

LOCAL BINARY PATTERN METHOD AND FEATURE SHAPE EXTRACTION FOR DETECTING BUTTERFLY IMAGE

*Dhian Satria Yudha Kartika¹, Darlis Herumurti², Anny Yuniarti³

¹Department of Information System, Faculty of Computer Science, Universitas Pembangunan Nasional “Veteran” Jawa Timur, Surabaya 60284, Indonesia

^{1,2,3}Department of Informatics Engineering, Faculty of Information Technology, Institut Teknologi Sepuluh Nopember (ITS), ITS Sukolilo, Surabaya 60111, Indonesia

*Corresponding Author, Received: 18 Dec. 2017, Revised: 28 March 2018, Accepted: 28 April 2018

ABSTRACT: Research in the field of information retrieval especially on image processing is proliferating. Various methods are developed to be able to detect images optimally and produce better accuracy. The process of image detection can use the dataset that exists around us. In this research, we use butterflies dataset, since the butterfly has unique colors, patterns, and diverse shapes. Therefore, we use local binary pattern method for texture feature extraction and region props for shape feature extraction. The results of each texture feature extraction and shape feature extraction will be a merging process. The results of the merging process get an accuracy of 66%. In addition, the system testing process with confusion matrix will produce 67.1% precision value, 66% recall and f-measure of 66.5%. The merging process of both methods shows the interplay of texture and shape extraction.

Keywords: *Local Binary Pattern, Image Processing, Classification, Butterfly Image, Feature Extraction*

1. INTRODUCTION

The development of research in the field of the image is directly proportional to the number of methods developed in the study. Research in the field of the image is widely used in various areas, for example, facial recognition using ESLGS (Extended Symmetric Local Graph Structure) method is an improvement over the previous method of SLGS [1]. Face recognition accuracy using the ESLGS method obtained an accuracy of 84.24%, compared with the previous method of SLGS of 80.59%. The advantage of the proposed method is to provide better performance in the accuracy and complexity of other operators. Another field of imagery research is the detection of tuna based on textures and shapes using gray level co-occurrence matrix (GLCM) [2]. This method adds geometric feature extraction of the region of interest (ROI).

The results are shown in the merger between the GLCM and ROI methods to obtain an accuracy value of 86.67% [2]. Several methods and related research in the field of other images include the identification of butterfly species automatically using local binary pattern (LBP) method to detect the texture characteristics on the wing and then classified using the artificial neural network (ANN) [3]. In the study, Kaya divide 50 datasets of butterfly species are grouped into five species. The unknown feature extraction process positioning on the butterfly wing is calculated for

LBP matrix. The process is to show the grayscale color distribution on the butterfly wings. The method in this study divided and compared the butterfly wings into 64 sub-blocks for feature extraction [3].

Research conducted by Kaya still uses one feature extraction. The texture feature extraction results will be better when added other feature extraction, e.g., color, and shape. The purpose of Kaya research is to increase the accuracy value in the classification process up to 98% [3]. Some of the earlier Kaya studies used several methods to detect and classify butterfly imagery entitled a computer vision system for the automatic identification of butterfly species via the Gabor-filter-based texture feature and extreme learning machine: GF + ELM [4].

In the research mentioned classification process using the conventional method by giving chemical substance to the dataset, the process needs a long time and expensive cost. So an alternative method is needed using Gabor Filter (GF) and Extreme Learning Machine (ELM). GF method used for texture detection on the image because it optimally detects spatial domains (pixel manipulation process of an image to generate a new image) and frequency.

Based on these studies [4] get 97% accuracy. Kayci and Kaya also conducted the study [3] using Gray-level co-occurrence matrix (GLCM) for automatic identification of butterfly images with an accuracy of 93.2% [5]. The related studies of

butterfly imagery were also performed using GLCM and LBP. Both methods compared the results and got 98.25% accuracy for GLCM and 96.45% for LBP [6]. Although the results of the previous study showed LBP was slightly lower than other methods, LBP was introduced to describe images well and widely used in computer vision, image processing and image retrieval of images, remote sensing and biomedical image analysis [7]. The advantage of using the LBP operator is its tolerance to changes in illumination, the lightweight computation that makes it possible to analyze images in real-time. [8].

In other research related to pattern and image that is pattern identification using algorithm based on digital correlation (signal) and image processing in Humera and Samina research [15]. Describes the process of merging between signals, images, and video based on correlation functions, variant differences, algorithms and math. In this research successfully applied in signal, audio, image, and video so that can be implemented in many patterns to detect the object.

In other studies related to feature color extraction, performed by Kartika using HSV color space method. The study used koi fish dataset which will be classified. In this study mentioned the basic components commonly used for research in the field of the image among other features of color, shape, and texture [9]. In Satria research related classification based on color in koi fish get an accuracy value of 97.92%. In classification testing using tools weka. The color feature extraction process is to convert the color from RGB to HSV color space then perform the process of color computing into color quantization. The purpose of inclusion of color feature extraction results in color quantization is to reduce the color feature extraction results. It aims to speed up the computation process to make it faster [10]. In related research, Yousef conducted a test on color feature extraction using only Hue values only and comparing when using Hue, Saturation, Value simultaneously. The resulting Saturation and Value values provide an increase in dimension values and add more information about images [11].

Therefore, this research proposes combining the result of color feature extraction using Color Quantization in HSV color space with the result of texture feature extraction using Local Binary Pattern. The results of the merging of the two feature extraction results will be calculated the value of its accuracy using the Support Vector Machine (SVM) method. The result of the merger of extraction results other than the calculated value of accuracy will perform performance analysis using confusion matrix. In the performance

analysis will be calculated the value of precision, recall, and f-measure.

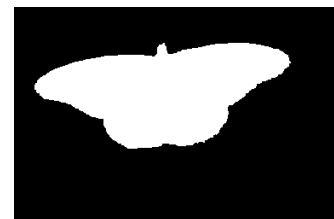
2. MATERIALS

In this study used a dataset previously used in Wang's research [12] in his study entitled Learning Models for Object Recognition from Natural Language Descriptions. At this stage the process of collecting and analyzing data to be used as a dataset. The data used in this study is a picture of butterflies as much as 890 images with JPEG and PNG format. Dataset image capture process varies, from the top, front, rear, right or left side. A total of 890 datasets are divided into ten classes: *Danaus plexippus*, *Heliconius charitonius*, *Heliconius erato*, *Junonia coenia*, *Lycaena phlaeas*, *Nymphalis antiopa*, *Papilio cresphontes*, *Pieris rapae*, *Vanessa atalanta*, and *Vanessa cardui*.

Figure 1 describes the stages of preprocessing data until the data is ready to perform the feature extraction process of color and texture feature extraction. The image represents 890 images used as datasets and the entire data will be processed as in Figure 1. Figure 1a shows the original image used as the dataset. Figure 1b is a mask of previous research [12], which is used for cropping data to obtain Fig. 1c. Figure 1c is an image after the noise is removed and ready for feature extraction.



(a) original dataset



(b) mask dataset



(c) noise removed

Fig. 1 Preprocessing

In the extraction process, the essential feature component is the color in the image, which will be converted into binary numbers. Furthermore, the feature of texture or pattern of each butterfly is also extracted. The butterfly has a unique texture and the pattern of each class is different and has its uniqueness. And the entire feature extraction process will be converted into binary numbers. Each more detailed extraction process will be explained at the next point.

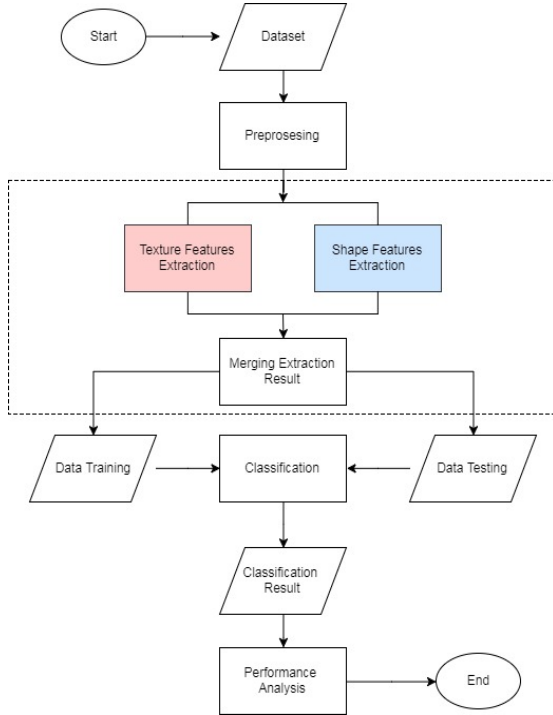


Fig 2. Research Methodology

3. METHOD

The method used in this study as shown in figure 2 Methodology Research states that the dataset that has been prepared in the research will be done preprocessing aimed at removing noise before the color feature extraction and texture feature extraction. Noise on the butterfly dataset is related backgrounds in the form of twigs or leaves and flowers where the butterfly settles. After the noise on the image is removed, then it is normalized to the dataset, i.e. resizing the image and it is necessary the output data has the same size [9]. In our case, all image sizes on the dataset will be normalized to the same size, which is 420x315 pixels.

After all the image is done normalization process, then extraction of color feature and texture feature extraction. The extraction results of each feature will be combined for the classification process. Before the classification process is done, the dataset will be divided into training data and

data testing. Data training is used to construct a classification model. After the classification model is formed then classification testing will be done to the previously separated data testing. The result of classification will show the accuracy value. Not enough to get the value of accuracy, the system already built will be tested performance. This performance test aims to assess the compatibility between the system developed with the results achieved. In this study, we use confusion matrix to analyze the performance.

3.1 Local Binary Pattern

LBP is a texture analysis method that uses statistical and structural models. LBP has the advantage that this method is invariant to the rotation (LBPROT), so it does not restrict the taking of images from multiple sources, e.g. the internet or taking objects directly. It is for this reason that the butterfly image research uses the LBPROT method.

$$LBP_{P,R} = \sum_{p=0}^{P-1} S(I_{p,R} - I_C) 2^{p-1-P} \quad (1)$$

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

P is the number of many neighbors, R is the radius between the center point and the neighboring point, $LBP_{P,R}$ is the decimal value that converts the binary value. I_C is the center pixel intensity value, $I_{p,R}$ is the pixel intensity value of the p-neighbor ($p = 0, 1, \dots, P-1$) with radius R. While $s(x)$ is the thresholding function [13]. The first LBP concept was introduced by Ojala [6] explaining that LBP is a great way to describe textures. In each pixel in the image, the binary code generated by the threshold value is equal to the pixel that is centered in the image [14].

The texture feature extraction process is a continuation of the preprocessing stage and the normalization of the data, where the image has been resized pixels subsequently converted to grayscale. The texture feature extraction process has been proposed, mentioning the extraction process using a local binary pattern (LBP) method that is invariant to rotation. The texture feature extraction process will be calculated based on the image's neighboring value from the center point. Among the number of neighbors 1, 2, 4, 8, 16, 32, 64, 128. So the resulting value on texture feature extraction as much as 256 bins (space) for texture features.

3.2 Region Props Property

Extraction of form features using Region Props. The Props Region is one of the functions in

Matlab, can be used to measure a set of properties of each region that has been labeled in the matrix. The positive integer is the element of the matrix corresponding to the corresponding region. In this research, the butterfly will be calculated including area, centroid, eccentricity, equivalent diameter, extent, major axis length, minor axis length, orientation, and perimeter.

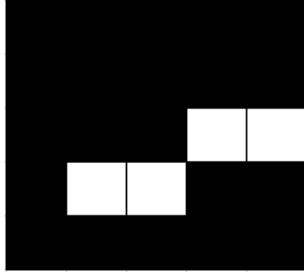


Fig. 3 Representation of the Region with an ellipse-shaped approach

In the Region Props function, an object is represented as a region with an ellipse approach. As shown in figure 3 shows a region of a set of white pixels represented by an ellipse-shaped approach. Figure 4 shows the major axis and minor axis as well as the white dot as the foci of the ellipse. The area property is defined as a scalar value of the actual number of pixels in the region. While the object-type approach features a ratio using the major axis length and minor axis length properties of the region props function. The major axis length and minor axis length properties are defined as a scalar value of the major axis length and minor axis length lengths of the elliptical

shape having the same second center moments and have been normalized.

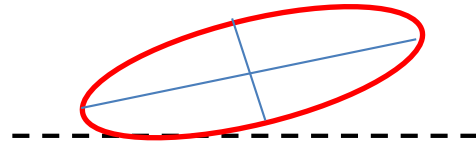


Fig. 4 Major axis length, minor axis length, and foci point on the ellipse

4. RESULT AND DISCUSSION

Based on the proposed methodology for feature texture extraction using Local Binary Pattern and feature extraction using region props method, then extraction process is done and get the following result.

4.1 Texture Extraction Features

The texture feature extraction results on the butterfly on table 1 below. The extraction process uses extraction method using binary pattern (LBP) method which is invariant to rotation. The texture feature extraction process is calculated by the number of neighbors 1, 2, 4, 8, 16, 32, 64, 128 from the center point. The resulting value on texture feature extraction is 256 bins (space) for texture features as in table 1.

Table 1. Texture Feature Extraction Result

Num	f1	...	f50	...	f100	...	f150	...	f200	...	f220	...	f256	Class
1	168	...	29	...	399	...	177	...	37	...	282	...	7	1
2	953	...	55	...	270	...	256	...	10	...	207	...	1	1
3	1117	...	65	...	839	...	335	...	11	...	159	...	4	1
4	874	...	87	...	894	...	304	...	2	...	159	...	9	1
...
100	2451	...	58	...	553	...	88	...	100	...	223	...	1372	2
101	6782	...	112	...	470	...	115	...	287	...	251	...	727	2
102	2837	...	25	...	329	...	174	...	1143	...	293	...	528	2
...
301	2374	...	20	...	222	...	127	...	575	...	531	...	761	4
302	6758	...	5	...	269	...	169	...	276	...	537	...	690	4
303	7251	...	9	...	485	...	94	...	523	...	221	...	4075	4
...
601	905	...	77	...	408	...	112	...	174	...	640	...	550	8
602	2397	...	63	...	552	...	76	...	195	...	127	...	393	8
603	8138	...	3	...	454	...	65	...	31	...	62	...	42	8
...
890	1263	...	11	...	417	...	113	...	54	...	340	...	10	10

Table 2. The result of Feature Shape Extraction

Num	Area	Perimeter	Ecc	Extent	Orientation	Equiv Diameter	Class
1	20321	734	0,888	0,496	-20,061	255826,1	1
2	22925	959	0,784	0,559	-1,044	288046,3	1
3	24902	932	0,823	0,607	-0,975	312500,5	1
4	23867	949	0,815	0,582	-0,426	299883,8	1
5	19982	698	0,901	0,489	-28,315	251264,5	1
...
250	27499	803	0,868	0,675	17,056	344846,3	3
251	19650	744	0,941	0,479	28,652	247243,3	3
252	29801	762	0,831	0,735	-6,719	375055,8	3
253	24048	806	0,879	0,593	13,693	301969,8	3
254	26298	811	0,817	0,659	-0,936	330859,9	3
...
889	26643	909	0,802	0,653	0,551	334391,1	10
890	20298	787	0,912	0,502	-26,748	254871,1	10

Table 3. Confusion Matrix

Class	1	2	3	4	5	6	7	8	9	10	Acc (%)
1	9	0	0	0	0	0	1	0	0	0	90
2	3	1	3	0	0	0	1	0	1	1	10
3	0	0	10	0	0	0	0	0	0	0	100
4	1	0	0	3	4	0	0	0	0	2	30
5	0	1	0	1	6	0	0	0	1	1	60
6	0	0	2	0	0	2	1	1	4	0	20
7	0	0	0	0	0	0	10	0	0	0	100
8	0	0	0	0	0	0	0	10	0	0	100
9	0	0	1	0	1	0	3	0	5	0	50
10	0	0	0	1	1	0	1	0	0	7	70

4.2 Shape Extraction Result

Form feature extraction results are calculated based on area, perimeter, eccentricity, extent and orientation values as can be seen in Table 2.

4.3 Classification

In the classification process shows the accuracy value of each feature extraction and the combination of feature extraction results. From the value of accuracy can be seen a good performance of some testing process or scenario is done. After the classification process, then the system will be tested. System testing process with Confusion Matrix. By calculating the value of Precision, Recall, and F-Measure. The results of the test system obtained in Table 3.

In table 3 the merging features of texture and form feature mention three classes that show 100% accuracy. Classes that show 100% accuracy mean all data testing in accordance with the classification model built by training data. There are three classes that show 100% accuracy value that is class 3, class 7 and class 8. There is one class that has a value of 90% accuracy is class 1. Class 10 has 70% accuracy. The rest of the accuracy value has a value of 10% in class 2, the accuracy of 205 in grade 6 and accuracy of 30% in grade 4. In class 2 training data and data testing have only 1 value in accordance with the model data training classification. The similarity of the scattered forms in class 1 and grade 3, there are similarities of datasets of 3 datasets. Similar features of the texture and features of the intercellular form occur because of the similarity of the texture factor or feature form factor. In the

form, the feature has a fairly low accuracy value due to the process of shooting unequal images from various directions and positions. So as to allow the shape of the butterfly wings to change and have no definite shape.

Table 4. Accuracy Value

Features	Acc (%)
Texture	68
Shape	49
Texture and Shape	66

In the process of combining the results of color feature extraction and texture features. In addition to analyzing the performance of each, in table 4 is calculated the value of accuracy. It aims to know how well and accurately the system in taking and matching between training data and data testing. Table 4 shows the accuracy value of each feature extraction result (texture and shape) as well as a combination of texture feature extraction and feature extraction. The accuracy value shows the combined feature extraction results at 256x160 pixels image size of 66% and the accuracy of the texture feature extract results by 68% and the accuracy of the form feature extraction results by 49%.

5. CONCLUSION

The study has successfully combination of the texture feature extraction results and the shape feature extraction is a combination of methods, which in previous studies have never existed. The classification of butterflies based on texture features and shape features an accuracy of 66%. The classification also performed on each texture feature an accuracy of 68% and the classification of feature shape a value of 49%.

The texture feature shows the dominant result compared to the shape feature, thus affecting the value of the merged accuracy. The future needs to be improved especially in the shooting process should have a standard, especially from the shooting side and the standard shape of the wings when in portrait with open wings or closed wings. Further research can use different methods to get maximum results. The current method needs to be tested on another dataset. To get better results and as a comparison.

6. REFERENCES

- [1] Saputra W. A., & Herumurti D. Integration GLCM and geometric feature extraction of the region of interest for classifying tuna. In

- Information & Communication Technology and Systems (ICTS), International Conference on, 2016, pp. 75-79. IEEE.
- [2] Kaya Y., Kayci L., & Uyar M. Automatic identification of butterfly species based on local binary patterns and artificial neural network. *Applied Soft Computing Journal*, 28, 2015, 132–137. <https://doi.org/10.1016/j.asoc.2014.11.046>.
- [3] Kaya Y., Kayci, L., & Tekin R. (2013). A Computer Vision System for the Automatic Identification of Butterfly Species via Gabor-Filter-Based Texture Features and Extreme Learning Machine: GF + ELM. *TEM Journal*, 2(1)
- [4] Kayci L., & Kaya Y. A vision system for automatic identification of butterfly species using a grey-level co-occurrence matrix and multinomial logistic regression. *Zoology in the Middle East*, 60(1), 2014, 57–64. <https://doi.org/10.1080/09397140.2014.892340>
- [5] Kaya Y., Kayci, L., Tekin R., & Faruk Ertuğrul, Ö. Evaluation of texture features for automatic detecting butterfly species using extreme learning machine. *Journal of Experimental & Theoretical Artificial Intelligence*, 26(2), 2014, 267–281. <https://doi.org/10.1080/0952813X.2013.861875>
- [6] Ojala T., Pietikäinen M., & Mäenpää T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7), 2002, 971–987. <https://doi.org/10.1109/TPAMI.2002.1017623>
- [7] Burçin K. & Vasif N. V. Down syndrome recognition using local binary patterns and statistical evaluation of the system. *Expert Systems with Applications*, 38(7), 2011, 8690–8695. <https://doi.org/10.1016/j.eswa.2011.01.076>
- [8] Satria D., Kartika Y. & Herumurti D. Koi Fish Classification based on HSV Color Space. *International Conference on Information, Communication Technology and System (ICTS)*, 5, 2016, 96–100
- [9] Suciati N., Kridanto A., Naufa, M. F. Machmud M. & Wicaksono, Y. Fast Discrete Curvelet Transform And HSV Color Features For Batik Image Classification, 2015, 99–104
- [10] Youssef S. M. ICTEDCT-CBIR: Integrating curvelet transform with enhanced dominant colors extraction and texture analysis for efficient content-based image retrieval. *Computers and Electrical Engineering*, 38(5), 2012, 1358–1376.

- <https://doi.org/10.1016/j.compeleceng.2012.05.010>
- [11] Wang J., Markert K. & Everingham, M. Learning models for object recognition from natural language descriptions. *Learning*, 2.1-2.11, 2009, Retrieved from <http://eprints.pascal-network.org/archive/00006257/>
- [12] Suciati, Nanik, Agri Krisdanto, Mohammad Farid Naufal, Muhammad Mahmud, Ardian Yusuf Wicaksono. "Fast discrete curvelet transform and HSV color features for batik image classification." *Information & Communication Technology and Systems (ICTS), International Conference on. IEEE*, 2015
- [13] Kurniawardhani A., Suciati N., & Ariesianti, I. Klasifikasi Citra Batik Menggunakan Metode Ekstraksi Ciri yang Invariant Terhadap Rotasi. *JUTI: Jurnal Ilmiah Teknologi Informasi*, 12(2), 2014, 48. <https://doi.org/10.12962/j24068535.v12i2.a322>
- [14] Ojala T., Pietikäinen, M., & Harwood D. A comparative study of texture measures with classification based on featured distributions. *Pattern Recognition*, 29(1), 1996, 51–59. [https://doi.org/10.1016/0031-3203\(95\)00067-4](https://doi.org/10.1016/0031-3203(95)00067-4)
- [15] Rafique, H., & Rafique, S. (2016). Review of correlation based algorithms in signal and image processing for pattern identification. *Int J GEOMATE*, 11(27), 2695-2703.

Copyright © Int. J. of GEOMATE. All rights reserved, including the making of copies unless permission is obtained from the copyright proprietors.
