A Deep Learning Framework for Landslide Detection in Support of Early Warning Systems

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Abstract. Landslides are sudden and destructive hazards that have a significant impact on human, economic, and environmental aspects, and their complex triggering factors make them particularly difficult, underscoring the importance of reliable Landslide Early Warning Systems (LEWS). Traditional approaches are often based on empirical thresholds or statistical models. They provide valuable insights but are generally constrained in accuracy and transferability across different regions. Recent advances in deep learning offer new opportunities by enabling the automatic extraction of spatial and geomorphic features from high-resolution imagery to digital elevation data. This study proposes a framework that incorporates different deep learning methods and a landslide dataset to enhance landslide detection in support of LEWS. The model integrates spectral and terrain variables, applies data augmentation to mitigate class imbalance, and is evaluated with precision, recall, F1-score, and IoU against conventional classifiers. Results demonstrate that the proposed approach improves detection accuracy and robustness in heterogeneous terrain, indicating its potential as a scalable and transferable component of operational early warning systems and risk management.

Keywords: Landslide Early Warning Systems; Deep Learning; Convolutional Neural Networks (CNNs); Transfer Learning.

1. Introduction

Landslides are one of the most destructive natural hazards, causing thousands of fatalities annually and inflicting severe economic and environmental damage all over the world [1]. Their occurrence is commonly associated with intense rainfall, seismic activity, volcanic eruptions, and anthropogenic disturbances such as deforestation and road construction [2]. The rapid onset and unpredictable nature of slope failures make them particularly challenging to forecast, especially in mountainous and densely populated areas.

Even after years of development in science and technology, there is no good way to stop a landslide. Given that physical prevention of landslides is often unfeasible, Landslide Early Warning Systems (LEWS) have become a vital instrument in disaster risk reduction. The primary function of LEWS is to provide timely alerts that allow authorities and communities have enough time to take preventive actions like evacuation and infrastructure protection to save lives and decrease economic impact. Early generations of LEWS mainly relied on empirical rainfall thresholds, which were highly site-specific and limited in prediction [3]. With development in remote sensing, Geographic Information Systems (GIS), and ground-based monitoring equipment, modern LEWS now integrate rainfall, hydrological, and geotechnical indicators into multi-sensor frameworks, substantially improving its accuracy and spatial coverage [4, 5].

With these technological developments, artificial intelligence (AI) has introduced new opportunities for hazard monitoring [6]. In particular, deep learning has shown remarkable success in image recognition and geospatial analysis tasks [7]. Unlike traditional machine learning algorithms that depend on manual feature engineering, deep learning methods such as convolutional neural networks (CNNs) can learn hierarchical features from a database, capturing spectral and spatial patterns that characterize landslides [8, 9]. Recent enhancements, including transfer learning and multiscale feature extraction, further strengthen the adaptability of CNN-based models, enabling them to generalize across diverse geomorphological contexts and detect landslides with varying shapes and sizes [10, 11]. These advances demonstrate the potential of deep learning to significantly strengthen LEWS by providing more accurate and scalable detection capabilities.

Despite this progress, challenges persist. Limited training datasets often constrain current models, reducing their transferability to other regions [12, 13]. Additionally, most studies emphasize spectral and basic topographic inputs, while underutilizing other critical variables such as rainfall history, soil type, and vegetation change[14]. Finally, while deep learning model and transfer learning approaches have improved accuracy in controlled experiments, their integration into operational LEWS remains limited, with issues of scalability, interpretability, and real-time application still unresolved [15].

This study summarizes the present studies on landslide detection, aiming to give future directions to enhance accuracy, robustness, and transferability in the context of early warning systems. It summarises state-of-the-art methods and the history of landslide early warning systems to guide future research.

2. Landslide Detection and Warning Techniques

Landslide Detection Techniques and the Landslide Early Warning System (LEWS) aim to identify the boundaries of landslides on the ground and give warnings before they occur.

2.1 History of Landslide Early Warning System

The development of Landslide Early Warning Systems (LEWS) reflects steady progress driven by advances in science and technology. In the 1980s, researchers first established the link between rainfall and slope failures, formulating rainfall intensity–duration thresholds as the basis for prediction [16]. During the 1990s, regional-scale systems emerged in places such as Italy and Hong Kong, marking the transition from empirical research to operational warning tools [17].

The 2000s introduced a technological leap, with remote sensing (RS), GIS, and geotechnical instrumentation enabling multi-parameter monitoring of slope stability, hydrology, and soil conditions [18]. By the 2010s, international collaborations and pilot projects expanded LEWS globally, emphasizing multi-scale frameworks and community-based participation to improve local effectiveness and trust [19].

In the 2020s, LEWS entered a new era shaped by real-time monitoring, IoT sensor networks, cloud platforms, and machine learning [20]. Modern systems now integrate massive datasets to deliver more accurate, location-specific alerts while also serving as decision-support tools that connect scientific modelling with emergency response and community preparedness [21]. The development of LEWS is shown in Figure 1.

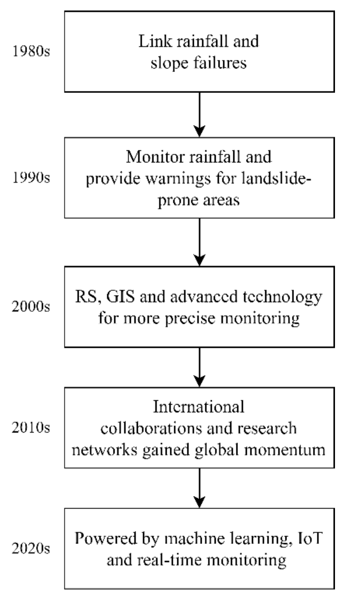

Figure 1 The history of LEWS

2.2 Present Techniques

2.2.1 Landslide Detection Using ML

In this study, the authors designed a comprehensive framework to evaluate conventional machine learning techniques and deep learning convolutional neural networks (CNNs) for landslide detection [22]. The experiments relied on RapidEye satellite imagery combined with topographic variables derived from a 5m DEM and a detailed field-based landslide inventory for training and validation. Two datasets were prepared: one composed solely of spectral features (four bands and NDVI), and another integrated with three topographic layers (slope, aspect, and plan curvature). The machine learning approaches included Random Forests, Support Vector Machines, and Artificial Neural Networks, each trained on thousands of samples derived from field polygons.

For the CNN models, the authors explored several architectural and training strategies. They tested multiple input window sizes, ranging from small patches (12×12, 16×16, 22×22 pixels) to larger contexts (32×32 and 48×48), to account for the highly variable shapes and extents of landslides. To overcome the limited availability of training data, they implemented a data augmentation strategy based on random window shifting, effectively doubling the training set. Furthermore, they experimented with different network depths: a four-layer CNN applied across all window sizes and a deeper seven-layer CNN (D-CNN) restricted to larger windows. Training employed standard convolutional and pooling operations with ReLU activations, optimized via backpropagation and stochastic gradient descent in a TensorFlow-based environment.

Model performance was assessed using precision, recall, F1-score, and particularly the mean intersection-over-union (mIOU), a metric adapted from computer vision. Results showed that CNNs did not universally outperform traditional methods; their effectiveness depended on design choices such as input scale and depth. The best performance was achieved with a four-layer CNN using a 16×16 window and spectral data only, yielding an mIOU of 78.26%. Incorporating topographic layers slightly reduced overall accuracy but improved discrimination between landslides and spectrally similar settlement areas. Random Forests also produced strong results (mIOU: 69.6%), while ANN underperformed in comparison. These findings highlight that CNNs hold promise for landslide mapping but require carefully tuned architectures, adequate training samples, and thoughtful use of ancillary data. The result is shown in Figure 2.

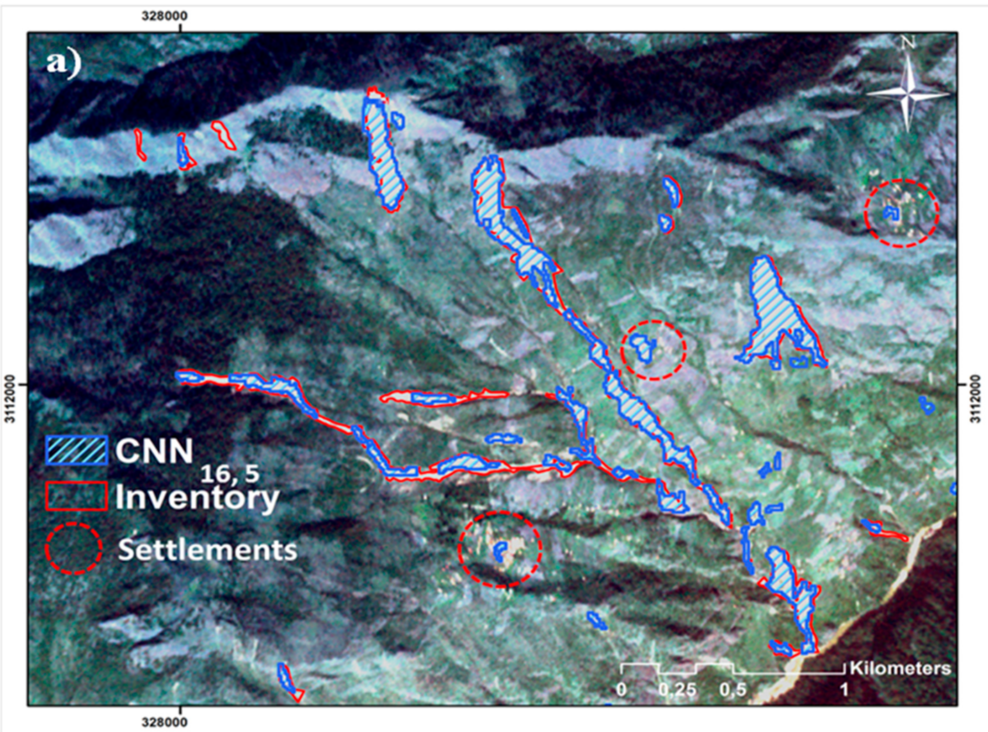

Figure 2 Enlarged map of CNN [22]

The study proposes an enhanced deep learning framework for landslide detection that integrates convolutional neural networks (CNNs) with transfer learning and multiscale feature extraction strategies [24]. The central objective was to address the limitations of traditional pixel-based and object-based methods, which often struggle with landslides' complex morphology and spectral variability, particularly in high-resolution remote sensing imagery.

The methodology began with the preparation of multi-source data. High-resolution satellite imagery provided the primary spectral inputs, while digital elevation model (DEM)-derived terrain attributes such as slope, aspect, and curvature were included to capture geomorphological context. A landslide inventory, mapped through expert visual interpretation, was used to generate labeled training and testing samples. Data augmentation was applied to reduce class imbalance between landslide and non-landslide areas, involving random cropping, rotation, and flipping of training patches to improve the model's generalization capability.

For model design, the authors adopted a CNN architecture pre-trained on a large-scale image dataset and fine-tuned it to the landslide detection task. The network included multiple convolutional and pooling layers for hierarchical feature learning and fully connected layers for classification. A multiscale input strategy was employed to enhance robustness across different landslide sizes and shapes: training samples of various window sizes were extracted, allowing the CNN to learn localized texture patterns and a broader topographic context. Additionally, the framework incorporated batch normalization and dropout techniques to stabilize training and prevent overfitting.

The training process utilized stochastic gradient descent with adaptive learning rate scheduling. Hyperparameters, including learning rate, batch size, and number of epochs, were optimized through grid search and cross-validation. Model evaluation used widely adopted performance metrics such as overall accuracy, precision, recall, F1-score, and intersection-over-union (IoU). Results were compared against traditional machine learning classifiers (e.g., Random Forest and SVM) and baseline CNN configurations without transfer learning or multiscale adaptation to quantify the improvements introduced by the proposed framework. The landslide susceptibility map is shown in Figure 3.

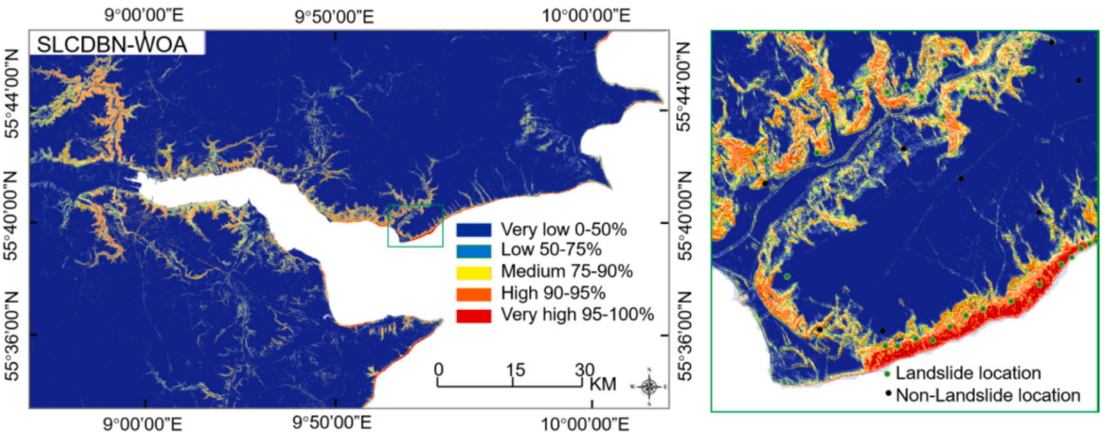

Figure 3 Landslide susceptibility map [24]

This methodological design demonstrates that transfer learning and multiscale feature extraction significantly improve CNNs' capacity to capture the heterogeneity of landslide features. The study highlights that carefully combining spectral, topographic, and data augmentation strategies can deliver robust detection performance in complex mountainous terrain, thereby advancing the application of deep learning in natural hazard mapping.

2.2.2 A Benchmark Landslide Inventory for Machine Learning in Hokkaido

This study presents the construction of a large-scale, open-access landslide inventory dataset for the Hokkaido region in northern Japan. The dataset is designed to support developing and benchmarking machine learning and deep learning approaches for landslide detection[23]. The methodology combined remote sensing imagery, digital elevation data, and extensive manual annotation to produce a standardized, high-quality dataset.

The dataset was built primarily using high-resolution aerial orthophotos from the Geospatial Information Authority of Japan (GSI), complemented by pre- and post-event satellite images. A 5 m resolution digital elevation model (DEM) was incorporated to capture topographic context, from which slope and other terrain derivatives were extracted. Landslide mapping was done through detailed visual interpretation by trained experts, who manually delineated landslide polygons based on geomorphic signatures visible in the imagery. This process included cross-checking against DEM-derived hillshades to ensure accurate boundary definition, particularly in densely vegetated or shadowed areas. Some of the images and labels are shown in Figure 4.

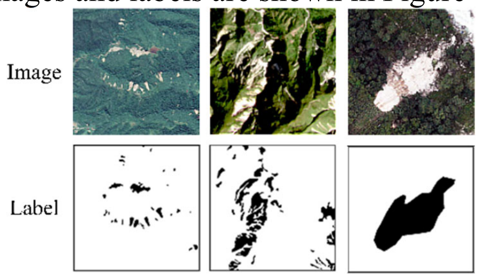

Figure 4 Images and Labels of Samples from the CAS Landslide Dataset

To guarantee reliability, a multi-stage quality control procedure was implemented. Multiple interpreters independently reviewed annotated polygons, and discrepancies were resolved through consensus. The dataset was also validated against existing official inventories and field reports where available. The database includes tens of thousands of landslides triggered by multiple typhoon and earthquake events, covering various geological and geomorphological settings across Hokkaido.

Beyond inventory creation, the authors structured the dataset to facilitate its direct use in machine learning experiments. Landslide and non-landslide samples were balanced and partitioned into training, validation, and testing subsets. The data were formatted in raster and vector forms, making them compatible with traditional classifiers and convolutional neural networks. Metadata regarding landslide type, size, and triggering event were also included, allowing for more detailed analyses such as event-specific susceptibility modeling.

Through this methodology, the authors established a reproducible framework for constructing benchmark-quality landslide datasets that integrate remote sensing, DEM analysis, and rigorous manual interpretation. The resulting Hokkaido inventory advances regional hazard assessment and provides a standardized reference for evaluating and comparing emerging machine learning approaches.

2.2.3 Deep Transfer Learning in Landslide Detection

This study introduces a deep learning-based approach for landslide detection that integrates convolutional neural networks (CNNs) with transfer learning. It aims to overcome challenges posed by limited training data and the heterogeneous nature of landslide features [25]. The methodology leverages high-resolution optical imagery, digital elevation model (DEM) derivatives, and a carefully constructed landslide inventory to develop a robust and transferable detection framework.

The input data consisted of multispectral satellite images combined with terrain attributes such as slope, aspect, and curvature extracted from DEMs. A landslide inventory derived from visual interpretation and field surveys provided ground truth labels for model training and validation. To address data scarcity and class imbalance, the authors applied extensive data augmentation, including random cropping, flipping, and rotation, thereby expanding the diversity of training samples. The environmental factors used in the analysis are shown in Figure 6.

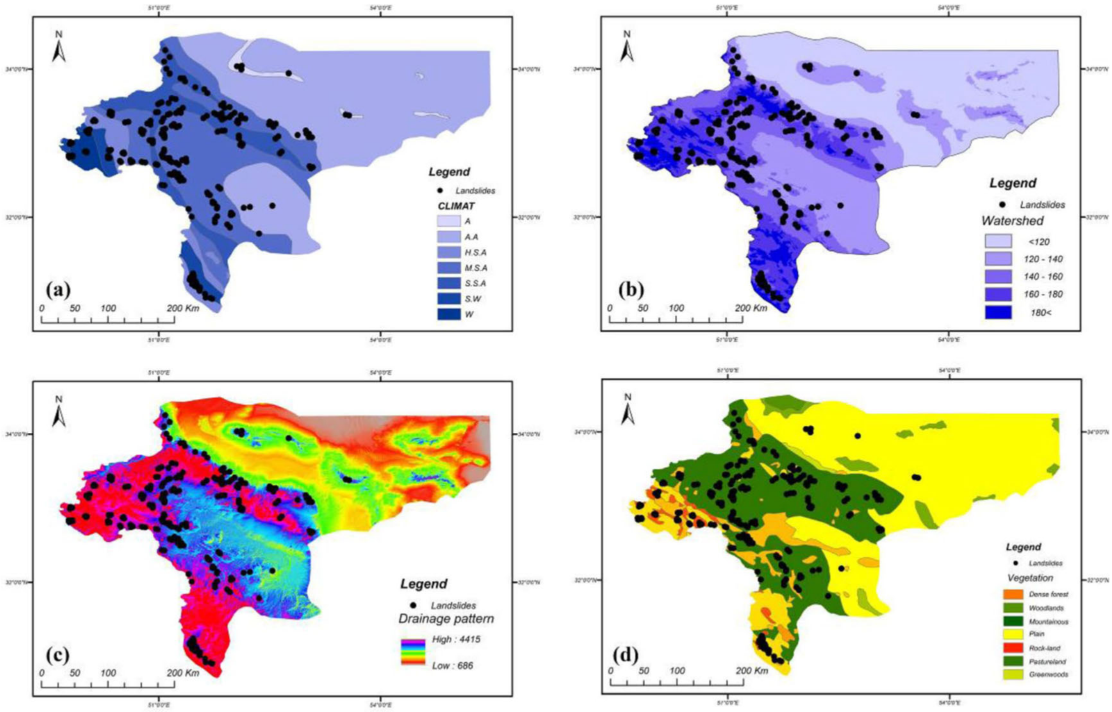

Figure 3 The environmental factors used in the analysis: (a) climate, (b) watershed, (c) drainage pattern, (d)
Vegetation [25]

The method's core is a CNN architecture pre-trained on large-scale natural image datasets (e.g., ImageNet) and fine-tuned for landslide detection. The transfer learning strategy allowed the network to exploit low-level features (edges, textures, and shapes) learned from generic images while adapting high-level representations to the geomorphic patterns of landslides. The CNN model was optimized through batch normalization, dropout regularization, and adaptive learning rate schedules to improve convergence and prevent overfitting.

The training process used stochastic gradient descent with momentum, and hyperparameters were tuned via cross-validation. Multiple configurations of CNN depth and input patch sizes were tested to evaluate the model's sensitivity to scale variations in landslide morphology. Model performance was quantitatively assessed using overall accuracy, precision, recall, F1-score, and intersection-over-union (IoU). Comparisons were made with traditional machine learning classifiers, such as Random Forests and Support Vector Machines, and baseline CNNs trained from scratch, to highlight the advantages of transfer learning.

Through this methodology, the study demonstrates that transfer learning substantially improves landslide detection accuracy, particularly when training data are limited. The integration of spectral and topographic information, combined with data augmentation and scale-aware CNN training, enhances the model's generalization ability across diverse terrain conditions.

3. Future Directions

Despite notable advances, several gaps remain evident in current landslide detection research. First, CNN-based approaches show strong potential, but their performance is highly sensitive to input window size, network depth, and training strategies, making results inconsistent across regions and datasets. Second, while benchmark datasets such as the Hokkaido inventory provide an essential foundation, there is still a lack of standardized, globally representative datasets that capture diverse geological and geomorphological conditions. Third, many studies deeply rely on spectral and basic DEM-derived variables, with limited exploration of additional geospatial information such as rainfall, soil type, or land use, which could enrich model interpretability. Fourth, most experiments are confined to pixel or patch level detection, with relatively limited attention to object-based or instancelevel approaches that could better capture landslide boundaries. Finally, although transfer learning improves generalization, its adaptability across different sensors, spatial resolutions, and geographic settings remains insufficiently tested.

Future research may address these gaps by developing more generalizable and transferable frameworks. A key priority is the creation of large-scale, multi-regional benchmark datasets that integrate spectral, topographic, geological, and climatic variables, enabling cross-regional model training and fair algorithm benchmarking. Advancing in deep learning architectures, such as transformer-based models and hybrid CNN–RNN or CNN–Graph approaches, could provide more effective multiscale feature representation and boundary delineation. Domain adaptation and self-supervised learning could reduce reliance on extensive labeled data, enhancing model robustness in data-scarce environments. In addition, integrating time-series remote sensing data and pre- and post-event imagery can support change detection, improving the identification of recent and evolving landslides. At the end, closer integration with hazard assessment frameworks—linking detection outputs with susceptibility, vulnerability, and risk modeling—would increase the operational value of these methods for disaster risk reduction and decision support.

4. Conclusion

Recent developments in landslide detection illustrate a clear methodological evolution: while conventional machine learning remains relevant, the growing integration of deep learning—particularly transfer learning and multiscale CNN frameworks—marks a decisive step forward. These advances collectively suggest not merely an improvement in accuracy, but a broader transformation in how landslide susceptibility is conceptualized and operationalized. The reliance on benchmark-quality datasets emphasizes that rigorous, standardized data preparation is as crucial as algorithmic sophistication, ensuring reproducibility and fair comparison across studies. Meanwhile, the consistent benefits of transfer learning highlight the value of leveraging general visual representations to adapt to geomorphic contexts, suggesting that future progress lies in balancing domain-specific expertise with scalable, cross-domain models.

Ultimately, these findings point to a paradigm where landslide detection becomes more robust, transferable, and responsive to the increasing availability of high-resolution remote sensing data. The challenge ahead is less about choosing between traditional and deep learning methods, and more about designing integrative frameworks that unite data quality, architectural innovation, and domain adaptation. In this way, landslide detection research enhances technical performance and contributes to the larger goal of building resilient and adaptive systems for disaster risk reduction.

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