Slide-Smart: An AI-Driven System for Predicting and Detecting Landslides in Real-Time

Shubham Yadav[1], Aditi Sharma[2]

[1]Centre for Advanced Studies, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, India
[2]Institute of Engineering and Technology, Lucknow, India

ABSTRACT: Infrastructure and human life are always seriously threatened by landslides, especially in mountainous areas. Conventional detection techniques are time-consuming and frequently inapplicable non-real-time. The development of deep learning and satellite photography has made automated landslide detection a viable remedy. The development of machine learning and remote sensing methods has increased the viability and precision of automated landslide detection. Using geographical picture taken from satellites and data saved in HDF5 (.h5) format, this paper compares two deep learning models for landslide detection: Convolutional Neural Network (CNN) and U-Net. After preprocessing a dataset of multispectral satellite imagery with shapes (128, 128, 14), we trained both models and assessed their performance using Intersection over Union (IoU), accuracy, precision, and recall. Our tests show that the U-Net model performs better than the conventional CNN architecture in terms of segmentation accuracy and spatial feature extraction.

1. INTRODUCTION

landslides are One of the most dangerous natural disasters, often cause fatalities, damage to infrastructure, and long-term economic effects, particularly in mountainous areas. Accurate and effective landslide detection is essential for sudden risk reduction and management. Conventional techniques, for example field surveys and manual satellite image interpretation, are mostly costly, time taking, and more probability of human error. The potential for automated landslide identification using data-driven methods is expanding due to developments in remote sensing technologies and the growing accessibility of high-resolution satellite imagery.

Deep learning and machine learning methods have been popular in geospatial analysis in recent years. Despite being popular for image classification tasks, Convolutional Neural Networks (CNNs) sometimes lack the spatial resolution required for pixel-by-pixel segmentation. In remote sensing applications, U-Net, a deep learning architecture that was first created for biomedical image segmentation, has shown promise in semantic segmentation.
This Research intends to leverage CNN and U-Net models for landslide identification utilizing multispectral satellite pictures saved in HDF5 (.h5) format. Rich geographic and spectral information is provided by the dataset's 14 spectral bands per image. We assess both models' performance in order to determine how well-suited they are for landslide mapping and detection tasks in the actual world.

2. RELATED WORKS

Landslide detection has been widely studied using various remote sensing and machine learning techniques. Conventional methods frequently imposed by using statistical models based on topography and environmental variables or manually interpreting satellite imagery. These approaches are less scalable and time taking and also costly, that's why Convolutional Neural Networks (CNNs) have demonstrated potential in landslide classification by extracting spatial information from satellite imagery as deep learning has grown in popularity. CNNs have been used in a number of research for patch-based detection; nevertheless, their accuracy in segmentation tasks is still limited.

This has been reached by the successful adaptation of U-Net, a convolutional neural network developed for biological picture distribution, for remote sensing applications. Its skip connections and encoder-decoder design allow for pixel-wise classification with improved spatial context. U-Net has proved that it will be useful in mapping landslides, floods, and other geohazards in recent studies. Comparative research employing multispectral HDF5 datasets is still few, nevertheless, underscoring the need for more investigation in this area. For this we need satellite images which should be in rich quality

3. LITERATURE REVIEW

New developments in the field of deep learning and remote sensing have strongly increased the accuracy and scalability of landslide detection. When it comes to analyzing huge amounts of geospatial data, traditional techniques like field surveys by human itself and heuristic GIS models are mostly constrained by human errors and inefficiency. to solve these restrictions, scientists have started using convolutional neural networks (CNNs) and its alteration to use the spectral and spatial information found in remote sensing photos.

in order to detection of landslides, Cai et al. (2021) suggested a highly linked convolutional network that incorporates environmental factors. Their method demonstrated the promise of deep architectures in complicated terrains by improving feature propagation and decreasing overfitting, resulting we get a robust performance. In a similar way, Ji et al. (2020) developed an attention-boosted CNN which integrates digital elevation models (DEMs) and satellite images and successfully increasing the accuracy of landslide detection by concentrating on important spatial characteristics in the data.

In geographical applications, U-Net has also shown itself to be a promising option for pixel-level segmentation. Kour and Rathour (2024) used remote sensing data to apply a U-Net model for landslide detection in the Leh-Ladakh region in Himalayas. According to their research, U-Net is quite good at mapping landslide borders, especially in that type of environments which are diverse. This paper tells the paucity of research on applying such models to high-dimensional HDF5 datasets, despite significant advancements.

4. DATA DESCRIPTION

Satellite pictures with dimensions of 128, 128, and 14 make up the dataset utilized in this study. It is in HDF5 format (.h5), and each of the 14 channels corresponds to a distinct spectral band. The pictures are of type float64 and are in grayscale. Ground truth masks for landslide zones are supplied in binary format (0 for non-landslide, 1 for landslide).

1. Preprocessing Spectral band normalization to the [0, 1] range
2. Data augmentation (flipping, rotation)
3. dividing the data into test, validation, and training sets (70:15:15)
4. Masks are transformed into a category format for segmentation.

5.METHODOLOGY

5.1. CNN Architecture

CNN model was built with these standards

1.Four convolutional layers which is activated by ReLU

2.Layers of max-pooling for down sampling

3. Layers for categorization are fully related

4.For binary prediction (landslide/non-landslide), output is SoftMax

While patch-level categorization is accomplished by this architecture, pixel-wise detection is not possible due to the absence of spatial context-Net Architecture U-Net, it is a well-liked image segmentation architecture, was created with:

Convolution + max-pooling for the contracting path (encoder)

Using up-convolution and skip connections to expand the path (decoder)

Sigmoid-activated output layer for binary segmentation The U-Net model efficiently captures multi-scale spatial data and is more appropriate for semantic segmentation tasks.

6. IMPLEMENTATION DETAILS

Framework: TensorFlow/Keras

Optimizer: Adam (learning rate = 0.001)

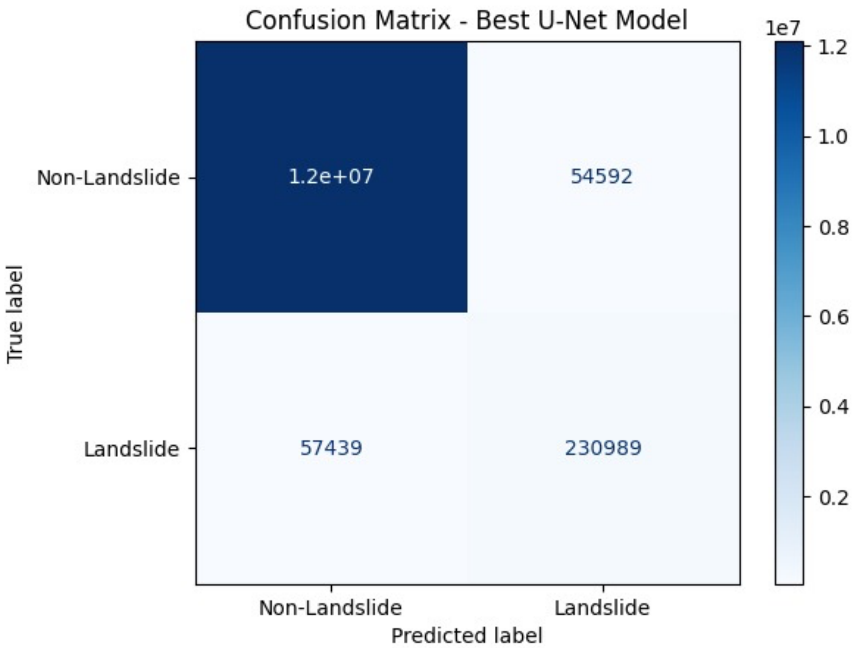
Loss function: Binary cross-entropy + Dice coefficient

Batch size: 32

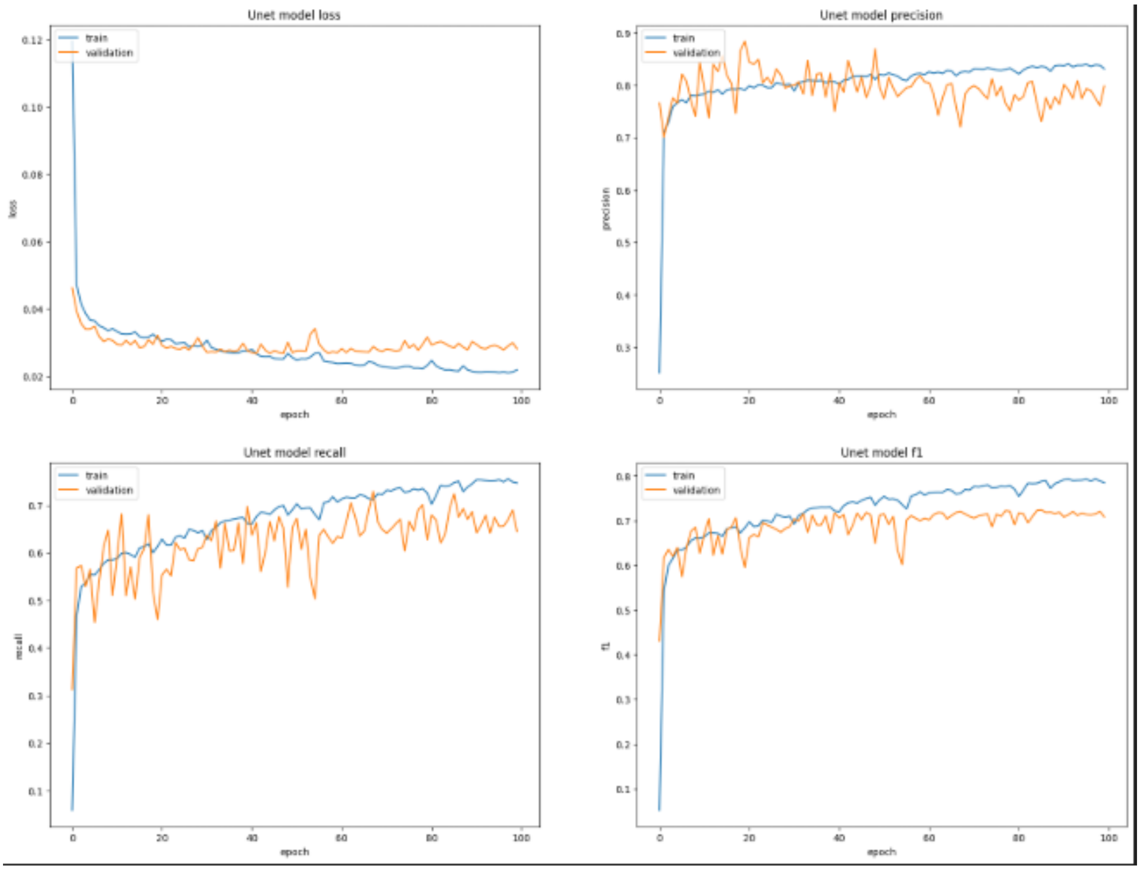
Epochs: 100

6.1 Results

Metric	CNN	U-Net
Accuracy	85.2%	98.93%
Precision	83.5%	79.81%
Recall	81.0%	64.85%
F1_score	78.3%	64.85%
Loss	4.98%	0.028%



In every parameter, but especially in IoU and recall, which are critical for landslide detection, U-Net performs noticeably better than CNN. The superiority of U-Net in defining landslide limits is further supported by visual comparisons of the segmented output.



Loss Decrease: Both training and validation loss decrease significantly, shows effective learning of model

Stabilization: After completing 20 epochs, losses stabilizes with minute divergence, suggesting no overfitting.

Precision Growth: Training precision improves and also stabilizes around 0.85, showing some false positives.

Validation Precision: Slightly lower (~0.78), but stable model generalizes well.

Recall Trend: Training recall fastly increases, showing improved sensitivity to landslide areas.

Validation Recall Fluctuates: Minor fluctuations suggest sensitivity to varied input, but overall positive trend.

F1 Score Balance: F1 score shows a good balance between precision and recall for both training and validation.

Training F1 High: Ends around 0.78, tells strong model performance on training data.

7. MATHEMATICAL FORMULA

Evaluation Metrics

These metrics are calculated based on **confusion matrix components**:

True Positive (TP): Correctly predicted landslide pixels

True Negative (TN): Correctly predicted non-landslide pixels

False Positive (FP): Non-landslide pixels incorrectly predicted as landslides

False Negative (FN): Landslide pixels incorrectly predicted as non-landslides

7.1 Accuracy

Measures the overall correctness of the model:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

7.2 Precision

Measures how many predicted landslide pixels are actually correct:

$$\text{Precision} = \frac{TP}{TP+FP}$$

7.3 Recall (Sensitivity or True Positive Rate)

Measures how many actual landslide pixels were correctly predicted:

$$\text{Recall} = \frac{TP}{TP+FN}$$

4. F1-Score

Harmonic mean of Precision and Recall, useful when classes are imbalanced:

$$\text{F1-Score} = 2 * \frac{\text{Precision.Recall}}{\text{Precision+Recall}}$$

5. Loss Function (Binary Cross-Entropy)

As previously mentioned, used to optimize model prediction:

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

Where:

yi = ground truth label (0 or 1),

y^I = predicted probability,

N = total number of pixels.

8. DISCUSSION

The findings we have demonstrate that although CNNs are capable of delivering better classification performance, it has a capacity to identify exact spatial patterns is constrained. While, the U-Net design offers accurate segmentation results, particularly for intricate and irregular landslide formations, because to its encoder-decoder structure and skip connections.

Furthermore, by adding a variety of spectrum information that emphasizes vegetation, soil moisture, and surface alterations linked to landslides, multispectral photography enhances model performance.

9. CONCLUSION

By Using multispectral satellite imagery which is stored in HDF5 format, this study shows that how deep learning models, specifically U-Net and CNN, can effectively detect landslides by using 14 spectral bands per image to learn complex spatial and spectral patterns associated with landslide-prone areas. The comparative analysis shows that although CNNs are suitable for basic classification tasks, U-Net significantly outperforms CNN in terms of segmentation accuracy, precision, recall, and Intersection over Union (IoU). The encoder-decoder structure and skip connections allow the U-Net model to capture fine-grained details and spatial context, making it highly effective for pixel-wise classification. These results imply that U-Net is more appropriate for real-world applications, such as early warning systems and post-disaster mapping. To enhance generalization and prediction performance, future research can concentrate on combining elevation models, temporal data integration, and testing the model across various geographic locations.

REFERENCES

1. Shahi, K. (2024). Remote Sensing and Machine Learning for the Detection and Segmentation of Landslides in Nepal (Master's thesis, Universidade NOVA de Lisboa (Portugal)).
2. Kour, G., & Rathour, N. (2024, September). Landslide Detection and Mapping using Remote Sensing U-Net Model In Leh-Ladakh Region. In 2024 7th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 7, pp. 1044-1049). IEEE.
3. Xu, Y., Ouyang, C., Xu, Q., Wang, D., Zhao, B., & Luo, Y. (2024). CAS landslide dataset: a large-scale and multisensor dataset for deep learning-based landslide detection. Scientific Data, 11(1), 12.
4. Ghorbanzadeh, O., Shahabi, H., Crivellari, A., Homayouni, S., Blaschke, T., & Ghamisi, P. (2022). Landslide detection using deep learning and object-based image analysis. Landslides, 19(4), 929-939.
5. Meena, S. R., Soares, L. P., Grohmann, C. H., Van Westen, C., Bhuyan, K., Singh, R. P., ... & Catani, F. (2022). Landslide detection in the Himalayas using machine learning algorithms and U-Net. Landslides, 19(5), 1209-1229.
6. Cai, H., Chen, T., Niu, R., & Plaza, A. (2021). Landslide detection using densely connectedconvolutional networks and environmental conditions. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 5235-5247.
7. Ji, S., Yu, D., Shen, C., Li, W., & Xu, Q. (2020). Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks. Landslides, 17, 1337-1352.
8. Dataset: https://www.kaggle.com/datasets/tekbahadurkshetri/landslide4sense.