

LEVERAGING UAVS AND MACHINE LEARNING FOR ENHANCED LANDSLIDE DETECTION AND RISK MANAGEMENT

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Landslides pose a significant threat to safety, demanding advanced detection and monitoring techniques to mitigate risks. This study explores an approach that benefits from recent advancements in both data acquisition and analysis methods. UAV-derived ultra-high-resolution digital elevation models and orthomosaic offer an accurate foundation for object-based image analysis to achieve highly accurate landslide detection. The widespread availability of high-resolution digital terrain models from UAVs, combined with advances in computer vision and ultra-high-resolution sensor technology, enables more precise landslide identification and characterization in engineering geology. Focusing on Atali, an extensive cut slope along NH-7, Uttarakhand, India that is frequently vulnerable to rockslides during monsoon seasons, this study highlights the necessity of detailed analysis to prevent and mitigate future hazards. We use the object-based image analysis technique with a thresholding value to segment UAV-derived orthomosaics into meaningful objects based on spectral, spatial, textural, and morphological attributes, providing a more coherent basis for classification. The digital surface model derived from the first UAV survey revealed that the slope is active, and thereafter, temporal flights at the Atali slope were also done. The slope and elevation values change over the monsoon cycle highlights the critical need for detailed analysis. By identifying distinctive landslide patterns within the UAV imagery, the random forest algorithm is used to produce an improved landslide detection technique with fewer false positives and negatives, leading to more reliable safety assessments. The preliminary results indicate the effectiveness of the combined OBIA-machine learning approach in delivering high-accuracy landslide classification. The detected landslide body serves as crucial data for detailed landslide mapping and has the potential to improve decision-making in engineering practices.

Keywords: Digital elevation model, landslide detection, machine learning, OBIA, UAV.

1. Introduction

Landslides, a frequent geological hazard in the Indian Himalayas, pose a significant threat to life, infrastructure, and the safety of commuters along National Highways (Sajwan and Ramana 2024). Extreme weather conditions and changes in rainfall patterns have necessitated robust landslide detection and monitoring systems (Dikshit et al. 2020). While traditional field surveys and measurement techniques can identify landslide areas and track their progression over time, they fall short in answering critical questions such as slope changes, area expansion, volume fluctuations, and, most importantly, the overall slope stability. Unmanned Aerial Vehicles (UAVs) offer a powerful tool for monitoring ground deformation rates. By capturing high-resolution imagery, UAVs can provide valuable insights into the factors influencing deformation, such as seasonal variations or rainfall events. As a relatively new addition to geotechnical tools, UAVs have proven to be highly effective in improving data accuracy, enhancing safety, and reducing project costs, risks, and labour requirements (Vishweshwaran and Sujatha 2024).

The primary limitations of satellite-based remote sensing for continuous monitoring of natural resources like forests, water bodies, and land are its high cost and temporal and spatial resolution constraints. UAV-based remote sensing has emerged as a powerful tool for natural resource management, offering several advantages over traditional satellite-based methods (P. K. Mishra and Rai 2021). UAVs are highly flexible, efficient, and cost-effective, enabling frequent data collection at high spatial and spectral resolution. By capturing data from multiple angles and altitudes, UAVs can mitigate the impact of spectral variability, particularly in water body surveys. This makes UAV technology a valuable asset for monitoring various natural resources, including forests, water bodies, and land use/land cover changes (V. Mishra et al. 2023).

The shift from traditional methods to advanced remote sensing techniques, such as UAV mapping and photogrammetry, has revolutionized landslide detection. These modern approaches offer greater precision and detail, enabling more accurate identification and monitoring of landslide events. Overtime Object-Based Image Analysis (OBIA) has been widely applied to UAV datasets to map landslide scars (Martha et al. 2010), (Karantanellis et al. 2020), and (Stumpf et al. 2013) achieving higher accuracy compared to pixel-based methods. Integrating multiple data types, including spectral, spatial, topographical, textural, and morphological features, object-based image analysis (OBIA) offers a powerful approach to detect landslides in orthorectified UAV imagery (Comert et al. 2019). By grouping pixels into homogeneous objects, OBIA enhances the accuracy of landslide identification (Ghorbanzadeh, Gholamnia, and Ghamisi 2023). Recent studies investigate the effectiveness of LiDAR and UAV-derived data in landslide susceptibility mapping using Random Forest models, aiming to identify the most accurate approach for mitigating landslide risk (França Pereira et al. 2023).

2. Study Area and UAV Dataset

This study focuses on an active rock debris slide in the Atali region of Uttarakhand, India, located at $30^{\circ}5'0.67''\text{N}$ $78^{\circ}26'10.21''\text{E}$ near the Ganga River, this slope is prone to landslides during the monsoon season, posing a threat to NH-7. To monitor this landslide efficiently and cost-effectively, UAV technology is employed to capture high-resolution aerial imagery and accurate GPS data (Kundal et al. 2024).

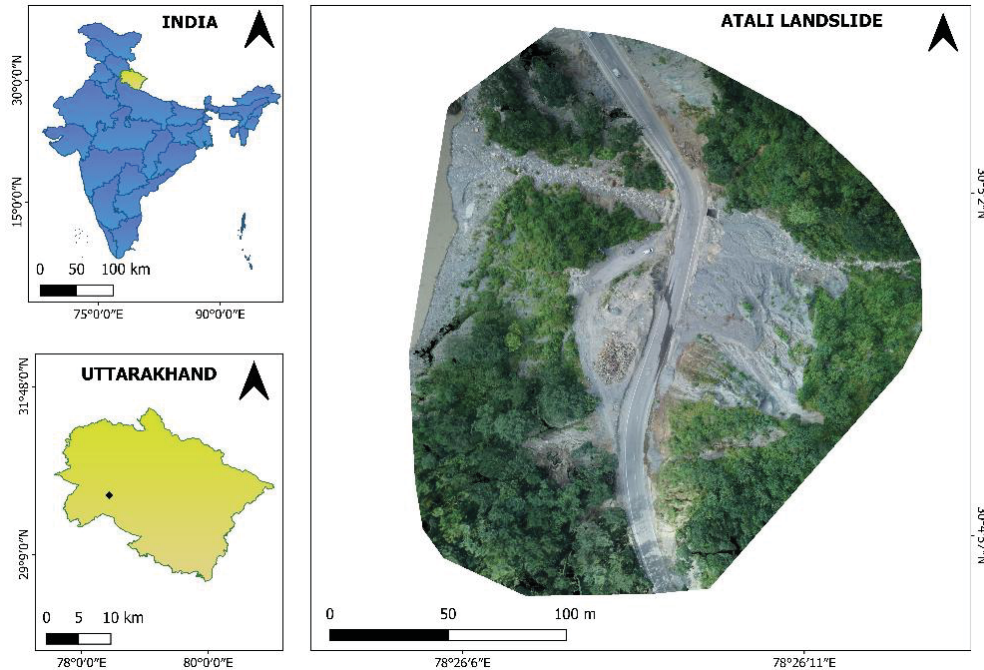


Figure 1 The Orthomosaic of the study area (Atali Landslide) is displayed in the map.

High-resolution (3.6 cm/pixel) digital elevation models (DEM) and orthomosaic were generated from UAV-derived images, providing detailed topographic information about the Atali landslide. The DEM, with an elevation range of 355 to 477 m, was used to create a slope map, revealing steep slopes ranging from 27° to 77° that contribute to the landslide's susceptibility (Kundal et al. 2024).

3. Object-Based Image Analysis (OBIA) Methodology

3.1. UAV Data Acquisition and Processing

The method employs a UAV survey approach involving data acquisition for the Atali landslide. The pre-processing involves a comprehensive flight plan designed using SNAP-M UAV, which is a micro-category survey-grade UAV considering factors such as ground sampling distance, flight altitude, and overlap settings. Subsequently, high-resolution images were captured using the UAV. Image standardization and georeferencing were performed to ensure accurate spatial alignment and ground referencing. The processed images were then utilized to generate dense point clouds through Structure from Motion (SfM) and Multi-View Stereo (MVS) techniques (Westoby et al. 2012). These point clouds were further processed to create orthomosaic images and digital elevation models (DEMs) for the slope.

3.2. Feature Extraction

Various techniques were employed to extract relevant features from the UAV-derived data. Using SNAP software, textural features, such as dissimilarity, entropy, and angular second moment, were derived from the Gray Level Co-occurrence Matrix (GLCM) (Amatya et al. 2021). Topographical features, including Digital Terrain Models (DTM), slope, and hillshade, were extracted from the DEM (Karantanellis et al. 2020) using ArcGIS Pro. Finally, spectral information was obtained directly from the RGB orthomosaic.

3.3. Data Integration and Pre-processing

The extracted textural, topographical, and spectral features used as classifiers were fused into a unified dataset. A training dataset was meticulously curated to train the machine learning model by extracting objects of known landslide occurrences and non-landslide regions.

3.4. Landslide Detection

Multi-Otsu thresholding was employed to segment the merged dataset into homogeneous objects. This technique, an extension of the binary Otsu method, is suitable for images with multimodal histograms, allowing for the identification of multiple classes (Suryani, Asmari, and Harjito 2021). By maximizing inter-class variance, the Otsu method effectively determines optimal threshold values to segment the image into distinct regions. The RGB orthomosaic was subjected to multi-Otsu thresholding, yielding several segmented regions based on three threshold levels (Singh et al. 2023). These segmented regions were subsequently vectorized manually using GIS (QGIS Development Team 2020) to create polygon datasets representing landslide and non-landslide areas.

A Random Forest classifier was trained on the prepared training dataset to categorize the segmented objects as landslides or non-landslides. The training dataset was constructed by manually delineating landslide and non-landslide areas on the UAV image derived from multiple landslide images in the Himalayas, ensuring a diverse dataset that can generalize well across different types of landslides and terrains, and intersecting them with the segmented objects. The dataset is then divided into training and testing sets, with a common approach being to allocate 70% for training and 30% for testing. This division ensures that the model is trained on a substantial portion of the data while reserving enough for validation and evaluation of its performance. The merged geodata layer, comprising distinct bands of information, served as the input for the Random Forest classifier. The model predicts landslide and non-landslide areas within the study region by training the classifiers on this dataset.

3.5. Output and Validation

The classified objects were integrated to create a detected landslide map, which was subsequently validated using a separate dataset to evaluate its overall accuracy, and F1 score.

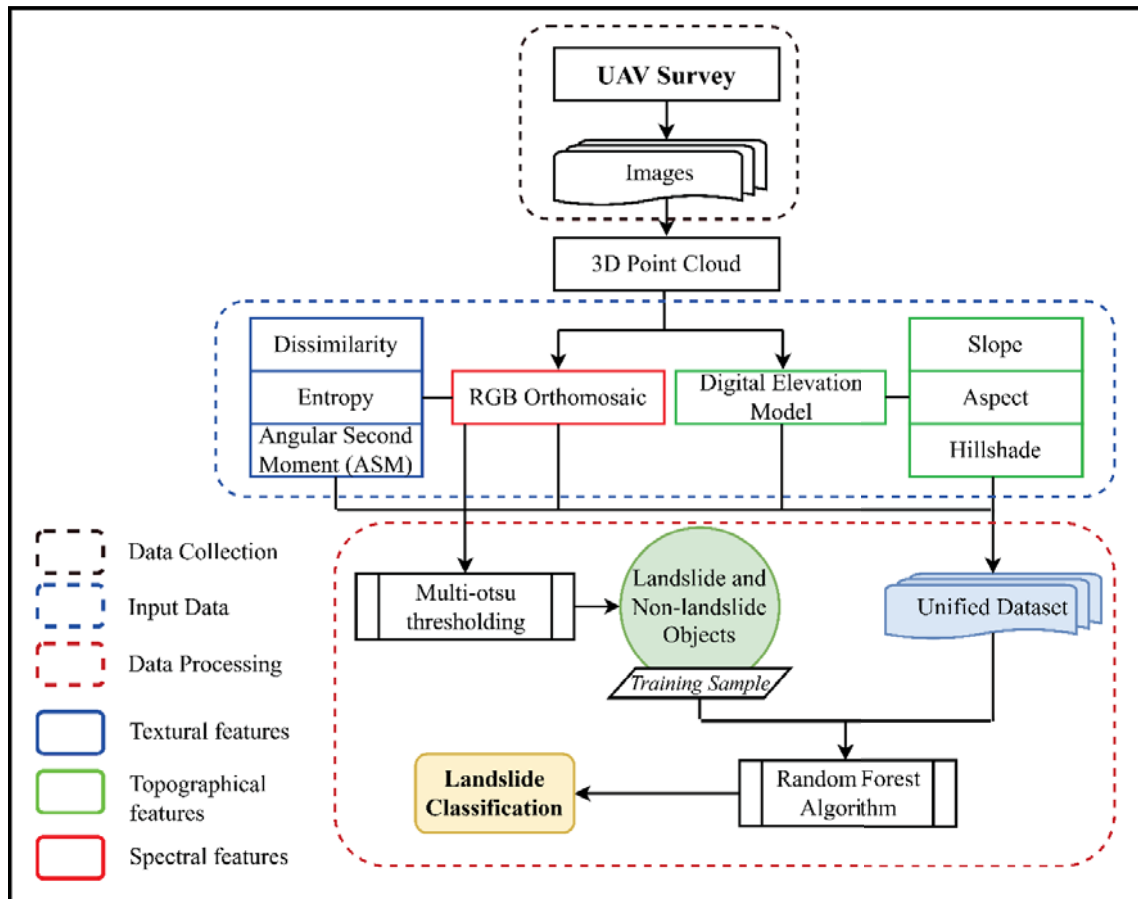


Figure 2 Methodology Workflow

4. Analysis and Results

4.1. Image Segmentation

Multi-Otsu thresholding was applied to the RGB orthomosaic to identify landslide and non-landslide areas. This technique effectively segmented the image into numerous fine-grained objects based on threshold levels derived

from the image histogram. These segmented objects form the basis for subsequent classification using the Random Forest machine learning algorithm.

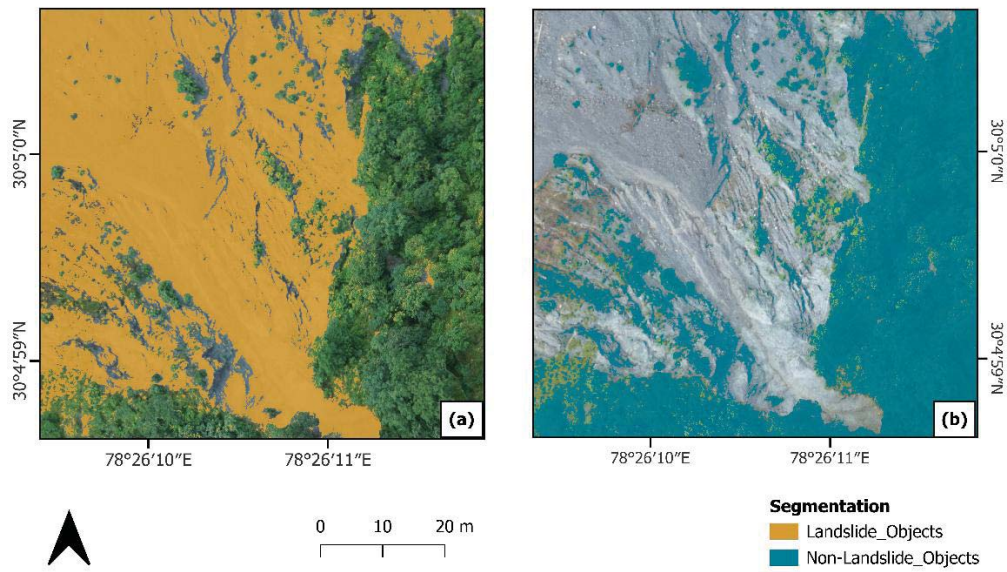


Figure 3 Segmentation of orthoimage in Landslide and Non-Landslide Objects using multi-Otsu thresholding

4.2. Object Classification

The segmented objects were classified as landslides or non-landslides using a Random Forest algorithm. The algorithm was trained on a dataset comprising manually delineated landslide and non-landslide areas. The output of the classification process was a GeoTIFF file with pixel values of 0 (non-landslide) and 1 (landslide).

To assess the accuracy of the classification, a confusion matrix was created. This matrix compared the predicted class labels with the ground truth labels for both training and validation datasets. By analyzing the confusion matrix, metrics such as overall accuracy, and F1-score were calculated to evaluate the performance of the proposed methodology.

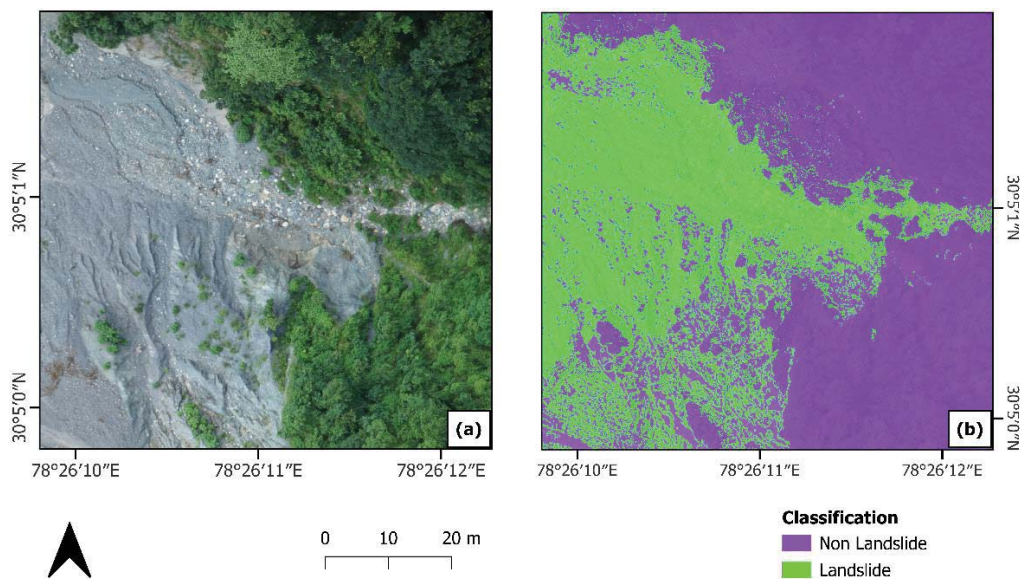


Figure 4 Object-based landslide detection using Random Forest Algorithm

Table 1. Confusion Matrix Result

Overall Accuracy (%)	F1-score (%)
96.8289	99.3007

Table 1 showcases the model's exceptional performance during prediction, achieving an accuracy exceeding 0.96 and an F-1 score of 0.99. The trained model was subsequently used to generate landslide masks from raw UAV orthomosaics.

Accuracy in a binary classification problem is generally defined as the proportion of correct predictions out of the total predictions made. It is calculated using the formula:

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

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Samples}}$$

Figure 6 visually compares the raw image, its ground truth mask, and the predicted mask. A manually determined optimal threshold of 0.66 effectively differentiated landslide and non-landslide areas. The predicted mask closely resembles the ground truth, suggesting high accuracy in landslide detection. The confusion matrix in Figure 5 provides a detailed performance breakdown, indicating 13,592 true negatives, 13,361 true positives, no false positives, and only 230 false negatives, further confirming the model's effectiveness.

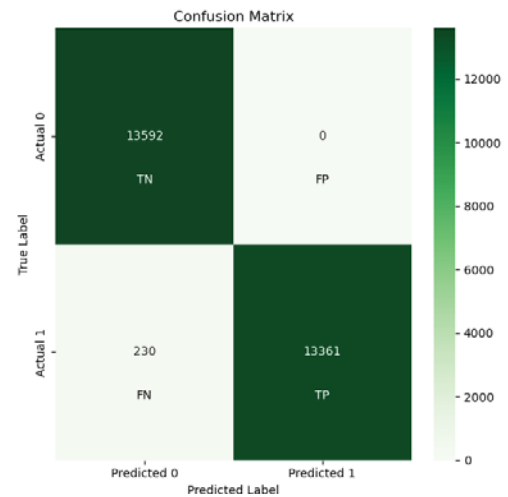


Figure 5 Confusion Matrix

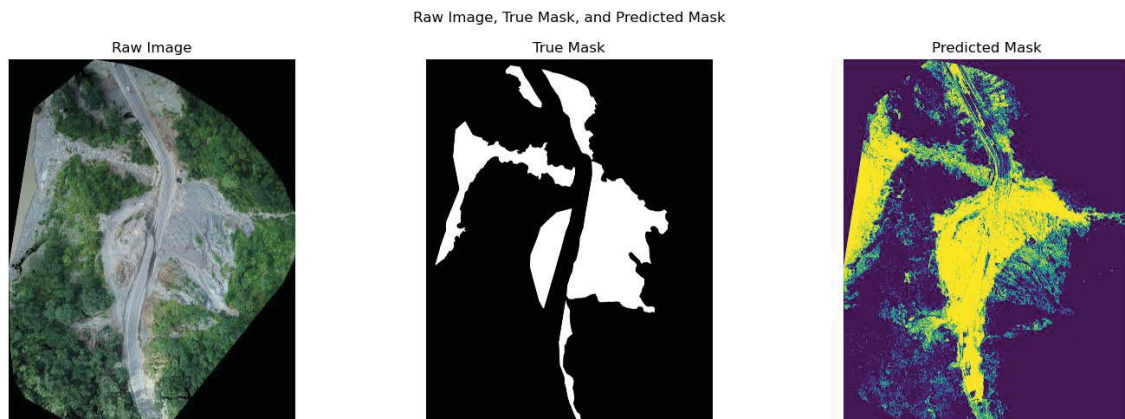


Figure 6 Raw Image, True Mask, and Predicted Mask

5. Discussion

The OBIA approach effectively detected over 97% of landslide and deposition zones in the study area. However, it struggled to accurately identify scarp zones, particularly in areas with higher vegetation and overshadowed regions. This underestimation highlights the challenges in defining the precise boundary of the landslide.

Incorporating alternative spectral and morphological features as classifiers can be beneficial to enhance the accuracy of landslide mapping. Additionally, optimizing the timing of UAV data acquisition to minimize shadowing and ensure optimal data quality is crucial.

6. Conclusion and Future Scope

UAVs and computer vision have revolutionized landslide studies, offering cost-effective and efficient data collection methods. By combining high-resolution imagery with object-based image analysis (OBIA), it is possible to detect and characterize landslide features accurately. While OBIA effectively identifies landslide and

non-landslide zones, challenges remain in detection in highly vegetation regions, especially in areas with steep and narrow slopes. Cross-grid UAV pattern flights offer better visibility and coverage by capturing images from multiple angles, reducing gaps, and providing more comprehensive data for 3D reconstruction, especially in complex terrains. Future research should prioritize refining OBIA techniques and incorporating field validation to improve the accuracy of landslide mapping, especially in the challenging terrain of the Indian Himalayas. Given the rainfall-induced nature of many landslides in this region, periodic UAV monitoring can provide essential insights into landslide evolution and potential hazards.

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