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Geological Disaster Recognition on Optical Remote Sensing Images Using Deep Learning

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Abstract

Geological disaster recognition, especially, landslide recognition, is of vital importance in disaster prevention, disaster monitoring and other applications. As more and more optical remote sensing images are available in recent years, landslide recognition on optical remote sensing images is in demand. Therefore, in this paper, we propose a deep learning based landslide recognition method for optical remote sensing images. In order to capture more distinct features hidden in landslide images, a particular wavelet transformation is proposed to be used as the preprocessing method. Next, a corrupting & denoising method is proposed to enhance the robustness of the model in recognize landslide features. Then, a deep auto-encoder network with multiple hidden layers is proposed to learn the high-level features and representations of each image. A softmax classifier is used for class prediction. Experiments are conducted on the remote sensing images from Google Earth. The experimental results indicate that the proposed *wavDAE* method outperforms the state-of-the-art classifiers both in efficiency and accuracy.

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Keywords: target recognition; deep learning; remote sensing image

1. Introduction

Geological disasters always affect the development of human society and economic progress [1]. Landslide is a serious natural disaster next only to earthquake and flood, which accounts for 50% - 90% of the total number of the geological disasters each year [2]. Thus, landslide recognition is of vital importance in disaster prevention, disaster monitoring and other applications [3]. Most of the existing research in landslide

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recognition focuses on synthetic aperture radar (SAR) images. Comparing with SAR images, optical remote sensing images have higher resolution and richer contents, which provide us more chances to recognize landslide disasters. Although some valuable studies have been conducted in the field of landslide disaster recognition, those research fruits are only applicable for SAR images rather than optical remote sensing images. As the number of satellite increases, the volume of optical remote sensing images is increasing dramatically. Therefore, automatic landslide recognition on optical remote sensing images has become a research hot spot in recent years [4, 5, 6].

Deep learning is a hot topic in machine learning and artificial intelligence, which imitates the mechanism of human brain in interpreting data [7]. Recently, deep learning showed great promise in many practical applications. For example, Google and Microsoft reduced the error rate of speech recognition by 20% - 30% by using deep neural network in 2012 [8]. Krizhevsky *et al* [9] used convolutional neural network (CNN) in ImageNet large scale visual recognition challenge (ILSVRC) in 2012, where the error rate of the first 5 options was reduced from 26.2% to 15.3%. By using CNN as the deep learning model, the DeepID project of Chinese University Hong Kong [10] achieved 97.45% accuracy in the outdoor face recognition database, and the DeepFace project of Facebook [11] achieved 97.35%, respectively. Then, the DeepID2 project of Chinese University Hong Kong improved the accuracy of the deep CNN model to 99.15% [12]. Based on the successful applications in the problem of object recognition, deep learning is promising in landslide disaster recognition.

Therefore, in this paper, we would like to explore disaster recognition on optical remote sensing images using deep learning based model and method. Particularly, auto-encoder has the ability to learn features from a large number of unlabeled samples with unsupervised learning. So we use deep learning model based on auto-encoder in our work. The proposed landslide recognition method consists of two phases, pre-processing (normalization and wavelet coefficients) and classification model training (landslide feature representation and recognition). The contribution of this paper can be summarized as follows:

- 1) Introduced 2-D wavelet coefficients in landslide raw images processing;
- 2) Implemented the deep auto-encoder network model;
- 3) Introduced corruption into the training model.

In order to demonstrate the performance of our proposed model, support vector machine (SVM) and artificial neural network (ANN) are implemented as the counterparts. Experiments were performed on a set of optical remote sensing images downloaded from Google Earth. Higher recognition rate was achieved by using our deep learning based method when comparing with SVM and ANN.

The rest of this paper is organized as follows. Section 2 overviews some related work on geological disaster recognition. Section 3 briefly introduces the basic deep auto-encoder algorithm. Section 4 describes the details of proposed model and method. Section 5 presents the experimental results and performance analysis. Section 6 summarizes the work and point out the future work.

2. Related Work

Research on geological disaster detection and recognition on remote sensing images has been conducted in recent years. For example, Japan and some European countries have made some achievements in landslide mapping, disaster monitoring and analysing, early warning, etc. [15]. Most of the methods for landslide detection and recognition include artificial visual interpretation [16], object oriented method and statistical model based methods.

In 1990's and the first decade in the 20th century, high resolution aerial images were applied in landslide detection and recognition. With the emergence of high resolution remote sensing satellites, optical remote sensing images are being used in landslide detection and recognition. Object oriented method was proposed. For example, Barlow *et al.* [17] used object oriented method to detect landslide in Landsat ETM+ images in Cascade mountain area, and recognize landslide with the aid of digital elevation model (DEM) data. Martin *et*

al. [18] used object oriented method to recognize landslide, which classified the landslides into soil-dominate landslide and bedrock-dominate landslide, and 65% accuracy was achieved.

Statistical model based methods include logistic regression, support vector machine (SVM) [19], artificial neural network (ANN) [20], etc. Song et al. proposed to use two multivariate statistical analysis methods, variable weighting and logistic regression [21] to model the landslides. Colubi proposed a logistic regression model using a novel kernel density estimation [22]. Lee et al. used the images data from Korea multipurpose satellite (KOMPSAT 1), and ANN was adopted to classify the training data set. The accuracy of Lee's ANN model is about 82.72%~86.10% [23]. Yao et al. compared the performance of SVM and the logistic regression model. The accuracy of SVM was higher than logistic regression on landslide data [24].

3. Auto-encoder Algorithm

3.1. Auto-encoder

We begin by recalling the traditional auto-encoder model to build deep networks. An auto-encoder takes an input vector $x \in [0,1]^d$, and first maps it to a hidden representation $y \in [0,1]^{d'}$ through a deterministic mapping $y = f_\theta(x) = s(Wx + b)$, parameterized by $\theta = \{W, b\}$. W is a $d' \times d$ weight matrix and b is a bias vector. The resulting latent representation y is then mapped back to a "reconstructed" vector $z \in [0,1]^d$ in input space $z = g_{\theta'}(y) = s(W'y + b')$ with $\theta' = \{W', b'\}$. The weight matrix W' of the reverse mapping may optionally be constrained by $W' = W^T$, in which case the auto-encoder is said to have *tied weights*. Each training $x^{(i)}$ is thus mapped to a corresponding $y^{(i)}$ and a reconstruction $z^{(i)}$. The parameters of this model are optimized to minimize the *average reconstruction error*:

$$\theta^*, \theta'^* = \arg \min_{\theta, \theta'} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, z^{(i)}) = \arg \min_{\theta, \theta'} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, g_{\theta'}(f_\theta(x^{(i)}))) \quad (1)$$

Where L is a loss function such as the traditional squared error $L(x, z) = \|x - z\|^2$. An alternative loss, suggested by the interpretation of x and z as either bit vectors or vectors of bit probabilities (Bernoullis) is the reconstruction cross-entropy:

$$L_H(x, z) = H(B_x || B_z) = - \sum_{k=1}^d [x_k \log z_k + (1 - x_k) \log(1 - z_k)] \quad (2)$$

Note that if x is a binary vector, $L_H(x, z)$ is a negative log-likelihood for the example x , given the Bernoulli parameters z . Equation 1 with $L = L_H$ can be written

$$\theta^*, \theta'^* = \arg \min_{\theta, \theta'} E_{q^0(x)} [L_H(X, g_{\theta'}(f_\theta(X)))] \quad (3)$$

Where $q^0(X)$ denotes the empirical distribution associated to our n training inputs.

3.2. Deep Auto-encoder Network Model (DAE)

As can be seen in Fig. 1, deep auto-encoder network has multi-hidden layers. The construction of deep auto-encoder network consists of two phases, layer-wise initialization and fine tuning. The deep auto-encoder has been used as a building block to train deep networks. In the layer-wise initialization, the representation of the k -th layer are used as the input for the $(k + 1)$ -th, and the $(k + 1)$ -th layer trained after the k -th has been trained. After a few layers have been trained, the connection weights, W , are used as initialization for a network

optimized with respect to a supervised training criterion. This greedy layer-wise procedure has been shown to yield significantly better local minima than random initialization of deep networks, achieving better generalization on a number of tasks.

After the layer-wise initialization, it is need to fine tuning. The whole DAE model is seen as a neural network and the connection weights, W , are optimized by back propagation algorithm (BP).

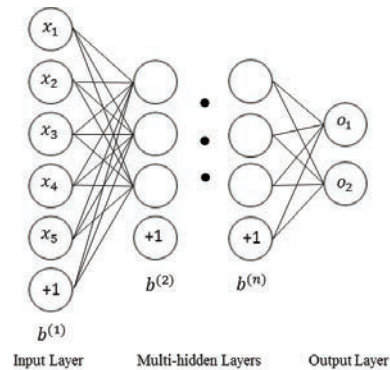


Fig. 1. The structure of deep auto-encoder (DAE)

4. Deep auto-encoder with wavelet coefficient (wacDAE)

In this paper, we would like to propose a DAE based landslide recognition method. The proposed method consists of four phases, shown in Figure 2.

Phase 1. Discrete Wavelet Transformation. Due to the fact that the resolution of optical remote sensing image is lower than that of optical images, we perform wavelet transformation to extract features rather than downscaling an image to a low-resolution version. Discrete wavelet transform (DWT) is well known for its capability in multi-resolution analysis and singularity detection. Thus, features extracted by wavelet transformation may contribute to a higher recognition rate than using the raw images.

Phase 2. Corrupting and denoising. In order to enhance the robustness of our proposed method, we proposed to add a corrupting & denoising layer, which is trained to be able to reconstruct an input from its corrupted version [28].

Phase 3. Feature extraction. Deep learning model is adopted to extract features out of the input optical remote sensing images. Usually, a deep learning model may consist of hidden layers, each of which represents a level of feature, and the higher the concept level the coarser the feature extracted. Initially, a deep neural network with multiple hidden layers is initialized with arbitrary numbers, and then, the network is fine-tuned by a supervised back propagation. It is an iterative approach until the network structure is able to fit the training data set. Actually, DAE is an implementation of such a deep neural network, where the input is reconstructed the input by the corresponding output of the network. In this paper, DAE is used as the feature extraction method.

Phase 4: Classification. The existing classifiers in data mining or machine learning domain can be adopted to classify the geological disasters, including SVM, ANN, etc.

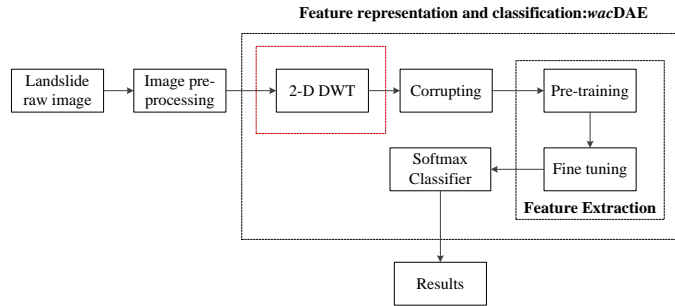


Fig. 2. Process flow of the landslide recognition method using deep auto-encoder network with wavelet transformation.

4.1. Discrete Wavelet Transformation

In the domain of landslide recognition, as the volume of the image data is usually huge, it may take tremendous of time to process. Therefore, compressed domain is often used to improve recognition efficiency which utilizes sparse features from both space and frequency domains. However, as the resolution of optical remote sensing image is lower than that of optical images, the recognition efficiency will definitely be degraded since the resolution is further reduced. Thus, in this paper, we propose to perform wavelet transformation on the raw images before feeding them into the deep network for training.

Discrete wavelet transform (DWT) has been widely used in many domains and applications. It has been verified superior in multi-resolution analysis and singularity detection. By using DWT, an image is decomposed into a low-frequency subband (denoted as LL) and several horizontal/vertical/diagonal high-frequency subbands (denoted as LH, HL, and HH). Different subbands describe different sparse features of input images. DWT provides localized information about the variation of the image around a certain point or its local regularity. Irregularities are sharpened by in the wavelet domain. The existence of discontinuities in an image will result in a local maxima in the wavelet domain. It has also been demonstrated that finding wavelet modulus local maxima is an effective way to detect the singularities [27]. As the singularities and irregular structures often contain rich information, thus, they are particularly valuable for object recognition. Moreover, the characteristics of singularities, represented by LL, are suitable for landslide detection with its unique intensity distribution comparing with that of the background.

Based on the aforementioned reasons, in this paper, we will use 2-D DWT to transform the raw image into the wavelet domain [26]. The subband LL will be fed into DAE as the inputs.

4.2. Corrupting and Denoising

In order to enhance the robustness of our proposed method, we proposed to add a corrupting & denoising layer, which is trained to be able to reconstruct an input from its corrupted version [28]. Actually, the operation of corrupting is to add some “noise” to the input image. This is done by first corrupting the input vector x to get a corrupted version \tilde{x} by means of a stochastic mapping $\tilde{x} \sim q_D(\tilde{x}|x)$. That is, for each input vector x , a pre-defined number of elements are randomly selected whose values are set to be 0, while the others remain untouched. All information about the chosen components is thus removed from that particular input pattern, and the auto-encoder will be trained to “fill-in” these artificially introduced “blanks”. Note that alternative corrupting noises could be considered. The corrupted input \tilde{x} is then mapped to a hidden representation by $y = f_\theta(\tilde{x}) = s(W\tilde{x} + b)$, thereby $z = g_{\theta'}(x) = s(W'y + b')$ will be reconstructed. As the parameters are trained to minimize the average reconstruction error, $L_H(x, z)$, over a training set, z will be close to the original input x .

4.3. DAE network

In our work, we construct the DAE network with one input layer, two hidden layers and a softmax classifier. The number of input nodes is the pixel size of each image, and the number of each hidden layer nodes is 100. The connection function between each unit is sigmoid function. Then we use a softmax classifier to classify images.

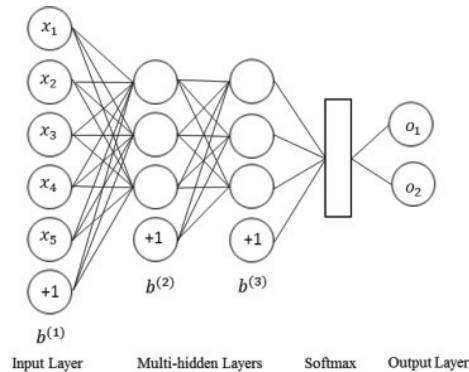


Fig. 3. wavDAE network

5. Experiments

5.1. Data Set

We download a set of optical remote sensing images from Google Earth, which contains 150 landslide and 150 non-landslide images with resolution 128×128 . In order to enhance the capability of the model to recognize landslides at different angles and different directions, we rotated the images to different directions, thus a larger dataset is created. Finally, we made an optical remote sensing image set with 1200 samples, 600 landslide and 600 non-landslide. 700 out of the 1200 images are randomly selected as the training set and the rest 500 images are used for testing.

5.2. Inputs of wavDAE

The raw images have to be preprocessed before training. Firstly, the RGB color images are transformed to gray images. As mentioned in Section 4 and Fig. 3, the low frequency (LL subband) of the input images is going to be fed in the wavDAE model. In the experiments, we use a 2-D DWT to reduce the number of dimensions and extract the wavelet features.

In order to remove the effect of the uneven illumination, top-hat transform (THT), is used for landslide extraction and background suppression. As a landslide part is usually brighter than other parts in the pictures, white THT is employed in our proposed method. The mathematical definition of white THT is as follows:

$$Tw(f) = f - f \circ b \quad (4)$$

where f is the input LL coefficients of the original image, \circ denotes the opening operation, and Tw denotes the enhanced image. In our experiments, b is set as a circular structuring element with a radius of 12.

5.3. Measurements

Precision, recall, accuracy are used to evaluate the performance of the proposed landslide recognition method:

$$\text{precision} = \frac{TP}{TP+FP} * 100\% \quad (5)$$

$$\text{recall} = \frac{TP}{TP+FN} * 100\% \quad (6)$$

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100\% \quad (7)$$

where True Positive (TP) denotes the number of positive samples classified into the positive class, and False Positive (FP) denotes the number of positive samples classified into the negative class. False Negative (FN) denotes the number of negative samples classified into the positive class, and True Negative (TN) denotes the number of negative samples classified into the negative class.

5.4. Experimental Results

A *wavDAE* network with one input layer, two hidden layers and a softmax classifier is implemented by using the open source tool, DeepLearnToolBox [29]. According to the parameter settings suggested in [30], grid search and optimization is adopted. In addition, the learning rate of the pre-training and fine tuning is set at 0.01, the size of mini-batch is set at 10, the number of iterations is set at 200 and the number of units in each hidden layer is set at 100.

- *The Effect of 2-D Wavelet Coefficient*

In this experiment, we explore how 2-D wavelet coefficient affects the recognition performance. DAE-2 is a basic deep auto-encoder model (-2 indicates two hidden layers), and the *wavDAE-2* is our proposed method with wavelet transformation. The percentage of noise is 0. And we verify the pre-training time, fine tuning time and the recognition result with different methods.

Table 1. Training time of different methods

Method	DAE-2	<i>wacDAE-2</i>
Pre-training Time (s)	1505.235	481.966
Fine Tuning Time (s)	651.479	206.284
Testing Time (s)	0.09	0.03
Overall Time (s)	2156.804	688.280

Table 2. Classification performances of different methods

Method	DAE-2	<i>wacDAE-2</i>
Precision (%)	97.15	97.18
Recall (%)	95.28	95.26
Accuracy (%)	96.23	96.20

From the Table 1, it is easy to observe that *wavDAE-2* method consumes only 1/3 of the training time for the basic deep auto-encoder model. Due to the feature extraction of wavelet transformation, the size of each image is 68×68 , smaller than that of the original image, 128×128 , thus, as a result, less execution time is

incurred. Although the training time of *wavDAE-2* is much less than that of *DAE-2*, comparable precision, recall and accuracy between *DAE-2* and *wavDAE-2* are achieved. It indicates that 2-D DWT can provide singularities and irregular structures of landslide images, which help *wavDAE-2* better understand the model. Thus, it is verified that the wavelet transformation step in *wavDAE-2* contributes to landslide recognition.

- *The Effect of Corrupting and Denoising*

In this experiment, we explore how “noise” affects the recognition performance. In the pre-processing stage of the *wavDAE-2* model, we add noise to the input data, where parameter ν is used to control how much noise is added, $\nu \in [0, 5\%, 10\%, 15\%, 20\%, 25\%, 30\%, 35\%]$.

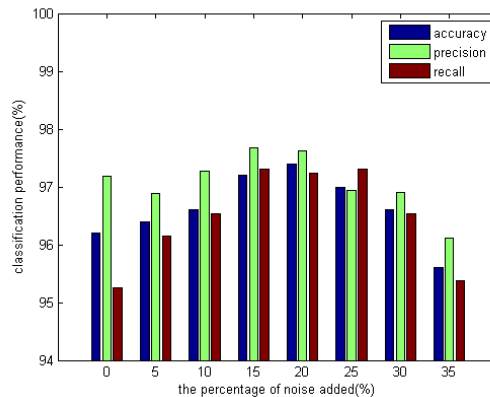


Fig. 4. The effect of noise in *wavDAE* model

Figure 4 presents the precision, accuracy and recall of the *wavDAE* method when we vary the percentage of noise added to the raw images. The *wavDAE* method with “noise” gets better classification performance. When the value of ν is 20%, the accuracy and precision reached the peak. When “noise” is added, the learning model will be trained to study how to remove the influence of corruption. It is easy to observe that appropriate corrupting and denoising can improve the robustness of the model and the recognition capability.

- *Comparison with other methods*

In this section, we compare the proposed *wavDAE* method with two state-of-the-art classifiers, Support Vector Machine (SVM) and Artificial Neural Network (ANN) in terms of precision, recall and accuracy. The SVM classifier is implemented in LIBSVM [31], where radial basis function (RBF) is used as the kernel function. ANN-2 is an artificial neural network (-2 indicates two hidden layers). In *wavDAE-2* method, the percentage of noise added to the data is set at 20% which is the best setup shown in Figure 4.

Table 3. Comparison of *wacDAE-2* with other methods

Performance	SVM _{rbf}	ANN-2	<i>wacDAE-2</i>
Precision (%)	96.27	95.90	97.62
Recall (%)	92.80	93.60	97.23
Accuracy (%)	94.60	94.80	97.40

From the Table 3, it is evident that *wavDAE-2* performs better than SVM with RBF kernel in all

measurements. SVM_{rbf} is a shallow learning algorithm. Comparing with SVM_{rbf} , $wavDAE-2$ is a deep learning model with multi-layers of feature extraction, thereby $wavDAE-2$ is able to better understand the features of landslide.

From the Table 3, it is evident that $wavDAE-2$ performs better than ANN-2 in all measurements too. In the $wavDAE-2$ model, each training $x^{(i)}$ is thus mapped to a corresponding $y^{(i)}$ and a reconstruction $z^{(i)}$. The connection weights, W , are initialized by the layer-wise initialization. Comparing with ANN-2, $wavDAE-2$ tends to use more appropriate initial values rather than arbitrary values. With the pre-training of each layer, the $wavDAE-2$ algorithm combines the advantages of unsupervised learning and supervised learning and explores the regularity of remote sensing data in space, and thus improves capability to classify.

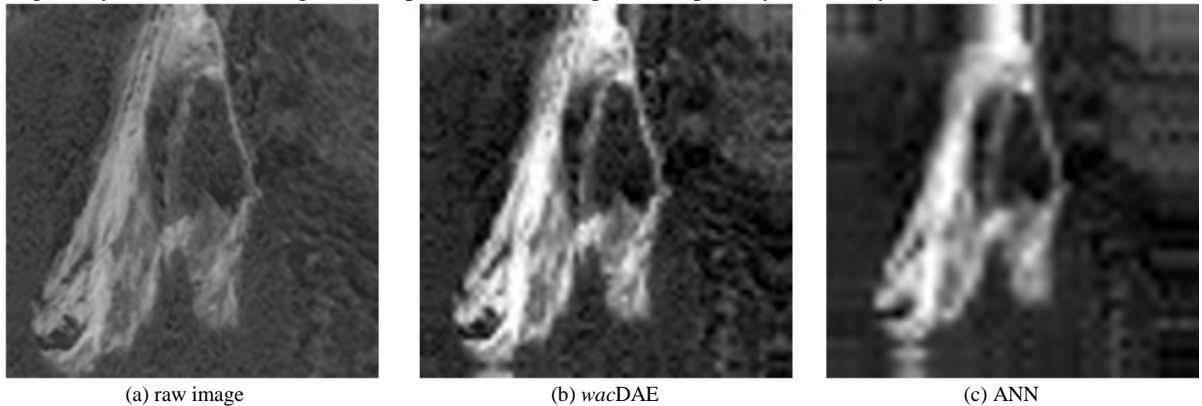


Fig. 5. The internal output of different methods

Figure 5 is an example that was misclassified by ANN-2. (a) presents the raw image, (b) presents the temporal output of the $wavDAE-2$ method, and (c) presents the temporal output of ANN-2 model. It indicates that the $wavDAE-2$ method has higher capability to capture more distinct features.

6. Conclusion and future work

Geological disaster recognition on optical remote sensing image has attracted great interest in the applications of disaster control and disaster relief. In this paper, we proposed a deep learning based landslide recognition method. 2-D wavelet transformation was proposed to be used as the preprocessing method aiming at capturing more distinct features and producing size-reduced images. Corrupting & denoising was proposed to enhance the robustness of the model in recognize patterns. Then, the enhanced images are fed in a deep auto-encoder network with 2 hidden layers for training. Experiments were performed on remote sensing images downloaded from Google Earth. The experimental results indicate that the $wavDAE$ method outperforms ANN and SVM in terms of precision, recall and accuracy.

In the future, we would like to verify the effectiveness of the proposed method on more real optical remote sensing datasets. Other methods for object recognition will be investigated and implemented for the purpose of performance comparison. In addition, we would like to investigate the impact of various parameters in the auto-encoder network, including the number of hidden layers, the number of units in each hidden layer, the initial connection weights, the learning rate, the batch size, etc., thereby to further optimize the topology of the network. Finally, in order to meet the requirement of big data applications, we will develop a high performance deep auto-encoder network on CUDA-enabled GPUs.

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