Assessment of Ensemble Classifiers Using the Bagging Technique for Improved Land Cover Classification of multispectral Satellite Images

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Abstract: *This study evaluates an approach for Land-Use Land-Cover classification (LULC) using multispectral satellite images. This proposed approach uses the Bagging Ensemble (BE) technique with Random Forest (RF) as a base classifier for improving classification performance by reducing errors and prediction variance. A pixel-based supervised classification technique with Principle Component Analysis (PCA) for feature selection from available attributes using a Landsat 8 image is developed. These attributes include coastal, visible, near-infrared, short-wave infrared and thermal bands in addition to Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). The study is performed in a heterogeneous coastal area divided into five classes: water, vegetation, grass-lake-type, sand, and building. To evaluate the classification accuracy of BE with RF, it is compared to BE with Support Vector Machine (SVM) and Neural Network (NN) as base classifiers. The results are evaluated using the following output: commission, omission errors, and overall accuracy. The results showed that the proposed approach using BE with RF outperforms SVM and NN classifiers with 93.3% overall accuracy. The BE with SVM and NN classifiers yielded 92.6% and 92.1% overall accuracy, respectively. It is revealed that using BE with RF as a base classifier outperforms other base classifiers as SVM and NN. In addition, omission and commission errors were reduced by using BE with RF and NN classifiers.*

Keywords: *Bagging; classification; ensemble; landsat satellite magery.*

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1. Introduction

Using multispectral images for Land-Use Land-cover (LULC) mapping has many advantages, including covering large areas, rapid acquisition to large amounts of data, and lower costs compared to ground methods [8, 36]. For accurate LULC classification, an appropriate algorithm is required. Hence, many researchers have put forth great effort to improve classification accuracy by developing various classification algorithms [14]. Recently, Ensemble Classifiers (EC), or efficient Multiple Classifiers Fusion (MCF), have been found to outperform single classifier systems [26]. By exploiting the advantages of different classification algorithms and reducing their uncorrelated errors by combining them, the overall accuracy can be improved [15].

Dara [15] and Benediksson *et al*. [6] demonstrated the various approaches for multiple classification fusion systems. The ensemble classifier can be applied using many techniques, such as bagging, boosting, Random Forest, majority voting, and the weighted sum of base classifiers. Du *et al*. [16] and Tzeng *et al*. [37] used various combinations of approaches including parallel bagging and sequential boosting classifier systems for classifying hyperspectral data. Salah *et al*. [34] Used fuzzy majority voting and Dempster-Shafer (DS) techniques for combining classification results of three different classifiers using Lidar and aerial images. Chu and Ge [14] used Feature Selection (FS) methods with Genetic Algorithm (GA) and multiple classifiers combination based on Dempster-Shafer Theory of Evidence for classifying land cover features using integration of SAR and satellite imagery. Guan *et al*. [19] applied Random Forests to automatically select the optimal and uncorrelated features for land-use classification using a combination of Lidar data and ortho-imagery. Boukir *et al*. [8] proposed a better ensemble algorithm depending on the margin theory as a fundamental for the new bagging technique to reduce both the required training data set and the complexity of ensemble approach, thereby enhancing the accuracy.

Bagging (bootstrap aggregating) is one of the most popular ensemble algorithms, designed originally for improving machine learning algorithms. Reducing the variance of unstable algorithms such as Neural Network (NN), Supper Vector Machine (SVM) and Decision trees through averaging different resamples is the main advantage of bagging technique. Consequently, the final results will be better than fitting a single base classifier to the training data set. In addition, bagging reduces the chances of over-fitting [22].

Zhuo [40] used boosting and bagging ensemble techniques with NN as base classifiers, and compared it against SVM and logistic regression models for binary prediction with financial time series data. The results show the bagging of NN was superior to SVM and logistics regression models, with a reduction of prediction variance.

Akar and Gungor [2] compared the random forest ensemble technique to SVM and gentle adaboosting (GAB) using two different satellite images, Ikonos and Quickbird. The results show RF outperforms SVM and GAB.

Kulkarni and Kelkar [26] applied bagging, boosting, and adaboosting ensemble techniques with backpropagation neural networks with different numbers of hidden neurons for classifying Landsat satellite imagery. These ensembles were compared with single backpropagation neural network and radial basis function network. The achieved results demonstrated the outperforming of ensemble techniques compared to single classifiers. Further, the three ensemble methods gave almost equal results.

Bagging and Random Forest techniques have been widely used for LCLU classification. This paper is probably, to the best of authors' knowledge, the first study for integrating these techniques for classifying multispectral satellite imagery.

The methodology proposed in this study uses Bagging Ensemble (BE) of Random Forest (RF) as the base classifier for LCLU classification. This proposed approach reduces the limitations of previous approaches, such as prediction variances, and thus improves the overall accuracy. The methodology is evaluated using Landsat8 imagery of the El-Burullus Lake in Egypt, and compared against two other previous methods. The criteria used to evaluate the results include commission, omission errors, and the overall accuracy of each classifier.

2. Study Area and Available Data

The study area consists of the El-Burullus Lake and its surroundings. It is a coastal heterogeneous area with a variety of features including land, buildings, water, vegetation, and lake plants [3]. Hence, it can serve as a very suitable test area for LCLU classification. Figure 1illustrates the study area.

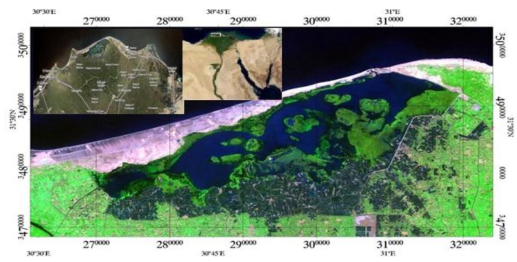


Figure 1. The study area (El-Burullus Lake, Nile-Delta, Egypt).

A Landsat8 satellite image with eleven multispectral bands is used for LCLU classification of the study area. The ten influencing bands for classification are one coastal (0.43-0.45 µm), three visible bands (0.45-0.68 µm), near-infrared (0.85-0.89 µm), two shortwave-infrared (1.56-2.30 µm), panchromatic (0.5-0.68 µm), and two thermal-infrared bands (10.6-12.5 µm). All bands have 30 m spatial resolution except panchromatic and thermal infrared that have 15 m and 100 m resolutions respectively [13]. The image was acquired on August 14, 2014 (see Figure 2).

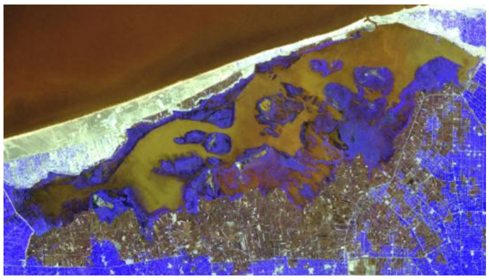


Figure 2. The Landsat-8 satellite image of the study area (14^{th} of August, 2014).

3. Methodology

The following subsections describe the methodology used in this research.

3.1. Imagery Data Pre-Processing

3.1.1. Computing the Spectral Top of Atmosphere Reflectance of Each Pixel Value using the Following Equation :

$$\rho\lambda = (M_p\, DN + A_p) / \sin(\theta_{SE}) \qquad (1)$$

Where:
$\rho\lambda$ = the top of atmosphere reflectance
DN = digital numbers recorded by the sensor
M_p = Band-specific multiplicative rescaling factor
A_p = Band-specific additive rescaling factor.
θ_{SE} = Local sun elevation angle in degrees.
M_p, A_p and θ_{SE} values were available in the image metadata file [27].

3.1.2. Calculating At-Satellite Brightness Temperature of Each Pixel Value of Thermal Infrared Bands using the Radiances Computed as Follows:

$$T = K_1 / Ln\,(K_2 / L\lambda + 1) \qquad (2)$$

Where:
T = At-satellite brightness temperature in Kelvin units
$L\lambda$ = Top of atmosphere spectral radiance equals to ($M_l\, DN + A_l$)
K_1 = Band 10-specific thermal conversion constant
K_2 = Band 11-specific thermal conversion constant.
K_1, K_2, M_l, and A_l values were available in the image metadata file [27].

3.2. Creation of Attributes

To improve the classification accuracy, two additional attributes, Normallized Difference Vegetation (NDVI) and Normalized Difference Water Index (NDWI), were created from the near-infrared and visible bands:

3.2.1. Normalized Difference Vegetation Index (NDVI)

The NDVI was first proposed by Rouse *et al*. [32] as an indicator to estimate vegetation areas using the relation between visible and near-infrared bands. The NDVI images improve the detection of vegetation areas and soil features. It is widely used in classification and green area extraction from satellite images and can be calculated using the following equation [28]:

$$NDVI = (NIR\text{-}RED) / (NIR+RED) \tag{3}$$

Where:
RED = the red band
NIR = the near-infrared band

3.2.2. Normalized Difference Water Index (NDWI)

McFeeters [30] proposed NDWI as an indicator to delineate water features and enhance their detection from satellite images. It is the contrary of NDVI, replacing the red band with green band. As a result the presence of water areas improved because the reflectance of water features is maximized by the green band and the vegetation or soil areas were repressed. It can be calculated using the following equation [31]:

$$NDWI = (NIR\text{-}Green) / (NIR+Green) \tag{4}$$

Where:
Green = the green band
NIR = the near-infrared band

3.3. Selecting Uncorrelated Attributes Using PCA Approach

Principal Component Approach (PCA) is considered the most widely used technique for dimension reduction and feature selection from massive data sets. It extracts relevant information and compresses data considerably without losing much information in the original data set [23]. In this approach, image bands are transformed to new bands known as principal components ordered by the amount of image variation they can elucidate [20]. These components are uncorrelated and orthogonal to each other. The first component expresses the highest possible variability in the original data and the next components represent the possible data variances in orthogonal directions [35].

3.4. Classification Algorithms

Three base classifiers were applied to LCLU classification: RF, SVM and, multi-layer perceptron NN with the Back-Propagation (BP) algorithm. The ensemble is then employed using the bagging technique.

3.4.1. Random Forest

The Random Forest (RF) is a collection of numerous decision trees which are generated by learning instance groups sampled independently from a training set [11]. To train the RF algorithm, multiple trees are created and each tree is trained on a bootstrapped sample of the training data with replacement. In this technique, each node will be split using the best among a subset of predictors randomly chosen at that node [25]. This random feature selection improves the overall accuracy, ensures the variation between sample trees, and avoids suffering from over-fitting. Finally, the majority voting technique is used for estimating the final prediction [18]. The number of input features, the number of variables used to split each node, and the number of grown trees are three necessary parameters for RF implementation [19]. Bootstrap samples are drawn from a certain percentage of the training data set. The remaining percentage of calibration samples, called out-of-bag data, is used to estimate the classification accuracy. For classification problems, setting the number of variables equal to the square root of the overall number of variables generally gives optimum results [10]. For splitting each node, an impurity or error node criterion must be assigned as an instance Gini diversity index which can be calculated using the following equation:

$$1 - \sum_i p^2\,(i) \tag{5}$$

Where: p (i) is the observed fraction of classes with class$i$ that reach the node.

The splitting is continued until reaching a Gini index of zero and the resulted node is a pure node. This means that one class is assigned for each final node.

3.4.2. Support Vector Machines (SVM)

Supper Vector Machines (SVM) is a supervised machine-learning technique developed by Vapnik and Cortes [38]. It is well adapted for solving linear, non-linear, and high dimensional space classification problems. Further, it is a powerful tool for multispectral and hyperspectral image classification that have small separated spectral values [7]. In this approach, classes are separated by determining an optimal hyper-plane through n-dimensional spectral space that maximizes the margin between these classes [24]. The nearest training samples (support vectors) in the training datasets are used to maximize the margin from the closest point to the optimal hyper-plane. The classification accuracy is directly proportional to the margin size [1]. Kernels are used for representing complex hyper-planes in non-linear SVM problems. Gaussian Radial Basis Function (RBF) is considered the best kernel for LCLU classification due to its high effectiveness. It requires defining a small number of parameters that performs better than other kernels and has vigorous capabilities for handling of remote sensing data [39].

3.4.3. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) have been widely used in remote sensing for classification and regression problems [29]. The Multi-Layer Perception (MLP) model using the BP algorithm is a supervised approach. It is widely used in displaying the non-linear relationship between input and output data [33]. The MLP consists of an input layer with a pre-defined number of neurons representing the available dataset, a hidden layer that demonstrates the network training/performance process, and an output layer presenting the output LCLU classes [22]. The backpropagation algorithm starts with initial network weights to find the least error values through comparing actual outputs with desired in an iterative process reaching a pre-defined level of accuracy [5].

The log sigmoid function, used for transferring the net inputs to the node outputs as its derivative, is easily computed and commonly used [12]. The BP is trained by the Levenberg-Marquard training algorithm for weight and bias values updating. It is the first-choice supervised algorithm that is highly recommended for training moderate-sized feed forward neural networks [4].

3.4.4. Bagging Ensemble

Bagging is an ensemble learning algorithm proposed by Breiman [9] to improve classification accuracy and prediction model performance by reducing variance and avoiding overfitting. The basic concept of bagging is to generate some independent samples with replacements from the available training set, fit a model to each bootstrap sample, and finally aggregate these models by majority voting [26]. For a standard training set *T* of size n, bagging generates m new training sets *Ti*, *i* = 1 to m each of size n′, by sampling from the training set uniformly and with replacement and *L* is weak learner. By sampling with replacement, some observations may be repeated whereas others may not be selected at all. If n′ and n are equal, then for large *n*, the set *Ti* is expected to have about 63 % of the unique samples of *T* replicated to have a full size data known as in-bag, the rest is known as out-of-bag.

This process is known as bootstrap sampling. The m bootstrap samples are used for fitting the m models and they return the class that receives the maximum number of votes *H* (*x*) [18]. The following steps illustrate Bagging algorithm [17]:

Algorithm 1:

For m = 1 to M do
T_m *= Random sample replacement (n,T)*
$h_m = L(T_m)$
end for
$H(x) = sign(\sum_{m=1}^{M} hm(x))$ *where* $h_m \in [-1, 1]$ *are the induced classifiers*
end Algorithm

Figure 3 illustrates the processing steps of deriving classified images from Landsat 8 imagery using different classifiers and the ensemble technique with base classifiers also performing the accuracy assessment for these images.

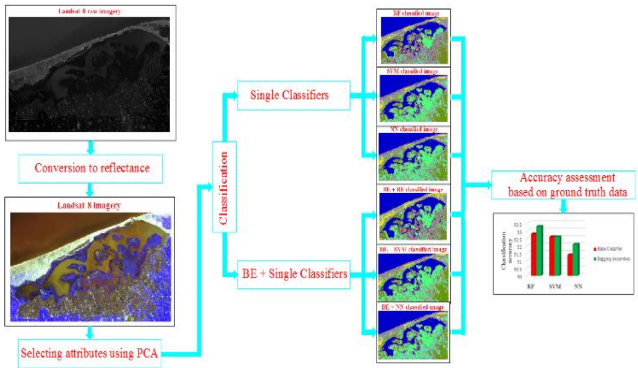


Figure 3. Work flow processing steps for classifying Landsat-8 images and comparing classification accuracy of each classifier.

4. Results and Discussion

The Landsat 8 multispectral image of the study area is pre-processed for LULC classification through converting the image pixel values to reflectance utilizing image metadata file values. The additional attributes of NDVI and NDWI are also calculated. Both steps were performed in an ENVI environment.

The PCA approach is applied to the calculated attributes for reducing redundancy and preserving the uncorrelated data. The input data is reduced to three principal components with 95% data variance. The base classifiers RF, SVM, and NN, are applied to the landsat imagery. Then, the bagging ensemble is used with these classifiers in a hierarchal structure. The classification approaches are performed in Matlab environment.

In order to assess the accuracy of each classifier used, reference data is extracted from Landsat satellite imagery using field trip signature measurements and old classified maps. The accuracy assessment is based on resulted commission, omission errors for each class, and overall accuracy, using 1000 pixels as a test data evenly distributed all over the study area. Table 1 illustrates the resulted assessment results.

Table 1. The commission, omission errors for all classes and overall accuracy of RF, SVM and NN base classifiers.

Classifier	Class	Com. Err.(%)	Om.Err. (%)	Overall Acc. (%)
Random Forest	Water	5.01	7.32	92.8
	Vegetation	4.15	6.73	
	Land	6.70	5.24	
	Buildings	12.44	10.66	
	Grass Lake	7.98	5.98	
SVM	Water	6.15	8.04	92.6
	Vegetation	3.69	6.28	
	Land	7.41	5.92	
	Buildings	11.37	8.78	
	Grass Lake	8.51	8.02	
NN	Water	7.5	10.63	91.4
	Vegetation	8.29	7.87	
	Land	9.79	2.78	
	Buildings	11.94	9.69	
	Grass Lake	5.32	11.44	

Bagging ensemble is then performed with RF, SVM, and NN as base classifiers in a hierarchal structure. The number of bagging trees after many trials is 10 trees, based on the out-of-bag error and the overall accuracy. The split of RF trees was created using Gini diversity index criterion. The created trees are not pruned and allowed to grow to maximum size. The optimum number of RF trees was determined based on overall accuracy and the random combinations of the three input variables. The best overall accuracy was achieved by using 10 RF trees. Table 2 lists the related accuracy assessment results.

Table 2. The commission, omission errors for all classes and overall accuracy of BE with RF, SVM and NN base classifiers.

Classifier	Class	Com. Err.(%)	Om. Err.(%)	Overall Acc. (%)
Bagging with Random Forest	Water	3.59	6.47	93.3
	Vegetation	4.61	2.82	
	Land	4.23	9.50	
	Buildings	14.69	7.22	
	Grass Lake	5.85	7.81	
Bagging with SVM	Water	4.62	7.00	92.6
	Vegetation	3.69	7.11	
	Land	6.35	7.81	
	Buildings	13.74	6.67	
	Grass Lake	8.51	8.51	
Bagging with NN	Water	5.13	8.87	92.1
	Vegetation	5.53	5.09	
	Land	7.41	6.42	
	Buildings	13.74	7.61	
	Grass Lake	7.45	11.68	

The commission and omission's errors illustrate the improvement of classification using BE with RF, SVM, and NN classifiers. Almost all classes of commission and omission errors were reduced except of the building class. With RF, the commission error rate fell from 7.18% to 6.76% and omission error from 7.25% to 6.59%. With respect to NN, the commission error rate fell from 8.48% to 7.93%, and omission error from 8.57% to 7.85%. Although the omission error using SVM fell from 7.43% to 7.38%, the commission error and the final overall accuracy did not improve. The efficiency of BE in reducing the variance of unstable algorithms, especially RF and NN, is confirmed. The BE improves the overall accuracy of RF classifier with 0.5% and NN classifier with 0.7%.

Regarding the complexity cost of proposed approach two factors were tested its computational time and space. Although BE increase the computational time and space with SVM and NN with about 7 times in average, this problem can be solved. Dividing the study area into successive zones and increasing the memory reduce this drawback. In addition, BE with RF hadless computational time and spacethan BE with SVM and NN.

Figure 4 Presents the improvement in classification accuracy at using BE with RF, SVM, and NN with the base classifiers.

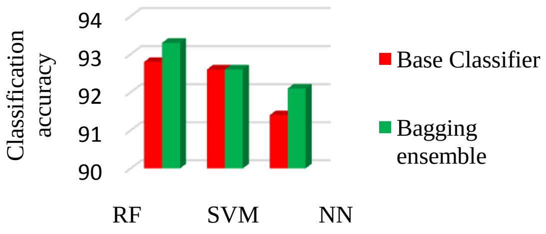
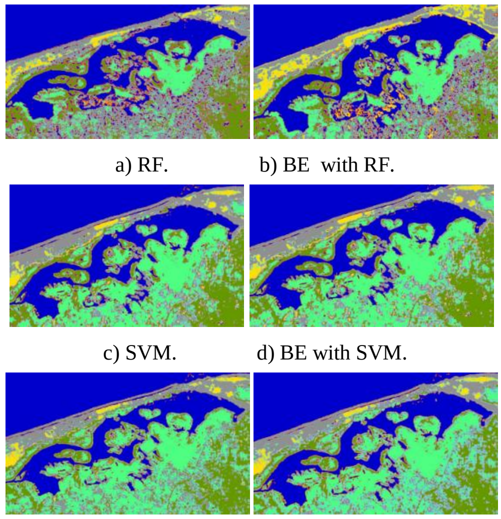


Figure 4 The improvement in overall classification accuracy at using BE with RF, SVM and NN base classifiers.

Figure 5 presents the classification results of RF, SVM, NN, BE with RF, BEwith SVM, and BE with NN classifiers.



a) RF. b) BE with RF.

c) SVM. d) BE with SVM.

e) NN. f) BE with NN.

Figure 5. Classification results of Landsat satellite imagery. Blue: water, Yellow: buildings, Grey: land, Green: Vegetation, Light green: grass lake.

5. Conclusions

In this research, a pixel-based methodology for LULC classification using the bagging ensemble with RF in a hierarchal structure is proposed and evaluated using satellite imagery of a coastal heterogeneous area. To validate the effectiveness of the proposed methodology over SVM and NN classifiers, classification was carried out using a Landsat 8 satellite image over Egypt's Lake El-Burullus and its surroundings. All necessary reference data were extracted by the interactive digitizing of the image. The overall accuracy when using RF, SVM, and NN base classifiers are 92.8%, 92.6% and 91.4% respectively. The Bagging ensemble yielded 92.6% with SVM and 92.1% with NN. Using BE with RF yielded a 93.3% overall accuracy rate. The BE also improved commission errors for all classifiers and reduced omission errors for RF and NN classifiers. Overall, the results confirm the outperformance of BE with RF to other base classifiers, such as SVM and NN.

References

[1] Adam E., Ismail R., and Mutanga O., "A Comparison of Selected Machine learning Classifiers in Mapping a South African Heterogeneous Coastal Zone: Testing the Utility of an Object Based Classification with Worldveiw-2 Imagery," *in Proceedings of Earth Resources and Environmental Remote Sensing*, Edinburgh, 2012.

[2] Akar O. and Gungor O., "Classification of Multispectral Images Using Random Forest Algorithm," *Geodesy and Geoinformation*, vol. 1, no. 2, pp. 105-112, 2012.

[3] Ali E., "Impact of Drain Water on Water Quality and Eutrophication Status of Lake Burullus, Egypt, A Southern Mediterranean Lagoon," *African Journal of Aquatic Science*, vol. 36, no. 3, pp. 267-277, 2011.

[4] Ananth R., "The Levenberg-Marquardt Algorithm.8," Available at: http://www.ananth.in/Notes_files/lmtut.pdf, Last Visited 2004.

[5] Behzad S., "Predicting the Trend of Land Use Changes Using Artificial Neural Network and Markov Chain Model (Case Study: Kermanshah City)," *Research Journal of Environmental and Earth Sciences*, vol. 6, no. 4, pp. 215-226, 2014.

[6] Benediktsson J., Chanussot J., and Mathieu F., "Multiple Classifier Systems in Remote Sensing: From Basics to Recent Developments," *Multiple Classifier Systems Lecture Notes in Computer Science*, Springer Berlin, pp. 501-512, 2007.

[7] Benjamin L. and Bernd B., "Data Mining and Support Vector Regression Machine Learning in Semiconductor Manufacturing to Improve Virtual Metrology," *in Proceedings of 46th Hawaii International Conference on System Sciences*, Maui, HI, pp. 3447-3456, 2013.

[8] Boukir S., Guo L. and Chehata N., "Classification of Remote Sensing Data using Margin-Based Ensemble Methods," *in Proceedings of Institute of Electrical and Electronics Engineers International Conference on Image Processing*, Melbourne, pp. 2601-2606, 2013.

[9] Breiman L., "Bagging Predictors," *Machine Learning*, vol. 24, no. 2, pp. 123-140, 1996.

[10] Breiman L., "Manual on Setting up, using, and Understanding Random Forest V3.1," Available, at:https://www.stat.berkeley.edu/~breiman/Using _random_forests_V3.1.pdf, Last Visited 2015.

[11] Breiman L., "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001.

[12] Ceyhun O. and Yalcin A., "Remote Sensing of Water Depths in Shallow Waters via Artificial Neural Networks," *Estuarine Coastaand Shelf Science*, vol. 89, no.1, pp. 89-96, 2010.

[13] Charlie L., "Landsat 8 Bands," http://landsat.gsfc.nasa.gov/?page_id=5377, Last Visited 2015.

[14] Chu H. and Ge L., "Combination of Genetic Algorithm and Dempster-Shafer Theory of Evidence for Land Cover Classification Using Integration of SAR and Optical Satellite Imagery," *International Society for Photogrammetry and Remote Sensing*, vol. XXXIX-B7, pp. 173-178, 2012.

[15] Dara R., Cooperative Training in Multiple Classifier Systems Theses, University of Waterloo, 2007.

[16] Du P., Zhang W., and Sun H., "Multiple Classifier Combination for Hyperspectral Remote Sensing Image Classification," *in Proceedings of 8th International Workshop on Multiple Classifier Systems*, Berlin, pp. 52-61, 2009.

[17] Galar M., Fernandez A., Barrenechea E., Bustince H., and Herrera F., "A Review on Ensembles for the Class Imbalance Problem: Bagging-, Boosting-, and Hybrid-Based Approaches," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 4, pp. 463-484, 2011.

[18] Ghimire B., Rogan J., Galiano V., Panday P., and Neeti N., "An Evaluation of Bagging, Boosting, and Random Forests for Land-Cover Classification in Cape Cod, Massachusetts, USA," *GIScience & Remote Sensing*, vol. 49, no. 5, pp. 623-643, 2012.

[19] Guan H., Yu J., Li J., and Luo L., "Random Forests-Based Feature Selection for Land-Use Classification Using LIDAR Data and Orthoimagery," *International Society for Photogrammetry and Remote Sensing*, vol. XXXIX-B7, pp. 203-208, 2012.

[20] Hladnik A., "Image Compression and Face Recognition: Two Image Processing Applications of Principal Component Analysis," *International Circular of Graphic Education and Research*, vol. 6, pp. 56-61, 2013.

[21] Inoue A. and Kilian L., "How Useful is Bagging in Forecasting Economic Time Series? A Case Study of US CPI Inflation," CEPR Discussion Paper no. 5304, Available at:

http://ssrn.com/abstract=872856, Last Visited 2014.

[22] Jayakumar K., Revathi T., and Karpagam S., "Intrusion Detection using Artificial Neural Networks with Best Set of Features," *The International Arab Journal of Information Technology*, vol. 12, no. 6A, pp. 728-734, 2015.

[23] Jolliffe I., *Principal Component Analysis*, John Wiley & Sons, 2014.

[24] Kavzoglu T. and Colkesen I., "A Kernel Functions Analysis for Support: Vector Machines for Land Cover Classification," *International Journal of Applied EarthObservation and Geoinformation*, vol. 11, no. 5, pp. 352-359, 2009.

[25] Kim H. and Sohn G., "Random Forests Based Multiple Classifier System for Power-Line Science Classification," *in Proceedings of International Archives Photogram Remote Sensing Spatial Information Sci*ence, Canada, pp. 253-258, 2011.

[26] Kulkarni S. and Kelkar V., "Classification of Multispectral Satellite Images Using Ensemble Techniques of Bagging, Boosting and Ada-Boost," *in Proceedings of International Conference on Communication Circuits, Systems, and Information Technology Applications*, Mumbai, pp. 253-258, 2014.

[27] Landsat-8., "Using the USGS Landsat 8 Product," Available at: http://landsat.usgs.gov/Landsat8_Using_Product.php, Last Visited 2014.

[28] Maskova Z., Zemek F., and Kvet J., "Normalized Difference Vegetation Index in the Management of Mountain Meadows," *Boreal Environment Research*, vol. 13, pp. 417-432, 2008.

[29] Mather P. and Tso B., *Classification Methods for Remotely Sensed Data*, CRC Press, 2009.

[30] McFeeters S., "The Use of the Normalized Difference Water Index In the Delineation of Open Water Features," *International Journal of Remote Sensing*, vol. 17, no. 7, pp. 1425-1432, 1996.

[31] McFeeters S., "Using the Normalized Difference Water Index within a Geographic Information System to Detect Swimming Pools for Mosquito Abatement: A Practical Approach," *Remote Sensing*, vol. 5, no. 7, pp. 3544-3561, 2013.

[32] Rouse J., Haas R., Schell J., and Deering D., "Monitoring Vegetation Systems in the Great Plains with ERTS," *NASA Goddard Space Flight Center*, 3rd *ERTS-1 Symposium*, NASA, pp. 309-317, 1974.

[33] Rumelhart D., Geoffrey E., and Robert J., "Learning Internal Representations by Error Propagation," *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, Cambridge, pp. 318-362, 1986.

[34] Salah M., Trinder J., Shaker A., Hamed M., and Elsagheer A., "Integrating Multiple Classifiers with Fuzzy Majority Voting for Improved Land Cover Classification," *in Proceedings of WG III/2 Point Cloud ISPRS*, At Saint-Mandé, pp. 7-12, 2010.

[35] Shlens J., A Tutorial on Principal Component Analysis, Cornell University Library Computer Science Learning, Available at: http://arxiv.org/abs/1404.1100, Last Visited 2015.

[36] Shota M. and Takuhiko M., "Accuracy Comparison of Land Cover Mapping using The Object- Oriented Image Classification with Machine Learning Algorithms," *in Proceedings of the 33rd Asian Conference on Remote Sensing*, 2012.

[37] Tzeng Y., Fan K., and Chen K., "An Adaptive Thresholding Multiple Classifiers System for Remote Sensing Image Classification," *Photogrammetry Engineering and Remote Sensing*, vol. 75, no. 6, pp. 679-687, 2009.

[38] Vapnik V. and Cortes C., "Support-Vector Networks," *Machine Learning*, vol. 20, no. 3, pp. 273-297, 1995.

[39] Yang X., Deb S., and Fong S., "Accelerated Particle Swarm Optimization and Support Vector Machine for Business Optimization and Applications," *in Proceedings of 3rd International Conference Networked Digital Technologies Communications in Computer and Information Science*, Macau, pp. 53-66, 2011.

[40] Zhuo Z., "Boosting and Bagging of Neural Networks with Applications to Financial Time Series," *Working paper, Department of Statistics*, University of Chicago, 2006.

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