

A Comprehensive Review and Analysis of Landslide Detection through Advanced Image Analysis Techniques

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Abstract—Landslides are among the most destructive natural hazards, causing substantial loss of life and property damage worldwide. Remote sensing through satellite imagery has emerged as a valuable tool for studying and monitoring landslides over large areas. This review paper provides a systematic examination of the application of satellite data and image processing techniques for landslide detection and mapping. The literature review conducted across major scientific databases yielded over 500 initial results, of which 35 papers were selected for final review based on relevance, rigor, and innovation. The review summarizes key trends, datasets, methods, and challenges related to landslide detection using optical, radar, and LiDAR data. Analysis reveals that integration of multiple sensors, use of machine learning algorithms, and object-based image analysis have significantly improved landslide detection accuracy. However, challenges remain in distinguishing landslide signals from noise, handling data gaps, and transferring models across different geographical settings. Satellite-based landslide detection has immense potential for hazard assessment and disaster response if current limitations can be addressed through multi-temporal analysis, model generalization, and combination with ground data. This review provides a synthesis of current research and identifies promising directions for future work toward an operational landslide detection system using satellite imagery.

Index Terms—Landslide detection, Optical imagery, Geological mapping, Object-based image analysis

I. INTRODUCTION

Large-scale economic losses and human deaths are annually caused by landslides, which are among the most damaging natural disasters in the world [1]. For the purpose of emergency response and catastrophe management, it is imperative that landslides be detected accurately and quickly across wide areas [2]. Remote sensing using satellites has become a potent tool for researching and tracking landslides at local, regional, and global scales in recent years. This review offers a thorough and critical evaluation of recent studies devoted to landslide detection and analysis using satellite photography. High-resolution topography data may be repeatedly acquired at different intervals thanks to the optical, radar, as well as LiDAR sensors installed on contemporary satellite platforms. Landslide inventories and trends may be extracted from such

multi-spectral, multi-temporal satellite datasets using digital image processing techniques. The published research that has used spectral analysis, object-based image analysis, change detection, visual interpretation, and more modern machine learning techniques for landslide recognition utilizing space-borne observational data are summarised in this review. The strengths and weaknesses of the current methods for processing satellite images are assessed. Important technical issues with data gaps, model transferability, and identifying landslide signals are highlighted. In order to fully utilize the potential of developing satellite remote sensing methods via integration with ground-based data, the study ends with recommendations regarding future research areas. These recommendations aim to build robust operational landslide detection systems.

A. Landslide-causing factors

Landslides happen when a slope falls imbalanced and can be caused by a variety of natural and human-caused events [3]. Earthquakes, volcanic eruptions, destabilization brought on by groundwater pressure equal to erosion of slope toes [4], [6], as well as vegetation damage from wildfires are examples of natural processes. On the other hand, human activities that cause instability and the incidence of landslides include the moving of rock or soil, mining, the use of explosives, pipe leaks, as well as construction of structures or roads on slopes. Water affects slope stability in two ways: it can contribute weight or function as a lubricant. Slopes are stabilised by trees and other flora, yet can become unstable due to earthquakes. All in all, these elements work together to cause landslides to occur.

B. Types and composition of landslides

This review examines the many classifications of landslides, taking into account elements including composition, slope development, and modes of movement. Though often linked with hilly terrain, landslides may also occur in locations with reduced elevation, posing difficulties such as cut and fill collapses, riverside collapses, and mine-waste pile collapses. The paper aims to provide a thorough investigation into existing

research, methodologies, along with findings related to landslides, emphasising common types, especially falls that include rapid geological content movement compared to steep slopes. This will allow for a broader understanding of landslides that goes beyond specific types alongside regional contexts. Mass earth movements that occur downhill are known as landslides [5], and they are classified according to the kind of motion along with material involved. Falls are the abrupt drop of small amounts of water-less rock or debris via fractures or joints from steep hillsides. Rocks topple as they spin or pivot forward owing to gravity from an attachment point [5]. Masses fall down weak zones within rock or soil to cause translational or rotational slides [5]. Translational slides go parallel to the slope, but rotational slides feature a curved failure zone as well as backtilt. Spreads are the consequence of materials liquefying laterally, frequently as a result of earthquakes. Mudflows and other similar flows include the flowing, saturated soils downslope. Combinations of processes, such as flows extending out, are displayed in complex presentations [7]. A few examples of the variables that affect the kind of landslide include the slope angle, moisture content, properties of the rock and soil, and seismic activity. Fig. 1 shows various remote sensing methods used along with their respective timelines. In order to classify, failure patterns along with geomorphic indicators are used to evaluate the motion and material qualities. The many mechanisms that result from the interplay of slope materials, morphologies, water, and seismic pressures are all evident in landslides.

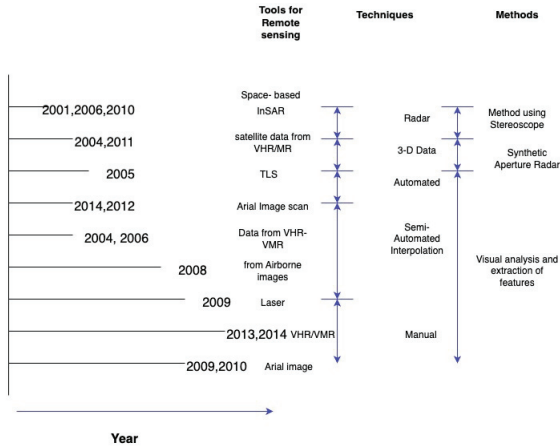


Fig. 1. Timeline depiction of remote sensing methods created for landslide examination

II. TECHNIQUES FOR DETECTING LANDSLIDES

Determining the limits of landslides on the ground while taking deformation of the surface and displaced mass into account is the main goal of landslide detection. One may identify the characteristics of landslides by visually examining their surface morphology, employing field mapping techniques, and using topographical representations obtained from remote sensing methods. Indirect feature interpretation from satellite images or aerial photogrammetry is used in the latter case.

A temporal overview of the development of remote sensing instruments for landslides studies is provided in Table 1 and Figure 1. The examined detection techniques may be broadly classified into two groups, as stated in Reference 10: traditional methods and novel, cutting-edge approaches.

A. Traditional methods for identifying landslides

Conventional techniques for identifying landslides include geomorphologic field surveys and visual inspection of orthophotographs or pictures taken during aerial surveys [8]. Analysing the features of landslides in the studied region is a part of geomorphologic field surveys, however older landslides might be difficult to identify because of decreased slope failure visibility [2], [9]. The goals of field mapping are to identify particular landslides, note their characteristics, and confirm inventory maps that already exist. The visual analysis of aerial images is based on stereoscopic analysis: which benefits from the accessibility of ancient stereo pairs, providing insights on historical landslides, but also requires experience and predetermined criteria. Features such as plant density, kind, height, and variations in vegetation cover are taken into account by the approach. Imaging scale, stereoscopic considerations, perfection and skill of the interpretation, and landslide detection quality are all related to one other.

B. Current methods

Reference 2 presents two new approaches to landslide detection: (i) Morphological analysis using HR-DEM; (ii) study of satellite data, including panchromatic, multiple band, and SAR pictures; and (iii) terrain analysis utilising aerial laser scanners such as ALS or ALSM [9]. The study of HR-DEM has recently made use of aerial laser scanners, specifically LiDAR, to get geological data. However, there are challenges in visualising VHR-DEM from LiDAR [10]. Since the 1970s, satellite imaging analysis has advanced by using multi-band pictures. Notable optical satellites that aid in landslide detection include GeoEye-1/2 and IKONOS. Using optical sensors, multispectral image analysis classifies landcover and incorporates semi-automated landslide analysis and NDVI maps [8]. Synthetic Aperture Radar (SAR) functions in all weather situations and penetrates clouds by using the microwave spectrum. SAR, and particularly DInSAR, provides centimetre to millimetre precision in the accurate identification of displaced surfaces across wide regions [8].

III. DEEP LEARNING METHODS EMPLOYING REMOTELY CAPTURED IMAGES TO EXAMINE LANDSLIDES

Three applications of deep learning are found in remote sensing: object recognition, transformation detection, and surface categorization.

Fig. 2 shows the basic connection between neurons inside a neural network. The advent of deep belief networks (DBNs) and autoencoders, as well as the potent results of convolutional neural networks (CNNs) in computer vision, are noteworthy developments [11], [12]. Managing massive volumes of hyper-spectral data, having few labelled examples, and dealing with

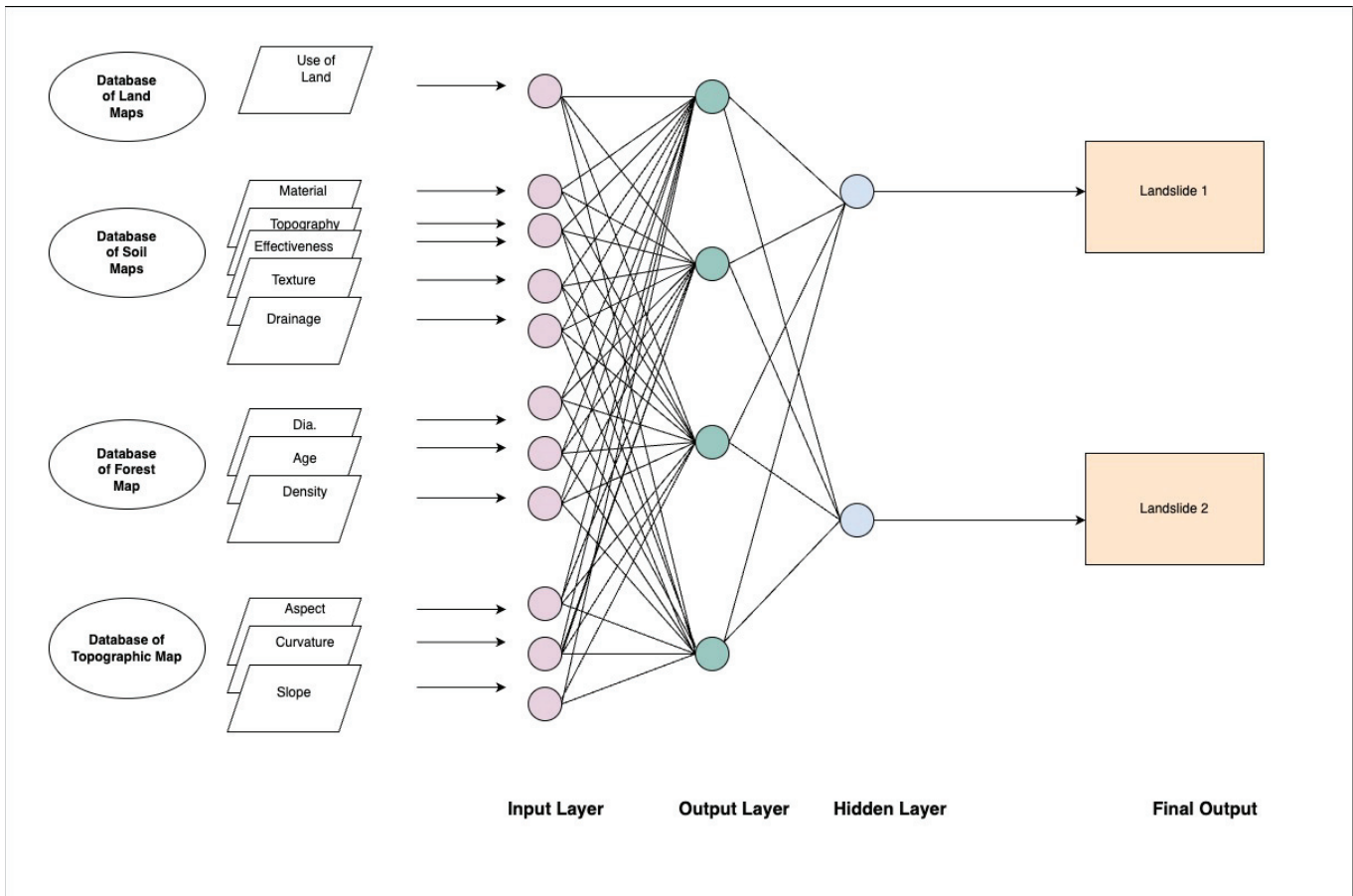


Fig. 2. An example of deep learning neural network's visual representation, showing the complex relationships connecting layers of neurons which enable the network to learn from input and carry out challenging tasks.

the complexity of remotely sensed pictures are some of the difficulties in merging remote sensing with deep learning [13]. In order to improve accuracy, recent research has investigated the application of CNNs for landslide detection, integrating topographic data with spectral bands, and creating object-based CNN techniques. Furthermore, transfer learning has been used to classify scenes by taking advantage of the greater availability of higher-resolution remote sensing data. For landslide detection, a number of deep learning models—Temporal Convolutional Neural Networks, or TempCNNs—have been used, demonstrating improvements in the manipulation of temporal and spectral information [14]. The use of CNN techniques has grown even more as remote sensing data has become more readily available, especially at higher resolutions. This is especially true when used with transfer learning to classify scenes [15].

A. Deep learning-based image segmentation methods for classifying land cover

Categorising areas or pixels in pictures is the main goal of surface classification in remote sensing, and deep learning models like Sparse Autoencoder, Deep Belief Network, and Convolutional Neural Network (CNN) are commonly em-

ployed for this purpose. Even if they are used for image classification, traditional networks like VGG Net and AlexNet have difficulties in integrative and multi-classification settings [18]. Fully Convolutional Networks (FCN) employ a CNN-based semantic segmentation technique to address issues [17]. FCN, however, has trouble with classification certainty and edge details. Then, an encoder-decoder architecture called SegNet is shown. It enhances the upsampling translation step by encoding using VGG-16 layers. Atrous convolution is incorporated into Deeplab for improved resolution, and Deeplab V3+ [18] integrates multiscale information to further improve this technique. To extract features and capture multiscale contextual knowledge, ResNet is utilised [19]. Semantic segmentation is the end result of the encoding and decoding phases in the broad landscape for deep learning techniques for surface categorization. Certain techniques also include post-enhancement processes to increase accuracy by minimising noise and optimising it.

B. Methods for detecting objects

Object recognition is an important job in remote sensing, especially when analysing high-resolution photos with 1.5–4 m spatial resolution. Fig. 3 shows basic layers inside the

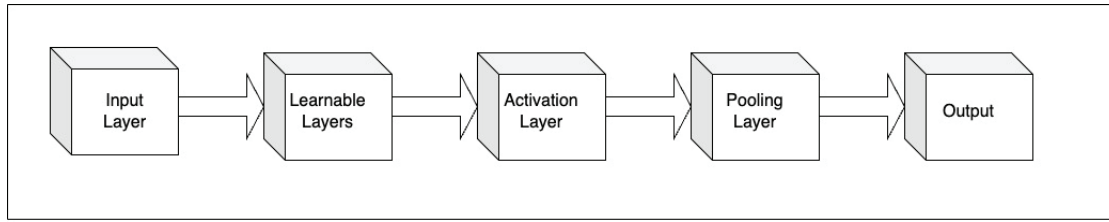


Fig. 3. An illustration of the different layers of deep learning, where the input is analysed through the interconnection of artificial neurons to uncover significant patterns.

TABLE I
TECHNIQUES FOR IMAGE SEGMENTATION

Citation	Techniques	Purpose	Architecture	Output	Others
[17]	Semantic Segmentation Model	To perform semantic segmentation	Complex	N-Channeled image	Pixel based semantic labelling
[17]	Fully Convolutional Network	Semantic Segmentation model	It will be developed on layers which are connected locally	Deconvolutional layer	Upsampling by decoder will be performed after performing downsampling by encoder.
[18]	Deep Labelling for Image Segmentation	Semantic Segmentation Model	Encoder-Decoder Architecture	Pixels will be labelled	keeps segmentation of the encoder-decoder architecture using the precision of the xception model
[18]	Visual Geometry Group	Scene Classification	13 layers of CNN and 3 layers of FCC	Eigen Vectors as output	Spacial Information will be recovered after interpreting the context by downsampling
[18]	AlexNet	Scene Classification	5 layers of convolutional layer followed by 3 layers of Max-Pooling	Eigen Vectors as output	Number of parameters used will be reduced

neural network. The region-based convolution neural network (R-CNN), that converts the object identification issue into a classification-based one, is the main deep learning model for object detection. Building on R-CNN, Mask-RCNN is used for object instance segmentation, and Fast R-CNN [20] and Faster R-CNN models [20] have been developed to speed up object identification. Additional methods for deep learning object recognition are SSD (Single Shot Multibox Detector) [23], YOLO (You Look Only Once) [18], and SPP-Net. The conventional way of locating objects in an image involves sliding windows; however, this approach is limited since objects might have various dimensions and aspect ratios. Table I shows various techniques used for image segmentation. The technique for selective search [21] is the primary method for producing candidate zones. CNN processes these zones to produce eigenvectors and then detect objects. In order to minimise overlapping candidate regions, spatial pyramid pooling networks (SPP-Net) [22] and Fast R-CNN are used. Faster R-CNN further improves efficiency by introducing the Region Proposal Network (RPN). SSD and YOLO help to preserve accuracy while improving the agility of object detection.

C. Methods for detecting changes

In order to discover changes brought about by either natural or man-made events, two remote sensing photographs of

the same region with varying temporal resolutions must be analysed. There are two primary strategies used by deep learning algorithms for change detection: either considering issues such as surface classification and categorising map places at the pixel level [25], or identifying the area of study points and calculating related changes. Using multitemporal and multispectral imaging, deep learning improves change detection by classifying remote sensing photos into groups such as bare soil, dry vegetation, man-made structures, and water [24].

IV. LANDSLIDE SUSCEPTIBILITY MAPPING USING MACHINE LEARNING

Using a variety of methods, including Support Vector Machines (SVM), Decision Trees, Neural Networks, Logistic Regression, Random Forest, along with Naïve Bayes Trees (NBT), machine learning is essential to the evaluation and prediction of landslide risk. These methods are used to identify landslides using high-resolution satellite Earth observation data, either on optical as well multi-band satellite imaging. Accuracy is improved by integrating with spectral plus topographic parameters. SVM, RBF Neural Nets, Kernel Logistic Regression, MLP Neural Nets [26], along with Logistic Model Trees are some of the methods used in pixel-based object recognition. Landslide susceptibility study benefits greatly

TABLE II
METHODS USED IN MACHINE LEARNING FOR OBJECT DETECTION

Citation	Method	Approach used	Description
[23]	Single-Shot detector	bounding boxes for multiple scales	feature maps are assigned with filters and then predictions are made to different scales
[20]	Convolutional Neural Network	Every region is assigned to different classes after distributing each image into different regions	The computational time and number of images required is high
[20]	Region-Based CNN	Selective Search	Each image is divided into 2000 regions
[18]	You Only Look Once	Single CNN	Prediction of all the images is done as classes and bounding boxes
[17]	FCNN	Region-based network	RPN is faster as compared to Selective Search
[23]	RetinaNet	Multi-box detector in one shot	Feature maps are generated for object detection at multiple scales using FPN
[22]	SPP-Net	Spatial Pyramid Pooling Network	Repetitive processing of candidate region will be eliminated
[20]	Feature vector	SoftMax classifier got generated using Region Of Interest	better training and testing time

from machine learning, which makes use of Decision Trees, Bagging, SVM, Neural Networks, Random Forest [27], including the hybrid Naïve Bayes Tree. Table II shows various methods that are used in machine learning for object detection. More recent work focuses on improved machine learning techniques, tackling problems with landslide area estimation, conditioning factor selection, and displacement prediction. SVM [28] is praised for kernel-based separation, Random Forest for accuracy as well as processing speed, Logistic Regression for testing simplicity and flexibility, and ANN for handling intricate nonlinear situations. The hybrid technique known as NBT, which combines Naïve Bayes and decision tree classifiers, shows promising results in landslide analysis. These machine learning methods are essential for mapping hazards, assessing the danger of landslides, and organising crisis responses.

V. ENSEMBLE METHODS FOR LANDSLIDE SUSCEPTIBILITY ANALYSIS

The two types of ensemble methods—homogeneous, which use a single algorithm across many data subsets, and heterogeneous [29], which integrate models from different algorithms—are essential for managing complicated high-dimensional data. A bootstrap sampling method called bagging lowers variance and improves classification accuracy. A popular boosting method called AdaBoost [30] builds a series of classifiers repeatedly by concentrating on successfully categorising data that has been incorrectly categorised in the past. LogitBoost [31] is an extension of AdaBoost that uses additional logistic regression in order to classification in place of exponential destruction as well as conditional Bernoulli-likelihood loss. Boosting and wagging are used in Multiboot

[32] to minimise variation and deviation. By using feature transformation via Principal Component Analysis [33] as well as linear transformation, Rotation Forest encourages the development of accurate and diverse base classifiers. In each cycle, this method generates data by using PCA, bootstrapping sampling, and partitioning input features into subsets. Particularly in landslide susceptibility modelling, where nuances in the data used for training can greatly affect prediction capabilities, these ensemble approaches help to develop strong and efficient models.

VI. CONCLUSION

Recent machine learning as well as deep learning methods for landslide detection utilising remote sensing data have been thoroughly reviewed in this article. Although there has been progress, more work has to be done in the areas of transfer learning for landslide identification, sample size augmentation, neural network architecture planning, which is and multi-source data fusion. Although object-based image analysis has potential, further study is needed to get the best segmentation and feature extraction. In complicated terrains such as tropical woods, effective identification may require the combination of topographical parameters and spectral fingerprints from various modalities. Combining several machine learning techniques into ensemble methods may improve the robustness and performance of the model. Additionally, more work is required in the thorough assessment of model generalizability with different training-testing ratios. The review synthesis as a whole emphasises that sophisticated deep learning has enormous potential to automatically identify landslides from a variety of remote sensing inputs. However, in order to convert these technologies into reliable, functional landslide detection

systems, more research on neural network architecture, multi-modal data integration, and model assessment is required.

VII. FUTURE SCOPE

Prospective avenues for future research encompass evaluating Mask R-CNN for landslide detection in various geographical regions and examining transfer learning to enhance the transportability of models. Our goal is to investigate how to increase model resilience and provide more training data by utilising GAN approaches. To fully realise the potential of AI-based landslide detection utilising satellite remote sensing, more investigation into the best deep learning architectures, integration of multi-sensor data, and stringent validation techniques will be necessary.

REFERENCES

- [1] Tapas R Martha, P Kamala, Josna Jose, K Vinod Kumar, and G Jai Sankar. Identification of new landslides from high resolution satellite data covering a large area using object-based change detection methods. *Journal of the Indian Society of Remote Sensing*, 44:515–524, 2016.
- [2] Tapas R Martha, Norman Kerle, Cees J Van Westen, Victor Jetten, and K Vinod Kumar. Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories. *ISPRS journal of photogrammetry and remote sensing*, 67:105–119, 2012.
- [3] Tolga Gorum, Xuanmei Fan, Cees J van Westen, Run Qiu Huang, Qiang Xu, Chuan Tang, and Gonghui Wang. Distribution pattern of earthquake-induced landslides triggered by the 12 may 2008 wenchuan earthquake. *Geomorphology*, 133(3-4):152–167, 2011.
- [4] Tapas R Martha, K Babu Govindharaj, and K Vinod Kumar. Damage and geological assessment of the 18 september 2011 mw 6.9 earthquake in sikkim, india using very high resolution satellite data. *Geoscience Frontiers*, 6(6):793–805, 2015.
- [5] S Madaan. Causes, effect and types of landslides. *Bull Seismolog Soc Am*, pages 9–10, 2017.
- [6] SPPradhanandTariqSiddique. Masswasting: an overview. *Landslides: Theory, Practice and Modelling*, pages 3–20, 2019.
- [7] Oldrich Hungr, Serge Leroueil, and Luciano Picarelli. The varnes classification of landslide types, an update. *Landslides*, 11:167–194, 2014.
- [8] Fausto Guzzetti, Alessandro Cesare Mondini, Mauro Cardinali, Federica Fiorucci, Michele Santangelo, and Kang-Tsung Chang. Landslide inventory maps: New tools for an old problem. *Earth-Science Reviews*, 112(1-2):42–66, 2012.
- [9] Zeljko Arbanas, SMihalic Arbanas, Martina Vivoda, Josip Peranic, S Dugonjic Jovanc'evic, and Vedran Jagodnik. Identification, monitoring and simulation of landslides in the rijeka river valley, croatia. In *Proceedings of the SATREPS workshop on landslide risk assessment technology*, pages 29–30. International Consortium on Landslides Kyoto, 2014.
- [10] Khamarrul Azahari Razak, MW Straatsma, CJ Van Westen, J-P Malet, and SM De Jong. Airborne laser scanning of forested landslides characterization: Terrain model quality and visualization. *Geomorphology*, 126(1-2):186–200, 2011.
- [11] Ying Li, Haokui Zhang, Xizhe Xue, Yenan Jiang, and Qiang Shen. Deep learning for remote sensing image classification: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(6):e1264, 2018.
- [12] Chenming Li, Yongchang Wang, Xiaoke Zhang, Hongmin Gao, Yao Yang, and Jiawei Wang. Deep belief network for spectral-spatial classification of hyperspectral remote sensor data. *Sensors*, 19(1):204, 2019.
- [13] Chengming Ye, Yao Li, Peng Cui, Li Liang, Saeid Pirasteh, Jose Marcato, Wesley Nunes Gonc alves, and Jonathan Li. 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, 2019.
- [14] Charlotte Pelletier, Geoffrey I Webb, and Francois Petitjean. Temporal convolutional neural network for the classification of satellite image time series. *Remote Sensing*, 11(5):523, 2019.
- [15] Heng Lu, Lei Ma, Xiao Fu, Chao Liu, Zhi Wang, Min Tang, and Naiwen Li. Landslides information extraction using object-oriented image analysis paradigm based on deep learning and transfer learning. *Remote Sensing*, 12(5):752, 2020.
- [16] Ming Zhu, Yongning He, and Qingyu He. A review of researches on deep learning in remote sensing application. *International Journal of Geosciences*, 10(1):1–11, 2019.
- [17] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.
- [18] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 801–818, 2018.
- [19] Myeongsuk Pak and Sanghoon Kim. A review of deep learning in image recognition. In *2017 4th international conference on computer applications and information processing technology (CAIPT)*, pages 1–3. IEEE, 2017.
- [20] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28, 2015.
- [21] Jasper RR Uijlings, Koen EA Van De Sande, Theo Gevers, and Arnold WM Smeulders. Selective search for object recognition. *International journal of computer vision*, 104:154–171, 2013.
- [22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. *IEEE transactions on pattern analysis and machine intelligence*, 37(9):1904–1916, 2015.
- [23] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In *Computer Vision—ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14*, pages 21–37. Springer, 2016.
- [24] John E Ball, Derek T Anderson, and Chee Seng Chan. Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. *Journal of applied remote sensing*, 11(4):042609–042609, 2017.
- [25] Omid Ghorbanzadeh, Thomas Blaschke, Khalil Gholamnia, Sansar Raj Meena, Dirk Tiede, and Jagannath Aryal. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. *Remote Sensing*, 11(2):196, 2019.
- [26] Dieu Tien Bui, Tran Anh Tuan, Harald Klempe, Biswajeet Pradhan, and Inge Revhaug. Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. *Landslides*, 13:361–378, 2016.
- [27] Natan Micheletti, Loris Foresti, Sylvain Robert, Michael Leuenberger, Andrea Pedrazzini, Michel Jaboyedoff, and Mikhail Kanevski. Machine learning feature selection methods for landslide susceptibility mapping. *Mathematical geosciences*, 46:33–57, 2014.
- [28] Yu Huang and Lu Zhao. Review on landslide susceptibility mapping using support vector machines. *Catena*, 165:520–529, 2018.
- [29] Prima Riza Kadavi, Chang-Wook Lee, and Saro Lee. Application of ensemble-based machine learning models to landslide susceptibility mapping. *Remote Sensing*, 10(8):1252, 2018.
- [30] Dieu Tien Bui, Tran Anh Tuan, Harald Klempe, Biswajeet Pradhan, and Inge Revhaug. Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. *Landslides*, 13:361–378, 2016.
- [31] Hamid Reza Pourghasemi, Amiya Gayen, Sungjae Park, Chang-Wook Lee, and Saro Lee. Assessment of landslide-prone areas and their zonation using logistic regression, logitboost, and naive bayes machine-learning algorithms. *Sustainability*, 10(10):3697, 2018.
- [32] Ataollah Shirzadi, Karim Solimani, Mahmood Habibnezhad, Ataollah Kaviani, Kamran Chapi, Himan Shahabi, Wei Chen, Khabat Khosravi, Binh Thai Pham, Biswajeet Pradhan, et al. Novel gis based machine learning algorithms for shallow landslide susceptibility mapping. *Sensors*, 18(11):3777, 2018.
- [33] Xiaohui Sun, Jianping Chen, Yiding Bao, Xudong Han, Jiewei Zhan, and Wei Peng. Landslide susceptibility mapping using logistic regression analysis along the jinsha river and its tributaries close to derong and deqin county, southwestern china. *ISPRS International Journal of Geo- Information*, 7(11):438, 2018.