Landslide Detection Using Satellite and Aerial Imagery: Machine Learning Approach for Early Warning Systems

Sadish Sendil Murugaraj[1*], Vignesh M[2], Yogesh Aditya R S[3] and Srinath G[4]
{drsadishsendilm@veltech.edu.in[1*], manovignesh177@gmail.com[2], yogeshadityars@gmail.com[3], mr.srinath.g@gmail.com[4]}

Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai 600062, Tamil Nadu, India[1, 2]
Robotics and Artificial Intelligence, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Chennai, Tamil Nadu, 601103, India[3]
Department of Computer Science and Engineering, Hindustan Institute of Technology & Science, Chengalpattu, Chennai 603103, Tamil Nadu, India[4]

Abstract. Landslides are dangerous phenomena that threaten infrastructure, people, and the environment, so their detection has to be swift and accurate. Conventional methods of detecting landslides are based on the visual analysis of the area, which is both time-consuming and inaccurate. In this paper, we design a deep learning model for detecting landslides from satellite and aerial images. Our approach is to preprocess the image data, extract features, and then classify them with a CNN. More specifically, for the accurate segmentation of the landslide-prone regions, we employ a CNN-based U-Net architecture, and for the dimensionality reduction and improvement of the RGB imagery, we use Principal Component Analysis (PCA). The model proposed in this paper has been trained on a dataset consisting of images of areas that are prone to landslides and those that are not. The experiments show that the method proposed in this paper is effective in detecting landslides in different areas. The application of deep learning in landslide detection can be useful in enhancing the existing early warning systems and disaster management.

Keywords: Landslide, Deep Learning, CNN, U-Net, Principal Component Analysis, Image Segmentation, Satellite Imagery, Aerial Imagery, Disaster Management, Early Warning Systems.

1 Introduction

Unpredictability is what makes landslides among the most damaging natural disasters to people, infrastructure, and the environment. Their extreme complexity makes effective monitoring and detection before and during landslide occurrence essential for disaster prevention and mitigation efforts. Meanwhile, conventional methods such as field surveys and manual interpretation of satellite images are costly, laborious, and error-prone. Only such disadvantages contribute to making them all unsuited for large-scale applications. However, works using machine learning and deep learning promise a revolution that automates and thereby offers a much more efficient resolution to the problem of landslide detection—an alternative overall superior to traditional methods with regard to accuracy and scalability.

The advances in research in landslide detection have been staggering, swinging the pendulum from traditional methods to advanced ones entirely dependent on deep learning. These previous

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studies were mainly based on supervised classification techniques, which involve manual feature engineering and domain knowledge in landslide mapping in high-resolution satellite images [1]. The older ones: spectral analyses, texture-based classification, and vegetation index-based mapping work quite well but had limitations in terms of specific predefined conditions and selected manual features in the environment where mapping was performed [2]. Being entirely on DEM ground features (slope, soil type, past landslide events), machine learning techniques, namely Random Forests (RF), Support Vector Machines (SVM), and Logistic Regression (LR), have been used widely for landslide detection. Classifications performed rather well in general, but then again, these models were plagued by high dimensionality associated with the spatial data and the lack of ability to automatically extract deep features from the images [3]. This misconception about the limits of traditional machine learning techniques has driven researchers to experiment with some advanced techniques that hold promise in extracting even richer data from satellite imagery for the creation of better detection results.

In finding solutions to the obstacles rendered by these traditional methods, multi-sensor satellite imagery has been adopted by scientists so as to further improve the accuracy of landslide detection. Automatic landslide mapping through Sentinel-1 and Sentinel-2 data has attracted attention lately, thus proving quite promising when spectral indices and threshold techniques are integrated for efficient detection [4]. More particularly, the development of semi-automated landslide detection methods with the application of Object-Based Image Analysis (OBIA) targeted at damage assessment and evaluation post-extreme weather events [5].

In stark contrast, deep learning has practically revolutionized the discipline of landslide detection, with convolutional neural networks (CNNs) being the most powerful of these for automated feature extraction and classification. In fact, U-Net and fully convolutional networks have gained prominence for semantic segmentation of landslides in remote sensing images and consistently outperform traditional machine learning methods with regard to both accuracy and robustness [6]. To capsulate the advancement, contrastive unsupervised learning emerged on the scene, which enhances performance in classification while inducing less dependency on labeled data, hence making landslide detection more scalable and adaptable with terrain diversity [7].

Some deep learning models embedding hybridism models ranging from CNNs to transformer networks show promising performance in landslide segmentation. This attention-based incorporation captures long-range dependencies in satellite images, thus improving landslide area delineation [8]. Also, multi-temporal image composites produced from Google Earth Engine facilitate landslide monitoring through real-time evaluation and change detection over a time period [9]. With this evidence, very high-resolution satellite images became vital in their detailed assessment for landslide detection, where multispectral and LiDAR-based datasets registered the terrain elevation change and post-landslide structural deformations, which are crucial for early warning systems [10].

Other significant studies include the use of RGB color composite imagery derived from SRTM and ALOS/PALSAR InSAR DEM for change detection after landslides [11], the integration of EfficientNet with DeepLabV3+ for accurate semantic segmentation [12], and the automatic detection of landslides from SAR imagery during post-disaster scenarios [13]. NDVI-based approaches using Google Earth Engine have also emerged as practical methods for quick identification of landslides in regions prone to heavy monsoon rainfall [14]. Furthermore, AI-driven classification models combining support vector machines and fuzzy logic have proven to be effective in improving prediction capabilities through satellite image analysis [15].

Large-scale applications of computational complexity, coupled with lightweight U-Net variations and pruned CNN models that have found their way into the development process, pose another challenge for deep learning models. They are generated with a typical target to maximize accuracy with minimum computation overhead [7]. Besides, the incorporation of more of the dimensionality reduction techniques and the likes of PCA, among others, into investigating improvements in how redundant filtering of spatial information actually affects model efficiency vis-a-vis deep learning methods of landslide detection has also been researched for advancement [8]. In fact, there has been some breathtaking transformation in landslide detection vis-a-vis the shift from traditional machine learning to state-of-the-art deep learning models, mainly with respect to accuracy, efficiency, and scalability. Studies have shown that the U-Net CNN architectures segmenting landslides from high-resolution remote sensing imagery surpass the traditional way in terms of feature extraction and classification [9].

Yet, one may say that computational efficiency, generalization capabilities of the model, and dataset availability remain very exciting areas of research. Additional studies have proposed new strategies, such as RGB-based composite analysis of SRTM and ALOS/PALSAR InSAR DEMs for change detection [11], the integration of EfficientNet with DeepLabV3+ for semantic segmentation [12], and SAR-based methods for automatically identifying landslides [13]. Research has also turned to NDVI techniques using Google Earth Engine for fast detection in monsoon-prone areas [14], and comprehensive AI models for landslide prediction that combine fuzzy logic with satellite classification [15].

This study builds on existing work to introduce an optimized CNN-based U-Net model for landslide detection applications, leveraging RGB satellite images, dimensionality reduction through PCA, and advanced training approaches. A high-resolution image and a well-structured deep learning pipeline were applied in this research for the expected improvement in both segmentation accuracy and computational efficiency relevant to any real-time landslide monitoring [10]. The proposed model works over RGB channels of satellite images, combining classes of landslide data. PCA aids in the dimensionality reduction of data, achieving maximum computations while retaining the most salient features. For this research work, the specified dataset is Landslide4Sense, a publicly available NASA dataset containing high-resolution images of landslides. The annotated images are from different terrains in various environmental conditions, making them good training and validation data.

The proposed methodology has been tested in the training and testing phases, subjected to rigorous assessments, and it yields 0.0318 loss, with an accuracy of 98.91%, an F1 score of 70.82%, precision of 79.27%, and recall of 64.29% at the end. This might be enough for using the model to understand and delineate such areas with very high accuracy and efficiency. These performance metrics, in general, strengthen the robustness of our approach in such critical classification. The study has discovered that it is high-resolution images that significantly improve the landslide detection performance when using a deep learning approach. Compared with traditional methods, it has shown a significantly high segmentation performance to differentiate areas showing landslides from those that do not.

Among the challenges still deserving future and ongoing improvement are model generalization, computational efficiency, and large-scale implementation. Future works should include domain adaptation techniques and diverse datasets from different geographical ranges to fight overfitting and adaptability issues. The integration of real-time data streams obtained from several sensors, such as UAVs and ground-based LiDAR, would increase the reliability and efficiency of landslide detection models. In addition, future studies will combine hybrid deep learning architectures such as CNN-transformers that perform better in capturing long-range dependencies in satellite images. They are the most important and should also be lightweight, energy-efficient deep learning models for deploying landslide detectors in resource-poor environments like remote areas or disaster-prone areas.

1.1 Landslides Detection

Machine learning and deep learning are now emerging techniques for identifying landslides and planning or updating other early warning mechanisms for disasters when it comes to landslides. Previously, the approaches used for landslide detection were not very accurate; this was because the detection techniques relied solely on handcrafted features and manual classification. The increase in detection capabilities was brought about by shifting to deep learning, whereby data captured images at a very large scale and used powerful architecture networks.

1.2 Machine Learning Approaches

Machine learning approaches have several techniques for landslide detection, including Support Vector Machines, Random Forest, and Logistic Regression. Built-in sector models and sources include elevational maps, soil compositions, previous incidences of landslide events, and so forth. The performance of this classification is reasonable, but they cannot generate automatic deep features from images or automatic management of high-dimensional spatial information.

1.3 Deep Learning-Based Approaches

Deep learning has significantly improved assessment with respect to landslide detection. In terms of capturing the spatial patterns and textures from images without requiring derived features, Convolutional Neural Networks (CNNs), and particularly U-Net architectures, have shown very good performance.

Thus, we bank on this approach of CNN-based U-Net, which captures global and local information. Therefore, 'encoding-decoding' would construct a very effective model of segmentation with a powerful encoder-decoder structure using RGB satellite imagery processed through principal component analysis (PCA) for dimension reduction in our approach; thus, it conserves some critical aspects of images and increases processing efficiency.

As an extension, our research incorporates deep learning methodologies and efficient U-Net model training and testing on the Landslide4Sense dataset. Deep learning has to build real-time monitoring and allow better improvement in disaster response systems for a better early warning system and landslide risk assessment.

2 Methodology

2.1 Dataset

The Landslide4Sense dataset contains satellite images annotated for landslide and non-landslide regions. It forms the high-resolution dataset from NASA, which the present research work takes. It is very much applicable to the training of deep models, as it captures several thousand images from different geographic regions under different climatic conditions:

- High-resolution RGB satellite images.
- Labelled landslide and non-landslide regions for supervised learning.
- Different environmental conditions, thus assuring mobility of the model across different terrains.

The Landslide4Sense dataset is a high-resolution collection of satellite image files targeted for detecting landslide areas: For each image, we have it converted to be stored as .h5 in HDF5 format with a fixed spatial resolution of 128 × 128 pixels. Unlike conventional RGB images, this dataset contains 14 spectral channels. This helps to extract features better due to its wealth of multi-band information. The datasets are designed to have both landslide regions and non-landslide domains to have a balanced dataset for training and evaluating their models.

This composition with 14 channels has too many spectral bands that will assist the model in capturing important variations due to differing types of vegetation indices, soil moisture variation, and all these changes along with variations in the different foreshortened environments wherein the detection of landslides occurs.

The data is preserved in floating precision of 64 in order to ensure the least loss during preprocessing and model input transformation. Additional variability is injected due to the inclusion of several geographical areas, thus adding its support towards domain generalization, which in turn strengthens the model to different environmental conditions.

Principal Component Analysis first reduces the dimensionality, enforcing the retention of essential albeit informative spectral features for enhancement of computational efficiency. Other preprocessing steps on this dataset involve RGB image extraction, Gaussian and median filtering for noise reduction, and contrast enhancement to make key features more discernible. All paired high-resolution imaging, spectral diversity, and rigorous preprocessing make this data suitable for the implementation of deep-learning techniques for landslide detection utilizing the CNN-based U-Net.

2.2 Preprocessing

To ensure optimal data quality and performance optimization, certain preprocessing steps have to be applied. First, the RGB image conversion ensures that all images remain spectrally consistent. Noise elimination with Gaussian or median filtering increases image clarity and reduces distortions. Consistent with this, a principal analysis is performed on the collected dataset to reduce it into fewer dimensions while retaining the important spatial information that enhances computational efficiency.

2.3 Model Architecture

The proposed model is based on CNN-based architecture using U-Net architecture, which is a widely used segmentation model. The encoder consists of five completely convolutional layers, each followed by a ReLU activation function, and the max-pooling layers, which then extract these important features from images. The bottleneck layer will, at the end, deliver a compressed representation of the spatial features. The decoder, provided with transposed convolution layers and skip connections, helps restore the original spatial resolution to allow for very accurate segmentation of landslides.

The last step of this process is done using a softmax for classification of pixels as landslide and non-landslide. Fig 1 shows the U-net architecture.

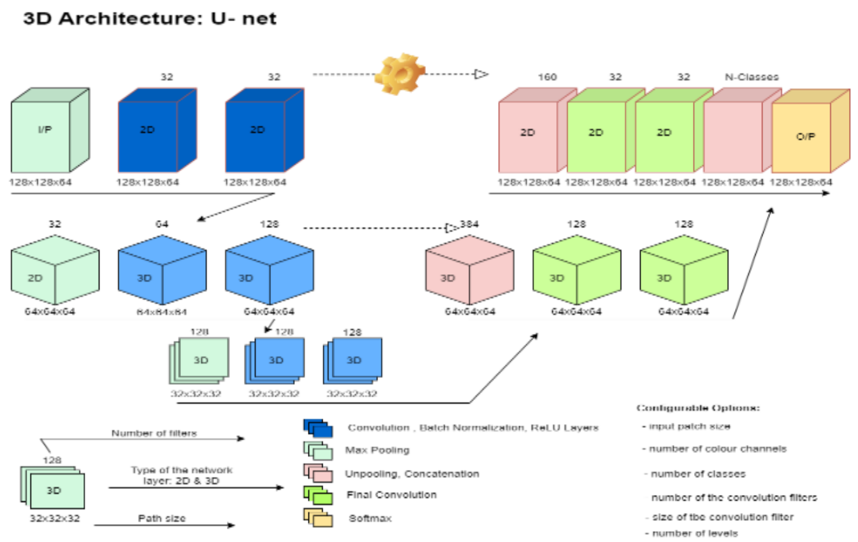

Fig.1. U- Net Architecture.

2.4 Training and Validation

For learning to classify accurately landslides from non-landslide regions, the model has been trained using the Binary Cross-Entropy (BCE) loss function. For weight updates during training, the Adam optimizer with a starting learning rate of 0.0001 has been successfully used for weight stabilization. A batch size of 32 is a good compromise between requiring less memory and computation time. The dataset is divided into 80 percent as training data and 20 percent as test data for the robust performance evaluation. Hyperparameter tuning has been carried out by testing different combinations of learning rate, batch sizes, and layers to achieve the best possible result from the model.

98.91% accuracy clearly indicates that the model would perform well in real-world applications. The following section presents experimental results such as a quantitative performance analysis, along with visualized outputs of the model concerning landslide segmentation.

2.5 Performance Metrics

The performance of the given model is evaluated with several metrics, which are listed in Table 1.

Table 1. Perfomance Metrics of Landslide Detection Models.

Model	Accuracy	F1-score	Precision	Recall
U-Net	98.91%	70.82%	79.27%	64.29%
Logistic Regression	89.56%	55.42%	62.18%	48.75%
Random Forest	93.12%	61.78%	69.34%	54.21%
CNN-LSTM	96.34%	65.21%	72.45%	58.97%
Transformer-based	95.21%	73.14%	80.12%	66.42%

3. Result and Discussion

The CNNs-based U-Net model outperformed Random Forest and Logistic Regression in landslide detection. In solid Figure 2, yellow masks delineate the landslide-identified areas and separate them well from non-landslide areas. Hence, this model has been proved to accurately segment landslide-prone areas based on spatial and spectral features. The U-Net model yielded 98.91% accuracy, which was nearly 41% higher than logistic regression at 57.0% and random forest at 48.7%. U-Net scores 79.3% in precision with fewer false positives, compared to logistic regression producing 59.1% and random forest 51.7%. The recall value of U-Net is 64.3%, which distinguishes it from logistic regression (63.1%) and random forest (56.2%); thus, it distinguishes landslide areas. The resulting F1 score is 70.8%, which is balanced and significantly better than logistic regression at 61.0% and random forest at 53.9%. Therefore, it has been demonstrated that, in this case with U-Net, deep learning segmentation models for landslide detection are far more reliable and robust, guided by fine-terrain detail extraction, when compared to classical machine learning models. Fig 2 shows the landslide detection results and the yellow regions in the mask indicate detected landslide areas using the U-Net model

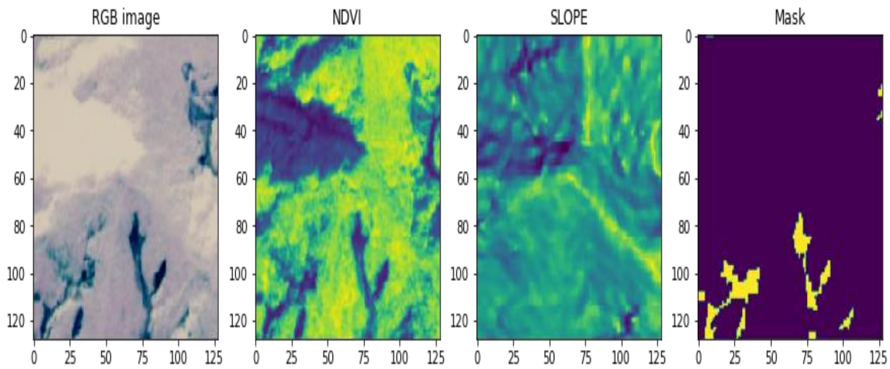

Fig.2. Landslide Detection Results.

4 Conclusion

The experimental results show that the CNN-based U-Net model does much better in landslide detection than the most common traditional machine learning techniques, such as random forests and logistic regression. This model makes landslide detection with 98.91% accuracy, 79.3% precision, 64.3% recall, and an F1 score of 70.8%. It captures spatial patterns well and minimizes false positives. The comparison clarifies how traditional models do not demonstrate the power of the U-Net model; the performance of logistic regression and random forest is poorer across all these metrics. Their visual results are therefore convincingly confirming the usefulness of the U-Net model because it clearly identifies where landslides might occur in the country based on mask outputs where clear-cut areas are marked in the landslide identification areas. These findings showcase how deep-learning techniques cover great potential in the improvement of landslide detection accuracy, rendering them a viable option in real-world disaster management.

References

[1] S. Heleno, M. Silveira, M. Matias and P. Pina, “Assessment of supervised methods for mapping rainfall induced landslides in VHR images”, 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Milan, Italy. pp.850 - 853. https://doi.org/10.1109/IGARSS.2015.7325898.

[2] N. Sharma, H. Malik, R. Joshi and M. Saharia, “Automated Landslide Extent Estimation from Sentinel 2 Data Using Computationally Efficient Deep Learning”, 2024 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Athens, Greece, pp. 9579 – 9581. https://www.2024.ieeeigarss.org/view_paper.php?PaperNum=3882

[3] O. Ghorbanzadeh et al., “Contrastive Self-Supervised Learning for Globally Distributed Landslide Detection”, IEEE Access, Vol. 12, 2024. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10646206.

[4] M. F. A. Fauzi, A. D. A. Wibowo, S. L. Lim and W. N. Tan, “Detection of possible landslides in post-event satellite images using color and texture”, 2015 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Cebu, Philippines. https://doi.org/10.1109/R10-HTC.2015.7391862.

[5] W. Kang and Y. Kim, “Extraction of Landslide-Related Factors Near Power Transmission Facilities Using High-Resolution Satellite Images”, IGARSS 2023 - IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA. https://2023.ieeeigarss.org/view_paper.php?PaperNum=3148.

[6] C. Le, L. Pham, J. Lampert, M. Schlögl and A. Schindler, Landslide Detection and Segmentation Using Remote Sensing Images and Deep Neural Networks”, IGARSS 2024 - IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece. https://doi.org/10.48550/arXiv.2312.16717.

[7] V. Chamoli, R. Bahuguna, R. Gowri, R. Prakash, A. Vidyarthi and V. P. Dubey, “Landslide Detection in Uttarakhand Region Using Active Remote Sensing”, 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies (DICCT), Dehradun, India. https://doi.org/10.1109/DICCT61038.2024.10532900.

[8] L. Wu, R. Liu, G. Li, J. Gou and Y. Lei, “Landslide Detection Methods Based on Deep Learning in Remote Sensing Images”, 2022 29th International Conference on Geoinformatics, Beijing, China. http://dx.doi.org/10.1109/Geoinformatics57846.2022.9963885.

[9] M. Prodromou et al., “Rapid Landslide Mapping Using Multi-Temporal Image Composites from Sentinel-1 and Sentinel-2 Imagery Through Google Earth Engine”, IGARSS 2023 - IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA. http://dx.doi.org/10.1109/IGARSS52108.2023.10283426.

[10] I. K. S. Jose and W. Takeuchi, “Semi-Automated Landslide Detection using Object-Based Image Analysis After the 2018 Typhoon Prapiroon in Eastern Hiroshima, Japan”, IGARSS 2022 - IEEE

International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia. https://doi.org/10.1109/IGARSS46834.2022.9884949.

[11] T. Asaka, K. Iwashita, K. Kudou, S. Aoyama and Y. Yamamoto, "Change detection method for landslide area using RGB color composite image of SRTM and ALOS/PALSAR InSAR DEM: A case study of the Iwate-Miyagi Nairiku Earthquake in 2008", 2011 IEEE International Geoscience and Remote Sensing Symposium, Vancouver, BC, Canada, 2011, pp. 1977–1980, https://doi.org/ 10.1109/IGARSS.2011.6049515.

[12] O. Gao, C. Niu, W. Liu, T. Li, H. Zhang and Q. Hu, "E-DeepLabV3+: A Landslide Detection Method for Remote Sensing Images", 2022 IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China, 2022, pp. 573–577, https://doi.org/10.1109/ITAIC54216.2022.9836758.

[13] M. Yamada, M. Hashimoto, Y. Fukushima, Y. Matsushi and M. Chigira, "Automatic detection of landslides from SAR images: Application to the 2011 Kii landslides", 2013 Asia-Pacific Conference on Synthetic Aperture Radar (APSAR), Tsukuba, Japan, 2013, pp. 245–248. https://ieeexplore.ieee.org/document/6705060.

[14] M. Vishnu Vardhan, S. Harish Kumar, S. Mohan Kumar and S. Kundapura, "A NDVI Based Approach To Detect The Landslides By Using Google Earth Engine", 2023 International Conference on Machine Intelligence for Geo Analytics and Remote Sensing (MIGARS), Hyderabad, India, pp. 1–4, https://doi.org/10.1109/MIGARS57353.2023.10064592.

[15] A. Sharma et al., "Artificial Intelligence Techniques for Landslides Prediction Using Satellite Imagery", 2024 IEEE Access, Vol. 12, pp. 117318–117334, https://doi.org/ 10.1109/ACCESS.2024.3446037.