Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 3, No. 2, September 2020, pp. 71 – 77
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Local Binary Pattern and Learning Vector Quantization for Classification of Principal Line of Palm-Hand

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Article Info
Article history:
Received Jul 06th, 2020
Revised Aug 10th, 2020
Accepted Aug 14th, 2020

Keyword:
Classification
LVQ
LBP
ROI
Palm-hand

ABSTRACT
Biometrics such as DNA, face, fingerprints, and iris still have disadvantages. The principal line of palm-hand biometric is expected to cover the weakness of the other biometrics. This research uses a dataset that amounted to 150 images of palms-hand of the left-hand side. The dataset sourced from 15 people; each was captured ten times. The cropping process uses the Region of Interest (ROI) Method. The Local Binary Pattern (LBP) is used in the feature extraction. The feature extraction process utilizes five statistical parameters. They include Mean, Variance, Skewness, Kurtosis, and Entropy. The Learning Vector Quantization (LVQ) is used to train the model to produce optimal weights. The Confusion matrix is used to evaluate the accuracy of the classification task. The experiment in this study used the learning rates of 0.01, 0.05, 0.1, 0.5, and 0.7. Based on the testing and the experimental results, the highest accuracy was obtained by the use of learning rate valued 0.5, achieving 80% of accuracy. In future work, we can explore with added the second-order statistics feature for better results.

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DOI: http://dx.doi.org/10.24014/ijaidm.v3i2.10236

1. INTRODUCTION

Self-identification is used to identify a person based on the characteristics or unique identities owned by the correspond person. There are three approaches in self-identification, namely possession-based, knowledge-based, and biometrics-based [1]. The disadvantages of the first and second approach methods are easy to steal, easy to share, and sometimes ignored information. On the other hand, the biometrics based has a more vital ability and a more permanent relationship between a person and his/her identity. To avoid the above mentioned deficiencies, a third approach method is a biometric [2].

Although biometrics is preferred as a self-identification tool, there are still some weaknesses in each of these physiological features. The disadvantages [3] include:

1. DNA, even though everyone has unique DNA, there are some exceptions for identically twins, it has a very complex verification process, and it is easy to lose the information.
2. The face shape that can change by the age.
3. Fingerprints, problems occur when the hands are wet, dirty, and there is residual pressure of the palm that remains on the sensor.
4. Iris, iris must be supported by a high quality input; if not, there might be an output error.

Based on these problems, a study of physiological characteristics is carried out to minimize these weaknesses. The physiological characteristics to be studied are the principal of palm-hand. The advantage is that the line characteristics can be obtained from low-resolution imagery, difficult to disguise, permanent, wider surface area compared to the fingerprints, and the patterns that will not change when the age increases [4]. The first publication about the application of palm biometric recognition was in 1998 [1] about fractal dimensions and degree of fractal to recognize palm characteristics.

The palm-hand has unique characteristics that promise to be an input of pattern recognition for the self-identification system. These unique characteristics include geometric features (length, width, and area of the palm), major lines (heart line, headline, and lifeline), features of tangled or weak lines, delta point characteristics, and traits [1]. The existence of palm-hand biometrics is expected to overcome various previously encountered in a biometrics system.

This study aims to measure the accuracy of the application of Region of Interest (ROI), Local Binary Pattern (LBP), and Learning Vector Quantization (LVQ) for classifying the principal line of palm-hand. The dataset used is self-collected. LBP is used as a feature extraction technique, and LVQ is used as a classification method. The features used are statistical characteristics. The parameters of the statistical characteristics used are Mean, Variance, Skewness, Kurtosis, and Entropy. LBP has essential properties for palmprint recognition[5]. The palmprint concept and the Principal Line of Palm-Hand are not much different, so this study uses LBP as a feature extraction method. LVQ is used as a classification algorithm because it has an excellent performance in terms of stability, asymptotic generalistic abilities, and it can be used in various cases[6]. It can also be used in other studies to solve classification problems[7]. The contribution of this research is the use of ROI to capture essential areas of the palm-hands.

2. RESEARCH METHOD

The steps taken in this research included preprocessing, feature extraction, classification, testing, and evaluation, as shown in Figure 1.

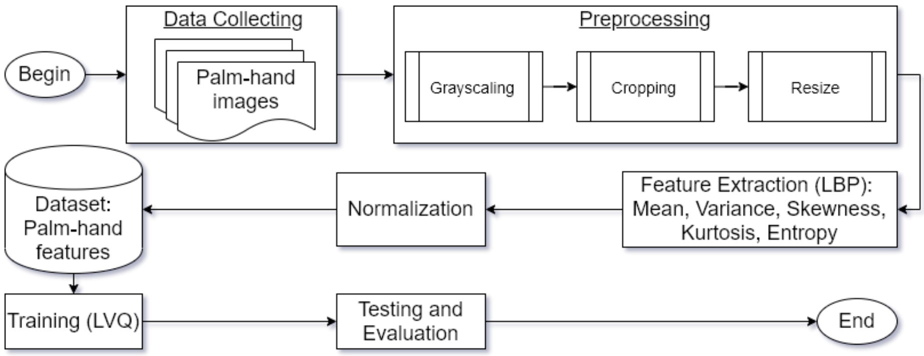


Figure 1. The research methodology of palm-hand classification in this self-identification study

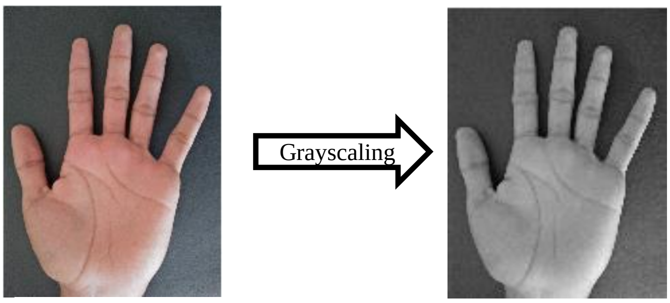
TABLE I. *Data Collection*

The dataset sourced from 15 participants. Each was captured ten times to obtain the total of 150 images. The palm used is on the left-hand side, and captured in a dark background.

TABLE II. *Preprocessing*

The techniques used in the preprocessing stages are grayscaling, cropping using ROI, and resizing.

a. *Grayscaling.* A palm-hand image consisting of Red, Green, and Blue (RGB) colors will be converted to a grayscale image, described in Figure 2.



(a) Original image (b) Grayscale image

Figure 2. Grayscaling

b. *Cropping.* The process of determining the ROI based on the centroid point. The process is the binary image, median filtering, and determining centroid. The equation used to get the centroid point as in formulas 1 and 2 [8].

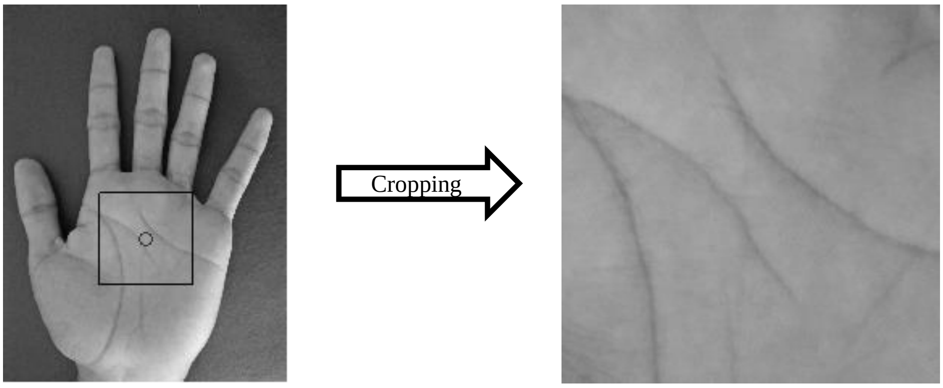
$$\bar{x} = \frac{1}{|R|} \sum_{(u,v) \in R} u \tag{1}$$

$$\bar{y} = \frac{1}{|R|} \sum_{(u,v) \in R} v \tag{2}$$

Where,

$\bar{x}$: mean of x (centroid of x coordinates)
$\bar{y}$: mean of y (centroid of y coordinates)
R : number of pixels
u : x coordinate point
v : y coordinate point

Cropping is used to take the principal line of palm-hand. The cropping area of the image based on the ROI process. Figure 3 illustrates the cropping process.



(a) ROI (b) Cropped image

Figure 3. (a) ROI, (b) Cropped image

c. *Resize.* This stage changes the size of each palm-hand image to 300 x 300 pixels to reduce computation time.

TABLE III. ***Feature Extraction***

The LBP is used as the feature extraction method. Each pixel block is given a threshold by the middle pixel, where if the middle pixel is higher than the neighbor pixel, then worth one, and if it is smaller than the neighbor pixel, then worth zero. The equation used to determine the threshold is equation 3 [9].

$$LBP_{R,N}(x,y) = \sum_{i=0}^{N-1} s(n_i - n_c)2^i, s(x) = \begin{cases} 1, x \geq 0 \\ 0, otherwise \end{cases} \tag{3}$$

Where n_c is the gray level of the center pixel of a local neighborhood. n_i is the gray levels of N equally spaced pixels on a circle of radius R. If $(n_i - n_c \geq 0)$ then $s(n_i - n_c) = 1$, and if $(n_i - n_c < 0)$ then $s(n_i - n_c) = 0$.

After each pixel value is changed to the LBP pixel value, the next is to find the statistical feature extraction value. The result of LBP processing is the new LBP pixel value collected into the matrix. After obtaining the LBP matrix, determine the value of the five parameters. They are Mean, Variance, Skewness, Kurtosis, Entropy [10].

a. *Mean* $(\mu) = \sum_n f_n p(f_n)$ (4)

b. *Variance* $(\sigma^2) = \sum_n (f_n - \mu)^2 p(f_n)$ (5)

c. *Skewness* $(\alpha_3) = \frac{1}{\sigma^3} \sum_n (f_n - \mu)^3 p(f_n)$ (6)

d. *Kurtosis* $(\alpha_4) = \frac{1}{\sigma^4} \sum_n (f_n - \mu)^4 p(f_n) - 3$ (7)

e. *Entropy* (H) $= -\sum_n p(f_n)\ .\ {}^2\log p(f_n)$ (8)

Where,

f_n : the intensity of gray

$p(f_n)$: histogram

TABLE IV. ***Normalization***

The results of feature extraction are then normalized using the following equation 9 [11]. All normalized data is used as a dataset because the parameter values have different ranges. The dataset is divided into 80% training set and 20% testing set.

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{9}$$

Where X is the dataset before normalized, and X* is the normalized dataset.

TABLE V. ***Training***

The following is the learning algorithm in the LVQ method [12][13][14].

1. Initialize vectors (x), learning rate (α), and weight (m), and the number of iterations
2. Checking stop condition, if false then do step 3 – 7
3. For each training input vector *x*, do steps 4 – 5
4. Find Euclidean Distance (*J*) so that $\|x - m_t\|$ is minimum
5. Update m_{t+1} as follows:

   IF *x* is classified correctly, THEN
   $m_{t+1} = m_t + \alpha_t[x_t - m_t]$
   ELSE
   $m_{t+1} = m_t - \alpha_t[x_t - m_t]$

6. Reduce α
7. Test stopping condition. The stop condition can be determined based on the number of iterations or the learning rate that has reached a minimum value.

TABLE VI. ***Testing and Evaluation***

For the testing and evaluation, the experiment was executed using various learning rates of the LVQ algorithm. The accuracy calculations are performed at each learning rate using the confusion matrix [15], as shown in Figure 4. It was conducted to evaluate the model.

Classification		Predicted Class	
		Class = YES	Class = NO
Observed Class	Class = YES	True Positive (TP)	False Negative (FN)
	Class = NO	False Positive (FP)	True Negative (TN)

Figure 4. Confussion Matrix [15]

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

3. RESULTS AND ANALYSIS

Figure 5 shows some palm-hand samples used in this research. Each image represents one person. All images of the dataset are converted to grayscale. The images are cropped based on the result points from the ROI calculation. ROI is essential to automate the cropping process. The cropping results are shown in Figure 6.

Figure 5. Sample of palm-hand image dataset

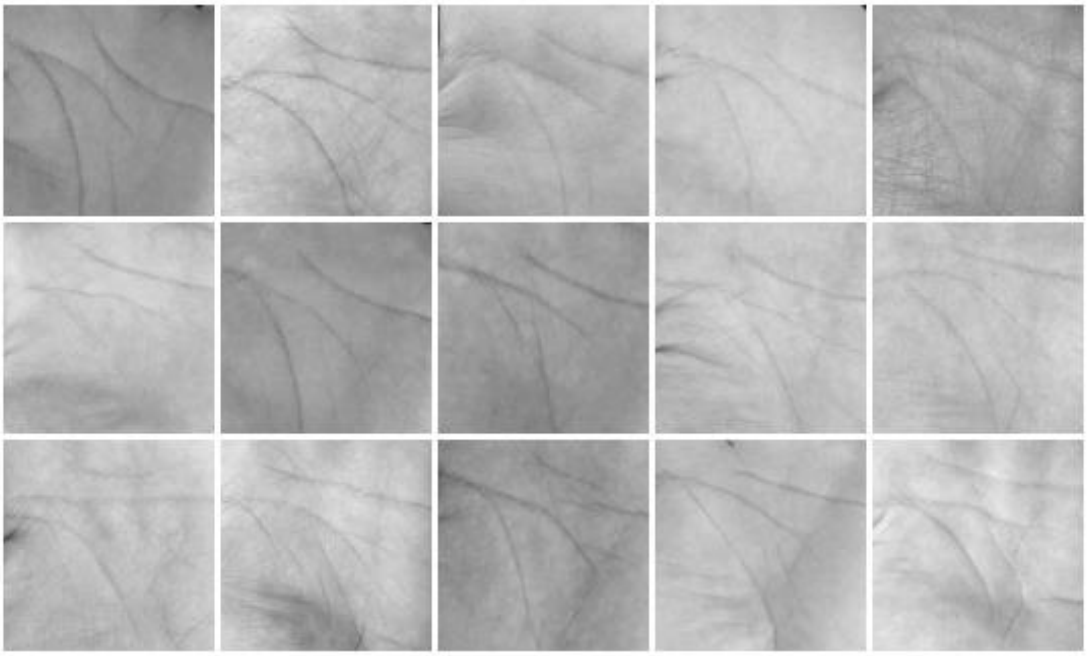


Figure 6. Sample of palm-hand image dataset after grayscaling, cropping, and resizing

The feature extraction process is carried out on all the data. All results of feature extraction are normalized.

Table 1. Dataset before normalize

No	Mean	Variance	Skewness	Kurtosis	Entropy	Target (T)
1.	102.7620	8582.9300	4.5404e-07	2.1211e-08	6.6241	1
2.	109.6950	8007.4100	3.2282e-07	2.4908e-08	6.5969	2
3.	101.7360	8307.8700	4.9239e-07	2.4003e-08	6.6031	3
4.	86.3619	7847.3400	9.2032e-07	3.1321e-08	6.2689	4
…	…	…	…	…	…	…
150.	113.1210	8597.1500	2.1522e-07	2.0004e-08	6.6955	15

Table 1 shows the dataset as the result of feature extraction. Each parameter must be normalized to uniform the range of values. The result of the normalized dataset is described in Table 2.

Table 2. Normalized dataset

No	Mean	Variance	Skewness	Kurtosis	Entropy	Target (T)
1.	0.4814	0.7005	0.4297	0.2354	0.6149	1
2.	0.6849	0.2562	0.2744	0.4748	0.5678	2
3.	0.4513	0.4882	0.4751	0.4162	0.5787	3
4.	0	0.1327	0.9817	0.8902	0	4
…	…	…	…	…	…	…
150.	0.811	0.7984	0.1303	0.1094	0.7614	15

The training set used is 80%, and the testing sets are 20% of the normalized dataset. The training set is used as an input vector on LVQ. The training process using LVQ requires an input vector of the five parameter values from the LBP calculation. The testing set is used in the testing process. All test results are calculated using a confusion matrix to measure accuracy, as shown in Figure 7.

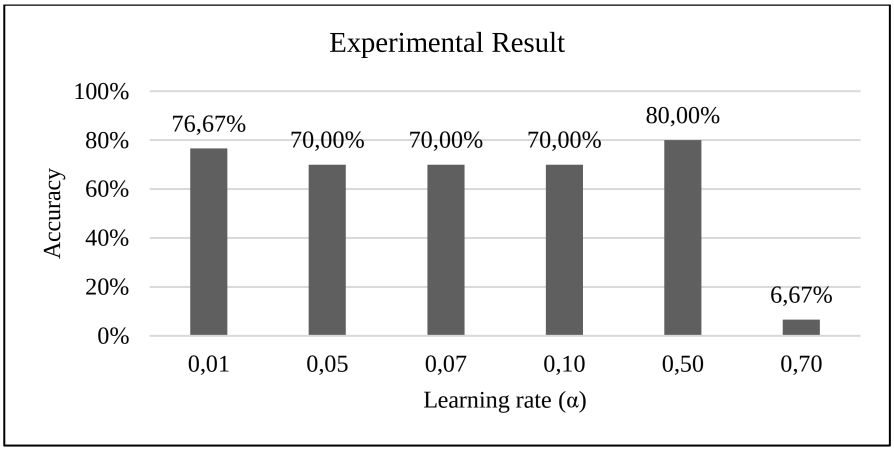


Figure 7. Experimental result

Figure 7 shows that the experimental results with various learning rate values are 0.01; 0.05; 0.1; 0.5; and 0.7 shows the results of variations accuracy. The highest accuracy reached 80% in the use of learning rate 0.5, and the lowest accuracy reached 6.67% in the learning rate 0.7. Based on the experimental results, in this case, it is better to use a learning rate below 0.5, because it produces relatively high accuracy.

4. CONCLUSION

Based on the experimental result on several learning rate values, it shows that the highest accuracy reaches 80% in the principal line of palm-hand image classification using LBP and LVQ. Some misclassification is because some main path images are not visible, so it is advisable to use another tool to produce clear main lines. This research can continue by testing several parts to improve accuracy, such as added second-order statistic features.

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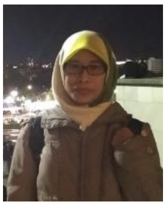

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