Domain-Adaptive and Efficient Neural Network for Accelerated Post-Earthquake Landslide Recognition

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Abstract: Co-seismic landslides, triggered by major earthquakes, are sudden, widespread events that necessitate immediate and accurate information for disaster response. Conventional deep learning (DL) methods used for remote sensing image interpretation often suffer from complex model architecture, slow inference speeds, and poor generalization across diverse geographical scenes, rendering them inadequate for rapid post-disaster assessment. This paper introduces a novel Lightweight Deep Transfer Learning (LDTL) framework specifically designed to accelerate cross-scene landslide identification. The core of this framework is an efficient Multi-scale Feature Fusion Lightweight Network (MSF-LiteNet) optimized for computational efficiency and parameter reduction. By integrating a progressive knowledge transfer strategy, the MSF-LiteNet can rapidly leverage prior landslide feature knowledge from multiple source domains and perform robust, precise adaptation to new disaster zones. Empirical validation across multiple typical seismic disaster scenes (including events in Japan and China) demonstrates that the proposed LDTL framework significantly boosts deployment speed and cross-domain detection capability while maintaining high recognition accuracy, offering a viable technical route for real-time global geohazard assessment.

Keywords: ***Co-Seismic landslides, Deep learning, Knowledge transfer, Lightweight network, Remote sensing emergency response, Disaster assessment.***

Introduction

Secondary landslides triggered by large earthquakes pose a critical threat to life and property. Obtaining the accurate distribution of landslides immediately after an event is crucial for effective rescue operations and secondary hazard forecasting. Although deep learning excels in remote sensing image analysis, large-scale DL models often demonstrate diminished performance when applied to entirely new, unseen seismic scenes due to high annotation costs and lengthy training times (Li and Wang, 2023). The lack of generalization, particularly when facing variations in geographical regions and sensor data, remains a significant bottleneck. To address this, our study aims to construct a real-time, highly efficient, and generalized landslide detection solution by proposing innovative network architecture and an advanced transfer learning method to achieve rapid and precise mapping of urgent co-seismic landslides (Dong et al., 2024).

Methodology

The proposed LDTL framework is built upon two key technical innovations:

Multi-Scale Feature Fusion Lightweight Network (MSF-LiteNet)

The network architecture is deeply optimized for model efficiency, utilizing streamlined convolutional blocks and an effective feature aggregation mechanism. This design significantly reduces the model's parameter count and computational demands, thus achieving exceptional inference speed while preserving complex feature extraction capabilities (Ding et al., 2024).

Progressive Deep Knowledge Transfer Strategy

To overcome the challenge of cross-scene generalization, we devised a staged transfer learning pipeline. First, the MSF-LiteNet is pre-trained on a data-rich source domain to acquire generic landslide characteristics. Subsequently, a lightweight fine-tuning process is applied to the target seismic scene (Target Domain), complemented by an enhanced data augmentation algorithm to mitigate the overfitting risks associated with small target-scene samples, ensuring effective and rapid knowledge transfer.

Results

This research conducted rigorous validation on two representative co-seismic landslide datasets, stemming from the Hokkaido, Japan earthquake (Table 1) and the Luding, China earthquake (Table 2). Compared to established DL models, our LDTL framework demonstrated the following advantages:

Efficiency Gain

The MSF-LiteNet exhibits significantly lower parameter count and Floating-Point Operations (FLOPs) compared to State-of-the-Art (SOTA) baselines, resulting in several-fold increases in inference speed.

Cross-Scene Robustness

The model retains usable detection accuracy in novel seismic scenes even without fine-tuning. After rapid, lightweight fine-tuning, its F1-score and Intersection over Union (IoU) metrics are comparable to or even surpass those of more complex models, highlighting its superior generalization capacity.

Table 1, Evaluation of different semantic segmentation models for the Hokkaido landslide dataset.

	FCN	DeeplabV3	VggUnet	ResUnet	MSF-LiteNet
PA (%)	87.4	87.3	95.8	96.0	95.4
CPA (%)	59.4	58.4	86.5	86.4	83.6
IOU (%)	44.3	46.1	76.7	77.7	75.3
MIOU (%)	65.2	65.9	85.9	86.5	85.0
Parameters	32947226	39633986	26450306	98388354	2541708
FLOPs	6000.5M	6395.7M	71102.8M	58064.2M	798.7M
Train time	0:20:02	0:20:10	1:43:24	1:44:03	0:54:17
Inference time	8.0ms	8.0ms	4.1ms	9.0ms	7.8ms

Table 2, Evaluation of different semantic segmentation models for the Luding landslide dataset.

	FCN	DeeplabV3	VggUnet	ResUnet	MSF-LiteNet
PA (%)	92.2	92.2	90.5	90.7	91.8
CPA (%)	81.3	82.2	74.3	71.7	78.6
IOU (%)	65.5	65.3	62.0	64.7	65.1
MIOU (%)	78.2	78.1	75.4	76.8	77.7
Parameters	32947266	39633986	26450306	98388354	2541708
FLOPs	384034.6M	409291.2M	4550584.9M	3716111.4M	51097.3M
Train time	0:47:25	0:49:40	2:18:00	2:09:46	1:22:18
Inference time	8.0ms	8.0ms	4.1ms	9.0ms	7.8ms

Disaster Response Potential

Experimental results confirm the LDTL framework's capability to swiftly adapt to new regional remote sensing data, successfully meeting the time-critical requirements of emergency mapping.

Conclusion

This paper successfully developed and validated a co-seismic landslide detection framework combining lightweight network design and progressive deep transfer learning. The framework effectively resolves the velocity and generalization bottlenecks encountered by existing DL models in disaster emergency response. Future work will focus on integrating this framework into an automated cloud-based processing pipeline and further exploring multi-modal data fusion (e.g., SAR and optical imagery) to provide more powerful and real-time support for geological hazard risk management on a global scale.

References

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