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# CLIMATE VARIABLES EFFECT ON EBONY LEAF MORPHOLOGY AND ITS REGIONAL IDENTIFICATION

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Ebony is a member of *Diospyros* genus, commercially used for furniture, sculpture, musical instruments and others. Ebony can be found to grow naturally in Sulawesi, Indonesia. According to the IUCN Red List of Threatened Species, ebony is included in the vulnerable category because of its decreasing population size due to the demand for the wood is not balanced by the successful cultivation. In the natural ecology, its growth performance is influenced by climate variables and soil properties which affects stand productivity and resilience including morphological responses. The extent to which leaf morphological responses due to climate variability have not been studied using extensive leaf samples collected from a wide range of natural distribution. The generated data that could be used to determine among others the suitability of growing sites and origins. This study aimed to analyse the variability of leaf morphology according to climatic condition and classify the morphology of ebony leaves by region based on support vector machine method. Results showed that climate variables such as temperature, rainfall and length of sun exposure have significant relationship to the morphology of ebony leaf. Moreover, the classification results by using support vector machine to identify ebony leaf morphology based on the region obtained a mean accuracy rate of 86.89%.

Keywords: Classification, ebony, environment, support vector machine

## INTRODUCTION

Ebony (*Diospyros* spp.) is a forest plant from the Ebenaceae family which is widespread in Indonesia. Among the seven species of ebony grown in Indonesia, the *Diospyros celebica* is the only one that is naturally found in Sulawesi (Soerianegara 1967). Ebony grows naturally in Poso, Donggala, and Parigi Regencies (Central Sulawesi); Gowa, Maros, Marru, Sidrap, Mamuju, and Luwu Regencies (South Sulawesi) and Gorontalo Province (Hendromono & Allo 2008). Ebony wood is the most common part used and belongs to robust wood class and shows shiny smooth wood pattern (Soerianegara 1967). Due to its durability and esthetic value, the wood is mainly exported to Japan and some European countries. The imbalance of high ebony wood demand and cultivation success caused the tree population to decrease in productivity. Hence in 1998, the IUCN Red List of Threatened Species classified ebony in the vulnerable category (IUCN 2019) and is included in the type of plants to be conserved according to the Ministry's Regulation of Forestry No:P.57/MENHUT-II/2008.

Climate change is predicted to be one of the contributing factors of plants extinction (Thuiller et al. 2005). Climate change will affect biological characteristics and modify an ecosystem's structures and functions (MacKinnon et al. 2008). Climate change caused changes in the rainy pattern, rainy season length, shift of the beginning of the rainy season, and increasing extreme climate events that significantly impact forestry sector and eventually affect tree's productivity. Efforts to overcome the ebony population decrease can be carried out through *in-situ* and *ex-situ* conservation and efforts towards sustainable utilisation (Sunaryo 2002). Environment condition in its habitat, such as altitude, light, and humidity is important for its growth (Allo 2002).

The leaf is one of the crucial parts of a plant that affects plant development and fast respond to habitat condition changes. As leaf plays a vital role in photosynthesis, the measurement of its shape is a challenging modeling problem due to the different shapes of leaves in each region. Therefore, a suitable modeling is required to discover plant characteristics and environmental conditions of the habitat location such as rainfall, temperature and humidity.

A study related to leaf morphology analysis carried out by Zhu et al. (2012), stated that the secondary venation density of the *Quercus variabilis* leaf population was positively correlated with the mean annual temperature. Another study showed that leaf area, leaf venation and leaf perimeter of the jujube plant was significantly related to temperature and rainfall (Li et al. 2015). In another study by Guerin et al. (2012) suggested that leaf width was negatively correlated to latitude and leaf area was negatively correlated to altitude. Furthermore, Zhang et al. (2018) showed that the *Parrotia subaequalis* had a significant relationship between venation intensity with environmental factors such as the mean annual temperature, mean rainfall and regional altitude. Therefore, this study was conducted with the objectives to analyse the relationship between climate variables with ebony leaf morphology and to conduct classification based on its natural habitats.

## MATERIALS AND METHODS

### Plant materials

Ebony leaf collection was conducted in 3 regions in its natural habitat in Sulawesi. The three locations were South Sulawesi, Central Sulawesi and West Sulawesi Provinces (Figure 1). Leaf collection was conducted by selecting up 20–25 sheets of the outer leaf on each tree. A total of 777 leaves were collected with 269 leaves from South Sulawesi, 327 leaves from Central Sulawesi and 81 leaves from West Sulawesi (Siregar et al. 2019). Climate data were obtained from the Meteorological, Climatological and Geophysical Agency from 2015 to 2019. The climate variables used were temperature, humidity, rainfall, sunlight exposure and wind velocity.

### Data preprocessing

Leaves collected were then subjected to the herbaria preservation procedure. After leaves were dried, scanning process was conducted to obtain digital pictures of each leaf. Subsequently, leaf image scaling process was conducted and the images were changed to grayscale image and a threshold process on the images was performed

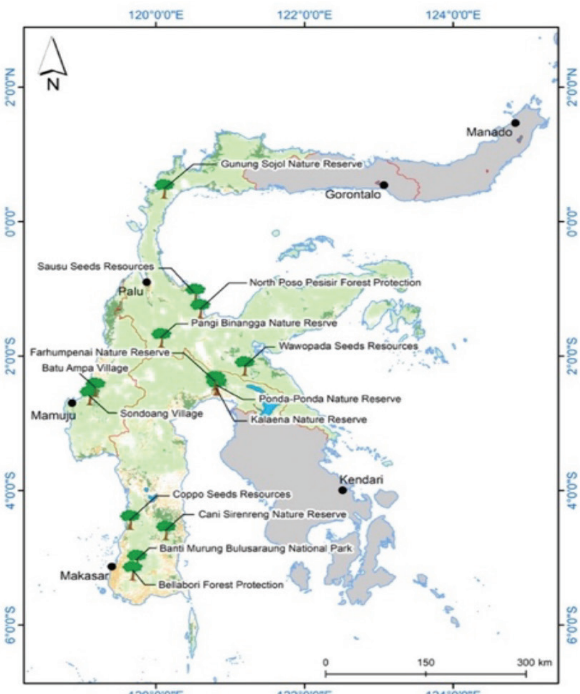


**Figure 1** Location for ebony leaves sampling (Siregar et al. 2019)

to distinguish background from the foreground (Figure 2).

Climate data obtained from Meteorological, Climatological and Geophysical Agency was then processed to address to the missing values. The method used to compliment missing climate variable values was by filling in the blank data with mean of its variable values.

## Feature extraction

In order to recognize an object in a picture, it is necessary to first extract several features or characteristics of the object. Primary features such as leaf area, leaf perimeter, leaf length, leaf width, convex area, convex perimeter and leaf casket were measured using an image analysis software or ImageJ. Derivative features were generated from calculated results of primary features combination, such as roundness, solidity, eccentricity, convexity, compactness, elongation, rectangularity, and aspect ratio. The formula of derivative features is shown in Table 1.

## Support vector machine

Support vector machine is a capable new technique for data classification and regression.

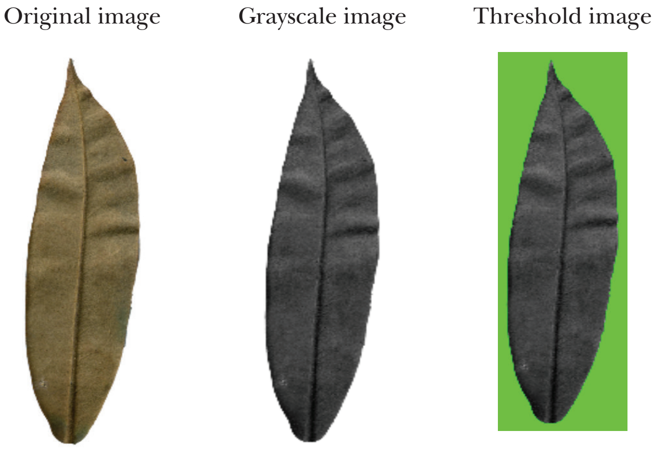


**Figure 2** Preprocessing of ebony leaf morphological data

**Table 1** Derivative features of leaf morphology

| Morphology features | Formula |
|---|---|
| Roundness | $\frac{\text{leaf area}}{\text{leaf length x leaf width}}$ |
| Solidity | $\frac{\text{leaf area}}{\text{convex area}}$ |
| Eccentricity | $\frac{\sqrt{(\text{leaf length}^2 - \text{leaf width}^2)}}{\text{leaf length}}$ |
| Convexity | $\frac{\text{convex perimeter}}{\text{perimeter}}$ |
| Compactness | $\frac{4 \text{ x } \pi \text{ x leaf area}}{\text{perimeter}}$ |
| Elongation | $1 - \frac{\text{leaf width}}{\text{leaf length}}$ |
| Rectangularity | $\frac{\text{leaf area}}{\text{leaf length x leaf width}}$ |
| Aspect ratio | $\frac{\text{leaf length}}{\text{leaf width}}$ |

After being developed in recent years, the technique has become an important topic in machine learning and pattern recognition because of its better theoretical basis which can compete with existing methods such as neural networks and decision tree. Support vector machine is a learning system for dividing data into two data groups using hypothetical space in the form of linear functions in a high-dimensional feature space. Support vector machine strategy is to try to find the best hyperplane in input space (Nugroho et al 2003).

Figure 3 illustrates that two classes which can be separated by a pair of parallel delimiters (hyperplane). The first parallel hyperplane field limits the first class while the second parallel hyperplane limits the second class, based on the equations below:

$$w^T \, . \, x_i + b \geq 1, \; for \; y_i = +1$$

$$w^T \, . \, x_i + b \leq -1, \; for \; y_i = -1$$

Generally, problems in the real-world domain or real world situations are rarely linear separable and are mostly non-linear. In order to resolve the non-linear issues, support vector machine technique is modified by inserting kernel functions. One kernel function that can be used on non-linear issues is the radial basis function kernel. A radial basis function kernel is a kernel that can improve a non-linearly map samples to higher dimensions. Therefore, in the new vector space, the hyperplane separating the two classes can be constructed.

## RESULTS AND DISCUSSION

### Feature extraction results analysis

After conducting feature extraction on Ebony leaf morphology, the mean of each feature was then calculated. The mean results of each leaf morphology can be seen in Table 2. After

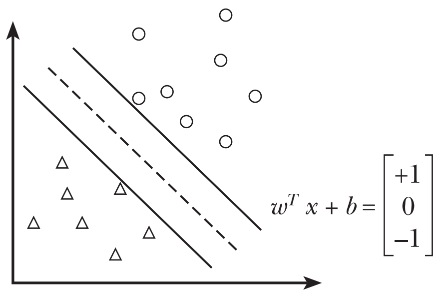


**Figure 3** Support vector machine linear data

**Table 2** Values of morphology features

| Morphology features | Value |
|---|---|
| Mean of leaf area | 80.106 |
| Mean of perimeter | 50.681 |
| Mean of circularity | 0.382 |
| Mean of leaf length | 22.513 |
| Mean of leaf width | 4.919 |
| Mean of aspect ratio | 4.436 |
| Mean of roundness | 0.228 |
| Mean of solidity | 0.967 |
| Mean of rectangle | 0.706 |
| Mean of elongation | 0.781 |
| Mean of eccentricity | 0.975 |
| Mean of convexhull area | 82.681 |
| Mean of convexhull perimeter | 47.136 |
| Mean of convexity | 0.930 |
| Mean of petiole | 0.851 |

obtaining values from each morphology features, normalisation using the Z-score normalization method was conducted. Normalisation is a scaling technique or a mapping technique (Shalabi 2006) to find a new range of existing ranges. Conducting data transformation with this normalisation increased the accuracy and efficiency level in the classification process (Patro & Sahu 2015). Results of the Z-score normalisation can be seen on Table 3**.** Subsequently, a box plot of each leaf morphology from each province was created from Table 3 data (Figure 4). A box plot showed data pattern in the form of mean, median, first and third quartile and identifies data considered as outliers (Sun dan Genton 2011). Figure 4 shows that South Sulawesi has the highest values on leave area features, leaf perimeter, leaf width, leaf length, convex hull area and convex hull perimeter. Meanwhile, West Sulawesi has similar values to each feature. Figure 4 also explain the different primary features od leaf morphology based on the regions.

## Relationship between climate variables and leaf morphology

Temperature is negatively correlated with primary features of ebony leaf morphology such as leaf area, leaf perimeter, leaf length, leaf width, convex area, convex perimeter, leaf casket and positively correlated to derivative features such as aspect ratio, elongation and eccentricity. Rainfall is positively correlated to primary morphology features and negatively correlated to derivative features such as aspect ratio, elongation, and eccentricity (Table 4).

The climate trend in Figure 5 also supported the observations. Over the past five years, the highest temperature value has been in the province of west Sulawesi, which has a lower leaf length of ebony compared to other provinces. While for rainfall, south and central Sulawesi has a high rainfall value that has a higher leaf length of ebony. Other climate variables such as humidity, sun exposure and wind velocity are also related to ebony leaf morphology, but their correlation values are low.

## Classification

Correlation analysis between features and target classes is performed to obtain the important features that can be used in the classification process. Table 5 shows leaf length is one of the important features used in classification. While the petiole, rectangle, and convexity features are features with very low correlation value to the target class so this feature is not used in the classification. The classification result indicates the accuracy in identifying ebony leaf's location or origin correctly. In these experiments, both methods were used. Firstly, support vector

**Table 3** Values of morphology features resulting from Z-Score normalisation

| Morphology features | Value |
|---|---|
| Mean of leaf area | $-3.657e^{-17}$ |
| Mean of perimeter | $-2.560e^{-16}$ |
| Mean of circularity | $-7.407e^{-16}$ |
| Mean of leaf length | $2.560e^{-16}$ |
| Mean of leaf width | $1.463e^{-16}$ |
| Mean of aspect ratio | $7.315e^{-17}$ |
| Mean of roundness | $-6.218e^{-16}$ |
| Mean of solidity | $3.795e^{-15}$ |
| Mean of rectangle | $-1.609e^{-15}$ |
| Mean of elongation | $1.646e^{-15}$ |
| Mean of eccentricity | $2.448e^{-14}$ |
| Mean of convexhull area | $-7.315e^{-17}$ |
| Mean of convexhull perimeter | $1.005e^{-15}$ |
| Mean of convexity | $-1.902e^{-15}$ |
| Mean of petiole | $-6.401e^{-17}$ |

 

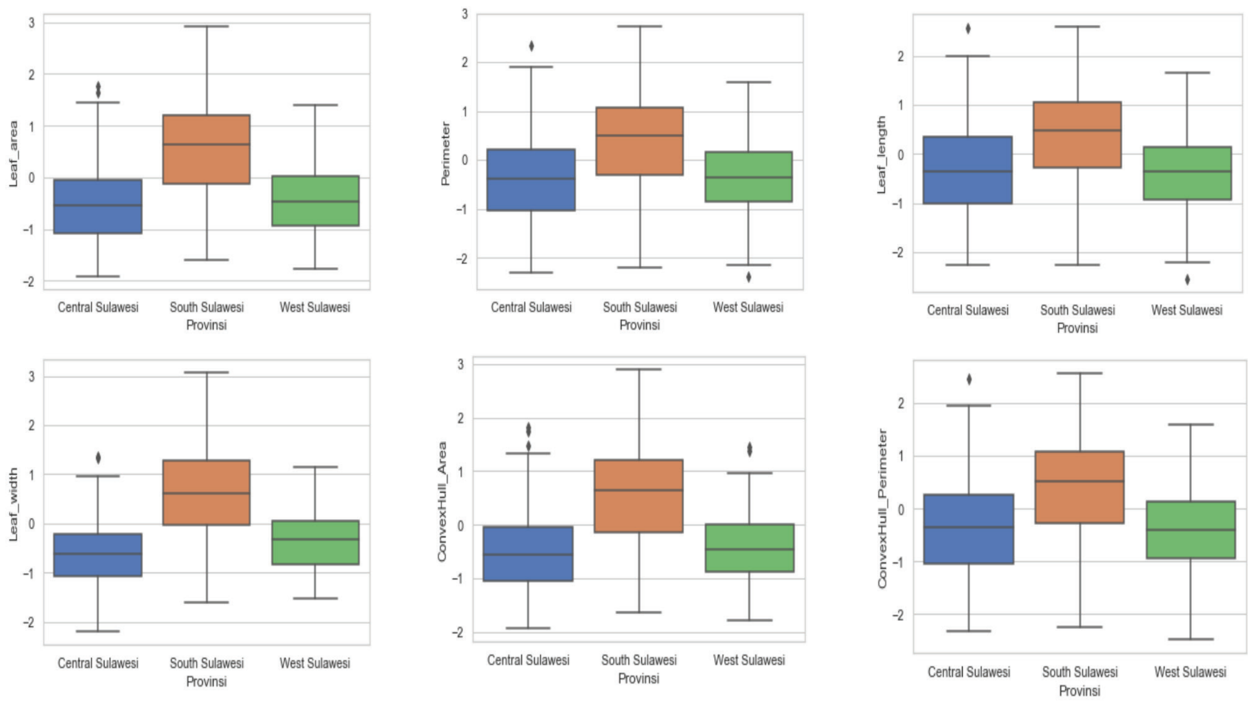


**Figure 4** Boxplot feature of leaf area, perimeter, leaf width, leaf length, convexhull area, convexhull perimeter for each region

**Table 4** Correlation of climate and morphology

| Feature Morphology | Temperature | Humidity | Rainfall | Long exposure to the sun | Wind velocity |
|---|---|---|---|---|---|
| Leaf area | -0.22 | -0.12 | 0.29 | 0.25 | -0.014 |
| Perimeter | -0.14 | -0.11 | 0.18 | 0.23 | 0.087 |
| Circularity | -0.31 | -0.01 | 0.37 | 0.038 | -0.36 |
| Leaf length | -0.13 | -0.08 | 0.17 | 0.2 | 0.091 |
| Leaf width | -0.28 | -0.14 | 0.35 | 0.26 | -0.092 |
| Aspect ratio | 0.28 | 0.1 | -0.4 | -0.17 | 0.29 |
| Roundness | -0.3 | -0.12 | 0.39 | 0.18 | -0.27 |
| Solidity | -0.23 | -0.03 | 0.21 | 0.099 | -0.2 |
| Rectangle | 0.036 | 0.026 | -0.06 | -0.058 | -0.087 |
| Elongation | 0.31 | 0.1 | -0.38 | -0.15 | 0.3 |
| Eccentricity | 0.31 | 0.11 | -0.37 | -0.15 | 0.29 |
| Convexhull Area | -0.21 | -0.12 | 0.28 | 0.25 | -0.006 |
| Convexhull Perimeter | -0.14 | -0.08 | 0.19 | 0.21 | 0.077 |
| Convexity | -0.058 | 0.26 | -0.08 | -0.34 | -0.13 |
| Petiole | -0.14 | -0.13 | 0.092 | -0.075 | -0.004 |

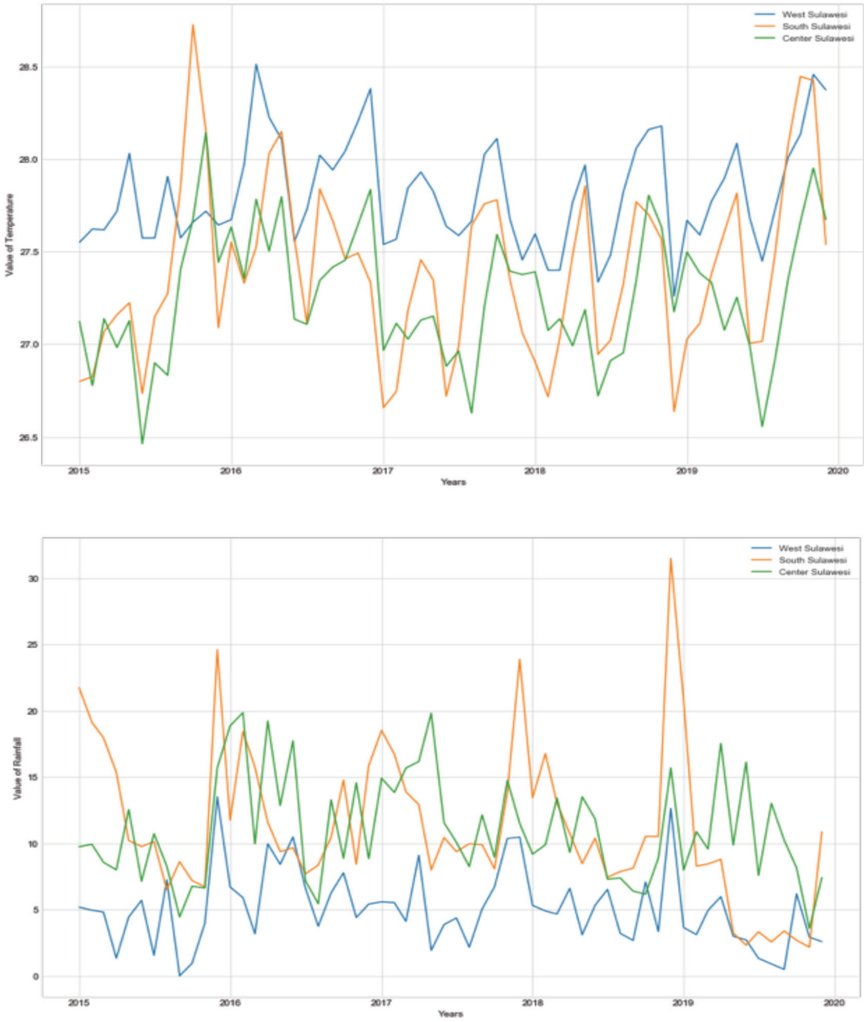


**Figure 5** Trends in temperature and rainfall

**Table 5** Correlation of morphology features with target

| Morphology features | Value |
|---|---|
| Leaf width | 0.519 |
| Leaf area | 0.470 |
| Convexhull area | 0.462 |
| Eccentricity | 0.417 |
| Roundness | 0.416 |
| Elongation | 0.416 |
| Circularity | 0.408 |
| Aspect Ratio | 0.399 |
| Convexhull perimeter | 0.361 |
| Perimeter | 0.353 |
| Leaf length | 0.341 |
| Solidity | 0.311 |
| Petiole | 0.246 |
| Rectangle | 0.032 |
| Convexity | 0.017 |

 

machine technique was used with different kernel linear, polynomial and radial basis function. Radial basis function kernel was employed because ebony leaves data set contained non-linearly separable. As a result, there are two parameters, parameter C and γ. Secondly, different classifier techniques such as K-NN and Naïve Bayes were used. The synthetic minority over-sampling technique method was used to overcome unbalance data (Table 6). The synthetic minority over-sampling technique hyperparameter with 3 nearest neighbours used. This method synthesised new samples of minority class to balance the dataset by resampling the minority class samples (Chawla et al. 2002).

The support vector machine kernel technique used was the radial basis function kernel with parameters of C = 1 and γ = 0.5. Classification results are presented in Figure 6. Based on Figure 6, West Sulawesi was classified as the best classification at 95%, followed by South Sulawesi with an accuracy level of 86%, and Central Sulawesi with an accuracy level of 82%. The mean accuracy value from testing results of each class at 87.6%.

Table 7 shows the accuracy comparison of different classifier methods using ebony leaves data sets. The results show that support vector machine method is the best method for this study. Accuracy of Naïve Bayes is at 63.0% and K-NN is ay 74.7%.

Misclassification in this study is due to the data used from leaf data of the same species. Thus creating value of morphological features of almost the same between the regions and some data are indicated as outliers.

## Weakness

Leaf data utilised were unbalanced and therefore additional leaf data were necessary, especially from West Sulawesi. Several other morphological features still lack such as ebony leaf venation which needed observation and attention in future collection.

**Table 6** Data distribution before and after SMOTE

| Location | Training data | Training data (SMOTE) | Testing data |
|---|---|---|---|
| South Sulawesi | 305 | 305 | 64 |
| Central Sulawesi | 256 | 305 | 71 |
| West Sulawesi | 60 | 305 | 21 |
| Total | 621 | 915 | 156 |

SMOTE = synthetic minority over-sampling technique method

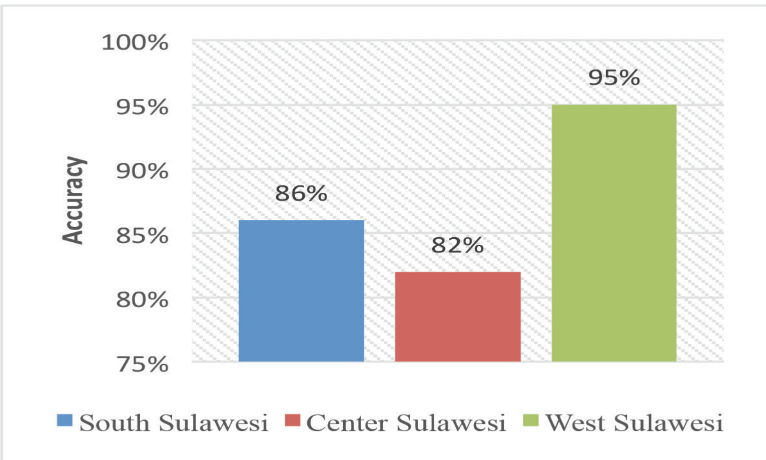


**Figure 6** Classification result using the support vector machine

**Table 7** Accuracy comparison of different classifier methods

| Classifier methods | Accuracy |
|---|---|
| Support vector machine | 87.6% |
| Naïve Bayes | 63.0% |
| K-NN | 74.7% |

## CONCLUSIONS

Ebony leaf collection was conducted in 3 regions in its natural habitat in Sulawesi island including South Sulawesi, Central Sulawesi, and West Sulawesi Provinces. The primary morphological features of ebony leaf extracted consisted of leaf area, leaf perimeter, leaf width, live length, convex area, convex perimeter and leaf casket. Leaf derivative features consist of circularity, roundness, solidity, rectangle, elongation, eccentricity and convexity. Environmental variables such as temperature and rainfall had significant impacts on the leaf morphology. On the contrary, features such as humidity, sun exposure and wind velocity had a low relationship with leaf morphology. Generally, it could be concluded that the classification model using the support vector machine technique with radial basis function kernel could differentiate leaf morphology based on the region with an accuracy level of 87.6%.

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