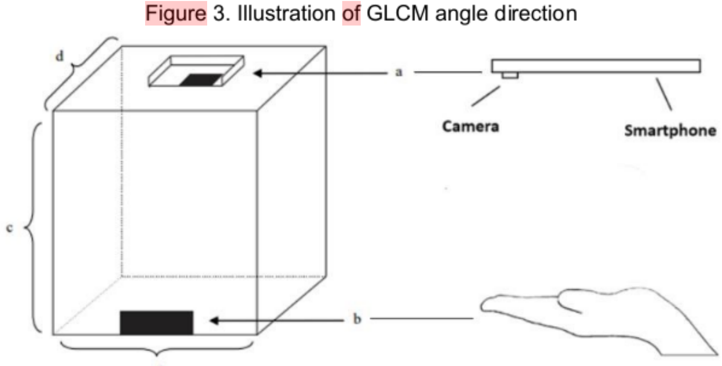

Figure 4. Illustration of GLCM angle direction

Information:

a : Where to put the Smartphone Camera

b : Holes for placing palms

c : Height 23,5 cm

d : Width 23,5 cm

e : Length 23 cm

The image acquisition size is set in such a way as to get good palm image results and according to the designed system. The following are the stages of taking a palm image:

a. Insert the palm of the hand into the prototype design with the position facing the camera.
b. The position of the palm is adjusted using the support on the prototype.
c. The back of the hand is attached to the base of the prototype.
d. Image acquisition of the palm must be stationary or without any movement.
e. Each individual who is taking an image changes the position of his palm in the tool, to be re-taken by repeating the desired number of images (10 times).

2. Pre-Processing

The second stage is Pre-processing which consists of 4 stages, namely:

a. Cropping. The cropping process is done to capture the important parts for the RoI with a size of 500 x 500 pixels.
b. Resizing. Image resizing is intended to simplify computation, changing the resolution of the input image to another resolution without removing information / important parts of the image to a size of 256 x 256 pixels in each training data image and test data image.
c. Sharpening. Sharpening is intended to make the image sharper, and clearer.
d. Grayscale. The input image of the smartphone camera has an RGB color image composition. The RGB input image is then converted to grayscale according to the needs of the system.

3. Feature Extraction

The third stage is feature extraction. At this stage, the system is designed using GLCM as the dependent dimension matrix:

a. Pre-processing image result.
b. Calculation of GLCM feature parameters (Eq. 6 to Eq. 9): Extracting statistical feature parameters (Contrast, Correlation, Energy, and Homogeneity) from the co-occurrence matrix.
c. The calculation results are then stored as data to perform classification using K-NN.

4. Classification

The fourth stage is classification using the KNN method to verify that the real test image is the correct user, so the name of the palm owner must be known by the system. Therefore, a database is required as the basis of the matching process between the test image and the existing training image.

5. Dataset and Recognition

The fifth stage is the dataset and recognition stage. Dataset is a collection of image data obtained based on training images and test images. Recognition is the matching of test data against training data that has been characterized by calculating ED.

6. Result and Analysis

This system produces a palm that has been verified according to identity. Next, the accuracy calculation is carried out. At this stage, the training data results are compared with the test data results. The closest distance is recognized as the searched image. The output results will then be known that the system has successfully detected the palm correctly using the k-fold CV method and the predict function in MATLAB. Figure 5 is the system design model represented in the flowchart.

Material

Table 1 is a list of material requirements for the design of the prototype system.

Table 1. List of equipment support

No	Item	Description
1	Processor Laptop	Intel®core™ i5-1035G1CPU@ 1.00Ghz (8 CPU) ~1.2 Ghz
2	Graphic Card Laptop	AMD Radeon 620 series
3	RAM Laptop	8192 MB
4	OS Laptop	Windows 10-64bit
5	Camera Smartphone	Poco X3Pro
6	Smartphone Application	IP Webcam
7	Resolution Smartphone	1920 x 1080
8	MATLAB	MATLAB 2020a

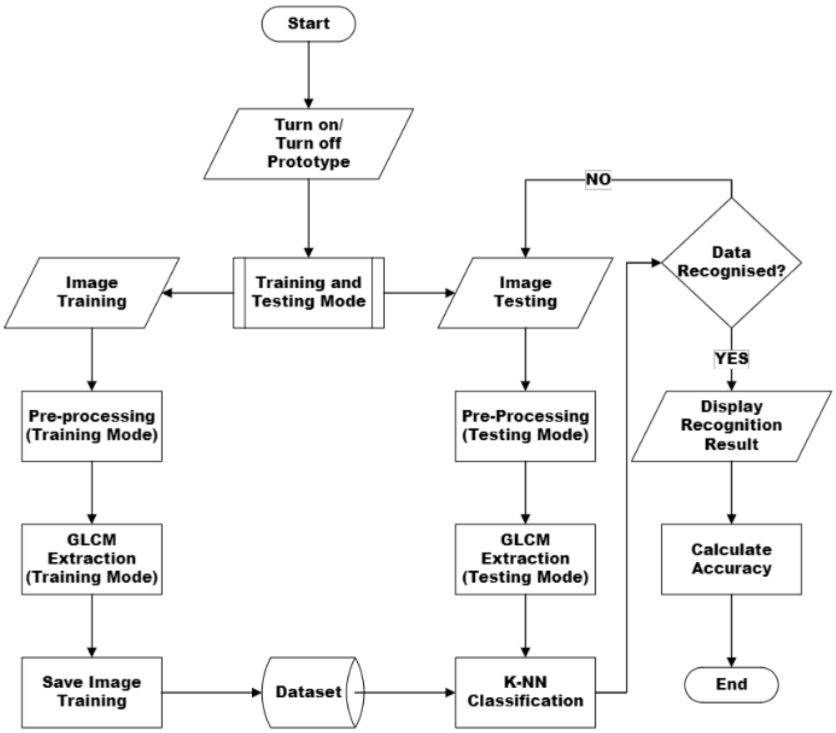

Figure 5. Flowchart system

RESULTS AND DISCUSSION

Figure 6 shows the actual results of the prototype. The test was conducted by collecting coloured palm images of 10 different individuals in JPEG format. The training and testing image acquisition process uses the prototype design shown in Figure 7.

Figure 6. Prototype design result

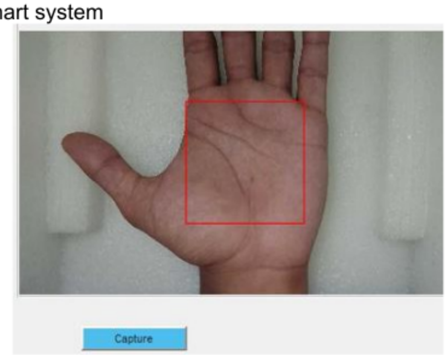

Figure 7. Image acquisition results

1. Training System Implementation Analysis

The implementation of the training system produces pre-processing data on the acquired image, then stored in the training dataset. The GUI (Graphical Unit Interface) page displays a capture push button that functions to capture images connected to a 1920x1080 resolution camera. The pre-processing button functions for cropping, resizing, sharpening, grayscaling and saving the pre-processing image results to the training dataset which is explained as follows:

a. Cropping
At this stage, the palm image that has been captured is then cropped so that the results focus on the ROI part as shown in Figure 8.

b. Resizing
Furthermore, the output image data that has been cropped is then resized as shown in Figure 9.

c. Sharpening
The resized output then enters the sharpening stage to increase pixel contrast or sharpen the colours in the image data shown in Figure 10.

d. Grayscaling
Figure 11 shows the grayscale results used to characterise the image using GLCM.

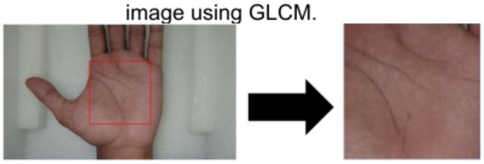

Figure 8. Proses cropping

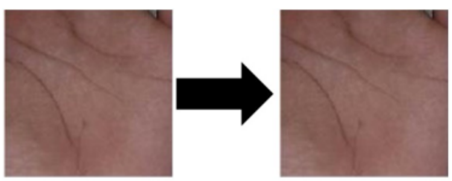

Figure 9. Proses resizing

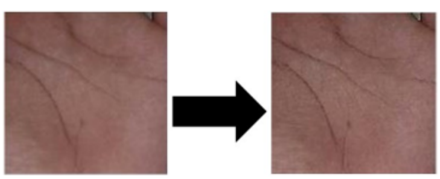

Figure 10. Proses sharpening

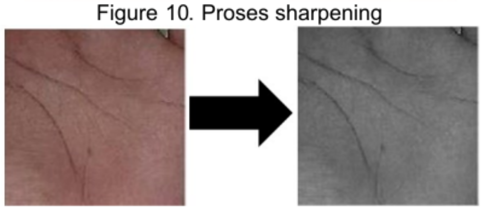

Figure 11. Proses grayscale

2. Analysis System Implementation Testing

The testing system is used for feature matching with KNN classification, then the test image against the training image in the dataset. The test results show that the recognition of the identity of the owner of the tested palm image can be seen in Figure 12.

On the GUI page there is a capture button, pre-processing button, and authentication button with the following explanation:

a. Capture button serves to take pictures connected via Camera with a resolution of 1920x1080.
b. The pre-processing button functions for cropping, resizing, sharpening and grayscaling.
c. Authentication button functions to perform feature matching which produces output in the form of recognition results or the identity of the owner of the identified palm.

3. Extraction and Classification

Table 2 shows the labelling based on the classification of the training image that has been done from the pre-processing results.

Table 2. Label line

No	Folder Training	Hostname	Label
1	A	Fadillah Achmad	1
2	B	Galang	2
3	C	Aditiya Bayu	3
4	D	Singgih Pratama	4
5	E	Aprilia Haryanti	5
6	F	Syahrul	6
7	G	Rafly Meidiaz	7
8	H	Nabilah Nuraini	8
9	I	Malik Shodik	9
10	J	Ahmad Rosyadi	10

The system testing stage is carried out using test data and training data. First, the system for palm owner identification. Second, using the 10-fold CV method to calculate accuracy using GLCM angles, namely angles 0°, 45°, 90°, and 135° using classification (KNN) k 1, 5 and 7. The system test scenario uses the 10-fold CV method with 10 iterations. The first test in the first fold uses 90 combined data from the 2nd subset to the 10th subset.

The analysis of this stage is that training data and testing data that have gone through the pre-processing stage are extracted using 4 GLCM extraction features, namely contrast, correlation, energy and homogeneity to extract their characteristics using angles of 0°, 45°, 90°, dan 135°.

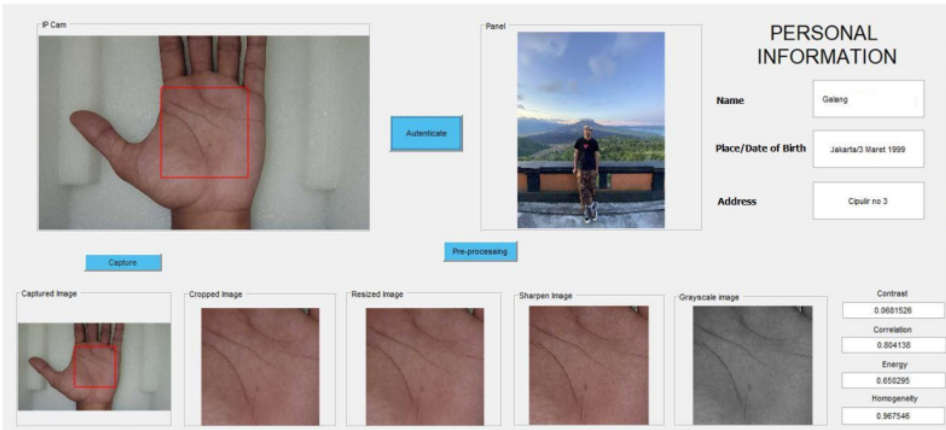

Figure 12. GUI page of the test system

System Analysis

Table 3 shows the result of the percentage of accuracy in each individual palm owner obtained based on testing using 10-fold CV at GLCM angles (0°, 45°, 90°, dan 135°) using k 1, 5 and 7. System analysis shows the highest percentage at angles 0° and 45° for user label 2. User label 9 has the highest percentage of accuracy at angles 45°, 90° and 135°. The lowest percentage was given to user labelled 3 at angles of 45°, 90° and 135°.

Table 4 shows the results using 10-fold CV at each angle (0°, 45°, 90°, and 135°) using k 1, 5 and 7. It can be analyzed that the experiment at 0° angle with k=1 shows the highest percentage of 72% among other experiments. While the lowest percentage was 60% in the 90° angle experiment with a value of k=7.

Table 3. Average accuracy of palms on each label

Label	K-Fold CV based on GLCM angle											
	1				5				7			
	0° (%)	45° (%)	90° (%)	135° (%)	0° (%)	45° (%)	90° (%)	135° (%)	0° (%)	45° (%)	90° (%)	135° (%)
1	60	30	60	60	60	40	40	50	50	40	60	40
2	**100**	**90**	70	90	**100**	**90**	80	90	**90**	**100**	80	90
3	60	*30*	*20*	*30*	70	*40*	*40*	*40*	50	*20*	*20*	*20*
4	80	90	90	70	70	70	70	60	70	60	70	50
5	40	40	40	30	50	60	50	60	70	60	50	70
6	50	30	40	40	70	50	40	60	60	50	30	60
7	60	70	70	80	40	60	60	40	40	70	60	40
8	90	80	90	90	80	80	80	80	70	80	80	80
9	100	**100**	**100**	**100**	70	**100**	**100**	**100**	90	**100**	**100**	**90**
10	80	70	70	70	70	60	60	50	80	70	50	70

Table 4. System accuracy testing

KNN	Fold	Angle															
		0°				45°				90°				135°			
		T	F	%	Mean	T	F	%	Mean	T	F	%	Mean	T	F	%	Mean
	1	6	4	60		7	3	70		6	4	60		5	5	50	
	2	6	4	60		3	7	30		3	7	30		4	6	40	
	3	6	4	60		7	3	70		6	4	60		8	2	80	
	4	6	4	60		6	4	60		7	3	70		8	2	80	
1	5	6	4	60	72	5	5	50	63	4	6	40	64	6	4	60	66
	6	7	3	70		7	3	70		8	2	80		6	4	60	
	7	8	2	80		8	2	80		7	3	70		8	2	80	
	8	8	2	80		5	5	50		6	4	60		5	5	50	
	9	9	1	90		8	2	80		9	1	90		9	1	90	
	10	10	0	100		7	3	70		8	2	80		7	3	70	

KNN	Fold	Angle															
		0°				45°				90°				135°			
		T	F	%	Mean	T	F	%	Mean	T	F	%	Mean	T	F	%	Mean
5	1	6	4	60	68	4	6	40	65	5	5	50	62	5	5	50	63
	2	3	7	30		4	6	40		2	8	20		4	6	40	
	3	3	7	30		7	3	70		5	5	50		4	6	40	
	4	6	4	60		9	1	90		8	2	80		6	4	60	
	5	8	2	80		5	5	50		5	5	50		6	4	60	
	6	7	3	70		6	4	60		8	2	80		7	3	70	
	7	8	2	80		8	2	80		8	2	80		8	2	80	
	8	8	2	80		6	4	60		8	2	80		5	5	50	
	9	10	0	100		8	2	80		8	2	80		10	0	100	
	10	9	1	90		8	2	80		7	3	70		8	2	80	
7	1	6	4	60	67	6	4	60	65	*4*	*6*	*40*	60	5	5	50	62
	2	4	6	40		2	8	20		*2*	*8*	*20*		4	6	40	
	3	4	6	40		5	5	50		*5*	*5*	*50*		4	6	40	
	4	6	4	60		9	1	90		*7*	*3*	*70*		7	3	70	
	5	6	4	60		7	3	70		*5*	*5*	*50*		7	3	70	
	6	8	2	80		7	3	70		*8*	*2*	*80*		7	3	70	
	7	7	3	70		7	3	70		*8*	*2*	*80*		5	5	50	
	8	8	2	80		6	4	60		*5*	*5*	*50*		6	4	60	
	9	10	0	100		8	2	80		*8*	*2*	*80*		9	1	90	
	10	8	2	80		8	2	80		*8*	*2*	*80*		8	2	80	

The performance of the palm image recognition system using the GLCM method and KNN classification shows an average ($\dot{X}$) object identification accuracy of 72% with a sample data used as many as 100 images (90 training data and 10 test data).

CONCLUSION

The research concluded that the system implementation produced the highest accuracy of 72% using 0° angle in GLCM and k=1 and the lowest at 90° and k=7 in K-NN. The advantage of the designed system is that it can recognise the identity of the palm print owner in real time. Factors that affect the results of the grouping can be caused by unequal shooting distance, poor lighting, and the pre-processing stage, especially in the cropping process that is not optimal. Suggestions for further research development are to add more training data to improve accuracy, add feature extraction methods (e.g., shape or colour features), and add a pre-processing stage to improve recognition accuracy as well as reduce noise and adjust brightness.

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