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Research paper

Comparison of Ensemble Methods for Malaysian Medicinal Leaf Images Identification and Classification

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Abstract

Malaysia has abundant natural resources especially plants which can be used for medicinal or herbal purposes. However, there is less research to preserve the knowledge of these resources to be utilized by the community in identifying useful medicinal plants using computing tools. In order to support this study, finding suitable method for identification and classification must be done in order to provide better classification performance. Ensemble methods are classification methods that combines several diverse classifiers which known to perform better than single classifiers. In this regard, the best ensemble method for this specific leaf image data need to be explored and Weka has been used as the platform to compare related ensemble methods. The study in this paper compares several ensemble classifiers where AdaboostM1 with Random Forest as base classifier provides the best technique to the nature of the shape-based Malaysian medicinal leaf images data. The ensemble classifier is also tested with other shape based dataset image domain and shows that the classifier is able to produce the best classification performance.

Keywords: *Medicinal plant, ensemble, AdaboostM1, Random Forest*

1. Introduction

Plants are among the most useful resources on earth and some of the plants are already at the risk of extinction [1]. It was reported that about 80% of the people in Asia and Africa rely on herbal medicine due to the fact that several of these resources are safe for human consumption and are also affordable [2].

In order to successfully implement the plant conservation, there are 16 targets grouped into five major headings for the target, namely: (1) understanding and documenting plant diversity (UDPD); (2) conserving plant diversity (CPD); (3) using plant diversity sustainably (UPDS); (4) promoting education and awareness about plant diversity (EAPD); and (5) building capacity for the conservation of plant diversity (CCPD) [3].

In Malaysia, the importance of medicinal plants (also known as herbal medicine) has been listed as one of the key research areas at the Institute for Medical Research, Ministry of Health. In order to leverage the importance of the resources, the Herbal Medicine Research Centre (HMRC) was formed in 2001 to conduct scientific studies of herbal products [4].

Medicinal plants have been frequently used by every race since the last generation. Older generations are believed to know more about medicinal leaves than the younger generation. The older generation had better learning time and had more exposure to various illness events, methods for treatment and their possible outcomes [5]. Nowadays, our younger generation lack of knowledge in recognizing the shapes or types of medicinal plants which are found in the jungles, riverbeds, or even in our home gardens. It could be fatal if poisonous plants are ingested accidentally. Various types of medicinal plants should be recorded, monitored and protected for the next generation. Therefore, an assistive identification and classification method is needed to help the community to identify which plants are safe for consumption by using easily available information.

2. Related Works

Studies on Malaysian medicinal plants are mostly on the physical scientific characteristics and consumption as seen in [6], [7], [8] and [9]. Only recently, computing works has been done in [10] which specifically started the study on the methods to classify Malaysian medicinal leaf images. In their work, method for feature extraction and classification has been described. However, the performance still needs to be enhanced in order to be deployed in a real leaf identification application. The best accuracy reported was only 65%.

Recent work in Malaysia related to plant species classification is found in [11], however this did not specifically address the Malaysian leaf images classification. The researcher uses lobes, sinuses and margins as methods to classify the leaf images. Based on eight species of plants, they reported accuracy up to 100%. However, they did not mention what kind of clustering/classification methods were used.

In similar works, a few studies on medicinal leaf images have been done in Indonesia and Thailand. The Thai herb leaf image recognition system developed by [12] employs several important components such as: 1) image collection; 2) image pre-processing; 3) training and recognition; and 4) results presentation. Their reported accuracy for matching using training that consists of 32 species and 1000 images was 93.29%.

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In Indonesia, [13] have described Indonesian medicinal plants identification and classification using a mixture of leaf features, such as texture, shape and colour. Based on 2448 images of 51 species, the reported average accuracy was 72.16% using the Probabilistic Neural Network (PNN) as a classifier. The researchers continued their work in [14], which shows an increased the classification performance to 74.51%. The study of the Indonesian leaf recognition system is continued in [15], where a mobile application for medicinal plant identification system using leaf textures called MedLeaf was developed. In this work, methods described in [15] were applied and the reported accuracy was 56.33%, which were based on texture features.

3. Ensemble Method

An ensemble method is defined as an approach that applies several single classifiers or may combine two or more diverse classifiers where the final judgment will be processed using a certain method (known as committee of experts decision) for classifying new unseen instances.
According to [16], in order to construct the ensemble classifiers, four approaches are normally followed: 1) combination level scheme to obtain the best combined ensemble using a similar set of training samples; 2) different types of classifier models (classifier level); 3) different sets of training samples (data level); and 4) different subsets of feature (feature level).
Weka [17], a machine learning tool for data mining provides specific methods to test the ensemble methods. The ensemble methods in Weka consist of several approaches mainly using approach 1 described above which are AdaboostM1, Bagging, Decorate, END, MultiBoostAB and MulticlassClassifier. The ensemble method called Multischeme enables several diverse classifiers to be combined for classification. These methods are specifically selected in this paper which they are directly working on creating the diverse combination of base classifiers into ensemble.
Boosting (Adaboost) and bagging (bootstrap aggregation) are the most popular techniques to construct the ensembles [18], that led to significant improvement in some application [19]. AdaboostM1 (adaptive boosting) was introduced by Freund and Schapire [20].
Bagging is an ensemble that was introduced by Breiman [21], where some base classifiers are induced by the similar learning algorithm and certain samples by bootstrapping. Prediction by the classifiers is finalized based on the equal weight majority voting [22]. This algorithm has been applied in many applications such as in [23], [24] with promising results.
DECORATE (Diverse Ensemble Creation by Oppositional Relabeling of Artificial Training Examples) is the ensemble method introduced by [25], which manipulates and builds diverse hypotheses using additional syntactically produced training examples. The main advantage of DECORATE is the concept of diversity in the ensemble constructed during the creation of artificial training instances.
Ensemble of Nested Dichotomies (END) [25] is constructed using standard statistical techniques in order to address polytomous classification problems with logistic regression. It was originally represented using binary trees that iteratively split a multiclass data into a system of dichotomies. END was reported to be more accurate than decision tree (C4.5) and logistic regression when applied directly to multiclass data. Provided that the ensembles are explicitly maximizing diversity together with the accuracy, single classifiers will always be outperformed by the ensemble [26], [27]. Ensembles that outperform single classifiers can be due to the improvements on the three areas, namely the statistical problem, the computational problem and the representation problem [16]. In [28], the ensemble is applied to ImageNet Large Scale Visual Recognition Challenge'10 with promising results and reduces the computational complexity during testing.
MultiBoostAB [29], is the extension of the boosting method specifically the AdaBoost algorithm that constructs strong decision committees. The algorithm combines AdaBoost and wagging together by reducing the AdaBoost's bias and variance. It was reported that by using the decision tree of C4.5, the method demonstrated a lower error more often when tested on a large representative of University of California Irvine (UCI) data sets.
Like its name, MulticlassClassifier works on multiclass data classification. According to the implementation of this method in [17], it is a metaclassifier specifically used for handling multiclass problems with 2-class methods (1-against-all and 1-against-1). The classifier is also able to employ error correcting output codes (random correction codes and exhaustive correction codes) in order to increase the classification accuracy.
In contrast with the above, the ensemble method found in [30], which specifically try to address the imbalance problem in multiclass data, was not always good for various dataset. The method was adapted in [10] to classify the medicinal leaf images, with the performance reported as 65%. This result takes into consideration the challenge in classifying high dimensionality features and the availability of only a few samples. Thus, based on the work in [10], this paper is focusing on exploring new methods to improve the classification performance on Malaysian medicinal leaf identification using a new ensemble methods.

4. Experiments

The dataset information related to Malaysian medicinal leaf images was acquired from [10] to follow closely the original dataset so comparisons can be made by using new ensemble methods. Species of the leaves are presented in Table 1.
The dataset contains features of shapes represented as angles of each point specified in the leaf. Thus, a full-leaf shape produces about 624 angles (using the default setting) which then become attributes. Table 2 shows the description of the experimental data.

Table 1: Leaf species for the experimental data

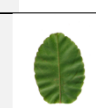
Class	Example	Name	Train	Test
1		Cemumar	11	4
2		Kapal Terbang	12	4
3		Kemumur Itik	11	4
4		Lakom	5	4
5		Mengkudu	6	4
Total			45	20

Table 2: Malaysian medicinal leaf dataset information

Description	Value #
#Examples	65
#Attributes	624
#Training	45
#Testing	20
#Majority	12
#Minority	5

The experiment uses six ensemble methods and four classifiers (Naïve Bayes (NB), Decision Tree (J48), Random Forest (RF), and Rules (PART)) found in Weka using their best settings. The results will be compared with the ensemble method used in [10]. Performance measure that was observed in each ensemble is the F-measure, which is normally used in measuring the true positive rate as well as the accuracy of positive prediction among the classes (in multiclass).

5. Results

Based on the experiment settings presented above, Table 3 shows the results of six ensemble methods with four different base classifiers.

Table 3: Ensemble methods' classification performance (in percentage %)

Ensemble Method	NB	J48	RF	PART
AdaboostM1	50	**70**	**70**	65
Bagging	50	60	**65**	55
Decorate	50	55	**60**	50
END	45	**65**	60	60
MultiBoostAB	55	**70**	**70**	60
MulticlassClassifier	45	**60**	50	**60**
Average (%)	49.17	**63.33**	62.50	58.33

The results in Table 3 are the best performance selected to be presented in this paper. Each ensemble method used a single classifier which produced up to 15 classifiers (as ensemble) and produces the classification accuracy on one dataset.

According to the results, ensemble methods using AdaboostM1 and MultiBoostAB almost produce similar performance which is 70% when using J48 or RF as base classifiers. The best base classifier in this experiment is the Decision Tree (J48) with an average performance in all ensemble methods at 63.33%. AdaboostM1 and MultiboostAB's performance outperformed the result obtained by ensemble method in [10] which produced 65%. This is due to the boosting method on the classifiers where AdaboostM1 started with one classifier and iteratively added another classifier to the ensemble until some criterion is reached. Generally, AdaboostM1 performed better than the other ensembles tested in this experiment.

The detailed accuracy by class when using AdaboostM1 with J48 and RF as base classifiers is shown in Table 4 and Table 5. According to the accuracy by class, it can be seen that AdaboostM1 with RF as the base classifier has better accuracy compared to using J48, although they have a similar percentage accuracy (70%). However, AdaboostM1 with J48 has the advantage of better classification on minority class as shown by F-measure in class leaf Lakom and Mengkudu, but lower performance on majority class. This is due to the boosting ensemble has focused too much on the minority class.

With the best model acquired from the experiments, another investigation is carried out using UCI Machine Learning benchmark leaf dataset (not medicinal leaf) [31]. Unlike the Malaysian medicinal leaf dataset which is shape-based only, the leaf dataset contains 340 instances from 30 species and 15 attributes describing shape and texture. The purpose of the investigation is to find out whether the best model for high dimensional shape-based data is suitable for combined shape and texture data. Table 6 shows the results from the experiments according to random splitting of 70:30 training and testing as used in the paper.

Table 4: Accuracy by class using AdaboostM1 and J48

	Precision	F-Measure	ROC Area	Class
	0.333	0.286	0.641	Cemumar
	1	0.4	0.734	Kapal Terbang
	0.5	0.667	0.813	Kemumur Itik
	1	1	1	Lakom
	1	1	1	Mengkudu
Avg.	0.767	0.67	0.838	

Table 5: Accuracy by class using AdaboostM1 and RF

	Precision	F-Measure	ROC Area	Class
	0.4	0.444	0.836	Cemumar
	1	0.857	0.938	Kapal Terbang
	0.571	0.727	0.93	Kemumur Itik
	1	0.4	0.914	Lakom
	1	1	1	Mengkudu
Avg.	0.794	0.686	0.923	

Table 6: Ensemble methods' classification performance (in percentage %) for benchmark leaf dataset [31]

Ensemble Method	NB	J48	RF	PART	Avg.
AdaboostM1	77.45	78.43	**82.35**	75.49	**78.43**
Bagging	74.51	72.55	**81.37**	68.63	74.26
Decorate	error	76.47	**83.33**	70.59	57.60
END	49.02	71.57	**80.39**	72.55	68.38
MultiBoostAB	77.45	75.49	**82.35**	77.45	78.19
MulticlassClassifier	77.45	54.90	**80.39**	61.76	68.63

According to the results in Table 6, the AdaBoostM1 followed by MultiBoostAB with RF are able to produce better classification average performance. However, END using RF shows slightly higher classification rate which is 83.33%. This rate is lower than reported accuracy in [31] (87% using Linear Discriminant Analysis). Considering that the data used in the study was only 171 instances from 15 different species, 340 instances and 30 species made a significant amount of data.

Another benchmark data from UCI Machine Learning that investigated is vehicle silhouette dataset [32]. The data is described by 18 shape features for identifying four vehicle types, where 753 instances used as training data and another 94 testing data was used in the experiment. The performance of the ensemble methods are presented in Table 7.

Table 7: Ensemble methods' classification performance (in percentage %) for benchmark vehicle silhouette dataset adapted from [32]

Ensemble Method	NB	J48	RF	PART	Avg.
AdaboostM1	48.93	**100**	**100**	**100**	87.23
Bagging	57.44	95.74	**98.93**	96.81	87.23
Decorate	51.06	**100**	**100**	**100**	**87.77**
END	48.93	98.94	**100**	96.81	86.17
MultiBoostAB	48.94	**100**	**100**	**100**	87.24
MulticlassClassifier	51.06	98.94	**100**	94.68	86.17
Average (%)	51.06	98.94	**99.82**	98.05	

Based on the result in Table 7, almost all of the methods produce similar performance except using Naïve Bayes as base classifier. Decorate ensemble is slightly higher average accuracy, followed by MultiBoostAB and AdaBoostM1. It can be seen that Random Forest is the best for ensemble base classifier for all methods.

On other shape data from [33], the original data is in the form of 2D coordinates which represent airplane shapes. The data consists of 210 instances [34], 1972 attributes and 7 airplane shape classes. In our experiment, the data is transformed into contour distance (using Euclidean distance measure) of each coordinates from the shape centroid. 10-cross fold validation is used to get the performance of the ensemble methods which presented in Table 8 [35].

Table 8: Ensemble methods' classification performance (in percentage %) for benchmark airplane shape data [33]

Ensemble Method	NB	J48	RF	PART	Avg.
AdaboostM1	80.48	87.14	**94.29**	88.57	87.62
Bagging	82.86	84.76	**91.90**	83.81	85.83
Decorate	79.52	89.52	**94.76**	90.00	**88.45**
END	77.62	90.95	**94.29**	87.62	87.62
MultiBoostAB	82.86	86.19	**94.29**	87.14	87.62
MulticlassClassifier	84.76	82.38	**93.33**	82.86	85.83
Average (%)	81.35	86.82	**93.81**	86.67	

The result in Table 8 shows that Decorate has performed slightly better than other ensembles and Random Forest [36] is the best base classifier while other ensemble almost have similar performance [37]. AdaboostM1 is actually not too far behind Decorate because it still provides the competitive performance [38] to both vehicle and airplane shape data.

6. Conclusion

In this paper, we investigate the performance of several ensemble and base classifiers. The study identified a promising ensemble method to identify and classify the medicinal leaf images' shape data. The experiment shows that the ensemble of AdaboostM1 with J48 and RF is capable to increase the identification performance for medicinal leaf dataset. The model is also tested on UCI benchmark leaf data and confirmed that the classifier is able to perform on different leaf feature extraction method. However, on non-leaf dataset, Decorate with Random Forest is the best algorithm for classifying very similar shape-based data. Thus, the method will further investigated and implemented in future development of hybrid classifier model which incorporating AdaboostM1, Random Forest, feature selection and sampling to improve medicinal leaf images classification and identification.

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