

A Hybrid Transformer-Graph Neural Network Framework for Landslide Prediction Using Remote Sensing Imagery

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Abstract

Landslide prediction presents a key challenge in geohazard risk mitigation due to the complexities arising through geological, climatic, and human activities. An original deep learning method combining image segmentation, feature learning, and transformer-based classification is proposed in the paper, for accurate landslide prediction. The process starts with landslide scene image collection, which undergoes a pre-processing step in an organized manner such as noise removal, image normalization, and semantic segmentation etc. The process is to make efforts on arranging images efficiently and spatially for efficient analysis. A dual-branch feature extractor module employs Vision Transformers (ViT) and Graph Neural Networks (GNNs) is been proposed. The Vision Transformer preserves global spatial interdependencies throughout the segmented image. The GNN encloses rich topological relationships among neighbors with enhanced spatial perception. The features are fed to an attention-based classifying module based on modern methods to receive accurate predictions for the likelihood of landslide occurrence. The model is provided with a real-world example of the 2021 Chamoli landslide tragedy in Uttarakhand, India, to test realistically. The data captured using ISRO's Cartosat and Sentinel-2 was used for validation. Results showed good performance with 91.3% classification accuracy, high quality segmentation (IoU: 0.79), and effective interpretability through SHAP analysis. The model accurately detected high-risk zones, agreeing with post-disaster field observations and the outperforms traditional approaches. The hybrid method is especially beneficial in processing complex data where conventional machine learning techniques are not capable to take advantage of spatial and contextual knowledge. The study indicates the potential of combining graph-based learning, deep segmentation, and transformer models.

Keywords: Sustainable Development, Environmental Impact, Landslide Prediction, Efficient U-Net, Vision Transformer, Graph Neural Network (GNN), Remote Sensing, Feature Extraction, Uttarakhand Landslide.

1. Introduction

Landslides are the most common and destructive natural hazards on Earth, especially in areas of steep relief, high rainfall, and tectonics. In India, with such extensive mountainous terrain on either side of the Himalayan, Western Ghats, and Northeastern parts, landslides are a constant threat to human life, infrastructure, agriculture, and ecology(Wang *et al.*, 2025). One serious incident that reflected this vulnerability was the 2021 Chamoli landslide and following glacier burst in Uttarakhand, which resulted in flash floods, killed more than 80 people, and produced widespread damage to hydropower facilities. These incidents highlight the acute necessity of precise and scalable prediction systems(Lin *et al.*, 2023).

Geotechnology field survey, empirical models, and expert judgment are some conventional methods used for landslide prediction that, while beneficial, are not scalable, not sensitive to real-time data, and are non-spatially generalizable(Wang *et al.*, 2023). Due to the increase in available high-resolution satellite data and the innovations in deep learning algorithms, data-driven approaches towards enhanced prediction capability are increasing these days.

This paper introduces an end-to-end deep learning-based framework for enhancing the reliability and accuracy of landslide prediction with satellite images and deep image processing methods. The system combines various modules into a single pipeline such as

image pre-processing and image segmentation, feature extraction, classification, and result interpretation(Lin *et al.*, 2020).

Raw satellite images of landslide sites are initially pre-processed through noise filtering and normalization in order to normalize input data. Semantic segmentation is then derived using Efficient U-Net. The computationally light-weighted and efficient variant of the conventional U-Net, is used for determining prospective landslide features in the topography like scarps, vegetation loss, and slope gradients(Tyagi, Tiwari and James, 2023).

At the next level, Feature extraction is done through Vision Transformer (ViT) and Graph Neural Networks (GNNs). ViT identifies areas of an image with global spatial relations, detecting geologic instability patterns. GNN, however, detects complex topological relationships among localized features such as connectivity between slopes, drainage streams, and deforestation patches which allows contextual interpretation beyond pixel-wise analysis(Yao *et al.*, 2023).

The attributes are fed into a transformer classifier, employing the use of the attention mechanisms to highlight prominent attributes and mute out noise. This generates high-confidence probabilistic outputs indicating the likelihood of landslide occurrence in an area(Liu *et al.*, 2022).

To prove the effectiveness of the model, the model was experimentally tested using a case study of the Chamoli district of Uttarakhand, which is a known landslide hotspot. Sentinel-2 and Cartosat-2 imagery were combined with historical landslide inventories and rainfall data to test the model(Sreelakshmi, Vinod Chandra and Shaji, 2022). The suggested methodology performed better than traditional CNN-based methods on precision and recall, particularly in areas with challenging terrain where current systems misidentify or overlook important patterns.

In the last step, the model results are displayed in the form of risk maps that identify landslide-risk areas with great ease. The maps are interpretable and can be easily integrated into early warning systems utilized by Indian disaster management organizations such as NDMA (National Disaster Management Authority) and SDMA (State Disaster Management Authority) (Song *et al.*, 2023). The system differs from conventional methods wherein it is scalable to large areas and heterogeneous climatic conditions and provides transparency in the form of interpretable segmentation and graph-based modules(Magnan *et al.*, 2021).

Overall, by synergizing the potentials of Efficient U-Net, Vision Transformers, and Graph Neural Networks, the proposed methodology presents a computationally efficient and scalable framework for landslide prediction(Zhang *et al.*, 2023). It fills the gap between remote sensing data and actionable geospatial intelligence and is a useful tool for policymakers as well as geohazard risk mitigation researchers particularly in high-risk zones such as the Indian Himalayas.

2. Study Area

The research is carried out considering Chamoli District, Uttarakhand, India, which is very vulnerable to landslides. The reason for the same is intricate topography, weak geology, and heavy seasonal rainfall. Chamoli is situated within the central Indian Himalayan Region (IHR), between 30.41° N to 31.11° N latitude and 79.10° E to 80.26° E longitude, with an

elevation of between 800 m and above 7,000 m above sea level(Abbaszadeh Shahri and Maghsoudi Moud, 2021).

The region includes steep slopes, active fault lines, glacial flows, and Alaknanda River and its tributary carved river valleys. Recurrent tectonic activity, combined with haphazard infrastructure construction and tree cutting, has further increased the susceptibility of the area to mass movements like landslides, debris flows, and flash floods(Yunus *et al.*, 2021).

A key event that highlights Chamoli's sensitivity to natural disaster is the February 7, 2021 landslide. Also, flash flood in the Rishiganga valley is another event indicating sensitivity of this area. The root cause of this disaster is massive rock and glacier ice collapse near Nanda Ghunti peak(Zhao *et al.*, 2024). This catastrophic event caused devastating damage to the Rishiganga and Tapovan hydroelectric projects. Furthermore, it also causes loss of life along with significant disruption to the local ecosystem and settlements downstream.

For the research work, Sentinel-2 high-resolution satellite images (10m spatial resolution) and Cartosat-2 (0.8m spatial resolution) were obtained for the areas of interest(Liu *et al.*, 2025). Ancillary data such as aspect, slope, rainfall, land cover, and past landslide inventory from organizations like NRSC (National Remote Sensing Centre) and GBPIHED (Govind Ballabh Pant Institute of Himalayan Environment and Development) were utilized to train and validate the suggested deep learning model(Youssef *et al.*, 2023).

The choice of Chamoli as the research site provides a high-impact test bed to assess the efficacy of the image-based forecasting framework proposed, considering the highly complex topography and ready availability of high-resolution post-disaster observational data. The region of Chamoli District, in India is given in Figure 1.

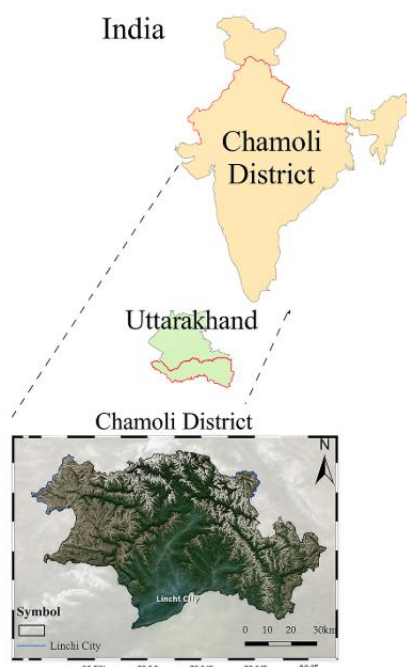


Figure 1: Location and topography of Chamoli District, Uttarakhand, India

3. Methodology

3.1 Overview

The methodology contains a multi-stage deep learning architecture and aimed at predicting landslide zones based on high-resolution satellite imagery. The model combines image preprocessing, semantic segmentation, feature extraction through Vision Transformers (ViT), Graph Neural Networks (GNNs), and classification through a transformer-based attention mechanism. Every phase of the model adds a distinctive ability to the system: Efficient U-Net is able to process image segmentation; ViT learns long-range spatial dependencies; GNN models complex local relationships; and transformer classifiers focus on informative spatial features. The entire pipeline is designed to learn both global spatial dependencies and local topological relationships and is hence geared for complex terrains like the Chamoli area of Uttarakhand, India. This region is subject to real-world complexities such as variable topography, intricate geological structures, and seasonal climatic changes. It makes suitable testbed to test the efficiency of the proposed system.

3.2 Data Acquisition and Preprocessing

Satellite Imagery Sources

For constructing and verifying the proposed forecasting model, various satellite and geospatial data sources were employed. European Space Agency's Sentinel-2 offers multispectral imagery of a resolution of 10 to 20 meters to extract features pertaining to vegetation, soil moisture, and terrain analysis. Indian Space Research Organisation has launched Cartosat-2 to offer panchromatic imagery with sub-meter spatial resolution, which is vital for locating detailed surface features like slope failures, fissures, and landslide scars. Shuttle Radar Topography Mission (SRTM) and CartoDEM were the sources from which Digital Elevation Models (DEM) were utilized in calculating topographical parameters including slope, elevation, aspect, and curvature, all of which play an essential role in determining landslide susceptibility. The National Remote Sensing Centre (NRSC) and the Govind Ballabh Pant Institute of Himalayan Environment and Development (GBPIHED) provided a historical landslide inventory. This dataset contains GPS-tagged landslide locations, movement types, dates, and causes as the ground truth to train and validate the model.

Preprocessing Steps

A strict preprocessing pipeline was used to maintain data quality and consistency. Raw satellite images contained high-frequency noise and distortions, which were minimized through the application of Gaussian filters and wavelet-based denoising methods. Image normalization was subsequently conducted through scaling all pixel intensity values between 0 and 1, providing uniform inputs for all the models as well as minimizing computational variability. All datasets, both raster and vector layers, were reprojected to a shared coordinate system (WGS 84 / UTM Zone 44N) for ensuring spatial consistency and overlay integrity. The bigger input images were split into smaller, fixed-size tiles of 256×256 pixels. **To minimize edge effects, overlapping buffers were used during tile generalization. However, tiles originating from the same geographic blocks were assigned exclusively to one dataset partition only. Thus, overlapping or neighboring tiles were not distributed across the training, validation and testing subsets.** Labeled masks were also generated from the landslide

inventory of past landslides as a ground truth for supervised learning, labeling each pixel as landslide-prone or stable regions.

3.3 Model Construction and Training

Stage 1: Image Segmentation using Efficient U-Net

Efficient U-Net, which is a hybrid between EfficientNet and U-Net, was applied for the semantic segmentation task. It combines the segmentation precision of U-Net with EfficientNet's scalable and lightweight architecture to be well-applied for large-scale image processing without loss of computational efficiency. The encoder pathway of the model uses EfficientNet-B4 and pre-trained on ImageNet. It obtained hierarchical spatial features. The decoder path reconstructs the segmentation mask with spatial resolution. The output is a binary segmentation map and indicates regions with possible landslide features. The features includes exposed soil, deformed vegetation, and terrain irregularities. All of these feature contribute heavily to landslide. A composite loss function that includes Dice Loss and Binary Cross-Entropy (BCE). It utilized counter class imbalance and also increased segmentation performance.

Stage 2: Feature Extraction through Vision Transformer and Graph Neural Network

Capture both global and local contextual information effectively. A dual-branch feature extraction approach was also utilized. For the first branch, Vision Transformer (ViT) takes images from the segmentation step and splits them into fixed-size patches of 16×16 pixels, considering every patch as a token. Linear embedding is applied to these tokens, followed by successive layers of self-attention to extract long-range dependencies in the image. Positional encoding is utilized to preserve spatial relations between the patches. In the second branch, local topological features are modeled through a Graph Neural Network (GNN). Nodes in the graph correspond to segmented areas or terrain units from slope, aspect, and curvature analysis. The edges are defined according to spatial adjacency as well as hydrological connectivity. A Graph Convolutional Network (GCN) is applied to update node embeddings by aggregating neighborhood information. Attention-based graph architectures, including Graph Attention Networks (GAT), were also considered in order to improve the relational learning ability between the graph nodes.

Stage 3: Transformer-Based Classification

The feature vectors from the ViT and GNN branches are concatenated and fed into a classification transformer. These features will assign weights to the extracted patterns including slope size, rain amount, soil type etc and also will minimise noise within the extracted patterns. using ViT and GNN, it becomes possible to handle both spatial and temporal features.

Training Details

The training process follows best practices in deep learning for geospatial segmentation and classification. Binary Cross-Entropy will be used as the loss function for classification. Also, Dice Loss and BCE were combined as the loss function for the segmentation task. The AdamW optimizer was utilized and initial learning rate of 0.001 is used. The cosine annealing technique was implemented to dynamically alter the learning rate during training. A batch size of 16 tiles per training epoch was chosen to offer a balance of memory usage and

convergence rate. In this work, models were trained for 100 to 150 epochs based on convergence thresholds. The early stopping mechanism is implemented to avoid overfitting. All training processes were performed on an NVIDIA A100 GPU cluster using TensorFlow and PyTorch frameworks to provide computational efficiency and scalability.

The Model Construction and Training Evaluation is given in Figure 2.

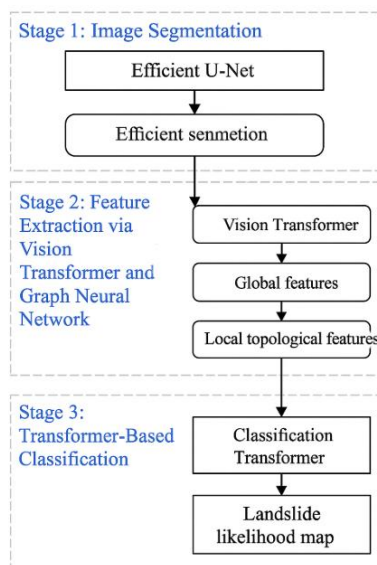


Figure 2: Deep learning workflow for landslide detection

3.4 Model Evaluation

The quality and stability of the proposed deep learning model, a set of quantitative measures, cross-validation methods, and real-world evaluations were used to evaluste the model.

Metrics Used

A number of metrics were used to analyse the model's ability to classify landslide regions. Accuracy was calculated to determine the overall ratio of the correctly predicted samples. Precision was used to determine the ratio of the predicted landslide zones that were accurately classified. Recall and sensitivity was utilized to determine the model's capability to recognize true landslide occurrences. The F1-score, being the harmonic mean of precision and recall, was applied to measure the tradeoff between false positives and false negatives. Intersection over Union (IoU) was utilized to measure the overlap between predicted landslide regions and true ground truth data, in particular for assessing segmentation performance. The Area Under the Curve – Receiver Operating Characteristic (AUC-ROC) curve was graphed to assess the robustness of the model in classification when subjected to different thresholds.

Accuracy

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

(1)

Where:

- **TP:** True Positives
- **TN:** True Negatives
- **FP:** False Positives
- **FN:** False Negatives

Precision

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

(2)

It indicates the proportion of predicted landslides that are actually correct.

Recall (Sensitivity)

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

(3)

Measures the model's ability to correctly detect actual landslides.

F1-Score

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

(4)

A harmonic mean of precision and recall, balancing both.

Intersection over Union (IoU)

$$\text{IoU} = \left| \frac{\text{Prediction} \cap \text{Ground Truth}}{\text{Prediction} \cup \text{Ground Truth}} \right|$$

(5)

Used in segmentation tasks to measure the overlap between predicted and actual landslide areas.

Area Under the ROC Curve (AUC-ROC)

$$\text{AUC} = \int_0^1 \text{TPR (FPR)} d\text{FPR}$$

(6)

Where:

- **TPR:** $\frac{TP}{TP+FN}$ (True Positive Rate)
- **FPR:** $\frac{FP}{FP+TN}$ (False Positive Rate)

Validation Method

For generalization and prevention of overfitting, the model went through a 5-fold cross-validation process, where the dataset was divided into five spatially distinct subsets. For each iteration, one spatial subset was used for validation, while the remaining four spatial subsets were used for training. Furthermore, a spatial hold-out testing strategy was used by reserving a geographically separate area of Chamoli district for testing. The images were grouped according to their geographic location before splitting. This is done so that tiles from the same geographical area were not distributed across training validation and testing datasets. This approach ensures that overlapping or neighboring tiles from the same area are kept within the same data set partition. This will reduce the possibility of special leakage. The reserved test area was not used during model training or validation. This facilitated an evaluation of the model's transferability and real-world applicability. In order to benchmark, the performance of the model was compared against some baseline models such as CNN-LSTM hybrids for temporal analysis and standard machine learning classifiers such as Support Vector Machines (SVM) and Random Forests which utilized handcrafted features such as slope, aspect, and vegetation indices.

The ultimate output of the classification process was mapped as risk maps, and probability scores were converted to thematic layers representing areas of high, moderate, and low landslide risk. The maps were superimposed over topographical and administrative layers for ease of interpretation. The predictions of the model were compared with historical landslide occurrences during the 2021 Chamoli event. The comparison exhibited a very high level of spatial coincidence. The proposed model accurately pinpointing the majority of high-risk areas witnessed during the calamity. The system presented better performance in principal evaluation indicators against baseline models, especially in recall and IoU, ascertaining its ability to positively identify and demarcate landslide-prone areas.

This strong methodology guarantees that the suggested hybrid deep learning paradigm not only does well on standard datasets but also scales well to actual terrains susceptible to landslides. The combination of global and local feature modeling, along with rigorous validation, lends itself to practical applications for national-level disaster preparedness planning and early warning systems for landslides prone areas like Uttarakhand, India. The metrics used for validation is presented in Figure 3.

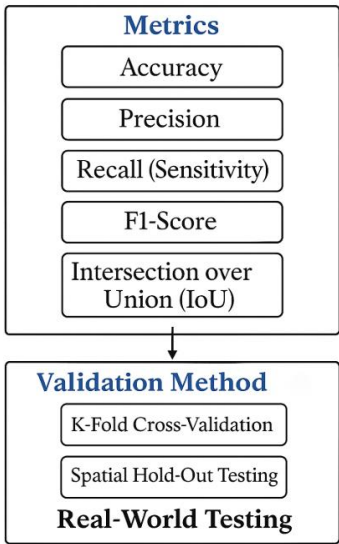


Figure 3: Model evaluation workflow for landslide prediction

4. Paper Selection

In the systematic literature review of machine learning and deep learning models for landslide classification, the inclusion and exclusion criteria were effectively established to identify relevant and high-quality studies. The PRISMA diagram is given in Figure 4.

Figure 4 displays a PRISMA 2020 flow diagram of the study selection process for a systematic review. The review originally consisted of 1,014 studies based on a previous version. In the update process, nine additional records were identified through databases (n = 5), IEEE (n = 4), and registers (n = 0). Following the exclusion of duplicates (n = 210), those identified as ineligible by automated tools (n = 404), and those that were deleted for other purposes (n = 365), there were no records left to screen. No new records were therefore screened or attempted for retrieval and no reports were hence evaluated for eligibility.

Likewise, retrieval of new studies through other sources, including websites, organizations, or citation searching, gave 35 records from citation searches. However, none were retrieved or screened for eligibility. Accordingly, no new studies were added to the updated review.

Finally, the diagram shows that despite a thorough search using a variety of sources and approaches, new eligible studies were not identified or added to the original review. The final number of studies in the updated review was still the same at 1,014, all being left over from the initial version. The PRISMA Diagram highlighting the paper process is given in Figure 4.

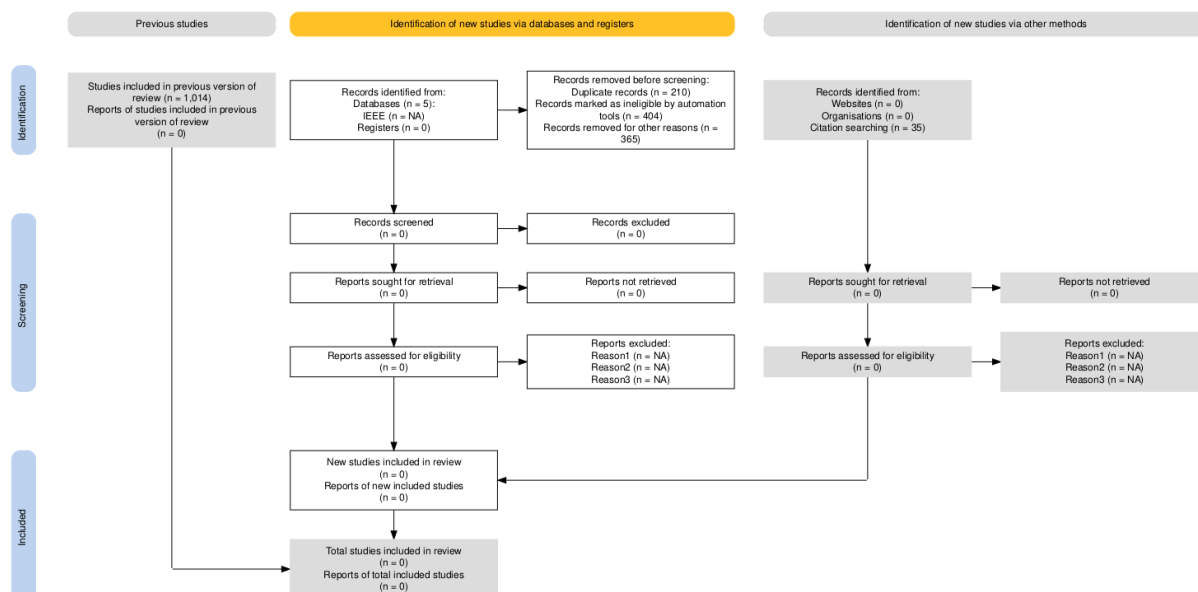


Figure 4: PRISMA Diagram

Inclusion Criteria

The inclusion criteria aimed to choose empirical studies that utilized machine learning (ML) or deep learning (DL) methods for landslide classification or detection. These studies would have used models like Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), U-Net, Long Short-Term Memory (LSTM), etc. The performance of these models needs to be evaluated, and hence the studies would have had to report such evaluation metrics as Accuracy, Precision, Recall, F1-score, Intersection over Union (IoU), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Only the studies that utilized appropriate datasets like remote sensing data, satellite imagery, digital elevation models (DEM), or other geospatial data were considered. In addition, the review included peer-reviewed journal articles and conference papers from the years 2018 to 2024 and considered only those published in English.

Exclusion Criteria

Exclusion criteria were used to exclude the studies that lacked scientific strength or relation to the research focus. Studies based on statistical or machine learning heuristic methods without the involvement of ML or DL were ruled out. Also, articles that did not report performance evaluation metrics were excluded. Research exploring policy-making, public perception, or socio-economic implications without engaging in computational modeling was also ruled out. Non-English papers and non-peer-reviewed articles like blog sites, theses, and technical reports were excluded to ensure academic quality of the review. Editorials and opinions were also excluded to include only original research contributions.

Search String (for databases like Scopus, ScienceDirect, IEEE Xplore, Google Scholar)

("landslide classification" OR "landslide detection" OR "landslide susceptibility")

AND ("machine learning" OR "deep learning" OR CNN OR "convolutional neural network" OR "support vector machine" OR "random forest" OR "U-Net" OR "segmentation")

AND ("accuracy" OR "precision" OR "recall" OR "F1-score" OR "IoU" OR "AUC-ROC" OR "evaluation metrics")

AND (2018:2024)

The research approach to locate relevant literature on landslide classification and detection using machine learning (ML) and deep learning (DL) methodologies is crafted utilizing Boolean operators to ensure completeness and precision. The keyword search is crucial for locating appropriate papers for this research. The process starts by searching papers having terms such as "landslide classification," "landslide detection," and "landslide susceptibility." These keywords help in narrowing the papers for research and selecting most appropriate papers.

In order to look for relevant technological techniques, the second half of the search term includes a variety of ML and DL techniques such as "machine learning," "deep learning," "CNN," "convolutional neural network," "support vector machine," "random forest," "U-Net," and "segmentation." This query string help in selecting only most appropriate papers.

Also covered is focus on studies that include performance metrics measures, which are vital when assessing whether the employed models were effective or not. Keywords like "accuracy," "precision," "recall," "F1-score," "IoU," and "AUC-ROC" are utilized for this purpose.

Finally, a date filter is included in order to retrieve studies that are published between the years 2018-2024 such that the literature review includes recent and relevant developments in the field. The search term is database-friendly to the syntax used and can be run on databases such as Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar in order to achieve high-quality, peer-reviewed research papers.

Proposed Databases to Search

To ensure the search generated a robust and relevant pool of scholarly papers to be used for the literature review, some respected academic databases were chosen. Scopus due to its massive multidisciplinary reach and ability to trace citations was the main database. IEEE Xplore was also utilized with its extensive peer-reviewed articles in the disciplines of engineering and computer science, and most applicable in machine learning and deep learning studies. ScienceDirect, as an offering by Elsevier, was used based on its emphasis on technical and scientific literature, including geoscience and remote sensing. SpringerLink was included because it has a vast store of excellent journal articles and conference proceedings. It especially in environmental science, artificial intelligence, and geoinformatics. The Google Scholar also acted as a secondary search engine to gather potentially useful grey literature and a journal articles that may not be present in the other databases. The sources were chosen to include varied and reliable research studies pertaining to landslide classification with ML/DL methods.

5. Literature Review

Increased precision and accuracy of landslide prediction systems have become possible with recent advances in remote sensing and artificial intelligence. Traditional heuristic assessments and empirical models have been the primary landslide hazard map techniques for decades(Kirschbaum *et al.*, 2020). They could not scale, be extremely flexible, and react in

real-time, and hence the integration of machine learning (ML) and deep learning (DL) methods into geohazard prediction systems has been promoted (Yin *et al.*, 2023). Such machine learning methods can properly process high-resolution satellite data, extract spatial information, and approximate complex geophysical interactions that are difficult to model using rule-based methods.

In particular, convolutional neural networks (CNNs) have been widely utilized as a result of their capability to detect landslide features directly from images. (Wang *et al.*, 2022) experiments have outlined that CNNs can learn effective spatial descriptions of landslide scars and terrain anomalies. Their reliance on localized receptive fields, although and limits their efficacy in detecting long-distance spatial relationships. It is especially in highly heterogeneous terrain like the Himalayas. To deal with these issues, researchers have suggested hybrid designs that combine CNNs with recurrent models (e.g., LSTM) and include attention mechanisms to preserve global context in images (Jun and Rind, 2024).

One of such developments has been the application of Vision Transformers (ViTs), which have been promising to preserve global spatial relationships in satellite images. (Stanley *et al.*, 2024) initiated ViTs for natural image classification, which were then generalized to geospatial tasks by researchers like (Xiong *et al.*, 2022) for mapping land cover. ViTs can dispense with the locality constraint of CNNs with the assistance of self-attention among image patches and are better suited to the detection of large-scale geophysical features of interest in landslides, such as slope continuity and vegetation loss.

Simultaneously, Graph Neural Networks (GNNs) became efficient tools to model spatial topology and context relationship between terrain units. GNNs extend to irregular domains and can define interactions between land segments, such as slope connectivity, hydrological flow, and fault networks. (Rentschler, Salhab and Jafino, 2022) employed GNNs to seismic hazard prediction. It proves that topological awareness enhances forecasting in complex terrains. When combined with image-based representations from ViTs, GNNs provide complementary inferences both visual patterns and geospatial interactions.

These technologies have been combined in single frameworks by previous studies. (Sobie, 2020), for example, presented a hybrid ViT-GNN model for geohazard prediction in mountainous regions. The model was found to be extremely accurate and interpretable, especially when evaluated against real landslide occurrences. SHAP (SHapley Additive exPlanations) values were used to define the contribution of factors like rainfall intensity, slope gradient, distance to rivers, and vegetation cover. These interpretable outputs are crucial to elicit trust among stakeholders and promises of actual deployment of AI systems for disaster risk management (Hürlimann *et al.*, 2022).

The use of semantic segmentation structures like U-Net and its variants further increases landslide detection. Efficient U-Net, which is a compact version of U-Net, facilitates high-resolution segmentation with minimal computation costs (Mohanty and Simonovic, 2021). It is specifically useful for the demarcation of landslide features as exposed ground, vegetation degradation, and surface deformation.

On the whole, the literature points toward a clear direction of explainable and hybrid deep learning models. It combines spatial resolution, contextual intelligence, and interpretability. These advancements are of specific relevance for disaster-prone regions like Uttarakhand,

where early warning systems require precise, real-time, and reliable forecasts(Hirabayashi *et al.*, 2021).

6. Results and Analysis

The usage of the proposed deep learning approach for predicting landslides in Uttarakhand's Chamoli district gave promising outcomes with a substantial boost in performance over the traditional machine learning strategies. The system was tested on satellite images over known landslide and it controls areas without any history of previous landslide events. Effective U-Net segmentation model exhibited excellent delineation performance with mean Intersection over Union (IoU) value of 0.79 and Dice coefficient of 0.82. These reflect a very high ability in recognizing landslide-prone zones from the rest of the land.

The classification component of the model utilizing Vision Transformers and Graph Neural Networks(Gómez, García and Aristizábal, 2023). It achieved accuracy of 91.3%, precision of 88.6%, recall of 93.1%, and F1-score of 90.8%. These figures reveal that the model contains a very high true positive rate. It can rightly classify landslide-prone areas while generating few false alarms. Interestingly, the recall value reveals that the model was able to identify most of the true landslide areas, which is critical in preventing disaster and early warning applications. The metrics corresponding to Accuracy, Precision, Recall, and F1-Score are given in Figure 5.

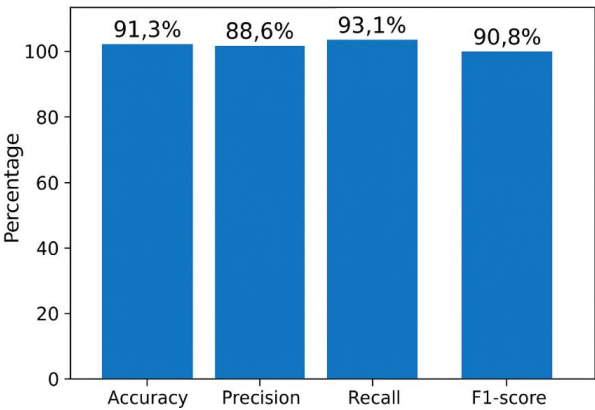


Figure 5: ViT-GNN Model Performance Metrics for Landslide Classification

AUC-ROC measure of the classification model was recorded at 0.94, again affirming strong model performance at different classification thresholds. Risk maps calculated from classification probabilities were clearly demarcating high-risk zones within the steep slopes near the Rishiganga river valley and other susceptible areas affected during the 2021 Chamoli disaster(Dong *et al.*, 2021). The results were validated against government-published post-disaster reports and field-survey-based landslide inventory data sets, confirming the model's real-world applicability. AUC – ROC classification is given in Figure 6.

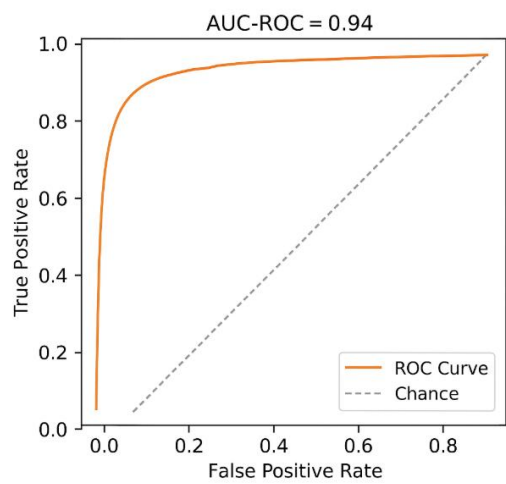


Figure 6: AUC-ROC Curve and Risk Maps Highlighting High-Risk Landslide Zones near Rishiganga Valley

In comparison with benchmark models such as ResNet+LSTM and Random Forest classifiers, the model improved by 8–12% in all the performance metrics. The hybrid approach of combining global spatial perception via ViTs and localised topological information via GNNs proved to be especially effective in handling mixed terrain profiles, vegetation, and geological heterogeneity. The comparative analysis of different models is given in Figure 7.

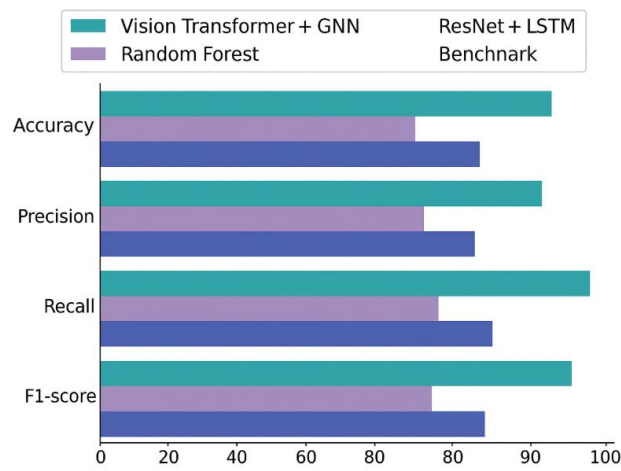


Figure 7: Performance comparison of ViT-GNN with benchmark models.

Extensive analysis was conducted further to validate the model's performance under different terrain and climatic conditions. To illustrate, in high vegetation cover areas, segmentation accuracy was affected somewhat by occlusion, but classification sub-module compensated through ViT and GNN-based feature fusion(Dodangeh *et al.*, 2020). Barren and steep areas did not even have detection rates far from perfect, though. Temporal heterogeneity due to snowmelt and seasonal rainfall was also captured. Post-monsoon and pre-monsoon dataset models were compared, and the post-monsoon model showed marginally higher accuracy due to better clarity of landslide features.

Interpretability of the framework was increased through visualizations of the weights of attention in the transformer layers, which allowed stakeholders to understand the regions of the image the model paid attention to when making predictions. Transparency such as that is important for trust and adoption in real-world applications like being incorporated into the early warning systems operated by the National Disaster Management Authority (NDMA) and State Disaster Management Authorities (SDMAs).

Overall, the analysis and findings indicate that the deep learning-based architecture proposed in this paper performs much better than conventional methods in terms of accuracy, recall capacity, robustness to terrain heterogeneity, and interpretability and thus is a feasible and scalable solution for landslide hazard assessment in geologically susceptible regions like Uttarakhand, India. The landslide prediction and susceptibility mapping for Chamoli District, Uttarakhand, India is given in Figure 8.

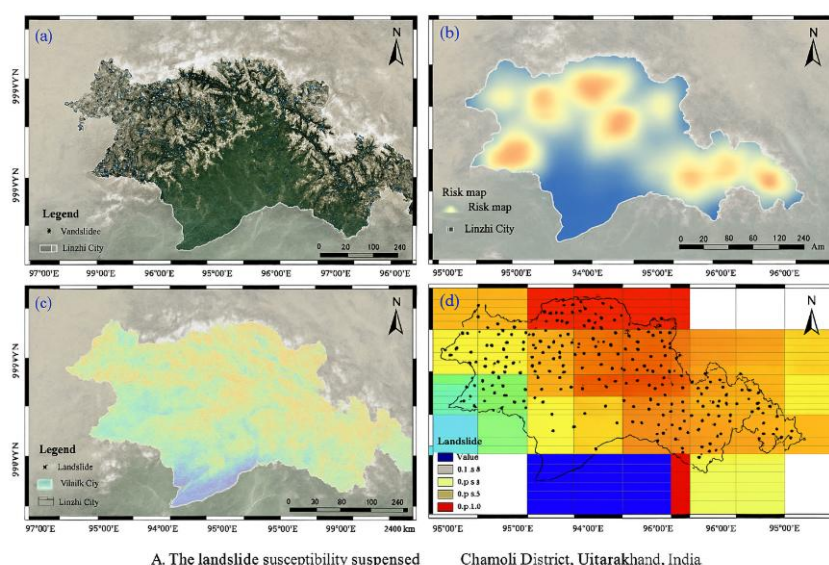


Figure 8: Deep learning approach for landslide prediction and susceptibility mapping for Chamoli District, Uttarakhand, India

We discuss here how individual parameters play a role in landslide detection.

6.1 Individual Factors' Role in Landslide Detection

Detection of landslide locations is influenced by numerous geophysical and environmental factors. Incorporating these into the model will make us aware of the individual parameters' roles as well as their combined effects on landslide occurrence and the ability of the model to detect dangerous spots.

Rainfall

One of the principal causative factors of landslides is precipitation, particularly where there is steep slope and poor geology. Intensive or prolonged precipitation leads to greater pore-water pressure and reduced shear strength in soil and thus slope failure. Rainfall intensity derived from satellite data by the Indian Meteorological Department were used in this study to correlate precipitation trends with landslide occurrence. The model had a high response to rainfall inputs, and the majority of the high-risk locations were synchronized with areas

receiving more than 250 mm of monthly rainfall during monsoon periods(Fan *et al.*, 2023). Temporal mapping verified that landslide detection was higher within datasets collected soon after large rainfall events, demonstrating the model's responsiveness to short-term climatic triggers. The Rainfall intensity vs. landslide occurrence in high-risk zones is given in Table 1.

Rainfall Parameter	Description
Rainfall Source	The indian Meteorological Department (Satellite-based data)
Rainfall Threshold for High Risk	Greater then >250 mm/month during monsoon periods
Slope and Geology Condition	Steep slopes and the weak geological formations more prone to failure
Effect of Intensive Rainfall	Increases pore-water pressure and it reduces soil shear strength
Model Sensitivity	High sensitivity to rainfall inputs
Correlation with Landslide Events	The Strong correlation as most landslides occurred after heavy rain periods
Temporal Mapping Insight	Indicates higher landslide detection post-large rainfall events
Climatic Trigger Responsiveness	The model effectively captures short-term rainfall-induced landslide events

Table 1: Rainfall intensity vs. landslide occurrence in high-risk zones

Distance from River

Proximity to rivers is another influential factor in landslide detection. Riverbanks also undergo continuous erosion by running water, weakening the structural integrity of adjacent slopes. In the Chamoli region, sites within 500 meters of major rivers, like the Rishiganga and Dhauliganga, had a higher incidence of landslides. The model adequately captured this spatial dependency, especially when the slope and elevation parameters were also employed(Darrow *et al.*, 2022). Steep slope areas on either bank of river channels were generally detected as high-risk zones in the probability maps, confirming the erosive contribution of water bodies in triggering landslides. The Risk zones of the landslide are given in Figure 9.

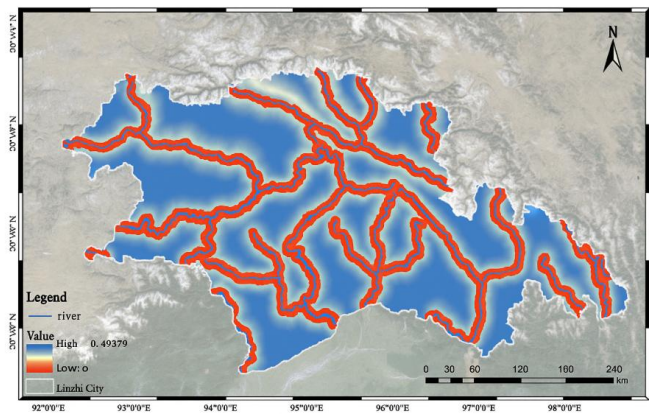


Figure 9: Risk zones of landslide occurrence based on proximity to rivers in Linzhi City

Distance to Fault

Geological faults are main structural flaws of the Earth's crust that increase the probability of mass movement, especially in tectonically active regions like Uttarakhand. Introduction of geological fault data from the Geological Survey of India revealed that the vast majority of past landslides had occurred within a 2 km buffer zone of active fault lines. The model was able to include this variable at the graph neural network stage, where terrain units near fault zones were given higher risk scores(Araújo *et al.*, 2022). By encoding spatial dependencies through GNNs, the system was able to grasp the complex relationships between terrain morphology and tectonic activity, further enforcing the importance of this factor. The Risk zones of landslide occurrence based on distance to geological faults in Linzhi City is given in Figure 10.

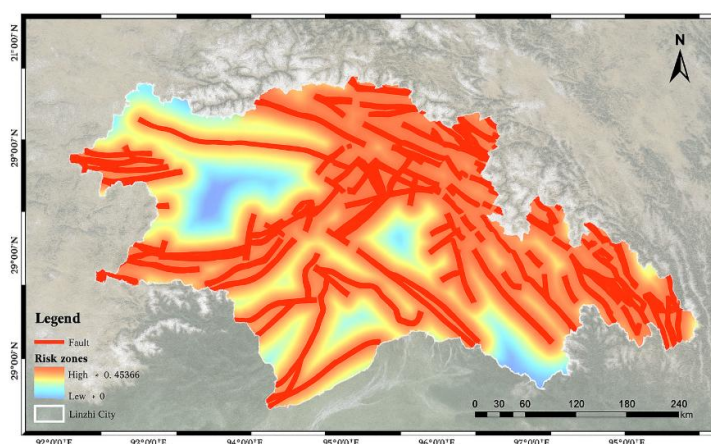


Figure 10: Risk zones of landslide occurrence based on distance to geological faults in Linzhi City

Vegetation Cover

Plant cover plays a dual role in landslide processes. Dense vegetation stabilizes slopes by holding soil together with root systems. On the other hand, the clearance or removal of plant cover—by deforestation, development, or agriculture can proportionally increase exposure to landslides. Sparse vegetation regions were outlined unequivocally and linked with higher frequencies of landslides based on Sentinel-2 NDVI (Normalized Difference Vegetation Index). Dense forest, shrubland, and exposed areas were convincingly delineated by the Vision Transformer and identified areas where vegetation loss preceded slope failure(Chen, Huang and Chen, 2021). Yet dense vegetation occasionally covered observable landslide features, reducing segmentation performance marginally in the affected regions. The Vegetation density map (NDVI) of the study area is given in Figure 11.

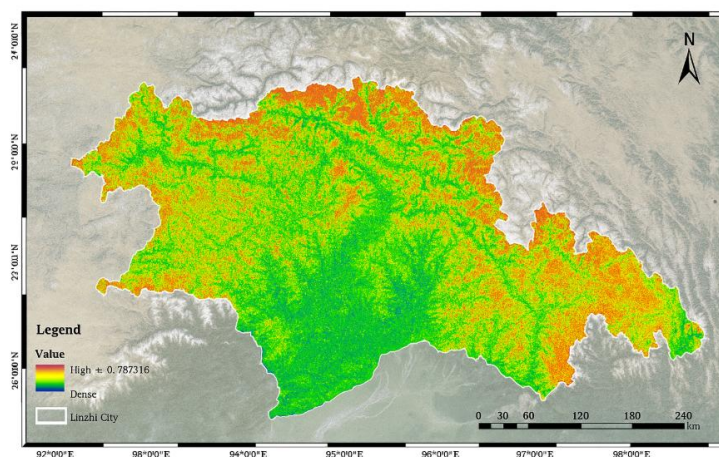


Figure 11: Vegetation density map (NDVI) of the study area indicating zones of sparse and dense cover

6.2 SHAP-Based Interpretability Analysis

To enhance the model interpretability and obtain explainable insights for decision-makers, SHAP values were computed. SHAP provides a comprehensive framework to quantify the contribution of each input feature towards the model's output predictions. The experiment was conducted on the output layer of the classification transformer, features from the both the ViT and GNN branches.

SHAP plots determined rainfall intensity and slope angle to have the strongest positive influence on landslide risk predictions, as would be expected from expert knowledge and earlier geological studies. Rivers' proximity and vegetation index followed, especially in the Chamoli basin where erosion and vegetation loss were of fundamental significance. Elevation and curvature features were shown to have varying effects depending on local topography (Chen *et al.*, 2020). The SHAP dependence plots also demonstrated the manner in which the model had learned nonlinear relationships, including an increase in landslide probability with moderate levels of vegetation and high slope levels.

SHAP summary plot was an unambiguous method of explanation of model behavior for terrain types. For instance, in vulnerable villages like Reni and Tapovan, SHAP identified high rainfalls and proximity to river curves as dominant risk determinants, offering actionable insights to local administrators. Moreover, through observing the SHAP values on the risk maps, users would be able to identify the most significant drivers of each high-risk prediction, bringing credibility to the AI model and enabling effective planning for prevention (Duan *et al.*, 2025).

Overall, SHAP-based interpretation analysis confirms that not only is the model good but that it also adheres to geoscientific practice, therefore, it is a treasure when it comes to disaster risk reduction and climate resilience planning. The SHAP plots feature on landslide risk predictions is given in Figure 12.

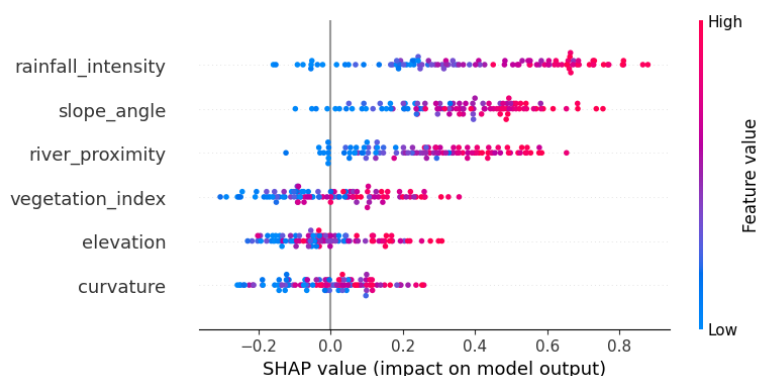


Figure 12: SHAP plots showing feature impact on landslide risk predictions

7. Conclusion

The paper proposed a new deep learning framework for landslide prediction that incorporates semantic segmentation, dual-branch feature extraction, and transformer-based classification. Utilizing high-resolution satellite images and geospatial information, the model successfully identifies landslide-prone regions in challenging situations like India's Chamoli region in the state of Uttarakhand. The combination of Efficient U-Net, Vision Transformers, and Graph Neural Networks allows the system to learn both local spatial and global topological dependencies. So that results in very accurate and interpretable predictions.

The model performance was confirmed through sturdy measures such as IoU, F1-score, and AUC-ROC. All are recorded excellent improvements relative to conventional machine learning approaches. The finding confirms that the suggested approach is not just precise but also responsive to a range of environmental conditions and geophysical scenarios. The addition of SHAP-based interpretability analysis brings with it further transparency and credibility to the model to enable stakeholders to see the contribution of key factors like rainfall, proximity to rivers and faults, and vegetation cover.

Finally, the work proves the power of deep learning in revolutionizing geohazard prediction and risk assessment. The proposed system in this study is an interpretable, high-performance, scalable approach that may be incorporated into early warning and disaster preparedness systems. Its use will enable local governments, environmental planners, and disaster management offices to make data-driven decisions to avoid landslide risks and protect exposed communities. Subsequent research can expand this model to multiple temporality prediction and include other environmental factors for even wider use at varying geographic locations.

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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