Mango Leaf Classification with Boundary Moments of Centroid Contour Distances as Shape Features

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***Abstract*—The previous research in mango leaf classification which used 270 features consisted of 256 texture features, 2 color features, and 2 shape features, could not achieve high classification performance. In this study, we conduct improvement by combining the previous features with the Boundary Moments of Centroid Contour Distance (CCD) and classify the combination features using Support Vector Machine with Linear and RBF kernels. The experiment results show that the combination features achieve higher classification performance compared to the previous features.**

Keywords—mango leaf, classification, Centroid Contour Distance, combination features, shape features

I. Introduction

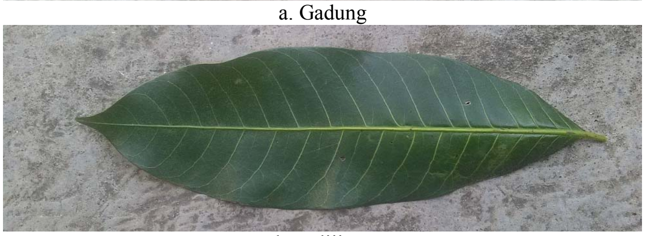
The previous research in mango leaf classification was begun by using texture as the main features. Furthermore, the next research in [1] selected some important texture features using Fisher's Discriminant Ratio to improve the performance. Both research use K-Nearest Neighbor as the classification method. The last research in [2] combined texture and color features with shape features. That research using Compactness and Circularity as the trivial features to improve the performance, then apply it to 3 varieties of mango leaf, each represented by 100 mango leaf. By using Support Vector Machine as the classification method, it achieved 71.33% of accuracy. The main features used in the last research are Weighted Rotation- and Scale-invariant Local Binary Pattern with average weight (WRSI-LBP-avg) [3], average and standard deviation [4] of gray-scale intensities, Compactness, and Circularity [4] of the leaf image, as the texture, color and shape features respectively. In this research, we conduct improvement by combining the features used in the previous research with the Boundary Moments of Centroid Contour Distance (CCD) [5].

In order to achieve good performance, we can conduct a combination of some features. The research in [6] combine the Readiness Potential (RP) and Event Related Desynchronization (ERD) to achieve better performance in the classification of multichannel electroencephalograph (EEG) based BCI studies. Features combination is also conducted by research in [5] by fusion the Band Limited Phase Only Correlation and Width Centroid Contour Distance for finger based biometrics. In experimental evaluation, the research [5] could achieve efficient recognition performance where the equal error rate (EER) was 1.78%. To achieve better performance, in this research, we use 388 features by combining 260 features from the previous research [2] and Boundary Moments of 128 new shape features. This new shape features are generated from Centroid Contour Distance (CCD) [5] with 128 point around perimeter. Another study in [7] also use a combination of texture and shape features to detect immature citrus using a combination of LBP and Hierarchical Contour Analysis (HCA), this research achieve 82.3% precision rate. Another research in [8] conduct combination of texture and shape features hierarchically with that from the texture modality, generated by the well reputed texture operator, namely Local Binary Patterns (LBP), for decision making, and the results achieved are superior to the state-of-the-art ones so far reported in the literature, which demonstrates its effectiveness. The research in [9] presents a Facial Expression Recognition (FER) method based on an automatic and more efficient facial decomposition into regions of interest (ROI) using texture/shape descriptors and SVM classifier. The experimental results show the superiority of facial decomposition against existing ones and reached recognition rates up to 96.06%. Another study also conduct agriculture classification is detection of plant leaf diseases using image segmentation and soft computing techniques [10]. That research uses the green component as a base to get the leaf disease area. By using SVM classifier, it achieves accuracy up to 95.71%

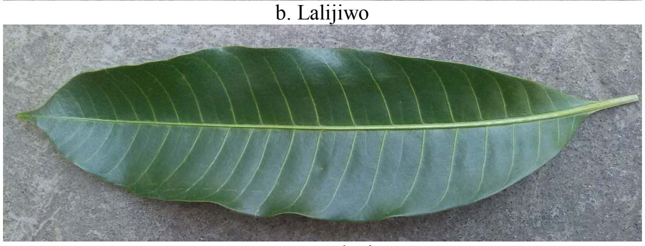
As the continuation of mango leaf classification research, we conduct multi-class classification for 3 mango varieties, namely Gadung, Lalijiwo, and Manalagi. The sample of each mango leaf image varieties is presented in Figure 1. For the classification method, we use Support Vector Machine (SVM) with the Linear, and RBF kernel. SVM is a convex optimization problem, which is an efficient algorithm to find the minimum global objective function. SVM also performs capacity control by maximizing the margin of decision boundary [11]. Apart from all that, the initial SVM design is for binary classes. In order to apply SVM to multi-class problems, we use some binary SVM with a multi-class solution design scheme. Examples of such schemes are one-against-all, one-against-one, and error correcting output code

[12]. For multi-class problem, we use one-against-all in the experiment.

a. Gadung



b. Lalijiwo



c. Manalagi

Fig. 1. Sample of mango leaf varieties

II. RESEARCH METHODOLOGY

A. Research Framework

The research framework for mango leaf classification is presented in Figure 2. This research is divided into several stages. They are as follow: (1) Image acquisition. This is the first stages, mango leaf is captured by phone cell camera with resolution 2592x1944 with normal effect. Each image contains one mango leaf; (2) Pre-processing 1. As the result of the acquisition environment, some of the acquisition results in some parts of the image object exposed to high-intensity light, so we have to remove this area; (3) Image segmentation. We use Otsu thresholding on Cr color component to segment the leaf area from background [13]; (4) Pre-processing 2. In this stage, we conduct some preprocessing, ie. morphological operations, resizing, cropping, and texture sampling; (5) Features extraction. We use 260 features used in previous research [2]. They are combined with 128 new shape features generated in this research. The new shape features are Centroid Contour Distance (CCD) [5]; (6) Data splitting. The data are split into 2 parts, ie. training and testing data. By 50:50 splitting, we prepare 50% proportion for training data and 50% proportion for testing data. We also use 2 fold cross validation in performance testing; (7) Training Data Reduction. In this stage, we conduct data reduction to simplify and speed up training computation; (8) Training in the classifier. In this stage, we conduct training with classification method; (9) Prediction. This is the last stages in our system. In this stage, we get the prediction result.

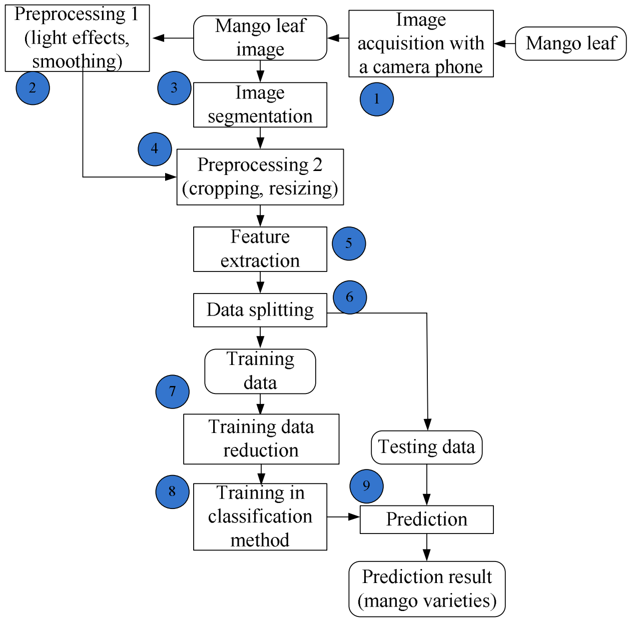


Fig. 2. Research Method

B. The Previous Features

The last research in mango leaf classification [2] uses 300 data, each data is represented by 260 features. The features consist of 256 Weighted Rotation- and Scale-invariant Local Binary Pattern features with average weights (WRSI-LBP-avg) texture features, 2 color features, and 2 shape features. The data are divided into three classes of mango varieties, namely Gadung, Lalijiwo, and Manalagi. Using SVM classification, it achieved up to 71.33% of accuracy.

C. Centroid Contour Distance (CCD) and Boundary Moments

Centroid Contour Distance (CCD) is centroid distance function, it is expressed by the distance of the boundary points $P_n(x(n), y(n)), n \in [1, N]$ from the centroid (g_x, g_y) (Eq. 1) of a shape [14].

$$r(n) = \left[(x(n) - g_x)^2 + (y(n) - g_y)^2\right]^{1/2} \quad (1)$$

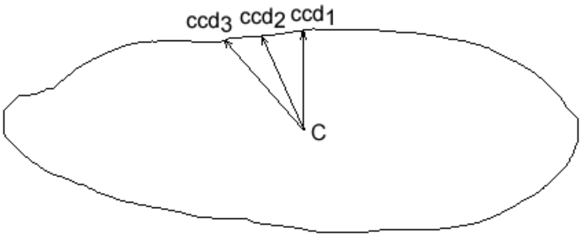
Due to the subtraction of centroid, which represents the position of the shape, from boundary coordinates, centroid distance function representation is invariant to translation. Centroid is the central pixel of the object area.

In this research, we generate 128 CCD shape features as new raw features used. We generate CCD by calculate distance from the centroid of mango leaf area to the boundary of the leaf. The CCD are calculated from the origin point then move clockwise by same distance from point to point boundary. We generate 128 CCD with same distance from point to point boundary. Figure 3 gives example, Figure 3(a) gives illustration of distance from centroid to the boundary, and Figure 3(b) gives illustration the distance of 128 CCD generated.

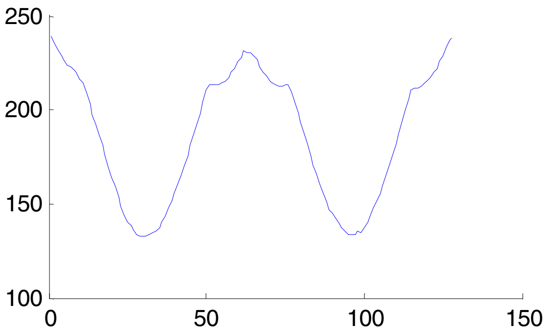
So, the CCD can give information by the distance, where each mango leaf have each shape feature itself. Due to the large CCD features, we convert it to Boundary Moments. We calculate Boundary Moments from CCD as new features used at the classification stage. Boundary Moments can be used to reduce the dimension of boundary representation by CCD [14]. Assume boundary points has represented by r(n), moment r-*th* and central moment m_r can be estimated as Eq. 2.

$$m_r = \frac{1}{N}\sum_{i=1}^{N}\left[z(i)\right]^r \text{ and } \mu_r = \frac{1}{N}\sum_{i=1}^{N}\left[z(i)-m_1\right]^r \quad (2)$$

where N is the number of boundary points. In this research, we use 128 points as representation of CCD.



a. Distance of each CCD



b. CCD diagram

Fig. 3. The Centroid Contour Distance (CCD) features

Less noise-sensitive shape descriptors can be obtained from F_1, F_2, and F_3 as Eq. 3.

$$F_1 = \frac{(\mu_2)^{1/2}}{m_1},\ F_2 = \frac{\mu_3}{(\mu_1)^{3/2}},\ \text{and } F_3 = \frac{\mu_4}{(\mu_2)^2} \quad (3)$$

Furthermore, we use F_1, F_2, and F_3 as new three features combined with the previous features.

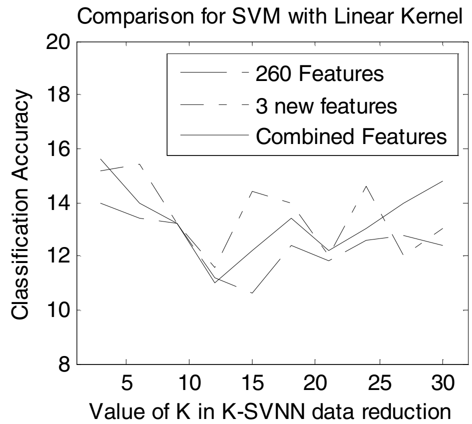
III. RESULTS AND DISCUSSIONS

The authors conduct experiments by comparing the performance between using 260 previous features and combination of previous feature with Boundary Moment of CCD. The CCD features are converted to be three Boundary Moments F1, F2, and F3. Related to the previous research, by using K-SVNN as data reduction method, we also conduct empirically testing with various value of K in K-SVNN data reduction. The various value of K used are 3, 6, 9, 12, 15, 18, 21, 24, 27, 30. The other new thing in our research is we use five class classification using Support Vector Machine (SVM). For testing method, we use 2-Fold Cross Validation, so we conduct 2 sessions with 50% data as training data and 50% data as testing data.

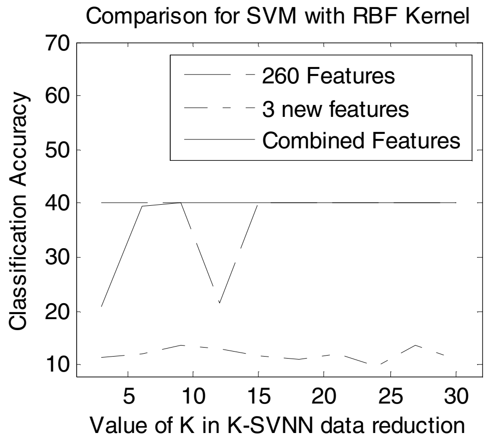
TABLE I. THE AVERAGE OF CLASSIFICATION ACCURACY

Features	SVM Classifier Accuracy (%)	
	Linear Kernel	**RBF Kernel**
260 features [2]	63.5	33.3
3 shape features	43.0	42.1
263 features (proposed features)	67.3	33.3

The results of our experiment are presented in Table 1. For the system with 260 features in the previous research, we get average classification accuracy only 63.5% for Linear kernel and 33.3% for RBF kernel. When we use only the Boundary Moments, we get worse accuracy for Linear kernel, 43.0%, but better accuracy for RBF kernel, 42.1%. The combination of all features, the accuracy increase 3.8%, so we get accuracy 67.3%. But for RBF kernel the accuracy remains on 33.3%. The increasing of accuracy is only 3.3, this is caused by the new shape feature is too small compared to previous features. So the new shape features can't give great impact to the classification system.



a. SVM with Linear kernel



b. SVM with RBF kernel

Fig. 4. Empirically testing result for various value of K in K-SVNN data reduction

The Figure 4 presents the graph result of empirically testing for Linear and RBF kernel respectively. The x-axis represents value of K in K-SVNN, the y-axis represents the accuracy achieved by SVM classification. The solid line represented accuracy result for combination of all features, while the dashed line represented accuracy result for 260 features, and the dash-dotted line represented accuracy result for new shape feature only. For Linear kernel, the accuracy tends to be higher for combination of all features than the 260 features. The results are different for the RBF kernel, we get the same accuracy for all option K value, it achieve 33% accuracy. The pattern value for 3 new shape features is lower compared to the other feature for Linear kernel, but higher for RBF kernel.

From the empirically testing and discussions, we conclude that system with the combination of all features achieved better classification performance compared to the system with previous features only. It gets better accuracy about 3.8%.

IV. CONCLUSION

From the experiment results, it is concluded that the system with the combination of the 260 feature from the previous research and 3 Boundary Moments features achieved better performance compared to the system with previous features only. It can improve the classification performance by up to 0.9% compared to using the previous feature only. We use 128 Centroid Contour Distance (CCD) as raw new shape features which are then converted into three Boundary Moments features. Since the performance of the combination of 256 WRSI-LBP-avg texture features, 2 color features, 2 shape features, plus 3 new form features Boundary Moments of CCD is still low then we plan to explore other features to improve the classification performance.

ACKNOWLEDGMENT

The authors give thanks to the Directorate of Research and Community Service (DRPM) DIKTI that fund Authors' research in the scheme of Inter-Universities Research Cooperation (PKPT) year 2018 between University of Bhayangkara Surabaya and Institut Teknologi Sepuluh Nopember, with contract number 009/SP2H/LT/K7/KM/2018 on 26 February 2018.

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