Land Use/ Cover Indices Classification of Satellite Images using Multiclass-SVM

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ABSTRACT

Land use and land cover information has become a vital component in current strategies for managing natural resources and monitoring environmental changes. For detection and classification of land cover, remote sensing has long been used as an excellent source of data for finding different types of data attribute present in the land cover. This paper presents land cover indices classification of satellite images using Multiclass-SVM classification algorithm. In this paper, four land cover indices: (1) building index, (2) water index, (3) vegetation index and (4) road index are classified. Then, confusion matrix is used to determine the accuracy of classifier for four different land cover indices.

Keyword: *land cover indices classification, Multiclass-SVM, Satellite Images*

1. INTRODUCTION

Remotely sensed data is among the significant data types used in classifying land cover and land-use distribution. Most of the applications and researches are in need of information and data on the types and distribution of land cover. Many researchers conducted studies on the use of land cover in especially urban areas and on obtaining information regarding land cover that would further lead to both qualitative and quantitative analysis of the findings[1].

The physical material on the surface of the earth such as water, vegetation building can be regarded as land cover. Therefore, for describing the data on the Earth surface, land cover is a fundamental parameter. When land cover area is utilized by people whether for development, conservation or mixed uses, it can be defined as land use. Accurate information of land cover is required for both scientific research (e.g. climate change modeling, flood prediction) and management (e.g. city planning, disaster mitigation). Satellite images consist of various images of the same object taken at different wavelengths in the visible, infrared or thermal range. Such images have been used for urban land cover classification [2] [3], urban planning [4], soil test, and to study forest dynamics [5].

In this paper, four land cover indices: building, road/land, vegetation/forest and water are classified from Google earth images using Multiclass-SVM. Before classification, the features of land cover indices are extracted and tranined using deep learning with AlexNet.

2. RELATED WORKS

In the past few years, there have been significant advances in remote sensing and high-resolution image processing, and a variety of Land Use and Land Cover (LULC) clas-sification algorithms have been developed in the recent past. For land cover classifica-tion, various machine learning algorithms have been used. As an advanced machine learning approach, deep learning has been successfully applied in the field of image recognition and classification in recent years [6–10]. By mimicking the hierarchical structure of the human brain, deep learning approaches, such as Deep Belief Networks (DBN), can exploit complex spatiotemporal statistical patterns implied in the studied data [11, 12]. For remotely sensed data, deep learning approaches can automatically extract more abstract, invariant features, thereby facilitating land cover mapping. In [13], Deep Belief Networks is applied for urban land cover classification using polari- metric synthetic aperture radar (PolSAR) data. Support vector machine (SVM), con-ventional neural networks (NN), and stochastic Expectation-Maximization (SEM) are then used to compare the results of DBN based classification approach. According to the experimental results, the DBN-based method outperforms three other approaches.

Two recently different deep learning architectures, CaffeNet and GoogLeNet are ap-plied in [14] for land use classification in remote sensing images with two standard datasets. The well-known UC Merced Land Use dataset and Brazilian Coffee Scenes dataset with markedly different characteristics are used to classify land cover with deep learning. Besides conventional training from scratch, pre-trained networks that are only fine-tuned on the target data are used to avoid overfitting problems and reduce design time. Romero et al., [15] very recently proposed an unsupervised deep feature extraction for remote sensing image classification. The authors suggested the use of greedy layer-wise unsupervised pre-training coupled with an algorithm for unsupervised learn-ing of sparse features. The proposed algorithm is tested on classification of aerial scenes, as well as land-use classification in very high resolution (VHR), or land-cover classification from multi- and hyper-spectral images.

The two combining techniques with DCNN: transfer learning (TL) with fine-tuning and data augmentation are employed in [16] for land cover classification of high-reso-lution imagery of UC Merced dataset. The CaffeNet, GoogLeNet, and ResNet archi-tectures are used with these techniques to classify the well-known UC Merced data set to achieve the land–cover classification accuracies of 97.8 ± 2.3%, 97.6 ± 2.6%, and 98.5 ± 1.4%.

3. STUDY AREA

The study area considered is Ayeyarwaddy Delta, Myanmar. It lies between north latitude 15° 40' and 18° 30' approximately and between cast longitude 94° 15' and 96° 15'. It covers about an area of 35,140 square kilometers. It is the main rice produced area in the country. It is a typical urban landscape of Myanmar. Cyclone Nargis was the worst natural disaster in the history of Myanmar. The cyclone affected area of the Ayeyarwady Delta covers some 23,500 km^2.

The disaster caused widespread destruction to homes and critical infrastructure, including roads, jetties, water and sanitation systems, fuel supplies and electricity. A large number of water supplies were contaminated and food stocks damaged or destroyed. The winds tore down trees and power lines, while the accompanying storm surge submerged countless villages. For this reason, it is needed to know land cover changes before and after Nargis Cyclone for regional planning, policy planning and understanding the impacts of disaster. The sample of input satellite images of Ayeyarwaddy Delta is shown in Fig-1.

Since the one scene of input contains multiple class of land cover, it is needed to consider the classification of multi-label classification framework.

Fig- 1. Sample images of Ayeyarwaddy Delta dataset

4. PROPOSED SYSTEM

For land cover classification with multiclass-SVM, the input satellite images are seg-mented into 25x25 pixel block for multi-label classification. Then, the features are ex-tracted from the segmented images using DCNN. After DCNN is used to extract fea-tures, then these features are trained and classified using Multiclass-SVM. The flow diagram of this approach is shown in Fig-2.

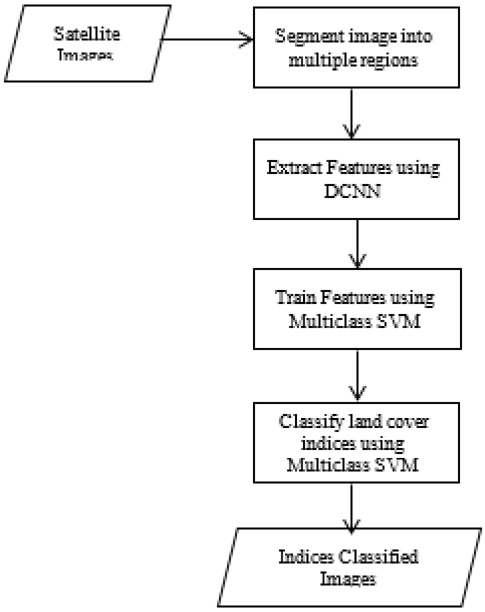


Fig-2. Flow Diagram of multi-label land cover classification using Multi-class SVM as classifier

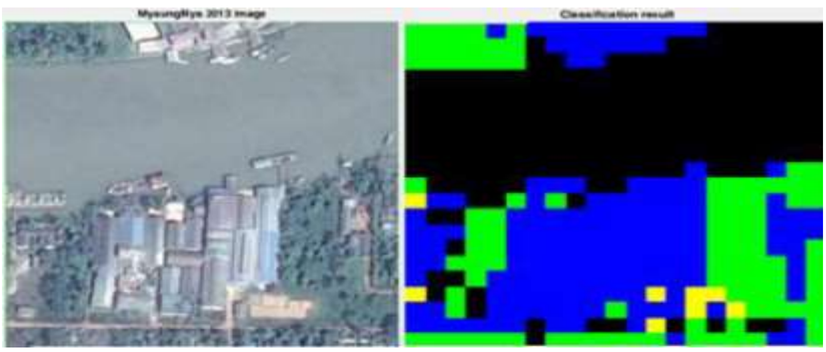
5. EXPERIMENTAL RESULTS

The number of images used for both training and testing stage in this experiment is shown in Table 1.

Table -1: Number of images used for experiment

Index	Total number of images
Building	582
Road	792
Vegetation	1923
Water	542

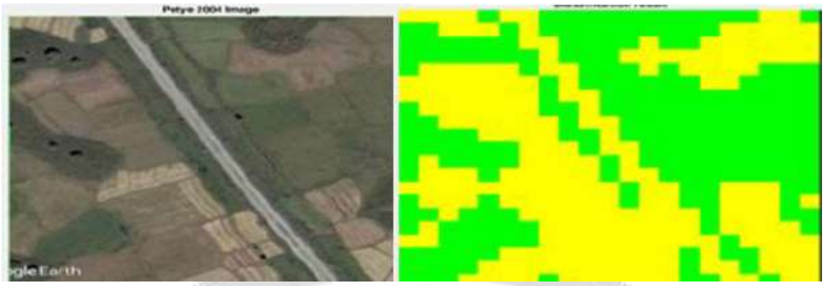
The results of land use/cover classification for MyaungMya Region and Petye Region of Ayeyarwaddy Delta using DCNN and Multiclass-SVM is shown Fig- 3 and 4.



(a) Original Image **(b) Classified Image**

Fig-3. Classification Results of MyaungMya Region

From the multi-label land cover classification image, the blue color is used to indicate the building index; yellow color is used for road/land index, green color for vegetation/forest index and black color for water index.



(a) Original Image **(b) Classified Image**

Fig-4. Classification Results of Petye Region

The classification results performance is calculated using confusion matrices for four land cover indices. The confusion matrix using Multiclass-SVM as classifier is shown in Table 2.

Table -2: Confusion Matrix using Multiclass-SVM as classifier

	Building	Road	Vegetation	Water
Building	0.79	0.02	0.14	0.05
Road	0.06	0.73	0.20	0.01
Vegetation	0.03	0.02	0.94	0.01
Water	0.01	0	0	0.98

By using Multiclass-SVM as classifier, 78.9% of building index, 72.7% road index, 94.2% of vegetation index and 98.1% of water index can be correctly classified.

6. CONCLUSIONS

This proposed system presents a technique for the multi-label land use and land cover classification for Ayeyarwaddy Delta using Google Earth satellite images. From the experimental results, it can be seen that AlexNet architecture can be used for multi-label land cover classification. In this paper, Multiclass-SVM classifier is used for classification of land use/cover. The land cover classification information of this proposed system can be used to calculate land cover change detection for Ayeyarwaddy Delta before and after Nargis Cyclone as its future work.

7. REFERENCES

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