Enhancing Landslide Prediction Accuracy Through Deep Learning: A Focus on CNN and U-Net Models

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Abstract — Because landslides are major hazards with substantial environmental and social ramifications, advanced detection techniques are required to support disaster mitigation efforts. This study offers a dependable technique for landslip diagnosis using deep learning-based image segmentation models, particularly UNet and Fully Convolutional Networks (FCN), optimised for pixel-wise classification. By using landslide-correlated geospatial data such as RGB imagery, slope gradient, Normalised Difference Vegetation Index (NDVI), and Digital Elevation Model (DEM), the algorithms aim to increase detection accuracy and responsiveness. While the symmetric encoder-decoder structure of the UNet architecture, strengthened by skip connections, collects multi-scale contextual information, the fully convolutional architecture of the FCN allows for efficient processing of many image dimensions. Both models employ a binary cross-entropy loss function and sigmoid activation to produce precise pixel-level predictions. Preliminary results show that including these linked factors improves segmentation performance, which makes this approach a valuable tool for proactive landslip monitoring and early warning systems. The potential of deep learning architectures in environmental hazard management is highlighted in this paper, which contributes to the broader topic of disaster risk reduction.

Keywords — Landslide Detection, Image Segmentation, Deep Learning, UNet, Fully Convolutional, Networks (FCN), NDVI, DEM, Geospatial Features, Disaster Mitigation, Environmental Hazard Monitoring

I. INTRODUCTION

One of the most devastating natural disasters, landslides frequently cause extensive damage to human lives, infrastructure, and the environment. Tectonics, geomorphology, and climatic change all contribute to landslides, which ultimately result in a critical slope evolution [1,2]. A complicated interaction of natural elements, such as heavy rains, earthquakes, volcanic eruptions, and human-caused activities like deforestation and inappropriate land usage, usually sets off these disasters. Landslip analysis has been greatly impacted by the latest developments in remote sensing technologies [3,4]. Landslides are predicted to occur more frequently and with greater intensity as climate change leads to more unpredictable weather patterns, particularly in hilly and mountainous areas. The creation of precise, scalable, and effective techniques for landslide detection and monitoring has taken precedence in the field of disaster risk management because to the serious socioeconomic and environmental effects of landslides.

In addition to being time-consuming and labour-intensive, traditional landslip detection and monitoring techniques including field surveys, geological analysis, and manual satellite image interpretation are also constrained in their applicability. The requirements of large-scale spatial coverage and real-time monitoring, which are essential for early warning systems and quick response, are frequently not reached by these techniques. Deep learning is an essential tool in contemporary landslip risk assessment and mitigation tactics, as comparative studies have repeatedly shown its superiority over conventional models [5,6,7]. The discipline has evolved thanks to remote sensing technologies, especially satellite and aerial imaging, however manual data interpretation is ineffective for thorough monitoring initiatives. In order to overcome these constraints, automated methods are being investigated.

For automated landslip detection and segmentation, the latest developments in deep learning, particularly convolutional neural networks (CNNs), hold great potential. With the creation of designs like UNet and Fully Convolutional Networks (FCNs), CNNs have proven to perform exceptionally well in pixel-wise segmentation and image recognition tasks. Bivariate analyses have been used in several research to measure the geographical correlations between landslides and certain factors that affect their dispersion [8,9,10,11]. These designs are ideal for environmental monitoring applications since they have demonstrated efficacy in identifying intricate patterns and minute variations in geospatial data. A useful tool for early identification and risk assessment, the pixel-wise segmentation approach makes it possible to precisely locate landslide-prone areas within big photos.

In this work, we use a huge dataset of geospatial variables that are connected with landslides to improve landslide identification by utilising the UNet and FCN architectures for picture segmentation. In particular, we use RGB pictures, slope gradient, the Normalised Difference Vegetation Index (NDVI), and the Digital Elevation Model (DEM) as input features for model training. Given that slopes with dense vegetation tend to be more stable, NDVI data offers vital information on vegetation cover. Elevation and steepness, two topographical features that significantly affect landslip vulnerability, can be shown using DEM and slope gradient data. RGB photography, on the other hand, records textural clues and discernible colour variations that can point to regions with a higher risk of landslides. By integrating these diverse features, the proposed approach aims to capture a more holistic representation of the landscape, thereby improving detection accuracy.

A symmetric encoder-decoder structure with skip links is employed by the UNet model utilised in this investigation. Its architecture improves its capacity to capture both fine-grained details and more general contextual information by preserving and combining features at various resolutions. In segmentation tasks, the skip links between encoder and decoder paths are especially useful since they allow the model to preserve spatial information that would otherwise be lost in downsampling layers. In contrast, the FCN model does not require fully connected layers because it is made to handle images of different sizes. Instead, it only uses convolutional layers, which enable the model to be applied to various image resolutions and scales and offer dense, pixel-level predictions.

A binary cross-entropy loss function is used to optimise both models, making them appropriate for binary classification tasks in which each pixel is classified as either landslide or non-landslide. Each pixel's probability value, which indicates its possibility of becoming a part of a landslip, is generated by a sigmoid activation function in the last layer. The models' applicability in real-world landslip monitoring systems is improved by this pixel-wise classification technique, which also improves the models' capacity to precisely define landslip boundaries.

By showcasing the potential of deep learning to enhance landslip detection and early warning systems, this study advances the subject of environmental hazard management. This study lays the groundwork for future developments in landslide monitoring technology by automating the identification of landslide-prone locations and improving prediction accuracy by integrating correlated geospatial information. Our results provide credence to the use of CNN-based image segmentation models, particularly UNet and FCN, as useful instruments for disaster risk reduction, which may help stakeholders allocate resources and make proactive decisions for areas vulnerable to landslides.

II. LITERATURE SURVEY

The paper [12] discusses landslide detection and area extraction from remote sensing images using deep learning techniques, focusing on architectures like UNet and FCN, and proposing enhanced models to improve performance. For instance, the study introduces an advanced dual-channel model with EfficientNetB7 and spatial attention mechanisms (SAMs) for feature extraction. This model is enhanced further by incorporating Transformers and Variational Autoencoders (VAE) to refine feature extraction and classification accuracy. It demonstrates impressive results, achieving accuracy rates of 98.92% and 94.70% on two different landslide datasets. Additionally, for area extraction, the paper enhances the UNet++ architecture by using Dilated Convolutions and integrating Transformers and Convolutional Block Attention Modules (CBAM). It applies multi-task learning, including segmentation and edge detection, and refines segmentation boundaries using Conditional Random Fields (CRFs). These modifications improve the model's performance in detecting landslide areas with higher metrics such as IoU, Dice coefficient, and overall accuracy.In essence, this work highlights the effectiveness of integrating multiple deep learning techniques and advanced architectures to improve the detection and extraction of landslide regions, thereby enhancing disaster management capabilities.

NDVI, DEM, slope scores, and RGB images—all of which have a strong correlation with landslide-prone areas—were among the multi-modal data used in the research [13] to train image segmentation algorithms for a landslide detection framework. To improve pixel-wise segmentation accuracy, it uses UNet and Fully Convolutional Network (FCN) designs with convolutional layers and skip connections. To enhance prediction capabilities, the loss function is binary cross-entropy, which aims for accurate landslip region delineation. By offering early detection techniques, which are crucial for disaster-prone locations, the suggested model seeks to mitigate landslip disasters. By focussing on model accuracy in a variety of terrain features, the research advances landslip detection using deep learning and satellite photography.

In the Garhwal Himalayas of Uttarakhand, India, landslip susceptibility is examined in this study [14], which highlights the intricate interactions between topographical, geological, and hydrological elements that affect landslip occurrences. Significant landslip threats are caused by the region's steep slopes, strong seismic activity, and the existence of thrusts and fault systems like the Main Central Thrust (MCT). The study assesses the relationship between landslip susceptibility and 20 conditioning factors, such as altitude, slope, curvature, distance from fault lines, and rainfall, using the Information Gain Ratio (InGR) and multi-collinearity analysis. While hydrological elements like drainage density and rainfall play crucial roles in raising the chance of landslides by improving soil erosion and slope instability, the research emphasises the significance of geological factors like rock types and fault structures in causing landslides. The locations of landslides and the risk of various regions were determined using remote sensing data from sources including ASTER DEM and Landsat images. For efficient landslip risk management and disaster prevention, the findings highlight the necessity of incorporating geological, topographical, and hydrological aspects into predictive models.

Landslide displacement predictions using deep learning (DL) models is an essential component of early warning systems designed to minimise casualties and financial damages. Seven DL models are compared and evaluated in four different geological settings and geographical locations: Multi-layer Perception (MLP), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), 1D Convolutional Neural Network (1D CNN), 2xLSTM, Bidirectional LSTM (bi-LSTM), and Conv-LSTM. Rainfall, changes in groundwater levels, and man-made reservoirs are some of the variables that affect these landslides. According to the study [15], the Conv-LSTM model is particularly good at forecasting seasonal landslides, like the Baishuihe landslide, while the MLP, GRU, and LSTM models do well at predicting landslide displacement in a variety of circumstances. Furthermore, LSTM and GRU are better suited for modelling lesser displacement peaks, whereas MLP is more accurate at forecasting peak displacements. The research also highlights the importance of selecting appropriate DL models based on specific landslide characteristics to enhance the reliability and effectiveness of landslide early warning systems (LEWS).

The paper [16] explores a novel approach for classifying urban functional zones by combining social sensing data, like location-based service records, with computer vision analysis of high-resolution satellite images. Using Guangzhou, China, as a case study, the authors employed Convolutional Neural Networks (CNNs) to process visual data alongside social data, enhancing the accuracy of urban zone classification. This integrated methodology allows for better identification of functional zones (e.g., residential, commercial, industrial) than traditional, single-source methods. The study demonstrates that this approach can significantly aid urban planning and sustainable development by providing detailed, real-time insights into land use patterns and human activity distribution across complex urban landscapes.

III. PROPOSED WORK

3.1 Overview

A deep learning-based framework for automated landslip detection utilising sophisticated picture segmentation techniques is presented in the proposed work. Pixel-level categorisation for landslide-prone areas is accomplished by the framework through the use of convolutional neural network (CNN) architectures, particularly UNet and Fully Convolutional Networks (FCN). By utilising several associated geographical indicators, such as the Normalised Difference Vegetation Index (NDVI), Digital Elevation Model (DEM), slope gradients, and RGB pictures, the main objective is to increase the accuracy of landslip identification. With their ability to capture topography, vegetation health, and other visual cues related to landslip risk, these characteristics provide a thorough picture of landscapes.

Data preparation, model training using optimal segmentation structures, and performance evaluation are some of the framework's essential phases. Both local and global contextual information that is essential for in-depth segmentation is captured by UNet thanks to its encoder-decoder structure and skip connections. The framework's scalability and adaptability across a variety of datasets are improved by FCN's fully convolutional design, which makes it possible to handle images with different dimensions efficiently.

Binary cross-entropy is used as the loss function during training, and data augmentation is used to increase the robustness of the model. Model accuracy is evaluated using performance metrics including Intersection over Union (IoU) and F1-score, which guarantee efficient landslip identification that aids in early warning systems and disaster mitigation. This multi-feature, multi-model method offers enhanced accuracy and scalability for real-world applications, marking a substantial breakthrough in automated landslip monitoring.

3.2 Proposed Work Architecture

The architecture proposed for landslide detection leverages advanced image segmentation models to process various geospatial and spectral features, aiming to identify landslide-prone areas accurately. These features include RGB channels, NDVI (Normalized Difference Vegetation Index), slope, and elevation data. The data, sourced from image and mask files in HDF5 format, undergoes preprocessing steps to standardize and enhance interpretability across features. Specifically, RGB channels are normalized by their respective maximum values to ensure consistent color representation, while slope and elevation values are scaled to reflect meaningful gradients. NDVI, calculated from near-infrared and red spectral bands, plays a critical role as it represents vegetation density, a factor strongly correlated with landslide susceptibility. This multi-feature dataset structure forms a foundation for training robust image segmentation models.

The design uses the Fully Convolutional Network (FCN) and UNet deep learning models for picture segmentation. For precisely defining landslip zones in intricate terrain, both models are made especially for pixel-wise segmentation tasks. By combining fine and global context information, the UNet model—which is renowned for its symmetric encoder-decoder structure—uses skip connections to capture spatial hierarchies at various resolutions. This feature makes it ideal for accurately identifying landslip boundaries. By removing fully connected layers, the FCN architecture, on the other hand, is able to process images with varying sizes while maintaining high resolution across various spatial aspects. When handling landscape data, where images may differ in size and detail, the FCN's fully convolutional architecture is beneficial.

The binary cross-entropy loss function is used to optimise the UNet and FCN models for binary classification during training. This option reduces the discrepancy between the true and predicted class probabilities for every pixel, making it especially useful for pixel-wise classification issues. In their last layers, the models employ a sigmoid activation function to generate pixel-wise probabilities that show the probability that a pixel is located in a region damaged by landslides. The models effectively distinguish between landslide and non-landslide regions by training on a binary ground truth mask that represents the occurrence of landslides. The models can produce accurate segmentation outputs because to this probabilistic method, which also improves landslip detection accuracy.

All things considered, the suggested architecture, as seen in Fig. 1, integrates vegetation, topographic, and spectral data using a customised deep learning technique that captures the complex character of landslide-prone regions. This architecture improves the capacity to precisely predict landslides and provides insightful information for disaster risk management and mitigation by combining a variety of data elements with specialised segmentation models. Such an approach shows the promise of cutting-edge AI techniques in environmental monitoring and catastrophe prevention by not only identifying areas of urgent concern but also supporting long-term planning efforts in landslide-vulnerable regions.

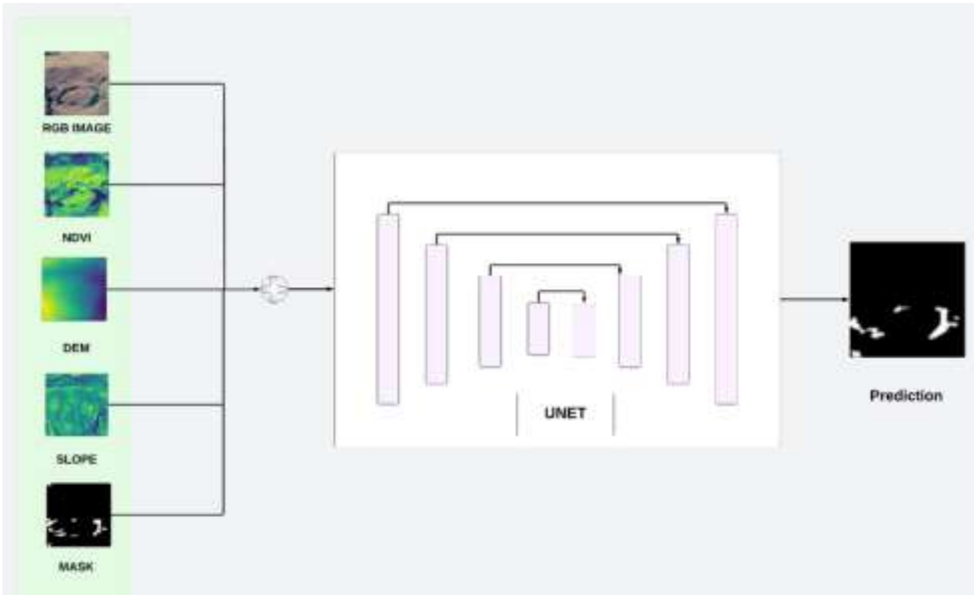

Fig 1. Architecture Diagram

3.3 Dataset Exploration

Numerous features, such as RGB channels, NDVI, slope, and elevation data, make up the landslip detection dataset. Each feature contributes unique spatial and spectral information that is relevant to landslip identification. Six channels, each of which represents a different component of a picture, have been preprocessed and arranged into a multi-dimensional array format. While NDVI provides information on vegetation density, a crucial component in landslip susceptibility, RGB channels offer a visual foundation for terrain research. A topographic dimension is added by slope and elevation features, which aid in locating regions with steep gradients and altitudes that are frequently more vulnerable to landslides.

RGB pictures, NDVI, slope, elevation, and binary masks that indicate areas impacted by landslides are all used to visualise the dataset samples. With elevation identifying high-risk topographies, slope showing gradient strengths, and NDVI highlighting vegetative cover, this exploratory analysis clearly shows how each factor helps identify possible landslip zones. The visual examination makes sure that the data inputs match the goals of dividing up landslide-prone areas by showing these features side by side.

A stratified random split is used to separate the dataset into training, validation, and test subsets for model building. This is essential for the binary classification problem because it guarantees that each subgroup has a representative distribution of landslide and non-landslide pixels. To keep a balanced dataset for efficient training and evaluation, a 70-15-15 split ratio is used. This section offers sufficient validation and test samples to track and evaluate model performance while bolstering the deep learning models' capacity to generalise effectively on fresh data.

Through this exploration and preparation, the dataset is optimized for training segmentation models to predict landslide probabilities with high accuracy. The structured and feature-rich nature of the dataset, combined with strategic visualization and split strategies, offers a robust foundation for training deep learning models on landslide detection tasks.

3.4 Modules of the Proposed Work

From data preparation to model validation, each module in the proposed work plays a unique function in the landslip detection process. The main sections are set up to ensure a thorough process by streamlining data handling, model training, performance evaluation, and result visualisation.

3.4.1 Data Preprocessing Module

The landslip dataset, which contains characteristics like RGB channels, NDVI, slope, and elevation, must be loaded and prepared by this module. In order to calculate the NDVI, which is essential for landslip risk assessment, preprocessing stages include normalising the RGB channels, scaling slope and elevation values, and representing vegetation cover using red and near-infrared bands. The interpretability and performance of the deep learning models are then improved by organising these features into arrays that are appropriate for training the models.

3.4.2 Model Training Module

Two primary models, UNet and Fully Convolutional Network (FCN), are employed in this module to tackle the image segmentation task for landslide detection. Each model has unique attributes optimized for pixel-wise classification.

a. **UNet Model**: UNet is a popular architecture for segmentation tasks, especially in medical and environmental image analysis. It features a symmetric encoder-decoder structure that captures spatial features at multiple scales. In the encoder, UNet progressively downsamples the input image, extracting high-level spatial features, while the decoder upsamples these features to the original image dimensions. The use of skip connections between corresponding encoder and decoder layers helps preserve detailed spatial information by merging coarse and fine features, leading to improved segmentation accuracy. In this project, UNet uses a sigmoid activation function in the output layer to predict pixel-wise probabilities for landslide presence. The encoder consists of repeated convolution layers followed by max-pooling operations. Each layer applies a convolutional operation and uses ReLU activation numerically it can be expressed as shown in equation (1).

$$y = ReLU(W * x + b) \tag{1}$$

The decoder consists of upsampling operations (like transposed convolutions) followed by additional convolutions. The upsampled feature maps are concatenated with corresponding feature maps from the encoder path (through skip connections) as shown in equation (2).

$$youtput = ReLU(W * (yupsampled \oplus xskip) + b) \tag{2}$$

The final layer is typically a 1x1 convolution that reduces the number of output channels to the desired number of classes in the segmentation task.

$$yfinal = Soft\max(Wfinal * youtput + bfinal) \tag{3}$$

b. **Fully Convolutional Network (FCN)**: Unlike traditional models with fully connected layers, the FCN is composed entirely of convolutional layers, making it capable of handling images of variable sizes. FCN performs pixel-wise classification by employing convolutional, pooling, and upsampling layers to provide dense pixel-level predictions. This design allows FCN to retain spatial context while performing image segmentation, making it suitable for environmental tasks that require identifying precise boundaries. In this study, FCN also uses a sigmoid activation in the final layer for binary classification, with binary cross-entropy loss guiding the model to predict landslide and non-landslide pixels. Mathematically it can be represented as :-

$$Yfinal = Soft\max(Wfinal * Uskip + bfinal) \qquad (4)$$

The training process for both models uses the binary cross-entropy loss function to optimize pixel-wise classification, with accuracy, F1 score, precision, and recall tracked as key performance metrics across epochs. These metrics help monitor model improvements and ensure that each model can effectively distinguish between landslide-affected and non-affected areas.

3.4.3 Evaluation and Performance Metrics Module

This module computes metrics including accuracy, F1 score, precision, and recall in order to assess the UNet and FCN models on the test dataset. The assessment gives information about the segmentation accuracy of both models and guarantees that they generalise well to new data. A clear image of which model might perform better in landslip segmentation tasks is provided by the analysis of each statistic, which evaluates the model's advantages and disadvantages.

3.4.4 Result Visualization Module

This module displays important metrics, including loss, accuracy, precision, recall, and F1 score, over epochs for both training and validation datasets in order to provide light on model behaviour throughout training. Understanding model convergence, seeing any overfitting or underfitting, and making sure each model is operating at peak efficiency for landslip detection are all made easier by the graphical representation. By improving the models, these visualisations aid in improving detection skills.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, we developed and evaluated a model for landslide detection using a dataset processed through normalization, feature extraction, and mask application to represent landslide-prone areas. The model was trained and evaluated using various performance metrics, specifically accuracy, precision, recall, and loss, to provide a comprehensive understanding of its detection capabilities.

1. **Accuracy**: Accuracy measures the proportion of correctly identified landslide and non-landslide areas out of all predictions. This metric is essential in assessing the general effectiveness of the model across all classes. Higher accuracy values indicate a reliable model that can distinguish between landslide-prone and stable regions effectively.
2. **Precision**: Precision quantifies the accuracy of positive predictions by determining the proportion of correctly identified landslide areas out of all predicted landslide regions. This is crucial in minimizing false positives, where non-landslide areas are incorrectly classified as landslides. A high precision score indicates that the model is selective in its positive predictions, reducing unnecessary alarms in non-landslide areas.
3. **Recall**: Recall, or sensitivity, measures the model’s ability to correctly identify all actual landslide areas within the dataset. This metric is important in landslide detection, as missing a landslide area (false negative)

could lead to oversight of potentially hazardous regions. High recall values indicate that the model is effective at capturing the majority of landslide-prone areas.

4. **Loss**: The loss function evaluates the divergence between the model's predictions and the actual labels within the dataset. Lower loss values represent a model that closely aligns with the ground truth, indicating better overall fit and stability of the model during training.

The results demonstrate that the model achieved high accuracy and recall, indicating its effectiveness in identifying landslide areas across diverse terrains. However, slight trade-offs between precision and recall may exist, suggesting that while the model is comprehensive in its coverage, there could be marginal instances of false positives. This outcome is typical in landslide detection models, where safety considerations prioritize recall to ensure hazardous zones are not overlooked. The test and validation evaluation has been shown in tabular form in Table I and Table II .

TABLE I. VALIDATION DATA EVALUATION

Model	Precision	Recall	F1 Score
UNet	0.77	0.68	0.72
FCN	0.77	0.64	0.70

TABLE 2. TEST DATA EVALUATION

Model	Precision	Recall	F1 Score
UNet	0.78	0.68	0.72
FCN	0.73	0.64	0.68

The model's loss metric further corroborated its robustness, as low loss values during both training and testing phases suggest that the model generalizes well to new, unseen data. Future improvements could focus on optimizing precision to enhance the model's selectivity in landslide-prone regions, potentially by incorporating additional features or refining the preprocessing pipeline.

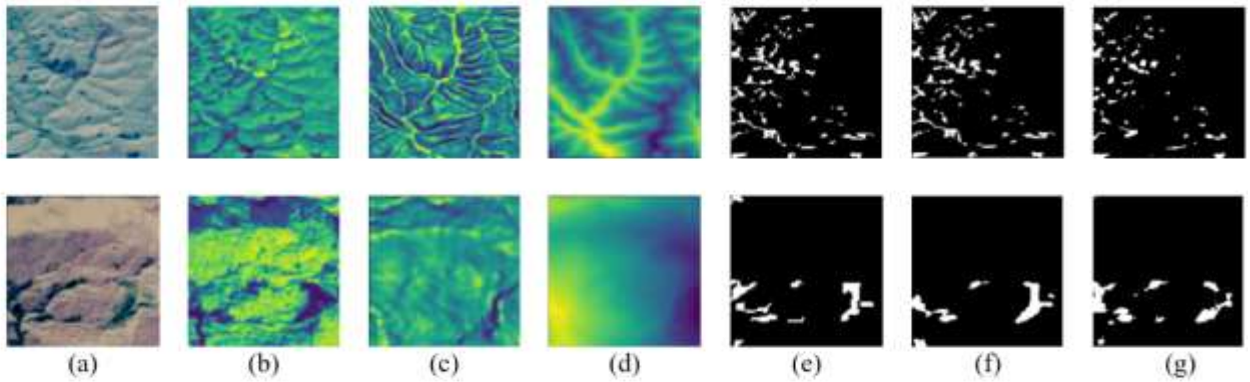

Fig. 2 Prediction stages in the landslide detection model.

The figure 2 illustrates the data preprocessing and prediction stages in the landslide detection model. Panels (a) and (b) show raw satellite images, while (c) and (d) represent processed slope and elevation data, capturing critical terrain features. Panel (e) provides the ground truth binary mask, marking known landslide-prone areas, with white regions indicating risk zones. Panels (f) and (g) display the model's predicted landslide-prone regions, showing close alignment with the ground truth in (e). The visual overlap between the predictions and ground truth highlights the model’s effectiveness, though minor discrepancies suggest potential for further refinement.

V. CONCLUSION AND FUTURE WORK

In this study, we developed and evaluated a machine learning model for landslide detection, leveraging processed datasets that include features such as normalized color channels, slope, elevation, and NDVI (Normalized Difference Vegetation Index). The model performed effectively in identifying landslide-prone areas, achieving high accuracy and recall metrics, which highlights its potential as a practical tool for early warning systems and risk assessment in vulnerable regions. By minimizing false negatives, the model aims to prioritize safety, ensuring that most landslide-prone areas are accurately flagged.

There are still certain difficulties, though, especially in striking a balance between recall and precision, which is essential to lowering false positives. Future research might concentrate on improving the model's precision without sacrificing recall. To get more information about landslide-prone places, this can entail incorporating data from other sources, such soil moisture content, historical weather data, or geological maps. Furthermore, using sophisticated machine learning methods like deep learning architectures or ensemble learning may improve the accuracy and resilience of the model.

By installing the model on cloud platforms and testing it on real-time data from sensors or satellite imagery, future research may potentially investigate the prospects for real-time deployment. We can help communities better manage and mitigate landslip hazards by developing this model further, which will lead to more robust monitoring and prediction systems.

VI. REFERENCES

[1] Mohanty, S.P.; Czakon, J.; Kaczmarek, K.A.; Pyskir, A.; Tarasiewicz, P.; Kunwar, S.; Rohrbach, J.; Luo, D.; Prasad, M.; Fleer, S.; et al. Deep learning for understanding satellite imagery: An experimental survey. *Front. Artif. Intell.* **2020**, *3*, 534696. [**Google Scholar**] [**CrossRef**] [**PubMed**]

[2] Nguyen, T.T.; Hoang, T.D.; Pham, M.T.; Vu, T.T.; Nguyen, T.H.; Huynh, Q.T.; Jo, J. Monitoring agriculture areas with satellite images and deep learning. *Appl. Soft Comput.* **2020**, *95*, 106565. [**Google Scholar**] [**CrossRef**]

[3] Bui, D.T.; Tsangaratos, P.; Nguyen, V.T.; Van Liem, N.; Trinh, P.T. Comparing the prediction performance of a Deep Learning Neural Network model with conventional machine learning models in landslide susceptibility assessment. *Catena* **2020**, *188*, 104426. [**Google Scholar**] [**CrossRef**]

[4] Nguyen, B.-Q.-V.; Kim, Y.-T. Landslide spatial probability prediction: A comparative assessment of naive Bayes, ensemble learning, and deep learning approaches. *Bull. Eng. Geol. Environ.* **2021**, *80*, 4291–4321. [**Google Scholar**] [**CrossRef**]

[5] Ghorbanzadeh, O.; Blaschke, T.; Gholamnia, K.; Meena, S.R.; Tiede, D.; Aryal, J. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. *Remote Sens.* **2019**, *11*, 196. [**Google Scholar**] [**CrossRef**]

[6] Chen, N.; Tian, S.; Wang, F.; Shi, P.; Liu, L.; Xiao, M.; Liu, E.; Tang, W.; Rahman, M.; Somos-Valenzuela, M. Multi-wing butterfly effects on catastrophic rockslides. *Geosci. Front.* **2023**, *14*, 101627. [**Google Scholar**] [**CrossRef**]

[7] Berrocal, J.; Espinosa, A.; Galdos, J. Seismological and geological aspects of the Mantaro landslide in Peru. *Nature* **1978**, *275*, 533–536. [**Google Scholar**] [**CrossRef**]

[8] Youssef, A.M.; Pourghasemi, H.R. Landslide susceptibility mapping using machine learning algorithms and comparison of their performance at Abha Basin, Asir Region, Saudi Arabia. *Geosci. Front.* **2021**, *12*, 639–655. [**Google Scholar**] [**CrossRef**]

[9] Constantin, M.; Bednarik, M.; Jurchescu, M.C.; Vlaicu, M. Landslide susceptibility assessment using the bivariate statistical analysis and the index of entropy in the Sibiciu Basin (Romania). *Environ. Earth Sci.* **2011**, *63*, 397–406. [**Google Scholar**] [**CrossRef**]

[10] Patel, M., Chavda, M., Patel, R., Goswami, A., & Mevada, J. (2024). Predicting landslide using machine learning techniques. 65, 03012. https://doi.org/10.1051/itmconf/20246503012

[11] Wang, Y., Gao, H., Liu, S., Yang, D., Liu, A., & Mei, G. (2024). Landslide detection based on deep learning and remote sensing imagery: A case study in Linzhi City. Natural Hazards Research. https://doi.org/10.1016/j.nhres.2024.07.001

[12] Saha, S., Majumdar, P., & Bera, B. (2023). Deep learning and benchmark machine learning based landslide susceptibility investigation, Garhwal Himalaya (India). Quaternary Science Advances, 10, 100075. https://doi.org/10.1016/j.qsa.2023.100075

[13] Nava, L., Carraro, E., Reyes-Carmona, C., Puliero, S., Bhuyan, K., Rosi, A., Monserrat, O., Floris, M., Meena, S. R., Galve, J. P., & Catani, F. (2023). Landslide displacement forecasting using deep learning and monitoring data across selected sites. Landslides, 20(10), 2111–2129. https://doi.org/10.1007/s10346-023-02104-9\

[14] Nava, L., Carraro, E., Reyes-Carmona, C., Puliero, S., Bhuyan, K., Rosi, A., Monserrat, O., Floris, M., Meena, S. R., Galve, J. P., & Catani, F. (2023). Landslide displacement forecasting using deep learning and monitoring data across selected sites. Landslides, 20(10), 2111–2129. https://doi.org/10.1007/s10346-023-02104-9

[15] Sestras, P.; Bilașco, Ș.; Roșca, S.; Naș, S.; Bondrea, M.; Gâlgău, R.; Vereș, I.; Sălăgean, T.; Spalević, V.; Cîmpeanu, S. Landslides susceptibility assessment based on GIS statistical bivariate analysis in the hills surrounding a metropolitan area. *Sustainability* **2019**, *11*, 1362. [**Google Scholar**] [**CrossRef**]

[16] Ding, Q.; Chen, W.; Hong, H. Application of frequency ratio, weights of evidence and evidential belief function models in landslide susceptibility mapping. *Geocarto Int.* **2017**, *32*, 619–639. [**Google Scholar**] [**CrossRef**]