



Touchless palm print recognition system design using Gray Level Co-occurrence Matrix feature with K-Nearest Neighbor classification in MATLAB

Agus Dendi Rochendi^{1,2}, Lukman Medriavin Silalahi^{2*}, Imelda Uli Vistalina Simanjuntak²

¹Research Center for Oceanographic Physic, Badan Riset dan Inovasi Nasional, Indonesia

²Department of Electrical Engineering, Faculty of Engineering, Universitas Mercu Buana, Indonesia

Abstract

This research designs a touchless fingerprint identification biometric system. This research problem stems from the user's need to change the conventional system to touchless in the hope of minimizing direct contact that can be scanned by someone who is not interested. This research aims to implement palm images in validating identity using GLCM (Gray-Level Co-occurrence Matrix) features with the K-Nearest Neighbours (K-NN) classification method in MATLAB. The identification process is divided into several stages: image acquisition, pre-processing, feature extraction with GLCM, and database matching using KNN classification. System testing uses the 10-fold cross validation method with 100 image samples (90 training images and 10 test images) that are tested in turn to calculate the average accuracy and analyze system performance. Furthermore, the test used GLCM angles (0°, 45°, 90° dan 135°) and K-NN with k values of 1, 5 and 7. The results showed the highest accuracy of 72% using an angle of 0° in GLCM and k=1 and the lowest at an angle of 90o and k=7 in K-NN. The advantage of this design is the recognition of the identity of the fingerprint owner in real time.

This is an open access article under the [CC BY-SA](#) license



Keywords:

Biometric;
Gray Level Co-occurrence Matrix;
K-Nearest Neighbor;
Palmprint Recognition;
Region of Interest;
Touchless;

Article History:

Received: September 6, 2023

Revised: December 2, 2023

Accepted: December 26, 2023

Published: June 2, 2024

Corresponding Author:

Lukman Medriavin Silalahi
Department of Electrical Engineering,
Faculty of Engineering, 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. Fingerprints are mostly used for employee attendance systems, mobile phone screen authentication, and identity cards [1, 2, 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 physical contact or called touchless to prevent the spread of the COVID-19 virus [4, 5, 6].

Like other biometric identifiers, the palm is believed to have critical properties, including

universality, uniqueness, and collectability. Using the human hand as an identifier, the molded 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 recognized as an effective and user-friendly biometric identifier for personal authentication [1, 7, 8].

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.

METHOD

Firstly, research conducted by [9] proposed the use of canny edge detection and GLCM (Gray Level Co-Occurrence Matrix) features. The pre-processing results are classified using K-Nearest Neighbours (KNN). 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, proposed a Region of Interest (RoI) 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 Support Vector Machine (SVM) classification, resulting in a recognition percentage of about 94.5% [10].

Third, research conducted by [11] 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 Euclidean Distance (ED). The recognition percentage is 94.33%, with minimum distance classification based on ED.

Fourth, based on the results of research conducted by [12], proposed a scheme to extract the RoI of palm images using Competitive Hand Valley Detection (CHVD) and ED techniques, then Local Binary Patterns (LBP) 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 [13, 14, 15] built a texture-based palm line image identification application using the Linear Discriminant Analysis (LDA) 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.

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

Equation (1) explains that a digital image is defined as a function $f(x,y)$, of M-rows and N-columns. The 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 and a two-dimensional function [16, 17, 18].

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.

Equation (2) is a channel value equation to indicate the colour internality at each pixel, from Red = Green = Blue, based on the derivative of (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, $N = 2^n$ and $G = 2^m$. N takes 256 or 512, grey G 64 to 256 for images, which can meet image processing needs. Equation (3) shows the number B as the number of bits required to store a digital image. R is the grey scale relationship of G: $G = 2^k$. When $M = N$ shown in (4).

Equations (1) to (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].

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

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

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

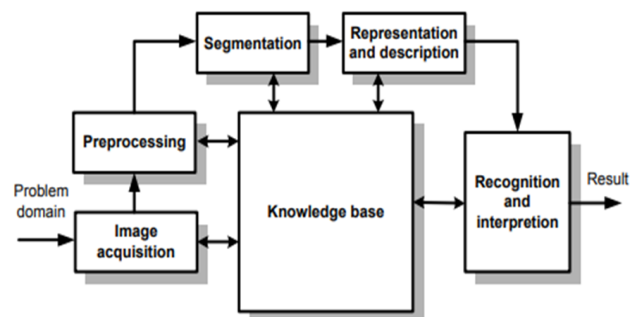


Figure 1. The steps of digital image processing

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 naturally or deform in other ways, such as rotation, stretching, and scale variability [21, 22, 23, 24]. Thus, RoI is an area localisation stage based on the classification and masking of a selected image part 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 in the same position to enable proper feature extraction.

$$d(H_1, H_2) = \frac{\sum_i (H_1(i) - \bar{H}_1)(H_2(i) - \bar{H}_2)}{\sqrt{\sum_i (H_1(i) - \bar{H}_1)^2 \sum_i (H_2(i) - \bar{H}_2)^2}} \quad (5)$$

$$\bar{H}_k = \frac{1}{N} \sum_j H_k(j)$$

Equation (5) is a comparison algorithm used to evaluate the similarity between two RoIs. Where H_i is the histogram RoI and N is the number of bins in the histogram. The range is 0-1 with higher correlation $d(H_1, H_2)$ 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. Conversely, a low image correlation score will be given if it cannot be extracted.

The next proposed palm texture feature extraction method is the GLCM algorithm [25]. 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 describes 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 the reference pixel and neighbour pixel based on the angle θ° to create a symmetric matrix. Finally, calculating GLCM features in four directions, namely 0° , 45° , 90° , and 135° [25, 26, 27, 28].

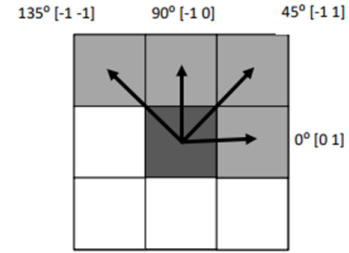


Figure 2. Illustration of GLCM angle direction

Once the co-occurrence matrix [29] is obtained, the image's characteristic features can be calculated. Several texture features 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 [31, 32].

1. Contrast is a measurement of light intensity from the degree of grey between neighbouring pixels shown in (6).

$$Contrast = \sum_i \sum_j (i - j)^2 C(i, j) \quad (6)$$

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 (7).

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

3. Energy is a measurement of texture uniformity. Energy will be high when the pixel values are similar to other pixels, as shown in (8).

$$Energy = C^2(i, j) \quad (8)$$

4. Homogeneity is a high-value texture when all pixels have the same value and is sensitive to the diagonal values shown in (9).

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

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 [33, 34, 35, 36] and GLCM texture features for feature extraction and MATLAB. Image matching based on the human palm matches the test image taken through the smartphone's IP camera directly with the training image 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, to obtain a more reliable identification and verification system.

The goal to be achieved is to implement a verifiable palm image for identity validation by utilizing GLCM features with the K-NN classification method with MATLAB software. Research results are utilized on topics in the Information and Communication Technology Field of Excellence.

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:

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. Where:

- 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 support from 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 their palm in the tool, to be re-taken by repeating the desired number of images (10 times).

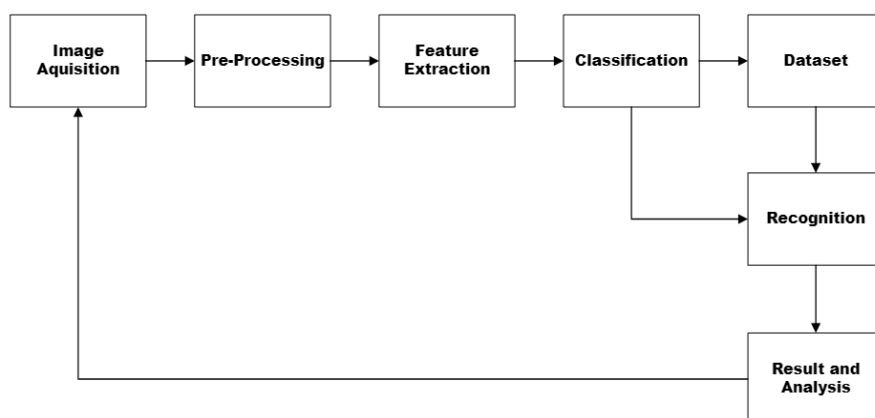


Figure 3. Illustration of GLCM angle direction

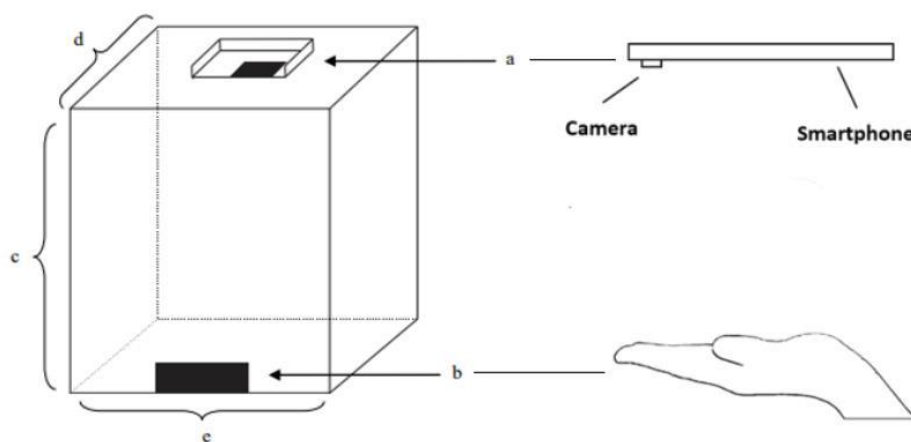


Figure 4. Illustration of GLCM angle direction

Pre-Processing

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

- Cropping. The cropping process is done to capture the important parts of the ROI with a size of 500 x 500 pixels.
- 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.
- Sharpening. Sharpening is intended to make the image sharper and clearer.
- Grayscale. The input image of the smartphone camera has an RGB color image composition.

Feature Extraction

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

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

Classification

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

between the test image and the existing training image.

Dataset and Recognition

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

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. 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

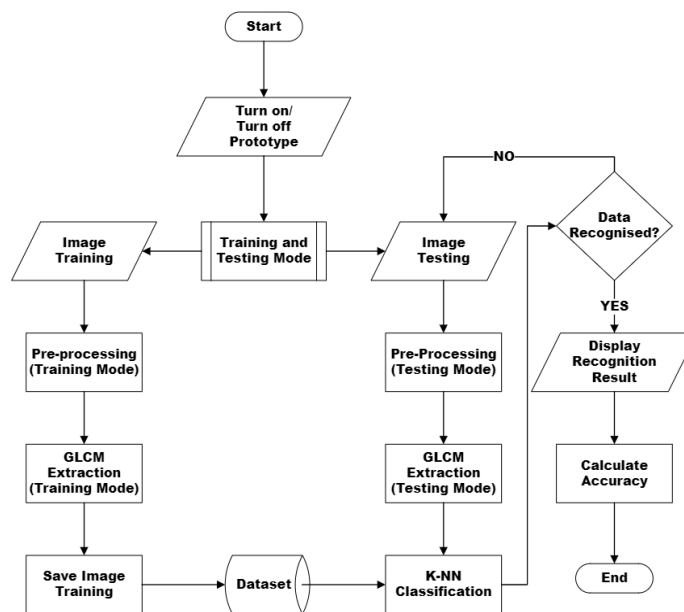


Figure 5. Flowchart system

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.

Training System Implementation Analysis

Implementing the training system produces pre-processing data on the acquired image, which is then stored in the training dataset. The Graphical Unit Interface (GUI) 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, gray scaling 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.



Figure 6. Prototype design result

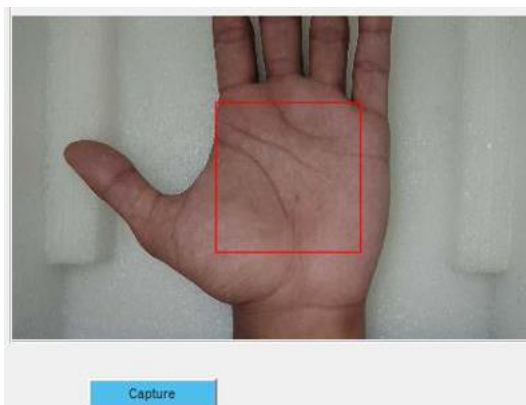


Figure 7. Image acquisition results

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 colors in the image data shown in Figure 10.

d. Gray scaling

Figure 11 shows the grayscale results used to characterize the image using GLCM.

Analysis System Implementation Testing

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

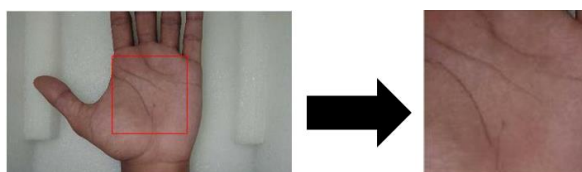


Figure 8. Proses cropping

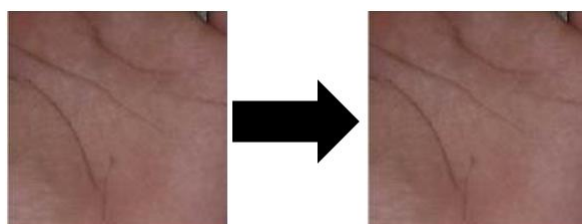


Figure 9. Proses resizing

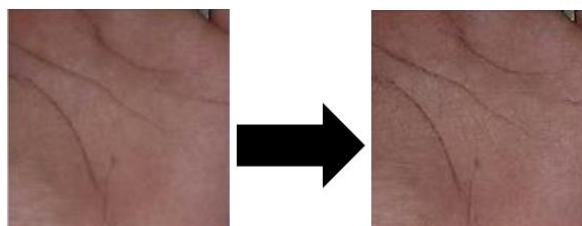


Figure 10. Proses sharpening

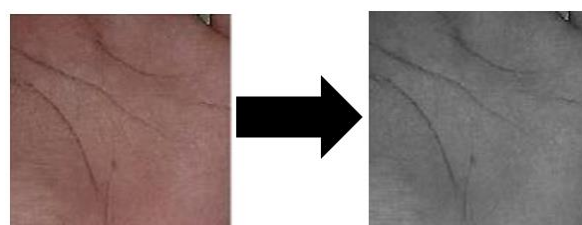


Figure 11. Proses grayscale

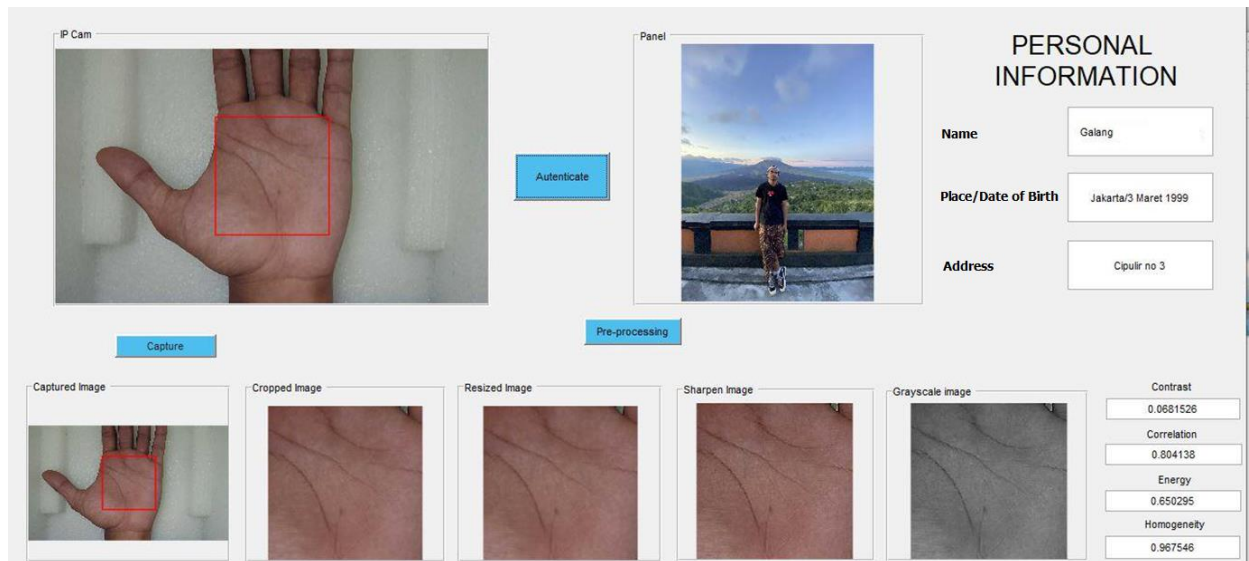


Figure 12. GUI page of the test system

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

- The capture button serves to take pictures connected via a Camera with a resolution of 1920x1080.
- The pre-processing button functions for cropping, resizing, sharpening and gray scaling.
- 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.

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.

The system testing stage is carried out using test data and training data. First is the system for palm owner identification. Second, the 10-fold CV method was used 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 ten iterations. The first fold test 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°.

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 accuracy percentage at angles 45°, 90° and 135°. The lowest percentage was given to user labelled three 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.

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

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

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	60	70	60	70	50	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°			
		T	F	%	Mean	T	F	%	Mean	T	F	%	Mean
1	1	6	4	60	72	7	3	70	63	6	4	60	64
	2	6	4	60		3	7	30		3	7	30	
	3	6	4	60		7	3	70		6	4	60	
	4	6	4	60		6	4	60		7	3	70	
	5	6	4	60		5	5	50		4	6	40	
	6	7	3	70		7	3	70		8	2	80	
	7	8	2	80		8	2	80		7	3	70	
	8	8	2	80		5	5	50		6	4	60	
	9	9	1	90		8	2	80		9	1	90	
	10	10	0	100		7	3	70		8	2	80	
5	1	6	4	60	68	4	6	40	65	5	5	50	62
	2	3	7	30		4	6	40		2	8	20	
	3	3	7	30		7	3	70		5	5	50	
	4	6	4	60		9	1	90		8	2	80	
	5	8	2	80		5	5	50		5	5	50	
	6	7	3	70		6	4	60		8	2	80	
	7	8	2	80		8	2	80		8	2	80	
	8	8	2	80		6	4	60		8	2	80	
	9	10	0	100		8	2	80		8	2	80	
	10	9	1	90		8	2	80		7	3	70	
7	1	6	4	60	67	6	4	60	65	4	6	40	60
	2	4	6	40		2	8	20		2	8	20	
	3	4	6	40		5	5	50		5	5	50	
	4	6	4	60		9	1	90		7	3	70	
	5	6	4	60		7	3	70		5	5	50	
	6	8	2	80		7	3	70		8	2	80	
	7	7	3	70		7	3	70		8	2	80	
	8	8	2	80		6	4	60		5	5	50	
	9	10	0	100		8	2	80		8	2	80	
	10	8	2	80		8	2	80		8	2	80	

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 when the cropping process is not optimal. Suggestions for further research are to add more training data to improve accuracy, add feature extraction methods, and add a pre-processing

stage to improve recognition accuracy, reduce noise, and adjust brightness.

ACKNOWLEDGMENT

I appreciate Universitas Mercu Buana for their invaluable support in fostering domestic collaborative research alongside Badan Riset dan Inovasi Nasional (BRIN). It is hoped that future research endeavors will continue to yield significant contributions.

REFERENCES

- [1] A. Genovese, V. Piuri, F. Scotti, and S. Vishwakarma, "Touchless Palmprint and Finger Texture Recognition: A Deep Learning

- Fusion Approach,” in *2019 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, Jun. 2019, pp. 1–6. doi: 10.1109/CIVEMSA45640.2019.9071620.
- [2] L. M. Silalahi, M. Ikhsan, S. Budiyo, I. U. Vistalina Simanjuntak, G. Osman, and A. D. Rochendi, “Designing a Thief Detection Prototype using Banana Pi M2+ Based Image Visual Capture Method and Email Notifications,” in *2022 5th International Conference of Computer and Informatics Engineering (IC2IE)*, 2022, pp. 293–296. doi: 10.1109/IC2IE56416.2022.9970065.
- [3] L. Mediavin Silalahi, I. Uli Vistalina Simanjuntak, F. Artadima Silaban, S. Budiyo, Heryanto, and M. Ikhsan, “Integration of opencv raspberry pi 3b+ and camera sensor in access control of vehicle ignition key system,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 909, no. 1, p. 12002, 2020, doi: 10.1088/1757-899x/909/1/012002.
- [4] Y. J. Chin et al., “Integrated biometrics template protection technique based on fingerprint and palmprint feature-level fusion,” *Inf. Fusion*, vol. 18, pp. 161–174, 2014, doi: 10.1016/j.inffus.2013.09.001.
- [5] L. M. Silalahi, S. Budiyo, I. U. V. Simanjuntak, F. A. Silaban, A. D. Rochendi, and W. A. Karimah, “Real-Time Examination System for New Students at Pandemic Time Covid 19 Using Fuzzy Logic,” *10th IEEE Int. Conf. Commun. Networks Satell. Comnetsat 2021 - Proc.*, pp. 219–224, 2021, doi: 10.1109/COMNETSAT53002.2021.9530832.
- [6] F. A. Mahaputra, I. U. V. Simanjuntak, Yuliza, Heryanto, A. D. Rochendi, and L. M. Silalahi, “Comparative Study Of Convolutional Neural Network And Haar Cascade Performance On Mask Detection Systems Using Matlab,” in *2022 9th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, Oct. 2022, pp. 74–78. doi: 10.23919/EECSI56542.2022.9946467.
- [7] L. J. Alwan and H. A. Alani, “Region of Interest Extraction of Palm Vein Image,” *International Journal of Scientific & Engineering Research*, vol. 7, no. 12, pp. 850–854, 2016.
- [8] R. Lionnie, C. Apriono, and D. Gunawan, “Face Mask Recognition with Realistic Fabric Face Mask Data Set: A Combination Using Surface Curvature and GLCM,” in *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, Apr. 2021, pp. 1–6. doi: 10.1109/IEMTRONICS52119.2021.9422532.
- [9] R. Utari et al., “Palm Print Recognition Using CANNY Edge Detection, Gray Level Co-Occurrence Matrix and Classified Using K-Nearest Neighbor,” in *Proceeding International Conference on Science (ICST)*, 2020, pp. 291–303.
- [10] S. Agarwal, P. K. Verma, and M. A. Khan, “An optimized palm print recognition approach using Gabor filter,” in *2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Jul. 2017, pp. 1–4. doi: 10.1109/ICCCNT.2017.8203919.
- [11] H. Heidari and A. Chalechale, “Biometric authentication using a deep learning approach based on different level fusion of finger knuckle print and fingernail,” *Expert Syst. Appl.*, vol. 191, p. 116278, 2022, doi: 10.1016/j.eswa.2021.116278.
- [12] M. M. H. Ali, A. T. Gaikwad, and P. Yannawar, “An Approach to Improve Palmprint Recognition Accuracy by using Different Region of Interest Methods with Local Binary Pattern Technique,” *Indian J. Sci. Technol.*, vol. 11, no. 22, 2018, doi: 10.17485/ijst/2018/v11i20/122752.
- [13] M. A. Khadija and W. Nurharjadmo, “Enhancing Indonesian customer complaint analysis: LDA topic modelling with BERT embeddings,” *SINERGI*, vol. 28, no. 1, pp. 153–162, 2024, doi: 10.22441/sinergi.2024.1.015.
- [14] Y. E. Wella et al., “Service quality dealer identification: the optimization of K-Means clustering,” *SINERGI*, vol. 27, no. 3, pp. 433–442, 2023, doi: 10.22441/sinergi.2023.3.014.
- [15] B. Pradinta, E. Ernawati, and E. P. Purwandari, “Identifikasi Citra Garis Telapak Tangan Menggunakan Metode Linear Discriminant Analysis Dengan Probabilitas Naïve Bayesian,” *Pseudocode*, vol. 4, no. 2, pp. 156–167, 2017, doi: 10.33369/pseudocode.4.2.156-167.
- [16] M. Cai, S. Wang, and C. Wu, “Research on real-time data transmission and multi-scale video image decomposition of embedded optical sensor array based on machine learning,” *Multimed. Tools Appl.*, vol. 81, no. 29, pp. 41407–41427, 2022, doi: 10.1007/s11042-020-09847-w.
- [17] A. V. Parfiryev, A. V. Dushkin, A. S. Dubrovin, and L. V. Stepanov, “Control of unmanned aerial vehicles based on the detection algorithm,” *J. Phys. Conf. Ser.*, vol. 1202, no. 1, p. 12014, Apr. 2019, doi: 10.1088/1742-6596/1202/1/012014.
- [18] J. Khandelwal et al., “DWT-SVD Based Image Steganography Using Threshold Value

- Encryption Method," *Comput. Mater. & Contin.*, vol. 72, no. 2, pp. 3299–3312, 2022, doi: 10.32604/cmc.2022.023116.
- [19] S. Zhao and B. Zhang, "Robust and adaptive algorithm for hyperspectral palmprint region of interest extraction," *IET Biometrics*, vol. 8, no. 6, pp. 391–400, 2019, doi: 10.1049/iet-bmt.2018.5051.
- [20] H. Wasmi, M. Al-Rifaei, A. Thunibat, and B. Al-Mahadeen, "Comparison between proposed Convolutional Neural Network and KNN For Finger Vein and Palm Print," in *2021 International Conference on Information Technology (ICIT)*, Jul. 2021, pp. 946–951. doi: 10.1109/ICIT52682.2021.9491737.
- [21] S. Prasad and T. Chai, "Palmprint for Individual's Personality Behavior Analysis," *The Computer Journal*, vol. 65, no. 2, pp. 355–370, 2020, doi: 10.1093/comjnl/bxaa045.
- [22] S. Zhao, L. Fei, and J. Wen, "Multiview-Learning-Based Generic Palmprint Recognition: A Literature Review," *Mathematics*, vol. 11, no. 5, 2023, doi: 10.3390/math11051261.
- [23] V. Sujitha and D. Chitra, "Highly secure palmprint based biometric template using fuzzy vault," *Concurr. Comput. Pract. Exp.*, vol. 31, no. 12, p. e4513, 2019, doi: <https://doi.org/10.1002/cpe.4513>.
- [24] N. A. A. Khalid et al., "Palmprint ROI Cropping Based on Enhanced Correlation Coefficient Maximisation Algorithm," in *2021 IEEE 11th International Conference on System Engineering and Technology (ICSET)*, Nov. 2021, pp. 269–274. doi: 10.1109/ICSET53708.2021.9612436.
- [25] F. D. Aferi, T. W. Purboyo, and R. E. Saputra, "Cotton texture segmentation based on image texture analysis using gray level co-occurrence matrix (GLCM) and Euclidean distance," *Int. J. Appl. Eng. Res.*, vol. 13, no. 1, pp. 449–455, 2018.
- [26] R. P. A. Pramesti et al., "Morphological and textural feature extractions from fungi images for development of automated morphology-based fungi identification system," *J. Bioteknologi Biosains Indonesia*, vol. 9, no. 2, pp. 227–236, 2022, doi: 10.29122/jbbi.v9i2.5512.
- [27] Y. Jusman, J. H. Lubis, S. N. A. M. Kanafiah, and M. I. Yusof, "Comparison of spine curvature images classification using support vector machine and K-nearest neighbors," *AIP Conf. Proc.*, vol. 2499, no. 1, p. 80001, 2022, doi: 10.1063/5.0105008.
- [28] A. Rachmad et al., "Classification of Tobacco Leaf Quality Using Feature Extraction of Gray Level Co-occurrence Matrix (GLCM) and K-Nearest Neighbor (K-NN)," in *Proceedings of the 1st International Conference on Neural Networks and Machine Learning 2022 (ICONNSMAL 2022)*, Atlantis Press, 2023, pp. 30–38. doi: 10.2991/978-94-6463-174-6_4.
- [29] P. Akhoundzadeh, H. Ebrahimnezhad, and G. Mirjalily, "Palm Print Recognition using Modified Local Features based on Sparse Classifier," in *2019 27th Iranian Conference on Electrical Engineering (ICEE)*, Apr. 2019, pp. 1429–1433. doi: 10.1109/IranianCEE.2019.8786708.
- [30] D. Zhao et al., "An Exploration of Architectural Design Factors with a Consideration of Natural Aspects Based on Web Crawling and Text Mining," *Mathematics*, vol. 10, no. 23, 2022, doi: 10.3390/math10234407.
- [31] C. A. Nurbani et al., "Measurement of Cholesterol Levels through Eye based on Co-Occurrence Matrix on Android," in *2019 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob)*, Nov. 2019, pp. 88–93. doi: 10.1109/APWiMob48441.2019.8964165.
- [32] K. Evandari, M. A. Soeleman, and R. A. Pramunendar, "BPNN Optimization With Genetic Algorithm For Classification of Tobacco Leaves With GLCM Extraction Features," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 7, no. 2 SE-Information Technology Articles, Mar. 2023, doi: 10.29207/resti.v7i2.4743.
- [33] T. Kadarina, Z. Iklima, R. Priambodo, R. Riandini, and R. Wardhani, "Dental caries classification using depthwise separable convolutional neural network for teledentistry system," *Bull. Electr. Eng. Informatics*, vol. 12, no. 2, pp. 940–949, 2023, doi: 10.11591/eei.v12i2.4428.
- [34] Y. Tian et al., "A Real-Time and Fast LiDAR-IMU-GNSS SLAM System with Point Cloud Semantic Graph Descriptor Loop-Closure Detection," *Adv. Intell. Syst.*, vol. n/a, no. n/a, p. 2300138, doi: 10.1002/aisy.202300138.
- [35] S. Susanto et al., "Effective and efficient approach in IoT Botnet detection," *SINERGI*, vol. 28, no. 1, pp. 31–42, 2024, doi: 10.22441/sinergi.2024.1.004
- [36] A. R. Faizabadi et al., "Learning a Multimodal 3D Face Embedding for Robust RGBD Face Recognition," *Journal of Integrated and Advanced Engineering (JIAE)*, vol. 3, no. 1, pp. 37–46, 2023, doi: 10.51662/jiae.v3i1.84