Recent Trends and advances in deep learning techniques for the classification of landslides using satellite images: comprehensive survey

Recent Trends and advances in deep learning techniques for the classification of landslides using satellite images: comprehensive survey

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Abstract. A landslide is a geographical catastrophe that occurs frequently in monsoon season and has a formidable impact over a wide range to pose risks to human lives and infrastructure worldwide. Traditional methods to classify and identify landslides are more time-consuming and less reliable. In the past few years artificial intelligence algorithms mainly, deep learning algorithms were used in many fields to detect and identify automatic disasters like landslides and earthquakes. Numerous research and classification approaches have been implemented in satellite image processing for the detection and prediction of landslides. The most challenging task in the classification and prediction of landslides from satellite imagery is to train the model with appropriate techniques and datasets which predict "accurately". Limited work has been done on high-resolution satellite images using convolution techniques. This article presents a comprehensive study of recent deep-learning approaches based on convolutional neural networks to achieve efficient classification of landslide satellite images. A few selected research articles on deep learning approaches based on CNN for automatic detection of landside from peer reviews journals etc. are considered for this study. "The performance of all surveyed articles is evaluated using accuracy recall precision and F 1 score parameters". This study illustrates the viability of deep learning approaches in learning complex and high-resolution satellite images for the classification and prediction of landslides.

1. Introduction

1.1 History and background of landslide classification

Landslide is a common and frequent serious geological hazard in hilly areas, which cause damage to the environment, and human and socioeconomic conditions of many countries. The trigger factor of landslides is rainfall, soil, earthquake, seismic shaking and unplanned construction. To rescue and prevent the recurrence of landslides timely and reliable and accurate measures are required [1]. In Himachal Pradesh's Kothipura district Mandi on 12 August 2017 a debris flow type landslide took place causing 47 fatalities. In 1977 at the same site, huge landslide took place and was reactivated again on 13 august 2007. Tension carks, antecedent rainfall, rock mass, rise in soil moisture and increase in seismic activities were various causes. Still its reoccurrence chances are possible so continuous monitoring from satellite provides use information or early alarming of the event [2]. A number of

landslides have occurred in the Kinnaur district of Himachal Pradesh causing a number of deaths and property loss by heavy rainfall seismic activities and unplanned construction [3].

There are numerous case studies based on field surveys that are used for landslide detection and monitoring. All the traditional approaches to detecting classifying and monitoring landslides are reliable but very time-consuming. Automatic landslide classification, detection and monitoring are possible with the advancement in satellite image processing. For analysis of landslide detection aerial images have been widely used and provide good accuracy [4,5]. data from the Digital elevation model perform a pivotal role in the detection and prediction of landslides by providing topographic information [6]. For landslide classification and prediction-number of machine learning algorithms were used. Machine learning classification schemes are categorized as SVM classifiers, clustering-based classifiers, learning-based classifiers, fuzzy classifiers, and Bayesian classifiers [7,8]. In supervised machine learning methods labeled high-resolution data is required for training and testing for automatic detection and classification. These classification machine learning algorithms are based on low-level features which result in poor classification accuracy [9].

Deep learning is a subset of machine learning that has evidenced its efficiency in classification and prediction with satellite images in the past few years. In Deep learning, images can be processed with convolutional neural networks and achieve good results [10][11] Deep learning models such as deep convolutional networks and deep brief net have yielded good results in segmentation, object classification and detection [12].

Nowadays, development in infrastructure and weather conditions are triggering many parameters of landslide. So automatic detection and early alarming systems pay an important role to save life and infrastructure.

1.2 Stages of landslide classification

Landslide classification and prediction are mainly divided into two categories. One depends on the type of images used for training and testing and the other depends on the type of algorithm used for training and testing. The resolution of Earth-observing satellite images is an important feature to be considered in satellite image classification. Spatial, spectral, temporal, radiometric and geometric are five types of resolution.

1. Spatial resolution, pixel size of an image representing the size of surface area. Once an image is acquired its spatial resolution is frozen.
2. Spectral resolution is defined by wavelength discrete segments of electromagnetic space interval.
3. Time resolution is defined by the number of days that pass between a collection of two images.
4. Radiometric resolution recodes many levels of brightness.
5. Geometric resolution represents a portion of the earth's surface in a single pixel and is known as ground sample distance.

There are two types of approaches used in identification: pixel-wise and object-based image analysis. Pixel-based landslide identification defines pixel values and changes in pixel values. Attribute features are used in object-oriented identification [13].

To train the model semantic segmentation algorithms such as DeepLab,Mask R CNN, U-Net and fully convolution network(FCN) are used to pre-process the data. The choice of algorithm depends on the application and requirement. The model is trained with the algorithms of the Convolutional neural network. Finally, the trained model performance is tested with random datasets.

1.3 Motivation

From last few years remote sensing data was used to monitor changes on the earth surface, landslide detections, post and pre-images of landslide areas, forest monitoring and environment changes [14,15,16]. Satellite remote sensing offer information on a large area for a short period of time and is useful for the detection and relief of disasters like landslide, Earthquake and, flood [17 ,18]. Satellite remote sensing image-based databases have become very beneficial for object classification and

prediction in the last few years. In low and medium resolution satellite images have the ambiguity of overlapping in spectral curves. High-resolution data can achieve high accuracy as compared to medium and low spatial resolution. High-resolution Satellite images database become very much in demand for real-time events such as landslides [19].

1.4 Objectives

The primary objectives of this research work are

1. To identify the research gap in the literature available on deep learning models in landslide satellite image classification, object detection and prediction.
2. Compare the result of different deep learning algorithms performed on landslide identification on the basis of four parameters: accuracy, precision, recall and f1 score
3. Explore the effect of optimization to enhance the performance of CNN-based deep learning models for identification of landslides from satellite imagery database.

1.5 Article selection strategy

For this comprehensive study, we select research papers based on deep learning algorithms for the automatic identification of landslides from IEEE Explore, Springer, Remote sensing journal, landslide journal, IEEE and science direct etc. All the articles are based on landslide identification with deep learning for the last few years with common ground and parameters for comparison. Use a common strategy to compare different techniques. Research articles are covering the study of various landslide-prone areas all over the world which help researchers to understand changing trends of parameters and is helpful for proposing an advanced technique for automatic identification of the landside.

1.6 Organization of the Article

The article is organized into different sections: Section 2 covers the overview of the available data sets used by all the articles considered in this work. Section 3 elaborates on related work in this area. Observations and findings are discussed in Section 4 on the basis of the research gap identified in related work**.** Section 5 explains the proposed algorithm and Section 6 concludes the paper.

2. Related Work

This comprehensive survey provides an overview of various deep-learning models that have been used in the analysis and classification of landslide satellite images. The main agenda of this article is to discuss the current deep learning model for landslide classification and identification toward improving identification accuracy. The last few years of research work is compared with accuracy, precision, recall and F1 score. This work proposes the recent trends, advantages and performance of deep learning methods in the identification of landslides. Bijie Land Slide Dataset [20] and Global Landslide Catalog Export [21] landslide datasets have been used in many research related to the automatic detection of landslides with convolutional neural networks. Most of the researchers used data sets that are available publically. In neural networks, data set plays a very important role in training and testing. Accuracy in the detection of landslides depends on how accurately the network was trained. The tainting dataset should be full of accurate information so the training of the model is accurate.
A comprehensive review of a few selected articles on the identification landslides is presented below.

Ji S et al. [20] designed an attention module to emphasize the different features of a complicated background landslide. The paper was focused on developing an accurate and time-efficient inventory, based on the recognition of latent landslides. The work has been done on high-resolution optical satellite images with a CNN model to detect landladies. The attention mechanism which is based on a human visual system was developed with a number of landslides with complex backgrounds. Attention Mechanism was combined with CNN to boost the result of CNN to extract more features from the background of the landslide. Bijie landslide database with 770 images was created. Design and attention module which combine spatial and channel attention map and known 3D spatial channel attention

module (3D SCAM) was designed and used in this work. The proposed 3D SCAM was trained with two-thirds of the images and results are compared with other attention modules. A few deep learning architectures such as VGGNet, ResNet, Inception, and DenseNet were evaluated with four attention modules as SE module, BAM Module, CBAM module, 3D SCAM module. Experimental result shows that ResNet50 with the proposed 3D SCAM bossed CNN provide the best result in all the combination. This research claims 97.7 % accuracy, 0.97 precision, 0.94 recall and F1 score was 0.95. The accuracy of the model is high with the attention module. In this attention module model can learn the characteristics of landslides very clearly.

Yang S et al. [22] developed a semantic segmentation-based deep learning automatic model for the identification of landslides. Three selected semantic algorithms U-Net, DeepLab3+ and PSPNet were used with different deep learning algorithms such as ResNet 50, MobileNet etc. as the backbone. An open-source Bijie landslide dataset was used for training and testing the different combinations of semantic algorithms with a backbone deep learning model. Images on this dataset were pre-processed with an augmentation technique to enhance the data and data cleaning. In the deep learning model training plays, a very important role and depends on three points: accurate information in the data set, suitable parameters, and methods adopted for training. In this model, 90% data was used in training and 10% was used for the validation process. Experimental results were evaluated on six combinations of three semantic segmentation models (U-Net, DeepLab3+ and PSPNet) with two different deep learning architectures as the backbone (VGG, ResNet50, MobileNet, Xception). The pixel-type classification was used in this work. The freezing training method was adopted so the backbone of the model was frozen which was full with large batch size and learning rate. Experimental evaluation of PSPNet model with ResNet50 as backbone network yield 91.18 mIou (Jaccard Index) high accuracy, 96% recall and 93.76% precision. The work done by the researchers has significant practical use in real-time. This work will help geologists and disaster management to identify landslides automatically which will be more efficient than manual methods which are more time-consuming to save life. The accuracy of work still can increase by using more datasets. The algorithm can be trained with high-resolution images to improve the accuracy in the identification of landslides.

Lui T et al. [23] designed a landslide detection mapping (LDM) model based on residual neural networks and Dense convolutional neural networks. ResNet and DenseNet take high spectral resolution data and conditioning factors and 70 % of the data was used for training and 30%data was used for testing. To create database two cities of the chain was taken as steady object which is China's water conservancy project. CNN, ResNet and DenseNet were trained with nineteen conditional factors and found application in the field of LDM. In all these three algorithms DensNet with remote sensing (RS) images yielded the best result. All three trained algorithm claim accuracy above 95% and densNet with RS images and condition factor claim 99% accuracy and recall and F1 score for this particular dataset. The learning efficiency of the model was enhanced with conditional factor and yielded good results in landslide identification.

Fu R et al. [24] proposed a study on post-earthquake seismic landslides. To determine the size of post-earthquake few images of post-earthquake seismic landslide satellite imagery data were used. The database was created from Post-quake images of unmanned air vehicles (UAV) over Wenchuan country of China. The database has an average 2000 m altitude and 0.25m spatial resolution with an image size of 5616*3744 pixels. In pre-processing steps the database images were reduced in size to remove the complexity and textual information was added to these seismic landslide images. To increase the number of images in the dataset data augmentation was done with image rotation and image flip. For training, 70% of data was used, 20 % for validation and the remaining 10% was used for testing. Mask R CNN framework can scan the image and mark the region of a landslide as a target and proposes a mask according to the marked region of interest. For identification and prediction of landslides in the real world required a large number of datasets and by using transfer learning this requirement can be reduced.

Three architectures of convolutional neural networks ResNet 50, ResNet 101 and Swin transformer was used as backbone networks. Among three backbone Swis Transformer with Mask R-CNN claims 82.2% accuracy, 93.28% precision, 87.41% recall and 90.25%F1 score. This model needs to improve the accuracy in the identification and prediction of landslides. Accuracy can be enhanced with the quality of post-quake landslide images. Instead of using UAV images satellite images with high spatial and spectral resolution can be used.

Ullo S L et al. [25] presented a landslide detection method that uses Mask R-CNN with pixel-based segmentation to identify object layouts. ResNet50 and ResNet 101 was used as the backbone for the proposed method and the result was evaluated with accuracy, recall, precision and F1 score. The main objective of this research was to detect landslides with pertained mask RCNN with limited data set and Augmentation was used on the training dataset to increase the volume. The dataset that was used in training and testing was created from different resources. Images collected were high-resolution digital photographs collected from UAV, search engines. Two data sets A and B were created. Data set A contains total160 images, 101 images were used for training, 28 were used for validation and 31 were used for testing. Data set B contains total121 images, 62 images were used for training 28 were used for validation and 31 were used for testing different resources. Experimental result shows that ResNet101 have better accuracy, recall, precision and F1 score over ResNet 50. ResNet 101 yields 97% accuracy for dataset A and 90% accuracy for data set B. RestNet 101 has 1 precision, 93% recall, and 0.97 f1 score. The main advantage of this research was mask R CNN can provide segmentation and detection of landslide at the same time. The result shows that with the higher number of training samples accuracy was high.

Ghorbanzadeh O et al. [26] presented a model which fuses object-based image analysis (OBIA) with a Fully convolution network. ResUnet as the predominate FCN model was trained and tested with Sentinel 2 database and design an combination of FCN-OBIA segmentation and classification using knowledge-based rules. In OBIA image difference indices were calculated between pre and post landslide. The data set used in training and testing was created from sentinel-2 images of Eastern Iburi Japan. The experimental results show that ResU-Net yield 50.24 mIOu, 76.15 precision,60.01 recall and 66.62 F1 score where as ResU Net OBIA yield 72.49 mIOu, 85.5 precision, 82.6 recall and 84.03 F1 score. In this work, it is observed that the ResU-Net model detect landslide correctly but have high false positive results. The result was more accurate and had fewer false positives by adding rule-based OBIA for a landslide to train ResU-Net.

3. Observations and findings

The basic purpose behind the wide variety of selected articles in this study is to observe the performance of existing techniques for landslide identification and prediction using satellite data. Another important purpose is to identify the research gap and based on the gap propose a new technique to achieve high performance in terms of Accuracy, Precision, recall, F1 score. These two purposes and our outcomes are discussed in the subsections below.

3.1. Observations and Findings

During this research, some findings will be helpful for future research direction and these are summarized in this section:

- In all the architecture data collection was the major part. Training and testing of the proposed algorithm were done with a satellite dataset of landslides.
- High-resolution images and a good training process can produce landslide identifiers and predictors with good performance.
- Images should be of the same size in both the training and testing time of architecture.

- For deep learning architectures training process requires high-speed machines with a great number of datasets.

3.2. Research gap identified

Landslide is a real-time event and it is very difficult to create a database with a very high number of images. Landslide events depend on a number of factors like rain soil weather conditions. Need to design a model with Convolutional neural network which takes care of different factors of landslide. Deep neural networks are difficult to understand and with complex architecture of networks prediction is very difficult. Convolutional Neural network architecture has practical applications in images classification, object detection, and semantic segmentation [20]. Semantic segmentation with pixel-level segmentation provides good results in image segmentation [22].

The articles in this study have very effective results in terms of accuracy, precision, recall and F1 score for landslide detection. There are few potential research gaps as follows:

- Performance: Accuracy plays the main role in the performance of an automatic detection landslide model. Selected literature articles were compared with common parameters: accuracy, precision, recall and f1 score. The range of accuracy lies between 80% to 92%. Semantic segmentation model PSPNet with ResNet50 as backbone achieves the highest mIOU at 91.18% this can be further improved by exploring false results. [22]. The Swis Transformer as backbone network with Mask R-CNN claims 82.2% accuracy [24]
- Method used: Convolutional neural network architecture such as ResNet50, ResNet101, VGG, DensNet, Google Net were used as the backbone with different approaches and provide different results. CNN along with spatial channel attention mechanism and high-resolution optical images yield high accuracy. Need more investigation on the superiority of spatial channel attention mechanism [20].
- Database: Need is high-resolution remote sensing image dataset for improving accuracy. Models were trained for selected datasets. Bijie landslide dataset was used but it is limited with 770 images of landslide and nonlandslide images. Some Dataset was created from images of unmanned air vehicles which contain different images from different sources. Instead of using UAV images satellite images with high spatial and spectral resolution can be used and will provide good result. [25] Training is limited with the dataset is the biggest research gap.
- Different type of landslide has different characteristics. The model based on Mask R-CNN with pixel-based segmentation and ResNet at the backbone does not specify whether the model tested for different types of landslide. Results are only compared in between ResNet 50 and RestNet 101 rather than the other potential object detector deep learning architecture. [25].

4. Discussion

In the last few years, there has been research that provides automatic landslide identification and prediction with convolutional neural networks that claim good accuracy. Accuracy can be enhanced by increasing the number of datasets and by considering the condition factors. In Real-time events, it is difficult to collect more satellite images of a particular area. Augmentation techniques can be performed over available data set to increase the number of training sets. Semantic segmentation which labels each pixel in an image with the corresponding class label provides detail, unlike basic image segmentation techniques. Important stages of landslide identification and prediction are satellite image collection, pre-processing the image dataset and increasing the number of images in the dataset, Training the designed model with backbone CNN Networks such as: ResNet v50, ResNet 101, DensNet, Google Net, VGG etc. Finally, test the model with the dataset.

In the proposed model we can combine attention mechanism and optimization algorithms. The optimization algorithm can update the weights and attention layer to minimize the loss function. To enhance accuracy regularization techniques such as Dropout and batch normalization can be used. While

creating a dataset enough care should be taken on conditional factors of landslide. The flow chart of the proposed model is shown in Fig. 1.

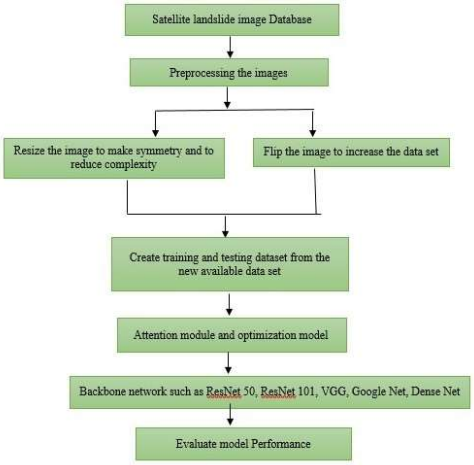

Fig. 1 Flow chart of proposed landslide detection model.

4.1. Dataset being used

Initially, we try our algorithm with open source Bijie landslide dataset which contains two sets of images one contains landslide images and the other is non landslide images. To increase the size of the dataset augmentation techniques can be applied. Later we try to test the model with practical events of landslides.

4.2. Expected outcomes

In our proposed model augmentation techniques will be used to increase the dataset and optimization and transfer learning will be used to enhance the accuracy of the detection of landslides. Enough care will be taken on the conditional factors of landslide to achieve accuracy between 93% to 96%. This model will be tested with inventory which will be created from the last two-year landslide events.

5. Conclusion

This comprehensive study proposed an automatic landslide detection model for a satellite landslide image database. Research gap has been identified in a number of automatic landslide detection models. Most of the selected landslide detection articles use the same backbone architecture of CNN such as ResNet 50, ResNet 101, DensNet, VGG etc., and are compared on four parameters: accuracy, precision, recall and f1 score. To collect the sufficient data for training and testing automatic or semiautomatic models is a challenging task in all the existing To overcome this problem real-time landslide event data can be increased with augmentation techniques. In the proposed model Attention mechanism can be used to enhance the accuracy of the identification and prediction of landslides. The work on the proposed method is to yield high accuracy in identification and prediction is in progress.

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