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LAND USE/COVER CHANGE DETECTION ANALYSIS USING DEEP LEARNING

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Abstract

In recent years, Deep Convolutional Neural Network (DCNN) has been used increasingly in image change detection works but there is a need to investigate its potential. This study aims to propose a technique for multi-labeled land use/ cover change detection using Google Earth Satellite images with deep convolutional neural network (DCNN). Temporal differencing method is used for calculation of land cover change area. Then the results of land cover classification are analyzed using confusion matrices. According to the tested results, 90.7% of building index, 82.9% road index, 87% of vegetation index and 90% of water index can be correctly classified using DCNN.

Keyword: Deep Convolutional Neural Network, Google Earth Satellite Images, Multi-labeled land use/ cover change detection, Temporal differencing, Confusion Matrices

1.INTRODUCTION

The physical material on the surface of the earth such as water, vegetation and building can be regarded as land cover (LC). Therefore, for describing the data and information on the Earth surface, land cover is regarded as a fundamental parameter. Land use(LU) can be defined as the usage of land cover areas for various purposes such as urbanization, conservation or farming. In modern world, Land use and Land cover (LULC) has been rapidly changing because human started managing their environment. Changes in LULC dates to prehistory, and are the direct and indirect consequence of human actions to secure essential resources for their being [1]. LULC therefore constitutes a key variable of the earth's system that has in general shown a close correlation with human activities and the physical environment [2]. Rapidly increasing human populations and expanding agricultural activities have brought about extensive land use changes throughout the world [3]. Therefore, the exact land use and land cover information has been applied in urban planning, flood prediction and disaster management.

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 [4]. Land cover change detection is the process of determining the changes associated with land use and land cover properties of geographical multi temporal remote sensing data. Remote sensing (RS) datasets provide significant information documenting the land-use and land-cover processes [5]. RS datasets provide coverages from regional to global scales [6]. Interpretation of RS datasets is a major way to understand the status and changes in both the natural and built environments. In recent decades, RS sensors and techniques have become increasingly sophisticated. They can provide a large volume of datasets with high quality and fine spatial resolution.

Due to easier access to data with higher volume and better quality as well as the development of advanced graphics processing units (GPU), deep learning (DL) has been widely promoted in many recent scientific literatures. DL consists of a collection of algorithms as the subset of machine learning (ML), specializing in learning hierarchy of concepts from very big data. DL methods have achieved incredible accuracy especially in classification tasks in areas such as speech recognition, computer vision, video analysis, and natural language processing [7,8]. In this study, four land cover indices: building, road/land, vegetation/forest and water are classified from Google earth images using deep convolutional neural network with AlexNet framework.

2.FRAMEWORK FOR LAND USE/COVER CHANGE ANALYSIS

The framework of proposed land use/cover change detection system is illustrated in figure 1. Firstly, the two-year satellite images are collected into the system. Then, these images are segmented into multiple regions with region overlapping algorithm. After then, these images are classified using Deep Convolution Neural Network(DCNN) with AlexNet framework. Finally, change detection process is applied by using temporal differencing and changed result and change map is displayed.

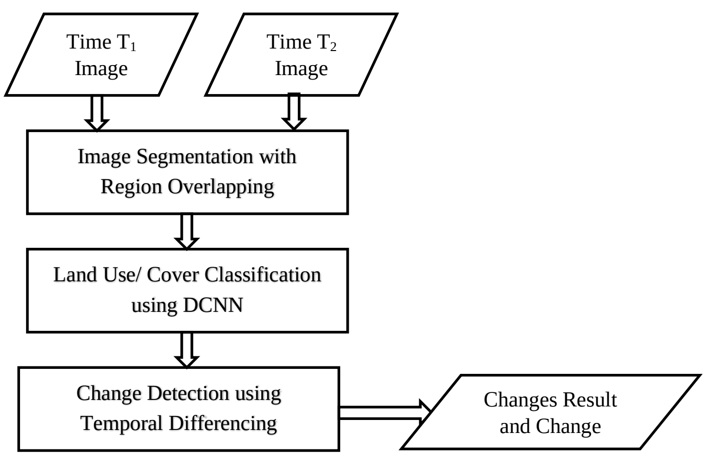

Figure 1: Framework of the proposed system

3.SYSTEM METHODOLOGY

In this section, the methodology applied in this study are explained detail.

3.1. Image Segmentation

For multi-label classification with DCNN, the images from the dataset are segmented into multiple regions. Since, the size of input satellite images used in this proposed system are 525x525 resolution, the images are segmented into 25x25 equal size block with region overlapping. Image Segmentation with region overlapping is shown in Figure 2. into the system. Then, these images are segmented into multiple regions with region overlapping algorithm. After then, these images are classified using Deep Convolution Neural Network(DCNN) with AlexNet framework. Finally, change detection process is applied by using temporal differencing and changed result and change map is displayed.

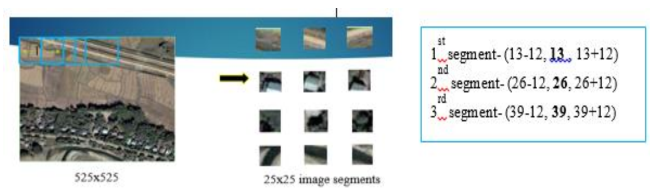

Figure 2: Image Segmentation with Region Overlapping

3.2. Index Classification

In this system, deep learning with AlexNet framework is used to classify four land cover classes: building index, water index, vegetation/forest index and road/land index. AlexNet is a CNN trained on more than a million images. AlexNet is most commonly used for image classification. It can classify images into 1000 different categories, including keyboards, computer mice, pencils, and other office equipment, as well as various breeds of dogs, cats, horses, and other animals. To use AlexNet for objects not trained in the original network, we can retrain it through transfer learning. The steps of land cover classification using AlexNet are as follows:

1. Load pre-trained AlexNet
2. Divide data into training and testing sets (80% randomize)
3. Extract training features using CNN
4. Extract features from deep layers using activations method
5. Train features using fast Stochastic Gradient Descent solver
6. Extract test features using the CNN

7. Pass CNN image features to trained classifier
8. Make a prediction using the classifier

3.3. Change Detection

After index classification, the changes between each index from the first image and second image are calculated. For changes calculation, temporal differencing algorithm is used for changes between the "T" image and "T+n" image. In this system, three index of change detection: RM for Remained Index, GR for Growth Index and DT for Death Index are calculated for two different image of the same region of Ayeyarwaddy Delta. Remained Index(RM) is set to 1 if land cover index (for example Building Index(Bidx)) existed in first image and also existed in second image. If the Building Index did not exist in first image and existed in second image, then it is regarded as Growth Index(GR). Death index(DT) is set to 1 if the building index existed in first image and did not exist in second image. The calculation of each index can be formulated in the following equations.

$$RM_{(i,j)}^{Bidx} = \begin{cases} RM_{(i,j)}^{Bidx} = 1, \ if \ Bidx_{(i,j)}^{T} = 1 \ \& \ Bidx_{(i,j)}^{T+n} = 1 \\ RM_{(i,j)}^{Bidx} = 0, \quad else \end{cases} \quad (1)$$

$$GR_{(i,j)}^{Bidx} = \begin{cases} GR_{(i,j)}^{Bidx} = 1, \ if \ Bidx_{(i,j)}^{T} = 0 \ \& \ Bidx_{(i,j)}^{T+n} = 1 \\ GR_{(i,j)}^{Bidx} = 0, \quad else \end{cases} \quad (2)$$

$$DT_{(i,j)}^{Bidx} = \begin{cases} DT_{(i,j)}^{Bidx} = 1, \ if \ Bidx_{(i,j)}^{T} = 1 \ \& \ Bidx_{(i,j)}^{T+n} = 0 \\ DT_{(i,j)}^{Bidx} = 0, \quad else \end{cases} \quad (3)$$

After three change detection index are calculated for each image, the change detection for the whole region is calculated as follow:

$$AreaRM = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} RM_{(i,j)}^{Bidx}}{M \times N} \quad (4)$$

$$AreaDT = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} DT_{(i,j)}^{Bidx}}{M \times N} \quad (5)$$

$$AreaGR = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} GR_{(i,j)}^{Bidx}}{M \times N} \quad (6)$$

4.DATA ANALYSIS AND EXPERIMENTAL RESULTS

The experiments are conducted on Google Earth satellite images of Talakwa District, Ayeyarwaddy Delta, Myanmar. The number of images used for the experiment is shown in Table 1.

Index	Total no: of images (training)	Total no: of images (testing)
Building	2309	948
Road	3108	1332
Vegetation	3143	1536
Water	3582	1098

Table 1. Number of images used for this experiment

Figure 3(a) and (b) show original satellite input image and classified images of 2013, 2015 and 2017. 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.

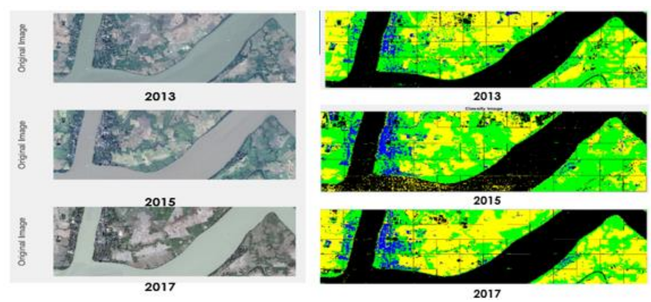

Figure 3: (a) Original Images and (b) Classified Images

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

	Building	Road	Vegetation	Water
Building	0.9070	0.0263	0.0637	0.0030
Road	0.0435	0.8288	0.1239	0.0038
Vegetation	0.0345	0.0905	0.8704	0.0046
Water	0.0209	0.0200	0.0510	0.9081

Table 2. Confusion Matrix of land cover indices

By using DCNN as classifier, 90.7% of building index, 82.9% road index, 87% of vegetation index and 90% of water index can be correctly classified. The overall accuracy of the classifier is 88.15. The statistical data and changed map of four land cover index of Talakwa region is shown in Figure 4 (a), (b), (c) and (d) respectively. From the changed map, Growth Index is indicated with blue color, Death index is indicated with red color and Remained Index with green color.

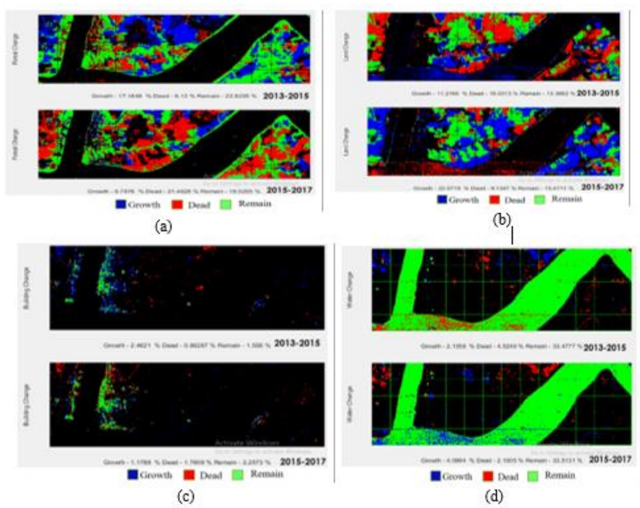

Figure 4. (a) Forest/Vegetation Changed Map (b) Road/Land Changed Map
(c) Building Changed Map (d) Water Changed Map

5.CONCLUSION

The contribution of this paper is to present a technique for the multi-label land use and land cover classification using Deep Convolutional Neural Network with AlexNet architecture. Google Earth satellite images. The effectiveness of the proposed method has been validated on Google earth images of Ayeyarwaddy Delta, Myanmar with various land cover changes because of Nargis Cyclone in May,2009. This land cover changes information aims to form valuable resources for urban planner and decision makers to decide the amount of land cover changes after the disaster and the impact of disaster.

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