Classifier Ensemble for Improving Land Cover Classification

LAMYAA GAMAL EL-DEEN TAHA

National Authority of Remote Sensing and Space Science
(NARSS)
EGYPT

Abstract—- Ensemble data mining methods, also known as classifier combination, are often used to improve the performance of classification. In this study, several MCS (classifier ensemble) techniques have been used to classify the RapidEye image. The main aim is to increase land cover discrimination of different classes and minimizing misclassification errors. Firstly, rectification of RapidEye image was performed. Secondly the maximum likelihood (MLC), minimum distance (MD), Support vector machine (SVM), artificial neural network(ANN) and spectral angler mapper (SAM) classifiers were carried out to classify the RapidEye image. Thirdly, the MCS techniques were applied using bagging and boosting (adaptive boosting (Adaboost)) algorithm of the combination of three classifiers (SVM, ANN and SAM) to integrate the classification results.
The outcomes of the proposed method demonstrate that the overall accuracy as well as commission and omission errors have been improved compared to the best single classifier.

***Keywords*—**Multiple classifier systems (MCS)-classifier Ensemble-remote sensing classifications-classifier fusion-multiple classifier combination-ensemble learning-Hybrid Classifier-Classifier combination – Bagging-boosting-RapidEye.

I. INTRODUCTION

Land cover classification is one of the widest used applications in the field of remote sensing. Land use and land cover (LULC) maps are remote sensing products that are used to classify areas into different landscapes [6]. The detailed knowledge of land cover is an important input variable for several environmental monitoring systems, e.g., in the fields of urban sprawl, land degradation or urban planning. At present, medium-resolution data is applied more universal on national scale study of land use (Liu et.al.,2012). New series of high spatial resolution (VHR) satellites such as RapidEye have enabled mapping.

The overall objective of image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes. The classification algorithms are important for the success of the land cover classification process. A large range of classification algorithms has been developed and applied for classifying remotely sensed data [2]. Different classification results may be obtained depending on the classifier(s) chosen.

Many previous researches have indicated that non-parametric classifiers may provide better classification results than parametric classifiers in complex landscapes. Among the most commonly used non-parametric classification approaches are neural networks, decision trees, support vector machines, and expert systems[15].

Researchers are continuously seeking to improve the classification accuracy. Taking advantage of the complementary information about image data provided by classifiers based on different mathematical concepts, the next natural frontier is the integration of multiple approaches into a unified framework. These studies suggest that combined classifiers perform better than the individual classifier used in making ensemble [19];[20].

Nowadays, multiple classifier system is widely used for land cover classification by remote sensing imagery. The aim is to effectively merge the results of the classifiers taking advantage of the benefits of each while reducing their weaknesses [20]. The resulting classifier is generally more accurate than any of the individual classifiers that make up the ensemble[1]. The performance of combined classifier is closely related to the selection of member classifiers, so it is necessary to analyse the diversity and consistency of member classifiers[3]. Diversity has been recognized an important characteristic in classifier combination [14].The essence of ensamble classification is to use classifiers which operate differently. Diversity measures are often divided into parts:

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TAHA L.G. is with the National Authority for Remote Sensing and Space Sciences, Cairo, Egypt (phone: 202- 26251218; fax: 202-26225800; e-mail: Lamyaa@narss.sci.eg

pairwise and non-pairwise. Pairwise measures include kappa statistics, double fault, disagreement, etc., and non-pairwise measures consist of entropy, weighted count of errors[4].

The traditional parametric classifiers such as the Minimum Distance, Maximum Likelihood (ML) classifiers have been used extensively [22] due to its acceptable accuracy and fast performance. However, the major limitation of the parametric algorithms is their reliance on the assumption of normal distribution of input data which is often not true for remotely sensed data [22]. This limitation makes it difficult for such parametric classifiers to handle complex datasets consisting of different kind of data such as multisource data. On the other hand, non-parametric classifiers such as the Artificial Neural Network (ANN) or Support Vector Machine (SVM) does not constrain to the assumption of normal distribution, and are therefore often considered more suitable for classifying remotely sensed data[2].

MCS is capable to integrate advantages and alleviate weaknesses of constituent classifiers. Furthermore, the MCS allows minimize the risk of poor selection. Several different approaches have been used to obtain classifier ensembles [18]. MCS involves different classification strategies such as parallel or hierarchical computing, Bagging and Boosting, and different classifier combination rules, such as majority voting, statistical techniques, sum, max, min, Product, fuzzy integral or evidence reasoning based on Dempster-Shafer evidence theory, and other fusion schemes [12];[7].

A trainable variant of majority voting is weighted majority voting, which applies a weight to each vote. The weight applied to each classifier can be obtained for example by estimating the accuracies of the classifiers on a validation set [20].The MCS can be generated in different ways, including combination of different classifiers or combination of the same classifiers with various versions of input training data [2]. Two popular approaches for creating accurate ensemble are Bagging and Boosting. Bagging uses bootstrap sampling to generate accurate ensemble. Boosting is a general method of producing a very accurate prediction rule by combining rough and moderately inaccurate learner [4]. Bagging, boosting, or a hybrid of both techniques may be used to improve classification performance in a non-parametric classification procedure [15].

The research objective is to make classifier ensemble using bagging and boosting in order to increase classification accuracy. In this paper, a set of classifiers were applied (maximum likelihood(MLC), minimum distance (MD), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Spectral Angler Mapper (SAM) classifiers) and compared. The best three classifiers were used to form classifier ensemble.

II.STUDY AREA AND DATA SET

The test site covers new administrative capital-Egypt. This region is a good for future development. In this study land use land cover is required for urban planning. The following data Sources were available:

- Multispectral Rapid Eye image of new administrative capital with resolution 5 m .Dated 2014. Fig 1depicts Distribution of differential GPS over the rectified image of RapidEye control points (blue) and check points (red).
- Thirty three ground control points observed using Differential GPS with accuracy 10 cm in x,y,z.

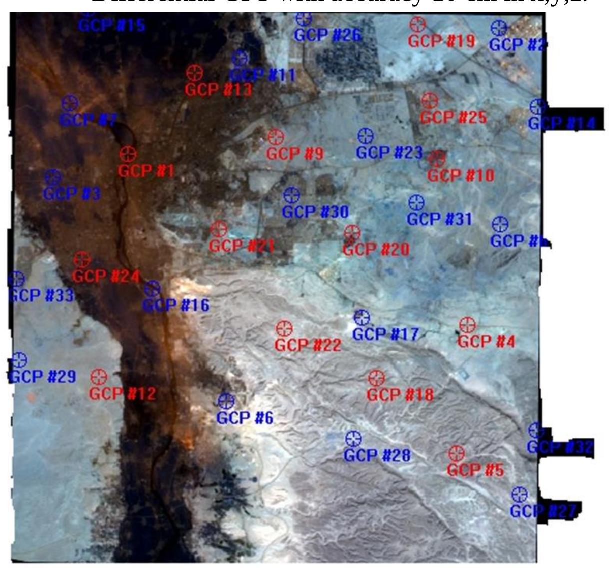

Fig 1. Distribution of differential GPS over the rectified image of RapidEye control points (blue) and check points (red).

III.METHODOLOGY

In this section, the processing chain that has been carried out for improvement of classification accuracy and producing of multiple classifier ensamples was discussed. The processing steps to achieve our objective as follows:

1-Image preprocessing.
2-Collection of GCPs.
3-Image rectification of RapidEye image.
4-Assessment of rectification accuracy using check points (horizontal accuracy).
5- Spectral signature collection.
6-Classification of the RapidEye image using five techniques.
7-Accuracy assessment.
8-Comparison between classification performances.

9-Producing of multiple classifier ensamples.

A. Rectification of RapidEye image

Rectification is used for the transformation of the image to the ground coordinate system to correct for these geometric distortions. One can transform or warp the raster image to map coordinates after collecting ground control points (control points may be ground control points (GCPs) obtained from GPS, map control points, or control points from another orthoimage). Warping uses a mathematical transformation to determine the correct map coordinate location for each cell in the raster [10].

Multispectral RapidEye image was radiometrically and geometrically corrected. Rectification has been performed using second order polynomial and resampled with nearest neighbor resampling to 5 m spatial resolution utilizing twenty well distributed DGPS control points and validated using an independent set of thirteen well distributed DGPS check points, World geodetic system 1984 (WGS84) datum and the universal transverse Mercator (UTM) coordinate system zone 36 were used. The total root mean square error for check points was 2.7m. ERDAS Imagine 2013 was used for the geometric correction.

B.Classification Techniques

A classifier is an algorithm that takes a set of parameters (or features) that characterize objects (or instances) and uses them to determine the type (or class) of each object [17].

The most common approach to the segmentation and interpretation of multi-spectral remotely sensed data for land cover mapping utilizes a suite of probabilistic classification and clustering algorithms. Supervised classifications may be considered to comprise three distinct stages: training, allocation and testing [5]. Supervised classifications exploit the radiometric properties of known 'training' regions to identify areas elsewhere on the image with similar spectral properties. The hypothesis is that land cover of the training regions is identical to regions elsewhere in the scene with similar spectral characteristics[23]. It is important and difficult to select training data that are truly representative of spectrally unique classes[23].

In this work, five classifiers have been performed. Maximum likelihood (MLC), minimum distance (MD), Support vector machine (SVM), artificial neural network (ANN) and spectral angler mapper (SAM) classifiers) were used and then compared.

B.1.Maximum likelihood classifier

Maximum likelihood (ML) classifier is the most commonly used supervised method in remote sensing. ML classifier is one of the statistical classifiers that depend on multivariate normal distribution of the data in each class[12]. By computing the mean spectral vector and covariance matrix for each spectral class from training samples, a decision function is generated to calculate the probability of a pixel belonging to this specific class according to Bayesian theorem. By comparing the probabilities of a pixel belonging to all classes, the pixel is then categorized into the class with the maximum probability [11].

B.2.Artificial Neural Network (ANN)

The MLP-BP model with three layers (input, hidden and output layer) was employed. The number of input neurons is equal to a number of input features, the number of neurons in the output layer is the number of land cover classes to be classified. The number of neuron in the hidden layer was determined by the sequential testing and validation process using the training data [12]. The sigmoid function was used as the transfer function. The other parameters were set as follows: maximum number of iteration: 1000; learning rate: 0.01-0.1; training momentum: 0.9

B.3.Support Vector Machine (SVM)

Support vector machines (SVMs) are supervised learning algorithms based on statistical learning theory, which are considered as heuristic algorithms [12]. The SVM classifier with radical basis function (RBF) kernel has been used because of its highly effective and robust in handling of remote sensing data [12]; [22]. In order to ensure the best accuracy the optimal value for the penalty parameter C and the width of the kernel function γ were determined.

In our experiment, radial basis function is adopted. Penalty parameter C is 150 and γ in kernel function is 0.170.

B.4.Minimum Distance (MD)

The minimum distance classification is performed by placing a pixel in the class of the nearest mean. It uses the mean vectors of each region of interest (ROI) and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the closest ROI class unless the user specifies standard deviation or distance thresholds, in which case some pixels may be unclassified if they do not meet the selected criteria. This method calculates the center for each group of pixels and measures the distance from the center of each group to the pixel being considered. The pixel is classified to the group with the nearest center. The center of the group then is recalculated each time a pixel is added or taken away. Feature vector is computed for these samples again and a distance Euclidean and Mahalanobis classifiers are used to classify the unknown samples [17].

B.5.Spectral Angler Mapper SAM

The SAM algorithm is a simply based on the measurement of the spectral similarity between two spectra. The spectral similarity can be obtained by considering each spectrum as a vector in q -dimensional space, where q is the number of bands. The SAM algorithm determines the spectral similarity between two spectra by calculating the angle between the two spectra, treating them as vectors in a space with dimensionality equal to the number of bands [21]

Visual interpretation of RapidEye image was carried out to identify main land covers within the study area. Six main classes were identified, i.e. water, roads, urban, desert, valley, vegetation. Training data were established by choosing thirty 30 ROI for each class. Here, five classification methods were compared: maximum likelihood (MLC), minimum distance (MD), Spectral angler mapper SAM, Support vector machine (SVM) and ANN. Accuracy assessment of the classifications were determined by means of a confusion matrix (sometimes called error matrix), which compares, on a class-by class basis, the relationship between reference data (ground truth) and the corresponding results of a classification. Such matrices are square, with the number of rows and columns equal to the number of classes. MLC classifies the classes that exist in the study area with a good agreement with the reference map. MLC classified the study area into 6 classes, with accuracy 89.82% (κ=0.83), Minimum distance (MDC) classified the study area into 6 classes, with accuracy 77.32% (κ=0.75). SAM classified the study area into 6 classes, with accuracy 94.62% (κ=0.89). ANN classified the study area into 6 classes, with accuracy 95.64% (κ=0.93). SVM classified the study area into 6 classes, with accuracy 96.33% (κ= 0.95). Fig 2. illustrates RapidEye image classified with Support Vector Machine (SVM) classifier. Fig 3. illustrates RapidEye image classified with Neural network classifier. Fig 4. depicts RapidEye image classified with Spectral angler mapper classifier. Fig 5. depicts RapidEye image classified with Maximum likelihood classifier. Fig 6. depicts RapidEye image classified with Minimum distance classifier.

All classifications were implemented in the ENVI 5.1. Table 1. shows overall accuracy and Kappa index of classifiers. Fig7 depicts over all accuracy and kappa index of different classifiers.

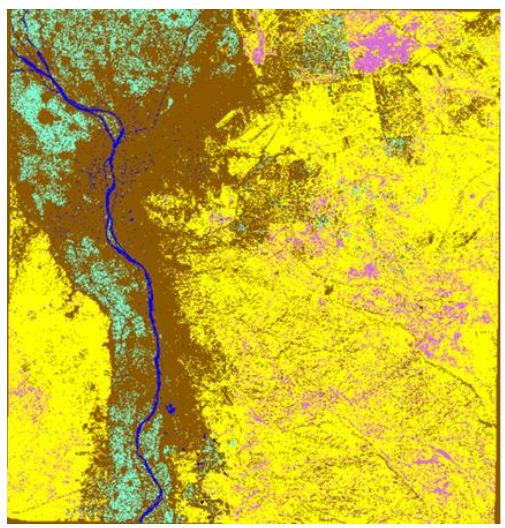

Fig 2. RapidEye image classified with Support Vector Machine (SVM) classifier.

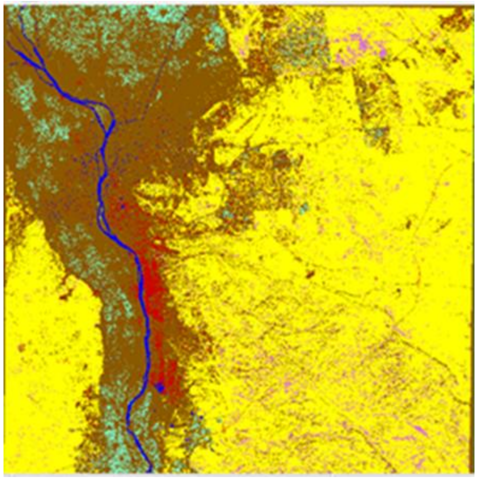

Fig 3. RapidEye image classified with Neural network classifier.

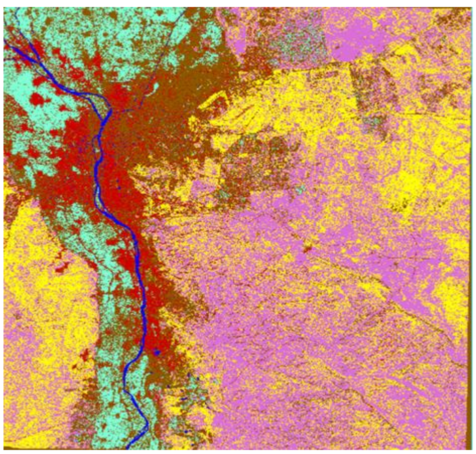

Fig 4. RapidEye image classified with Spectral angler mapper classifier.

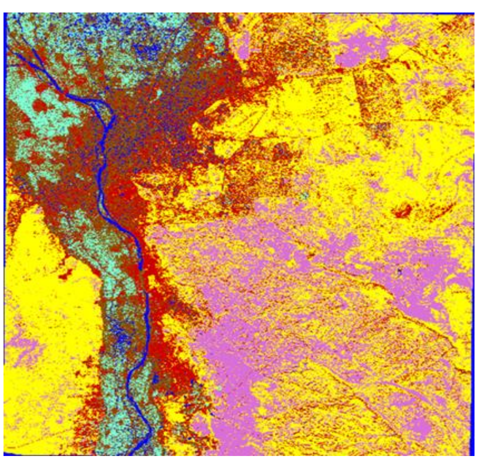

Fig 5. RapidEye image classified with Maximum likelihood classifier.

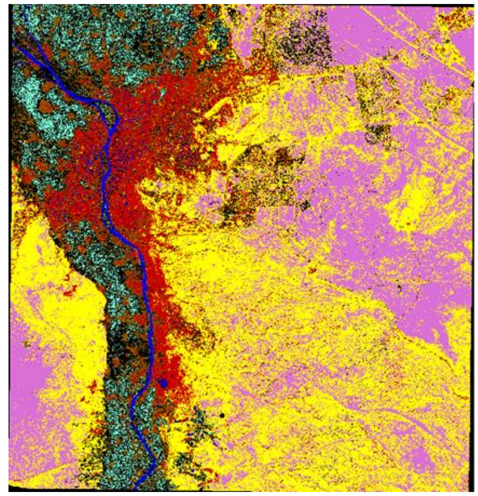

Fig 6. RapidEye image classified with Minimum distance classifier.

Table 1. Overall accuracy and Kappa index of classifiers.

classifier	Overall accuracy	Kappa index
Maximum likelihood classification	89.82%	0.83
Minimum distance(MDC)	77.32%	0.75
SAM	94.62%	0.89
ANN	95.64%	0.93
SVM	96.33%	0.95

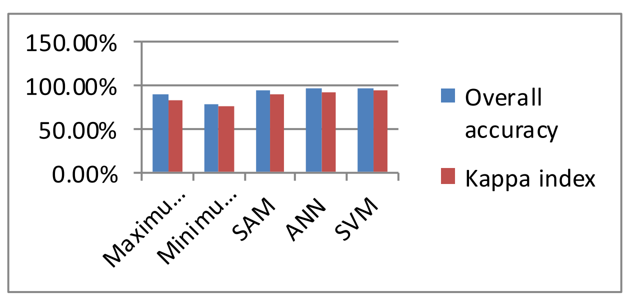

Fig7. Overall accuracy and kappa index of different classifiers.

C. Classifier ensemble

One effective solution is to generate a classifier ensemble by combining some individual classifiers, which is named as multiple classifier system (MCS) or classifier ensemble [14].

C.1.Selection of optimum classifiers

A good multiple classifier system depends on not only combination rules, but also member classifiers selected from a classifier pool. Nowadays, how to select optimal set of member classifiers has been raised in attention as this is one of the critical issues to the success of MCS [3].

C.2.Bagging and Boosting

Bagging: Arcing (adaptive reweighting and combining) is a generic term that refers to reusing or selecting data in order to improve classification performance. Bagging was the first effective method of ensemble learning and is one of the simplest methods of arcing. In this algorithm, n samples are selected at random from a training set with k samples, and instructive iteration is exerted to create some different bags, and each bag is classified by vote to predict its class.
The meta-algorithm, which is a special case of model averaging, was originally designed for classification and is usually applied to decision tree models, but it can be used with any type of classification model. The method uses multiple versions of a training set by using the bootstrap, i.e. sampling with replacement. Each of these data sets is used to train a different model, increasing diversity among individuals. The outputs of the individual models are combined by voting the individual outputs to create a final ensemble output [8] .
Boosting: is a meta-learning algorithm which is based on the question posed by Kearns “can a set of weak learners create a single strong learner?”. A weak learner is defined to be a classifier which is only slightly better than random labeling. In contrast, a strong learner is a classifier that is arbitrarily well-correlated with the true classification.
Boosting is the most widely used ensemble method and one of the most powerful learning ideas introduced in the last twenty years. Boosting can process data with weights of training examples, and the weights of misclassified samples are increased to concentrate the learning algorithm on specific samples. After the weights of training sets are updated, a new (particular) classifier is generated. A final classifier is calculated as a combination of particular classifiers [16].
A final classifier is calculated as a combination of particular classifiers. Bagging has been shown to reduce the variance of the classification, while boosting reduces both the variance and the bias of the classification. So in most cases, boosting can produce more accurate classification results than Bagging. However, the computation time of boosting is more than bagging, and boosting is sensitive to noise[8].
The iterations of adaBoost and bagging are ten (10). Table 2 shows overall accuracy and kappa index of adaBoost and Bagging using different base classifier. Fig8. depicts bagging and boosting of the three base classifiers.

Table 2. Overall accuracy and kappa index of adaBoost and bagging using different base classifier.

Classifier	**Overall accuracy**	**Kappa index**
SAM	94.82%	0.87
Bagging	95.32%	0.92
Adaboost	92.48%	0.92
ANN	95.64%	0.93
Bagging	98.01%	0.96
Adaboost	96.56%	0.94
SVM	96.33%	0.95
Bagging	92.32%	0.91
Adaboost	97.32%	0.98

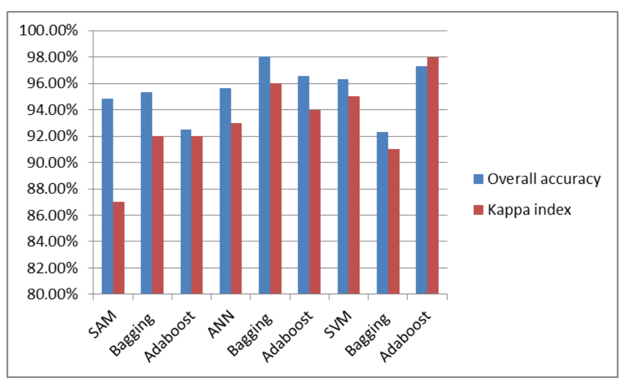

Fig8. Bagging and boosting of the three base classifiers.

IV. RESULTS AND DISCUSSION

This paper deals with the performance of classification using ensemble data mining methods. Firstly, image rectification of RapidEye image has been performed using second order polynomial and resampled with nearest neighbor resampling to 5 m spatial resolution utilizing twenty well distributed DGPS control points and validated using an independent set of thirteen well distributed DGPS check points. The total root mean square error for check points was 2.7m. ERDAS Imagine 2013 was used for the geometric correction.

Secondly five classification approaches were trained parallel on the same RapidEye image. The maximum likelihood (MLC), minimum distance (MD), Support vector machine (SVM), artificial neural network(ANN) and spectral angler mapper (SAM) classifiers were carried out to classify the RapidEye image. Samples were collected for these six classes for the five approaches. It is appeared that the SVM classifier provided the highest classification accuracy. The ANN classifier is second best classifier. Based on table1 and figure 7, it is clear that different classifiers give different accuracies. In the classification result of maximum likelihood classification (Approach 1), an overall accuracy of 89.82% percent was achieved. The following compares other approaches with approach 1, so as to determine whether change of the classifier will improve the classification accuracy or not. In contrast, Minimum distance (MDC) (approach 2) has a poorer performance than approach 1, with an overall classification accuracy of 77.32%percent.

The overall classification accuracy of approach 3, which used the SAM, is 94.62 percent, a slight improvement was achieved compared to approach 1. Approach 4 (ANN) clearly outperforms Approach 1. The overall accuracy of 95.64percent was achieved, an improvement of 0.82 percent. The classification accuracies of most LULC classes have improved.

Approach 5 (SVM) produces an overall accuracy of 96.33percent. Approach 5 is similar to Approach 4, in increasing accuracy because it is a soft classification technique.

Also, the classifiers have shown the different performance on the specific classes, indicating that the classifier performing well for one class may be poor for other classes. From the above analysis, it is necessary to combine multiple classifiers to find a better result than any individual classifiers.

So, the MCS techniques were applied using bagging and boosting (Adaboost) algorithm of the combination of three base classifiers (SVM, ANN and SAM) to integrate the classification results. It is observed that the results of classifier ensemble method obtain higher overall accuracies than the worst classifier (MDC). Also, the multiple classifier system outperformed the single classifier and gave a noticeable improvement in the classification accuracy. The results shows also that while the overall classification accuracies were slightly improved, the commission and omission errors were reduced considerably compared with the best individual classifier.

V.CONCLUSIONS AND FURTHER WORK

This research uses multiple classifiers combination for increasing the classification accuracy. In this study image rectification of RapidEye was performed. After that a set of classification were carried out (the maximum likelihood(MLC), minimum distance (MD), support vector machine (SVM), artificial neural network(ANN) and spectral angler mapper (SAM) classifiers) to classify the RapidEye image. Classifier ensemble using bagging and boosting (Adaboost) algorithm has been performed based on three base classifiers SAM, SVM and ANN. Experimental results demonstrate that MCS can effectively improve the accuracy of remote sensing image classifications compared to the separate use of different classifiers. The bagging and boosting algorithms with ANN classifiers, in general, gave considerable improvements compared to the performance of the original classifiers. The SVM-Bagging algorithm has noticeable decrease in classification accuracy. The SVM-Adaboost.M1 gave significant increases in overall accuracy (up to 97.32%). Experiments should be made for bagging and boosting with different number of classifiers. It is recommended to test majority voting, weighted voting, dempster Shafer evidence (D-S evidence) theory, and fuzzy integral.

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