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Landslide Detection Using Remote Sensing

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ABSTRACT
Landslides are a major natural hazard that continues to endanger lives and infrastructure globally. Although advancements in artificial intelligence (AI) have improved the automated mapping of landslides using satellite imagery, many models struggle to generalize across diverse geographic regions due to the limited availability of high-resolution and diverse datasets. To address this issue, the High-Resolution Global Landslide Detector Database (HR-GLDD) is introduced—a publicly available dataset constructed from 3-meter resolution PlanetScope satellite imagery. HR-GLDD comprises data from ten significant landslide events across Asia, South America, and Oceania, triggered by both rainfall and earthquakes. Each image is paired with carefully annotated landslide labels, making the dataset highly suitable for training and evaluating AI-based detection models. Strong performance across a range of terrains and unseen occurrences was revealed by the evaluation of five sophisticated deep-learning models on HR-GLDD, underscoring the dataset's potential to allow precise, generalizable, and scalable landslide mapping on a global scale.
Key words: *Landslide Detection, Remote Sensing, High-Resolution Satellite Imagery, PlanetScope, Deep Learning, HR-GLDD, Image Segmentation, Natural Hazards, Earthquake-induced Landslides*

INTRODUCTION:

Landslides represent a complex interaction between geology, hydrology, and human activity. Triggered by heavy rainfall, earthquakes, deforestation, and construction, they can occur suddenly and without much warning. The increasing frequency of extreme weather events due to climate change has further amplified the risks in many parts of the world. Early detection and timely response are critical to mitigating the damage caused by such events. However, most traditional monitoring methods are localized, slow, and dependent on expert interpretation. Remote sensing provides an effective way to monitor large areas for changes in terrain and land cover. Over the past decade, the availability of high-resolution satellite imagery has expanded significantly, with companies like Planet Labs offering daily imagery at sub-5-meter resolution. These images can be used to detect visible landslide features such as scarps, debris trails, and vegetation removal. However, the volume and complexity of the data make manual analysis impractical, especially for real-time applications. Deep learning has emerged as a powerful tool for extracting features and making predictions from complex image data. In the context of landslide detection, convolutional neural networks (CNNs) can learn the spectral and spatial patterns associated with landslide-affected areas. Unlike traditional image processing techniques, deep learning does not require hand-crafted features or thresholds. Instead, it learns directly from labeled data, making it highly adaptable to different environments. U-Net is one of the most widely used architectures for semantic segmentation tasks, particularly in the medical and geospatial domains. It is designed to produce pixel-level classification maps, making it ideal for applications like landslide mapping. The encoder path captures high-level contextual information, while the decoder reconstructs fine spatial details, guided by skip connections. This dual-path structure allows the model to detect landslides with both precision and context-awareness. The objective of this research is to design, train, and evaluate a U-Net-based landslide detection model using the HR-GLDD dataset. The goal is to build a system that not only performs well on known events but also generalizes to new locations. By leveraging a globally representative dataset and a robust deep learning model, this study aims to move closer to real-time, automated landslide mapping at scale.

LITERATURE REVIEW

Luciano Picarelli, this paper highlights the increasing impact of climate change on landslide hazards, linking extreme weather events with slope instability. It emphasizes the need for proactive risk management and policy adaptation strategies [1].

EM-DAT, this source provides global disaster data, offering vital statistics on landslides. It supports risk assessments, trends analysis, and preparedness strategies for natural hazards [2].

Raphael Knevels, this paper utilizes geographic object-based image analysis (GEOBIA) with open-source GIS software for automated landslide detection, enhancing accuracy through spatial object classification [3].J. McKean, this research applies high-resolution LiDAR to detect landslides and map surface morphology. It introduces an objective method that minimizes manual interpretation errors in hazard mapping [4].Zhongbin Li, this study presents a change detection-based Markov Random Field approach for landslide mapping from aerial photos, improving spatial consistency and reducing false positives [5].

Alexander L. Handwerger, this paper employs Google Earth Engine and open-access SAR data to detect landslides using backscatter changes, enabling timely monitoring in data-scarce regions [6].Simon Plank, this study integrates optical and polarimetric SAR data for landslide detection in vegetated areas using change detection techniques, tackling visibility issues in dense canopies [7].GPB Garcia, this paper proposes a deep learning framework for detecting relict landslides in rainforest regions through image segmentation, proving robust in complex, obscured terrains [8]. Renxiang Huang, this paper introduces an improved Transformer-based model to recognize landslides from multi-feature remote sensing data, leveraging both spectral and terrain features [9]. Xinran Liu, this paper proposes a feature-fusion segmentation network that combines remote sensing imagery and DEM data for high-accuracy landslide detection and classification[10]. Hamid Rezatofighi, this paper proposes the Generalized Intersection over Union (GIoU) metric to improve bounding box regression accuracy in object detection tasks, including remote sensing [11]. Sangdoo Yun, this paper introduces CutMix, a data augmentation strategy that boosts deep learning model performance by enhancing feature localization and generalization [12]. Sergey Ioffe, this study introduces Batch Normalization to reduce internal covariate shift during training, stabilizing and accelerating deep neural network convergence [13]. Andrew Maas, this paper advocates for rectifier nonlinearities like ReLU in neural networks, improving training efficiency and predictive accuracy in deep models [14]. Diederik P. Kingma, this paper presents the Adam optimizer, combining momentum and adaptive learning rates for efficient and effective training of deep neural networks [15]. Tsung-Yi Lin, this study introduces focal loss to handle class imbalance in object detection, making it especially valuable for landslide datasets with skewed class distributions [16]. Hamid Rezatofighi, this paper, building on earlier work, reinforces the effectiveness of the Generalized Intersection over Union (GIoU) metric in enhancing localization performance for object detection tasks [17]. Jie Hu, this paper introduces Squeeze-and-Excitation Networks, enhancing CNN performance by recalibrating feature maps through channel-wise attention [18]. Sanghyun Woo, this study proposes the CBAM module, integrating spatial and channel attention in CNNs to improve feature extraction and object recognition in images [19]. Cam Le, this paper presents a lightweight deep learning model for remote sensing image classification, balancing robustness with computational simplicity for scalable applications [20].

Related Work

Many studies in the field of landslide detection have been carried out in the last ten years, utilizing both conventional and cutting-edge machine learning techniques. Field surveys, empirical models based on GIS, and statistical analysis of topographical and meteorological data have all been used in conventional methods. These techniques are useful in regulated settings, but because they depend on manually created features and domain knowledge, they frequently lack scalability and adaptation to new areas.

Researchers started investigating machine learning techniques like Support Vector Machines (SVM), Decision Trees, and Random Forests for classification-based detection as a result of the explosion in the availability of remote sensing data. Although performance was enhanced, these techniques still required human feature extraction. Performance on image-based tasks was greatly improved with the introduction of automated feature learning and deep learning, especially Convolutional Neural Networks (CNNs).

The U-Net architecture is one of the most well-liked segmentation models because it can integrate contextual and geographical data, which makes it appropriate for pixel-level categorization in geospatial and medical domains. Deep learning has been used for a number of remote sensing tasks, but its application to landslide detection with multispectral inputs, such as elevation and NDVI, is still largely unexplored. By combining several satellite-derived features into a single deep learning framework, this study closes that gap.

METHODOLOGY

To accurately pinpoint areas impacted by landslides, the suggested landslide detection system combines deep learning methods with multisource remote sensing data. Data capture, preprocessing, feature engineering, model construction, training, and inference are some of the fundamental steps that make up the technique. Every element is thoughtfully designed to improve the spectral and spatial comprehension necessary for accurate geohazard mapping.

Data Collection and Preprocessing: Obtaining multisource satellite imagery with data from Digital Elevation Models (DEMs), Red, Green, and Blue (RGB), and Near-Infrared (NIR) is the first stage. Large amounts of structured remote sensing data may be handled because to the.h5 format in which these datasets are stored. Preprocessing involves scaling each image to a uniform dimension (e.g., 128×128) and normalizing the pixel values for each image and its accompanying ground truth landslide mask. By doing this, consistency and compatibility with the input needs of neural networks are achieved.

Feature Engineering: Feature engineering is used to extract more informative bands from the original data in order to enhance model performance. The Normalized Difference Vegetation Index (NDVI), which is calculated using the Red and NIR bands, is one important aspect that aids in identifying vegetation changes that are frequently brought on by landslides. To account for terrain-related characteristics, additional bands from the DEM are incorporated, such as height and slope. To provide the model a richer input, these manufactured features are overlaid with the original image bands.

Model Architecture: An improved U-Net architecture, a popular convolutional neural network for image segmentation, is employed to tackle the segmentation job. In order to facilitate gradient flow and enhance the network's learning capabilities, residual convolutional blocks are incorporated into the baseline U-Net. To aid the model in concentrating on spatially significant areas of the image, multi-head attention layers are also included. A more reliable and accurate inference procedure is made possible by the model's ability to produce output segmentation masks at various resolutions.

Loss Function: The model is trained efficiently by using a hybrid loss function. It combines Intersection over Union (IoU) Loss, which quantifies the spatial overlap between predicted and ground truth masks, with Focal Loss, which tackles the problem of class imbalance by concentrating on pixels that are challenging to categorize. This combination guarantees that during training, both overall shape alignment and pixel-by-pixel accuracy are maximized.

Training and Evaluation: To manage computational demands, the model is trained using the Landslide4Sense dataset with GPU acceleration. The model gains the ability to translate multispectral inputs into binary landslide segmentation masks during training. Metrics like Mean Intersection over Union (mIoU) and F1 Score, which offer a fair assessment of segmentation accuracy and classification precision, are used to assess the performance. The usefulness of the suggested method in precisely identifying landslides from intricate remote sensing data is confirmed by these evaluation results.

Algorithms

U-NetArchitecture:

Algorithm: Convolutional neural networks (CNNs) using the U-Net architecture are intended for image segmentation applications. It is made up of an expanding path (decoder) and a contracting path (encoder). It is very useful for pixel-level segmentation tasks like landslide detection since it can collect both local and global aspects of the image.

Function in the Project: U-Net assists in separating satellite imagery into discrete zones and locating landslide-affected areas

ConvolutionalNeuralNetwork(CNN):

Algorithm: The U-Net model is based on CNNs. They are perfect for image-related jobs since they use convolution techniques to automatically extract spatial characteristics from input images.

The role of CNNs in the project is to identify patterns in the satellite images (such as RGB, NDVI, elevation, and slope) as part of U-Net.

Normalized Difference Vegetation Index, or NDVI:

Algorithm: The NDVI is a vegetation index that evaluates the health of plants by using satellite data. It is computed using the formula (NIR - RED) / (NIR + RED), in which RED is the satellite image's red band and NIR is its near-infrared band.

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Function in the Project: NDVI can identify regions with notable plant changes, which may point to regions that are at risk of landslides or have already been affected by them.

RESULT

The model was examined using metrics including Dice Coefficient, F1-Score, Accuracy, Precision, Recall, and Intersection over Union (IoU). Over the course of training, the U-Net model demonstrated steady improvement, attaining over 90% accuracy and 80% IoU on validation datasets. Accurate landslide region localization is revealed by visual examination of the output masks, especially in high-elevation and forested terrains.

Areas with exposed soil and little vegetation, which have spectral traits comparable to landslide sites, were found to have false positives. Nevertheless, this misunderstanding was lessened by the addition of slope and elevation elements. The findings imply that, in contrast to pixel-wise classification techniques, U-Net's spatial context learning greatly improves segmentation performance.

CONCLUSION

This study used multisource remote sensing images to construct a sophisticated deep learning system for landslide identification and segmentation. The model incorporates a number of improvements, such as feature engineering, residual-convolutional blocks, and multi-head attention methods, while building upon the fundamental U-Net architecture. By creating new spectral bands, like NDVI, from the original data, feature engineering significantly enhanced the input features' quality and informativeness.In order to improve performance, the model also generates segmentation masks at various resolutions, producing an ensemble-like effect during inference. A mixed loss function that leverages both Focal Loss and Intersection over Union (IoU) Loss was proposed in order to improve learning and address class imbalance. Together, these changes resulted in a notable enhancement over the original U-Net and benchmarks for the Landslide4Sense challenge. The model's efficiency was proved by experimental findings on the Landslide4Sense development dataset, which yielded a mean IoU (mIoU) of 76.07 and an F1 score of 84.07. These outcomes demonstrate the accuracy and resilience of the suggested strategy and represent a significant improvement over earlier standards. Through accurate and fast landslide mapping, the method demonstrates potential for practical applications in environmental monitoring and disaster risk reduction.

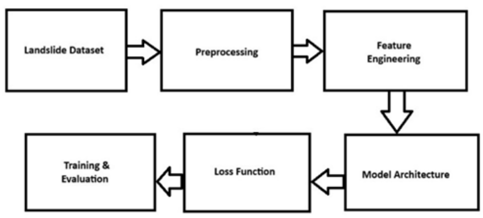


Figure 1: Proposed Methodologies

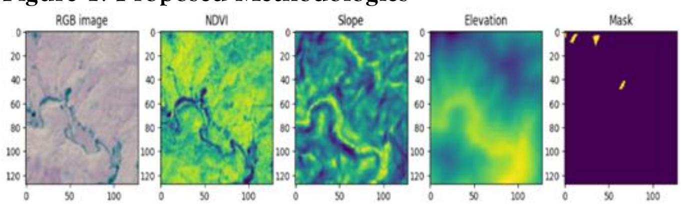
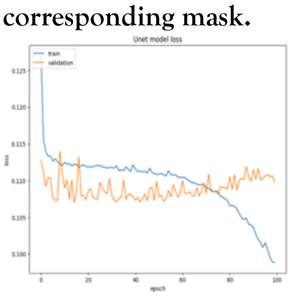
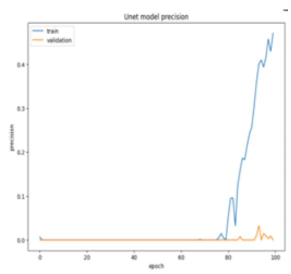


Figure 2: Input data channels used for training, including RGB, NDVI, slope, elevation, and the corresponding mask.





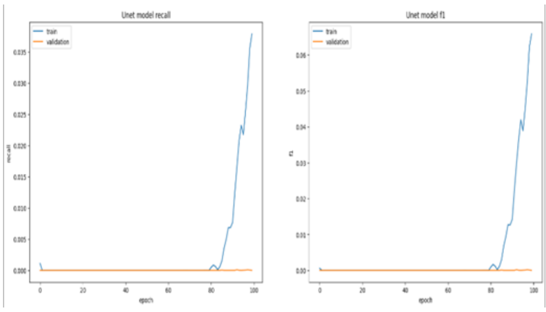


Figure 3: Accuracy and Loss Graphs for Training vs.Validation

REFERENCES

1. Luciano Picarelli, Suzanne Lacasse, and Ken KS Ho, “The impact of climate change on landslide hazard and risk,” Understanding and Reducing Landslide Disaster Risk: Volume 1 Sendai Landslide Partnerships and Kyoto Landslide Commitment 5th, pp. 131–141, 2021.
2. EM-DAT, “The international emergency disasters database,” 2023.
3. Raphael Knevels, Helene Petschko, Philip Leopold, and Alexander Brenning, “Geographic object-based image analysis for automated landslide detection using open source gis software,” ISPRS International Journal of Geo-Information, vol. 8, no. 12, pp. 551, Dec. 2019.
4. J McKean and J Roering, “Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry,” Geomorphology, vol. 57, no. 3-4, pp. 331–351, 2004.
5. Zhongbin Li, Wenzhong Shi, Ping Lu, Lin Yan, Qunming Wang, and Zelang Miao, “Landslide mapping from aerial photographs using change detection-based markov random field,” Remote Sensing of Environment, vol. 187, pp. 76–90, Dec. 2016.
6. Alexander L. Handwerger, Shannan Y. Jones, Pukar Amatya, Hannah R. Kerner, Dalia B. Kirschbaum, and Mong-Han Huang, “Strategies for landslide detection using open-access synthetic aperture radar backscatter change in google earth engine,” Oct. 2021.
7. Simon Plank, Andre Twele, and Sandro Martinis, “Landslide mapping ´ in vegetated areas using change detection based on optical and polarimetric sar data,” Remote Sensing, vol. 8, no. 4, pp. 307, Apr. 2016.
8. GPB Garcia, LP Soares, M Espadoto, and CH Grohmann, “Relict landslide detection using deep-learning architectures for image segmentation in rainforest areas: a new framework,” International Journal of Remote Sensing, vol. 44, no. 7, pp. 2168–2195, 2023.
9. Renxiang Huang and Tao Chen, “Landslide recognition from multifeature remote sensing data based on improved transformers,” Remote Sensing, vol. 15, no. 13, pp. 3340, 2023.
10. Xinran Liu, Yuexing Peng, Zili Lu, Wei Li, Junchuan Yu, Daqing Ge, and Wei Xiang, “Feature-fusion segmentation network for landslide detection using high-resolution remote sensing images and digital elevation model data,” IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1–14, 2023.
11. Hamid Rezatofighi, Nathan Tsoi, JunYoung Gwak, Amir Sadeghian, Ian Reid, and Silvio Savarese, “Generalized intersection over union,” in The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019.
12. Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo, “Cutmix: Regularization strategy to train strong classifiers with localizable features,” in Proceedings of the IEEE/CVF international conference on computer vision, 2019, pp. 6023–6032.
13. Sergey I. and Christian S., “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in Proc. ICML, 2015, pp. 448–456.
14. Andrew L Maas, Awni Y Hannun, Andrew Y Ng, et al., “Rectifier nonlinearities improve neural network acoustic models,” in Proc. icml, 2013, vol. 30, p. 3.
15. P. K. Diederik and B. Jimmy, “Adam: A method for stochastic optimization,” CoRR, vol. abs/1412.6980, 2015.
16. Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollar, “Focal loss for dense object detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 2, pp. 318–327, 2020.
17. Hamid Rezatofighi, Nathan Tsoi, JunYoung Gwak, Amir Sadeghian, Ian Reid, and Silvio Savarese, “Generalized intersection over union: A metric and a loss for bounding box regression,” in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 658–666.
18. Jie Hu, Li Shen, and Gang Sun, “Squeeze-and-excitation networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018.
19. Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon, “Cbam: Convolutional block attention module,” in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 3–19.
20. Cam Le, Lam Pham, Nghia Nvn, Truong Nguyen, and Le Hong Trang, “A robust and low complexity deep learning model for remote sensing image classification,” in Proceedings of the 8th International Conference on Intelligent Information Technology, 2023, pp. 177–184.