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Application of Machine Learning Approaches for Land Cover Classification

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***Abstract*-- Land cover classification has become an interesting research area in the field of remote sensing. Machine learning techniques have shown great success for various application in the domain of land cover classification. This paper focuses on the classification of land covers obtained from high resolution images using two well-known classification methods by integrating with object-based segmentation technique. First, graph-based minimal spanning tree segmentation was applied to segment the original image pixels into objects. The segmented objects were then used to obtained spectral, spatial and texture features which were then combined to form a single high dimensional feature vector. These features were then used to train and test the artificial neural network (ANN) and support vector machine (SVM). The proposed method was evaluated on a dataset consisting of high resolution multi-spectral images with four classes (tea area, other trees, roads and builds, bare land). The experiments showed that ANN was more accuracy as it scored average accuracy of 82.60% while SVM produced 73.66%. Moreover, when postprocessing using majority analysis was applied, the average accuracy improved to 86.18%.**

Keywords- land cover classification, support vector machine, artificial neural networks, graph-based segmentation

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I. INTRODUCTION

Today, digital image processing and machine learning approaches are combined to derive useful information from images. One of these research areas where these are used is the extraction of land cover from remotely sensed images. Land cover are physical areas on the soil surface forests, wetlands, streams, bare areas, impermeable surfaces on the soil, areas form the land cover. Various methods are used to extract land cover from images obtained by remote sensing systems. NDVI (Normalized Vegetation Difference) and classification methods are commonly used to vegetation information. NDVI is a measurement that uses the plant's viability by exploiting its greenness information. This measurement is made by the difference between near infrared (NIR) reflected by vegetation and red light absorbed by vegetation. NDVI is always between -1 and +1. The other objects such as water body, roads, bare soil etc. can also be distinguished using the NADI information as it approaches -1. The value of NDVI closer to + 1indidates more dense, green and healthy vegetation.

The main objective of land cover classification is to group objects with similar spectral properties. The classification process can be generally be pixel-based or object-based. Pixel-based classification is performs analysis using each pixel. This classification method has been used extensively until the 2000s. Image resolution has increased with the development of remote image sensing systems. Accordingly, the object-oriented classification method has been developed. In this classification method, the segmentation (image segmentation) process is applied to the pixels where pixels' color, frequency, brightness, neighborhood etc. are used to group similar pixels into objects. Thus, instead of individual pixels, these objects are taken into account. SLIC (Simple Linear Iterative Clustering), Mean-Shift, K-Means are among the main algorithms used for segmentation [1].

The most commonly used methods for classification are based on machine learning approaches. Machine learning techniques can be generally divided into two main categories as supervised and unsupervised learning. In supervised learning, a certain number of pixels in the image are tagged (labeled) and trained, and then these trained data are used for classification. Support vector machines (SVM), artificial neural networks (ANN), decision trees, maximum likelihood, random forests are among the main algorithms used for classification. In unsupervised learning, no labeling process is applied to the data. The system automatically tries to find the relationship between the data.

Images taken with remote image sensing systems can be used in various areas after being classified. For example, land cover maps obtained after the classification process can be used in areas such as geomorphology, Geographic Information Systems (GIS). Thanks to these maps, scientists can track changes on the earth and produce solutions to any problem that may arise. Therefore, these maps are currently needed.

In our study, we investigated two well-known supervised approaches for land cover classification: SVM and ANN. Both spectral and spatial features were derived from the high resolution images and fed into the classifier to obtain four different land cover classes: tea area, other trees, roads and builds, bare land.

II. LITERATURE REVIEW

This section highlights some of the developments made in the field of remote sensing for land cover classification using various artificial intelligence techniques.

In [2], authors examined the accuracy, configuration, speed and capacity ratios of some supervised learning algorithms (SVM, Random Forest, Logistic Regression, etc.) used to classify spectral data on hyperspectral data. It has been observed that SVM is successful on hyperspectral data.

[3] studied the extraction of hazelnut trees from high resolution orthophoto maps. They compared object and pixel-based classification techniques. The SVM algorithm used for object-based classification produced more successful results than the maximum likelihood algorithm used for pixel-based classification (Overall accuracy SVM: 85.99%, ML: 75.83%).

Similarly, in [4] supervised learning algorithms SVM, artificial neural networks (ANN) and random forests were used for classification of ground cover (tea trees, other trees, bare areas, impermeable surfaces). Accuracy rates for tea trees were 87% for SVM, 89% for YSA and 86% for RF.

Chen et al. made a land cover classification with object-oriented super resolution mapping (OSRM) method for the mixed pixel problem (edge pixels of areas where areas differ in the images). As a result of their experiment, it has been explained that OSRM produces more land cover details for mixed objects [5].

Pipaud et al. discussed the classification of alluvial fans using mean-shift method for segmentation and SVM for classifier in object-oriented classification. As a result of the study, they concluded that mean-shift and SVM-based classification is an effective method for the description and classification of a certain place shape [1].

In their study, Zhu et al. Classified the hyperspectral image using the General Adverserial Network (GAN) method, which basically consists of two neural networks. As a result, it has been found that GANs give better results than traditional neural networks [6].

Junior et al., using eCognition and WEKA software, classified soybean plantations using geographic object-oriented image analysis (GEOBIA) and data mining, and an accuracy rate of 76% was achieved [7].

Ruiz and authors developed the Iterative K-Nearest Neighbors (IKNN) technique to classify images obtained by unmanned aerial vehicles (UAVs). This technique gave 90% accuracy compared to SVM and traditional KNN [8].

Shi and authors SVM conducted a study on the mapping of remote sensor images. To better examine the effectiveness of SVM, the Gwinnett County area, which is a complex land use and composed of different land covers, was used as the study area. In the study, SVM and MLC, one of the traditional classifiers, were compared for land cover classification. It has been observed that both methods make correct classification for the classification process in certain land cover categories. However, it has been observed that the classification accuracy of SVM method exceeds MLC in classes with complex pixels and classes with similar spectral properties. As a result, they confirmed that SVM performed better than MLC, one of the classifiers widely used in the remote sensing community [9].

Rudrapal and authors Samson performed a classification process on the hyperspectral data set. In order to better understand the data, clustering was first performed with K-Means, one of the unsupervised learning techniques. Then, the classification process was made with SVM. In the classification made on a total of 4 classes as soil, water, plant and human structures, the overall accuracy rate was found to be more than 90%. It has also been observed that SVM gives good results on a poorly trained hyperspectral data [10].

Kalkan and authors compared pixel-based and object-based classification methods using IKONOS imagery. ERDAS image software was used for pixel-based classification and e-Cognition software for object-based classification. They obtained an overall accuracy rate of 92.91% for pixel-based classifier and 98.39% for object-based classification [11].

Gürcan and authors made a land classification using Göktürk-2 satellite images. Comparing the Least Squares method and the Maximum likelihood algorithm, they obtained an average accuracy of 96.51% and 83.13%, respectively [12].

Ustüner and authors conducted a study on land cover / use classification of LANDSAT-8 satellite imagery. Within the scope of the study, SVM, random forests, KNN machine learning algorithms were used for classification process. As a result of the classification, SVM algorithm gave the highest accuracy rate (96.2%) [13][14].

III. DATASET AND MEHODS

A. Dataset

Rize province, where tea plants are grown extensively, was chosen as the study area. Studies have been carried out on 5 multi-spectral images, approximately 7164x9360 in size, obtained by remote image sensing systems. The images were taken using airborne UltraCam-X digital aerial camera with 30 cm ground sample distance (GSD). These data were obtained EMI Group Inc. The images shows that there are dense tea areas, other trees, uncultivated bare areas, roads and buildings (Fig. 1).

Fig. 1. A small portion of a sample image used in this work

B. *Train Dataset*

In order to classify in supervised learning, data must be trained first. For each class small patches were extracted consisting of a number of pixels. These patches were obtained from randomly selected two images by visual inspection. The areas were selected in such a way that they represent the respective classes without overlapping. The sample numbers of educated classes are given in Table 1.

TABLE 1. TRAINING DATASET SELECTION

No	***Classes***	***Training Samples***
1	Tea Area	26
2	Other Trees	18
3	Roads & Builds	16
4	Bare Land	17

C. *Classification*

From each image, a set of spectral and spatial features were obtained and then these feature vectors were fed into the classifier for classification. Instead of obtaining features based on each pixel, we first employed graph-based minimal spanning tree segmentation to transform to an object-based representation and then from each object features were derived. This not only reduced the number features but also obtained more discriminating features for each object. In this study, two most widely used classifiers were investigated: SVM and ANN. These classifiers have also used commonly for the classification of remotely sensed images.

SVM is a non-parametric supervised classifier. It does not require the distribution information of the data, but it needs the labels to train the data. SVMs have proven to be powerful algorithms as they can process high dimensional data with even limited number of trained data [2], [10]. SVMs are based on binary classification by creating a hyperplane at maximum distance between the members of two groups on the same plane. SVM can be applied to linear and nonlinear data. However, in data that are not separated linearly, the data is made linearly separable in a high dimensional area by using the kernel function. Polynomial kernel and Radial Basis function (RBF) are examples of kernel functions. In our study we employed RBF kernel for its efficiency and robustness and SVM tries to

$$W(\alpha)=\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j K(\mathbf{x}_i\cdot\mathbf{x}_j)$$
$$with\ 0\le\alpha_i\le C\ ;\ i=1..l \qquad (1)$$
$$and\ \sum_{i=1}^{l}\alpha_i y_i=0$$

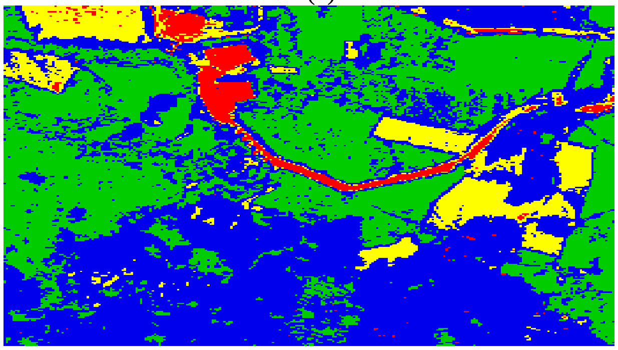
maximize the margin using following equation:
where alphas are Lagrange Multipliers, K (x, y) is kernel function and C is cost.

ANN is another non-parametric supervised classifier that is also widely used in classifying remotely sensed images. This model, inspired by the human brain and nervous system, can produce solutions to complex nonlinear classification problems. In this work, a three-layered feed-forward neural network model was used with input, hidden, output neurons. The input neuron has fixed number of neurons as matching the input vector while the output layer has just 4 neurons representing each class. The number of neurons can be varied and in our case 200 neurons with single layer produced optimal results. Moreover, sigmoidal activation function was used for the neurons in the network.

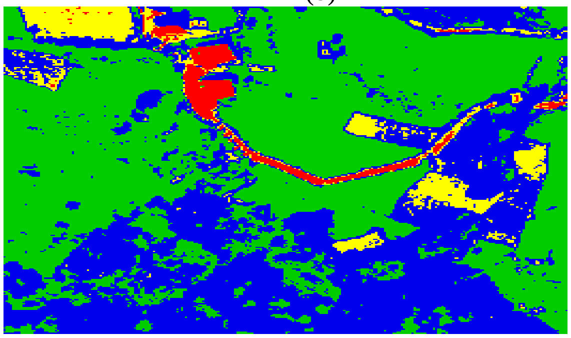
IV. EXPERIMENTAL RESULTS

To make land cover classification from multi-spectral images, we first prepared training examples for each class. Since the classification accuracy is based on training examples, we made our choices in clear spectral regions that are not complex. The number of samples we selected for each class are summarized in Table 1. The reason for the small number of samples is to answer the question of what classification accuracy can be achieved with little training data.

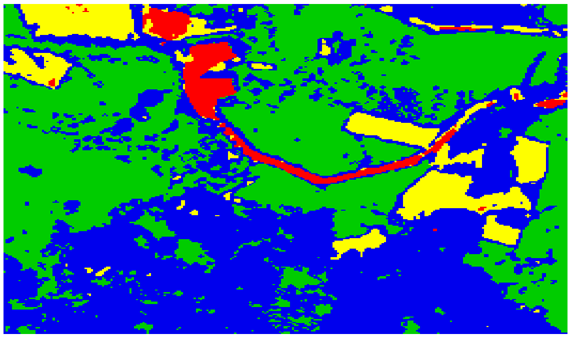
(a)



(b)



(c)



(d)

Fig. 2. (a) Unclassified Image, (b) SVM Classification Result, (c) ANN Classification result, (d) Majority analysis map applied after the classification process.

A K-fold cross validation was applied for validation of the model. The dataset was partitioned into K sub-data sets. During training process, a single sub-data is used for validation while rest of the data is used for training. This process is repeated K times and errors were calculated for each iteration. Finally, the total errors are estimated for validation by averaging all the errors in overall all repetition. This way the model is trained using all the training examples.

The supervised classifiers generally require tuning of some parameter values. For SVM two parameters were obtained by empirical method: cost and gamma. The gamma kernel function value was set to 0.333 while cost was set to 250. Similarly, for ANN the learning rate was set at 0.2, momentum at 0.9 and number of neurons at the hidden layer were set to 200 while keeping other parameters constant.

After the models were trained, the final test images were presented for producing the final land cover maps. The results obtained for each classifier were post-processed to improve the accuracy of the classification. These techniques include morphological opening and closing to remove small holes within objects and to create a smooth boundary between different classes. Moreover, the obtained binary maps were passed through a majority analysis step to further improve the classification accuracy. The main objective of majority analysis is to assign a pixel to the dominating class in the neighborhood. The classification map generated obtained after the majority analysis is shown in Figure 2 (d).

Table II summarizes the results obtained for SVM and ANN classifiers. The average accuracy for SVM and ANN was 73.66% and 85.10% respectively. The overall results indicate that ANN was more effective for land cover classification compared to the SVM classifier. Similarly, for each class, the accuracy obtained for ANN was better than SVM. The results obtained for tea areas and other trees remained low for the SVM classifier. This can be ascribed to the spectral similarity between these two classes as both has similar vegetation index, but their texture was different which was not captured by SVM in some cases. The application of majority analysis produced highly satisfactory results which produced 88.18% average accuracy for all classes. Moreover, the accuracy for each class was also higher thank both SVM and ANN classifiers. These results indicate that majority analysis as a postprocessing step is useful for obtained higher classification accuracy for land cover classification.

Table 2. THE CLASSIFICATION ACCURACY (%) OF THE CLASSIFIERS

Classes	**Used Classifiers**		
	SVM	***ANN***	***Majority Analysis***
Tea Area	68.43	82.08	88.63
Other Trees	69.67	80.04	83.46
Roads and Buildings	71.06	79.25	82.38
Bare Land	85.51	89.01	90.25
Average	**73.66**	**82.60**	**86.18**

V. CONCLUSION

In this study, the problem of land cover classification from remotely sensed multi-spectral images is investigated. The spectral and spatial features were combined and used two commonly used supervised classifiers (SVM and ANN) for classification. Four classes of interest were defined (tea areas, other trees, road and build areas and bare land). Moreover, we selected relatively a smaller number of training samples compared to the test samples to fit the natural settings of the environment. The experimental results showed that ANN was more effective than SVM in terms of accuracy for each class. Moreover, the postprocessing using majority analysis increased the overall accuracy of the classification.

No doubt, the proposed method has certain limitations such as there were misclassifications between tea and other types of trees due to spectral similarity. As a future study, we will focus on applying automatic features extraction using deep learning-based approach, such as convolutional neural networks (CNNs). This approach will help obtained highly discriminative features that will ultimately help increase the classification accuracy. Moreover, as deep learning requires larger training data, therefore, we will prepare more training samples with labels for each class.

VI. ACKNOWLEDGMENT

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