Full Paper

IMPROVING THE IDENTIFICATION AND CLASSIFICATION OF MALAYSIAN MEDICINAL LEAF IMAGES USING ENSEMBLE METHOD

Article history
Received

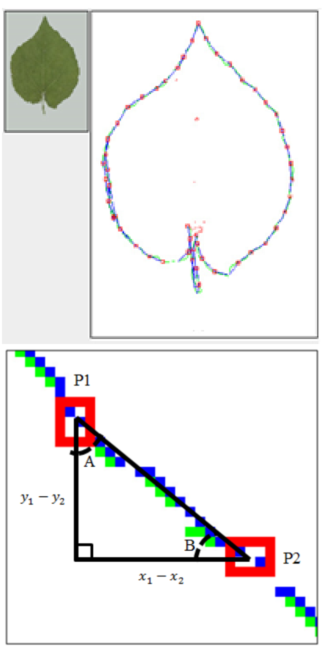
Received in revised form

Accepted

Mohd Shamrie Sainin[a*], Faudziah Ahmad[a], Rayner Alfred[b]

[a]School of Computing, UUM, 06010, Sintok, Kedah, Malaysia
[b]Faculty of Computing and Informatics, Malaysia

*Corresponding author
shamrie@uum.edu.my



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. This paper presents the implementation of digital opportunities for Malaysian medicinal plants via leaf image identification and classification. Of late, experts in traditional medicine and herbs have become few and the younger generation are mostly unknowledgeable about the medicinal and herbal properties of the plants. Therefore, this work is important in assisting the community (rural and urban) to identify and possibly share the knowledge of Malaysian medicinal plants with the future generation. The focus of this paper is to prepare the identification phase before the actual system is developed. Thus, the implementation of such a system is vital in order to enable the community to preserve these important resources.

Keywords: Malaysian medicinal plant, classification, ensemble learning

1.0 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]. However, plant experts are decreasing and are slowly forgotten by the younger generation. Thus, efforts to conserve and protect these resources are at a high stake. With the advancement of current technology, the identification and classification of plants become inexpensive (e.g. leaves sampling, photography and database).

According to the Convention on Biological Diversity (CBD), 188 countries signed and adopted the documentation of Global Strategy for Plant Conservation (GSPC) for conserving plant diversity [3]. In order to successfully implement this plan, 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).

Efforts to understand and document plant diversity continue to grow where there are a number of projects held in order to document the flora diversity around the globe. The documentation includes various data and images of all kinds of plants. Taking this as part of this paper's motivation, plant image recognition and classification is very much required to further support the conservation efforts as specified in UPDS.

Medicinal plants are a large group of plants used in medicine for the purpose of treatment or prevention, which provides health-promoting characteristics. In simple words, medicinal plants or leaves are known as herb. Medicinal plants were used as early as 3000 B.C. as described in ancient Chinese and Egyptian papyrus writings. 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.

2.0 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%.

In Indonesia, [13] have described Indonesian medicinal plants identification and classification using a mixture of leaf features, such as texture, shape and colour. They used the Local Binary Pattern Variance to extract important features such as leaf texture and morphological features from a leaf's shape. Another feature is the colour moment from leaf colour's distribution. 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], using an Android mobile application for identifying the Indonesian medicinal plant images based on texture and colour features of digital leaf images. In this work, they investigated the effectiveness of the Fuzzy Local Binary Pattern (FLBP) and the Fuzzy Colour Histogram (FCH) for medicinal plants identification. Fusion of both methods and using the similar number of leaf images has increased the classification performance to 74.51%. The study of the Indonesian leaf recognition system is continued by [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.

3.0 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.

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) is one of the family algorithms in boosting which was introduced by Freund and Schapire [20]. The AdaboostM1 algorithm is presented in Figure 1.

Algorithm: AdaBoost.M1
Input: sequence of m examples $\langle(x_1, y_1), \dots, (x_m, y_m)\rangle$
with labels $y_i \in= \{1, \dots, k\}$
weak learning algorithm **WeakLearn**
integer T specifying number of iterations
Initialize $D_1(i) = 1/m$ for all i
Do for $t = 1,2, \dots, T$:
1. Call WeakLearn with distribution D_t.
2. Get back a hypothesis $h_t : X \rightarrow Y$.
3. Calculate the error of h_t : $\epsilon_t \sum_{i:h_t(x_i)\neq y_i} D_t(i)$.
   If $\epsilon_t > 1/2$, then set $T = t - 1$ and abort loop.
4. Set $\beta_t = \epsilon_t/(1-\epsilon_t)$.
5. Update distribution D_t:
   $$D_{t+1}(i) = \frac{D_{t(i)}}{Z_t} \times \begin{cases} \beta_t \; if \; h_t(x_i) = y_i \\ 1 \; Otherwise \end{cases}$$
   Where Z_t is normalization constant
   (chosen so that D_{t+1} will be a distribution).

Output: final hypothesis:
$$h_{fin}(x) = arg \max_{y\in Y} \sum_{t:h_t(x)=y} log \frac{1}{\beta_t}$$

Figure 1 AdaboostM1 algorithm [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. Figure 2 shows the Bagging algorithm.

Algorithm: Bagging
Training: In each iteration $t, t = 1, \dots, T$
Randomly sample with replacement N samples from the training set
Train a chosen "base model" on the samples
Testing:For each text example
Start all trained base models
Predict by combining results of all T trained models:
Regression: averaging
Classification: majority vote

Figure 2 Bagging algorithm

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. The algorithm is summarized in Figure 3.

Algorithm: DECORATE
Input:
BaseLearn – base learning algorithm
T – set of m training examples $< (x_1, y_1), \dots, (x_m, y_m) >$
with labels $y_i \in Y$
C_{size} – desired ensemble size
I_{max} – maximum number of iterations to build an ensemble
R_{size} – factor that determines number of artificial example to generate

1. $i = 1$
2. $trials = 1$
3. $C_i = BaseLearn(T)$
4. Initialize ensemble, $C^* = \{C_i\}$
5. Compute ensemble error, $\varepsilon = \frac{\sum_{x_j \in T, C^*(x_j)\neq y_j} 1}{m}$
6. While $i < C_{size}$ and $trials < I_{max}$
7. Generate $R_{size} \times |T|$ training examples, R, based on distribution of training data
8. Label example in R with probability of class labels inversely proportional to prediction of C^*
9. $T = T \cup R$
10. $C' = BaseLearn(T)$
11. $C^* = C^* \cup \{C'\}$
12. $T = T - R$, remove the artificial data
13. Compute training error, ε',of C^*
14. If $\varepsilon' \leq \varepsilon$
15. $i = i + 1$
16. $\varepsilon = \varepsilon'$
17. Otherwise,
18. $C^* = C^* - \{C'\}$
19. $trials = trials + 1$

Figure 3 DECORATE algorithm

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. Ensembles are not only shown to be more accurate than any single classifier, but they should be diverse to learn different 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. The algorithm is shown in Figure 4.

Algorithm: MultiBoost
Input:
S, a sequence of m examples $\langle (x_1, y_1), \dots, (x_m, y_m) \rangle$ with labels $y_i \in= Y$.
Base learning algorithm BaseLearn.
Integer T specifying the number of iterations.
Vector of integers I_i specifying the iteration at which each subcommittee
$i \geq 1$ should terminate.

1. $S' = S$ with instance weights assigned to be 1.
2. Set $k = 1$.
3. For $t = 1$ to T {
4. If $I_k = t$ then
5. reset S' to random weights drawn from continuous Poisson distribution.
6. standardize S' to sum to n.
7. increment k.
8. $C_t = BaseLearn(S')$.
9. $\varepsilon_t = \frac{\sum_{x_j \epsilon S' : C_t(x_j) \neq y_j} weight(x_j)}{m}$
10. If $\varepsilon_t > 0.5$ then
11. reset S' to random weights drawn from continuous Poisson distribution.
12. standardize S' to sum to n.
13. increment k.
14. Go to Step 8.
15. Otherwise if $\varepsilon_t = 0$ then
16. set β_t to 10^{10}
17. reset S' to random weights drawn from continuous Poisson distribution.
18. standardize S' to sum to n.
19. increment k.
20. Otherwise,
21. $\beta_t = \frac{\varepsilon_t}{(1-\varepsilon_t)}$.
22. For each $x_j \in S'$,
23. Divide $weight(x_j)$ by $2\varepsilon_t$ if $C_t(x_j) \neq y_j$ and $2(1-\varepsilon_t)$ otherwise.
24. If $weight(x_j) < 10^{-8}$, set $weight(x_j)$ to 10^{-8}.
25. }
26. **Output**: final classifier
27. $C^*(x) = arg \max_{y \in Y} \sum_{t:C_t(x)=y} log \frac{1}{\beta_t}$

Figure 4 Multiboost algorithm

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.

4.0 EXPERIMENTS

The dataset 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.

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

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.

The experiment uses six ensemble methods and five classifiers (Naïve Bayes (NB), Decision Tree (J48), Random Forest (RF), Rules (PART) and Radial Basis Function Network (RBFN)) found in Weka using their best settings to increase the classification performance. 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).

Table 2 Malaysian medicinal leaf dataset information

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

5.0 RESULTS

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

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

Ensemble Method	NB	J48	RF	PART	RBFN
AdaboostM1	50	**70**	**70**	65	60
Bagging	50	60	**65**	55	50
Decorate	50	55	**60**	50	-
END	45	**65**	60	60	50
MultiBoostAB	55	**70**	**70**	60	45
MulticlassClassifier	45	**60**	50	**60**	55
Average (%)	49.17	**63.33**	62.50	58.33	43.33

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.

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	

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.

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	

6.0 CONCLUSION

This study identified promising ensemble methods to identify and classify the Malaysian medicinal leaf images' shape data. The experiment shows that the ensemble of AdaboostM1 with J48 and RF is capable to increase the identification performance. Thus, the method can be implemented in future applications of Malaysian medicinal leaf image identification with further enhancement related feature extraction, machine learning approaches and retrieval.

Acknowledgement

This research is fully supported by Fundamental Research Scheme (FRGS) grant, 13142 (2014). The authors fully acknowledge the Ministry of Higher Education (MOHE) and Universiti Utara Malaysia for the approved fund, which makes this important research viable and effective.

References

[1] Kulkarni, A. H., Rai, H. M., Jahagirdar, K. A., and Upparamani, P. S. 2013. A Leaf Recognition Technique for Plant Classification Using RBPNN and Zernike Moments. *International Journal of Advanced Research in Computer and Communication Engineering*. 2(1): 984–988.

[2] Chemburkar, A., Sartape, A., Gawade, A., and Somawanshi, P. 2014. Automated Tool for Plant Leaf Classification Using Morphological Features. *International Journal Of Engineering And Computer Science*. 3(11): 9098–9102.

[3] Krupnick, G. A. and Kress, W. J. 2005. Plant Conservation: A Natural History Approach. *The Plant Press*.

[4] HMRC. Introduction to Herbal Medicine Research Centre (HMRC). 2011. [Online]. Available: http://www.imr.gov.my/en/hmrc.html.

[5] Quinlan, M. B. and Quinlan, R. J. 2007. Modernization and Medicinal Plant Knowledge in a Caribbean Horticultural Village. *International Journal for the Analysis of Health*. 21(2): 169–192.

[6] Kadir, A. A. 1998. Biodiversity Prospecting Of Tropical Plants For Medicinal Uses. *In Proceedings of the Third National Congress on Genetics*.

[7] Jantan, I. 2004. Medicinal Plant Research in Malaysia: Scientific Interests and Advances. *Jurnal Sains Kesihatan Malaysia*. 2(2): 27–46.

[8] Ong, H. C., Zuki, R. M., and Milow, P. 2011. Traditional Knowledge of Medicinal Plants among the Malay Villagers in Kampung Mak Kemas, Terengganu, Malaysia. *Ethno Med*. 5(3): 175–185.

[9] Zakaria, M. and Mohd, M. A. 2010. *Traditional Malay Medicinal Plants*. Institut Terjemahan Negara Malaysia.

[10] Sainin, M. S., Ghazali, T. K., and Alfred, R. 2014. Malaysian Medicinal Plant Leaf Shape Identification and Classification. *In Proceedings of the Knowledge Management International Conference and Exhibition*. 578–583.

[11] Bong, M.-F., Sulong, G., Kumoi, R., and Rahim, M. S. M. 2015. Classify The Plant Species Based on Lobes, Sinuses and margin. *Jurnal Teknologi*. 75(2): 27–31.

[12] Pornpanomchai, C., Rimdusit, S., Tanasap, P., and Chaiyod, C. 2011. Thai Herb Leaf Image Recognition System (THLIRS). *Kasetsart Journal (Natural Science)*. 045(3): 551–562.

[13] Herdiyeni, Y. and Santoni, M. M. 2012. Combination of Morphological, Local Binary Pattern Variance and Color Moments Features for Indonesian Medicinal Plants Identification. *In Proceedings of the International Conference on Advanced Computer Science and Informations*. 255–259.

[14] Herdiyeni, Y. and Wahyuni, N. K. S. 2012. Mobile Application for Indonesian Medicinal Plants Identification using Fuzzy Local Binary Pattern and Fuzzy Color Histogram. *In Proceedings of the International Conference on Advanced Computer Science and Information Systems (ICACSIS2012)*.

[15] Prasvita, D. S. and Herdiyeni, Y. 2013. Medleaf Mobile Application for Medicinal Plant Identification Based on Leaf Image. *Advanced Science Enginering Information Technology*. 2(2): 5–8.

[16] Guo, X., Yin, Y., Dong, C., Yang, G., and Zhou, G. 2008. On the Class Imbalance Problem. *In Proceedings of the Fourth International Conference on Natural Computation, ICNC'08*. 4: 192–201.

[17] Witten, I. and Frank, E. 2000. *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann.

[18] Dietterich, T. G. 2000. Ensemble methods in machine learning. *In Proceedings of the IEEE Transactions on Multiple Classifier Systems, Man, and Cybernetics Part B: Cybernetics*. 1857: 1–15.

[19] Galar, M., Fernandez, A., Barrenechea, E., Bustince, H., and Herrera, F. 2012. A Review on Ensembles for the Class ImbalanceProblem: Bagging-, Boosting-, and Hybrid-Based Approaches. *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*. 42(4): 463–484.

[20] Freund, Y. and Schapire, R. 1996. Experiments with a new boosting algorithm. *In Proceedings of the International Conference on Machine Learning*. 148–156.

[21] Breiman, L. 1996. Bagging Predictors. *Machine Learning*. 24(2): 123–140.

[22] Jerzy Błaszczyński, Stefanowski, J., and Idkowiak, Ł. 2013. Extending Bagging for Imbalanced Data. *In Proceedings of the 8th International Conference on Computer Recognition Systems CORES*. 269–278.

[23] Yao, B., Zhao, Z., Liu, K., and Cai, A. 2015. Bagging based metric learning for person re-identification. *In Proceedings of the IEEE International Conference on Multimedia and Expo (ICME)*. 1–6.

[24] Gaikwad, D. P. and Thool, R. C. 2015. Intrusion Detection System Using Bagging Ensemble Method of Machine Learning. *In Proceedings of the International Conference on Computing Communication Control and Automation (ICCUBEA)*. 291 – 295.

[25] Melville, P. and Mooney, R. J. 2004. Creating Diversity In Ensembles Using Artificial Data. *Information Fusion*. 6: 99–111.

[26] Gu, S. and Jin, Y. 2014. Generating diverse and accurate classifier ensembles using multi-objective optimization. *In Proceedings of the IEEE Symposium on Computational Intelligence in Multi-Criteria Decision-Making (MCDM)*. 9–15.

[27] Gu, S., Cheng, R., and Jin, Y. 2015. Multi-objective ensemble generation. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*. 5(5): 234–245.

[28] Ramisa, A. and Torras, C. 2013. Large-scale image classification using ensembles of nested dichotomies. *Frontiers in Artificial Intelligence and Applications*. 256: 87–90.

[29] Webb, G. I. 2000. MultiBoosting: A Technique for Combining Boosting and Wagging. *Machine Learning*. 40: 159–196.

[30] Sainin, M. S. and Alfred, R. 2012. A Direct Ensemble Classifier for Imbalanced Multiclass Learning. *In Proceedings of the International conference on Data Mining Optimization (DMO2012)*. 59–66.