ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940
www.ijsem.org
Vol 18, Issuse.1 March 2024

ANALYSIS OF SATELLITE IMAGES FOR DISASTER DETECTION USING CNN

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ABSTRACT

Analysis of satellite images plays an increasingly vital role in environment and climate monitoring, especially in detecting and managing natural disaster. In this paper, we proposed an automatic disaster detection system by implementing one of the advance deep learning techniques, convolutional neural network (CNN), to analysis satellite images. The neural network consists of 3 convolutional layers, followed by max-pooling layers after each convolutional layer, and 2 fully connected layers. We created our own disaster detection training data patches, which is currently focusing on 2 main disasters in Japan and Thailand: landslide and flood. Each disaster's training data set consists of 30000~40000 patches and all patches are trained automatically in CNN to extract region where disaster occurred instantaneously. The results reveal accuracy of 80%~90% for both disaster detection. The results presented here may facilitate improvements in detecting natural disaster efficiently by establishing automatic disaster detection system.

Index Terms— convolutional neural network, disaster detection, difference extraction, satellite images

1. INTRODUCTION

In the recent decades, disaster detection has been one of the major interesting research subjects due to the great loss of human lives after disaster occurred. Researchers have studied the effect of changes occurred due to disaster using sensors [1] and simple image processing techniques [2]. Previous research findings show that disaster detection systems have a few major problems, which includes observing occurrence of disaster in limited range. This is due to limited amount of disaster detection sensor and gets information through verbal hence has low accuracy. Furthermore, operators also face difficulty in disaster detection due to massive amount of satellite images to be observed in short period of time. Hence, this may lead to misjudgment or overlook of occurrence of disaster. In general, as observed from prior studies, it is difficult to obtain performance enhancement on disaster detection and management immediately. Therefore, motivation for this paper is to establish automatic disaster detection system by observing occurrence of disaster in a wider range through satellite images and observing every single disaster assisted by deep learning techniques.

2. METHODOLOGY

To demonstrate the potential of this approach and its suitability for this application, CNN is implemented as major techniques to detect occurrence of disaster. Aerial images (pre-disaster and post-disaster images) with same spatial information but different time series information regarded to landslide and flood are taken directly from Google Earth as input images. Disaster detection system proposed by our system consists of 2 phases: train phase and test phase.

2.1. Train Phase

This phase focus on learning all possible pattern of disasters especially landslide and flood using CNN as a database needed for disaster detection in the test phase.
First, we create training patches (Fig. 1) by trimming pre-disaster, post-disaster, and ground truth images of each scene into 32x32 pixels sized patches. Training patches of pre- disaster and post-disaster from same position are combined. Then, each combined training patches are compared with ground truth patches. Next, we label the training patches as
0 or 1. 0 means change occurred or disaster occurred. Meanwhile, 1 refers to no change occurred, or disaster do not occur. When change rate (white color region in the ground truth) is less than or equal to 10%, it is labeled as 0. On the other hand, when change rate (white color region in the ground truth) is more than 10%, it is labeled as 1. All training patched and labels, which are saved in text file, are trained by CNN to get disaster features.

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www.ijsem.org
Vol 18, Issuse.1 March 2024

2.2. Test Phase

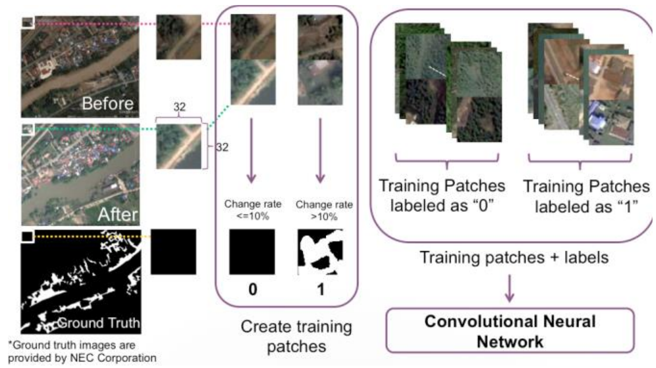

Fig. 1: Train phase of disaster detection system

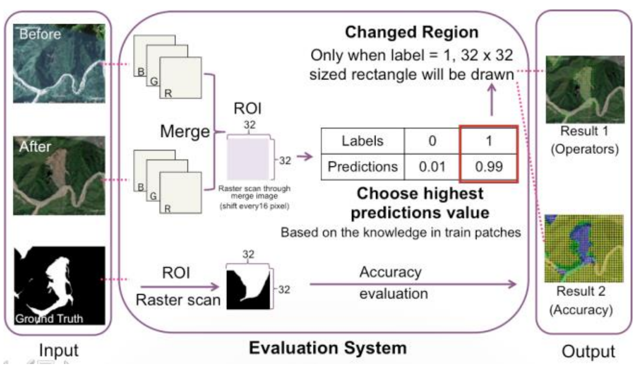

Fig. 2: Test phase of disaster detection system

Test phase (Fig. 2) is important for evaluation by extracting disaster region and preparing disaster detection result for operator usage.
First, RGB channels of pre-disaster and post-disaster (6 channels) are merged into 1 image. Then, raster scan is conducted to this image by sliding over 16 pixels to obtain best predictions value of disaster occurrence. Based on the knowledge obtained in train phase, the highest predictions value with label 1 only will be extracted and 32x32 pixel sized rectangle will be drawn. The drawn region refers to disaster region (refer to Result 1 in Fig. 2).
In order to evaluate the accuracy of disaster region, output in Result 1 is compared with ground truth images by undergoing raster scan on a region of interest of 32x32 pixel. Accuracy is calculated based on precision, recall and f-measure. This result is shown in Result 2 in Fig. 2.

3. CONVOLUTIONAL NEURAL NETWORK

In recent years, CNN have much attention in computer vision area. CNN can be trained as robust feature extractors from raw pixel values and at the same time, learn classifiers for object recognition tasks [3], regressors for human pose estimation tasks [4], or mappings for semantic segmentation task[5]. The characteristic of CNN is alternatively stacked convolutional layers and spatial polling layers often followed by one or more fully connected layers as in multi-layer perceptron. Fig.3 shows the base architecture of our CNN. A convolutional layer has a number of filters and convolves them on an input image for extracting features. A pooling layer applies subsampling to the output of the next lower layer for achieving translational invariance.

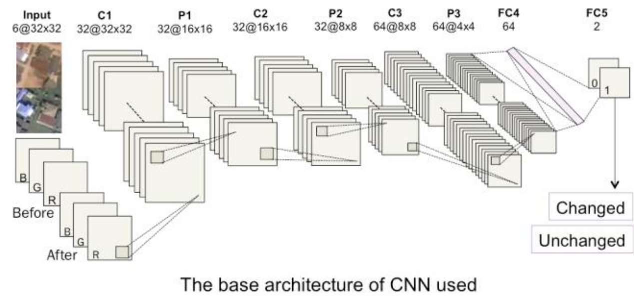

Fig. 3: Base architecture of CNN used.

4. RESULTS

Experimental setup for this paper is shown as below:

Landslide experiment.

- 18 train data sets (2200 patches/set)
- 17 test data sets (2200 patches/set)
- Data sets: All over Japan (34 prefectures)

Flood experiment

- 9 train data sets (2200 patches/set)
- 13 test data sets (2200 patches/set)
- Data sets: Chao Phraya River, Thailand

For each set of data, we have 5 aerial images which includes the input and output images:

1. Pre-disaster aerial image (Google Earth)
2. Post-disaster aerial image (Google Earth)
3. Ground truth for disaster detection (provided by NEC corporation)
4. Accuracy of disaster detection output
5. Disaster detection output for operator usage

Refer to the output image of accuracy in Fig. 4 and Fig. 5, we have 4 colors shown in the output.

1. TP (Dark blue): True Positive
2. TN (Yellow): True Negative
3. FP (Red): False Positive
4. FN (Green): False Negative

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Each color represents the parameters used to calculate the accuracy (precision, recall and f-measure) of disaster detection when compare with ground truth.

P: Precision

$$precision = \frac{TP}{FP + TP}$$

R: Recall

$$recall = \frac{TP}{FN + TP}$$

F: F-measure

$$F - measure = 2 \times \frac{precision \times recall}{precision + recall}$$

4.1. Landslide

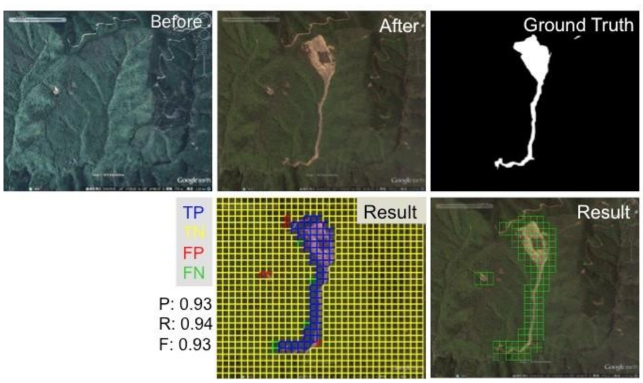

Fig. 4: Result of landslide

4.2. Flood

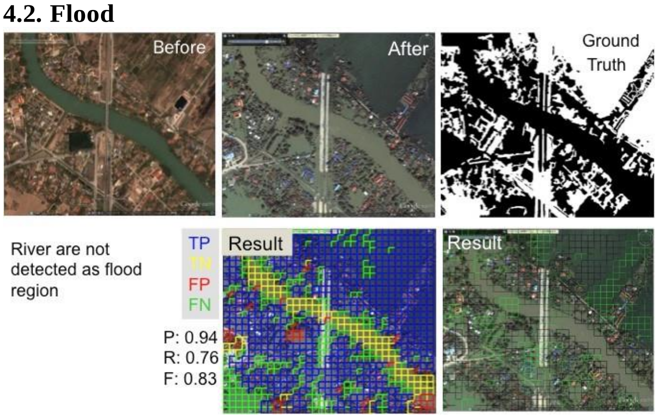

Fig. 5: Result of flood

4.3. Comparison with Previous Method

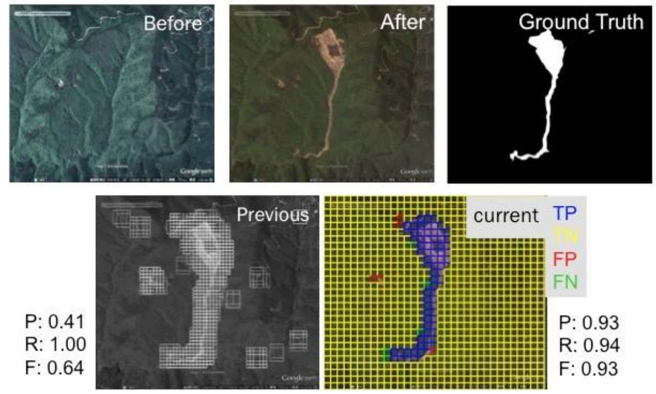

Fig. 6: Comparison with previous method

5. DISSCUSIONS AND CONCLUSION

Analysis of satellite images for disaster detection with the implementation of CNN in automatic difference extraction for disaster region is proposed. According to the result in Fig. 4 and Fig. 5 (a part of our results for landslide and flood), f-measure of disaster detection for landslide and flood is around 80%~90%. Our proposed method can extract disaster region automatically with high accuracy. Furthermore, our proposed method shows great improvement in precision, recall and f-measure. This is because, our proposed method merged RGB channels for pre-disaster and post-disaster, which is 6 channels in total to extract disaster region via CNN without losing any color information. Meanwhile, previous method only uses 2 channels, which is gray-scale pre-disaster in 1 channel (R or G or B channel) and gray-scale post-disaster in another 1 channel (R or G or B channel), to extract disaster region by simple subtraction method. Hence, extracting disaster region without losing original color information for both pre-disaster and post-disaster is a novel method and shows better result when compare to previous method.

Besides, the input datasets (pre-disaster aerial image, post-disaster aerial image and ground truth for disaster detection) used in our research has been undergone alignment before training process. This is to ensure no misdetection occurred due to misalignment even though alignment of satellite images is a challenging task.

Furthermore, our datasets have similar color variation, mostly taken on sunny day. Combination of different color variation (sunny day, rainy day, snow etc.) will be a challenging task. Hence, pre-processing of the images before undergone training will be needed to increase the variation (able to detect precisely and robust to all kind of weather) and reliability of our disaster detection system.

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ISSN2454-9940
www.ijsem.org
Vol 18, Issuse.1 March 2024

Finally, type of image pattern and amount of train patches affect the accuracy of results. Various pattern and massive amount of train patches give better result.
As a conclusion, the results presented here may facilitate improvements in detecting natural disaster efficiently by establishing automatic disaster detection system.

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