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LAND COVER MAPPING WITH ADVANCED CLASSIFICATION ALGORITHMS

ABSTRACT

Remote sensing technologies are used in many applications to extract information from the surface of the earth. Image classification, which is one of the most widely-used ways of information extraction, is a controversial topic in remote sensing. This is because all classification algorithms introduced in the literature cause classification errors to some extent. Simple classification algorithms like Minimum Distance, Parallelepiped and Mahalanobis Distance commit a large amount of classification errors. This, of course, has encouraged the remote sensing community to develop more advanced classification algorithms to further increase classification accuracy. This study uses sophisticated classification algorithms Support Vector Machines (SVM), k-Nearest Neighbour (kNN) and Artificial Neural Network (ANN) to classify a WorldView-2 multispectral image in order to produce land cover maps. The accuracies of the produced thematic maps were evaluated with randomly-selected control points. The SVM algorithm classified the imagery with the best classification accuracy of 72.38%.

Keywords: Image Classification, Support Vector Machines, k-Nearest Neighbour, Artificial Neural Network

1. INTRODUCTION

In the last decades, remote sensing technologies have been widely used to monitor the surface of the earth. Many remote sensing applications rely on the investigation of land use and land cover, which are generally obtained through classification of imageries. Image classification is simply grouping pixels with respect to their colour characteristics, i.e. the pixels with similar grey values are assigned to the same class. Various image classification algorithms have been introduced in the literature, some of which are parametric while some non-parametric. Parametric algorithms use statistical parameters (variance, covariance, mean etc.) derived from training data, which is obtained by the analyst by collecting training pixels from the pure parts of the classes in imagery. The Minimum Distance, Maximum Likelihood and Fisher Linear Discriminant are some of the widely-used parametric classifiers. The Random Forest (RF), Boosting, Artificial Neural Networks (ANN), k-nearest neighbour (kNN) and Support Vector Machines (SVM) are some of the commonly-used non-parametric classifiers. These classifiers are also referred to as machine learning algorithms. Instead of the statistical parameters derived from training data, non-parametric classifiers make use of the

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training data itself [1]. The main objective of learning is to generate a classification model [1 and 2]. Machine learning-based classification is a two-step process. In the first step, some portion of the data is specified as training data (pixels in our case) and classification is performed to the training data to generate the classification model. In the second step, the generated model is applied to the test data, which is composed of the pixels other than training data/pixels. Test results are evaluated to find out whether or not the used model works fine. If it does, then the model is applied to all data [1].

2. RESEARCH SIGNIFICANCE

The aim of this study was to investigate the use of non-parametric machine learning algorithms kNN, ANN and SVM to produce land cover maps. The use of advanced classifiers enables the production of accurate land cover maps.

3. STUDY AREA AND DATA PREPARATION

In the study, a WorldView-2 multispectral imagery (2m spatial resolution) of Sürmene, a province of the city of Trabzon in Turkey, was used to produce land cover maps. The study area, which can be seen in Figure 1, covers an area of 86 ha.

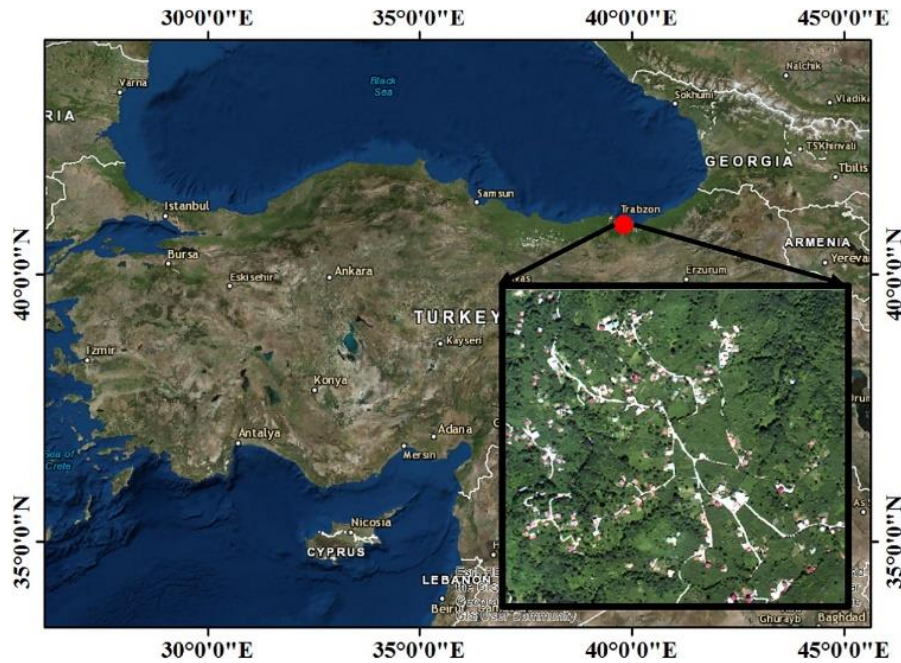


Figure 1. Study area

Since the imagery came as geometrically and atmospherically corrected, there was no need to conduct any pre-processing procedures. Visual examination of the study area revealed that there were 8 classes in the study area; building 1 (brick roofed), building 2 (concrete roofed), road, soil, shadow, tea, hazelnut and forest. Afterwards, a total number of 3276 training and 868 test pixels were collected for all classes.

4. METHODOLOGY

The kNN, which is an instance-based classification method, uses data samples to estimate the class of an object. It does not utilize a model to classify objects. In other words, it does not create a



classification model like other machine learning algorithms or artificial intelligence techniques such as the decision trees, artificial neural networks, support vector machines etc. The most important parameters of the kNN classifier are the distance metric and number of neighbours. The analyst should specify both the optimum distance metric and number of neighbours. Selecting the optimum parameters is very challenging in image classification. Since the performance of this classifier highly depends on these parameters, the analysts should pay plenty of attention to decide the optimum parameters. The basic steps of the kNN classifier are given as;

Algorithm 1. The basic steps of the kNN classification process

- i)** Prepare a sample dataset
 - a.** Divide the dataset into three parts as training (Q), testing and validation
- ii)** Select a classification function
 - a.** Majority voting
 - b.** Distance-weighted voting
- iii)** Decide on the most suitable metric and number of neighbours
 - a.** Try different metrics and investigate the performance of the kNN
 - b.** Measure the performance of the algorithm for different neighbouring numbers
 - c.** Save the best metric (m) and neighbour count (n) for problem
- iv)** Use the m , n and Q to classify a query object (q') in kNN
 - a.** Measure the distances between the q' and Q and create a distance matrix
 - b.** Sort the distances and determine the k -nearest neighbours of q' and specify their classes
 - c.** Use a classification function (step ii) within the classes of k -neighbours of q'
 - d.** Return the class of q'

The SVM is a statistical learning theory-based supervised classification algorithm that usually performs great with noisy and complex data [3]. The main aim of this classifier is to find the optimum decision function that separate two classes. In other words, it is based on the definition of the hyperplane that best separate two classes [4]. In cases where classes are linearly separable, two parallel planes maximizing the margin between the classes are generated and the optimum hyperplane is placed in the middle of these planes. However, in most cases, it is not possible to separate classes linearly (e.g. satellite imageries). In such cases, some kernel functions are used to transform the data into a higher-dimensional space where there is a greater chance to separate the classes. A hyperplane is formed with support vectors, which are the points closest to other classes. Further information about the SVM classifier can be found in [4 and 5]. The gamma (γ) and penalty (C) are the most effective parameters of this classifier. The use of ANN classifier in image classification dates back to the later 1980s. Key et al. [6], Benediktsson et al. [7] and Lee et al. [8] were among the first researchers who used Neural Networks in image classification. According to this classifier, network learns the regularities in the training data and builds the rules. The analyst should build the architecture of the network [9]. A simple neural network consists of three layers [10 and 11]. The input layer, which is on the left, includes the features to be used in classification process. No operations are performed in this layer. The layer in the middle is called 'hidden' and classification is performed in this layer.



Kanellopoulos and Wilkinson [12] stated that one hidden layer is adequate for most applications. If more than one hidden layer is used, then learning capacity of the network increases, leading to an increase in the training time [13]. Classification results are produced in the output layer, which is on the right [11 and 14]. The most commonly-used model for neural networks is the Back-Propagation algorithm, in which the classes are separated depending on some weights. The Back-Propagation algorithm minimizes the root mean square errors of all patterns in the network output [15]. The ANN classification was performed with the ENVI software. The software uses 4 parameters to perform ANN [16]: (1) the training threshold contribution parameter, which specifies the contribution of the internal weight with respect to the activation level of the node, (2) the training rate, which specifies the magnitude of the adjusted weights, (3) the training momentum, which allows setting a training rate without oscillations, (4) the training RMS exit criteria, which stops the training process.

5. EXPERIMENTAL RESULTS AND DISCUSSION

The image was classified with the kNN, SVM and ANN classifiers by using 3276 training pixels. Accuracy of 868 test pixels were evaluated by comparing their reference values with class values in the thematic images. Implementation of the kNN classifier with different k-values and distance metrics gave the testing results presented in Table 1.

Table 1. Testing Results for the kNN classifier

Distance Metric	k-value	Number of Misclassified Data Samples in the Testing Dataset	Percentage of Correctly Classified Data Samples in the Testing Dataset
Euclidean	6	100	88.48
	7	103	88.13
	8	102	88.25
	9	100	88.48
	10	97	88.83
	11	97	88.83
Manhattan	6	98	88.71
	7	97	88.83
	8	95	89.05
	9	94	89.17
	10	99	88.59
	11	98	88.71

As seen in Table 1, the optimum k-value was found 9 and Manhattan distance was found to be the optimum distance metric, which was the reason that these parameters were used in the classification process.

Table 2 shows the confusion matrix of the kNN testing result. As seen in the table, the shadow class had the highest testing accuracy, whereas the hazelnut class had the lowest testing accuracy. Examination of the table revealed that the tea, hazelnut and forest classes mixed each other, which was expected due to the fact that these features have similar spectral characteristics. It can also be seen from the table that the kNN algorithm caused the road class to mix the building2 class. The overall testing accuracy was found 89.17% for the kNN algorithm.



Table 2. Confusion Matrix of the kNN testing result

		Classes							Total	Acc.(%)	
		Build 1	Build 2	Road	Soil	Shad.	Tea	Hazel.			Forest
Reference	Build 1	86	0	0	3	1	0	0	0	90	95.56%
	Build 2	0	52	2	0	0	0	0	0	54	96.30%
	Road	0	10	84	0	0	0	0	0	94	89.36%
	Soil	5	0	5	57	0	0	0	0	67	85.07%
	Shad.	0	0	0	0	70	0	0	1	71	98.59%
	Tea	0	0	0	0	0	116	12	0	128	90.62%
	Hazel.	0	0	0	0	0	12	141	19	172	81.98%
	Forest	0	0	0	0	1	1	22	168	192	87.50%
Total		91	62	91	60	72	129	175	188	868	
Test Accuracy=89.17%											

In the study, the ENVI software was used to perform SVM classification. The radial basis function was used as the kernel function. The optimum γ and C parameters were found by means of the two-fold cross-validation technique. The grid search method was used to investigate the optimum parameters during cross-validation. Hsu et al. [17] stated that it is practical to use exponentially growing sequences of γ and C parameters (for example, $C=2^{-5}, 2^{-3}, \dots, 2^{15}$; $\gamma=2^{-15}, 2^{-13}, \dots, 2^3$) to specify parameters of good quality. The optimum parameters for the C and γ parameters were found 2^{15} and 2^{-2} , respectively. Table 3 depicts the confusion matrix of the SVM testing result. As seen in the table, the testing accuracy was found 100% for the shadow class. The lowest testing accuracy (84.04%) was found in the road class. As seen in the table, the SVM algorithm was more successful than the kNN algorithm in distinguishing the tea, hazelnut and forest classes. It should also be noted that the SVM algorithm mixed the road class to the building2 and soil classes in testing process. Overall testing accuracy was found 90.21%, which was the highest overall testing accuracy achieved in this study.

Table 3. Confusion matrix of the SVM testing result

		Classes							Total	Acc.(%)	
		Build 1	Build 2	Road	Soil	Shad.	Tea	Hazel.			Forest
Reference	Build 1	88	0	0	1	1	0	0	0	90	97.78%
	Build 2	0	51	3	0	0	0	0	0	54	94.44%
	Road	0	15	79	0	0	0	0	0	94	84.04%
	Soil	2	0	7	58	0	0	0	0	67	86.57%
	Shad.	0	0	0	0	71	0	0	0	71	100.00%
	Tea	0	0	0	0	0	114	14	0	128	89.06%
	Hazel.	0	0	0	0	0	5	148	19	172	86.05%
	Forest	0	0	0	0	1	1	16	174	192	90.62%
Total		90	66	89	59	73	120	178	193	868	
Test Accuracy=90.21%											

The training threshold contribution, training rate, training momentum and training RMS exit criteria parameters used by the ANN algorithm were set to 0.9, 0.2, 0.9 and 0.1, respectively. It should also be noted that only one hidden layer was used and logistic activation function was used to perform the ANN. Table 4 presents the confusion matrix of the ANN testing result. The table depicts that the shadow class had the highest testing accuracy. The soil class was found to have the lowest testing accuracy (77.61%). A considerable amount of tea, hazelnut and forest pixels mixed each other. The SVM algorithm mixed the building1, building2, road and soil classes to some extent. Overall testing accuracy was found 88.48% for the ANN algorithm, which was the lowest overall testing accuracy obtained in this study.



Table 4. Confusion matrix of the ANN testing result

		Classes								Total	Acc. (%)
		Build 1	Build 2	Road	Soil	Shad.	Tea	Hazel.	Forest		
Reference	Build 1	87	0	0	2	1	0	0	0	90	96.67%
	Build 2	0	50	4	0	0	0	0	0	54	92.59%
	Road	0	4	90	0	0	0	0	0	94	95.74%
	Soil	8	0	7	52	0	0	0	0	67	77.61%
	Shad.	0	0	0	0	70	0	0	1	71	98.59%
	Tea	0	0	0	0	0	115	10	3	128	89.84%
	Hazel.	0	0	0	0	0	18	144	10	172	83.72%
	Forest	0	0	0	0	0	4	28	160	192	83.33%
Total	95	54	101	54	71	137	182	174	868		
Test Accuracy=88.48%											

The performance of each classification algorithm was evaluated by means of the points that were distributed randomly over the study area. The overall accuracy of each classification algorithm was computed by using the reference and estimated class values of these points. The number of these randomly distributed points plays a significant role in a successful performance investigation. Theoretically, the more test points, the more robust performance investigation. However, an excessive number of test points is likely to make the performance evaluation process less time-efficient. On the other hand, an insufficient number of test points may yield misleading performance evaluation results. In this study, the minimum number of required test points was estimated with the multinomial distribution approach proposed by Congalton and Green [18]. If there is no information about the area of each land cover class, the minimum number of required test points n is estimated as [18, 19 and 20];

$$n = \frac{B}{4b^2} \quad (1)$$

where, $B = a/k$ (a is the confidence interval and k is the number of classes) and b is the desired accuracy. In this study, the confidence interval a was chosen 95%. Since there are 8 classes in the study area, B was computed as 0.00625. Examination of the χ^2 distribution table revealed that the 0.00625 value corresponds to 7.48 in one degree of freedom. Hence, the minimum number of required test points n was computed as 748 ($7.48/(4 \times 0.05^2)$). As a result, 800 randomly distributed test points were decided to use to investigate the performances of the classification algorithms. The actual (reference) classes of these points were specified by means of the high-resolution multispectral and panchromatic WorldView-2 images. The producer's accuracy, user's accuracy and overall accuracy values calculated for the classification algorithms are given in the following. Note that the producer's accuracy is the ratio between the correctly classified pixels and all pixels of that ground truth class, whereas the user's accuracy is referred to the fraction of correctly classified pixels with regard to all pixels classified as this class in the classified image [21]. The overall classification accuracy is calculated by dividing the total number of correctly classified pixels to the total number of pixels. Table 5 gives the producer's accuracy, user's accuracy, overall accuracy and overall kappa statistics values for the kNN result. As seen in the table, tea class had the lowest user's accuracy, whereas shadow class had the highest user's accuracy. The building2 class had the lowest producer's accuracy, whereas the soil class had the highest producer's accuracy. The overall classification accuracy and kappa statistics value were found 68% and 60.04%, respectively.

Table 5. Post-classification accuracies for the kNN result

Classes	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Building1	26	35	22	84.62%	62.86%
Building2	27	19	14	51.85%	73.68%
Road	56	49	40	71.43%	81.63%
Soil	47	78	43	91.49%	55.13%
Shadow	80	48	48	60.00%	100.00%
Tea	95	129	63	66.32%	48.84%
Hazelnut	233	255	177	75.97%	69.41%
Forest	236	187	137	58.05%	73.26%
Overall Classification Accuracy=68.00%					
Overall Kappa Statistics=60.04%					

Table 6. Post-classification accuracies for the SVM result

Classes	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Building1	26	38	25	96.15%	65.79%
Building2	27	28	18	66.67%	64.29%
Road	56	45	39	69.64%	86.67%
Soil	47	63	42	89.36%	66.67%
Shadow	80	60	57	71.25%	95.00%
Tea	95	103	61	64.21%	59.22%
Hazelnut	233	239	169	72.53%	70.71%
Forest	236	224	168	71.19%	75.00%
Overall Classification Accuracy=72.38%					
Overall Kappa Statistics=65.31%					

Table 6 depicts the producer's accuracy, user's accuracy, overall accuracy and overall kappa statistics values for the SVM result. As seen in the table, tea class had the lowest user's accuracy, whereas shadow class had the highest user's accuracy. The tea class had the lowest producer's accuracy, whereas the building1 class had the highest producer's accuracy. The overall classification accuracy and kappa statistics value were found 72.38% and 65.31%, respectively. Table 7 presents the producer's accuracy, user's accuracy, overall accuracy and overall kappa statistics values for the ANN result. As seen in the table, tea class had the lowest user's accuracy, whereas shadow class had the highest user's accuracy. The building1 and building2 classed were found to have the highest and lowest producer's accuracies, respectively. The overall classification accuracy and kappa statistics value were found 70.25% and 62.99%, respectively.

Table 7. Post-classification accuracies for the ANN result

Classes	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Building1	26	35	24	92.31%	68.57%
Building2	27	18	15	55.56%	83.33%
Road	56	64	48	85.71%	75.00%
Soil	47	50	37	78.72%	74.00%
Shadow	80	51	50	62.50%	98.04%
Tea	95	160	75	78.95%	46.88%
Hazelnut	233	228	166	71.24%	72.81%
Forest	236	194	147	62.29%	75.77%
Overall Classification Accuracy=70.25%					
Overall Kappa Statistics=62.99%					

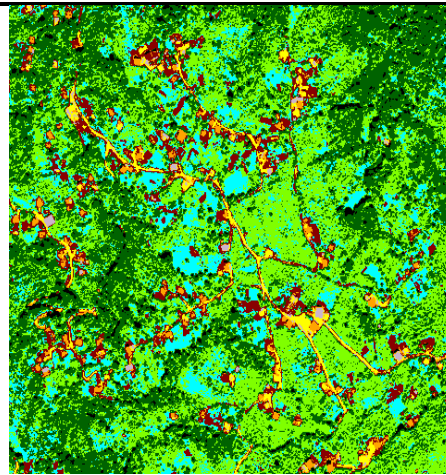
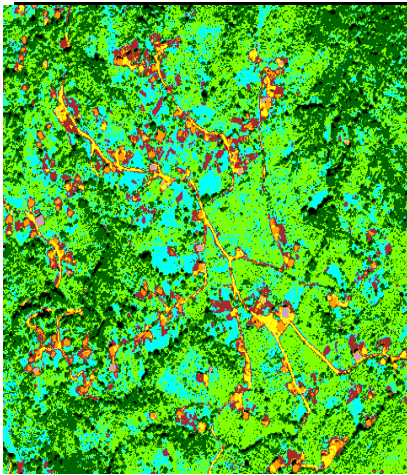


Figure 2. kNN classification result

Figure 3. SVM classification result

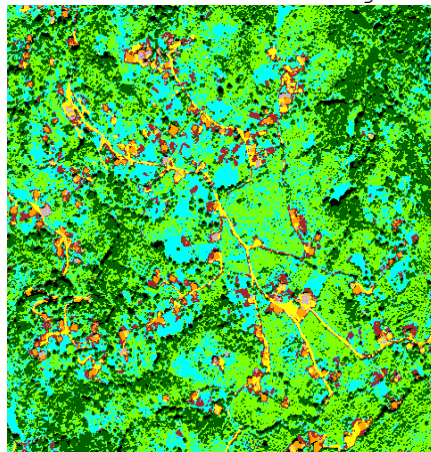


Figure 4. ANN classification result

Testing and overall classification results indicated that the SVM algorithm performed best. Despite the fact that the kNN algorithm gave better testing results than the ANN, it was found to be less accurate than the ANN in terms of overall accuracy. As mentioned before, the overall accuracy was computed by means of randomly selected test points. In such cases, test points may correspond to the areas having different spectral characteristics than training points. This, of course, made it more challenging for used algorithms to decide the classes, which was the reason for the decrease in overall classification accuracy, compared to the testing accuracy. In such cases, the ANN performed better than the kNN. Classification accuracies of the tea, hazelnut and forest classes were found to be smaller, which was expected due to the colour similarity of these classes. This was also supported by the user's accuracy results, which were relatively smaller than the producer's accuracy results. The same is true for the road and building2 classes.

6. CONCLUSION

This study utilized three advanced classification algorithms kNN, SVM and ANN to map an area by means of a high-resolution satellite imagery. The results showed that the SVM algorithm gave the best overall classification performance. The ANN algorithm followed it with a small margin. Post-classification accuracies revealed the fact that all algorithms presented similar performances. Hence, all three algorithms can be used for land cover mapping purposes. The SVM



algorithm classified the tea, hazelnut and forest classes, which have similar spectral characteristics, with a relatively higher accuracy. Therefore, it may be reasonable to use the SVM algorithm to discern classes with similar colours.

NOTICE

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