

# Automatic Recognition of Land Instability



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**Abstract:** Land instabilities are frequent in vulnerable areas because of the conjunction of several triggers. Therefore, it is necessary to identify areas at risk and to propose preventive comfort solutions. The risk is getting worse if landslide affects road network. As a result, it reduces the security of users, the opening of areas and the access of the population. Automatic recognition of land instabilities is useful in the field of new mobility and smart infrastructures. Indeed, this recognition helps the autopilot system installed in vehicles to detect land instabilities even in bad weather allowing the conditional autonomy to monitor the environment and then the vehicle is able to recognize the land instabilities and acts accordingly. Otherwise, it allows the development of intelligent and smart infrastructures for the protection of the platform and the support of slopes at risk. This automation will reduce the time needed to provide solutions and help diagnose potential risks at an early stage with the optimization of maintenance cost. This article proposes to apply a deep learning method for the recognition of land instabilities collected on roads from visual surveys or captured images of roads. Since landslide types are multiple and require special study to classify them distinctly, this paper aims to apply the deep convolutional neural network (DCNN) using pre-trained AlexNet model to distinguish two classes presence of land instability on the roadway and absence of land instabilities. The results of classification are satisfactory with saving time in identifying risk areas with excellent accuracy (85%) and efficiency and high F1-score (89.12%).

**Index Terms:** Deep Convolutional Neural Network, roads, landslides recognition, smart infrastructures

## I. INTRODUCTION

Land instabilities present real danger for users and real handicap for the social and economic development. Several studies concludes that the conjunction of triggering factors induce to land instabilities. For example, Rif chain in northern Morocco is characterized by rugged terrain characterized by a varied altimetry and a steep slope [1]. Maximum rainfall is in November and December, with July and August being dry, with thunderstorms at the top. These rains can be continuous, with torrential rain [2]. They feed the highly fractured and weakened soil [3], causing the infiltration of water into marls, limestone marls and clay formations [4]. Due to the

importance of rainfall [5], the imperviousness of the vegetation cover and the mountainous nature make the runoff relatively large and make the irregular flows characterized by a torrential flow during floods [6].

In addition, there is a divergence in stratigraphy marked by steep slopes and heterogeneous and contrasted lithology, especially in faults [3] [7] [8]. Consequently, due to the conjunction of several triggering factors [9], landslides are numerous, with variable types which are active after heavy rainfall and then threaten human, natural and material resources [10] affecting the equipment, essential for socioeconomic development such as infrastructure and transport. In particular, the road network is the most affected, recording significant damage [2].

## II. ANALYSIS OF THE PHENOMENA ENCOUNTERED

The study aims to distinguish between presence of land instability on roads and roads with stable environment. In general, the study of ground movements [11] is complex; it depends on the variety of materials and slopes involved. The collapses [11] are a rocky cliff or the creep of a soft layer found along some wadis. Slides [11] occur in environments composed of loose materials and are the most common family of mass movement, notably in the form of rotational landslides. In this type of movement occurs a tilting of the mass slid along a more or less circular surface. Sliding can be deep or superficial. Slow movements under the application of constant forces characterize creep [11]. It evolves with small displacements towards an ultimate state, which can be either the stability or the rupture. It manifests itself for example by a slow advance of ground on the road and the work of comfort. The flows [11] are likened to a transport of materials by water, differentiating the muddy flows that usually accompany large landslides and stony flows or debris.

Due to the complexity of studying land movement [12] [13] and the difficulty of identifying some cases in the field [14], this paper aims to automatically detect land instabilities across the road environment in order to use this concept in the field of new mobility and smart infrastructures. It proposes to apply deep learning for the recognition of landslides across the road using transfer learning with Alexnet neural network to train and test a new network for fast and accurate classification.

## III. DEEP CONVOLUTIONAL NEURAL NETWORK FOR IMAGE RECOGNITION

The deep Convolutional neural network (DCNN) is an automatic learning technique that uses artificial neural network.

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The interest of deep learning methods has emerged because of the powerful techniques used in several fields such as object detection, object classification, automatic image counting, automatic natural language processing, medical image analysis, drug discovery, speech and video recognition, etc. These methods learn features directly from data or via transfer learning methods with pre-trained networks (AlexNet [13] [15] [16], GoogleNet [17], Vgg-16 [18], Vgg-19 [18]). Using a pretrained network makes learning much faster and easier than learning from scratch. The purpose of this study is to classify automatically captured images of road or visual records into two classes using Matlab [19].

### A. Alexnet Architecture

The Alexnet architecture [15] is commonly used in object recognition and image classification. In this paper, the goal is to apply AlexNet DCNN and to use transfer learning [15] for automatic image recognition. As the classifier distinguishes between two classes (presence of land instabilities across the road and absence of land instabilities across the road), the fully connected layer (fc) becomes two neurons in step of Fig. a. Thus, the result of the classification corresponds to two classes (current instability of land on roads and roads with stable environment).

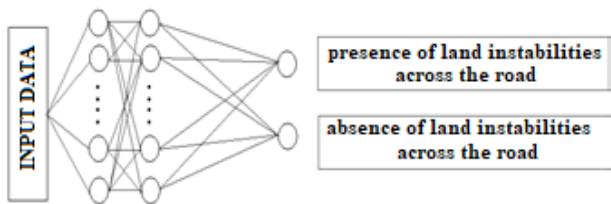


Fig. a: the process of classification into “presence of land instabilities across the road” class and “absence of land instabilities across the road” class

### B. Image Preprocessing

Input images are collected on roads from visual surveys or captured images. Before processing, input data must be preprocessed. In fact, the datastore contains a total of 200 RGB input images and is composed of two folders named with the respective labels (presence of land instabilities across the road and absence of land instabilities across the road) according to the two classes. Using transfer learning with AlexNet [15], the input images are preprocessed to match the expected input size of the Alexnet neural network [20]. Once preprocessed, the image Datastore is divided into images for training (50%) and images for the test (50%) needed to evaluate network performance.

### C. Training algorithm

During neural network processing, stochastic gradient descent with momentum (sgdm) is typically used to monitor learning progress [15] [21].

## IV. RESULTS AND DISCUSSION

Once the new neural network is structured, the images preprocessed and the learning progress option set, the new

classifier is ready for training in Matlab [19] to recognize patterns from training data based on the stability environment of the road. The training is done using CPU processor and takes 50010 seconds for processing, but less if using graphic processor GPU. Then the trained network classifies the test images, makes predictions, compares the results obtained and confirms the actual outputs. Finally, validation is established to ensure high quality and accuracy and high efficiency of the new classifier. In fact, network accuracy and table of confusion and F1-score confirm the effectiveness of the new neural network and confirm the correct prediction based on input training data.

### A. Network accuracy

The accuracy of a new classifier is calculated by dividing the total number of correct predictions by the total number of the input test images [15] [20] according to (1).

$$\text{Network Accuracy} = \frac{\text{Total of Correct Predictions}}{\text{Total of predictions}} \quad (1)$$

$$\text{Network Accuracy} = \frac{85}{100} = 85\% \quad (2)$$

The accuracy is high when it reaches 100% and low when it is 0%. In our study, the network accuracy is 85% (2) which allows the new classifier to accurately classify both classes.

### B. Table of Confusion

Table of confusion [13] [15] [20] is a table commonly used to describe the performance of the new classifier performance based on the image test to confirm the predictions of the classifier and the true values of the output images, as well as to differentiate all instances individually between the new classifier predictions and actual results. The table of confusion or confusion matrix is a more detailed analysis than the accuracy of the network and is composed of rows and columns. The rows represent the instances in the predicted classes and the columns represent the instances in actual classes. In this study, the table of confusion is a two-dimensional 2 x 2 matrix and its visualization is shown in the figure. b.

		Actual class	
		Road pavement stable	Road pavement instable
Predicted class	Road pavement stable	61	10
	Road pavement instable	5	24

Figure. b: Table of Confusion

The table of confusion reports the true positive, false positive, false negative and true negative as shown in fig. c.

		Actual class	
		Road pavement stable	Road pavement instable
Predicted class	Road pavement stable	61 True positive	10 False positive
	Road pavement instable	5 False negative	24 True negative

Figure. c: Confusion Matrix reports true positive, true negative, false positive, true negative

C.F1-score

The F1- score measures the accuracy of the test [22]. It is the harmonic mean of sensitivity r and the precision p. The best F1-score is 100% and the low is 0%

The precision p is the ratio of correct positive results to total of the positive results [22]. It is also called PPV (positive predictive value). It represents the fraction of relevant instances among the collected instances (3).

$$p = \frac{TP}{TP+FP} = \frac{61}{61+10} = 86\% \quad (3)$$

The recall r or sensitivity [22] corresponds to the true positive rate (Eq. 3). This is the fraction of the instances relevant to correctly collected instances (4).

$$r = \frac{TP}{TP+FN} = \frac{61}{61+5} = 92.4\% \quad (4)$$

The F1-score combines precision and recall and measures the harmonic mean (5). The F1 score is usually more useful and more sophisticated than the accuracy of the network especially when the distribution of classes is unequal and takes into account false positives and false negatives.

$$F1 - score = 2 \frac{precision \cdot recall}{precision + recall} = 89.12\% \quad (5)$$

D.Discussion

In terms of accuracy, the network has excellent efficient and high accuracy 85% (2). It is also confirmed by the F1-score which reaches 89.12% (5) taking into account the unequal distribution of classes.

A summary of the results with examples from our study is presented below:

True Positives: The image resized to 227x227, which is a small image size, but it gives maximum information in panoramic view of the road in its environment. The network learned the characteristics of instability according to the condition of the road and the instability of the slope. Some examples are presented in (Fig. d).



Fig. d: Some True positive images

False positives: The error comes from the concentration of images on the pavement only. As a result, the network is unaware that pavement degradation has been caused by landslides and land instabilities or completely misunderstands the image. It is useful to use clear images and panoramic images taking into account the road environment for better performance. According to Meziane et al. [21], the impermeability of pavement and presence of water have a direct impact on the triggering of landslides especially in vulnerable areas. Similarly, the deterioration of the roadway contributes to trigger landslides due to the infiltration of water by a degraded pavement. The greater the water infiltration, the more the soil saturates and a landslide can be triggered on a large scale [21]. As a result, the new trained classifier does not accurately predict occurrences of pavement unstable based solely on pavement conditions. Fig.e illustrates some false positive images.

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The upper image gives a zoom of the corner of the pulled off pavement, the middle part shows a slip point where pavement has experienced significant open-hole cracking and the last image shows only part of the pavement with muds (mudslide). All over these distresses are caused by land instabilities across the roadway.



**Fig. e: Some false positive images**

False negative images illustrate the degradation of the roadway in the absence of land instability and landslides. The first image (Fig. f) shows the pavement shoulders spall. The middle image illustrates the pavement in a very advanced state of degradation and the last shows a large extent of tearing of the wear layer. The error comes from the concentration of the image on the pavement only. To this end, in order to achieve high efficiency and accuracy, the images must contain as much information as possible, including the pavement environment, in order to correctly extract the occurrences of the input images.



**Fig. f: Some False negative images**

True negative images show compliance between predictions and actual output. The results are satisfactory because the network classifies correctly pavement in good condition without degradation. (Fig. g).



**Fig. g: Some true Negative images**

It classifies all cases distinguishing between the absence of risk and the presence of landslide risk concerning the safety of the users and the level of human and material damage specific to the neighboring population or even to the socio-economic level of the region. As a result, this automatic recognition has a direct impact on the collection of risk areas, especially at the road network level, in order to activate preventive solutions to block the deterioration of road conditions and protect them to be able to ensure an acceptable quality of service.

## V. CONCLUSION

The deep Convolutional neural network (DCNN) is an automatic learning technique that has emerged because of the powerful techniques used in several fields. This study focuses on the recognition of land instabilities in the road network environment using transfer-learning technique with the pre-trained AlexNet neural network. The automation allows distinguishing two classes presence of land instabilities on the roadway or absence of land instabilities in images collected on roads from visual surveys or captured images of roads. The results of classification are satisfactory. The processing lasts 50010 seconds using CPU. Therefore, it identifies risk areas

automatically instead of manual recognition and subjective recording. The accuracy is high (85%) and the F1-score is excellent (89.12%). Automatic recognition of landslides is useful in the fields of new mobility and smart infrastructures in order to reduce risk and increase users' safety.

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