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ADVANCED LANDSLIDE DETECTION

[1]S. Prathap, [2]P. Akhilandeshwari, [3]G. Samhitha, [4]D. Maniharika, [5]A. Sai Abhigna

[1]Assistant Professor, Department of CSE(DS), Malla Reddy Engineering College for Women (Autonomous Institution – UGC, Govt. of India), Hyderabad, INDIA.

[2345]UG,Department of CSE(DS), Malla Reddy Engineering College for Women (Autonomous Institution – UGC, Govt. of India), Hyderabad , INDIA

Abstract

Landslide detection is crucial for natural disaster risk management. Deep-learning-based object-detection algorithms have been shown to be effective in landslide studies. However, advanced algorithms currently used for landslide detection require high computational complexity and memory requirements, limiting their practical applicability. In this study, we developed a high-resolution dataset for landslide-prone regions in China by extracting historical landslide remote sensing images from the Google Earth platform. We propose a lightweight LP-CNN algorithm based on CNNv5, with a more-lightweight backbone that incorporates our designed PartitionNet and neck equipped with CSPCrossStage. We constructed and added the vertical and horizontal (VH) block to the backbone, which explores and aggregates long-range information with two directions, while consuming a small amount of computational cost. A new feature fusion structure is proposed to boost information flow and enhance the location accuracy. To speed up the model learning process and improve the accuracy, the SCYLLA-IoU (SIoU) bounding box regression loss function was used to replace the complete IoU (CIoU) loss function. The experimental results demonstrated that our proposed model achieved the highest detection performance (53.7% of Precision, 49% of AP50 and 25.5% of AP50:95) with a speed of 74 fps. Compared to the CNNv5 model, the proposed model achieved 4% improvement for Precision, 2.6% improvement for AP50, and 2.5% for AP50:95, while reducing the model parameters and FLOPs by 38.4% and 53.1%, respectively. The results

indicated that the proposed lightweight method provides a technical guidance for achieving reliable and real-time automatic landslide detection and can be used for disaster prevention and mitigation.

Keywords:
landslide detection; **remote sensing image**; **deep learning**; **LP-CNN**; **CNNv5**

1. Introduction

Landslides are severe geological hazards that widely occur in mountainous environments with slopes and frequently lead to chain reactions such as mountain collapses and debris flows, which can pose serious risks to human life and property. Therefore, enhancing the detection and early warning systems for landslide-related geological catastrophes holds considerable implications in the context of China's endeavors towards disaster mitigation and risk reduction [1,2].

Traditional landslide detection methods primarily rely on geologists, which often entails significant manpower and financial investments. However, the effectiveness of these methods may not always meet expectations. In light of the advancements in satellite imaging accuracy, researchers have increasingly proposed landslide detection approaches that leverage optical image data. Concurrently, machine learning has become increasingly popular in the field of landslide detection. Besides, the emergence of convolutional neural networks (CNNs) has led to the successful application of deep-learning-based object recognition algorithms in landslide detection, and they have gradually become mainstream. In contrast to machine learning approaches, deep learning techniques abandon the complicated artificially designed features, which adopt deeper convolutional neural networks to automatically acquire distinguishing characteristics. Furthermore, the data sample capacity of deep learning for landslide detection can be extensive, rendering it more appropriate for large-scale landslide identification and endowing it with a more-robust generalization capability. Although deep-learning-based algorithms have shown success in detecting landslides, they still face some challenges: These models necessitate substantial computational resources and numerous parameters, leading to diminished inference efficiency. As a result, employing them in power-limited contexts or embedded platforms with the objective of achieving real-time detection becomes challenging. Moreover, the scarcity of open-source repositories containing high-spatial-resolution images of landslides hampers the effective training and validation of these models.

To tackle these challenges, we constructed a landslide dataset utilizing the Google Earth platform in this study. This paper presents a lightweight framework named LP-CNN, which achieves real-time landslide detection. Our contributions are as follows:

(1) We propose the Partition module and form a new feature extraction network named PartitionNet to replace the backbone of CNNv5, which brings better performance, while reducing drastically the redundant parameters and computational complexity.

(2) A new feature-exploiting module named the VH block is constructed and added to the backbone to retain the information after down-sampling and to explore long-range information with a small computational cost.

(3) We designed a new feature fusion structure and propose a CSPCrossStage module instead of C3 in the neck of the model to boost information flow and enhance the location accuracy of multi-scale landslides with less computing resource.

(4) The SIoU loss function and the attention mechanisms were introduced to expedite the convergence speed during training and enhance the detection accuracy of the model.

2. Related Work

Landslide detection can generally be categorized into two approaches: traditional methods of landslide identification and automatic identification methods based on machine learning algorithms.

Traditional methods of landslide detection often rely on field surveys conducted by experienced geologists, complemented by instrumental imaging techniques for analysis. These methods involve on-site inspections, geological mapping, and the collection of ground truth data, for example using interferometry synthetic aperture radar (InSAR) technology to obtain multi-temporal data to observe whether the slope is deformed, which can be used as a basis to infer potential landslides [3]. While traditional methods have been widely practiced and have proven effective, they have the limitations of being time-consuming and resource-intensive.

The second category predominantly utilizes pre-existing datasets of landslides and facilitates automatic identification through the construction of algorithmic models. Generally, automatic landslide detection techniques can be categorized into machine learning approaches and deep learning approaches. Machine learning algorithms encompass methods such as Bayesian, logistic regression, support vector machines (SVMs), random forests, and artificial neural networks [4,5,6,7], which can utilize various features related to landslide occurrence, such as texture and terrain information for classification and prediction. For instance, Pourghasemi [8] applied random forest to evaluate the sensitivity of landslides, and Tien [9] utilized SVM and kernel logistic regression for landslide recognition. Artificial neural networks, including pulse-coupled neural networks (PCNNs) and spiking neural networks, have been shown to possess outstanding capabilities in image fusion and computer vision applications [10,11].

Owing to the swift advancements in hardware equipment and artificial intelligence, deep learning techniques have emerged as an additional potent data-driven approach for detection. Consequently, a multitude of sophisticated object-detection algorithms have surfaced, including two-stage object-detection algorithms represented by region-based convolutional neural networks (RCNNs), Fast R-CNN, and Faster R-CNN [12,13] and single-stage object detection networks represented by the SSD algorithm [14] and the CNN algorithm series [15,16,17,18]. For instance, Ju [19] selected the CNNv3 and Mask RCNN algorithms to achieve automatic recognition of loess landslides, with an optimal average precision of 18.9%. Ji [20] proposed an enhanced convolutional neural network for landslide detection of Bijie City, which demonstrated the effectiveness of a new

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landslide prediction based on the dataset. Hou [21] incorporated a coordinate attention mechanism [22] to enhance the CNNX [23] object-detection model, effectively tackling the problem of the poor detection of complex mixed landslides. Tang [24] proposed SegFormer, a model based on the Transformer architecture, which is capable of automatically detecting landslides.

3. Method

In this section, we begin by reviewing our baseline model CNNv5 and then provide a comprehensive description of the LP-CNN model (Figure 1). We discuss the network structure, the VH block, the new PAN feature fusion structure, the loss function, and the attention module.

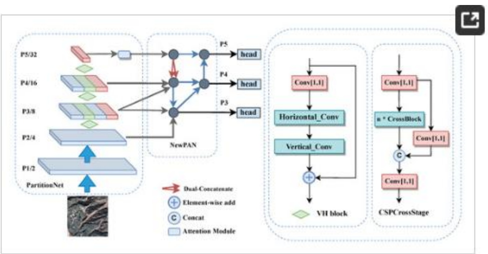

Figure 1. Framework of our proposed LP-CNN.

OLOv5 is composed of three primary elements: the CSPDarkNet backbone with the C3 block, the path aggregation network (PAN) [33] neck with the spatial pyramid pooling feature (SPPF) layer [34], and the detection head. The C3 block contains three general convolutional and bottleneck modules and was inspired by CSPNet [35]. Within this block, the feature map is bifurcated into two sections: one segment traverses the bottleneck module, while the other is conveyed to the convolutional module and subsequently merged with the first portion. The PAN structure facilitates information flow and feature aggregation from bottom to top, and the SPPF layer in CNNv5 serves to aggregate multi-scale contextual information from feature maps. Various data augmentation methods, such as mosaic augmentation, are employed within the model to mitigate data imbalance issues associated with small, medium, and large objects present in the dataset. In addition, the model employs the complete intersection over union (CIoU) [36] bounding box regression loss function for optimizing the model's ability to accurately localize objects.

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Datasets' Collection

The study area is situated at the junction of southern Gansu Province and eastern Qinghai Province, characterized by a dry climate, low average annual precipitation, and sparse vegetation. To identify landslides in this region, we obtained remote sensing images from the Google Earth Engine platform. As the original images were too large and did not meet the requirements for object detection, we used a Python library to crop them into JPEG format images with a size of 2000 × 2000 px. As shown in figure, each image was then annotated and visually explained for landslide identification. In this study, a total of 15,301 landslides were marked.

Figure 2. Original datasets. GT boxes denote the real landslide area.

The cross-cutting method refers to dividing an image into several overlapping patches with a certain stride, and each patch can be regarded as a small image for further processing. In this study, the cross-cutting method was used to divide the 2000 × 2000 px images into several 640 × 640 px images to maintain the integrity of the image texture. This methodology effectively enhances the utilization of image information and avoids information loss caused by image compression. After processing, the dataset was partitioned into training and validation sets at an 8:2 ratio, with 5434 for the training set and 1461 for the validation set obtained after screening. It comprised two categories: landslides and non-landslides.

4 Results

In contrast to the CNNv5s model, our experiments showed that using the SIoU loss function could achieve better location results and accuracy, for which the Precision increased from 49.7% to 51.9%, AP50 increased from 46.4% to 47.9%, and AP50:95 increased from 23.0% to 24.4%. Additionally, using only our proposed network PartitionNet to replace the backbone of the model led to a 38.2% reduction in the quantity of parameters and a 53.4% reduction in the FLOPs, while increasing the Precision,

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AP50, and AP50:95. With the introduction of the CBAM attention module and our proposed VH block, we obtained a 1.6% AP50 improvement and a 0.5% AP50:95 improvement with slightly increased Params and FLOPs compared to the model of the backbone of PartitionNet. Furthermore, using the NewPAN feature fusion structure and CSPCrossStage resulted in a 38.1% reduction in the quantity of parameters compared to the CNNv5s baseline model and a 4.2% reduction compared to the proposed model that used the previous PAN structure.

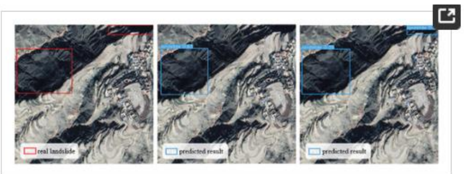

Figure 3. Real landslide and predicted results of the CNNv5s and LP-CNN models.

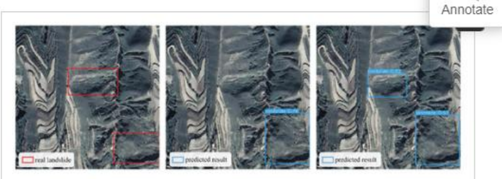

Figure 4. Real landslide and predicted results of the CNNv5s and LP-CNN models.

Firstly, the detection results demonstrated that our proposed model exhibited higher precision and average precision (AP) compared to the other models, indicating its ability to achieve a relatively low false positive rate even in complex situations. However, it is worth mentioning that the model detected landslides with relatively low confidence.

Secondly, regarding small target detection, the model designed in this study exhibited limitations in detecting small objects, which is a known challenge in detection tasks. To address this issue, further exploration in future work can involve incorporating multi-scale structures into the model and adopting more-advanced data enhancement methods.

Thirdly, for landslide detection, the scarcity of datasets and the diversity of landslide types contributed to the challenges in achieving accurate identification. For instance, in the case of loess landslides, their colors often closely resemble the surrounding environment, making it difficult for experts to accurately annotate landslide datasets and extract distinctive features for model training.

Lastly, in terms of integration and application in landslide prevention and control systems, the lightweight design of our model offers advantages such as reduced computational burden and memory consumption. These characteristics render it suitable for deployment on power-constrained devices, including unmanned aerial systems (UASs). Integrating the model with UASs would thereby enable efficient and comprehensive monitoring of areas prone to landslides. This integration demonstrates promising prospects in augmenting early warning systems, facilitating real-time monitoring for landslide prevention and management.

5 Conclusions

This paper presented LP-CNN, a new lightweight landslide-detection model based on the CNN algorithm and a comprehensive landslide dataset. The proposed model addressed the challenges of accurate landslide detection in remote sensing images with varying spectral, texture, terrain, landslide type, and scale characteristics. LP-CNN comprises several key components that contribute to its superior performance, including the PartitionNet backbone, the VH block, the new feature fusion structure, the CSPCrossStage module, the SIoU loss function, and the CBAM attention mechanism. The experimental results demonstrated that the proposed model outperformed CNNv5 and the other models in terms of the AP, parameters, and FLOPs. LP-CNN has the potential to be deployed on power-constrained devices for real-time automatic detection of landslides. However, further research is needed to improve the detection frame rate and model accuracy and expand the dataset to reduce error detection problems. Overall, this work provides a promising solution to the problem of real-time landslide detection and contributes to the development of lightweight detection models for landslides.

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