Heterogeneous Ensemble for Imaginary Scene Classification

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Abstract: In data mining, identifying the best individual technique to achieve very reliable and accurate classification has always been considered as an important but non-trivial task. This paper presents a novel approach - heterogeneous ensemble technique, to avoid the task and also to increase the accuracy of classification. It combines the models that are generated by using methodologically different learning algorithms and selected with different rules of utilizing both accuracy of individual modules and also diversity among the models. The key strategy is to select the most accurate model among all the generated models as the core model, and then select a number of models that are more diverse from the most accurate model to build the heterogeneous ensemble. The framework of the proposed approach has been implemented and tested on a real-world data to classify imaginary scenes. The results show our approach outperforms other the state of the art methods, including Bayesian network, SVM and AdaBoost.

1 INTRODUCTION

Data has been increasing rapidly not only in sheer quantity but also in complexity and variety of multimedia. This increase poses a significant challenge for data mining field to develop new methods and techniques to analyse and mine large datasets more effectively, including image and text data. Classifying imaginary scenes has become a problem that many researchers have been working to solve (Lazebnik et al., 2006; Wallraven et al., 2003). Finding a solution is crucial because such classification is used to support myriad tasks such as localization, mapping, and navigation (Siagian and Itti, 2007). Understanding scene classification further helps to understand images and recognize various objects in the images (Hotta, 2008). Studies on imaginary scene classification requires two phases. The first is to extract the features contained in image datasets (Yang et al., 2007; Lazebnik et al., 2006; Grauman and Darrell, 2005). The second is to apply suitable and useful classification methods (Yang et al., 2007; Wallraven et al., 2003), such as ensemble.

An ensemble (Dietterich, 2000) combines multiple models with the aim of achieving better results usually via a grating technique in the field of machine learning, which can be useful for scene classification. However, when attempting to build an effective ensemble several factors need to be considered. The first factor is the accuracy gained for each individual model in the ensemble members (Caruana et al., 2004). The second factor is the diversity among the member models in the ensemble (Caruana et al., 2004) (Wang, 2008; Zenobi and Cunningham, 2001). The third factor is the number of models that are combined to build the ensemble (Zhang et al., 2005). The decision fusion function used in the ensemble also affects the results (Liu et al., 2000).

This paper presents a heterogeneous ensemble for scene classification because it is a complex multiple-class problem that has overwhelmed single models but could be better dealt with ensemble methods to achieve two benefits. One benefit is that an ensemble is more likely to outperform individual models (Brown et al., 2005; Wang et al., 2003). Another benefit of an ensemble is the reliability it offers (Wang, 2008). Using this problem as a case study, this work also investigates how much the ensemble members affect the accuracy of the results of imaginary scene classification, in terms of the accuracy of the individual models selected, the diversity among the models, and the size of the ensemble.

The rest of the paper is organized as follows. Section 2 will briefly discuss several of the previous studies in the field. Section 3 will detail our methods, listing the tools and programs used in the research. Section 4 provides details of the experiment conducted and our results. Section 5 will present our conclusions and suggestions for the future work.

2 RELATED WORK

Many scene classification studies have been previously conducted. A notable study was done by (Oliva and Torralba, 2001) using a dataset called 8 Scene Categories Dataset. Their experiment involved classifying images and their annotations into eight categories using the support vector machine technique, by training 100 instances from each class and testing the rest. They achieved 83.70% accuracy.

(Bosch et al., 2006) also studied scene classification. They started the study by recognizing all possible objects in the image, and then classifying each image regrading to its objects. They used pLSA (Hofmann, 2001) to represent objects in the images. The pLSA originally devolved as topic discovery in a text but it was used in this research because images were represented as frequency of visual words. The k-Nearest Neighbour (k-NN) algorithm was used as a classification method in three different datasets.

(Yang et al., 2007) conducted an experiment on scene classification using keypoint as a method to extract features from images. In their experiment, images were described as a bag of visual words. They demonstrated that their methods outperform others using two benchmark datasets: TRECVID 2005 corpus and PASCAL 2005 corpus. The keypoint approach was originally created to classify text datasets, and was found to be useful for image classification as conducted in this experiment and others, including in (Lowe, 2004), (Ke and Sukthankar, 2004), (Mikolajczyk and Schmid, 2004).

(Lertampaiporn et al., 2013) applied a heterogeneous ensemble for pre-miRNA in their experiment by using voting for a set of classifiers including a support vector machine, k-NN and random forests.

Scene classification has been studied from the view of homogeneous ensemble methods. (Yan et al., 2003) applied an homogeneous ensemble of SVM models to classify rare classes on scene classification. Their experiment was conducted on a dataset called (TREC 02 Video Track), and was compared with other approaches applied to the same dataset. The results obtained in the experiment outperformed other methods with 11% improvement in the best case.

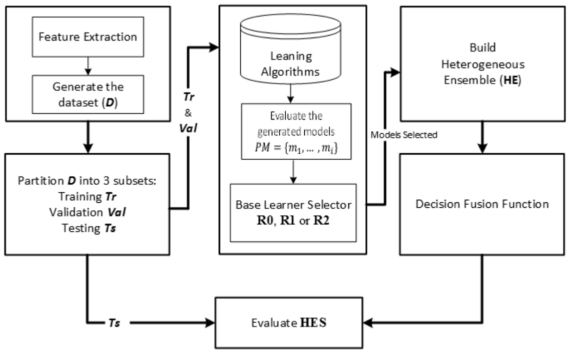
(Giacinto and Roli, 2001)enforced neural network ensemble for image classification on a dataset of multi-sensor remote-sensing images. They focused on classifying a bunch of pixels related to different images for different classes. The experimental results they obtained demonstrated the effectiveness of homogeneous neural network ensemble, with the level of accuracy achieved in the experiment being higher than the best accuracy of individual neural network models.

In summary, the previous studies used different features and methods for scene classification , but these studies were limited in terms of the type of features extracted from images and the methods used as most experiments were conducted using just one classification model, for example support vector machine and k-NN approaches, whilst other studies used homogeneous ensemble. Heterogeneous ensemble was not used for classifying image scene.

3 THE HETEROGENEOUS ENSEMBLE SYSTEM (HES)

3.1 The Framework of the HES

The proposed heterogeneous ensemble system as shown in Fig.1, consists five main components: 1, feature extraction and data formation; 2, data partition; 3, heterogeneous model generation and evaluation; 4, ensemble construction and 5, decision fusion function. The key idea of the proposed heterogeneous ensemble system (HES) is to generate methodologically different models, hence called heterogeneous models, by different learning algorithms, as the member candidates and then build an ensemble with the rules as defined below.



Feature Extraction
Generate the dataset (***D***)
Partition ***D*** into 3 subsets: Training ***Tr*** Validation ***Val*** Testing ***Ts***
Tr & ***Val***
Leaning Algorithms
Evaluate the generated models $PM = \{m_1, \dots, m_i\}$
Base Learner Selector **R0**, **R1** or **R2**
Models Selected
Build Heterogeneous Ensemble (**HE**)
Decision Fusion Function
Ts
Evaluate **HES**

Figure 1: The general framework for HES.

The main operations of the HES are shown by Algorithm (1). It starts by dividing D into training dataset and testing dataset Ts. The training dataset was further divided to train dataset Tr for training the classifiers $C_i \in C$ and validation dataset Val for evaluating each C_i. Different learning algorithms are called from the learning algorithms base to generate $|C|$ models,which are stored in a model pool PM.

Algorithm 1: Algorithm for Building **HES**.

```
1:  Input:  D dataset, C base learners, ensemble size |Φ|
    and the selected rule R.
2:  Output: Acc(HES).
3:  Divide D to Train 75% and Ts 25%
4:  Divide the training data to Tr 75% and Val 25%
5:  let N = |Φ|
6:  for $i$ = 1 to |C| do
7:      $m_i$ = model resulted from training Tr on $C_i$
8:      add $m_i$ to PM
9:      Evaluate $m_i$ on Val
10: end for
11: Call the selected rule R
12: Evaluate HES on Ts
```

3.2 Rules for Building Different HES

Different rules can be devised to build various heterogeneous ensembles based on different strategies and purposes. Three rules R0, R1, and R2 are defined in this study as the demonstration of concept in utilising the accuracy as a model selection criterion alone, or both accuracy and diversity measures.

Fig.2. shows all the three rules and the details of these rules are described as follows.

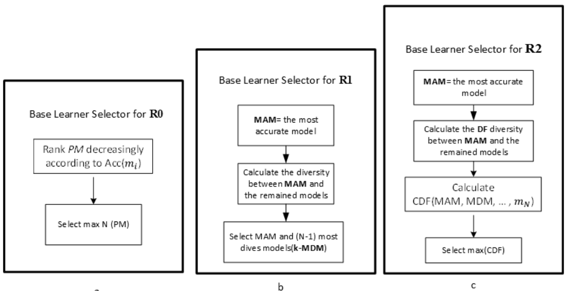

Base Learner Selector for R0
Rank PM decreasingly according to Acc(m_i)
Select max N (PM)
Base Learner Selector for R1
MAM= the most accurate model
Calculate the diversity between MAM and the remained models
Select MAM and (N-1) most dives models(k-MDM)
Base Learner Selector for R2
MAM= the most accurate model
Calculate the DF diversity between MAM and the remained models
Calculate CDF(MAM, MDM, ... , m_N)
Select max(CDF)
a
b
c

Figure 2: Main steps for R0, R1 and R2 in HES.

3.2.1 Rule R0:

To build an HES, this rule only considers the accuracy of individual models only. Algorithm (2) describes how it works where the HES will first sort models in the *PM* in a descending order according to the accuracy of each individual model *Acc*(m_i) on *Val.* Then, the most accurate *N* models are selected from *PM* to be added to Φ. This is the basic rule applied in HES, and also forms a part of all other rules in the system. Fig. 2a illustrates how this rule works. To select the models we need to use equation (1).

$$m_i = max^{\bullet} Acc(m_j), m_j \in PM^{\bullet} \; i = 1...N \qquad (1)$$

Algorithm 2 : Algorithm for **R0**.

```
1: Input: PM
2: Output: The selected models
3: sort models in the PM decreasingly according to
   acc($m_i$)
4: select first N models from PM
5: add selected models to Φ
```

3.2.2 Rule R1:

To build an HES, this rule considers both accuracy and diversity measured by pair-wise diversity. Algorithm (3) describes how it works. In this rule, **HES** first selects the most accurate model *MAM* from *PM* to be added to Φ. Then this model is removed from the pool *PM.*

$$m_1 = max^{\bullet} Acc(m_j), m_j \in PM^{\bullet} \qquad (2)$$

Then, the diversity measured by (Double- Fault)*DF* (Giacinto and Roli, 2001) between *MAM* and every model in the pool *PM* is calculated using a pairwise strategy to fill the models needed for the finalΦ. Then *PM* is sorted in the decreasing order according to their diversity *DF* to select *N-1* most di- verse models from the pool *PM* to be added to the final Φ. Equation(3) is applied for this stage. The models selected in this rule are *MAM* and *N-1* most diverse models from *MAM* in the pool *PM*. Fig.2b, illustrates how this rule works.

$$m_i = max^{\bullet} DF(m_1, m_j), m_j \in PM^{\bullet} \; i = 2...N \qquad (3)$$

Algorithm 3 : Algorithm for **R1**.

```
1:  Input: PM
2:  Output: The selected models
3:  MAM=the most accurate model in PM
4:  add MAM to Φ
5:  remove MAM from PM
6:  for $i$ = 1 to |PM| do
7:      calculate DF_ diversity (MAM ,$m_i$)
8:  end for
9:  sort PM decreasingly according to their diversity
10: select first (N-1)models
11: add selected models to Φ
```

3.2.3 Rule R2:

This rule uses both accuracy and two diversity measures: *DF* and (Coincident Failure Diversity) *CFD* (Partridge and Krzanowski, 1997). Algorithm (4) describes the procedure of R2. In this rule, the first model m_1 to be selected for the Φ is chosen as in equation (2) in R1, which is *MAM*. The second model m_2 to be selected for Φ is the most diverse model *MDM* from the most accurate model in the pool *PM*. To calculate *MDM*, equation (4) is used.

$$m_2 = max\, DF(m_1, m_j), m_j \in PM \qquad (4)$$

In this rule, we generate a number of combinatorics *J*, subsets of models ϕ_i from the pool of models PM and equation (5) to calculate this number.

$$J = \binom{|PM|}{N-2} \qquad (5)$$

Each combinatory ϕ_i includes *MAM* and *MDM*, and the remaining models needed to reach to *N* are added from the pool *PM* to compute the diversity *CFD*. Thus the maximum diverse subset ϕ_i ensemble is chosen for the final Φ. Fig.2c, illustrates how this rule works.

$$HES = max\, CFD(\Phi \Leftarrow m_j), m_j \in PM \qquad (6)$$

Algorithm 4 : Algorithm for **R2**.

```
Input: $PM$
Output: The selected models
$MAM$=the most accurate model in $PM$
remove $MAM$ from $PM$
for $i = 1$ to $|PM|$ do
    calculate $DF$ diversity ($MAM$ ,$m_i$)
end for
$MDM$ = the most divers model from $MAM$
remove $MDM$ from $PM$
$J$= The number of Combinations subsets $\binom{|PM|}{N-2}$
for $i = 1$ to $j$ do
    $\phi_i$ =the $i^{th}$ combinations subset from $PM$
    add MAM and MDM to $\phi_i$
    calculate $CFD$ diversity $\phi_i$
end for
add the most divers $\phi_i$ to $\Phi$
```

3.3 Implemetation of HES

The HES is implemented with Java, based on Weka API. Thus, the experiment was carried out on a normal PC, with an I7 processor and 16 GB RAM. As HES is flexible for selecting candidate classifiers, we have selected 11 deferent base classifiers that are provided in the WEKA library. These base classifiers are: trees(*J48, RandomTree, REPTree*), bayes(*NaiveBayes, BayesNet*), function(*SMO*), rules(*JRip, PART*) and Lazy(*IBk, LWL, KStar*).

4 EXPERIMENT DESIGN AND RESULTS

4.1 Dataset

We conducted our experiment using a benchmark dataset called 8 Scene Categories Dataset (Oliva and Torralba, 2001),which was divided into two parts: images and their annotations. The relevant part is in the annotation folder which, contains 2688 XML files categorized into eight groups, and each XML file contains a number of tags that describe an image.The annotations were dealt with as text and used in this inexpedient. The features were extracted from this text, and we obtained 2866 instances, 782 attributes and 8 classes.

4.2 Experiment Design and Results

We conducted a series of experiments investigating three rules in HES. They are generated by changing two factors. The first is the rule used in the experiment, which are R0, R1 and R2. The second is the ensemble size, which are 3, 5, 7 and 9. Running all possible combination of these parameters, and repeating them for five different runs lead to conduct 60 experiments in total.

The results (mean and standard deviation) of using R0, R1 and R2 with different numbers of models in HES are shown in Fig.3,4 and 5, over 5 runs on each figure.

The results for all five runs on all three rules are about as accurate as those of the most accurate model MAM but more reliable because the single best model varied in different runs and could be much worse in some runs. In this study the most accurate model was not stable for all the five runs it some times *BayesNet* and other times *SMO*. This negatively impacts reliability. Thus, ensemble accuracy wins against the most accurate model in certain instances.

The most significant finding from applying the three rules was the stable improvement of the level of the accuracy when R2 is applied, as seen in Fig. 5. The observable reason for that is R2 considers more diversity measures than R0 and R1. Considering more diverse models provided an opportunity to achieve stable results even if the mean accuracy for these models was low. This is a clear evidence that can increase reliability whilst maintaining high accuracy.

Another observable finding from the results is that increasing the number of models used in the ensemble supported with the diversity among them lead to more stable results, as shown in Fig. 5. For R2, when more than five models were selected for the ensemble, the results became more stable.

When there were three models in R2, the accuracy was lower than for the other rules. That was probably because when the size of an HES is as small as 3, adding a more diverse but less accurate model to it, the diversity introduced is not enough to compensate

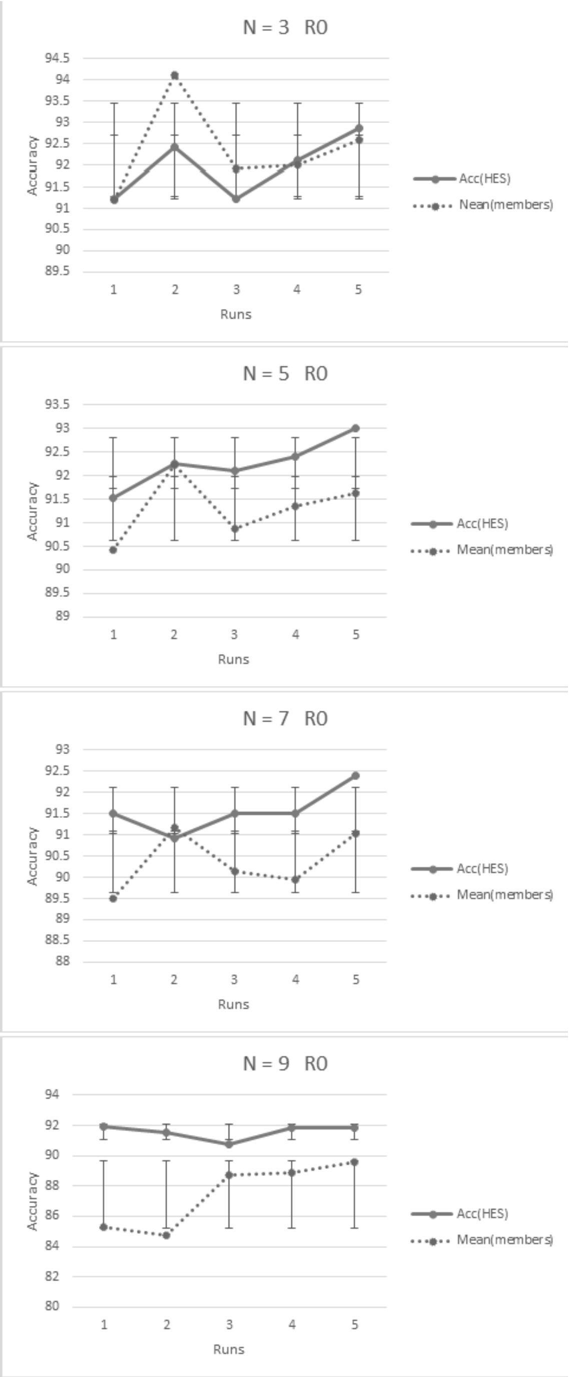


Figure 3: All HES results for the rule R0. The size of ensemble 3, 5, 7 and 9 are shown in each sub-graph respectively. Tow lines (solid and dashed) are the accuracy of HES and the mean accuracy for models that are chosen for the HES respectively. The stranded deviation is shown whiskers over 5 runs.

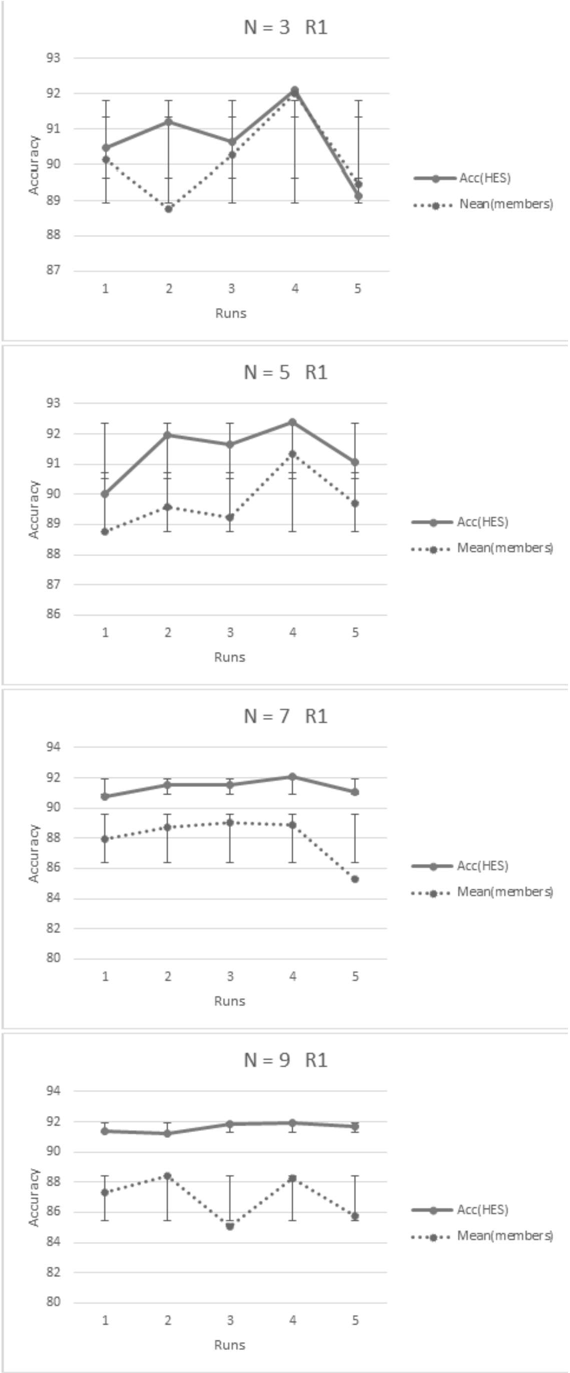


Figure 4: All HES results for the rule R1. The size of ensemble 3, 5, 7 and 9 are shown in each sub-graph respectively. Tow lines (solid and dashed) are the accuracy of HES and the mean accuracy for models that are chosen for the HES respectively. The stranded deviation is shown whiskers over 5 runs.

the loss of the accuracy caused by the third less accurate mode, so the chance for using the diversity measure is more likely to be effective when the number of models for the ensemble is increasing.

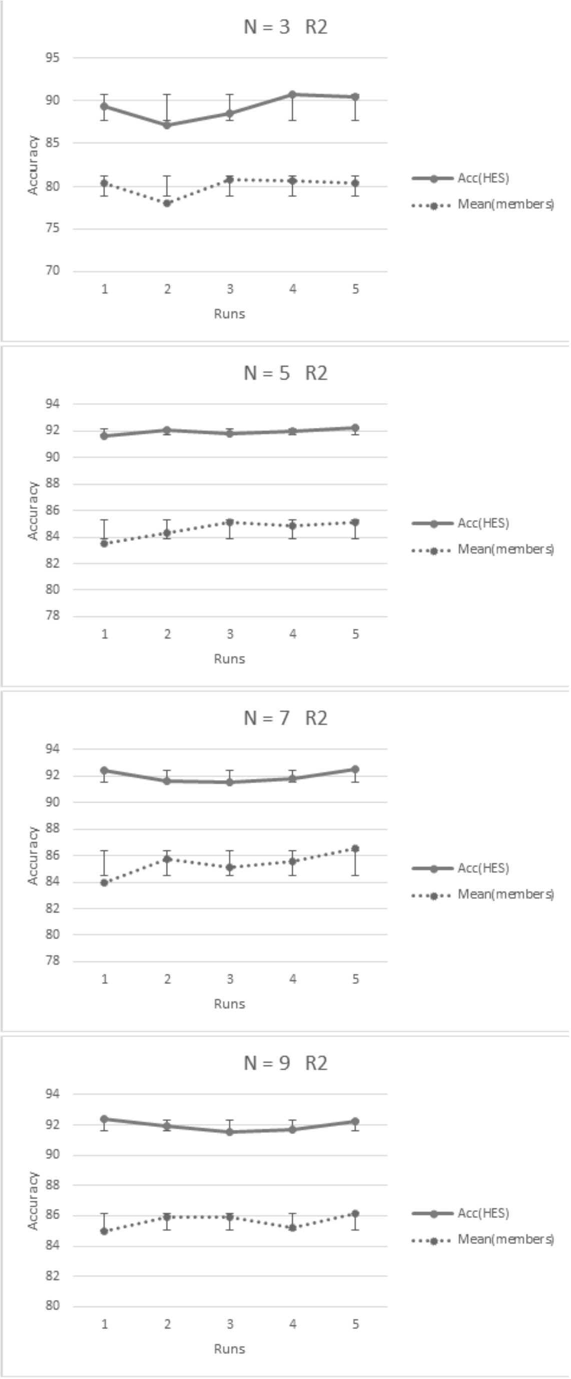


Figure 5: All HES results for the rule R2. The size of ensemble 3, 5, 7 and 9 are shown in each sub-graph respectively. Tow lines (solid and dashed) are the accuracy of HES and the mean accuracy for models that are chosen for the HES respectively. The stranded deviation is shown whiskers over 5 runs.

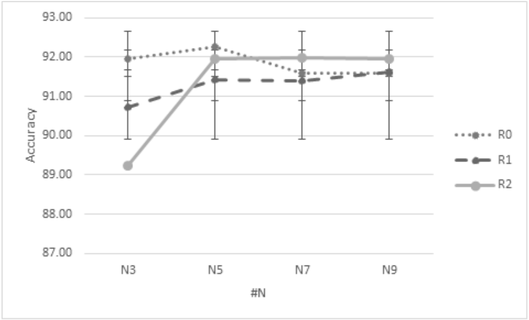


Figure 6: Comparing all three rules in four different sizes of the HES.

4.3 Comparison of the Results

The comparison was carried out with some other ensemble methods, including various homogeneous ensemble built with AdaBoost algorithm for each base classifier used in HES.

Table 1 shows the mean results for homogeneous ensemble over all the five runs conducted. It can be seen that these homogeneous ensembles produced quite different or unstable accuracy for the task with the highest up to 90.83% and lowest down to 77.74%.

Table 1: The mean of the accuracy for five runs using AdaBoostM1 method for each base classifier in HES.

Base Classifier	Mean Accuracy	SD
J48	89.61	0.80
RandomTree	84.26	184
REP-Tree	88.33	0.52
NaiveBayes	90.71	0.44
BayesNet	90.57	0.65
SMO	90.83	0.27
JRip	88.24	0.32
PART	89.23	0.60
IBk	86.37	0.62
LWL	77.74	4.01
KStar	86.76	0.69

Table 2 shows the comparison between the homogeneous ensemble and (R0, R1 and R3) in HES. It is very clear that heterogeneous ensemble constructed by any of the three rules are the best and improved the average accuracy as much as 3.5%.

Table 2: The comparison results between the homogeneous ensemble and HES for all the three rules.

	Mean Accuracy	SD
homogeneous Ensemble	87.51	3.84
Rule R0	91.85	0.33
Rule R1	91.29	0.39
Rule R2	91.29	1.37

5 CONCLUSION AND FUTURE WORK

This study used an imaginary scene classification problem as a testing case to investigate the capability of heterogeneous ensembles built with the ruls that consider either accuracy of individual models or diversity, or both.Three rules are devised specifically using accuracy of individual models and the diversity measurements among these models for an ensemble.The results for HES are much better than the previous studies (Oliva and Torralba, 2001) that used individual models for imaginary scene classification and the state-of-the-art for the homogeneous ensemble, which used all base classifiers used in HES. The increasing diversity among the models selected for the ensemble was found to be advantageous, leading to more stable and reliable results. Our research found that increasing the number of models also affects the ensembles results. This indicated that diversity is more effective when used with a higher number of models selected for the ensemble. It can therefore be concluded that combining models results in high accuracy and diversity for an ensemble has considerable advantages in terms of the ensemble's accuracy.

Various questions for future work emerge from this paper. First, this research covered only the annotations part of the dataset. It could be useful to involve the images part directly. Second, only three rules were used in this experiment; future work should consider more rules with different measures for ensemble selecting models. Third, more experiments will be conducted by using more datasets.

REFERENCES

Bosch, A., Zisserman, A., and Muñoz, X. (2006). Scene classification via plsa. In *Computer Vision–ECCV 2006*, pages 517–530. Springer.

Brown, G., Wyatt, J., Harris, R., and Yao, X. (2005). Diversity creation methods: a survey and categorisation. *Information Fusion*, 6(1):5–20.

Caruana, R., Niculescu-Mizil, A., Crew, G., and Ksikes, A. (2004). Ensemble selection from libraries of models. In *Proceedings of the twenty-first international conference on Machine learning*, page 18. ACM.

Dietterich, T. G. (2000). *Ensemble methods in machine learning*, pages 1–15. Springer.

Giacinto, G. and Roli, F. (2001). Design of effective neural network ensembles for image classification purposes. *Image and Vision Computing*, 19(9):699–707.

Grauman, K. and Darrell, T. (2005). The pyramid match kernel: Discriminative classification with sets of image features. In *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on*, volume 2, pages 1458–1465. IEEE.

Hofmann, T. (2001). Unsupervised learning by probabilistic latent semantic analysis. *Machine learning*, 42(1-2):177–196.

Hotta, K. (2008). Scene classification based on multi-resolution orientation histogram of gabor features. In *Computer Vision Systems*, pages 291–301. Springer.

Ke, Y. and Sukthankar, R. (2004). Pca-sift: A more distinctive representation for local image descriptors. In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, volume 2, pages II–506. IEEE.

Lazebnik, S., Schmid, C., and Ponce, J. (2006). Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories. In *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*, volume 2, pages 2169–2178. IEEE.

Lertampaiporn, S., Thammarongtham, C., Nukoolkit, C., Kaewkamnerdpong, B., and Ruengjitchatchawalya, M. (2013). Heterogeneous ensemble approach with discriminative features and modified-smotebagging for pre-mirna classification. *Nucleic acids research*, 41(1):e21–e21.

Liu, Y., Yao, X., and Higuchi, T. (2000). Evolutionary ensembles with negative correlation learning. *Evolutionary Computation, IEEE Transactions on*, 4(4):380–387.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110.

Mikolajczyk, K. and Schmid, C. (2004). Scale & affine invariant interest point detectors. *International journal of computer vision*, 60(1):63–86.

Oliva, A. and Torralba, A. (2001). Modeling the shape of the scene: A holistic representation of the spatial envelope. *International journal of computer vision*, 42(3):145–175.

Partridge, D. and Krzanowski, W. (1997). Software diversity: practical statistics for its measurement and exploitation. *Information and software technology*, 39(10):707–717.

Siagian, C. and Itti, L. (2007). Rapid biologically-inspired scene classification using features shared with visual attention. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 29(2):300–312.

Wallraven, C., Caputo, B., and Graf, A. (2003). Recognition with local features: the kernel recipe. In *Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on*, pages 257–264. IEEE.

Wang, H., Fan, W., Yu, P. S., and Han, J. (2003). Mining concept-drifting data streams using ensemble classifiers. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 226–235. ACM.

Wang, W. (2008). Some fundamental issues in ensemble methods. In *Neural Networks, 2008. IJCNN 2008.(IEEE World Congress on Computational In-*

telligence). IEEE International Joint Conference on, pages 2243–2250. IEEE.

Yan, R., Liu, Y., Jin, R., and Hauptmann, A. (2003). On predicting rare classes with svm ensembles in scene classification. In *Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03). 2003 IEEE International Conference on*, volume 3, pages III–21. IEEE.

Yang, J., Jiang, Y.-G., Hauptmann, A. G., and Ngo, C.-W. (2007). Evaluating bag-of-visual-words representations in scene classification. In *Proceedings of the international workshop on Workshop on multimedia information retrieval*, pages 197–206. ACM.

Zenobi, G. and Cunningham, P. (2001). *Using diversity in preparing ensembles of classifiers based on different feature subsets to minimize generalization error*, pages 576–587. Springer.

Zhang, S., Cohen, I., Goldszmidt, M., Symons, J., and Fox, A. (2005). Ensembles of models for automated diagnosis of system performance problems. In *Dependable Systems and Networks, 2005. DSN 2005. Proceedings. International Conference on*, pages 644– 653. IEEE.