Territory-wide Identification of Geological Features on Aerial Photographs Using Machine Learning for Slope Safety Management

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Abstract. In Hong Kong, the natural terrain is susceptible to rain induced landslides. These landslides are usually of small-to-medium scale, involving the failure of soil within the top one to two meters of the surface mantle. A comprehensive historical landslide database and distribution of geological features are crucial for understanding the landslide susceptibility of natural terrain. The location of natural terrain landslides and other geological features are currently identified from aerial photograph interpretation (API) by experienced engineering geologists. With about 10,000 aerial photographs taken annually, there are strong initiatives to apply machine learning to facilitate the identification process. A method combining machine learning technology and image analysis methodology was developed to help automatically and objectively acquire the location and geometric information of landslides. The model was trained using geo-referenced aerial photographs together with manually mapped landslide boundaries within pilot study areas in Hong Kong. The trained model was then applied to extract landslide data from aerial photographs taken at other areas and time with promising results. Similar machine learning techniques can also be utilized to identify geological features, such as rock outcrops, from remote sensing imageries. Indeed, a territory-wide rock outcrop map for the natural terrain of Hong Kong has been produced using such approaches. The above applications can provide useful data on landslide susceptibility and facilitate the identification of vulnerable catchments for natural terrain hazard studies. This paper introduces the workflows and the architecture design of the neural networks applied. The extraction results, the applications of the techniques and the way forward are discussed.

Keywords: Machine Learning, Natural Terrain Landslides, Rock Outcrop, Landslide Susceptibility, Aerial Photographs.

1 Introduction

Natural terrain covers over 60% of the land area of Hong Kong. With high annual rainfall (about 2300 mm) and close proximity of developments to natural terrain, Hong Kong is under constant threat from landslides. Slope safety management has been of high importance to secure the lives and properties of citizens. A comprehensive historical landslide database and distribution of geological features are crucial for understanding the landslide susceptibility of natural terrain. With the advancement in artificial intelligence (AI) and computing powers, the Geotechnical Engineering Office (GEO) of the Government of the Hong Kong Special Administrative Region has initiated two pilot studies to explore the applications of AI in slope safety management:

(a) a pilot study on automatic identification of rock outcrops on natural hillsides throughout Hong Kong; and

(b) a study to explore and develop the use of machine learning for systematic identification of recent natural terrain landslides from digital aerial photography.

The studies are carried out in collaboration with the Department of Land Surveying and Geo-informatics of the Hong Kong Polytechnic University. This paper presents the background, workflow and some findings of the studies so far.

2 Pilot Study 1: Automatic Identification of Rock Outcrops on Natural Hillsides

2.1 Objective of the Study

This pilot study explores the potential of using deep learning to analyse remote sensing data to identify rock exposure on the natural terrain throughout the entire territory of Hong Kong in an efficient manner. It serves as the first attempt to use computer vision in engineering geological mapping in Hong Kong and yielded results that will be useful in enhancing the landslide susceptibility analysis for natural terrain in Hong Kong.

2.2 Methodology

The main source of data is ortho-rectified aerial photographs obtained from Lands Department. Other supplementary data such as multispectral satellite imageries, airborne light detection and ranging (LiDAR) survey results, the Enhanced Natural Terrain Landslide Inventory (ENTLI) (MFJV, 2007) and the extent of urban area published by Planning Department in 2016 were used to further enhance the results, as appropriate.

The convolutional neural network (CNN) technique of AI has been adopted for the task. The CNN is a type of deep learning algorithm (which is a technique for multi-layer artificial neural network that are designed for highly non-linear problems) commonly adopted for image recognition purposes. It has also been applied for land use classification and land cover mapping using satellite imageries.

This study adopted a pre-trained CNN architecture VGGNet (Simonyan & Zisserman, 2014) with 16 layers of neurons. The first 13 convolutional layers were pre-trained with images from ImageNet in order to maintain the generalization ability of the network. For the purpose of this study, an additional 12,000 sample images were extracted from the ortho-rectified aerial photographs of Hong Kong and classified into five different types, viz. rock outcrops, grassland, woodland, badland and urban area. These 12,000 images were used to train the last three fully-connected layers and fine-tune the network for building the applicability to the Hong Kong conditions (Wong, 2018) (Fig. 1). Among the sample images, 90% were used to train the model whilst the remaining 10% were reserved for testing. After training, the model was applied to the ortho-rectified aerial photographs of the entire Hong Kong territory for identifying rock outcrops. The workflow of the process is given in Fig. 2.

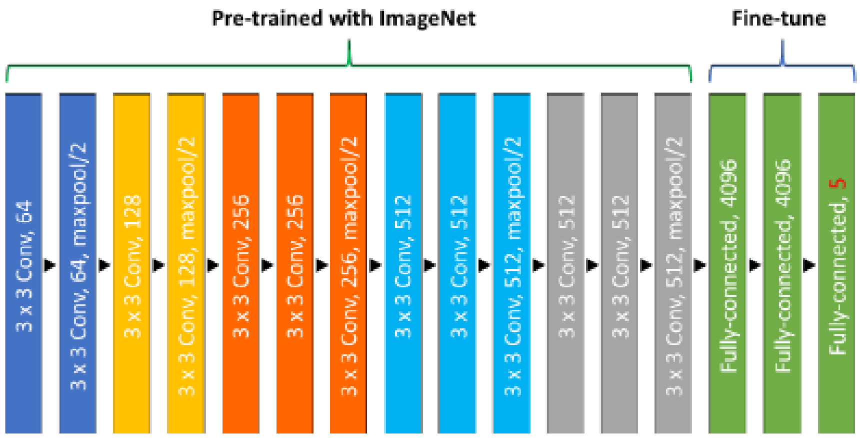


Fig. 1. The architecture design of the VGG-16 network used.

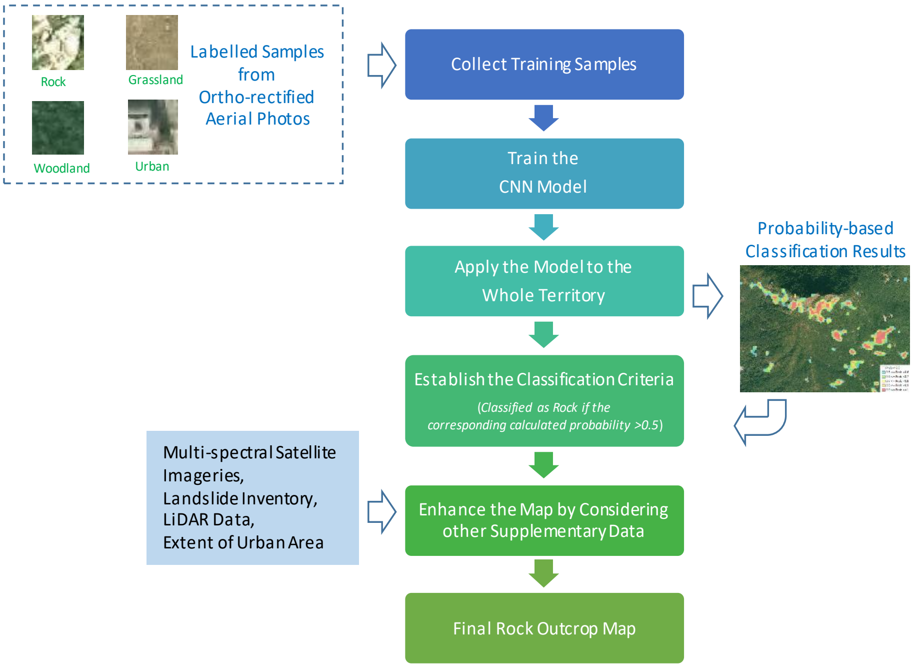


Fig. 2. Workflow of identification of rock outcrops by deep learning.

2.3 Results and Validation

The model produced a territory-wide rock outcrop map with a resolution of 5 m. An extract of the rock outcrop map produced by the model is shown in Fig. 3. In order to validate the rock outcrop identified using the model, the results were compared against the extent of rock outcrops identified by engineering geologists based on the same set of aerial photographs in three selected study areas, namely Mount High West, Tin Wan and Castle Peak. The samples were not collected from these study areas for training and testing of the CNN model. The method and the results of accuracy assessment are illustrated in Fig. 4. The resulting precision rates and recall rates are over 70%.

The pilot study produced a territory-wide rock outcrop map using deep learning technique for processing ortho-rectified aerial photographs with a reasonably high accuracy. The map can be used to further enhance the resolution of the landslide susceptibility analysis. The results of the study demonstrated the potential of a wider application of AI for automatic identification of other geological features on the natural terrain in Hong Kong, such as landslides, in remote sensing imageries.

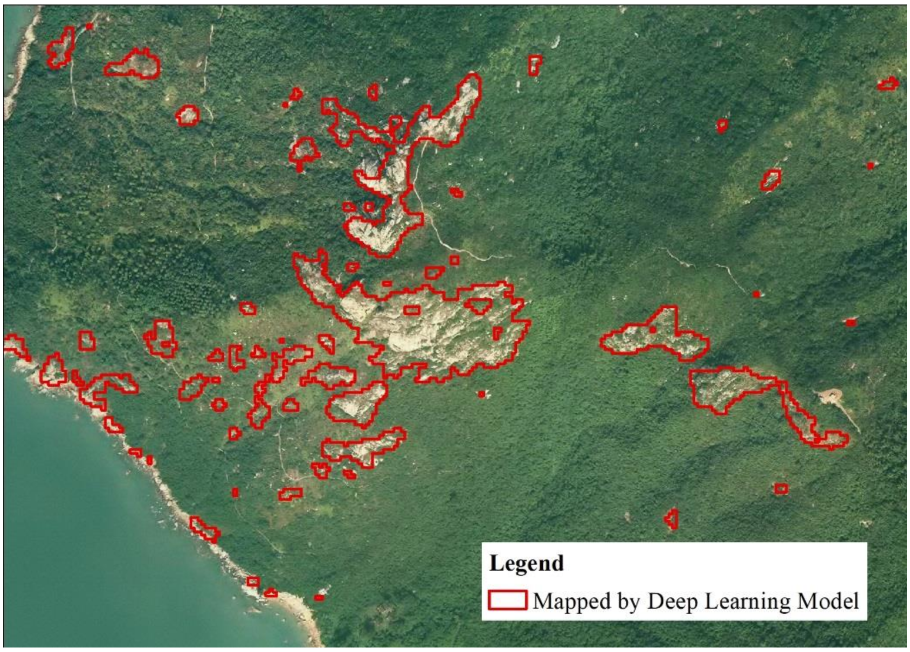


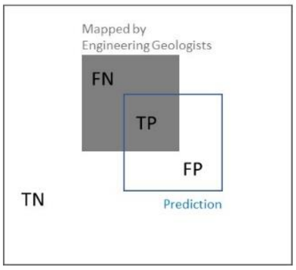
Fig. 3. Extract of the territory-wide rock outcrop map produced by the model.

Confusion Matrix		Prediction: Positive	Prediction: Negative
Mapped by Engineering Geologists	True	True Positive (TP)	False Negative (FN)
	False	False Positive (FP)	True Negative (TN)

$$Precision\ (P) = \frac{TP}{TP + FP}$$

$$Recall\ (R) = \frac{TP}{TP + FN}$$

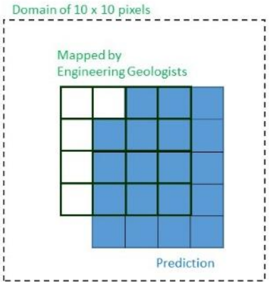
$$F1\ Score = \frac{2 \times P \times R}{P + R}$$

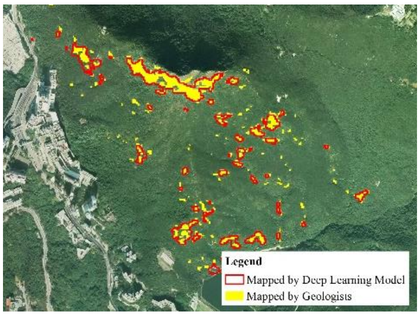


Example for Illustration:

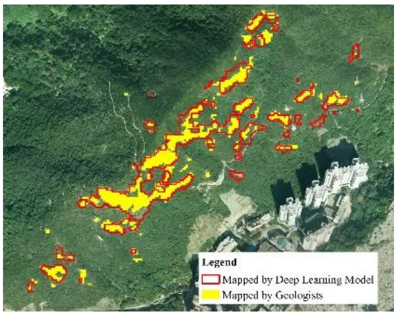
TP = 11 FN = 5
FP = 8 TN = 76

Precision = 57.9 %
Recall = 68.8 %
F1 Score= 0.63

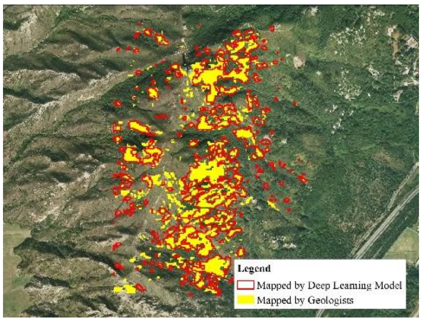




Trial Area 1: Mount High West



Trial Area 2: Tin Wan



Trial Area 3: Castle Peak

Trial Area	Precision Rate	Recall Rate	F1 Score
Mount High West	73.7%	74.5%	0.74
Tin Wan	84.9%	69.7%	0.77
Castle Peak	73.6%	72.1%	0.73

Fig. 4. The methods of accuracy assessment for rock outcrops identified by the model.

3 Pilot Study 2: Automatic Identification of Recent Natural Terrain Landslides

3.1 Objective of the Study

A review of aerial photographs taken between 1924 and 2016 identified the presence of about 110,000 landslide scars within natural terrain hillsides in Hong Kong (GEO, 2016). The locations of the landslide crowns and debris trails associated with these events were documented in the ENTLI. Currently, regular updating of the ENTLI is conducted by manual inspection and interpretation of aerial photographs. With about 10,000 new aerial photographs taken in Hong Kong each year, this process is both time-consuming and labour intensive, requiring notable experienced professional input. With the advancement in digital image processing techniques and machine learning technology, computerized algorithm can be applied to facilitate the landslide-identification process. The objective of the study was to develop a computerized algorithm with deep learning capability that allows automatic and systematic identification of recent natural terrain landslides from digital aerial photography.

3.2 Methodology

Traditional image processing techniques can be used to identify recent natural terrain landslides by observing changes to spectral values or other characteristics within images, for example, normalized difference vegetation index. The techniques can be divided into two groups: feature extraction and change detection. The feature extraction technique uses only the post-landslide images (Fig. 5) while both the pre-landslide and post-landslide images are used in change detection (Fig. 6) (Arup & Shi, 2019). Potential landslide candidates with spectral values (or other characteristics being studied) falling within a certain range (for feature extraction) or with difference in values between the pre-landslide and post-landslide images being higher than a certain threshold (for change detection) are identified as landslides.

Apart from using the two traditional techniques, deep learning techniques can also be applied to identify recent natural terrain landslides. Deep learning technology can be combined with image analysis methodology to automatically acquire accurate location and geometric information of targeted objects, in our cases recent natural terrain landslides. A total of three image processing techniques were employed in the study, one of which involved deep learning-based method whilst the other two approaches used traditional image processing methods (Arup & Shi, 2019). For the deep learning-based method, a modified Residual Neural Network (ResNet) was applied. ResNet (He et al., 2016) was used instead of VGG-16 (as per Pilot Study 1) because of its lower complexity and lower system memory requirements, which are essential in view of the more complex tasks involved in this pilot study (for example, extraction of landslide boundaries).

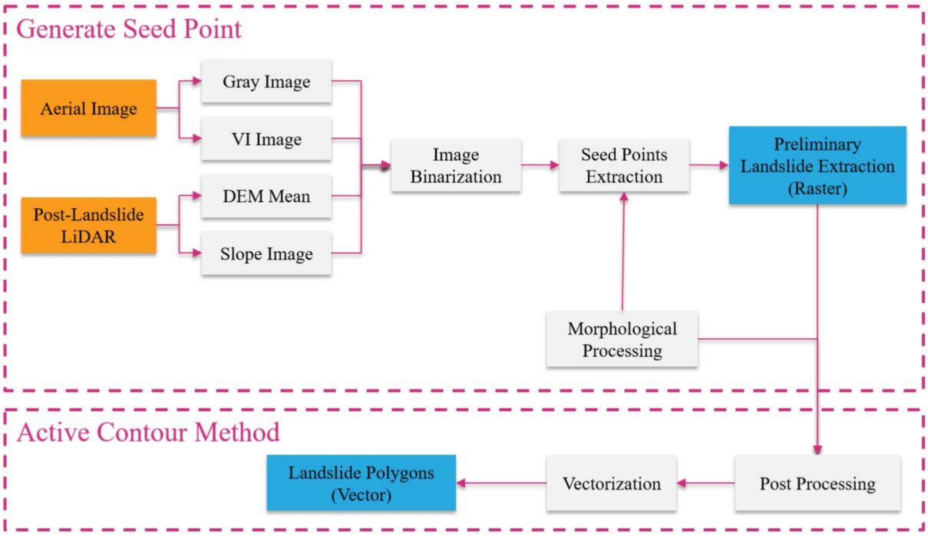


Fig. 5. Principle of landslide identification by feature extraction technique.

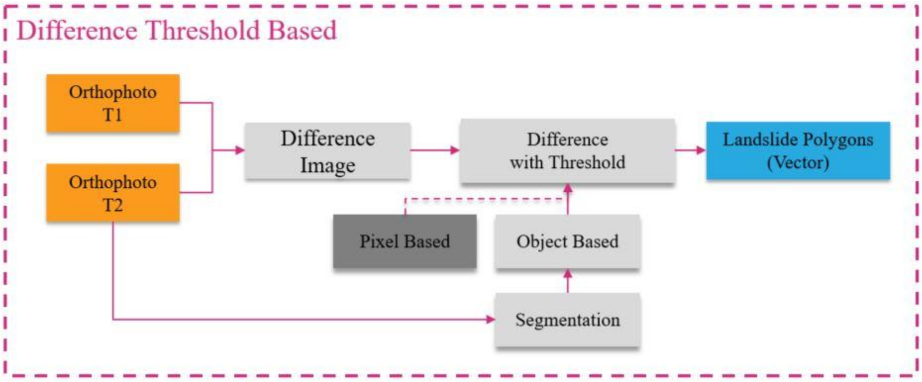


Fig. 6. Principle of landslide identification by change detection technique.

Similar to Pilot Study 1, CNN was applied to analyze visual imageries. A training model was developed first by using ground truth data of the ortho-rectified aerial photographs. 60%, 30% and 10% of the data was used for training, testing and validation purpose respectively. The workflow for deep learning-based method is shown in Fig. 7.

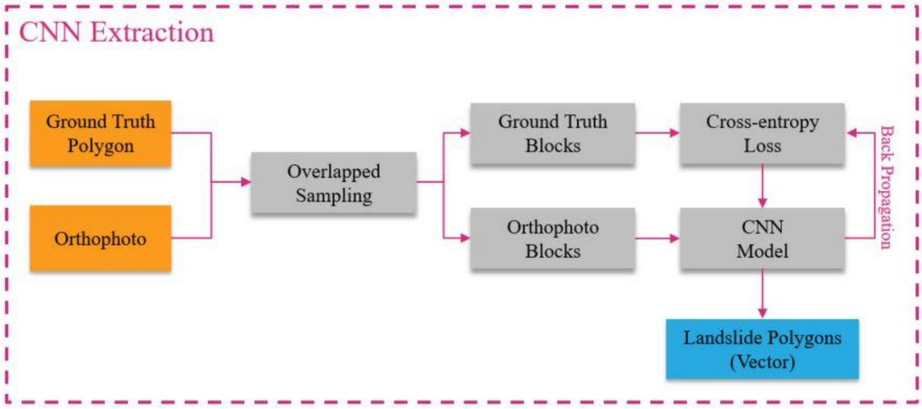


Fig. 7. Workflow for landslide identification by deep learning-based method.

For all of the three image processing techniques discussed, ortho-rectified aerial photographs were input into the computerized algorithm after data pre-processing. The boundary of individual identified landslide features was then delineated automatically as polygons in a Geographic Information System (GIS) platform. Post-processing optimization was subsequently applied to refine the boundary of the identified landslide features.

The extracted landslide boundaries were compared with the manually mapped landslides based on the inspection of ortho-rectified aerial photographs. The confusion matrix and equations for accuracy assessment were the same as Pilot Study 1, shown in Fig. 4. The landslide extraction results were based on the performance of successfully identifying each individual landslide. The precision rate represents the percentage of extracted landslides that are true landslides while the recall rate gives an indication about the omission of landslides by the algorithm.

3.3 Study Areas and Preliminary Results

Trial studies were conducted for sites at Tai O, West Lantau and Sharp Peak, Sai Kung (Fig. 8), in which widespread landsliding occurred due to heavy rainfall in June 2008 and May 2014 respectively. Examples of the aerial photographs used for the trials are shown in Fig. 9 and Fig. 10, while the preliminary extraction results are shown in Fig. 11 to Fig. 13 (Arup & Shi, 2019).

Fig. 8. The two pilot study areas in Tai O, West Lantau and Sharp Peak, Sai Kung.

Fig. 9. Pre-landslide image of Tai O, West Lantau taken in 2008.

Fig. 10. Post-landslide image of Tai O, West Lantau taken in 2009.

Fig. 11. Preliminary landslide extraction results by traditional image feature extraction at Tai O, West Lantau.

Fig. 12. Preliminary landslide extraction results by traditional image difference-based change detection extraction at Tai O, West Lantau. Some rock outcrops/beaches are mistaken as landslides due to the presence of shadows, changes in land cover and vegetation, difference in image capturing date, time and nadir point etc.

Fig. 13. Preliminary landslide extraction results by deep learning-based extraction at Tai O, West Lantau.

The accuracy assessment from the pilot study (Table 1) suggest that deep learning-based technique provide higher accuracy than the traditional image processing techniques, with precision rate and recall rate of about 90%. Similar accuracy can also be achieved when applying the trained CNN model on imageries taken at different area and different time.

Table 1. Preliminary quantitative assessment results of the pilot study at Tai O, West Lantau (Arup & Shi, 2019).

Image Processing Technique	Precision Rate	Recall Rate	F1 Score
1) Traditional image feature extraction	63%	58%	0.60
2) Traditional image difference-based change detection extraction	52%	89%	0.66
3) Deep learning-based extraction	88%	93%	0.90

3.4 Future Work

More trial areas with different landslide characteristics and geology will be studied. With the additional training data from different study areas, the applicability and performance of the algorithm is expected to be further improved. In addition, the automatic generation of other landslide attributes, for example, landslide source width, source area and travel angle etc. will be developed.

Up to date, the pilot study has revealed the potential for adopting deep learning in recognizing landslides on aerial photographs. It is anticipated that the trained computer algorithm will be deployed to carry out efficient regular updating of the ENTLI. Updated data can be used in preliminary landslide hazard assessments and detailed landslide-related studies after verification.

4 Discussion

The two pilot studies demonstrated the high efficiency and accuracy in identifying historical landslides and geological features using machine learning techniques. Their location and distribution are valuable information for the updating of landslide susceptibility maps. It also facilitates the prioritization of vulnerable catchments for natural terrain hazard studies that call for landslip prevention and mitigation works. The distribution of landslides after major rainstorm can be obtained quickly for timely emergency response.

The promising extraction results support that similar machine learning technology, when combined with image processing techniques, can be applied to other similar geotechnical and geological studies when sufficient training data is available.

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