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Classifying The Swallow Nest Quality Using Support Vector Machine Based on Computer Vision

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***Abstract*— Swallow Nest is a valuable export commodity, particularly in Indonesia. It is produced when a swallow's saliva hardens and is frequently encountered in high-rise buildings. Swallow nests can be utilized to treat various ailments in the medical sector. The price of a swallow nest varies according to its quality, which is commonly classified into three grades: quality 1 (Q1), quality 2 (Q2), and quality 3 (Q3). Q1 is of the highest quality, while Q3 is of the lowest. Each grade has a different physical appearance. Currently, many people lack knowledge regarding the grade of a swallow nest. Therefore, a method is needed to automatically classify the quality of swallow nests based on computer vision. The proposed method consists of several main processes, including image acquisition, ROI detection, pre-processing, segmentation, feature extraction, and classification. The feature extraction was applied based on shapes, followed by the Support Vector Machine (SVM) implementation in the classification process. This process was performed with cross-validation using the k-fold values of 5. The performance evaluation was done using three parameters: precision, recall, and accuracy, by achieving the value of 90.6%, 89.3%, and 89.3%, respectively.**

***Keywords*— Swallow nest, image processing, shape features, machine learning, cross-validation.**

I. INTRODUCTION

Swallow nest is one of the animal export commodities with a high selling value. It results from swallow's saliva, which then hardens and is often found in caves and swallow buildings. Swallow's nest consists of several parts, namely the foot of the nest, the foundation of the nest, the walls of the nest, the lips of the nest, and the bottom of the nest. The nest is generally shiny white with a solid and rigid exterior. The high selling price and export demand for swallow nests certainly have certain functions or benefits.

Swallow nests are utilized in the health industry to remedy respiratory disorders, boost vitality, and ancient medicine. Additionally, it can help maintain the body's freshness, boost energy, limit cancer growth, improve focus, act as a protein source for people with diabetes, neutralize the effects of alcohol, preserve the beauty, and reduce fever. Swallow's nest may also be processed and used as a raw material for various daily needs, including soup, cosmetics, beverages, supplements, and face creams.

Swallow nests are often classified into three categories by the buyer or sorter to determine the price of each nest. The classifications are as follows: Quality 1 (Q1), Quality 2 (Q2), and Quality 3 (Q3), with Q1 being the most expensive and Q3 being the least costly. Each category has different characteristics: (1) Q1 has a bowl-shaped (defect-free) angle, indicating the highest quality; (2) Q2 has an elbow-shaped angle, indicating a medium-quality; and (3) Q3 is the lowest-quality form of pieces or imperfect nests, indicating the lowest price.

The process of sorting swallow nests was applied manually by the farmers or buyers swallowing nests on a small scale. They have to sort each one individually by examining the specifics of the shape of the swallow nest to determine the quality category. It required considerable effort and was time-consuming. Therefore, a system to classify the swallow nests based on each quality is needed.

There has been no previous study that examined the quality of swallow nests using computer vision. However, several studies on computer vision regarding food processing have been applied [1], such as eggs [2], [3], apricots [4],[5], palm oil [6], [7], and pomegranate [8]. Generally, the steps required to develop this system include pre-processing, segmentation, feature extraction, and classification [9]–[11]. In pre-processing, the tasks usually performed include resizing [12] and converting color spaces [13]. Subsequently, popular segmentation methods were applied, i.e., edge detection [13], [14], clustering, and threshold. The features extracted for food object consist of color [9], [15], shape [4], and texture [16]. Additionally, K-Nearest Neighbor (KNN) [9], [14], [17], SVM [4], [17], [18], Naïve Bayes [4], [17], [19], and Decision Tree [4] are frequently used in the classification process.

Several earlier computer vision-based works have been successfully utilized in food processing. A unique classification approach was proposed based on FSCABC–FNN [20]. The color histogram, Unser's texture, and form features were combined. According to the testing data, the FSCABC–FNN attained a significant classification accuracy of 89.1%. It is superior to the GA–FNN, the PSO–FNN, the ABC–FNN, and the SVM. The current study offers a novel Sequential Multiple Image-based Convolutional Neural Network BiLSTM (SMI-CNN-BiLSTM) model for efficiently classifying dirty, bleeding, cracked, and robust eggs. The suggested model extracted deep features from egg photos by employing a pre-trained residual network (DenseNet201) model and then feeding the extracted features into the Bidirectional Long-Short-Term Memory (BiLSTM). Based on in-depth features and BiLSTM, the suggested model achieved effective results in detecting faulty eggs. The testing results indicated that the proposed model achieved a superior accuracy score of 99.17%, a 5% performance improvement over state-of-the-art approaches [2]. Additionally, utilizing the proposed approach, the accuracy of volume estimation of potatoes, citrus, and tomatoes is 92.54%, 88.82%, and 89.02%, respectively. For potato, citrus, and tomato, the proposed technique accuracy was 92.98%, 89.31%, and 88.56%, respectively [21].

This study focuses on developing methods for determining the quality of swallow nests. The shape of the swallow's nest indicates the difference in quality. The proposed method was created utilizing the Otsu threshold algorithm to extract the segmented bird's nest area shape characteristic. Additionally, the classification was implemented in several methods, including Decision Tree, KNN, Naive Bayes, and SVM.

II. MATERIALS AND METHODS

The developed method aims to classify the quality of swallow nests based on image processing-based shape features. The process stages consist of six processes, including image acquisition, region of interest (ROI) detection, pre-processing, segmentation, feature extraction, and classification. This method required an image of a swallow nest as the input data consisting of three types as the ROI detection process. Furthermore, pre-processing was carried out to simplify the following procedure, followed by a segmentation process to separate the swallow nest area from the background. The results of the segmentation image became the input to the feature extraction process. The feature extraction aims to generate shape feature values to identify the characteristics of coffee beans. In the final stage, a classification process was carried out to determine the quality level class of swallow nests from image input data. The classification results were divided into three classes, namely quality 1 (Q1), quality 2 (Q2), and quality 3 (Q3). This study provides an overview of the implementation of different machine learning techniques in analyzing swallow nest images to determine the quality. The main stage in the swallow nest classification method based on shape features is depicted in Fig. 1.

A. Image Acquisition

The image in the dataset was acquired by placing the swallow nests in a minibox size 40 × 30 × 30 cm with a single lamp and captured using an Oppo A83 smartphone with a resolution of 28 Mega Pixels (4160 × 3120 pixels). The lamp was a LED strip of white color with a length of 33 cm and a power of 220 V. The distance between the lamp to the object was ±30 cm using the artificial background of black color. Image data acquisition results consist of three types of quality. The characteristic of Q1 has bowl-shaped with a minimum width of 4.6 cm on the outside. Subsequently, Q2 is right-angled or angular, and Q3 has a splinter or imperfect nest. The data collected is 150 image data divided into (50 quality 1, 50 quality 2, and 50 quality 3). The example image of the swallow nest image is shown in Fig. 2.

B. Region of Interest (ROI)

This process was required to construct a sub-image in which swallow nest objects occupy most of the area. Therefore, the image size and computing time were reduced. Without the ROI detection process, all picture pixels were processed uniformly. This procedure begins by resizing 0.5 of the original image 4160 × 3120 pixels into 416 × 312 pixels. Furthermore, thresholding with the Otsu method was applied to the swallow nests area and background as a boundary for forming ROI images [22], [23]. The image of the results of each step in the ROI detection process is shown in Fig. 3.

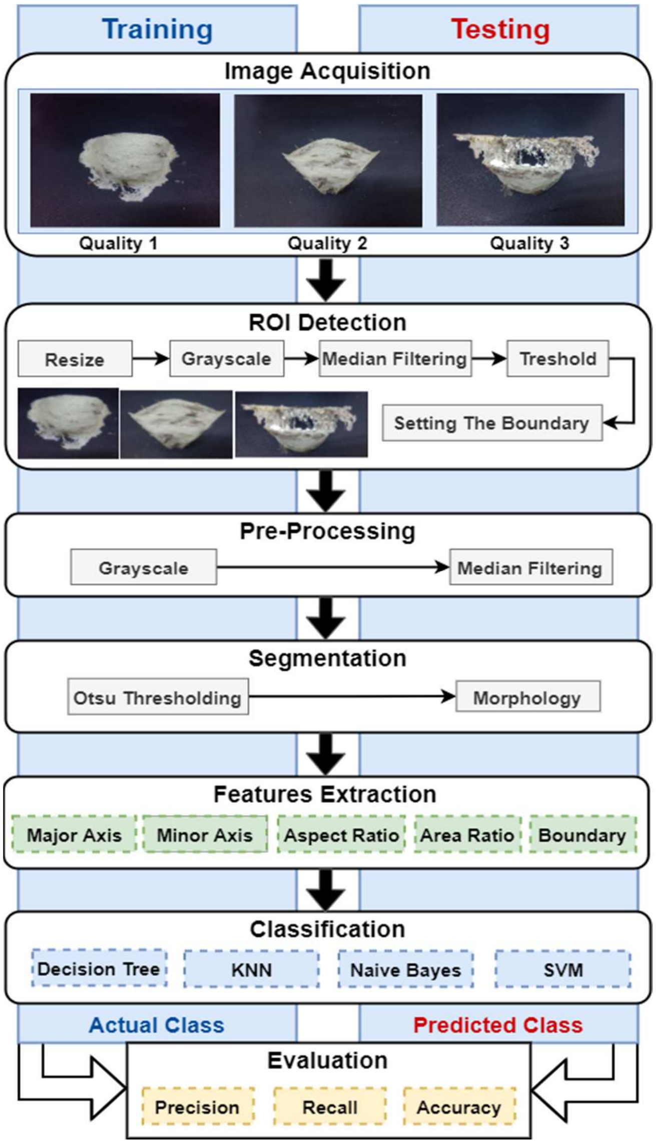


Fig. 1. An overview of the main process of the proposed method

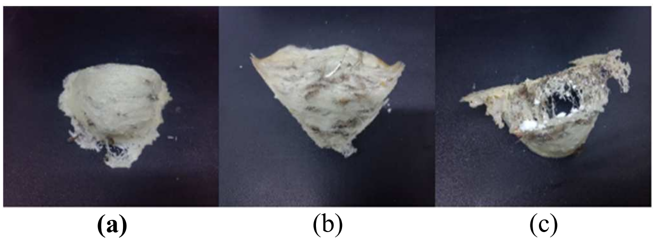
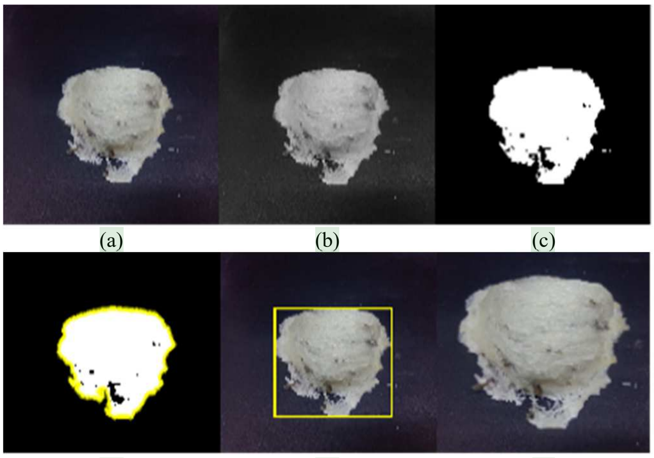


Fig. 2. The example of swallow nets: (a) Quality 1, (b) Quality 2, and (c) Quality 3

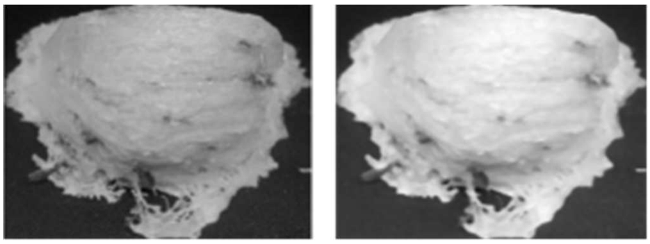
C. Pre-processing

Pre-processing was applied to the ROI image to generate a suitable image for the subsequent process, reducing noise and simplifying the process. In this study, pre-processing begins with converting the RGB color space to grayscale. The following step was to convert it to a median filter image to eliminate noise from the previous image. The results of this process is shown in Fig. 4.



(a) (b) (c) (d) (e) (f)

Fig. 3. ROI detection process: (a) resize image, (b) median filtering, (c) Otsu threshold, (d) boundary, (e) bounding Box, (f) ROI Result



(a) (b)

Fig. 4. Pre-processing result: (a) grayscale, (b) median filtering

D. Segmentation

Segmentation aimed to separate the swallow nest area, and the remaining background due to the feature extraction only carried out to the swallow nest area. The segmentation process was implemented using Otsu thresholding [23], [24]. Afterward, the morphological approach was performed using an erosion operation against the resulting binary image of the Otsu thresholding to obtain the appropriate area. The resulting image of segmentation is depicted in Fig. 5.

(a) (b) (c)

Fig. 5. Segmentation result: (a) median filtering, (b) binary image, and (c) segmentation image.

E. Feature Extraction

In order to differentiate the quality of the swallow nest, shape features were extracted. Those features, including aspect ratio, area, boundary, major axis, and minor axis, are defined as follows.

1. Aspect Ratio (AR)

This feature is the ratio of the length of the minor axis (W) to the major axis (L). The overview of aspect ratio is depicted in Fig. 6(b) based on Fig. 6(a) and defined as follows:

$$AR = \frac{W}{L} \tag{1}$$

2. Boundary Ratio (BR)

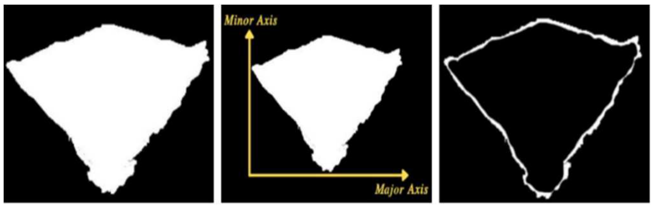
The boundary feature (B) was generated by comparing the pixel number of the swallow nest edge (indicated by the white pixels) and the total number of pixels in the image. The illustration of the Boundary ratio is shown in Fig. 6(c).

3. Area Ratio (A)

The area ratio (A) was obtained by computing the white pixel number of the swallow nest area. The illustration of the Area Ratio is depicted in Figure 6(a).

4. Minor (M) and Major (N) axis

Based on the object's center, the minor axis is the shortest diameter while the major axis is the longest. The illustration of both features is shown in Fig. 6(b). Furthermore, the result examples of feature extraction are shown on Table I.



(a) (b) (c)

Fig. 6. Shape feature illustration: (a) area ratio, (b) minor-major axis and aspect ratio, (c) boundary ratio

TABLE I. FEATURE EXTRACTION RESULT EXAMPLE

Image	Grade	Features
	Q1	AR: 1.3507 BR: 0.6958 A: 23382 M: 204.611 N: 151.509
	Q2	AR: 1.682 BR: 0.6559 A: 29539 M: 257.188 N: 152.522
	Q3	AR: 2.6291 BR: 0.6008 A: 23317 M: 297.305 N: 113.158

F. Classification

A machine learning approach was used to carry out the classification process. Artificial intelligence is a subfield of machine learning. It encompasses algorithm design and development. Machine learning has grown in popularity because it entails algorithms capable of extracting relevant information from data and employing that information in self-learning to get the desired classification or prediction result [1]. Four classifiers were used in this study: KNN, Naive Bayes, Decision Tree, and SVM [4] since these classifiers have been successfully implemented in various cases. The classification process was applied using cross-validation with the k-fold value of 3, 5, and 10.

III. RESULT AND DISCUSSION

In this study, three parameters were used to evaluate the proposed method: precision, recall, and accuracy. Those were generated using a multiclass confusion matrix to determine the proposed method's robustness. The evaluation parameters were defined as following [25]:

$$precision = \frac{TC}{TC + FP} \times 100 \quad (2)$$

$$recall = \frac{TC}{TC + FN} \times 100 \quad (3)$$

$$accuracy = \frac{TC}{TC + FP + FN} \times 100 \quad (4)$$

The true class (TC) metric indicates the proportion of correctly classified test data (actual class equal to output class). The terms false-positive (FP) and false-negative (FN) refer to the number of misclassified test results.

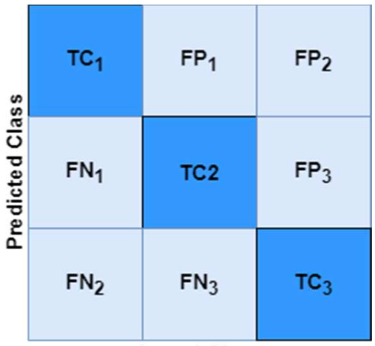


Fig. 7. Confusion Matrix Multiclass

The method evaluation was carried out by implementing several testing scenarios. Four classifiers, including Decision Tree, KNN, Naïve Bayes, and SVM, were tested using different K-Fold values with 3, 5, and 10. This method was implemented against the dataset consisting of three levels of swallow nest quality (Q1, Q2, and Q3), where each quality level includes 50 images; therefore, the total image obtained of 150 images. The evaluation results based on the value of precision, recall, and accuracy were summarized in Table II.

TABLE II. THE COMPARISON OF CLASSIFICATION RESULTS USING FOUR CLASSIFIERS

K-fold	Classifier	Precision	Recall	Accuracy
3	Decision Tree	84%	84%	84%
	KNN	82,5%	82%	82%
	Naïve Bayes	79,6%	79,3%	79,3%
	SVM	89,2%	88,7%	88,7%
5	Decision Tree	85,9%	86%	86%
	KNN	83,1%	82,7%	82,7%
	Naïve Bayes	80,7%	80,7%	80,7%
	SVM	90,6%	89,3%	89,3%
10	Decision Tree	81,6%	81,3%	81,3%
	KNN	82,8%	82%	82%
	Naïve Bayes	79,4%	79,3%	79,4%
	SVM	90%	88,7%	88,7%

Table II shows the implementation of the k-fold value of 3, 5, and 10 for each classifier. It indicated the SVM method successfully achieved the highest performance with all the k-fold values. The accuracy for the k-fold value of 3, 5, and 10 gained 88.7%, 89.3%, and 88.7%, respectively. While, the lowest result was obtained using the Naïve Bayes method in each the k-fold value that achieved the accuracy of 79.3%, 80.7%, and 79.4%. Overall, the k-fold value of 5 yields the best result for each classifier. The confusion matrix of the swallow nest quality classification with the highest accuracy value is depicted in Fig. 8.

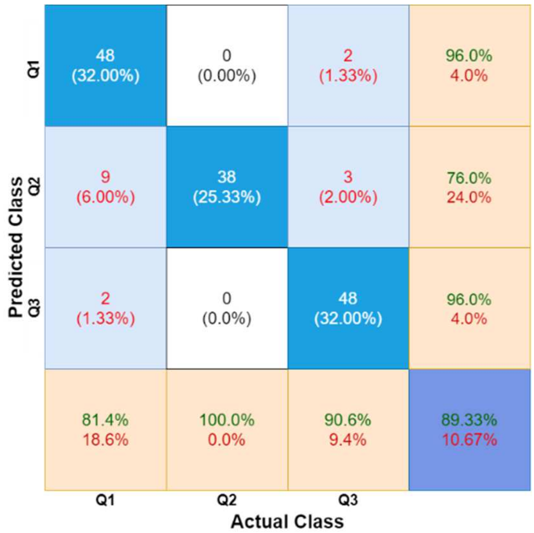


Fig. 8. Confusion matrix of the SVM classifier with k-fold = 5

IV. CONCLUSION

This study presents a method for classifying the quality of swallow nests. The quality was classified into three categories and was composed of five distinct processes (ROI detection, pre-processing, segmentation, features extraction, and classification). In order to decrease the noise in the ROI detection process, median filtering was applied, followed by Otsu thresholding. Subsequently, pre-processing was performed, including converting the ROI image to grayscale and then median filtering to reduce noise. Afterward, segmentation was used to eliminate the background areas. Furthermore, the shape features were extracted, and the value of the features was fed into the SVM classifier. The proposed method achieved the highest performance with the k-fold value of 5, indicated by the accuracy values of 89.3%. This method may have been developed to generate more powerful features by extracting additional features such as color, texture, and shape. Therefore, the method performance can be increased.

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a) Quality 1, (b) Quality 2, and (c)Quality 3

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shown inFig

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in Fig. 8.Fig. 8. Confusion matrix of the SVM classifier

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TABLE II.THE COMPARISON OF

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