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Landslide Detection Using ML and Deep Learning

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ABSTRACT

Landslide classification[1] is a new approach for detecting landslides. Landslide detection study will help in detecting the landslides and help early warning signs so that immediate safety actions should be taken. In recent times, deep learning[2] has brought advances in processing images, video, audio, and speech. It permits computational models that comprise multiprocessing layers to learn with representation of data with multi-level abstraction. Deep learning models find patterns in data sets This project utilizes the advantages of dense convolutional networks （DenseNets）[3] and their modified technique to solve the three proposed problems. For this purpose, we created a new landslide sample library. The proposed method achieves a training accuracy of 85% and validation accuracy[4] was about 81.25%.

Keywords: Landslide classification, Deep learning, DenseNet, Validation Accuracy

I. INTRODUCTION

Environmental disasters are unpredictable and occur due to heavy rainfall. Landslide causes loss of life, human settlement, agriculture and lead to damage of communication routes. The term landslide describes many types of downhill earth movements ranging from rapidly moving catastrophic rock descend rapidly down a mountainside (Avalanches) and debris of something wrecked which flows in mountainous regions to more slowly moving earth slides [5]. Therefore different technologies has to be developed to capture relevant signals with minimum monitoring delay. Wireless sensors are one of the cutting edge technology that can quickly respond to rapid changes of data and send the sensed data to a data analysis centre in areas where cabling is inappropriate.

Landslides refers to the slip phenomenon of slope rock soil along the through shear plane, which is caused by human activity and environmental conditions. Landslides happen in a variety of environment portrayed by either gentle or steep slope inclinations ranging from mountains to coastal reefs and also even underwater. The factors such as an earthquake, a heavy rainfall, floods, construction work on the slope which triggers the landslides by affecting the stability of the slope. Landslide geological disasters often cause environmental disruptions, casualties, and severe threats to human life and property. Various factors such as the higher rate of unplanned urbanization, deforestation, and unpredicted rainfall resulting in the increase of landslide problems which seems to be more challenging in the future.

II. MATERIALS & METHODOLOGY

Image analysis and classification in the Earth sciences and in the broader field of remote sensing has a long and successful history that has now undergone a huge step forward due to the capability of computers to manage and process big data with artificial intelligence methods. When dealing in particular with image classification and object recognition, the highest performances, at the present state of the art, are those provided by deep learning tools, such as CNNs, that are capable of performing classification tasks directly from images rather than by using pre-selected features of them (Krizhevsky et al. 2012; He et al. 2015a; Shin et al. 2016). A CNN[6] combines multiple nonlinear processing layers using simple elements working in parallel. The layers are interconnected by nodes and each layer uses the previous layer's output as input. Differently from other machine learning systems, CNNs may autonomously extract features from images, use them in the learning process, select only the most useful of them (activations) and then implement a highly accurate object recognition machine, based on a set of training images (Russakovsky et al. 2015; Shin et al. 2016).

However, the training of a deep CNN with tens or hundreds of layers over a large data set of images is a non-trivial task that requires a huge

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computational effort preceded by a similarly large undertaking that is necessary for collecting and labelling hundred thousands, if not millions, of training images (Russakovsky et al. 2015). As an example, the general-purpose image classification CNN AlexNet (Krizhevsky et al. 2012), which is quite simple and has only eight learnable layers, uses 61 million parameters trained over several million labelled images. Luckily, such heavy duties have already been accomplished by the leading computer vision research groups for general-purpose image analysis and can be fruitfully exploited as a starting base for a much simpler process of specialized training called transfer learning (Shin et al. 2016).Transfer learning consists in the specialized training of a subset of the deepest layers of a CNN that has been already trained for similar, but more general, classification purposes. An entire class of such public-domain CNNs exists offering various levels of flexibility, complexity and accuracy, depending on the user requirements. By picking one of such pre-trained, non-specialized networks, it is possible to substitute the deepest layers and retrain them to fit very specialized tasks such as the classification of landforms characterized by mass wasting and landslides. Because most of the classification capability of the network has already been obtained, transfer learning can be performed with a relatively small number of specialized images belonging to the target category. Furthermore, the usage of a general-purpose object recognition CNN strongly enhances the capability of detecting single objects set against a complex background which may include other landscape features such as trees, buildings, clouds, roads, people and animals.

In this paper, we selected four among the best performing CNN architectures for image recognition and object detection as related to the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al. 2015) and tested them by transfer learning on a dataset of labelled landscape images containing verified landforms belonging to five categories ('landslide', 'scree deposit', 'rock cliff', 'alluvial fan' and 'slope without mass movements').The choice of the five categories is based on the following reasons: landslides are the target object for the detection system we want to develop; scree deposits, alluvial fans and rock cliffs are typical landforms that can be erroneously classified as landslides and that, therefore, have to be discriminated from them; finally, 'slope without mass movements' is the label assigned to any image in the dataset where none of the previous categories is present, according to a careful expert-based selection process. Most of the selected 'slope without mass movements' images, however, purposefully contain objects that can be mistaken for slope processes, such as mid-slope roads, buildings, cultivated fields, retaining walls and rivers. This should contribute to a more effective training of the network and decrease the degree of overfitting (Zhou et al. 2016; Lee et al. 2017).

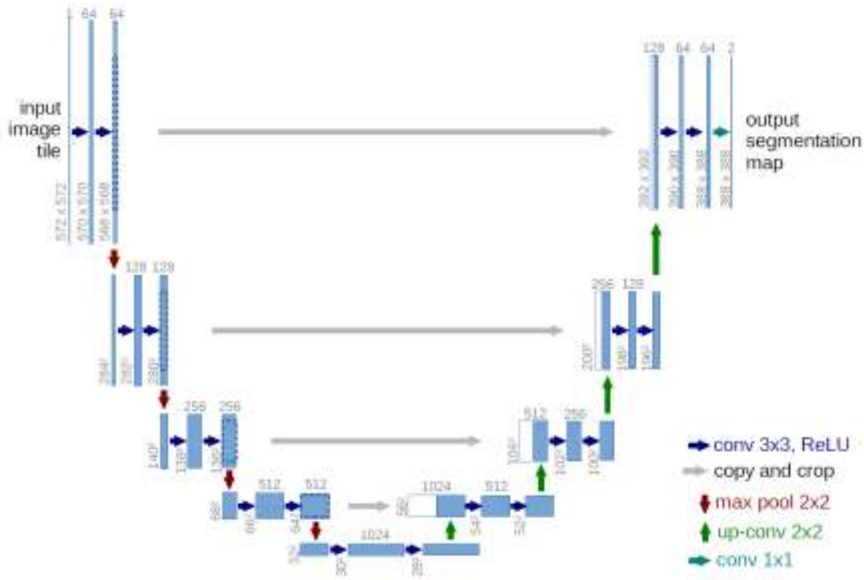

Figure 6 U-Net architecture - contracting path and expansive path

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After covering the contracting path, the image then moves to the expansive path. Throughout this path the image will at each step be converted back and finally reach its original dimensions. This stage can also be called as upsampling as the image gets resized to original. This stage consists of transposition, concatenation followed by two convolutional layers. The transposed convolution is an upsampling method that expands the size of images. Soon after this the image get upsized from 28x28x1024 to 56x56x512, following which some concatenation is done to match the size of the image in the contracting path. So the size now becomes 56x56x1024. This process is repeated three more times to reach the top last layer.

The energy function [7] does pixel wise softmax computation to classify the target classes and the loss function used here is cross entropy loss function.

$$p_k(\mathbf{x}) = \exp(a_k(\mathbf{x}))/\left(\sum_{k'=1}^{K}\exp(a_{k'}(\mathbf{x}))\right)$$

The proposed architecture in the paper is shown in Figure 7. Here as we have previously discussed, we take the input data and then make two copies. One would be a grayscale version of the input images and other will be the binary mask of all the input images that has been subjected to threshold segmentation. Both use the grayscale and thresholding functionalities in OpenCV [8]to achieve this. Then the images are splitted into train, test and validation sets. Normal python code is used to split the images. After this the U-net is created using keras. Each layer is created and then the loss function, metrics are mentioned in the compile section of the code. Finally the model is trained using the fit function where in tensorflow acts as a backend and executes the code. The neural network will learn from this pixel wise segmentation and it
will be capable to do segmentation on any unknown image.Finally the model weights are saved in a h5 file format so that it can be loaded for further testing purposes.

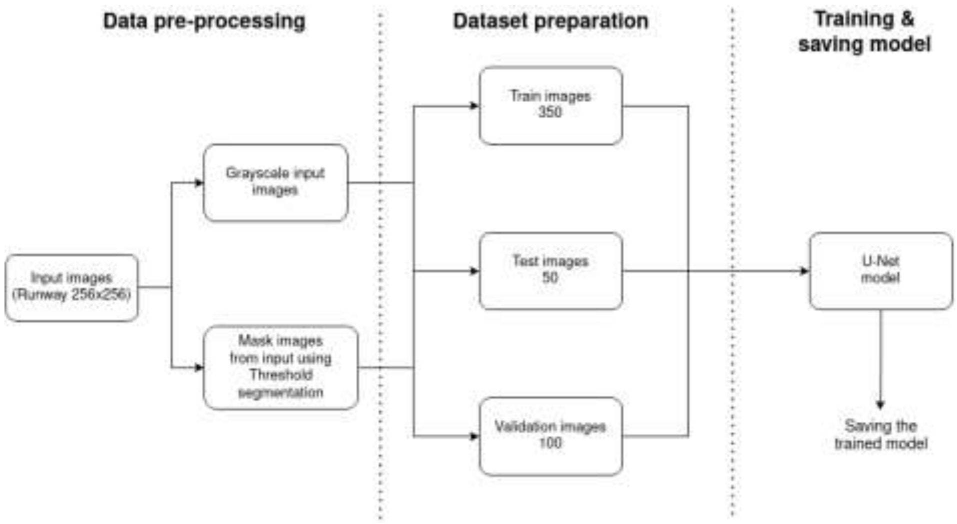

Figure 7 Proposed architecture

III. RESULTS AND DISCUSSION

The model was trained for 30 epochs and training was completed after 3 hours. The Google Colab GPU instance was used to train the model. Figure 8 shows the training logs in the google colab.The model training accuracy was 85% and validation accuracy was about 81.25%. The Figure 9 shows the train vs validation loss. The Figure 10 shows the output segmented image when an unknown runway image is given as input to the trained U-Net model.

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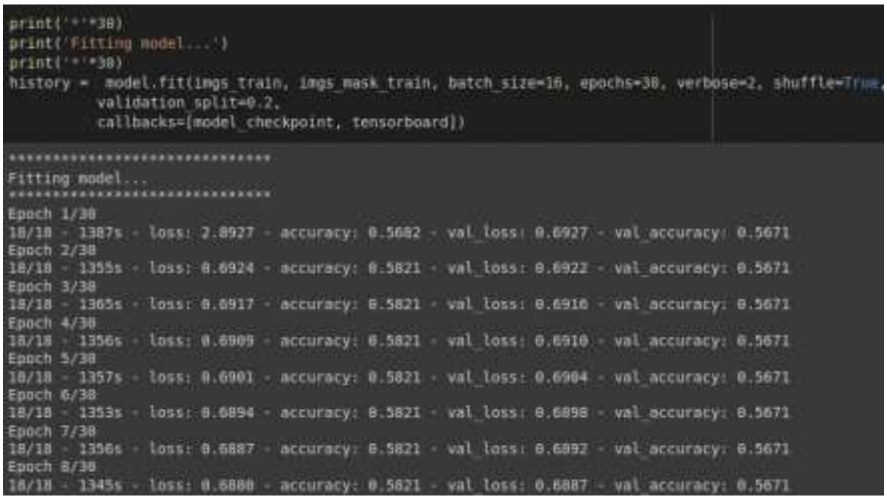

```
print('*'*30)
print('Fitting model...')
print('*'*30)
history =  model.fit(imgs_train, imgs_mask_train, batch_size=16, epochs=30, verbose=2, shuffle=True,
          validation_split=0.2,
          callbacks=[model_checkpoint, tensorboard])

******************************
Fitting model...
******************************
Epoch 1/30
18/18 - 1387s - loss: 2.8927 - accuracy: 0.5682 - val_loss: 0.6927 - val_accuracy: 0.5671
Epoch 2/30
18/18 - 1355s - loss: 0.6924 - accuracy: 0.5821 - val_loss: 0.6922 - val_accuracy: 0.5671
Epoch 3/30
18/18 - 1365s - loss: 0.6917 - accuracy: 0.5821 - val_loss: 0.6916 - val_accuracy: 0.5671
Epoch 4/30
18/18 - 1356s - loss: 0.6909 - accuracy: 0.5821 - val_loss: 0.6910 - val_accuracy: 0.5671
Epoch 5/30
18/18 - 1357s - loss: 0.6901 - accuracy: 0.5821 - val_loss: 0.6904 - val_accuracy: 0.5671
Epoch 6/30
18/18 - 1353s - loss: 0.6894 - accuracy: 0.5821 - val_loss: 0.6898 - val_accuracy: 0.5671
Epoch 7/30
18/18 - 1356s - loss: 0.6887 - accuracy: 0.5821 - val_loss: 0.6892 - val_accuracy: 0.5671
Epoch 8/30
18/18 - 1345s - loss: 0.6880 - accuracy: 0.5821 - val_loss: 0.6887 - val_accuracy: 0.5671
```

Figure 8 Model training output log from Google colab

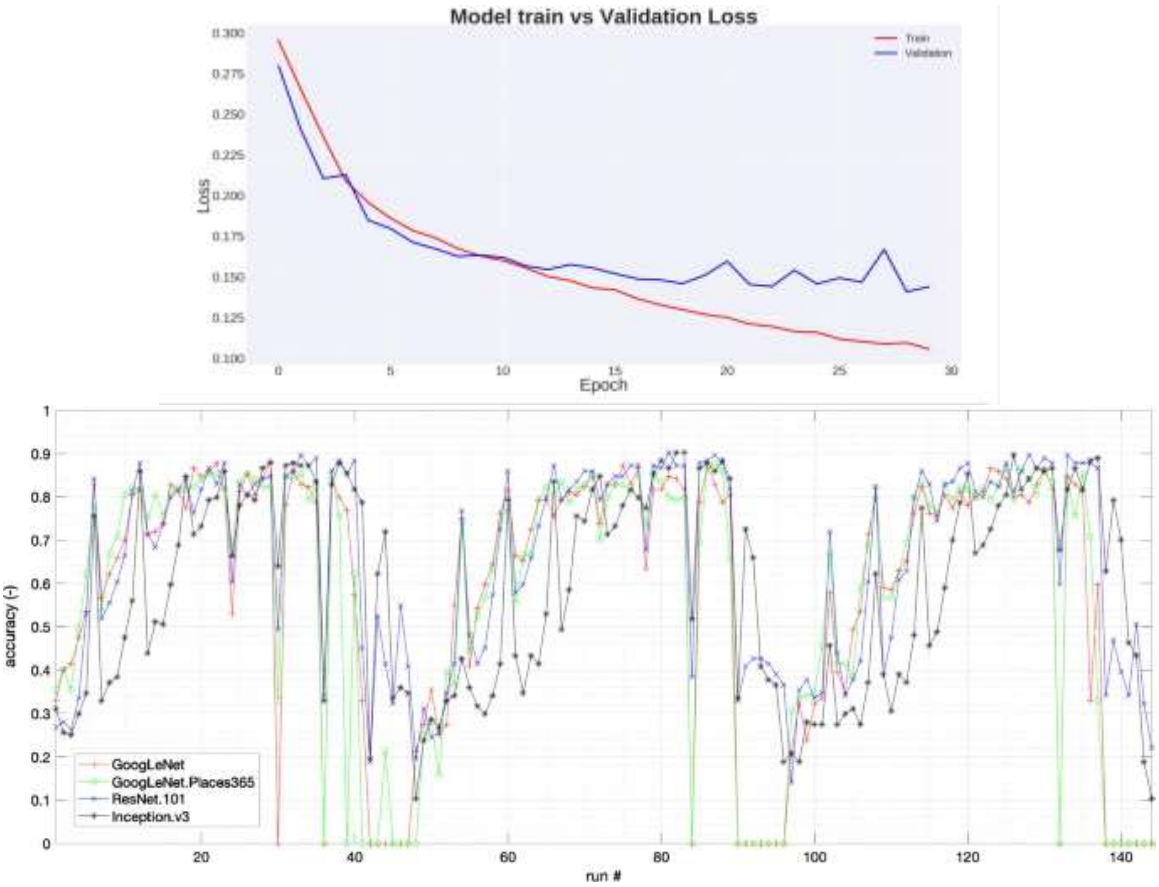

Figure 9 The model train vs validation loss plot

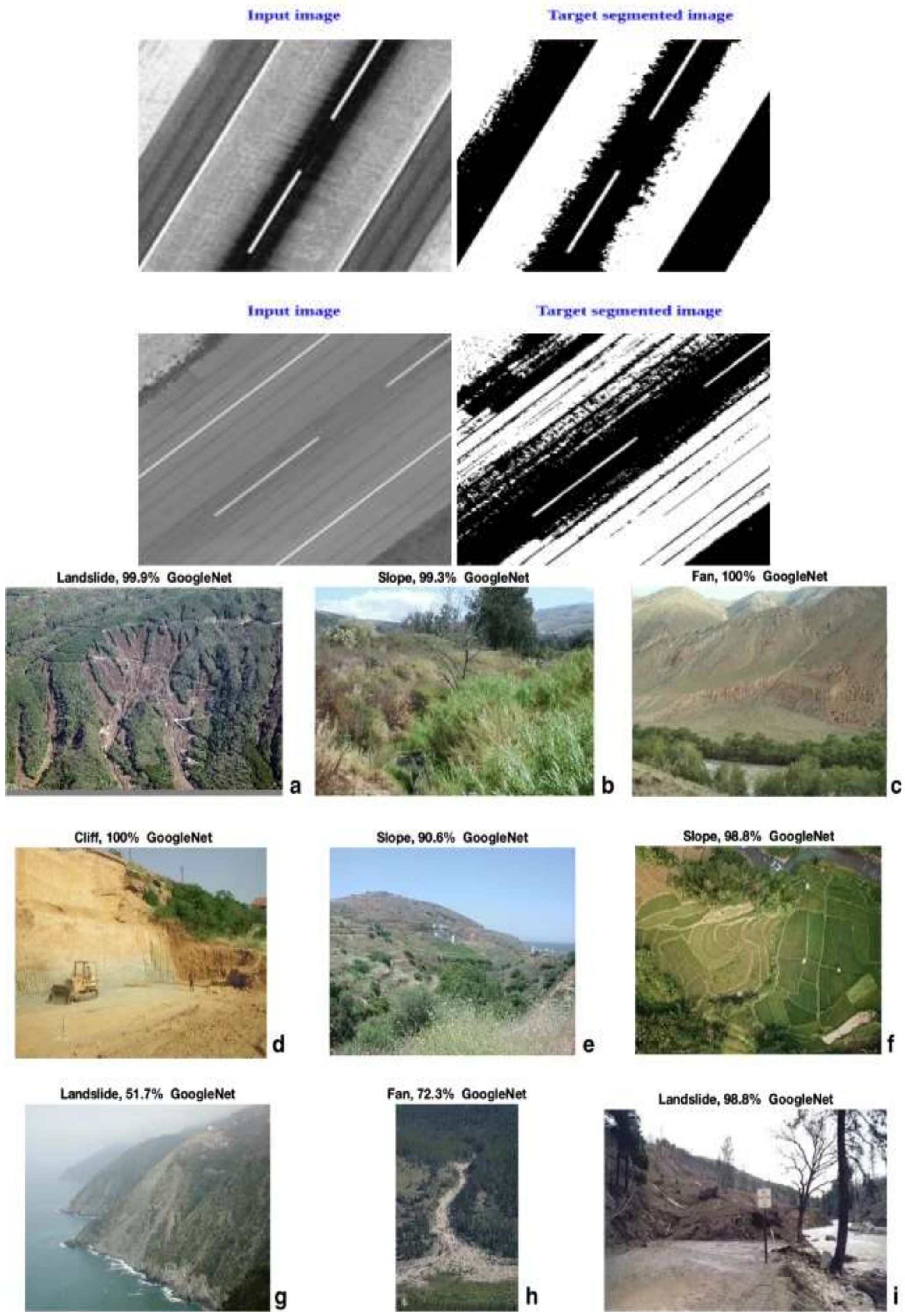

Figure 10 The input image and output segment comparison

IV. CONCLUSIONS

A set of powerful convolutional neural networks publicly available have been adapted to recognize typical mass movement landforms within non-nadiral and non-standard pictures by transfer learning. The best parameter sets for the four tested algorithms have been determined by an iterative optimization procedure covering 576 different configurations. The accuracy and error analysis of such training runs shows that classification performances of such post-trained CNNs are consistently higher than those of the general-purpose original architectures and suitable for the usage in automated data mining of crowdsourced images. Furthermore, preliminary tests with basic and more advanced hardware configurations show that at least two of the optimal CNNs developed (Go-LanDLC and In-LanDLC) are compatible with usage in UAV and generic robot applications for automated survey and guidance, provided that some technical adjustments on image acquisition and pre-processing are made. A slight modification of the way the algorithm is applied may also allow for a quasi-real-time scan of satellite VHR optical RGB images in a moving-window mode, thus potentially improving the capability of existing automated mapping tools. The four different versions of LanDLC are freely available for research purposes in the ONNX format under a CC BY NC 3.0 licence, as electronic supplementary material..

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