A Probabilistic Approach for Predicting Landslides by Learning a Self-Aligned Deep Convolutional Model

Ainaz Hajimoradlou
University of British Columbia

Gioachino Roberti
Minerva Intelligence

David Poole
University of British Columbia

Abstract

Landslides are movement of soil and rock under the influence of gravity. They are common phenomena that cause significant human and economic losses every year. To reduce the impact of landslides, experts have developed tools to identify areas that are more likely to generate landslides. We propose a novel statistical approach for predicting landslides using deep convolutional networks. Using a standardized dataset of georeferenced images consisting of slope, elevation, land cover, lithology, rock age, and rock family as inputs, we deliver a landslide susceptibility map as output. We call our model a Self-Aligned Convolutional Neural Network, SACNN, as it follows the ground surface at multiple scales to predict possible landslide occurrence for a single point. To validate our method, we compare it to several baselines, including linear regression, a neural network, and a convolutional network, using log-likelihood error and Receiver Operating Characteristic curves on the test set. We show that our model performs better than the other proposed baselines, suggesting that such deep convolutional models are effective in heterogenous datasets for improving landslide susceptibility maps, which has the potential to reduce the human and economic cost of these events.

1 INTRODUCTION

Landslides, the downslope movement of Earth materials under the influence of gravity, are common and destructive phenomena. Despite the number of studies focusing on landslide mapping [Guzzetti et al., 2012] and landslide spatial and temporal probability prediction [Reichenbach et al., 2018, Baron and Ottowitz, 2012], real-world applications are scarce and landslides cause significant life and economic losses every year [Petley, 2012]. There are three different approaches to landslide susceptibility mapping: expert-based, physical-based, and statistical approaches. Expert-based methods rely on the qualitative judgment of a domain expert, while physical-based approaches model the stability of a slope given physical parameters such as geotechnical rock and soil properties, and calculate the equilibrium between destabilizing factors and slope strength, but often require more information than is available at scale. Statistical models rely on the statistical analysis of large landslide databases and their relation with landscape attributes. Landscape attributes typically include internal (e.g. slope angle, rock type, etc.) and external (e.g. rainfall) properties of the slope. These data are then used to map the spatial and/or temporal probability of slope failure [Baron and Ottowitz, 2012]. The spatial probability of landslide occurrence is usually referred to as the susceptibility map. When the magnitude and the temporal component (e.g. frequency and triggers) are also considered, it is referred to as a hazard map [Baron and Ottowitz, 2012].

Statistical approaches for predicting landslides have significantly increased in recent years. However, they mostly apply models such as linear logistic regression, Support Vector Machines (SVM), or neural networks [Reichenbach et al., 2018]. In this study, we propose a novel convolutional model which we call a Self-Aligned Convolutional Neural Network, SACNN, for producing susceptibility maps. Convolutional Neural Networks, CNNs, form a category of neural network models with tied parameters [LeCun et al., 1999]. CNN with pooling layers can capture both local and global features of an image which has been proven extremely useful in many vision tasks such as object recognition, image classification, and object detection.
We are interested in predicting the landslide probability for each point on the ground. The output of our model is a probability map with the same resolution as the input features. We use a fully convolutional model [Shelhamer et al., 2017] for this purpose. These models have been widely used for image segmentation [Ronneberger et al., 2015] [Noh et al., 2015] and usually consist of down-sampling and up-sampling stages. One of the popular models in this category is UNet [Ronneberger et al., 2015], which our architecture is also based on. The down-sampling stage consists of convolutions with pooling layers and tries to create a set of compact features capturing both local and global properties of the input features. The up-sampling stage typically consists of convolution transpose layers which are mainly doing the inverse of pooling but with learning parameters. We don’t use convolution transpose layers in our model as they produce checkerboard artifacts in the final image [Aitken et al., 2017]. Instead, we use interpolation for up-sampling. It has been proven that adding skip connections to a fully convolutional model improves its performance [Drozdzal et al., 2016] [Mao et al., 2016]. As short skip connections has been shown to work only in very deep networks, we only apply long connections to our model.

To produce good susceptibility maps for landslides, we are interested in learning filters that can follow the ground surface and extract features towards the up-hill direction. For this to work, we need the CNN model to preserve orientational information of landslides to each other but this is not possible using traditional techniques, when the filters align themselves up, down, left, and right, which corresponds to north, south, east, and west. Capsul networks [Sabour et al., 2017] [Ahmad et al., 2018] have been recently proposed to address this issue however, they are not suitable for the task of landslide prediction. We add a pre-processing stage to our CNN model to find the best directions for each pixel at multiple scales and then learn hidden features according to those directions. We call this model a Self-Aligned CNN as the model first aligns itself to a specific set of orientations and then learns a classifier.

The contributions of our paper are:

- We provide an open-source dataset with a standard set of features. The dataset consists of several input features such as the slope, elevation, rock types with age and family, and land cover, along with the ground truth in the shape of landslide polygons which can be used in both a supervised and unsupervised learning framework.

- We propose a novel statistical approach for predicting landslides using deep convolutional networks. We develop a model that can capture each pixel’s orientation at three different ranges to classify a landslide. We use ranges of 30, 100, and 300 meters in our model. These scales can also be optimized using cross-validation.

- We define several baseline models for comparison. We provide five different baselines including a Random model, a linear logistic regression (LLR), a neural network (NN), and a self-aligned neural network (SANN) model without any convolutions to compare our model’s performance against them.

- We provide a way to use CNN models with heterogeneous datasets for predicting landslides rather than only using images in our models.

2 RELATED WORK

Producing susceptibility maps by statistical approaches is not new in the landslide community. Many people have been using models such as logistic regression, SVM, and random forests.
Catani et al., 2013 used random forests to generate susceptibility maps emphasizing on sensitivity and scaling issues. Micheletti et al., 2013a and Youssef et al., 2014 also used random forest models in predicting landslides for Switzerland and Wadi Tayyab Basin in Saudi Arabia. Some have developed software packages using random forests for susceptibility mapping Behnia and Blais-Stevens, 2017. Micheletti et al., 2013b generate several susceptibility mappings using SVMs, random forests, and Adaboost. Atkinson and Massari, 1998, Ayalew and Yamagishi, 2005, and Davis et al., 2006 focus on linear regression for predicting landslides due to its simplicity and easy training procedure. There is a volume of approaches that formulate the problem in a probabilistic framework such as Bayesian networks Heckmann et al., 2015, Lombardo et al., 2018, Neural networks and convolutional models are among more recent approaches for susceptibility mapping. Luo X, 2019 and Tien Bui et al., 2015 use neural networks to assess mine landslide susceptibility and to predict shallow landslide hazards. Ghorbanzadeh et al., 2019 and Wang et al., 2019 use a CNN model for detecting landslides from satellite images. However, most of these models are quite simple and do not have a large receptive field of view. Moreover, they learn a model to recognize landslides from satellite images but we are interested in predicting them given geospatial data.

3 DATASET

The dataset used for predicting landslides is from an Italian open-source database. The dataset contains both continuous and categorical features in the shape of rasters and vector files respectively. Continuous features including slope and DEM\(^1\) contain out of range values while categorical features such as rock type, land cover, rock age, and rock family, have several no-data points. To use such data in a CNN, we converted each vector map to a raster after removing no-data samples. We then prepared a new dataset of rasters and vector files respectively. Continuous features including slope and Digital Elevation Model (DEM)\(^2\) contain out of range values while categorical features such as rock type, land cover, rock age, and rock family, have several no-data points. To use such data in a CNN, we converted each vector map to a raster after removing no-data samples. We then prepared a new dataset of rasters and vector files respectively.

As we wanted to propose a baseline framework for this type of problem, we needed to come up with a standard set of features for our categorical data. Therefore, we decided to choose 44 rock types, 5 land covers, 5 rock families, and 38 rock ages, based on the INSPIRE terminology, as the one-hot encoding for our categorical data. INSPIRE is an open-source project for standardizing spatial data across countries in Europe. Using the INSPIRE terminology, we ended up with 94 standard input features. Anyone using the INSPIRE terminology should be able to compare their results with our proposed baselines and further use our prepared dataset.

Each pixel in our prepared dataset has a 10 meters resolution and the images are 21005x19500 pixels resulting in an area with approximately 210 (km) width and 195 (km) height. This area is Veneto, a region of Italy. We used this region since it expands over both mountains and flat zones close to the sea. The ratio of landslides in this region is below 1% which makes the dataset extremely imbalanced. The landslides in Veneto include both mountainous and less steep areas which are good for training our model. Unfortunately, the landslides do not usually contain information about the date of occurrence. All of these characteristics make this dataset challenging from the machine learning point of view.

The rasters in the dataset are too large to fit into memory when training. Instead, we divide each raster, an input feature, into smaller images of size 500x500, which we call patches. We further feed mini-batches of these patches into our model for training. Since we want to produce a coherent probability map for the whole region, we use patches that overlap each other. For this purpose, we pad each patch with 64 pixels on each side resulting in 628x628 images. This padding number is used to ensure that the overlap between patches is bigger than the receptive field of view of our networks. We partitioned these patches into training, testing, and validation sets.

4 SELF-ALIGNED DEEP NETWORK

The slope is considered one of the main conditioning factors in causing landslides. The LLR baseline that we learned also confirms this claim as the slope’s weight is among the top 5 learned weights. Traditional CNN filters are oriented vertically in an image, but the important orientation is up-hill and downhill for landslides. Based on this, we propose a Self-Aligned CNN model with filters that align themselves according to the up-hill direction and extract features alongside that direction. As illustrated in Figure [1], we find the highest elevation value for each pixel in the image at three different ranges and extract relevant features at those located points. Because space is at a premium for batch size, we selected a subset of 22 features for this purpose. These features are chosen based on our trained LLR baseline. If we define the LLR’s weight vector by \(w\), each feature is chosen

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\(1\) Digital Elevation Model

\(2\) Infrastructure for Spatial Information in Europe: https://inspire.ec.europa.eu
such that $|w_i| >= 0.2$. The code is available under https://github.com/ainazHjm/Landslide.

4.1 Architecture

Our Self-Aligned CNN architecture consists of a preprocessing module and four layers of down-sampling and up-sampling as in Figure 2. The preprocessing module takes the elevation map along with other input features from the dataset as inputs and outputs 22 aligned features for each looking distance. We use 30, 100, and 300 meters as looking distance in our experiments but it can also be considered a hyper-parameter and be optimized using cross-validation. The preprocessing module outputs 66 aligned features that we further feed into the convolutional network along with the original 94 features. We apply long skip connections between each sampling layer for our SACNN architecture similar to UNet. Each down-sampling layer consists of two convolution layers followed by ReLU as non-linearity and a max-pooling layer. Every up-sampling layer includes an up-sampling module to interpolate the data followed by convolutions and ReLU. In the end, we apply a Sigmoid function to the output of the model to obtain probabilities.

4.2 Training

We partition image patches after shuffling such that 80% of the data is used for training, 10% for testing, and the other 10% for validation. We use the negative log-likelihood loss to train our model. However, as the training data is extremely imbalanced, we use oversampling to balance the data to some extent. As landslides are quite rare, we don’t want the model to become overconfident when predicting them. Since we want to train our model on patches and preserve the spatial relation between pixels, we don’t oversample landslide pixels but rather patches that have at least one positive label. By oversampling those patches, we are oversampling both landslides and non-landslide pixel points. After doing this, the distribution of landslides stays below 1%. This oversampling technique can also be seen as a type of data augmentation which provides more training data. We use an oversampling ratio of 5 in our experiments.

We propose several baselines to compare our model against them including linear logistic regression, NN, CNN, and a Self-Aligned NN model that uses preprocessing combined with a neural network. Table 1 shows the hyper-parameters used for training each of these models. We optimized the learning rate and the optimizer with 5-fold cross-validation for one epoch. The batch size is chosen such that we can fit the maximum number of samples in 12 GB memory of a TitanXP GPU. The number of epochs is also chosen to fully train each model. We validate our models at each epoch and reduce the learning rate if the validation error keeps increasing for patience number of epochs to avoid overfitting.

5 RESULTS

Since time scale is not provided for landslides, the output probabilities are for undefined time period, and therefore should only be interpreted as relative scales. Figure 4a shows the probability distribution map (susceptibility map) obtained by our model on the whole region of Veneto. The corresponding ground truth is
Table 1: Training Hyper-Parameters. \( LR \) and \( BS \) represent the learning rate and the batch size respectively.

| MODEL | OPTIMIZER | LR   | EPOCHS | BS   | DECAY | PATIENCE |
|-------|-----------|------|--------|------|-------|----------|
| LLR   | Adam      | 0.125| 10     | 15   | 0.001 | 2        |
| NN    | Adam      | 0.125| 10     | 13   | 0.001 | 2        |
| SANN  | Adam      | 0.0156|15     | 10   | 0.001 | 2        |
| CNN   | SGD       | 0.125| 20     | 12   | 0.001 | 2        |
| SACNN | Adam      | 0.001| 30     | 9    | 0.001 | 2        |

Table 2: Negative Log Likelihood Loss

| METHOD | TEST ERR | TRAIN ERR |
|--------|----------|-----------|
| Random | 0.16     | 0.18      |
| LLR    | 0.055    | 0.057     |
| NN     | 0.052    | 0.055     |
| SANN   | 0.048    | 0.052     |
| CNN    | 0.047    | 0.051     |
| SACNN  | **0.046**| 0.050     |

Figure 3: This image shows the data partitioning used for the whole region of Veneto. Light purple, blue, and green colors are used to represent train, validation, and test sets respectively. The white background shows no-data points.

Also available in Figure 4b. Since the prediction map is too big and it is hard to differentiate between the outputs of the baselines, we show a smaller region of the map to compare various outputs against each other with their corresponding ground truth. The chosen area of interest, as shown in Figure 5, includes both landslide polygons and non-landslide areas. We chose this region as it has a variety of terrain. We also illustrate the number of patches that were used for training, validation, and testing in the whole region in Figure 3.

5.1 Evaluation

We define \( p_n = 0.987 \) as the ratio of negative/zero labels and \( p_p = 0.013 \) as the ratio of positive/one labels in the training set. We propose a baseline model called Random that predicts 0.001 in \( p_n \) of the times and predicts 0.999 in \( p_p \) of the times. Given \( p_n \) and \( p_p \), we can easily calculate the expected negative log-likelihood on the training set, which is approximately equal to 0.18. We can find the expected error with the same calculations on the test set as well. We compare the test and training errors of our other baselines with the Random model to make sure that the learned models perform better than Random as shown in Table 2.

We evaluate our models by the Receiver Operating Characteristic (ROC) curve and negative log-likelihood error on the test set to see how much they can differentiate between distinct classes. The Area Under the Curve (AUC) is also reported in Figure 6. Our model, SACNN, is able to achieve the best result in all metrics as in Figure 4 and Table 2, conferring the significance of using aligned features for predicting landslides. Although SANN achieves higher test error than the CNN baseline, it obtains the same AUC as CNN on the test set, suggesting that alignment alone can improve the model performance by great extent. However, the best result is obtained by using both convolutions and alignment as in our proposed model, SACNN. The validation curves of all baselines is also provided in Figure 7.

6 CONCLUSION

Landslides are the movement of ground under the force of gravity. They are common phenomena that can cause significant casualties. There have been many approaches to produce susceptibility maps to reduce the impact of landslides including expert-based, physics-based, and statistical methods. All of these meth-
Figure 4: SACNN probability map of 21005x19500 resolution for Veneto and its corresponding ground truth. Red regions correspond to higher probabilities and blue regions are areas with probabilities close to zero. Red polygons represent observed landslides in the Veneto region.

... have their flaws and lack a standard set of features. We provide a standardized open-source dataset with the same terminology as INSPIRE so that anyone who uses the INSPIRE terminology can compare their results to our proposed baselines. We also propose a novel statistical approach for predicting landslides using machine learning. We introduce a deep convolutional model, called SACNN, that can follow the ground surface and align itself with the ground contour lines to extract relevant features. We evaluate our model by ROC curves and negative log-likelihood error and show that it can achieve the best results on the test set among all the baselines. Our results suggest that this type of statistical approach is effective for generating susceptibility maps which in turn has the potential to alleviate human and financial losses caused by landslides.

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Figure 5: The acquired probability maps for a small region in Veneto and its corresponding ground truth. The resolution of the images are 2500x2500 pixels.
Figure 6: ROC curves from all models on the test set.

Figure 7: Negative log-likelihood error of all models on the validation set in the first 10 epochs.

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