

## Exploring deep learning for landslide mapping: A comprehensive review

Zhi-qiang Yang<sup>a, b</sup>, Wen-wen Qi<sup>b, c</sup>, Chong Xu<sup>b, c, \*</sup>, Xiao-yi Shao<sup>b, c</sup>

<sup>a</sup> College of Surveying and Geo-Informatics, Tongji University, Shanghai 200092, China

<sup>b</sup> National Institute of Natural Hazards, Ministry of Emergency Management, Beijing 100085, China

<sup>c</sup> Key Laboratory of Compound and Chained Natural Hazards Dynamics, Ministry of Emergency Management of China, Beijing 100085, China

### ARTICLE INFO

#### Article history:

Received 8 March 2024

Received in revised form 14 April 2024

Accepted 16 April 2024

Available online 25 April 2024

#### Keywords:

Landslide Mapping

Quantitative hazard assessment

Deep learning

Artificial intelligence

Neural network

Big data

Geological hazard survey engineering

### ABSTRACT

A detailed and accurate inventory map of landslides is crucial for quantitative hazard assessment and land planning. Traditional methods relying on change detection and object-oriented approaches have been criticized for their dependence on expert knowledge and subjective factors. Recent advancements in high-resolution satellite imagery, coupled with the rapid development of artificial intelligence, particularly data-driven deep learning algorithms (DL) such as convolutional neural networks (CNN), have provided rich feature indicators for landslide mapping, overcoming previous limitations. In this review paper, 77 representative DL-based landslide detection methods applied in various environments over the past seven years were examined. This study analyzed the structures of different DL networks, discussed five main application scenarios, and assessed both the advancements and limitations of DL in geological hazard analysis. The results indicated that the increasing number of articles per year reflects growing interest in landslide mapping by artificial intelligence, with U-Net-based structures gaining prominence due to their flexibility in feature extraction and generalization. Finally, we explored the hindrances of DL in landslide hazard research based on the above research content. Challenges such as black-box operations and sample dependence persist, warranting further theoretical research and future application of DL in landslide detection.

©2024 China Geology Editorial Office.

## 1. Introduction

According to World Health Organization (WHO), between 1998 and 2017, landslides affected an estimated  $4.8 \times 10^6$  people and killed more than  $18 \times 10^3$  as a result of extreme weather caused by global change. Furthermore, as China is located in the southeastern part of the Eurasian Plate, at the confluence of two major global tectonic seismic zones, seismicity is characterized by high frequency and intensity, with 18 earthquakes of magnitude 5 or higher occurring in China in 2023, including the  $M_S$  6.2 earthquake in Jishishan County, Gansu Province, China, with 3767 coseismic landslides triggered (Chen B et al., 2023). Hence, the coupling of strong earthquakes and extreme weather has exacerbated the probability of landslide disasters in China, causing serious

impacts on lives, the economy, and infrastructure. A landslide is a mass movement of rock, debris, or soil down a slope under the influence of gravity (Glade T, 2001), which can also evolve into geological hazards causing human casualties and damage to manufactured and natural structures (Malamud BD et al., 2004; Pardeshi SD et al., 2013). Detailed and comprehensive seismic landslide inventories are confirmed as an essential component of landslide susceptibility and risk assessment (Wieczorek GF, 1984; Van Westen CJ et al., 2008; Guzzetti F et al., 2012). The quality and completeness of landslide inventories affect the reliability of landslide investigations. In addition, the legacy effect of landslide evolution leads to a greater chance of landslides occurring on existing landslide paths in the next decade (Casadei M et al., 2003; Samia J et al., 2017). Therefore, making landslide distribution is the first step in studying landslide hazards and evaluating landslide susceptibility (Fan XM et al., 2019; Zhong C et al., 2020).

Early landslide making relied on field surveys using a variety of measurement equipment such as displacement meters, stress meters, and hydrometers (Brardinoni F et al.,

First author: E-mail address: [yangzhiqiang20@mails.ucas.ac.cn](mailto:yangzhiqiang20@mails.ucas.ac.cn) (Zhi-qiang Yang).

\* Corresponding author: E-mail address: [xc11111111@126.com](mailto:xc11111111@126.com) (Chong Xu).

Literary editor: Xi-jie Chen

doi:10.31035/cg2024032

2096-5192/© 2024 China Geology Editorial Office.

2003; Duman TY et al., 2005; Xu C et al., 2015; Zhong C et al., 2020). However, this method is inefficient for making landslides over large areas because (1) it requires much time, materials, and labor; (2) it is not possible to accurately identify all parts of a landslide where the terrain is mounded hills and where vegetation is tall or dense (Hu Q et al., 2019). Since the advent of remote sensing, visual interpretation remains the most common method for identifying landslides and producing maps (Zhong C et al., 2020). Initially, aerial photographs were the primary data source (Carrara A et al., 1991; Coe JA et al., 1997), followed by satellite remote sensing imagery (Xu C et al., 2014; Shao XY et al., 2019; Huang YD et al., 2021), which requires human-computer interaction by trained professionals and is overall expensive and time-consuming despite the high accuracy of visual interpretation.

With the continuous development of advanced earth observation technology in remote sensing, hyperspectral image data with high spatial resolution and free satellite data availability provide potent data support for rapid and comprehensive target assessment (Chacón J et al., 2006; Hong Y et al., 2007), and have been used for natural disaster monitoring (Poursanidis D and Chrysoulakis N, 2017) and global climate change (Yang J et al., 2013). Among them, NASA researchers have calculated the global distribution of rainfall-triggered landslides from 1950 to the present based on time series remote sensing imagery and media information (Fig. 1). To effectively utilize the delicate feature information carried by remote sensing images, many efforts have been made to "automate" remote sensing image interpretation to accomplish landslide identification, which is roughly divided into (1) pixel-based landslide identification; (2) object-oriented landslide identification analysis; (3) machine learning-based models.

Pixel-based landslide extraction is based on the principle that landslides have different spectral information in different bands, and landslides are extracted by pixel-level statistical

operations. It mainly consists of change detection (Zhao W et al., 2017; Lu P et al., 2021) and threshold setting (Postance B et al., 2018). Object-oriented image analysis (OBIA) clusters landslides into networked homogeneous objects based on the assumption that neighboring pixels belong to the same class, and identify landslides by maximizing their shape, statistical, spectral, and textural features (Duman TY et al., 2005; Moosavi V et al., 2014). However, in the face of high spectral variance, the above methods lead to increased intra-class variability, which reduces accuracy (Woodcock CE and Strahler AH, 1987). In addition, OBIA requires users to select features for different data, which usually requires significant human interaction and expertise (Stumpf A and Kerle N, 2011; Li ZB et al., 2016).

Machine learning aims to automatically learn meaningful relationships and patterns from instances and observations without making assumptions about the distribution of the data (Maxwell AE et al., 2018; Yang ZQ et al., 2022). Commonly used methods include (1) support vector machines (SVM) (Noble WS, 2006); (2) single decision trees (DT) (Song YY and Lu Y, 2015); (3) random forests (RF) (Breiman L, 2001); (4) artificial neural networks (ANN) (Abiodun OI et al., 2018); (5) logistic regression (LR) (Nick TG and Campbell KM, 2007). Extensive studies have generally found that machine learning-based landslide extraction models are more accurate and less time-consuming when dealing with complex data with a high-dimensional feature space (Micheletti N et al., 2014; Wang HJ et al., 2021; Tehrani FS et al., 2022). However, as the amount of image information increases, high-dimension features often lead to model overfitting or the introduction of noise, resulting in degradation of performance (Assilzadeh H et al., 2010; Hu Q et al., 2019).

The surge of high-resolution and hyperspectral imaging sensors has caused earth observation data to be characterized by four "V's": volume, variety, velocity, and veracity (Chi MM et al., 2016; Liu P et al., 2018; Li YS et al., 2021), which has prompted researchers to realize the importance of mining

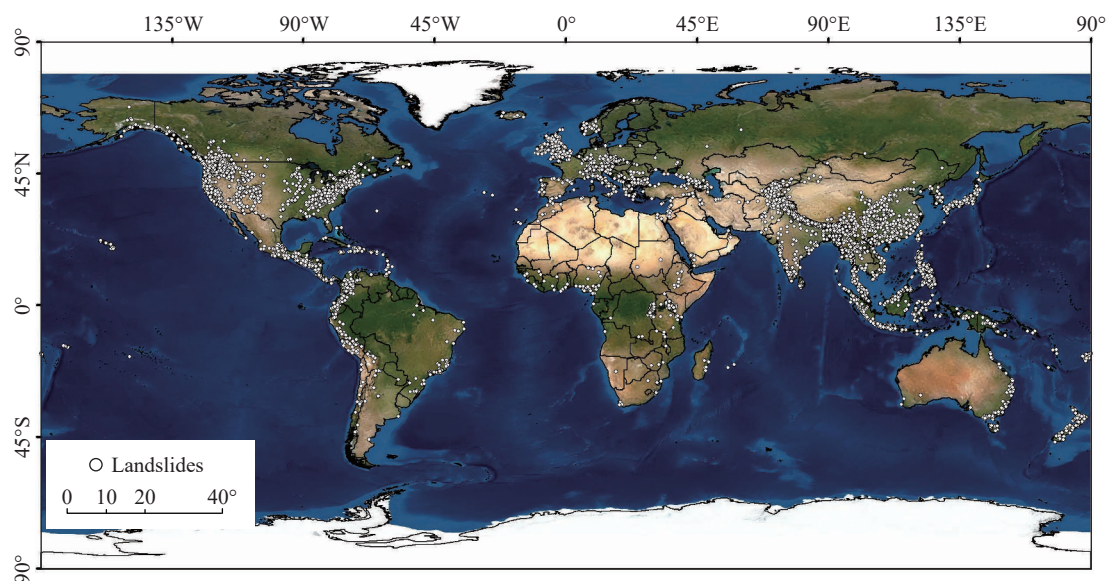


Fig. 1. Global landslide catalog points collected by NASA (detailed information found in the website <https://maps.nccs.nasa.gov/>).

earth big data gradually (Zhang X et al., 2021). In recent decades, artificial neural networks have made great progress, gradually evolving into deep architectures with stronger learning capabilities, collectively known as deep learning (Ball JE et al., 2017; Zhu XX et al., 2017). Deep learning networks with a hierarchical structure can automatically transform raw data into higher-level representations, gradually attracting the interest of geohazard researchers and began to be applied in various landslide analyses (LeCun Y et al., 2015; Cheng G et al., 2020; Janiesch C et al., 2021). When focusing on landslide making, the role of deep learning is to extract landslide-related pixels from the complex background information in the imagery, which tends to have different morphological characteristics, and in the worst-case scenario, the landslides are very small and difficult to distinguish compared to the background objects, as shown in Fig. 2.

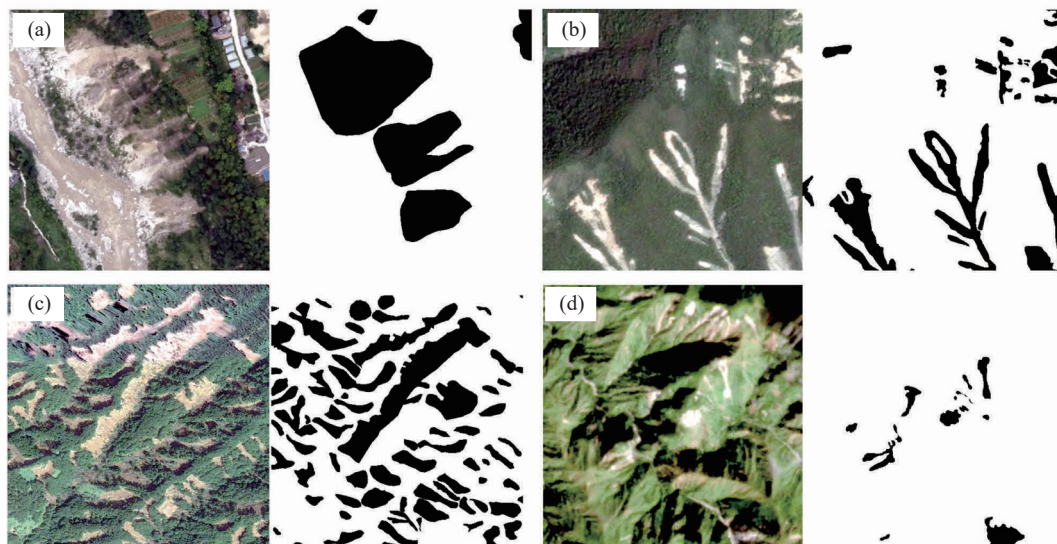
In this work, a comprehensive examination of landslide-making through the utilization of deep learning techniques alongside multi-source remote sensing data is offered. Unlike previous studies, which primarily focused on analyzing landslide mechanisms and employed machine learning algorithms for predictive purposes, our work delves deeper into the intricacies of algorithm selection and optimization. By meticulously comparing the structural characteristics of various deep learning algorithms, this study provide a nuanced understanding of their applicability in landslide detection tasks. Furthermore, this study not only identifies the prevailing challenges encountered in integrating deep learning into geohazard analysis but also proposes innovative solutions to address them. This distinct approach distinguishes the work as a pioneering endeavor in advancing the field of landslide detection and mapping through the lens of deep learning methodologies. The main contents include (1) describing the construction of our literature database; (2) introducing the background of typical deep learning frameworks; (3)

analyzing the practical applications and advantages of various deep learning models in landslide detection; and (4) discussing the challenges and prospects of deep learning in landslide analysis.

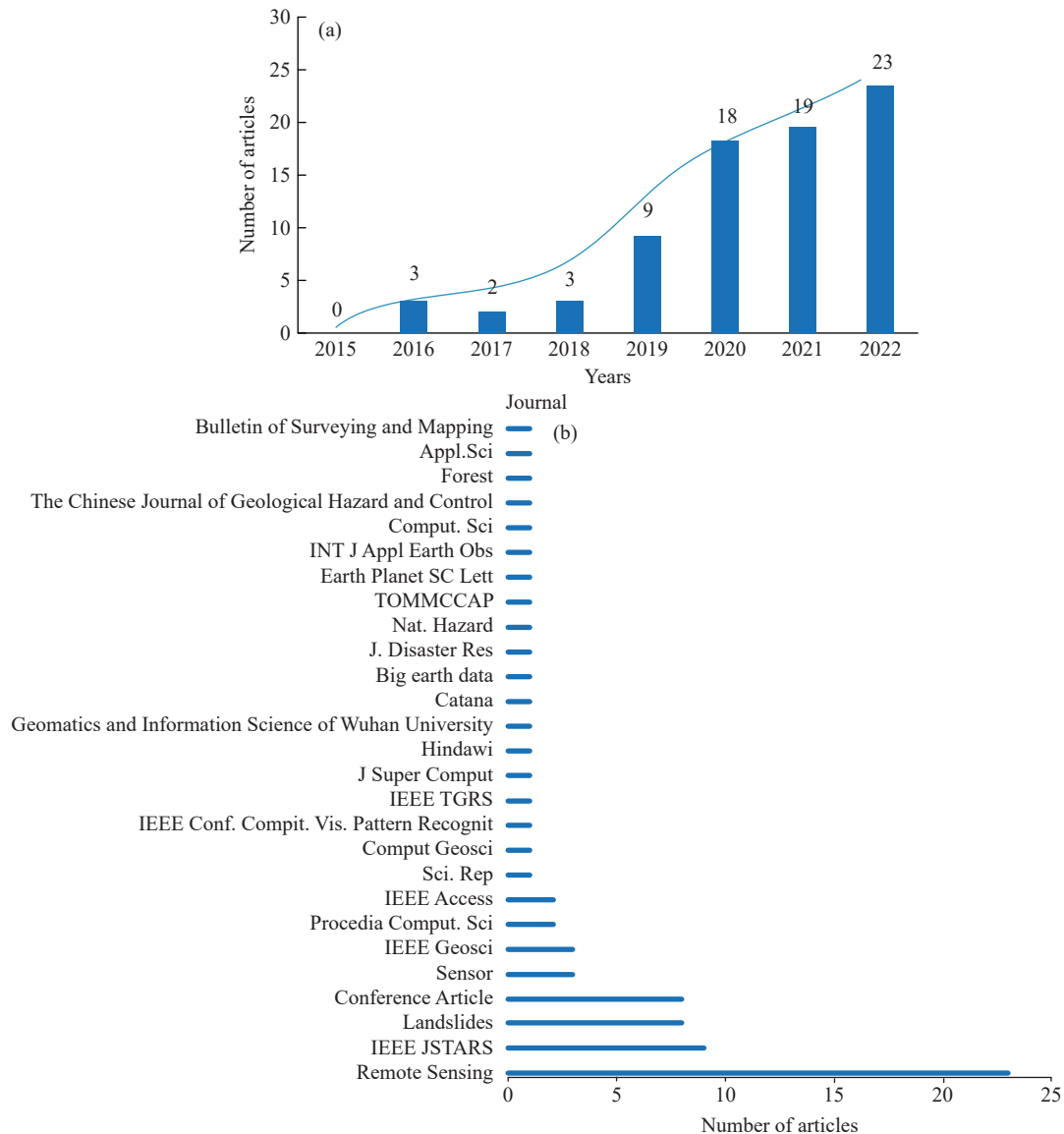
## 2. Literature selection and database construction

Considering the development context of deep learning, we set the publication period from January 2015 to September 2022 to sort out all the slippery slopes based on deep learning considerations as much as possible. We first considered our previous relevant research articles in constructing the literature database. Then we searched the peer-reviewed articles in the core collection of the “Web of Science” online platform using keywords and Boolean search terms AND, OR, NOT, SAME, NEAR, applied to “title,” “abstract,” and “subject” (Huang YD et al., 2022). The keywords we used were “Landslide”, “Slope”, “Failure”, “Detection”, “Identification”, “Recognition”, “Extraction”, “Deep learning”, and “CNN” (Ma ZJ and Mei G, 2021; Mondini AC et al., 2021). It is worth mentioning that in the following, we will not make a distinction between identification, recognition, extraction, and detection, all these terms represent one thing.

By setting multiple combinations of repeated searches, a total of 127 candidate articles were identified through iterative searches utilizing various combinations of keywords. Subsequently, each article's title, abstract, and keywords were meticulously scrutinized, resulting in the exclusion of irrelevant publications, including 22 review articles and patents. The final literature database comprises 77 articles published in diverse peer-reviewed journals spanning from January 2015 to September 2022, including 69 articles in academic journals, mainly published in 26 international journals. 8 articles were published in academic conference



**Fig. 2.** Morphology of landslides in remote sensing images in different regions and corresponding manual labels. Landslides in different areas show significant differences in remote sensing images. a-Coseismic landslides triggered by the 2022  $M_S$  6.2 Luding (Sichuan, China) earthquake; b-2013 rainfall-triggered landslides in Tianshui (Gansu, China); c-Coseismic landslides triggered by the 2018  $M_W$  6.6 Iburi, Japan earthquake; d-Coseismic landslides  $M_S$  8.0 Wenchuan (Sichuan, China) earthquake.



**Fig. 3.** Literature database information. a–Number of articles published per year from 2015.1–2022.9; b–name of the journal in which the literature was published.

journals. As seen in Fig. 3, the number of articles published per year is increasing, with the highest growth rate in 2022. In addition, 30% of the articles were published in Remote Sensing, 12% in IEEE Journal of selected topics in applied earth observations and remote sensing, and 10% in Landslides. The first conclusion we draw is that although deep learning has been gradually developed and applied to simple classification and feature extraction tasks before 2015 (Fakoor R et al., 2013; Sun Y et al., 2014), it is not sufficient to perform landslide extraction tasks with its performance, mainly because (1) the shallow structure of the network is not sufficient to extract complex landslide feature information; (2) statistical learning methods such as machine learning can largely satisfy the landslide mapping requirements; (3) deep learning models have not spread from the computer domain to the earth science domain.

To further characterize our controlled studies in detail, we selected three main categories of information, namely: (1) Factors triggering landslides, (2) types of deep learning

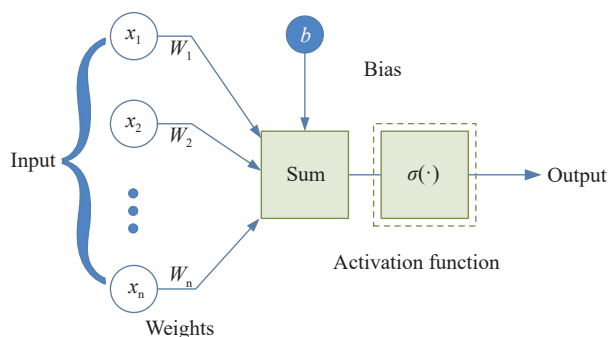
models, and (3) types of data. The authors found 41 research articles that do not explicitly provide information on the primary landslide event triggers. However, it is safe to assume that landslide morphology is clearly distinguished from background information, with 19 articles designing extraction models for earthquake-induced landslides. Nine articles focus on extracting rainfall-induced landslides. Six articles aim to extract landslide morphology in loess areas, and only two articles address landslide distribution on the national scale. Regarding the deep learning network models adopted, 79% of the landslide extraction models used convolutional neural networks as the main framework, and 12% of the models used an object detection framework to identify landslides, which are the two most dominant deep learning models adopted in the related literature in the last eight years. As for the data type, nearly 45 articles used only RGB-band image data, the most common and easily accessible satellite image data. Thirty-one articles introduced topographic and geomorphological factors in addition to the visible band. The

authors further found that 77% of the studies provided information about DEM and SLOPE, which proved essential for discriminating landslide development patterns and locations (Dai FC and Lee CF, 2002; Saha AK et al., 2005). Only three researchers explored the ability to extract landslides from all-weather radar imagery data to address the issue that hyperspectral imagery is susceptible to severe weather conditions. Overall, we believe that the landslide feature information used in almost all articles is limited. The authors recommend that more accurate information be provided when presenting the results of landslide detection and making studies. We also found that less than 10% of the studies provided information on image pre-processing methods for the input imagery. The authors attribute this low percentage to the fact that most of the articles were written by researchers who were not specialists in the direction of professional remote sensing but rather geologists or cross-disciplinary research scholars. Ultimately, all models were validated by comparing them with accurate manually drawn landslide distribution maps. This is the only way so far, indicating that landslide extraction models need manually annotated data to evaluate their performance even unsupervised models.

### 3. Types of deep learning algorithm

In this section, the authors provide a brief overview of deep learning and outline 6 typical deep learning models for geohazard analysis. These models can be divided into three types: (1) convolutional neural network; (2) object detection model; (3) deep generative model.

Deep learning originated from artificial neural networks (Janiesch C et al., 2021). Usually, ANN consists of a set of connected neurons that propagate through a neural network with a few nonlinear activation functions and parameters (LeCun Y et al., 2015). In each layer, the input is obtained by a linear transformation of the previous layer, and the output is converted into a nonlinear expression by the activation function (Fig. 4). The series of layers between the input and output are called hidden layers (Ma ZJ and Mei G, 2021). Theoretically, the more parameters, the higher the complexity of the model and the larger the capacity, which means it can simulate more complex expressions. However, the training of

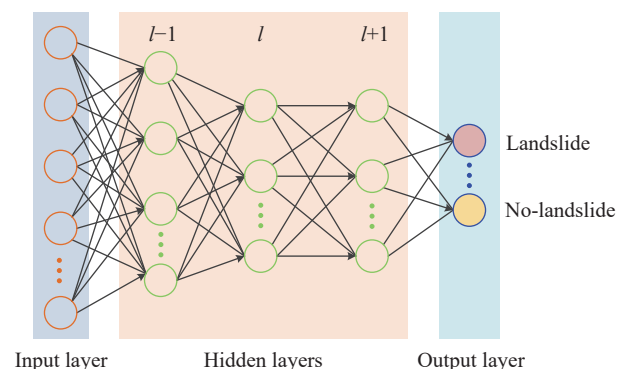


**Fig. 4.** Process of forward propagation of artificial neural networks. All inputs transformed by linear transformation and fed into activation functions converting to nonlinear expressions as outputs.

complex models is prone to overfitting (Ball JE et al., 2017; Cheng G et al., 2020). With the advent of cloud computing and big data, computing power can significantly alleviate the inefficiency of the movement, and the significant increase in training data can reduce the risk of overfitting (Mohan A et al., 2021; Yang ZQ and Xu C, 2022). As a result, complex models represented by deep learning are receiving more and more attention. Multiple fully connected neural networks forming a multilayer perceptron (MLP) is the simplest and most basic deep learning model (Fig. 5). For a fully connected deep neural network, The current layer is connected to all neurons in the previous layer (Gardner MW and Dorling SR, 1998), and the expression is shown as follows.

$$x(l) = \sigma(W(l) \cdot x(l-1) + b(l)) \quad (1)$$

The training process of deep learning follows an empirical risk minimization paradigm, where each parameter in the model is optimized by forwarding and backward propagation. The output in the forward propagation process is the difference between the true value and the predicted value based on a defined loss function (Yang ZQ and Xu C, 2022; Yang ZQ et al., 2022). In the backward propagation process, the gradient descent algorithm is generally used to update the model parameters and minimize losses. Generally, deep learning models are usually divided into two main categories, including supervised learning and unsupervised learning (Zhu XX et al., 2017). Supervised learning aims to learn a model that accepts labeled features as input and outputs predictions for the target variable. Unsupervised learning models the data directly and seeks to describe the input data by learning valuable attributes of the training set without labels. In recent years, deep learning-based models have been applied to geohazard extraction (Ghorbanzadeh O et al., 2019; Fang CY et al., 2022; Meena SR et al., 2022). Previous studies have proved that deep learning outperforms traditional machine learning under remote sensing extensive data conditions. In addition, transfer learning has gradually improved the deep learning training paradigm, which extends the application of deep learning models to specific tasks, making it possible to alleviate the problem of difficult-to-train models due to



**Fig. 5.** Structure of Multilayer perceptron. Each neuron connected to all neurons in the previous layer, and the final output is two classes characterizing landslide and no-landslide.

exogenous factors such as computer hardware performance and insufficient datasets.

### 3.1. Convolutional Neural Network

Convolutional neural networks can effectively capture abstract features from raw images. Recently, CNN has become one of the most successful and popular deep learning models due to its great flexibility in terms of local connectivity, weight sharing, and sparse connection (Simonyan K and Zisserman A, 2015; Ma ZJ and Mei G, 2021). Although it was initially designed for computer vision tasks. Typically, CNN consists of three layers, a convolutional layer, a pooling layer, and a fully connected layer (Fig. 6). Among them, the convolutional layer aims to extract features and enable the model to integrate features more effectively with spatial contextual information from the input data (Cheng G et al., 2020; Kattenborn T et al., 2021). Specifically, convolution is a simple linear process in which a convolution kernel of a specified size slides regularly over the input data in certain steps and computes the dot product between elements in that localized region to extract features. To reduce the number of learnable parameters and increase the robustness of the image, pooling layers are often used to down-sample the features extracted from the convolutional layer. The two main types of pooling layers are maximum pooling and average pooling (Yi YN and Zhang WC, 2020).

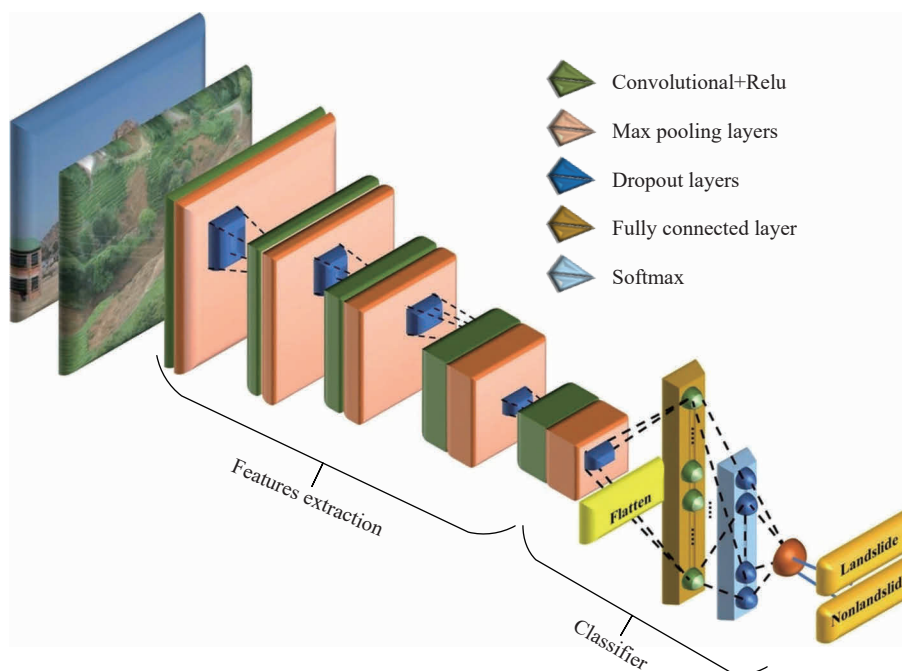
CNN has been applied to landslide detection in high-resolution images by researchers who are not specialized in computer science due to the popularity of computer courses and the development of the Internet (Yang ZQ et al., 2022). With its capability in high-dimension feature extraction, CNN-based models such as VGG, ResNet, and DensNet, have

shown outstanding advantages in various applications of geohazard identification (Liu T et al., 2021). Among them, VGG is the most basic network used for feature extraction, which reduces parameters by employing smaller convolutional kernels, and is usually embedded in different networks as the backbone (Li C et al., 2021); ResNet contains a series of residual blocks that can solve the gradient disappearance problem and allows training intense networks of up to one thousand layers, which is an important reason why different CNN variants have broken the user limit on image classification and segmentation in recent years (He KM et al., 2016); Compared to ResNet, DenseNet proposes a dense connectivity mechanism, where each layer is connected to all previous layers, thus enabling feature reuse and improving efficiency (Huang G et al., 2018).

On the other hand, an end-to-end trained convolutional neural network for semantic segmentation task is constructed based on a classification network by converting the fully connected layers into convolutional layers as shown in Fig. 7, called fully convolutional network (Long J et al., 2015). Its appearance opens up a new idea for semantic segmentation tasks. The advantages of FCN over classical CNN are: (1) Avoiding the loss of spatial information; (2) significantly reducing the computational parameters involved; and (3) increasing the representation capability. Therefore, FCN is more suitable for segmentation tasks. In recent years, many models based on encoder-decoder architecture have emerged to enhance the ability of FCN in the field of geohazard analysis (Yi YN and Zhang WC, 2020).

#### 3.1.1. U-Net

As the most common variant of FCN in geohazard analysis, U-Net was initially designed for medical images



**Fig. 6.** Typical convolutional neural network, the network implements feature extraction by stacking multiple convolutional layers, then the feature flattening fed into the fully connected layer as a classification result (modified from Hacıfendioglu K et al., 2021).

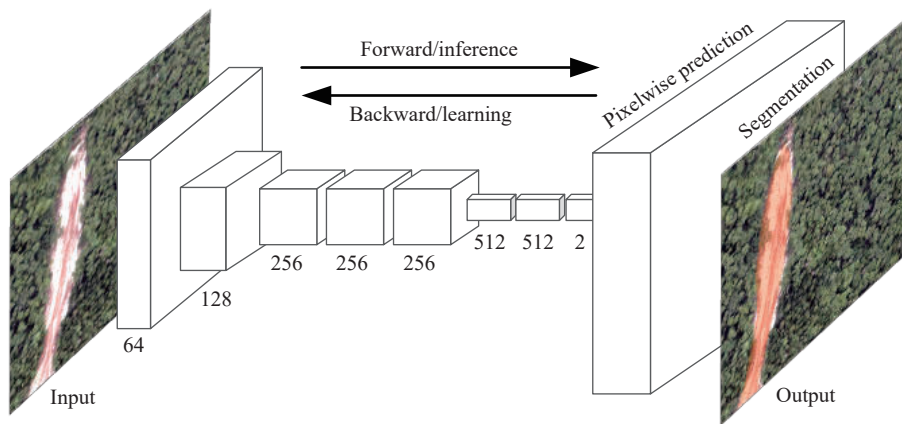
(Ronneberger O et al., 2015). The model has an encoder-decoder architecture similar to the U (Fig. 8), which is proposed to reduce the loss of feature and spatial location information during complete convolutional network pooling (Liu P et al., 2020; Soares LP et al., 2020). U-Net architecture consists of a systolic path (encoder) for capturing low-level representations and an extended path (decoder) for reproducing high-level representations. Specifically, the systolic path gradually reduces the spatial dimension for deeper feature information, whereas the extended path receives information from the encoder part by using jump connections to achieve more refined localization (Su ZY et al., 2021).

In the model, the input image is transformed into a high-

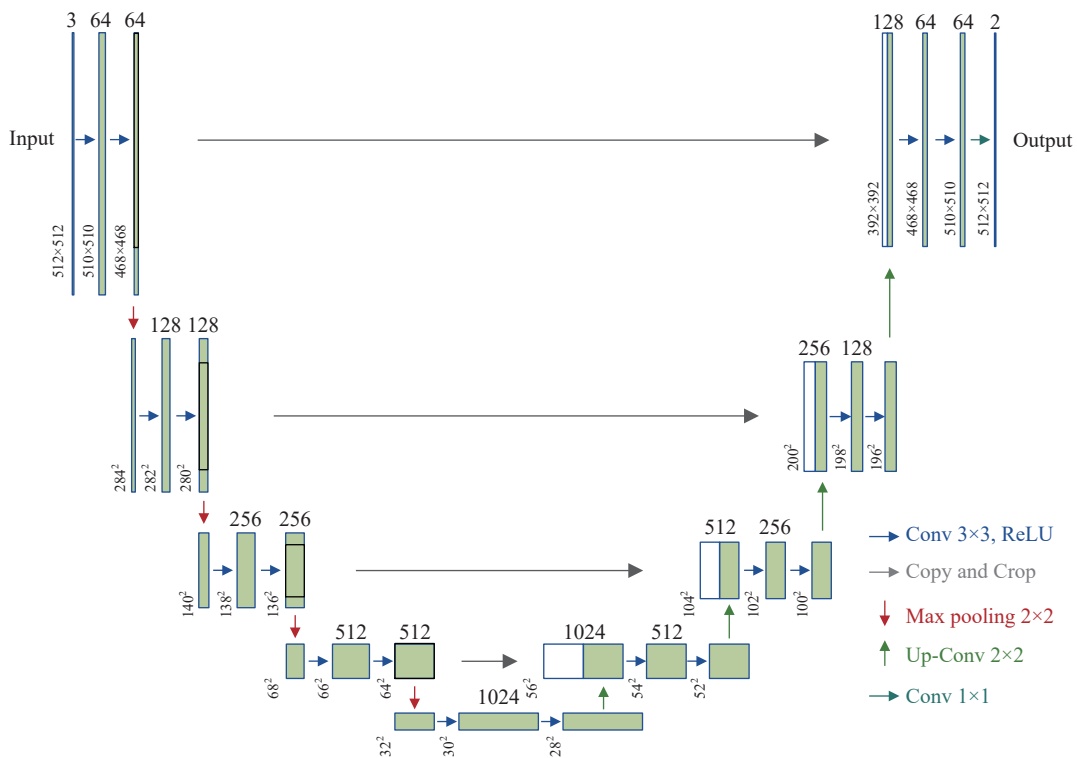
dimensional feature map by successive down-sampling and then recovered to a feature map with the exact resolution as the original image by the same number of up-sampling. Each layer has a hopping operation that ensures that features from different layers can be efficiently transferred to the final feature map (Bragagnolo L et al., 2021). In the last layer, a sigmoid function outputs category predictions in the 0-1 probability range. Overall, the U-Net architecture enhances the fine-grained aggregation details from the encoder path to the corresponding layer in the decoder path by skiing the connection between the encoder and decoder paths.

### 3.1.2. ResNet

Usually, deep learning-based models with deeper layers



**Fig. 7.** Typical structure of a fully convolutional network. The feature map restored to the same size as the input in the final by up-sampling to achieve pixel-by-pixel classification.



**Fig. 8.** Structure of U-Net. The network has a symmetric structure, the encoder layer achieves feature extraction by continuously deepening and narrowing the feature map, and the decoder layer achieves pixel-by-pixel classification through an inverse process.

have better performance but also lead to model degradation. To address this issue, the combination of the concept of residual representation with CNN models was proposed to form a block structure with residual learning, thus constituting a residual learning network to resolve model degradation issues (He KM et al., 2016). The core of this structure is to superimpose a residual function-making layer on top of the shallow network, which helps to backpropagate the gradient and solve the gradient disappearance problem by establishing shortcuts between the front and back layers so that the network can be trained to improve accuracy (Konishi T et al., 2019; Lei T et al., 2019; Ghorbanzadeh O et al., 2022). The expression of the residual learning block is as follows.

$$y = F(x_i) + x_i \tag{2}$$

where  $x_i$  and  $y$  are the input and output vectors of the  $i$ -th residual block under consideration, and the function  $F(x_i)$  denotes the residual making to be learned. As shown in Fig. 9, the residual block consists of three convolutional layers and a shortcut connection, and the output of each residual block is added to the stacked convolutional layers and output. Overall, ResNet ensures that the input information can be fully propagated between all layers by using a shortcut.

ResNet can effectively avoid gradient loss or explosion when its network becomes very deep. As a landmark network in landslide mapping, its mathematical theory is not complicated, but it has advanced the generation of abundant networks. Many researchers have demonstrated the advantages of ResNet in image information feature extraction (Qi WW et al., 2020; Yi YN and Zhang WC, 2020; Yang ZQ et al., 2022).

### 3.1.3. DenseNet

DenseNet is an innovation of ResNet, the basic idea is as

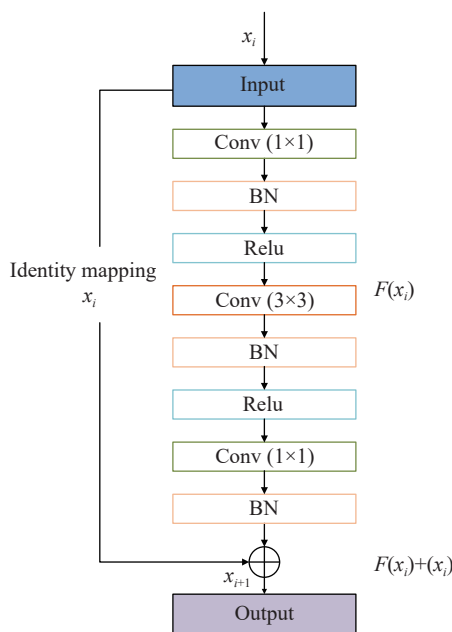


Fig. 9. Structure of residual block. The final output convolved and summed with the original inputs.

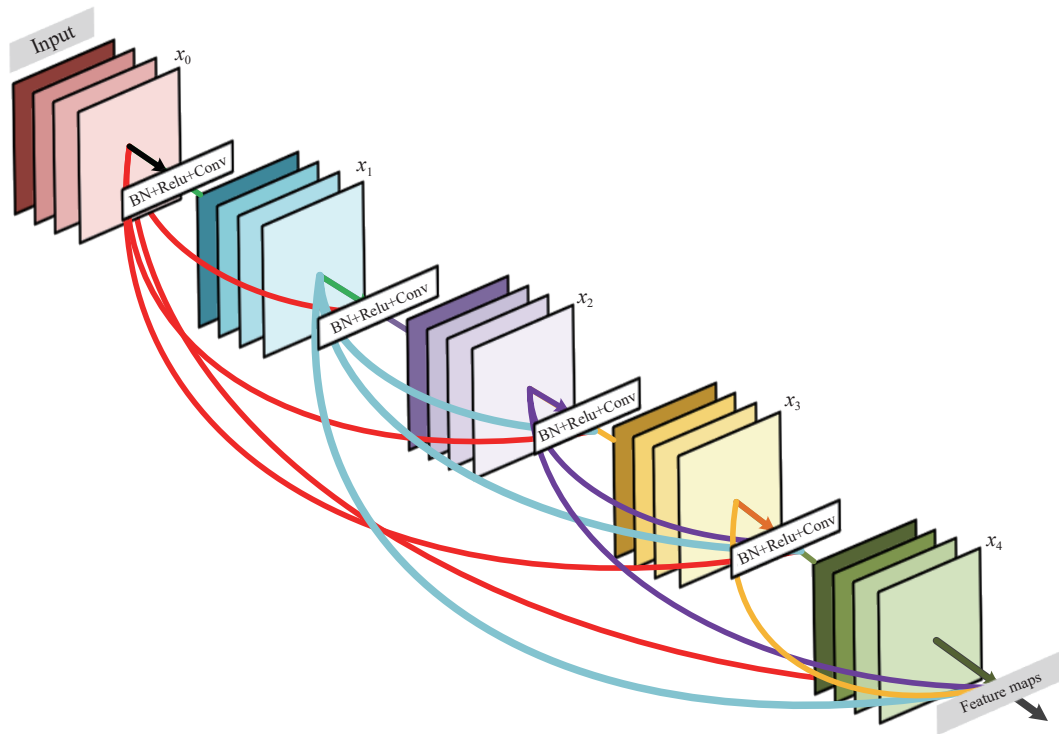
same as ResNet. By establishes a dense connection between all the previous layers and the last layers to ensure that information can be transferred between layers (Huang G et al., 2018). Another advantage of DenseNet is feature reuse by connecting features on channels, which reduces the number of parameters. These characteristics allow DenseNet to perform better than ResNet with fewer parameters and computational costs, optimizing the information flow and gradients across the network (Li C et al., 2021; Liu T et al., 2021). In addition, DenseNet layers are narrower than other networks and can reduce redundancy by introducing fewer feature maps for learning (Fig. 10).

DenseNet consists of a dense block and a transition layer, the former consists of a normalization layer, activation function, and convolution layer, the latter connects two adjacent dense blocks, which facilitate the feature maps and gradients transferring efficiently between dense blocks. Besides, DenseNet can reduce the number of parameters by using dense blocks. Due to the modification of transfer ways for information and gradient, it is highly resistant to overfitting. Moreover, it can be trained effectively even if the samples are relatively insufficient because the connected dense blocks have a regularization effect (Zhang JM et al., 2019).

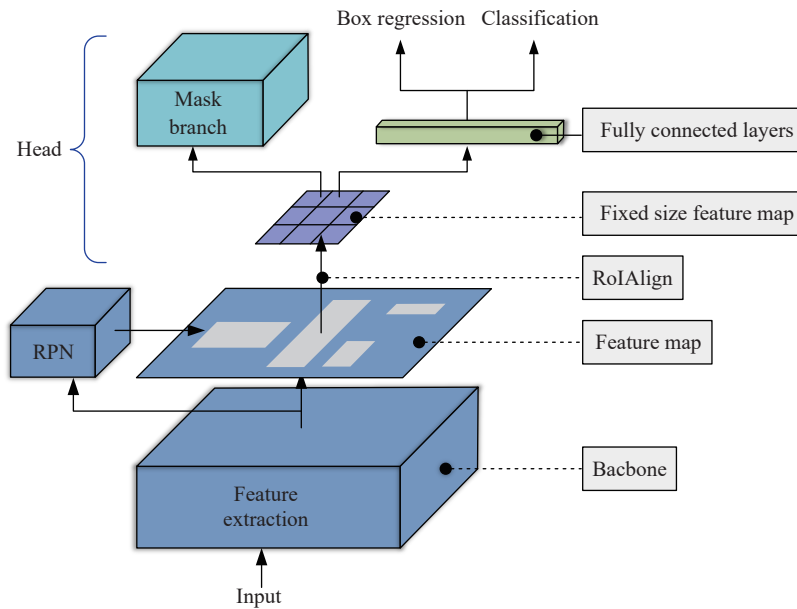
### 3.1.4. Mask R-CNN

Object detection models generally consist of object classification and target localization, called R-CNN. The network extracts the potential target frames via training and filtering based on image features, and then the category of the target frames is obtained through the object classification, which is achieved by converting feature maps into category probabilities through the classification layer. At the same time, the boundary locations of the target frame are generated by target localization, which is achieved through the precise regression of the target frame (Ma ZJ and Mei G, 2021; Mohan A et al., 2021). In landslide mapping, object detection can complete the classification and localization tasks of landslides in stages, the former refers to distinguishing landslides and the latter is to obtain the external rectangle of the landslide boundary (Yao GL et al., 2022). In the object detection task, the most commonly used network structure is Mask R-CNN, which is an extension of Faster R-CNN with adding a parallel branch to the existing bounding box to predict the mask for instance segmentation (He KM et al., 2018; Ju YZ et al., 2022; Liu Y et al., 2022).

Mask R-CNN is a flexible framework with many improvements proposed, which are derived from Faster R-CNN and FCN (Fig. 11). Different tasks can be applied in Mask R-CNN with different branches embedded. It can accomplish a variety of tasks (Bharati P and Pramanik A, 2020). In the network, the FCN is added on the head of the original Faster R-CNN to generate the corresponding mask branches. Mask R-CNN consists of two phases, In the first phase, network generates proposals regions that may contain



**Fig. 10.** Structure of DenseNet (modified from Huang G et al., 2018). The network consists of 5 layers of dense blocks. Each layer takes all preceding feature maps as input.



**Fig. 11.** Structure of Mask R-CNN. The final result has three branches including box location, classification, and semantic segmentation.

targets by region proposal networks (RPN), and then classifies the proposals and generates bounding boxes and masks in the second phase (Anantharaman R et al., 2018; Fu R et al., 2022). Besides, Mask R-CNN proposes an ROI Align method to solve the region mismatch problem in Faster R-CNN (He KM et al., 2018; Liu J and Li PF, 2018; Zhu GH et al., 2020). Considering the fixed structure of the framework, fewer studies use the R-CNN series of models for landslide mapping, so here we aim to provide a brief overview of the Mask R-CNN context.

### 3.2. Deep Generative Models

Generative models are an effective way to learn different data distributions in unsupervised learning. All generative models aim to learn the actual data distribution of the training set so that new data with some variation can be generated further, considering that it is not always feasible to learn the exact distribution of data implicitly or explicitly. Hence, generative models are applied to learn a function that approximates the model distribution to the actual distribution

(Salakhutdinov R, 2015). Specifically, the deep generative model finds and expresses the probability distribution of the data where only the unlabeled data is inputted (Nalisnick E et al., 2019). In addition to generating data, it can be used for semi-supervised learning. For example, the model is first trained with unlabeled data to extract features, then the model is trained with the labels to reduce time. Specific deep generative models include restricted Boltzmann machines (RBM), deep belief networks (DBN), autoencoders (AE), generative adversarial networks (GAN), etc.

3.2.1. Deep belief networks

Deep Belief Network can be used not only to identify features and classify data but also to generate data (Hua YM et al., 2015). It consists of a restricted Boltzmann machine stack (Fig. 12a). The RBM is composed of a two-layer network: (1) The hidden layer  $h$ ; (2) the visible layer  $v$  where the visible layer processes the input data and the hidden layer encodes the data by downscaling and various data coding mechanisms (Larochelle H et al., 2012; Sohn I, 2021). In DBN, each pair of two layers can be considered an RBM (Fig. 12b). This learning strategy allows DBN to automatically extract increasingly abstract representations from large amounts of unlabeled data. Unlike most deep learning models, DBN replaces the loss function used for minimization with an

energy function during training. Thus, the goal of training is to determine the parameters that minimize the energy (Larochelle H et al., 2012; Zhang N et al., 2018). The energy function is defined by the equation

$$E(v, h) = - \sum_{i,j} v_i h_j W_{i,j} - \sum_i v_i a_i - \sum_j h_j b_j \tag{3}$$

where the input data is multiplied by the specified weight  $W$ , the input value plus a deviation  $b$ , and  $i$  denotes the  $i$ th visible cell, and  $j$  denotes the  $j$ th hidden cell,  $v_i$  and  $h_j$  denote the state of the corresponding visible and the hidden neurons.

DBN exhibits the following advantages: (1) Avoids the gradient disappearance problem; (2) avoids the problem of overfitting and underfitting, and enhances the model’s generalization; (3) fast training speed and low computational complexity. In recent years, the excellent feature extraction capability of DBN has been successfully applied to extract more essential features from remote sensing images (Long LJ et al., 2021; Ma ZJ and Mei G, 2021).

3.2.2. Autoencoders

Autoencoders are a standard generative model that can reveal latent features without any labeled data and have an excellent performance in denoising data (Liou CY et al., 2014; Meng QX et al., 2017). As shown in Fig. 13, AE

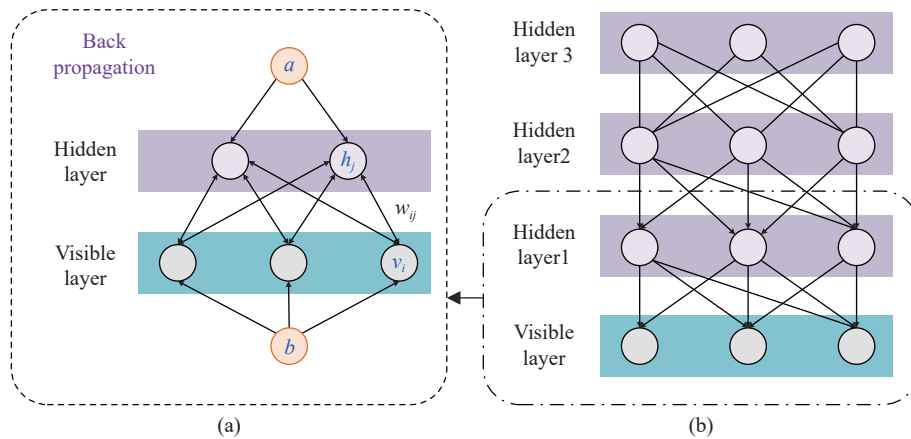


Fig. 12. a–Structure of restricted Boltzmann machine; b–deep belief network, network extracts and reconstructs of input features by stacking multiple RBM.

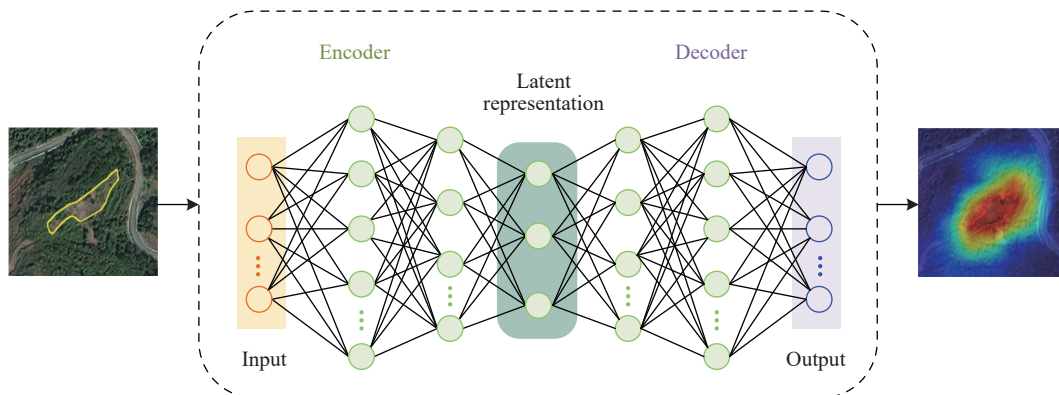


Fig. 13. Structure of Autoencoder, where the encoder projects the high-dimensional inputs into low-dimensional hidden variables thus learning the most features; the decoder restores the hidden variables to the initial dimensions.

typically consists of an encoder and a decoder connected by a hidden layer. The encoder compresses the high latitude information into the hidden layer, while the decoder can reproduce the data (Tschannen M et al., 2018).

Specifically, the self-encoder first converts the input information into a low-dimensional representation and then reconstructs the initial input information using the low-dimensional representation in the decoder part.

$$h = \sigma(Wx + b) \quad (4)$$

$$x' = \sigma'(W'h + b) \quad (5)$$

The versatility of AE depends heavily on the design of the encoder and decoder networks. For example, the encoder and decoder can be MLP, RNN, or CNN. To this extent, it extends the applicability of AE-based models in the face of different tasks. Besides, since the autoencoder can extract useful features from unlabeled data, depth-generating models with autoencoder have been introduced into current geohazard analysis (Amit SNKB et al., 2016; Qin SW et al., 2021). Finally, since the AE has significant advantages in dealing with label imbalances in the dataset, which are common in geohazard-related tasks, it is eminently appropriate for generating models with excellent generalization capabilities when addressing the case of only small samples of landslides.

#### 4. Deep learning-based landslide detection approach

This section focuses on applying deep learning algorithms in landslide hazard extraction over the past nearly seven years. Based on the generalization in section 2, the authors briefly outline four typical ways in which deep learning is applied: (1) semantic segmentation using post-landslide images; (2) change detection using pre- and post-landslide image data; (3) object detection using spectral and spatial information; (4) unsupervised learning for mitigating limited samples; (5) fusion algorithms. These models are designed to address specific problems in the general workflow of landslide analysis, as shown in Fig. 14.

##### 4.1. Classification and segmentation using post-landslide images

The earliest deep learning-based models extracted features of monolithic landslides with only a small subset of convolutional layers (Yu H et al., 2017). To suppress the influence of image noise, Bui T et al. (2019) implemented a two-dimensional empirical modal solution to refine the convolutional features in the image preprocessing stage. Ghorbanzadeh O et al. (2019) first verified the superiority of CNNs over machine learning algorithms and discussed the effects of image size and sampling methods on the model (Ghorbanzadeh O and Blaschke T, 2019). Apart from remote

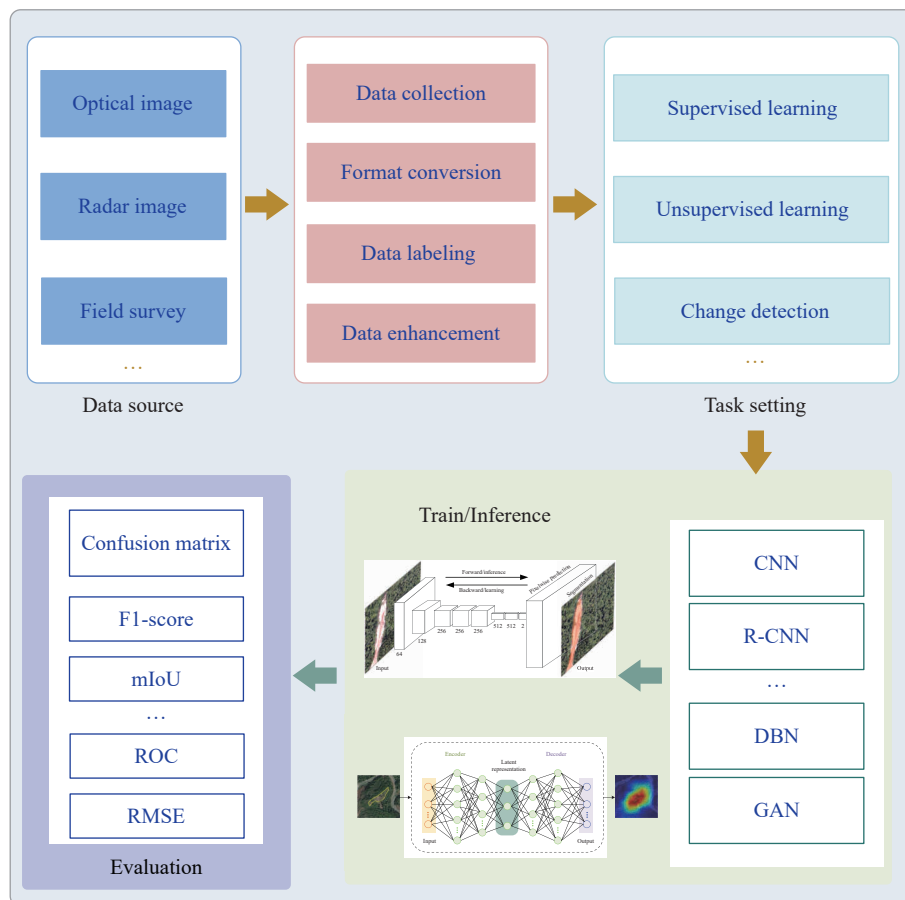


Fig. 14. A general workflow of deep learning application for landslide analysis.

sensing imagery, Catani F (2021) used a convolutional neural network to perform fast landslide classification on social media images, and the results can contribute to landslide early warning. Considering the limited information carried by single imagery, researchers have attempted to enhance the feature information by introducing topographic data into the samples (Sameen MI and Pradhan B, 2019; Ghorbanzadeh O et al., 2021). In addition, the combination of Synthetic Aperture Radar (SAR) imagery was shown to enable highly accurate landslide identification under severe weather conditions (Nava L et al., 2022). It is noteworthy that, according to the literature database, Yu et al. were the first to apply convolutional neural networks to the task of landslide extraction at the national scale (Yu B et al., 2020). On the other hand, since data-driven deep learning models require data volume, Ji SP et al. (2020) produced the first open large-scale landslide dataset based on TripleSat satellite imagery. Ghorbanzadeh O et al. (2022) generated a reference benchmark for accuracy comparisons for landslide detection tasks and named it Landslide4Sense, a repository that contains 3,799 images extracted from Sentinel-2 and combines optical information with elevation information.

Compared to utilizing a fully connected network to achieve classification, fully convolutional networks featured with end-to-end CNN were shown to be advantageous in landslide feature extraction and information restoration (Yi YN and Zhang WC, 2020). The FCN increases the versatility of the model structure, enabling the model to capitalize on the effective information of landslides at different feature scales (Fig. 15). As a typical fully convolutional network U-Net, with its unique U-shaped structure that allows the model to take into account both deep and shallow landslide information and is capable of completing the stable training using a small number of samples (Bragagnolo L et al., 2021; Meena SR et al., 2022). In the U-shaped structure, the encoding and decoding layers serve as the landslide feature extraction and restoration parts, respectively, where different encoder structures significantly affect the performance of the model (Prakash N et al., 2020; Qi WW et al., 2020; Zhang PF et al., 2020; Catani F, 2021). Further, for different landslide types and images, the related work designed different network structures based on the U-Net structure, aiming at suppressing image noise and improving the fine-grainedness of feature maps (Fang CY et al., 2022; Yang ZQ and Xu C, 2022; Yu B et al., 2022). Besides, some research studies focused on the

model generalization ability and evaluated the robustness of the U-Net structure in different geological environments (Ghorbanzadeh O et al., 2021; Soares LP et al., 2022). To address the problem that the shallow features could not be adequately extracted in the encoder layers, Liu P et al. (2020) fused three new bands to the samples and embedded residual units in the network. Interestingly, Schönfeldt E et al. (2022) found that U-Net performs better in extracting optical image features. Huang J et al. (2022) designed a network containing different feature extraction branches aiming to efficiently utilize both optical and terrain features through a feature fusion module.

As another commonly used semantic segmentation feature extraction structure, DenseNet also shows a unique prediction ability in landslide hazards. It can alleviate the dilemma of sparse samples and inefficiency faced by deep learning in landslide detection and has the advantages of fewer model parameters and faster convergence (Cai H et al., 2021). Furthermore, in the study of Liu T et al. (2021), ResNet and DenseNet structures were used to extract landslide sample features consisting of RGB and nineteen terrain factors, and the experimental results confirmed the advantages of DenseNet in accurately detecting landslides. Besides, Li C et al. (2021) investigated several FCN networks, including VGG, ResNet, DenseNet, and U-Net. The results showed that larger sample sets can improve the performance of VGG, ResNet, and DenseNet, while deeper layers can improve the detection results of ResNet and DenseNet. Similarly, researchers can design different variants based on the DensNet network to efficiently integrate multi-scale features and contextual information (Xia W et al., 2021). In addition to U-Net and DenseNet frameworks, the DeepLab series and PSPNet have also been adapted for landslide mapping (Yang S et al., 2022).

#### 4.2. Change detection using pre- and post-landslide image data

Landslide detection can be considered as change detection due to the impact of landslide occurrence on the landscape. In recent years, change detection models based on deep learning can extract change pixels by directly superimposing the bitemporal remote sensing images without the need for artificial value thresholds as shown in Fig. 16. Because the specific change information extraction is directly derived

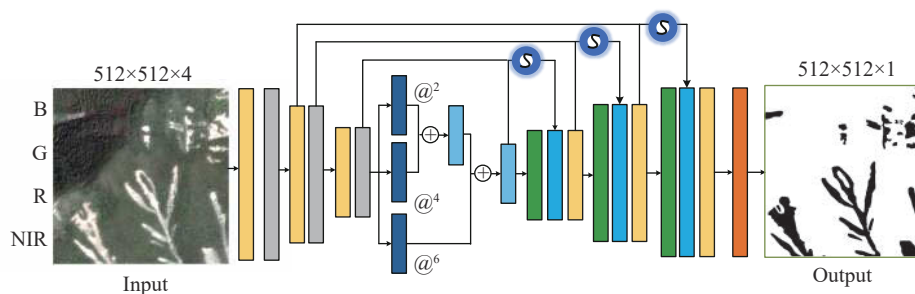


Fig. 15. Extraction of landslides in single images based on FCN (modified from Yi YN and Zhang WC, 2020).

from the autonomous learning and the step-by-step convolutional operation in the network (Amit SNKB et al., 2016; Ding AZ et al., 2016; Amit SNKB and Aoki Y, 2017). Further, Wang Y et al. (2019) attempted to add normalized difference vegetation index and near-infrared spectrum to the images to enhance landslide features. However, landslide detection that treats spatial information or topographic features in the diachronic phase independently usually performs poorly. Hence, Chen Z et al. (2018) designed deep convolutional neural networks to extract feature information and learn the robust representation of features, then the Manhattan distances between features are calculated to measure the degree of information change, followed by spatial-temporal scenario learning for candidate landslides extraction.

Another challenge in landslide change detection is the existence of severe spatial uncertainty in the landslide area, which increases the difficulty of extracting helpful landslide features from the images. To improve the accuracy of localization in landslide detection, Lei T et al. (2019) developed a deep learning model, which introduces a pyramid pooling module in multi-scale features fusion to capture a broader range of receptive fields, resulting in better localization and usage of context. In addition, to effectively reduce the impact of pseudo-variation caused by differences in phenology rather than landslide events, Lv ZY et al. (2020) developed a novel dual-path network that consists of two collaborative modules. The first module aims at reducing redundancy and simultaneously extracting abundant features from bitemporal images. The second module utilizes dense convolutional layers for joint learning, which can establish the relationship between the deep features and the ground reference. Moreover, Shi WZ et al. (2021) proposed a sample selection strategy for generating training datasets based on historical landslides to ensure data balance and constructed a dual-stream CNN to implement change detection, which reduces the requirement for training samples while ensuring model performance.

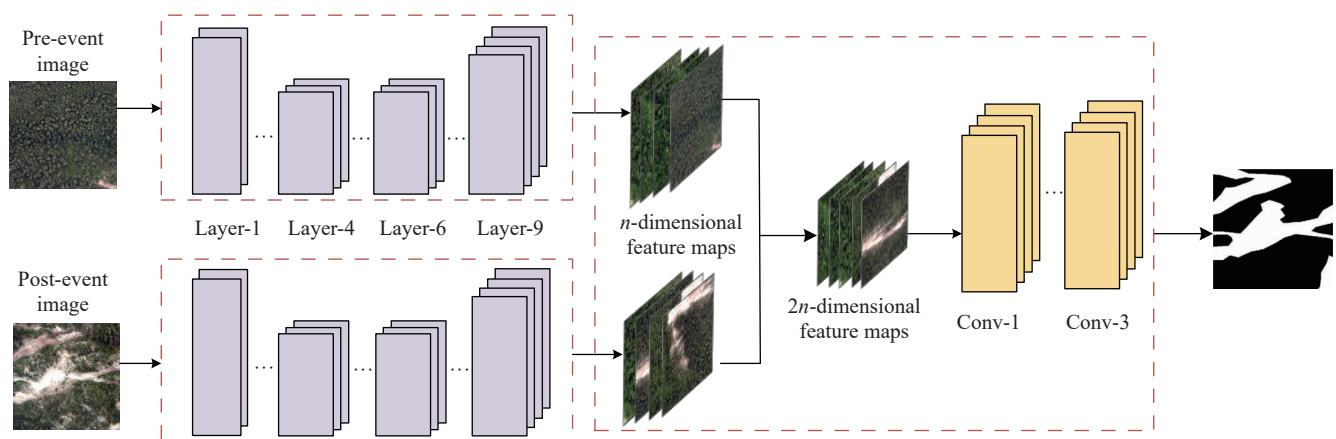
In deep learning-based change detection methods, U-Net and ResNet can also be used to extract information, which can

minimize information loss and thus enhance the representativeness of the network (Su ZY et al., 2021). In addition, related studies have shown that the introduction of bitemporal SAR data can alleviate the difficulty of rapid landslide mapping in the absence of optical images (Konishi T et al., 2019; Nava L et al., 2022). Although the above deep learning-based models have excellent performance in the landslide detection task, rigorous radiometric corrections are required to match image information accurately. To avoid this issue, Yu B et al. (2021) proposed a change detection method based on a two-branch Matrix SegNet, which requires only the Google Earth imagery to learn landslide features at multiple scales and aspect ratios.

#### 4.3. Object detection using spectral and spatial information

In the landslide mapping task, the final result of object detection includes classification, localization, and segmentation (Pang DD et al., 2022; Yao GL et al., 2022). For instance, Ullo S et al. (2021) employed Mask R-CNN for the automatic identification of loess landslides. The results indicated that the proposed model is a robust method for loess landslide mapping using Google Earth images as the data source (Fig. 17). Similarly, for loess landslides, Ju YQ et al. (2020, 2022) evaluated the detection performance of various object detection models with a small number of samples, including the one-stage algorithm RetinaNet, YOLO v3 and the two-stage algorithm Mask R-CNN. The results showed that Mask R-CNN obtained the highest accuracy.

Similarly, related researchers attempted to incorporate SAR information into the sample data, aiming to improve the accuracy of landslide identification. For example, Liu Y et al. (2022) designed a novel Mask R-CNN with ResNext integration, then the InSAR observations instance was patched and fed into the network to refine segmentation results and improve the model resilience to noise. Besides, Guo HJ et al. (2022) tested the feasibility of the YOLO model and SBAS-InSAR in detecting alpine landslides. Further, Cheng LB et al. (2021) designed an improved YOLO v4 model, aiming to increase the model inference speed by introducing an attention mechanism.



**Fig. 16.** Deep learning-based change detection, the two-branch network learns separate features for the pre-and post-event images, then stacks the two feature maps (modified from Lv et al., 2020).

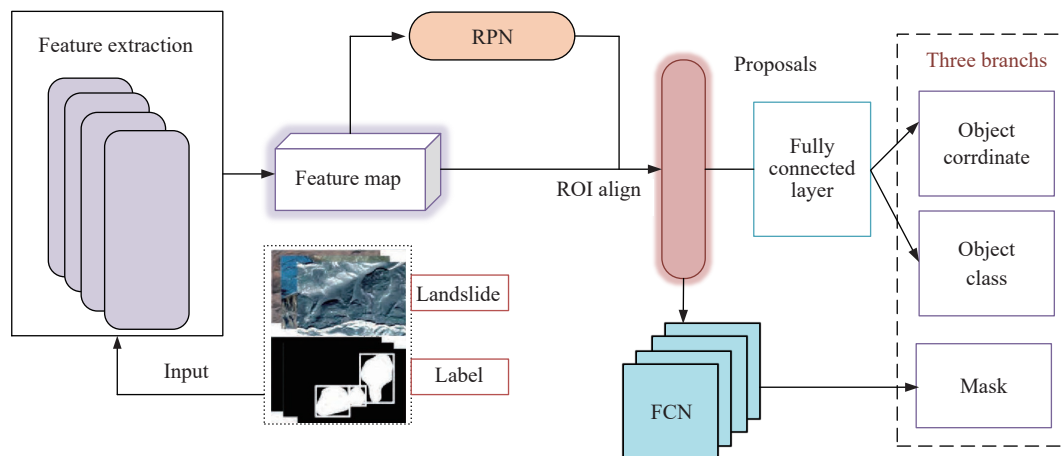
Interestingly, [Tanatipuknon A et al. \(2021\)](#) attempted to train two Faster R-CNN models simultaneously and extract features by inputting optical image and elevation information respectively. Considering that the effects of different feature extraction layers on the model performance have not been discussed in previous work, [Fu R et al. \(2022\)](#) explore the impact of feature extraction layers on model performance by selecting the swin transformer and ResNet series as the backbone for Faster R-CNN. Then, the trained models were deployed to different scenarios using transfer learning. The results indicated that the swin transformer adapted to capturing global semantic information outperformed others. In addition, [Shi Y et al. \(2022\)](#) explored a dual-tasks network combining semantic segmentation and object detection for loess landslide detection, and the results validated that the proposed model performs better capability with simultaneously conducting the landslide location and mask segmentation.

#### 4.4. Unsupervised learning for mitigating limited samples

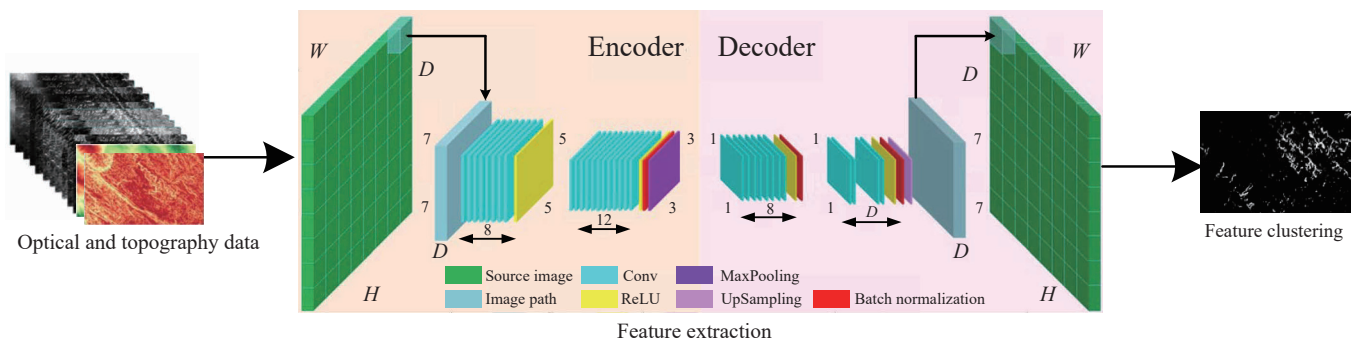
In recent years, various unsupervised deep learning models have been applied to landslide mapping, aiming to alleviate the demand for high-quality labeled samples. These models can fully exploit the high sparsity and nonlinear high-level features under unlabeled or less-labeled conditions. On

the one hand, the autoencoder structure as feature extraction can be employed as the encoder part of the unsupervised learning-based network for high-level landslide information dimension reduction, which then performs the classification of the landslides directly ([Liu Y and Wu LZ, 2016](#); [Shahabi H et al., 2021](#)). On the other hand, as shown in [Fig 18](#), the decoder part can be implemented with different structures to accomplish the downstream tasks, such as SVM, LR, and CNN ([Liu Y and Wu LZ, 2018](#); [Ye CM et al., 2019](#); [Long LJ et al., 2021](#); [Mabu S et al., 2021](#)).

Considering the high spectral heterogeneity of the ultra-high resolution (VHR) images renders sample labeling time-consuming, thus, related works have focused on mining multilevel representations in spatio-temporal images through semi-supervised or unsupervised networks to learn discriminative features to generate pseudo landslide labels ([Zhang XK et al., 2021](#)). Further, [Tang XC et al. \(2021\)](#) introduced multi-instance learning (MIL), aiming to extract landslide features as an instance which are then mapped to bag-level labels for reduction of dependency on labels. Moreover, [Zhou et al.](#) proposed a two-step method combining class activation maps (CAMs) and GAN to recognize landslides, where the former is allied for the initial landslide location, and the GAN is conducted to generate fake labels ([Zhou YX et al., 2022](#)). Finally, [He HQ et al. \(2022\)](#) proposed a semi-supervised GAN-based landslide mapping model,



**Fig. 17.** Landslide localization and delineation using Mask R-CNN, the network achieves pixel-by-pixel segmentation by adding a branch to Faster-RCNN (modified from [Ullo S et al., 2021](#)).



**Fig. 18.** A general framework of landslide mapping based on unsupervised learning, essentially a process of feature extraction and clustering without the participation of labels (modified from [Shahabi H et al., 2021](#)).

aiming to learn deep feature information and reduce the requirement of the number of labeled samples.

To address the rapid adaptability of the trained model in different study areas, Qin SW et al. (2021) designed a distant domain transfer learning method aimed at transferring landslide information from completely different source domains, thus improving the landslide extraction accuracy with a small number of labeled samples. However, the large variation in landslide features across scenarios still leads to fewer fast cross-scene landslide detection schemes. Xu QS et al. (2022) proposed a robust deep migration learning scheme to extract deep information through a multi-scale feature fusion framework and by introducing a novel adaptive trigonometric fork module to efficiently integrate valuable features at different scales. Subsequently, an adversarial domain adaptive network was developed to extract landslides under different scenarios.

#### 4.5. Fusion algorithm

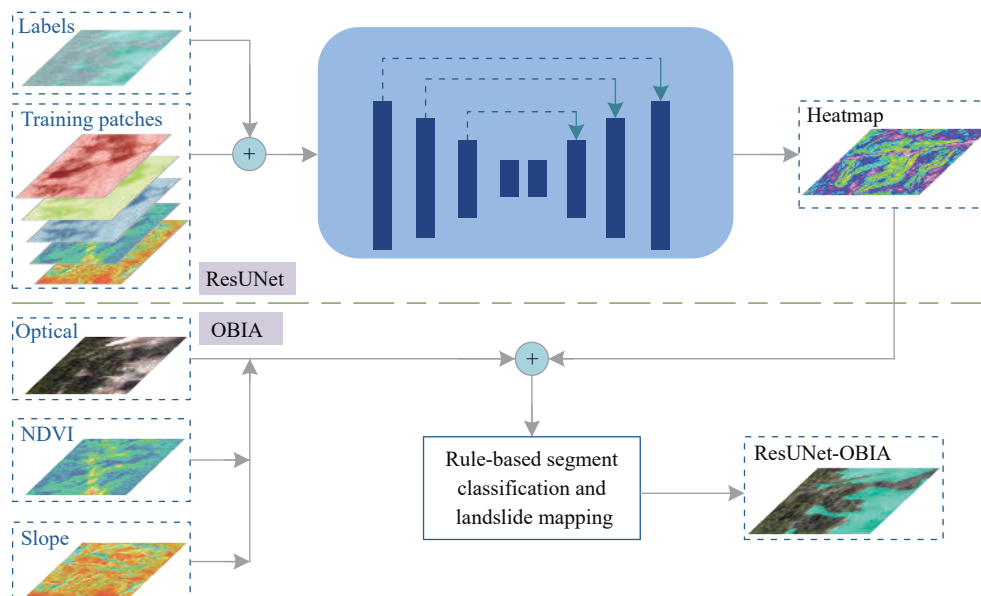
Fusion algorithms aim to integrate results from multiple image processing algorithms to improve the accuracy of landslide recognition. For example, Bui T et al. (2020) proposed an algorithm that combines deep learning with image transformation for detecting landslide locations in a satellite imagery system. Additionally, Ghorbanzadeh O et al. (2022a, 2022b) explored the feasibility of a combination of OBIA and DL-based model, aiming to introduce more a priori knowledge (Fig. 19). Besides, Lu H et al. (2020) integrated OBIA with CNN, in which the OBIA is used to obtain landslide objects, and then fed into the deep learning model. On the other hand, Zhang M et al. (2021) proposed a neural network combining change detection and multiple instance learning for landslide mapping, the proposed model only be trained by scene-level samples, aiming to reduce the need for pixel-level samples.

It has been demonstrated that the convolutional kernel in CNN can extract local features of the target, but is incapable of fully capturing contextual information. In contrast, the self-attention mechanism in the transformer allows it to capture global contextual information at the beginning of models (Dosovitskiy A et al., 2021). For this, Yang ZQ et al. (2022) made the first attempt to integrate the transformer into U-Net for landslide detection with small data sets, aiming to enhance the network's ability to extract the global context of landslides. In addition, the proposed model introduces spatial and channel attention modules in the decoder to effectively suppress the noise generated from the convolution and transformer. Similarly, Tang XC et al. (2022) introduced a new transformer-based model called SegFormer into coseismic landslide detection, the results confirmed the importance of global information in landslide extraction.

## 5. Discussion

### 5.1. Future challenges

The advent of deep learning has improved the efficiency in generating landslide inventories, making faster making of large-scale event landslides possible. Overall, when using single images for landslide detection, it may struggle to detect landslides triggered by a single event accurately. In contrast, change detection methods offer a solution, but they often necessitate both images from the same sensors and cloud-free conditions and have a huge demand for computational power. To accelerate training speed, employing the object detection-based algorithm is preferable over semantic segmentation methods, which typically pinpoint landslide bounding boxes in images. Unsupervised learning methods excel in sample utilization, generalization, and adaptability compared to supervised learning. They can circumvent the costs and constraints associated with labeled data, making them



**Fig. 19.** Landslide mapping combining the OBIA and FCN, the final result fused with the outputs of two independent models (modified from Ghorbanzadeh O et al., 2022).

particularly advantageous in regions with sparse image coverage or new scenarios. Fusion algorithms demand a comprehensive understanding of different deep learning structures, landslide characteristics, and image properties, enabling them to integrate complementary methods for the enhancement of the overall generalization capacity.

In general, the application of deep learning in the landslide community is still in its early stages, with several challenges to be addressed in the future.

(i) Data-driven deep learning necessitates a high quantity and quality of samples, previous studies predominantly employed pre-trained weights from objects in the natural domain for model convergence, which deviate considerably from landslide morphology and may lead the model to learn erroneous features.

(ii) Existing studies have utilized samples from the same sensor, resolution, and format, diverging from the characteristics of the Earth's big data as emphasized in the introduction. This limitation hinders the model's capacity to exploit temporal and hyperspectral bands for landslide feature extraction.

(iii) Considerable research efforts have been devoted to designing intricate feature extraction layers to enhance accuracy, rather than delving into the physical interpretability of deep learning models, which is not conducive to the optimization and development of models for landslide scenarios.

(iiii) Both sample size and model structure have a significant impact on model complexity, with existing high-precision model architectures inevitably leading to an increase in training parameters. This often necessitates significant computational throughput and higher memory consumption, limiting the emergency application of models.

## 5.2. Prospects

Overall, deep learning-based methods for landslide extraction have proliferated in recent years. In future endeavors, we urge landslide hazard researchers to generate high-quality, standardized labeled datasets based on their accumulated work, which is crucial for addressing the aforementioned challenges. Fortunately, two relatively large landslide datasets are already publicly available, albeit with shortcomings in terms of spectral band and resolution (Ghorbanzadeh O et al., 2022; Xu YL et al., 2024). Furthermore, enhancing the interpretability of models entails constraining the model through the integration of properties related to landslide geomechanics and spectrum. However, this approach places demands on the expertise and mathematical analysis skills of researchers. Besides, more attention should be paid to enhancing the generalization capabilities. This entails researchers not only designing models capable of leveraging multi-scale and global features to train robust weights from existing extensive labeled datasets but also exploring more effective domain knowledge transfer methods, such as domain adaptive networks or reinforcement learning, aiming to adapt to new disaster

scenarios and reduce the reliance on big volume of samples and computational resources.

## 6. Conclusions

In this paper, we highlight the development process of different deep learning models in landslide-making applications over the last seven years and further comment on future challenges and opportunities. First, a database of 77 peer-reviewed articles was created to be used to analyze based on the WOS. By systematically analyzing the literature, we conclude that (1) different deep learning models have been widely used for landslide making; (2) the vast majority of models are based on supervised learning, which often makes the training too dependent on labels; (3) the uncertainty of deep learning and the complexity of landslide mechanisms make the application of deep learning models in the field of geological hazards face several challenges.

Although deep learning methodologies have emerged as superior alternatives to traditional approaches, as evidenced by numerous studies. However, the efficacy of deep learning hinges on the availability of substantial volumes of labeled data, a challenge that remains unresolved, particularly in the realm of unsupervised learning. Moreover, existing frameworks predominantly rely on convolutional kernels, thereby constraining the extraction of global information from images. Moving forward, it is imperative for future research to prioritize the establishment of standardized landslide datasets to facilitate methodological comparisons. Additionally, there is a pressing need to enrich deep learning models by integrating a broader array of landslide characteristics, thereby enhancing the interpretability of these models. Furthermore, exploring novel learning paradigms such as transfer learning and adversarial generative networks holds promise for bolstering the generalization capabilities of models, particularly in scenarios characterized by limited samples and computational resources.

In summary, this paper serves as a comprehensive guide for individuals entering the domain of deep learning in landslide mapping. By shedding light on current progress and challenges, this paper seeks to stimulate the development of innovative, computationally feasible models that can contribute to collective efforts aimed at mitigating the impacts of landslides.

## CRedit authorship contribution statement

Zhi-qiang Yang contributed to the analysis of the article and wrote the manuscript; Wen-wen Qi contributed to the conception of the study; Chong Xu provided guidance, and revised the structure and layout of the manuscript; Xiao-yi Shao provided materials for the manuscript. All authors discussed the results and contributed to the final manuscript.

## Declaration of competing interest

No conflict of interest exists in the submission of this

manuscript, and the manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed

## Acknowledgments

This study was supported by the National Key Research and Development Program of China (2021YFB3901205) and the National Institute of Natural Hazards, Ministry of Emergency Management of China (2023-JBKY-57).

## References

- Abiodun OI, Jantan A, Omolara AE, Dada KV, Mohamed NA, Arshad H. 2018. State of the art in artificial neural network applications: A survey. *Heliyon*, 4(11). doi: [10.1016/j.heliyon.2018.e00938](https://doi.org/10.1016/j.heliyon.2018.e00938).
- Amit SNKB, Aoki Y (2017). Disaster detection from aerial imagery with convolutional neural network. 2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing, 239–245. doi: [10.1109/KCIC.2017.8228593](https://doi.org/10.1109/KCIC.2017.8228593).
- Amit SNKB, Shiraishi S, Inoshita T, Aoki Y. 2016. Analysis of satellite images for disaster detection. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 5189–5192. doi: [10.1109/IGARSS.2016.7730352](https://doi.org/10.1109/IGARSS.2016.7730352).
- Anantharaman R, Velazquez M, Lee Y (2018). Utilizing Mask R-CNN for detection and segmentation of oral diseases. 2018 IEEE International Conference on Bioinformatics and Biomedicine, 2197–2204. doi: [10.1109/BIBM.2018.8621112](https://doi.org/10.1109/BIBM.2018.8621112)
- Assilzadeh H, Levy JK, Wang X. 2010. Landslide catastrophes and disaster risk reduction: A GIS framework for landslide prevention and management. *Remote Sensing*, 2(9), 2259–2273. doi: [10.3390/rs2092259](https://doi.org/10.3390/rs2092259).
- Ball JE, Anderson DT, Chan CS. 2017. A comprehensive survey of deep learning in remote sensing: Theories, tools, and challenges for the community. *Journal of Applied Remote Sensing*, 11(04), 042609–042609. doi: [10.1117/1.JRS.11.042609](https://doi.org/10.1117/1.JRS.11.042609).
- Bharati P, Pramanik A. 2020. Deep learning techniques—R-CNN to Mask R-CNN: A survey. *Computational Intelligence in Pattern Recognition*, 999, 657–668. doi: [10.1007/978-981-13-9042-5\\_56](https://doi.org/10.1007/978-981-13-9042-5_56).
- Bragagnolo L, Rezende LR, da Silva RV, Grzybowski JMV. 2021. Convolutional neural networks applied to semantic segmentation of landslide scars. *Catena*, 105189. doi: [10.1016/j.catena.2021.105189](https://doi.org/10.1016/j.catena.2021.105189).
- Brardinoni F, Slaymaker O, Hassan MA. 2003. Landslide inventory in a rugged forested watershed: A comparison between air-photo and field survey data. *Geomorphology*, 54(3–4), 179–196. doi: [10.1016/S0169-555X\(02\)00355-0](https://doi.org/10.1016/S0169-555X(02)00355-0).
- Breiman L. 2001. Random forests. *Machine Learning*, 45(1), 5–32. doi: [10.1023/A:1010933404324](https://doi.org/10.1023/A:1010933404324).
- Bui T, Du P, Lum K, Chen C, Shiu S. 2019. Using BEMD in cnn to identify landslide in satellite image. *International Conference on System Science and Engineering*, 94–97. doi: [10.1109/ICSSE.2019.8823128](https://doi.org/10.1109/ICSSE.2019.8823128).
- Bui T, Du P, Lum K, Loh C, Tan K. 2020. Deep learning for landslide recognition in satellite architecture. *IEEE Access*, 8, 143665–143678. doi: [10.1109/ACCESS.2020.3014305](https://doi.org/10.1109/ACCESS.2020.3014305).
- Cai H, Chen T, Niu R, Plaza A. 2021. Landslide detection using densely connected convolutional networks and environmental conditions. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 5235–5247. doi: [10.1109/jstars.2021.3079196](https://doi.org/10.1109/jstars.2021.3079196).
- Carrara A, Cardinali M, Detti R, Guzzetti F, Pasqui V, Reichenbach P. 1991. GIS techniques and statistical models in evaluating landslide hazard. *Earth Surface Processes and Landforms*, 16(5), 427–445. doi: [10.1002/esp.470](https://doi.org/10.1002/esp.470).
- Casadei M, Dietrich WE, Miller NL. 2003. Testing a model for predicting the timing and location of shallow landslide initiation in soil-mantled landscapes. *Earth Surface Processes and Landforms*, 28(9), 925–950. doi: [10.1002/esp.3290160505](https://doi.org/10.1002/esp.3290160505).
- Catani F. 2021. Landslide detection by deep learning of non-nadir and crowdsourced optical images. *Landslides*, 18(3), 1025–1044. doi: [10.1007/s10346-020-01513-4](https://doi.org/10.1007/s10346-020-01513-4).
- Chacón J, Irigaray C, Fernández T, El Hamdouni R. 2006. Engineering geology maps: Landslides and geographical information systems. *Bulletin of Engineering Geology and the Environment*, 65(4), 341–411. doi: [10.1007/s10064-006-0064-z](https://doi.org/10.1007/s10064-006-0064-z).
- Chen B, Song C, Chen Y, Li ZH, Yu, Liu HH, Jiang H, Liu ZJ, Cai XM, Neng YH, Zhu S, Du JT, Li ZF, Zhao ZX, Li SJ, Zhu W, Peng JB. 2023. Emergency identification and influencing factor analysis of coseismic landslides and building damages induced by the 2023  $M_s$  6.2 Jishishan (Gansu, China) earthquake. *Geomatics and Information Science of Wuhan University*, 1–16 (in Chinese with English abstract). doi: [10.13203/J.whugis.20230497](https://doi.org/10.13203/J.whugis.20230497)
- Chen Z, Zhang YF, Ouyang C, Zhang F, Ma J. 2018. Automated landslides detection for mountain cities using multi-temporal remote sensing imagery. *Sensors*, 18(3), 821. doi: [10.3390/s18030821](https://doi.org/10.3390/s18030821).
- Cheng G, Xie XX, Han JW, Guo L, Xia GS. 2020. Remote sensing image scene classification meets deep learning: Challenges, methods, benchmarks, and opportunities. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 3735–3756. doi: [10.1109/jstars.2020.3005403](https://doi.org/10.1109/jstars.2020.3005403).
- Cheng LB, Li J, Duan P, Wang MG. 2021. A small attentional YOLO model for landslide detection from satellite remote sensing images. *Landslides*, 18(8), 2751–2765. doi: [10.1007/s10346-021-01694-6](https://doi.org/10.1007/s10346-021-01694-6).
- Chi MM, Plaza A, Benediktsson JA, Sun ZY, Shen JS, Zhu YY. 2016. Big data for remote sensing: Challenges and opportunities. *Proceedings of the IEEE*, 104(11), 2207–2219. doi: [10.1109/jproc.2016.2598228](https://doi.org/10.1109/jproc.2016.2598228).
- Coe JA, Glancy PA, Whitney JW. 1997. Volumetric analysis and hydrologic characterization of a modern debris flow near Yucca Mountain, Nevada. *Geomorphology*, 20(1–2), 11–28. doi: [10.1016/S0169-555X\(97\)00008-1](https://doi.org/10.1016/S0169-555X(97)00008-1).
- Dai FC, Lee CF. 2002. Landslide characteristics and slope instability modeling using GIS, Lantau Island, Hong Kong. *Geomorphology*, 42(3–4), 213–228. doi: [10.1016/S0169-555X\(01\)00087-3](https://doi.org/10.1016/S0169-555X(01)00087-3).
- Ding AZ, Zhang QY, Zhou XM, Dai BC. 2016. Automatic recognition of landslide based on CNN and texture change detection. 2016 31st Youth Academic Annual Conference of Chinese Association of Automation, 444–448. doi: [10.1109/YAC.2016.7804935](https://doi.org/10.1109/YAC.2016.7804935).
- Dosovitskiy A, Beyer L, Kolesnikov A, Weissenborn D, Zhai X, Unterthiner T, Dehghani M, Minderer M, Heigold G, Gelly S, Uszkoreit J, Houlsby N. 2021. An image is worth 16x16 words: Transformers for image recognition at scale. doi: [10.48550/arXiv.2010.11929](https://doi.org/10.48550/arXiv.2010.11929).
- Duman TY, Çan T, Emre Ö, Keçer M, Doğan A, Ateş Ş, Durmaz S. 2005. Landslide inventory of northwestern Anatolia, Turkey. *Engineering Geology*, 77(1–2), 99–114. doi: [10.1016/j.enggeo.2004.08.005](https://doi.org/10.1016/j.enggeo.2004.08.005).
- Fakoor R, Ladhak F, Nazi A, Huber M. 2013. Using deep learning to enhance cancer diagnosis and classification. *Proceedings of the International Conference on Machine Learning*, 28, 3937–3949.
- Fan XM, Scaringi G, Korup O, West AJ, Van Westen CJ, Tanyas H, Hovius N, Hales TC, Jibson RW, Allstadt KE, Zhang LM, Evans SG, Xu C, Li G, Pei XJ, Xu Q, Huang RQ. 2019. Earthquake-induced chains of geologic hazards: Patterns, mechanisms, and impacts. *Reviews of Geophysics*, 57(2), 421–503. doi: [10.1029/2018RG000626](https://doi.org/10.1029/2018RG000626).

- Fang CY, Fan XM, Zhong H, Lombardo L, Tanyas H, Wang X. 2022. A novel historical landslide detection approach based on LiDAR and lightweight attention U-Net. *Remote Sensing*, 14(17), 4357. doi: [10.3390/rs14174357](https://doi.org/10.3390/rs14174357).
- Fu R, He J, Liu G, Li WL, Mao JQ, He MH, Lin YY. 2022. Fast seismic landslide detection based on improved Mask R-CNN. *Remote Sensing*, 14(16), 3928. doi: [10.3390/rs14163928](https://doi.org/10.3390/rs14163928).
- Gardner MW, Dorling SR. 1998. Artificial neural networks (the multilayer perceptron)—A review of applications in the atmospheric sciences. *Atmospheric Environment*, 32(14-15), 2627–2636. doi: [10.1016/S1352-2310\(97\)00447-0](https://doi.org/10.1016/S1352-2310(97)00447-0).
- Ghorbanzadeh O, Blaschke T. 2019. Optimizing sample patches selection of CNN to improve the mIOU on landslide detection. *Proceedings of the 5th International Conference on Geographical Information Systems Theory, Applications and Management*, 1(33–40). doi: [10.5220/0007675300330040](https://doi.org/10.5220/0007675300330040).
- Ghorbanzadeh O, Blaschke T, Gholamnia K, Meena S, Tiede D, Aryal J. 2019. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. *Remote Sensing*, 11(2), 196. doi: [10.3390/rs11020196](https://doi.org/10.3390/rs11020196).
- Ghorbanzadeh O, Crivellari A, Ghamisi P, Shahabi H, Blaschke T. 2021. A comprehensive transferability evaluation of U-Net and ResU-Net for landslide detection from Sentinel-2 data (case study areas from Taiwan, China, and Japan). *Scientific Reports*, 11(1), 14629. doi: [10.1038/s41598-021-94190-9](https://doi.org/10.1038/s41598-021-94190-9).
- Ghorbanzadeh O, Gholamnia K, Ghamisi P. 2022. The application of ResU-Net and OBIA for landslide detection from multi-temporal Sentinel-2 images. *Big Earth Data*, 7(4), 961–985. doi: [10.1080/20964471.2022.2031544](https://doi.org/10.1080/20964471.2022.2031544).
- Ghorbanzadeh O, Shahabi H, Crivellari A, Homayouni S, Blaschke T, Ghamisi P. 2022. Landslide detection using deep learning and object-based image analysis. *Landslides*, 19(4), 929–939. doi: [10.1007/s10346-021-01843-x](https://doi.org/10.1007/s10346-021-01843-x).
- Ghorbanzadeh O, Xu Y, Ghamisi P, Kopp M, Kreil D. 2022. Landslide4Sense: Reference benchmark data and deep learning models for landslide detection. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1–17. doi: [10.1109/TGRS.2022.3215209](https://doi.org/10.1109/TGRS.2022.3215209).
- Glade T. 2001. *Landslide Hazard Assessment and Historical Landslide Data—An Inseparable Couple?* Springer, Netherlands, 153–168.
- Guo HJ, Yi BJ, Yao QX, Gao P, Li H, Sun JX, Zhong C. 2022. Identification of landslides in mountainous area with the combination of SBAS-InSAR and Yolo model. *Sensors*, 22(16), 6235. doi: [10.3390/s22166235](https://doi.org/10.3390/s22166235).
- Guzzetti F, Mondini AC, Cardinali M, Fiorucci F, Santangelo M, Chang K-T. 2012. Landslide inventory maps: New tools for an old problem. *Earth-Science Reviews*, 112(1–2), 42–66. doi: [10.1016/j.earscirev.2012.02.001](https://doi.org/10.1016/j.earscirev.2012.02.001).
- Hacıefendioğlu K, Demir G, Başağa HB. 2021. Landslide detection using visualization techniques for deep convolutional neural network models. *Natural Hazards*, 109(1), 329–350. doi: [10.1007/s11069-021-04838-y](https://doi.org/10.1007/s11069-021-04838-y).
- He HQ, Li CC, Yang RH, Zeng HE, Li L, Zhu YF. 2022. Multisource data fusion and adversarial nets for landslide extraction from UAV-photogrammetry-derived data. *Remote Sensing*, 14(13), 3059. doi: [10.3390/rs14133059](https://doi.org/10.3390/rs14133059).
- He KM, Gkioxari G, Dollár P, Girshick R. 2018. Mask R-CNN. *arXiv preprint arXiv: 1703.06870*. doi: [10.48550/arXiv.1703.06870](https://doi.org/10.48550/arXiv.1703.06870).
- He KM, Zhang XY, Ren SQ, Sun J. 2016. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition. 770–778. doi: [10.1109/CVPR.2016.90](https://doi.org/10.1109/CVPR.2016.90).
- Hong Y, Adler R, Huffman G. 2007. Use of satellite remote sensing data in the mapping of global landslide susceptibility. *Natural Hazards*, 43(2), 245–256. doi: [10.1007/s11069-006-9104-z](https://doi.org/10.1007/s11069-006-9104-z).
- Hu Q, Zhou Y, Wang SX, Wang FT, Wang HJ. 2019. Improving the accuracy of landslide detection in “Off-site” area by machine learning model portability comparison: A case study of Jiuzhaigou earthquake, China. *Remote Sensing*, 11(21), 2530. doi: [10.3390/rs11212530](https://doi.org/10.3390/rs11212530).
- Hua YM, Guo JH, Zhao H. 2015. Deep belief networks and deep learning. *Proceedings of 2015 International Conference on Intelligent Computing and Internet of Things*, 1–4. doi: [10.1109/ICAIIOT.2015.7111524](https://doi.org/10.1109/ICAIIOT.2015.7111524).
- Huang G, Liu Z, van der Maaten L, Weinberger KQ. 2018. Densely connected convolutional networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition, 2261–2269. doi: [10.1109/CVPR.2017.243](https://doi.org/10.1109/CVPR.2017.243).
- Huang J, Li X, Chen F, Cui R, Li HM, Du BW. 2022. A deep learning recognition model for landslide terrain based on multi-source data fusion. *The Chinese Journal of Geological Hazard and Control*, 33(2), 33–41. doi: [10.16031/j.cnki.issn.1003-8035.2022.02-05](https://doi.org/10.16031/j.cnki.issn.1003-8035.2022.02-05).
- Huang YD, Xu C, Zhang XJ, Li L. 2022. Bibliometric analysis of landslide research based on the WOS database. *Natural Hazards Research*, 2(2), 49–61. doi: [10.1016/j.nhres.2022.02.001](https://doi.org/10.1016/j.nhres.2022.02.001).
- Huang YD, Xu C, Zhang XL, Xue CJ, Wang SY. 2021. An updated database and spatial distribution of landslides triggered by the Milin, Tibet Mw6. 4 earthquake of 18 November 2017. *Journal of Earth Science*, 32(5), 1069–1078. doi: [10.1007/s12583-021-1433-z](https://doi.org/10.1007/s12583-021-1433-z).
- Janiesch C, Zschech P, Heinrich K. 2021. Machine learning and deep learning. *Electronic Markets*, 31(3), 685–695. doi: [10.1007/s12525-021-00475-2](https://doi.org/10.1007/s12525-021-00475-2).
- Ji SP, Yu DW, Shen CY, Li WL, Xu Q. 2020. Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks. *Landslides*, 17(6), 1337–1352. doi: [10.1007/s10346-020-01353-2](https://doi.org/10.1007/s10346-020-01353-2).
- Ju YQ, Xu Q, Jin SC, Li WL, Dong XJ, Guo QH. 2020. Automatic object detection of loess landslide based on deep learning. *Geomatics and Information Science of Wuhan University*, 45(11), 1747–1755. doi: [10.13203/j.whugis20200132](https://doi.org/10.13203/j.whugis20200132).
- Ju YZ, Xu Q, Jin SC, Li WL, Su YJ, Dong XJ, Guo QH. 2022. Loess landslide detection using object detection algorithms in northwest China. *Remote Sensing*, 14(5), 1182. doi: [10.3390/rs14051182](https://doi.org/10.3390/rs14051182).
- Kattenborn T, Leitloff J, Schiefer F, Hinz S. 2021. Review on convolutional neural networks (CNN) in vegetation remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 173, 24–49. doi: [10.1016/j.isprsjprs.2020.12.010](https://doi.org/10.1016/j.isprsjprs.2020.12.010).
- Konishi T, Suga Y, Notarnicola C, Pierdicca N, Bovenga F, Santi E. 2019. Landslide detection with ALOS-2/PALSAR-2 data using convolutional neural networks: A case study of 2018 Hokkaido Eastern Iburu earthquake. *Active and Passive Microwave Remote Sensing for Environmental Monitoring III*, 111540. doi: [10.1117/12.2531695](https://doi.org/10.1117/12.2531695).
- Larochelle H, Mandel M, Pascanu R, Bengio Y. 2012. Learning algorithms for the classification restricted boltzmann machine. *Journal of Machine Learning Research*, 13(22), 643–669.
- LeCun Y, Bengio Y, Hinton G. 2015. Deep learning. *Nature*, 521(7553), 436–444. doi: [10.1038/nature14539](https://doi.org/10.1038/nature14539).
- Lei T, Zhang Q, Xue DH, Chen T, Meng HY, Nandi AK. 2019. End-to-end change detection using a symmetric fully convolutional network for landslide mapping. *IEEE International Conference on Acoustics, Speech and Signal Processing*, 3027–3031. doi: [10.1109/ICASSP.2019.8682802](https://doi.org/10.1109/ICASSP.2019.8682802).
- Lei T, Zhang YX, Lv ZY, Li SY, Liu SG, Nandi AK. 2019. Landslide inventory mapping from bitemporal images using deep convolutional neural networks. *IEEE Geoscience and Remote Sensing Letters*, 16(6), 982–986. doi: [10.1109/lgrs.2018.2889307](https://doi.org/10.1109/lgrs.2018.2889307).
- Li C, Yi BJ, Gao P, Li H, Sun JX, Chen XY, Zhong C. 2021. Valuable clues for DCNN-based landslide detection from a comparative assessment in the wenchuan earthquake area. *Sensors*, 21(15)doi:

- 10.3390/s21155191.
- Li YS, Ma JY, Zhang YJ. 2021. Image retrieval from remote sensing big data: A survey. *Information Fusion*, 67, 94–115. doi: [10.1016/j.inffus.2020.10.008](https://doi.org/10.1016/j.inffus.2020.10.008).
- Li ZB, Shi WZ, Myint SW, Lu P, Wang QM. 2016. Semi-automated landslide inventory mapping from bitemporal aerial photographs using change detection and level set method. *Remote Sensing of Environment*, 175, 215–230. doi: [10.1016/j.rse.2016.01.003](https://doi.org/10.1016/j.rse.2016.01.003).
- Liou CY, Cheng WC, Liou JW, Liou DR. 2014. Autoencoder for words. *Neurocomputing*, 139, 84–96. doi: [10.1016/j.neucom.2013.09.055](https://doi.org/10.1016/j.neucom.2013.09.055).
- Liu J, Li PF. 2018. A Mask R-CNN model with improved region proposal network for medical ultrasound image. *Intelligent Computing Theories and Application*, 10955, 26–33. doi: [10.1007/978-3-319-95933-7\\_4](https://doi.org/10.1007/978-3-319-95933-7_4).
- Liu P, Di LP, Du Q, Wang LZ. 2018. Remote sensing big data: Theory, methods and applications. *Remote Sensing*, 10(5), 711. doi: [10.3390/rs10050711](https://doi.org/10.3390/rs10050711).
- Liu P, Wei YM, Wang QJ, Chen Y, Xie JJ. 2020. Research on post-earthquake landslide extraction algorithm based on improved U-Net model. *Remote Sensing*, 12(5), 894. doi: [10.3390/rs12050894](https://doi.org/10.3390/rs12050894).
- Liu T, Chen T, Niu RQ, Plaza A. 2021. Landslide detection mapping employing CNN, ResNet, and DenseNet in the Three Gorges Reservoir, China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 11417–11428. doi: [10.1109/jstars.2021.3117975](https://doi.org/10.1109/jstars.2021.3117975).
- Liu Y, Wu LZ. 2016. Geological disaster recognition on optical remote sensing images using deep learning. *Procedia Computer Science*, 91, 566–575. doi: [10.1016/j.procs.2016.07.144](https://doi.org/10.1016/j.procs.2016.07.144).
- Liu Y, Wu LZ. 2018. High performance geological disaster recognition using deep learning. *Procedia Computer Science*, 139, 529–536. doi: [10.1016/j.procs.2018.10.237](https://doi.org/10.1016/j.procs.2018.10.237).
- Liu Y, Yao X, Gu ZK, Zhou ZK, Liu XH, Chen XM, Wei SF. 2022. Study of the automatic recognition of landslides by using InSAR images and the improved Mask R-CNN model in the eastern Tibet Plateau. *Remote Sensing*, 14(14), 3362. doi: [10.3390/rs14143362](https://doi.org/10.3390/rs14143362).
- Long J, Shelhamer E, Darrell T. 2015. Fully convolutional networks for semantic segmentation. 2015 IEEE Conference on Computer Vision and Pattern Recognition, 3431–3440. doi: [10.1109/CVPR.2015.7298965](https://doi.org/10.1109/CVPR.2015.7298965).
- Long LJ, He F, Liu HJ. 2021. The use of remote sensing satellite using deep learning in emergency monitoring of high-level landslides disaster in Jinsha River. *The Journal of Supercomputing*, 77(8), 8728–8744. doi: [10.1007/s11227-020-03604-4](https://doi.org/10.1007/s11227-020-03604-4).
- Lu H, Ma L, Fu X, Liu C, Wang Z, Tang M, Li NW. 2020. Landslides information extraction using Object-Oriented image analysis paradigm based on deep learning and transfer learning. *Remote Sensing*, 12(5), 752. doi: [10.3390/rs12050752](https://doi.org/10.3390/rs12050752).
- Lu P, Shi WY, Wang QM, Li ZB, Qin YY, Fan XM. 2021. Coseismic landslide mapping using Sentinel-2 10m fused NIR narrow, red-edge, and SWIR bands. *Landslides*, 18(6), 2017–2037. doi: [10.1007/s10346-021-01636-2](https://doi.org/10.1007/s10346-021-01636-2).
- Lv ZY, Liu TF, Kong XB, Shi C, Benediktsson JA. 2020. Landslide inventory mapping with bitemporal aerial remote sensing images based on the dual-path fully convolutional network. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 4575–4584. doi: [10.1109/jstars.2020.2980895](https://doi.org/10.1109/jstars.2020.2980895).
- Ma ZJ, Mei G. 2021. Deep learning for geological hazards analysis: Data, models, applications, and opportunities. *Earth-Science Reviews*, 223, 103858. doi: [10.1016/j.earscirev.2021.103858](https://doi.org/10.1016/j.earscirev.2021.103858).
- Mabu S, Hirata S, Kuremoto T. 2021. Landslide area detection from synthetic aperture radar images using convolutional adversarial autoencoder and one-class SVM. *Proceedings of International Conference on Artificial Life and Robotics*, 26, 575–580. doi: [10.5954/ICAROB.2021.GS4-1](https://doi.org/10.5954/ICAROB.2021.GS4-1).
- Malamud BD, Turcotte DL, Guzzetti F, Reichenbach P. 2004. Landslide inventories and their statistical properties. *Earth Surface Processes and Landforms*, 29(6), 687–711. doi: [10.1002/esp.1064](https://doi.org/10.1002/esp.1064).
- Maxwell AE, Warner TA, Fang F. 2018. Implementation of machine learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9), 2784–2817. doi: [10.1080/01431161.2018.1433343](https://doi.org/10.1080/01431161.2018.1433343).
- Meena SR, Soares LP, Grohmann CH, van Westen C, Bhuyan K, Singh RP, Floris M, Catani F. 2022. Landslide detection in the Himalayas using machine learning algorithms and U-Net. *Landslides*, 19(5), 1209–1229. doi: [10.1007/s10346-022-01861-3](https://doi.org/10.1007/s10346-022-01861-3).
- Meng QX, Catchpoole D, Skillicom D, Kennedy PJ. 2017. Relational autoencoder for feature extraction. 2017 International Joint Conference on Neural Networks, 364–371. doi: [10.1109/IJCNN.2017.7965877](https://doi.org/10.1109/IJCNN.2017.7965877).
- Micheletti N, Foresti L, Robert S, Leuenberger M, Pedrazzini A, Jaboyedoff M, Kanevski M. 2014. Machine learning feature selection methods for landslide susceptibility mapping. *Mathematical Geosciences*, 46(1), 33–57. doi: [10.1007/s11004-013-9511-0](https://doi.org/10.1007/s11004-013-9511-0).
- Mohan A, Singh AK, Kumar B, Dwivedi R. 2021. Review on remote sensing methods for landslide detection using machine and deep learning. *Transactions on Emerging Telecommunications Technologies*, 32(7). doi: [10.1002/ett.3998](https://doi.org/10.1002/ett.3998).
- Mondini AC, Guzzetti F, Chang K-T, Monserrat O, Martha TR, Manconi A. 2021. Landslide failures detection and mapping using synthetic aperture radar: Past, present and future. *Earth-Science Reviews*, 216. doi: [10.1016/j.earscirev.2021.103574](https://doi.org/10.1016/j.earscirev.2021.103574).
- Moosavi V, Talebi A, Shirmohammadi B. 2014. Producing a landslide inventory map using pixel-based and object-oriented approaches optimized by Taguchi method. *Geomorphology*, 204, 646–656. doi: [10.1016/j.geomorph.2013.09.012](https://doi.org/10.1016/j.geomorph.2013.09.012).
- Nalisnick E, Matsukawa A, Teh YW, Gorur D, Lakshminarayanan B. 2019. Do deep generative models know what they don't know? arXiv preprint arXiv: 1810.09136. doi: [10.48550/arXiv.1810.09136](https://doi.org/10.48550/arXiv.1810.09136).
- Nava L, Bhuyan K, Meena SR, Monserrat O, Catani F. 2022. Rapid mapping of landslides on SAR data by attention U-Net. *Remote Sensing*, 14(6), 1449. doi: [10.3390/rs14061449](https://doi.org/10.3390/rs14061449).
- Nick TG, Campbell KM. 2007. Logistic regression, NJ, Humana Press. 404, 273–301. doi: [10.1007/978-1-59745-530-5\\_14](https://doi.org/10.1007/978-1-59745-530-5_14).
- Noble WS. 2006. What is a support vector machine? *Nature Biotechnology*, 24(12). doi: [10.1038/nbt1206-1565](https://doi.org/10.1038/nbt1206-1565).
- Pang DD, Liu G, He J, Li WL, Fu R. 2022. Automatic remote sensing identification of coseismic landslides using deep learning methods. *Forests*, 13(8), 1213. doi: [10.3390/f13081213](https://doi.org/10.3390/f13081213).
- Pardeshi SD, Autade SE, Pardeshi SS. 2013. Landslide hazard assessment: Recent trends and techniques. *SpringerPlus*, 2(1), 523. doi: [10.1186/2193-1801-2-523](https://doi.org/10.1186/2193-1801-2-523).
- Postance B, Hillier J, Dijkstra T, Dixon N. 2018. Comparing threshold definition techniques for rainfall-induced landslides: A national assessment using radar rainfall: Comparing threshold techniques for rainfall induced landslides. *Earth Surface Processes and Landforms*, 43(2), 553–560. doi: [10.1002/esp.4202](https://doi.org/10.1002/esp.4202).
- Poursanidis D, Chrysoulakis N. 2017. Remote Sensing, natural hazards and the contribution of ESA Sentinels missions. *Remote Sensing Applications: Society and Environment*, 6, 25–38. doi: [10.1016/j.rsase.2017.02.001](https://doi.org/10.1016/j.rsase.2017.02.001).
- Prakash N, Manconi A, Loew S. 2020. Mapping landslides on EO data: Performance of deep learning models vs. Traditional machine learning models. *Remote Sensing*, 12(3), 346. doi: [10.3390/rs12030346](https://doi.org/10.3390/rs12030346).
- Qi WW, Wei MF, Yang WT, Xu C, Ma C. 2020. Automatic mapping of landslides by the ResU-Net. *Remote Sensing*, 12(15), 2487. doi: [10.3390/rs12152487](https://doi.org/10.3390/rs12152487).
- Qin SW, Guo X, Sun JB, Qiao SS, Zhang LS, Yao JY, Cheng QS, Zhang

- YQ. 2021. Landslide detection from open satellite imagery using distant domain transfer learning. *Remote Sensing*, 13(17), 3383. doi: [10.3390/rs13173383](https://doi.org/10.3390/rs13173383).
- Ronneberger O, Fischer P, Brox T (2015). U-Net: Convolutional networks for biomedical image segmentation. arXiv preprint arXiv: 1505.04597, doi: [10.48550/arXiv.1505.04597](https://doi.org/10.48550/arXiv.1505.04597).
- Saha AK, Gupta RP, Sarkar I, Arora MK, Csaplovics E. 2005. An approach for GIS-based statistical landslide susceptibility zonation—with a case study in the Himalayas. *Landslides*, 2(1), 61–69. doi: [10.1007/s10346-004-0039-8](https://doi.org/10.1007/s10346-004-0039-8).
- Salakhutdinov R. 2015. Learning Deep Generative Models. Annual review of statistics and its application, 2(1), 361–385. doi: [10.1146/annurev-statistics-010814-020120](https://doi.org/10.1146/annurev-statistics-010814-020120).
- Sameen MI, Pradhan B. 2019. Landslide detection using residual networks and the fusion of spectral and topographic information. *IEEE Access*, 7, 114363–114373. doi: [10.1109/access.2019.2935761](https://doi.org/10.1109/access.2019.2935761).
- Samia J, Temme A, Bregt A, Wallinga J, Guzzetti F, Ardizzone F, Rossi M. 2017. Do landslides follow landslides? Insights in path dependency from a multi-temporal landslide inventory. *Landslides*, 14(2), 547–558. doi: [10.1007/s10346-016-0739-x](https://doi.org/10.1007/s10346-016-0739-x).
- Schönfeldt E, Winocur D, Pánek T, Korup O. 2022. Deep learning reveals one of Earth's largest landslide terrain in Patagonia. *Earth and Planetary Science Letters*, 593. doi: [10.1016/j.epsl.2022.117642](https://doi.org/10.1016/j.epsl.2022.117642).
- Shahabi H, Rahimzad M, Tavakkoli Piralilou S, Ghorbanzadeh O, Homayouni S, Blaschke T, Lim S, Ghamisi P. 2021. Unsupervised deep learning for landslide detection from multispectral Sentinel-2 imagery. *Remote Sensing*, 13(22), 4698. doi: [10.3390/rs13224698](https://doi.org/10.3390/rs13224698).
- Shao XY, Ma SY, Xu C, Zhang PF, Wen BY, Tian YY, Zhou Q, Cui YL. 2019. Planet image-based inventorying and machine learning-based susceptibility mapping for the landslides triggered by the 2018 Mw6.6 Tomakomai, Japan earthquake. *Remote Sensing*, 11(8), 978. doi: [10.3390/rs11080978](https://doi.org/10.3390/rs11080978).
- Shi WZ, Zhang M, Ke HF, Fang X, Zhan Z, Chen SX. 2021. Landslide recognition by deep convolutional neural network and change detection. *IEEE Transactions on Geoscience and Remote Sensing*, 59(6), 4654–4672. doi: [10.1109/tgrs.2020.3015826](https://doi.org/10.1109/tgrs.2020.3015826).
- Shi Y, Shi LL, Niu MJ, Zhao K. 2022. Multi-task automatic identification of loess landslide based on one-stage instance segmentation network. *Bulletin of Survey and Mapping*, 0(4), 26–31. doi: [10.13474/j.cnki.11-2246.2022.0105](https://doi.org/10.13474/j.cnki.11-2246.2022.0105).
- Simonyan K, Zisserman A. 2015. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv: 1409.1556, doi: [10.48550/arXiv.1409.1556](https://doi.org/10.48550/arXiv.1409.1556).
- Soares LP, Dias HC, Garcia GPB, Grohmann CH. 2022. Landslide segmentation with deeplearning: Evaluating model generalization in rainfall-induced landslides in Brazil. *Remote Sensing*, 14(9), 2237. doi: [10.3390/rs14092237](https://doi.org/10.3390/rs14092237).
- Soares LP, Dias HC, Grohmann CH. 2020. Landslide segmentation with U-Net: Evaluating different sampling methods and patch sizes. arXiv preprint arXiv: 2007.06672, doi: [10.48550/arXiv.2007.06672](https://doi.org/10.48550/arXiv.2007.06672).
- Sohn I. 2021. Deep belief network based intrusion detection techniques: A survey. *Expert Systems with Applications*, 167. doi: [10.1016/j.eswa.2020.114170](https://doi.org/10.1016/j.eswa.2020.114170).
- Song YY, Lu Y. 2015. Decision tree methods: Applications for classification and prediction. *Shanghai Archives of Psychiatry*, 27(2), 130–5. doi: [10.11919/j.issn.1002-0829.215044](https://doi.org/10.11919/j.issn.1002-0829.215044).
- Stumpf A, Kerle N. 2011. Object-oriented mapping of landslides using random forests. *Remote Sensing of Environment*, 115(10), 2564–2577. doi: [10.1016/j.rse.2011.05.013](https://doi.org/10.1016/j.rse.2011.05.013).
- Su ZY, Chow JK, Tan PS, Wu J, Ho YK, Wang YH. 2021. Deep convolutional neural network-based pixel-wise landslide inventory mapping. *Landslides*, 18(4), 1421–1443. doi: [10.1007/s10346-020-01557-6](https://doi.org/10.1007/s10346-020-01557-6).
- Sun Y, Wang XG, Tang XO. 2014. Deep learningface representation from predicting 10,000 classes. 2014 IEEE Conference on Computer Vision and Pattern Recognition, 1891–1898. doi: [10.1109/CVPR.2014.244](https://doi.org/10.1109/CVPR.2014.244).
- Tanatipuknon A, Aimmanee P, Watanabe Y, Murata KT, Wakai A, Sato G, Hung HV, Tungpimolrut K, Keerativittayanun S, Karnjana J. 2021. Study on combining two faster R-CNN models for landslide detection with a classification decision tree to Improve the detection performance. *Journal of Disaster Research*, 16(4), 588–595. doi: [10.20965/jdr.2021.p0588](https://doi.org/10.20965/jdr.2021.p0588).
- Tang XC, Liu MZ, Zhong H, Ju YZ, Li WL, Xu Q. 2021. MILL: Channel attention-based deep multiple instance learning for landslide recognition. *ACM Transactions on Multimedia Computing, Communications, and Applications*, 17(2s), 1–11. doi: [10.1145/3454009](https://doi.org/10.1145/3454009).
- Tang XC, Tu ZH, Wang Y, Liu MZ, Li DF, Fan XM. 2022. Automatic detection of coseismic landslides using a new transformer method. *Remote Sensing*, 14(12), 2884. doi: [10.3390/rs14122884](https://doi.org/10.3390/rs14122884).
- Tehrani FS, Calvello M, Liu Z, Zhang L, Lacasse S. 2022. Machine learning and landslide studies: Recent advances and applications. *Natural Hazards*, 114, 1197–1245. doi: [10.1007/s11069-022-05423-7](https://doi.org/10.1007/s11069-022-05423-7).
- Tschannen M, Bachem O, Lucic M. 2018. Recent advances in autoencoder-based representation learning. arXiv preprint arXiv: 1812.05069, doi: [10.48550/arXiv.1812.05069](https://doi.org/10.48550/arXiv.1812.05069).
- Ullo S, Mohan A, Sebastianelli A, Ahamed S, Kumar B, Dwivedi R, Sinha GR. 2021. A new Mask R-CNN-based method for improved landslide detection. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 3799–3810. doi: [10.1109/jstars.2021.3064981](https://doi.org/10.1109/jstars.2021.3064981).
- Van Westen CJ, Castellanos E, Kuriakose SL. 2008. Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. *Engineering Geology*, 102(3–4), 112–131. doi: [10.1016/j.enggeo.2008.03.010](https://doi.org/10.1016/j.enggeo.2008.03.010).
- Wang HJ, Zhang LM, Yin KS, Luo HY, Li JH. 2021. Landslide identification using machine learning. *Geoscience Frontiers*, 12(1), 351–364. doi: [10.1016/j.gsf.2020.02.012](https://doi.org/10.1016/j.gsf.2020.02.012).
- Wang Y, Wang XF, Jian JF. 2019. Remote sensing landslide recognition based on convolutional neural network. *Mathematical Problems in Engineering*, 2019, 1–12. doi: [10.1155/2019/8389368](https://doi.org/10.1155/2019/8389368).
- Wieczorek GF. 1984. Preparing a detailed landslide inventory map for hazard evaluation and reduction. *Environmental & Engineering Geoscience*, xxi(3), 337–342. doi: [10.2113/gsegeosci.xxi.3.337](https://doi.org/10.2113/gsegeosci.xxi.3.337).
- Woodcock CE, Strahler AH. 1987. The factor of scale in remote sensing. *Remote Sensing of Environment*, 21(3), 311–332. doi: [10.1016/0034-4257\(87\)90015-0](https://doi.org/10.1016/0034-4257(87)90015-0).
- Xia W, Chen J, Liu JB, Ma CH, Liu W. 2021. Landslide extraction from high-resolution remote sensing imagery using fully convolutional spectral topographic fusion network. *Remote Sensing*, 13(24), 5116. doi: [10.3390/rs13245116](https://doi.org/10.3390/rs13245116).
- Xu C, Xu XW, Shyu JBH, Gao MX, Tan XB, Ran YK, Zheng WJ. 2015. Landslides triggered by the 20 April 2013 Lushan, China, Mw 6.6 earthquake from field investigations and preliminary analyses. *Landslides*, 12(2), 365–385. doi: [10.1007/s10346-014-0546-1](https://doi.org/10.1007/s10346-014-0546-1).
- Xu C, Xu XW, Yao X, Dai FC. 2014. Three (nearly) complete inventories of landslides triggered by the May 12, 2008 Wenchuan Mw 7.9 earthquake of China and their spatial distribution statistical analysis. *Landslides*, 11(3), 441–46. doi: [10.1007/s10346-013-0404-6](https://doi.org/10.1007/s10346-013-0404-6).
- Xu QS, Ouyang CJ, Jiang TH, Yuan X, Fan XM, Cheng DX. 2022. MFFNet and ADANet: A robust deep transfer learning method and its application in high precision and fast cross-scene recognition of earthquake-induced landslides. *Landslides*, 19(7), 1617–1647. doi: [10.1007/s10346-022-01847-1](https://doi.org/10.1007/s10346-022-01847-1).
- Xu YL, Ouyang CJ, Xu QS, Wang DP, Zhao B, Luo YT. 2024. CAS Landslide Dataset: A Large-Scale and Multisensor Dataset for Deep Learning-Based Landslide Detection. *Scientific Data*, 11(1), 12. doi: [10.1038/s41598-024-54444-1](https://doi.org/10.1038/s41598-024-54444-1).

- 10.1038/s41597-023-02847-z.
- Yang J, Gong P, Fu R, Zhang MH, Chen JM, Liang SL, Xu B, Shi JC, Dickinson R. 2013. The role of satellite remote sensing in climate change studies. *Nature Climate Change*, 3(10), 875–883. doi: [10.1038/nclimate1908](https://doi.org/10.1038/nclimate1908).
- Yang S, Wang YZ, Wang PZ, Mu JQ, Jiao ST, Zhao XP, Wang ZH, Wang KJ, Zhu YQ. 2022. Automatic identification of landslides based on deep learning. *Applied Sciences*, 12(16), 8153. doi: [10.3390/app12168153](https://doi.org/10.3390/app12168153).
- Yang ZQ, Xu C. 2022. Efficient detection of earthquake-triggered landslides based on U-Net++: An example of the 2018 Hokkaido eastern Iburi (Japan) Mw 6.6 earthquake. *Remote Sensing*, 14(12), 2826. doi: [10.3390/rs14122826](https://doi.org/10.3390/rs14122826).
- Yang ZQ, Xu C, Li L. 2022. Landslide detection based on ResU-Net with transformer and CBAM embedded: Two examples with geologically different environments. *Remote Sensing*, 14(12), 2885. doi: [10.3390/rs14122885](https://doi.org/10.3390/rs14122885).
- Yao GL, Zhou WL, Liu MZ, Xu Q, Wang HH, Li J, Ju YZ. 2022. An empirical study of the convolution neural networks based detection on object with ambiguous boundary in remote sensing imagery—A case of potential loess landslide. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 15, 323–338. doi: [10.1109/jstars.2021.3132416](https://doi.org/10.1109/jstars.2021.3132416).
- Ye CM, Li Y, Cui P, Liang L, Pirasteh S, Marcato J, Goncalves WN, Li J. 2019. Landslide detection of hyperspectral remote sensing data based on deep learning with constraints. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 12(12), 5047–5060. doi: [10.1109/jstars.2019.2951725](https://doi.org/10.1109/jstars.2019.2951725).
- Yi YN, Zhang WC. 2020. A new deep-learning-based approach for earthquake triggered landslide detection from single Temporal RapidEye satellite imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 6166–6176. doi: [10.1109/jstars.2020.3028855](https://doi.org/10.1109/jstars.2020.3028855).
- Yu B, Chen F, Xu C. 2020. Landslide detection based on contour-based deep learning framework in case of national scale of Nepal in 2015. *Computers & Geosciences*, 135. doi: [10.1016/j.cageo.2019.104388](https://doi.org/10.1016/j.cageo.2019.104388).
- Yu B, Chen F, Xu C, Wang L, Wang N. 2021. Matrix SegNet: A practical deep learning framework for landslide mapping from images of different areas with different spatial resolutions. *Remote Sensing*, 13(16), 3158. doi: [10.3390/rs13163158](https://doi.org/10.3390/rs13163158).
- Yu B, Xu C, Chen F, Wang N, Wang L. 2022. HADeenNet: A hierarchical-attention multi-scale deconvolution network for landslide detection. *International Journal of Applied Earth Observation and Geoinformation*, 111. doi: [10.1016/j.jag.2022.102853](https://doi.org/10.1016/j.jag.2022.102853).
- Yu H, Ma Y, Wang LF, Zhai YS, Wang XQ. 2017. A landslide intelligent detection method based on CNN and RSG\_R. 2017 IEEE International Conference on Mechatronics and Automation, 40–44. doi: [10.1109/ICMA.2017.8015785](https://doi.org/10.1109/ICMA.2017.8015785).
- Zhang JM, Lu CQ, Li XD, Kim HJ, Wang J. 2019. A full convolutional network based on DenseNet for remote sensing scene classification. *Mathematical Biosciences and Engineering*, 16(5), 3345–3367. doi: [10.3934/mbe.2019167](https://doi.org/10.3934/mbe.2019167).
- Zhang M, Shi WZ, Chen SX, Zhan Z, Shi ZC. 2021. Deep multiple instance learning for landslide mapping. *IEEE Geoscience and Remote Sensing Letters*, 18(10), 1711–1715. doi: [10.1109/lgrs.2020.3007183](https://doi.org/10.1109/lgrs.2020.3007183).
- Zhang N, Ding SF, Zhang J, Xue Y. 2018. An overview of restricted boltzmann machines. *Neurocomputing*, 275, 1186–1199. doi: [10.1016/j.neucom.2017.09.065](https://doi.org/10.1016/j.neucom.2017.09.065).
- Zhang PF, Xu C, Ma SY, Shao XY, Tian YY, Wen BY. 2020. Automatic extraction of seismic landslides in large areas with complex environments based on deep learning: An example of the 2018 Iburi earthquake, Japan. *Remote Sensing*, 12 (23), 3992. doi: [10.3390/rs12233992](https://doi.org/10.3390/rs12233992).
- Zhang X, Zhou YN, Luo JC. 2021. Deep learning for processing and analysis of remote sensing big data: A technical review. *Big Earth Data*, 6 (4), 527–560. doi: [10.1080/20964471.2021.1964879](https://doi.org/10.1080/20964471.2021.1964879).
- Zhang XK, Pun MO, Liu M. 2021. Semi-supervised multi temporal deep representation fusion network for landslide mapping from aerial orthophotos. *Remote Sensing*, 13(4), 548. doi: [10.3390/rs13040548](https://doi.org/10.3390/rs13040548).
- Zhao W, Li AN, Nan X, Zhang ZJ, Lei GB. 2017. Postearthquake landslides mapping from Landsat-8 data for the 2015 Nepal earthquake using a pixel-based change detection method. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10(5), 1758–1768. doi: [10.1109/jstars.2017.2661802](https://doi.org/10.1109/jstars.2017.2661802).
- Zhong C, Liu Y, Gao P, Chen WL, Li H, Hou Y, Nuremanguli T, Ma HJ. 2020. Landslide mapping with remote sensing: Challenges and opportunities. *International Journal of Remote Sensing*, 41(4), 1555–1581. doi: [10.1080/01431161.2019.1672904](https://doi.org/10.1080/01431161.2019.1672904).
- Zhou YX, Wang HH, Yang RH, Yao GL, Xu Q, Zhang XJ. 2022. A novel weakly supervised remote sensing landslide semantic segmentation method: Combining CAM and cycleGAN algorithms. *Remote Sensing*, 14(15), 3650. doi: [10.3390/rs14153650](https://doi.org/10.3390/rs14153650).
- Zhu GH, Piao ZW, Kim SC (2020). Tooth detection and segmentation with Mask R-CNN. 2020 International Conference on Artificial Intelligence in Information and Communication, 070–072. doi: [10.1109/ICAIIIC48513.2020.9065216](https://doi.org/10.1109/ICAIIIC48513.2020.9065216).
- Zhu XX, Tuia D, Mou LC, Xia GS, Zhang LP, Xu F, Fraundorfer F. 2017. Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8–36. doi: [10.1109/mgrs.2017.2762307](https://doi.org/10.1109/mgrs.2017.2762307).