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Butterfly species identification using glcm features and edge detection using KNN (K-Nearest Neighbor) and decision tree algorithm (C.45)

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ABSTRACT

Butterflies are insects come from the kingdom Animalia, which are the Insecta class, the Lepidoptera order, and the sub-order of Rhopalocera. Butterflies can classified according to the patterns found on the butterfly's wings. Butterfly species have different patterns based on pigment, scale structure, and sunlight fall structure. The weakness of the human eye in specific the patterns in butterflies is the foundation in basis butterfly identification based on pattern recognition. This study used 3 butterfly species: Adonis, Black Hairstreak, and Gray Hairstreak. The butterfly dataset used was 150 which were obtained online. The pre-processing stage used segmentation and edge detection methods. The feature extraction stage used the Gray-level Co-occurrence Matrix (GLCM) method which extracted 8 shape and texture features including area, perimeter, metric, eccentricity, contrast, correlation, energy, and homogeneity. Classification phase used K-Nearest Neighbor (KNN) method with the values of k = 3, 5, 7, 9, 11, 13, 15, 17, and 19 as well as the Decision Tree method (C.45). The results of the identification of butterflies with the highest accuracy were obtained by the KNN Algorithm on the testing with a value of k = 3 of 93.33%, and the accuracy results using the Decision Tree method (C.45) is 84.44% while the results of identification using an application made using the GUI Matlab2017 with the KNN algorithm obtained an accuracy of 93.33% with a value of k= 3.

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1. Introduction

Butterflies are insects that come from the kingdom Animalia, which is the Insecta class, the order of Lepidoptera, and the sub-order of Rhopalocera. Butterflies have large and colorful wings and antennae that can be used to distinguish them from a moth. Butterfly antennae are filiform and clublike whereas moth antennae are usually hairy and/or serrated which can be seen with the naked eye (Afny Syazwany Abu Zarim and Ahmad 2014). Djunijanti Peggie said that butterflies are only a small part, namely 17,500 species or <12% of the 155,000 species of Lepidoptera in the world, and the largest part is moths. Although the number of species is much less than moths, butterflies are more commonly known for their diurnal (diurnal) activity and bright and attractive colors (Peggie 2017)(Purwowidodo 2015) . Butterflies play an important role in the ecosystem especially in the process of pollination and natural pest control, it is used to test the effects of habitat loss and environmental changes which are

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symbols of an important part in the environment, acting as pollinators, food sources, and markers of biological well-being (Ghazanfar et al. 2016). Its intrinsic value that has evolved since 150 million years ago makes it rich in biodiversity and worthy of conservation. From its aesthetic value, these insects represent the essence of nature that represents freedom, beauty, and peace. In the world of education, these insects teach perfect metamorphosis and insect migration, and in the world of health and economics, one of which plays an important role in making ecotourism (Anon 2019). Currently, reliable methods for butterfly identification are inefficient due to the butterfly's complex shape (Kang, Cho, and Lee 2014). Some butterfly shapes have the same pattern but different structures. It is difficult for entomologists to identify butterfly species. Collecting, recognizing, and physically archiving specimen images is tedious and costly for entomologists and must also refer to taxonomy and manual processing images to identify species, so it is necessary to have applications that can accelerate identification (Feng, Bhanu, and Heraty 2016). Therefore, this study emphasizes the identification results.

The research conducted by Yilmaz Kaya only used one feature extraction. The results will be better when adding other feature extractions, such as colors and shapes (Kaya, Kayci, and Uyar 2015). Several previous studies used several methods to detect and to classify butterfly images entitled computer vision systems for automatic identification of butterfly species through Gabor-based texture features and extreme machine learning: GF + ELM (Kayci and Kaya 2014). In these studies, it was stated that the classification process uses conventional methods by providing chemical substances to the dataset requires a long time and is expensive. Therefore, an alternative method is needed using the Gabor Filter (GF) and Extreme Learning Machine (ELM). The GF method is used for texture detection in images because it optimally detects the spatial domain (the process of manipulating the pixels of an image to produce a new image) and frequency.

With the role of butterflies in life in various aspects but with the problem of identification which is still not easy enough to do, the researcher sees this as a research topic which in this study proposes the identification of butterfly species using the GLCM feature which extracts 8 shape and texture features including area, perimeter, metric, eccentricity, contrast, correlation, energy, and homogeneity with the segmentation using k-means and Canny edge detection. Classification phase used K-Nearest Neighbor (KNN) method with values of k = 3, 5, 7, 9, 11, 13, 15, 17, and 19 as well as the Decision Tree method (C.45). The data used were butterfly images obtained from an online dataset of 150 images consisting of 3 species, namely Adonis, Black hairstreak, and Gray hairstreak.

2. Method

In this study, the stages of the research methodology carried out are described in the following chart:

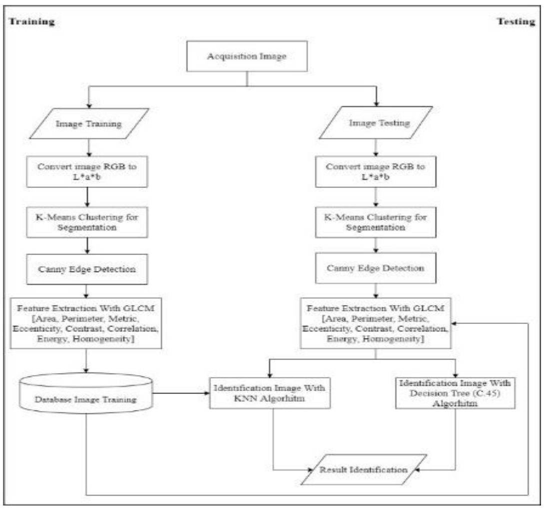

Figure 1. Research stages

Figure 1 shows the research flow used in this study, namely the acquisition of images obtained online through the page www.kaggle.com with the file name of Butterfly Images-50 Species uploaded by Gerry in the .jpg format, the distribution of training and testing datasets, and color conversion from RGB to L * a * b as a basis before segmentation using k-means. After the segmentation, the edges are detected using canny edge detection to see the outlines of the butterfly wings. Furthermore, feature extraction is carried out using GLCM (Gray Level Co-occurrence Matrix) by taking shape and texture values consisting of metric, eccentricity, contrast, correlation, energy, homogeneity, area, and perimeter. The next step is the identification process, this process is carried out by 2 algorithms namely the KNN (K-Nearest Neighbor) algorithm and the Decision Tree algorithm (C.45). The last process is the identification result by looking at the comparison of the results of the accuracy of the two algorithms used.

3. Results and Discussions

Results of RGB to L * a * b Color Conversion

The original image with the RGB (Red Green Blue) color space for easy segmentation using the k-means method is converted into the L * a * b color space which has a complete color composition according to the theory in the previous discussion. L * a * b makes the image accentuate a part of the object from its background. The distance between two colors, each with its color space location, refers to the color difference that can calculated (Zhang et al. 2018)(Atina 2017)(Ghazanfar et al. 2016)(World Symposium on Web Applications and Networking 2. 2015 Sousse et al. 2015). The results of the RGB to L * a * b color conversion for each type of butterfly species studied are as follows:

Table 2. The results of RGB to L * a * b color conversion

No.	Butterfly Species	RGB	L*a*b
1	Adonis		
2	Black Hairstreak		
3	Gray Hairstreak		

Table 2 shows the results of the color conversion of the butterfly image from the original image which has the RGB color space converted into the L * a * b color space. It appears that the object color is different from the background color, so this will make it easier for the k-means method to segment the image.

Segmentation Results With K-Means

The image of a butterfly whose color space has been converted was then segmented using the k-means clustering method to separate the object from the background. The k-means clustering method in performing image segmentation utilizes the intensity/ gray level of the image. This image intensity is what underlies the image clustering. The different intensities will be grouped into different clusters (Permadi and Murinto 2015). The following shows the segmentation results of each butterfly species using the k-means clustering method.

Table 3. Segmentation results using k-means

No.	Butterfly Species	RGB	L*a*b	K-Means
1	Adonis			
2	Black Hairstreak			
3	Gray Hairstreak			

Table 3. shows the results of the butterfly image segmentation which aims to separate the background from the butterfly object. The background is covered with a black layer, and the object is taken and ready for feature extraction as a first step for identification.

The Results of Edge Detection with Canny Edge Detection

Edge detection was performed on the result of butterfly image segmentation using k-means clustering to take patterns from the wings and bodies of each type of butterfly. The canny edge detector operator was chosen because of its greater overall performance (Olaniyi et al. 2017). The key factor in feature extraction is the ability to detect the presence of object edges in the image. Detection edge is the first step to enclosing information in an image. The results of edge detection using the canny edge detection method are as follows.

Table 4. Edge detection results with canny

No.	Butterfly Species	RGB	L*a*b	K-Means	Edge Detection
1	Adonis				
2	Black Hairstreak				
3	Gray Hairstreak				

Table 4. shows the results of image edge detection of a butterfly, which aims to create a butterfly wing pattern that becomes the characteristic of each species.

The Results of Feature Extraction with Gray Level Co-occurrence Matrix (GLCM)

The butterfly image whose edge detection has been obtained using canny edge detection then performed feature extraction using the Gray Level Co-occurrence Matrix (GLCM) by taking shape and texture values, namely the value of metric, eccentricity, contrast, correlation, energy, homogeneity, area, and perimeter. Butterfly image data used is training data which will later become a butterfly image database and become a reference for the identification process. The following results from the feature extraction of butterfly images using GLCM are presented in table 5.

Table 5. The results of feature extraction using GLCM

Image	area	perimeter	metric	eccentricity	contras	correlation	energy	homogeneity	Name of butterfly
1	34	60,761	0,1157	0,9608	2,5947	0,2732	0,6859	0,8829	adonis
2	795	1340,648	0,0056	0,8026	2,1352	0,2765	0,7138	0,8958	adonis
3	1252	2140,279	0,0034	0,7246	1,9529	0,2791	0,6936	0,8867	adonis
4	618	1010,296	0,0076	0,9609	2,1143	0,2832	0,7068	0,8930	adonis
5	77	134,158	0,0538	0,9970	2,8987	0,2730	0,6966	0,8850	adonis
....	....	....	....	....	....	....	....	....	....
30	1294	2096,971	0,0037	0,7487	2,3664	0,2816	0,7142	0,8936	adonis
31	24	30,542	0,3233	0,7025	2,2626	0,2534	0,6480	0,8681	black hairstreak
32	17	24,654	0,3515	0,9666	1,3856	0,3010	0,7919	0,9281	black hairstreak
33	115	200,404	0,0360	0,9454	1,0875	0,2768	0,7048	0,8998	black hairstreak
34	395	662,948	0,0113	0,9241	0,9610	0,2719	0,6797	0,8966	black hairstreak
35	326	560,491	0,0130	0,9754	1,9343	0,2564	0,6461	0,8719	black hairstreak
....	....	....	....	....	....	....	....	....	....
60	326	560,491	0,0130	0,9754	1,9343	0,2564	0,6461	0,8719	black hairstreak
61	3	3,92	2,4533	0,9428	1,5410	0,2753	0,6841	0,8911	gray hairstreak
62	161	265,152	0,0288	0,9847	2,5765	0,2633	0,6694	0,8760	gray hairstreak
63	726	1080,111	0,0078	0,9353	1,5113	0,2704	0,6761	0,8888	gray hairstreak
64	5	7,013	1,2775	0,9315	1,9342	0,2654	0,7072	0,8925	gray hairstreak
65	20	18,732	0,7163	0,8308	2,0712	0,2897	0,7171	0,8982	gray hairstreak
....	....	....	....	....	....	....	....	....	....
90	215	362,859	0,0205	0,9974	2,1194	0,2683	0,6641	0,8788	gray hairstreak

Table 4 shows the results of feature extraction from GLCM by taking the values of shape and texture metric, eccentricity, contrast, correlation, energy, homogeneity, area, and perimeter. There are 90 images extracted in which each species gets 30 images that will be used as a reference or training dataset for the identification process.

Image Identification Results Using the K-Nearest Neighbor (KNN) Algorithm

After obtaining the shape and texture feature values using GLCM, the identification process was carried out using the KNN (K-Nearest Neighbor) algorithm through the RapidMiner application. In this study, the k values used were 3, 5, 7, 9, 11, 13, 15, 17, and 19. The results of identification using the K-Nearest Neighbor (KNN) algorithm are presented in table 6.

Table 6. Identification results using KNN algorithm

Value of k	Precision and Recall	Level of Accuracy in Each Class			Level of accuracy
		AD	BH	GH	
3	Precision	88,24%	93,10%	100%	93,33%
	Recall	100%	90%	90%	
5	Precision	75,68%	83,33%	86,96%	81,11%
	Recall	93,33%	83,33%	66,67%	
7	Precision	82,35%	63,64%	73,91%	73,33%
	Recall	93,33%	70%	56,67%	
9	Precision	80,65%	60,53%	71,43%	70%
	Recall	83,33%	76,67%	50%	
11	Precision	64,86%	57,14%	56%	60%

	Recall	80%	53,33%	46,67%	
13	Precision	64,86%	61,29%	68,18%	64,44%
	Recall	80%	63,33%	50%	
15	Precision	54,76%	70,83%	66,67%	62,22%
	Recall	76,67%	56,67%	53,33%	
17	Precision	52,08%	66,67%	71,43%	60%
	Recall	83,33%	46,67%	50%	
19	Precision	52,63%	56,67%	68,18%	57,78%
	Recall	66,67%	56,67%	50%	

Table 6 above shows the level of accuracy in each test with varying k values, and it was found that the highest level of accuracy on the test with a value of k = 3 is 93.33 while the lowest level of accuracy is obtained with a value of k = 19 of 57.78%.

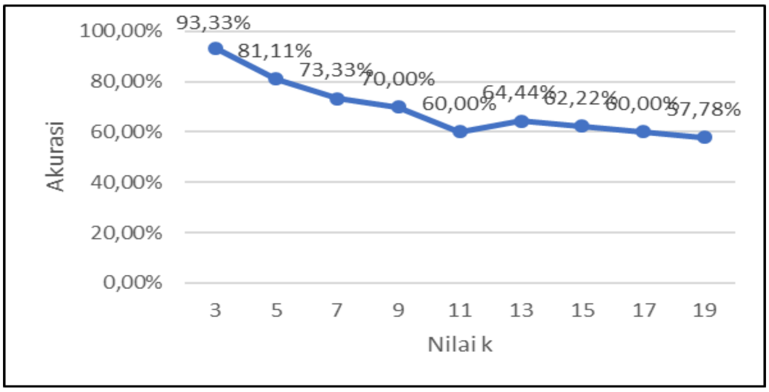

Figure 2. Accuracy comparison graph for each value of k

Figure 2 shows Accuracy of the graph comparison level obtained from each k value used in the identification process. It can be seen that the highest result is obtained with a value of k = 3 of 93.33% while the lowest level of accuracy is obtained with a value of k = 19 of 57.78%.

Image Identification Results Using Decision Tree Algorithm (C.45)

Besides the KNN algorithm, the decision tree algorithm (C.45) is also used to see the results of identification comparisons. For the decision tree algorithm (C.45), the classification results can be seen from the tree formed from the shape feature extraction value and GLCM texture. The tree form produced by the decision tree algorithm (C.45) is presented in Figure 3.

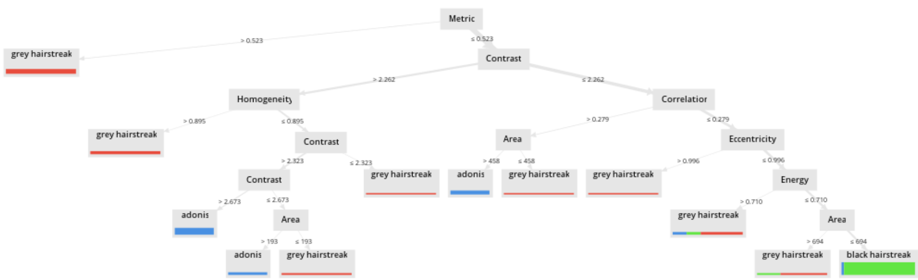

Figure 3. Algorithm decision tree (C.45)

From Figure 3 above, data on the distribution of the studied butterfly species is obtained by looking at the values of GLCM feature extraction. The following is an explanation of the decision tree: a) If the metric value is more than 0.523 px, the gray hairstreak butterfly species are recognized; b) If the metric value is less than or equal to 0.523 px, the contrast value is more than 2.265 px, and the homogeneity value is more than 0.895, then the gray hairstreak butterfly species is recognized; c) If the metric value is less than or equal to 0.523 px, the contrast value is more than 2.265 px, the homogeneity value is less than or equal to 0.895 px, the contrast value is more than 2.323 px, and the contrast value is more than 2.673 px, then the adonis butterfly species will be recognized; d) If the metric value is less than or equal to 0.523 px, contrast value is more than 2.265 px, homogeneity value is less than or equal to 0.895 px, contrast value is more than 2.323 px, contrast value is less than or equal to 2.673 px, and area value is more than 193, px then recognizable adonis butterfly species; e) If the metric value is less than or equal to 0.523 px, contrast value is more than 2.265 px, homogeneity value is less than or equal to 0.895 px, contrast value is more than 2.323 px, contrast value is less than or equal to 2.673 px, and area value is less than or equal to 193 px, then the adonis butterfly species is recognized.

Accuracy results are also obtained from identification using the decision tree algorithm (C.45) through the Rapid Miner application which is presented in table 7.

Table 7. Identification results using decision tree algorithm (C.45)

Decision Tree	(C.45)	Precision and Recall	Level of Accuracy in Each Class			Level of accuracy
			AD	BH	GH	
		Precision	90,91%	100%	72,50%	84,44%
		Recall	100%	56,67%	96,67%	

Table 6 above shows the results of testing accuracy with the Decision Tree Algorithm (C.45) using the Rapid Miner application which obtained an accuracy of 84.44%.

Final Result of Identification

The results of identification that have been carried out using KNN and Decision Tree algorithm show that the test results based on the feature extraction of Gray level Co-occurrence Matrix (GLCM) with KNN Algorithm have the highest level of accuracy at k = 3 of 93.33% while the accuracy obtained by the Decision Tree Algorithm is 84,44%. Thus, the KNN Algorithm obtained the highest accuracy compared to the Decision Tree Algorithm. Based on the identification results with the highest accuracy obtained by the KNN Algorithm, a desktop-based application was created using MATLAB2017 GUI. The following shows the program interface that has been created.

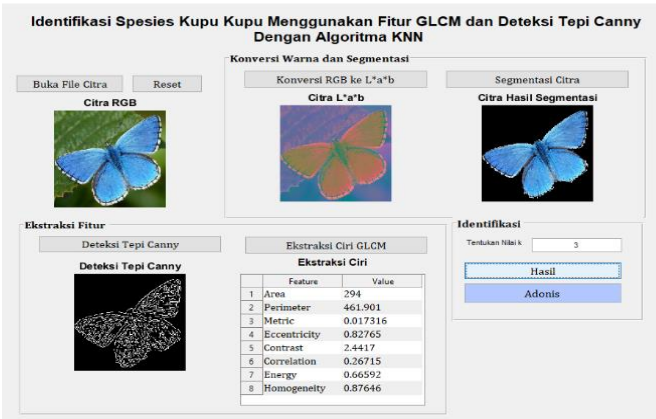

Figure 4. Application interface for butterfly species identification using MATLAB 2017 GUI

Figure 4. obtained an accuracy of 93.33% with a value of k = 3. The results of the distribution of identification results carried out using the application presented in the configuration matrix table are as follows.

Table 8. Confusion matrix on identification result of KNN algorithm with k = 3

	Confusion Matrix			ACC %
	adonis	black hairstreak	gray hairstreak	
adonis	20	0	0	100
black hairstreak	1	18	1	90

gray hairstreak	1	1	18	90
	Mean of Accuracy			93,33

Table 8 above shows the results of the identification distribution using the KNN algorithm with a value of k = 3 which is the highest accuracy result with an accuracy value of 93.33%. It can be seen that the adonis butterfly species obtained perfect results with an accuracy of 100%, followed by black hairstreak and gray hairstreak species which each obtained an accuracy of 90%.

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