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A novel deep learning based spatial ensemble approach and segment anything model for landslide risk assessment in Chamoli district of Garhwal Himalayas

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This study aims at introducing novel “Spatial Ensemble” approach for landslide risk assessment (LRA). For this purpose, the present work focuses on three different algorithms that includes a state-of-the-art deep learning DenseNet Neural Network, and 2 popular benchmark algorithms of MLPNN and XGBoost. The spatial ensemble approach in LRA focuses on generating two distinct types of “Landslide Impedance Composite Maps”, where the first one predicts the broadest possible danger zones covering the maximum extent with potential landslide occurrences across the study area. The second map targets the places in all probability to encounter landslides, by demarcating specific locations with the greatest risk of landslide occurrences to prioritize accuracy and precision, making sure that areas with highest levels of risk receive detailed attention. The outcome of the second map has helped during field verification, leading to identification of a new landslide in close proximity of human settlements and buildings. It is a crucial finding as this study applies state-of-the-art auto-detection algorithm of Segment Anything Model (SAM) to detect buildings automatically in close proximity which is accurate and time-saving alternative to land use maps, for risk assessment. And finally, a landslide risk zone is developed to delineate the building vulnerability around the landslide, which is validated against cracked buildings and presence of fault lines in the area. Thus, this research combines cutting-edge technologies with robust field observations, to introduce a novel and stepped approach of landslide risk assessment.

Keywords Spatial ensemble, Landslide impedance mapping, Segment anything model (SAM), Deep learning, Joshimath

Landslides, which are another type of mass wasting, refer to the downward displacement of soil, rock, and debris due to the force of gravity¹. Natural disasters like this do significant harm worldwide, leading to many casualties and extensive destruction of property annually¹. In order to fully understand the extent of this danger, we refer to the worldwide catastrophic landslide database, which covers the time frame from 2004 to 2010. Annually, there was an average of 374 extremely destructive landslides occurs globally, resulting in over 4,617 deaths each year². Landslide Susceptibility Mapping (LSM) is a crucial procedure for reducing risk related to landslides. It is a spatial representation that assesses and classifies the region with different levels of vulnerability to landslides, providing a measure of the probability of landslide occurrence. The LSM incorporates a range of landslide preconditioning factors, such as geological, geomorphological, environmental, and anthropogenic aspects. Literature has shown multiple techniques that has been employed to develop LSMs, ranging from heuristic and semi-quantitative approaches to quantitative, probabilistic, and multi-criteria decision-making methods³. In the early twentieth century, research work heavily relied on statistical, data mining, and soft computing models such as Logistic Regression, frequency ratio, and the analytical hierarchy process (AHP). However, these approaches face the difficulty of capturing non-linear connections as their ability to find relationship among the variables is limited to linear connections³. Recent research conducted between 2010 and 2020 have seen a significant increase in the use of data science in geospatial analysis for LSM. Advanced machine learning (ML) methods,

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including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, Random Forest (RF), Naïve Bayes, Multi-Layer Perceptron Neural Networks (MLPNN), and XGBoost, have been used to improve the accuracy of predictions². Deep Learning (DL), an advanced subset of Machine Learning (ML), is distinguished for its ability to effectively train complex parameters and capture non-linear relationships. DL models outperform traditional ML algorithms in predicting accuracy by detecting hidden non-linear complex connections between preconditioning parameters and landslide occurrences⁴.

For Accurate Landslide Susceptibility Mapping careful selection of appropriate preconditioning factors, broadly geological, geomorphological, environmental, and anthropogenic and recognizing the complex relationship of variables is crucial. These variables include a wide range of attributes, including soil properties, slope, precipitation, land use land cover and many more⁵. Thus, Multiple preconditioning factors increases the data complexity and often exhibits non-linear relationships. Conventional machine learning algorithms encounter difficulties in accurately capturing these complex patterns. To overcome the struggle of conventional ML, neural network-based approach became popular in Landslide prediction^{6,7}. Among these, the Multi-Layer Perceptron Neural Network (MLPNN) stands out⁸. Recent years have witnessed a shift in computation approach with the advent of deep learning (DL) models, as it excels at handling large and complex datasets especially for landslide susceptibility. These models possess the ability to acquire multiple characteristics or features and hidden connections, which makes them very suitable for the task of predicting landslide zones. Therefore, their capacity to capture non-linear relationships and represent complex interactions among preconditioning elements has improved their accuracy in predicting LSM⁹.

This paper presents a novel approach that combines the new deep learning algorithms with conventional machine learning approaches spatially. More precisely, we integrate the DenseNet Neural Network (DenseNet NN)¹⁰ with the Multi-Layer Perceptron Neural Network (MLPNN)¹¹ and XGBoost¹² by using an unique method of spatial ensemble technique to accurately predict the potential occurrence of landslides in the study area for the first time that aligns with the ground reality.

Field verification is essential for improving the precision of landslide prediction models. The process initiates with conducting on-site visits to the study area in order to verify and enhance the accuracy of the landslide susceptibility model. Two widely used measures for assessing the efficacy of a landslide susceptibility model are the Area Under the Receiver Operating Characteristic Curve (AUC ROC) and the F1 Score^{9,13,14}. Based on the output of the Spatial Ensemble Map and field investigation, a fresh landslide crown is detected. The identification of a freshly formed landslide crown, signifies the vulnerability of the area.

The accurate assessment of landslide vulnerability, depends on understanding the magnitude and extent of the potential danger. The affected landslide crown area, is crucial in this assessment. By delineating the boundaries of the landslide crown, and creating a demarcation zone around the vulnerable region, we can gain insights into the maximum spatial reach of the event. The application of the Segment Anything Model (SAM) to locate structures surrounding the landslide buffer location can be a unique and innovative approach. SAM, which has been pretrained on over 11 million images and 1 billion masks, is created by Meta AI¹⁵. It offers an important breakthrough in image segmentation in this field of remote sensing. SAM's exceptional generalization qualities enable it to work successfully over a wide range of imagine datasets without requiring further training for new objects¹⁶. Zero-shot learning, a critical feature, enables it to analyze and respond to input data that it has not expressly encountered during the training process^{17,18} unlike traditional models that rely solely on explicit examples. SAM's effectiveness is boosted by its use of large-scale datasets and powerful neural network architectures, which enable it to interpret visual context and content¹⁹. It has a user-friendly interface that requires minimal input and segment using only a bounding box, a single point, or even prompt text for assistance⁷. Thus, this functionality demonstrates the feasibility of combining large-scale data with modern machine learning algorithms that simplifies the annotation process by eliminating human work and computing overhead. Unlike conventional solutions, which need extensive annotations for each new item, SAM provides a time-saving solution¹⁶.

So, this study attempts to integrate remote sensing technologies with real world observations. The amalgamation of SAM, SET theory with AI based data driven decision making algorithms and field investigation can have a great potential for gaining new insights in the risk assessment of landslide and can be established as a novel approach towards landslide risk assessment.

Study area

The study area comprises of entire Chamoli district, situated in the northern Himalayan region of Uttarakhand, India (30.2937° N, 79.5603° E) comprising an area of around 8000 km^{3,20}. The study area is drained by Alakananda river, comprising of several tributary rivers like Saraswati, Nandakini, Dhauri Ganga, Pindar, Ramganga and many other rivers of the Himalayas²⁰. The region is characterized by a diverse range of ecological and topographical features. The southern region is enveloped by dense forests, while the higher altitudes, reaching between 1,000 to 5,000 m above mean sea level, exhibit sparse vegetation and are predominantly snow-covered. Moderate altitudes are primarily covered with coniferous trees. The higher elevations, specifically those above 4,500 m, are subject to permanent snow cover, which extends down to 2,800 m during the winter season. The study area is divided into five distinct tectonic zones, each with unique sedimentary and metamorphic formations. The southernmost zone, Siwalik Himalaya, is followed by the Lesser Himalayan Sequence (LHS), with high-grade metamorphic rocks. The Tethyan Himalayan Sequence (THS) is a vast expanse of sedimentary rock strata. The northernmost boundary is the Indus-Tsangpo-Suture Zone (ITSZ), marking the collision interface between Indian and Eurasian plates²¹. Climatic conditions in the region are equally diverse; summer temperatures fluctuate between 15 °C and 30 °C from March to September, while the winter months from November to February often see temperatures below 0°C²². The area presents a complex dynamic landscape, characterized by deep gorges, glaciated valleys, rugged topography and dissected terrain is intricately shaped by the headwaters

of the Alaknanda River, which carve out an extensive drainage network throughout the area²³. Heavy monsoon precipitation is experienced during the months of July to late September having mean annual rainfall varying between 80 to 260 cm according to the data recorded by Tropical Rain Mapping Mission (TRMM) from 1998 to 2010²⁴. The study area in Fig. 1 experiences geomorphological challenges due to heavy monsoonal rainfall, causing devastating landslides. The study area covers important pilgrimage destinations, such as the Kedarnath and Badrinath temples, which attract an impressive number of Hindu devotees to the district. The tourist season extends from May to October, during which the route becomes dangerous due frequent landslides during the monsoon period. Unfortunately, a recurring occurrence of landslides leads to the unfortunate loss of many tourists' lives.

Research methodology

Dataset and data pre-processing

For this study, 18 parameters are developed as the preconditioning factors of landslide. These parameters are chosen based on the existing literature and field experience^{22,23}. The preconditioning factors are provided in Table 1. There are 1740 polygons are collected as the landslide inventory data from field visits, satellite images²⁵ and from the Indian government repository of Bhukosh Portal under Geological Survey of India²⁶. To complement the landslide inventory data and balance the dataset, an equal number of 1740 polygons representing non-landslide (stable) areas were selected. This selection was carried out using Stratified Random Sampling to account for the diverse geological, geomorphological, and land cover conditions within the study area. By stratifying the area based on these factors before randomly choosing non-landslide points, we ensured a fair and representative distribution of all relevant conditions²⁷. The preconditioning factors were identified as the triggering factors for landslides, as outlined in Table 1, are sourced from various data repositories such as SRTM DEM, Bhukosh, ESA World Cover, and IMD, includes both continuous and discrete variables. Some parameters, like elevation and distance from roads, are quantified as continuous variables. Other parameters, such as Land Use Land Cover (LULC), which includes categories like vegetation and other land classes, are discrete. For discrete parameters like LULC, weights ranging from 1 to 10 were assigned based on their significance in influencing landslide susceptibility. This weighting ensures that the dataset accurately reflects the impact of various factors, thereby enhancing the precision of the landslide susceptibility models. Multicollinearity analysis has been performed and Variance Inflation Factor (VIF) is calculated over the dataset to check the collinearity among the preconditioning factors²³.

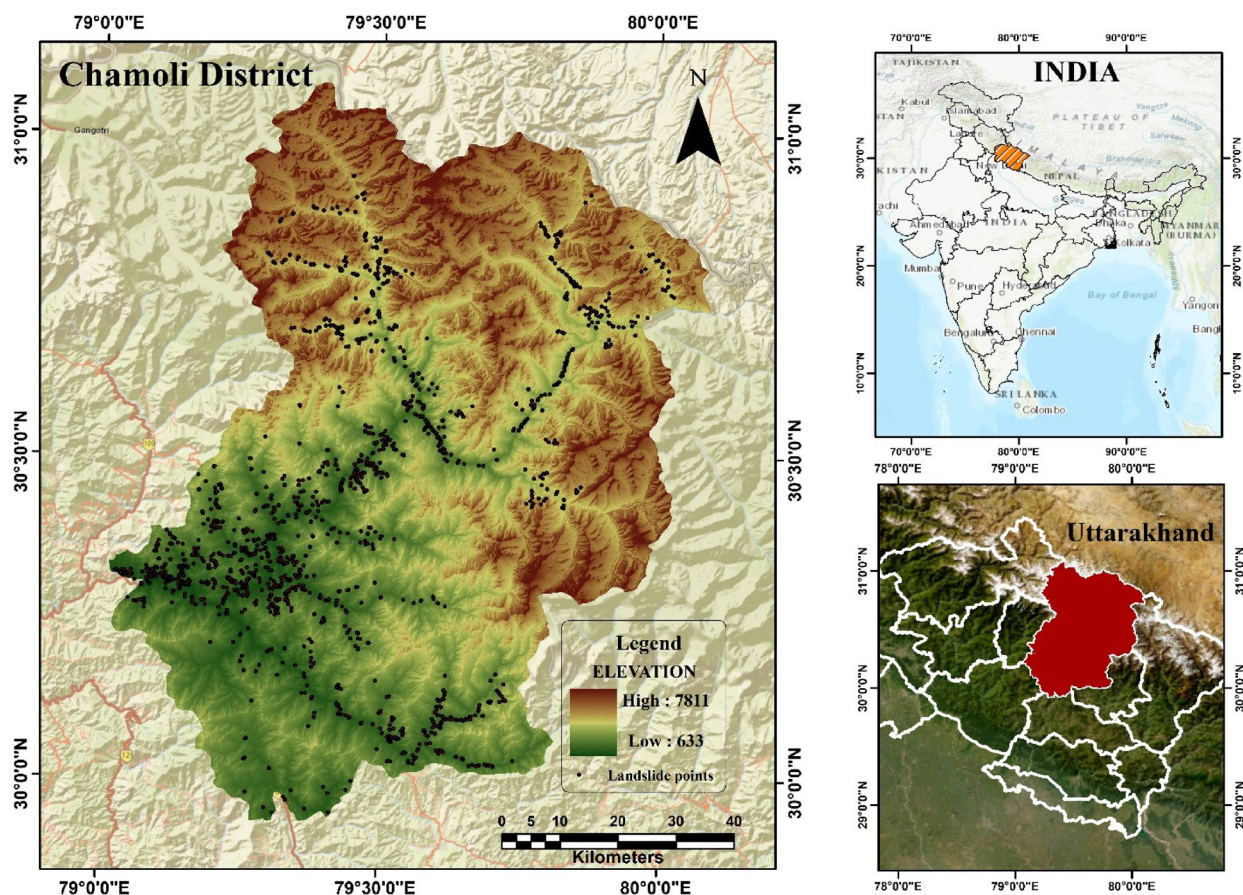


Fig. 1. Study Area Map of Chamoli District, Uttarakhand, India; Landslide Points collected from Government repository data of Geological Survey of India.

Sl no	Class	Triggering factors	Data source	Tolerance	VIF
1	Geomorphological	Aspect	SRTM DEM	0.956	1.046
2		Curvature	SRTM DEM	0.872	1.147
3		Elevation	SRTM DEM	0.875	1.38
4		Geomorphology	Bhukosh	0.922	1.084
5		Relative relief	SRTM DEM	0.897	1.115
6		Slope	SRTM DEM	0.641	1.56
7	Geological	Lineament density	SRTM DEM	0.825	1.213
8		LULC	ESA World Cover	0.787	1.27
9		Geology	Bhukosh	0.804	1.244
10		Soil	Bhukosh	0.554	1.804
11		Stream power index	SRTM DEM	0.653	1.531
12		TRI	SRTM DEM	0.989	1.011
13		TWI	SRTM DEM	0.896	1.115
14	Environmental	MNDWI	SRTM DEM	0.841	1.22
15		NDVI	SRTM DEM	0.739	1.352
16		Rainfall	IMD	0.908	1.102
17	Anthropogenic activity	Distance from road	OSM, Google Map	0.361	2.77
18		Road density	OSM, Google Map	0.52	1.922

Table 1. Variables along with VIF and tolerance values used in LSM creation.

$$VIF_j = \frac{1}{(1 - R_j^2)}$$

where R_j^2 is the coefficient of determination of the regression of variable j on all the other predictors.

Upon completing the database of pre-conditioning factors and landslide inventory, the data undergoes standardization using the ‘StandardScaler’ feature. This pre-processing technique normalizes the dataset characteristics, ensuring each feature has a mean of 0 and a standard deviation of 1. The standardized value, is calculated using the formula:

$$X_{scaled} = \frac{(X - \mu)}{\sigma}$$

where X is the original feature value. μ is the mean of the feature. σ is the standard deviation of the feature. Standardization prevents the influence of features with larger ranges over those with smaller ranges, resulting in more accurate and impartial outcomes.

Methodology

The research involved a series of phases, starting with a practical field visit to identify accessible landslides as depicted in Fig. 2. This provided insights into real-world conditions and challenges. The next stage was the development of a robust database focusing on 18 key parameters chosen based on their potential influence on landslide occurrences for Landslide susceptibility mapping (LSM). The research uses advanced computational models, including the state of the art DenseNet neural network (DenseNet NN), a new and improved architecture in Convolutional Neural Networks (CNNs) to predict LSM²⁸. This model is recognized for its ability to process complex data patterns efficiently and accurately²⁹. Two popular machine learning models, Multi-Layer Perceptron Neural Network (MLPNN) and Extreme Gradient Boosting (XGBoost), are also developed as a benchmark model for their effectiveness in landslide^{8,30,31} prediction tasks (Fig. 3).

For performing the deep learning algorithm for prediction of LSM, first the dataset is divided into two subsets: a training set, which consists of 70% of the data, and a testing set, which includes the remaining 30%. This partitioning enables the model to effectively acquire knowledge from the training data and assess its performance on testing dataset.

The MLPNN is a technique used in artificial neural networks (ANN) to estimate functions and recognize patterns³². It consists of three layers: input, hidden, and output, each with customizable neurons according to the task. The input layers represent variables influencing landslides, while the output layers provide graded and probabilistic outcomes⁸. MLPNN is a unique computation model that mimics biological neural networks by arranging neurons in a hierarchical structure and very popular in LSM prediction³³. In the MLPNN model, the “logistic” activation function was selected to implement the logistic sigmoid function in the network’s hidden layers. This choice introduces non-linear elements, allowing the model to accurately identify complex patterns and relationships in the input data. Additionally, setting the random state parameter to 42 ensures the repeatability of results by initializing the random number generator with a predetermined seed after several trials and errors.

(Hidden Layers: For each neuron j in the hidden layer, the output h_j is calculated).

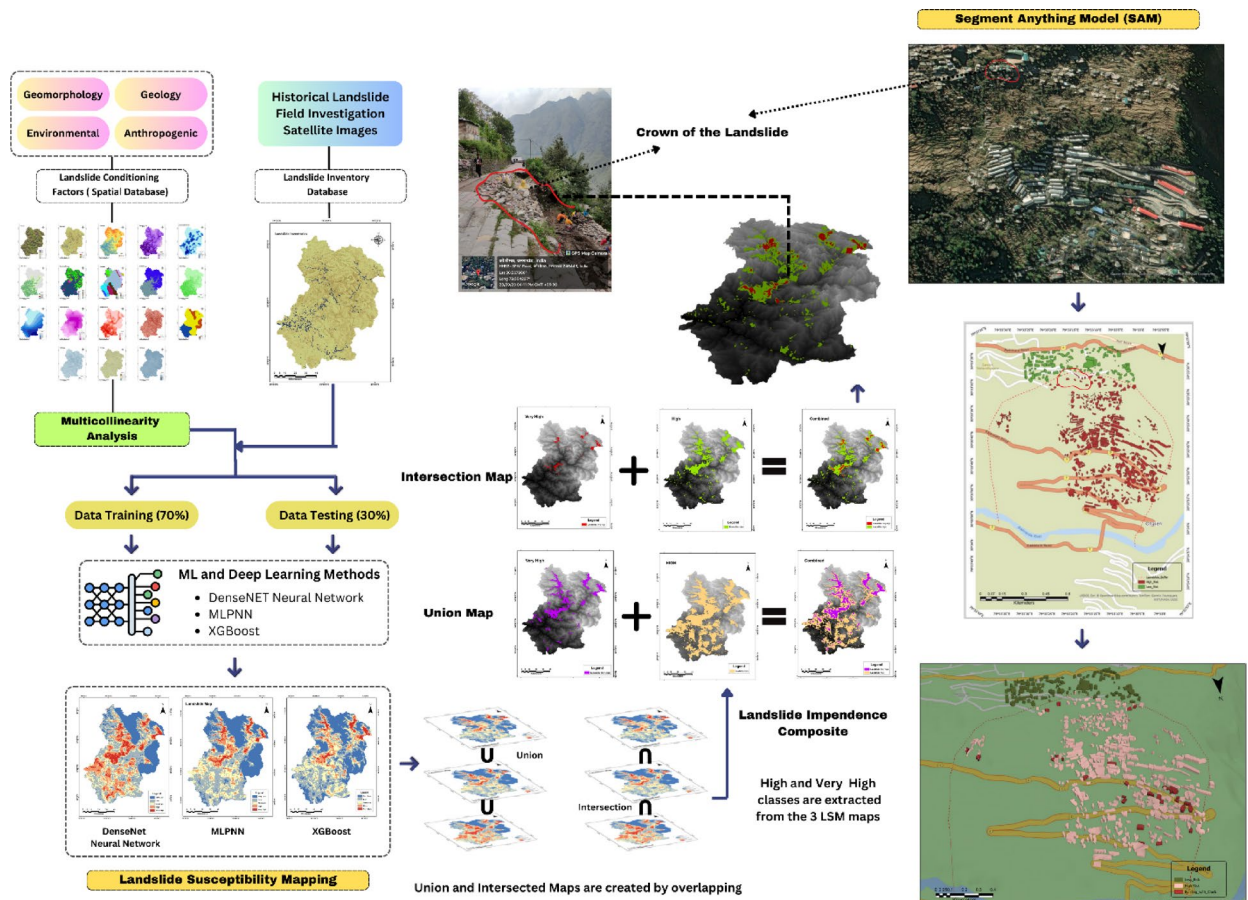


Fig. 2. Detailed stepped methodological flowchart of the research.

$$h_j = \sigma \left(\sum w_{ij} * x_i + b_j \right)$$

(w_{ij} is the weight associated with the input i and neuron j ; x_i is the input; b_j is the bias term for neuron j ; σ is the activation function (e.g., sigmoid, ReLU).

(**Output Layer:** For the output neuron k , the output y_k is calculated)

$$y_k = \sigma \left(\sum w_{jk} * h_j + b_k \right)$$

(h_j is the output from the hidden layer neuron j ; b_k is the bias term for the output neuron k .)

(**Loss Function:** L measures the difference between the predicted output and the actual output)

$$L = (1/N) \sum (y_i - \hat{y}_i)^2$$

(y_i is the actual output; $\hat{y}_i$ is the predicted output; N is the number of samples).

(Backpropagation: weights are updated using the gradient descent algorithm to minimize the loss function)

$$w_{ij} := w_{ij} - \eta \left(\frac{\partial L}{\partial w_{ij}} \right)$$

(η is the learning rate; $\frac{\partial L}{\partial w_{ij}}$ is the gradient of the loss function with respect to the weight w_{ij} .)

XGBoost is a machine learning algorithm that uses a gradient boosting tree model to make predictions¹². It focuses on managing model complexity and preventing overfitting, which happens when a model performs well on training data but poorly on new data³⁰. XGBoost can perform parallel computation, handle multiple tasks at once, and optimize memory usage. It is especially useful for processing sparse data, such as Landslide and non-Landslide Points. To improve performance, hyperparameters such as learning rate, subsample ratio, tree depth, and boosting iterations is fine-tuned³³. The basic mechanism of XGBoost is to generate a predictive model by assembling a boosting ensemble of weak classification trees and optimizing the loss function with

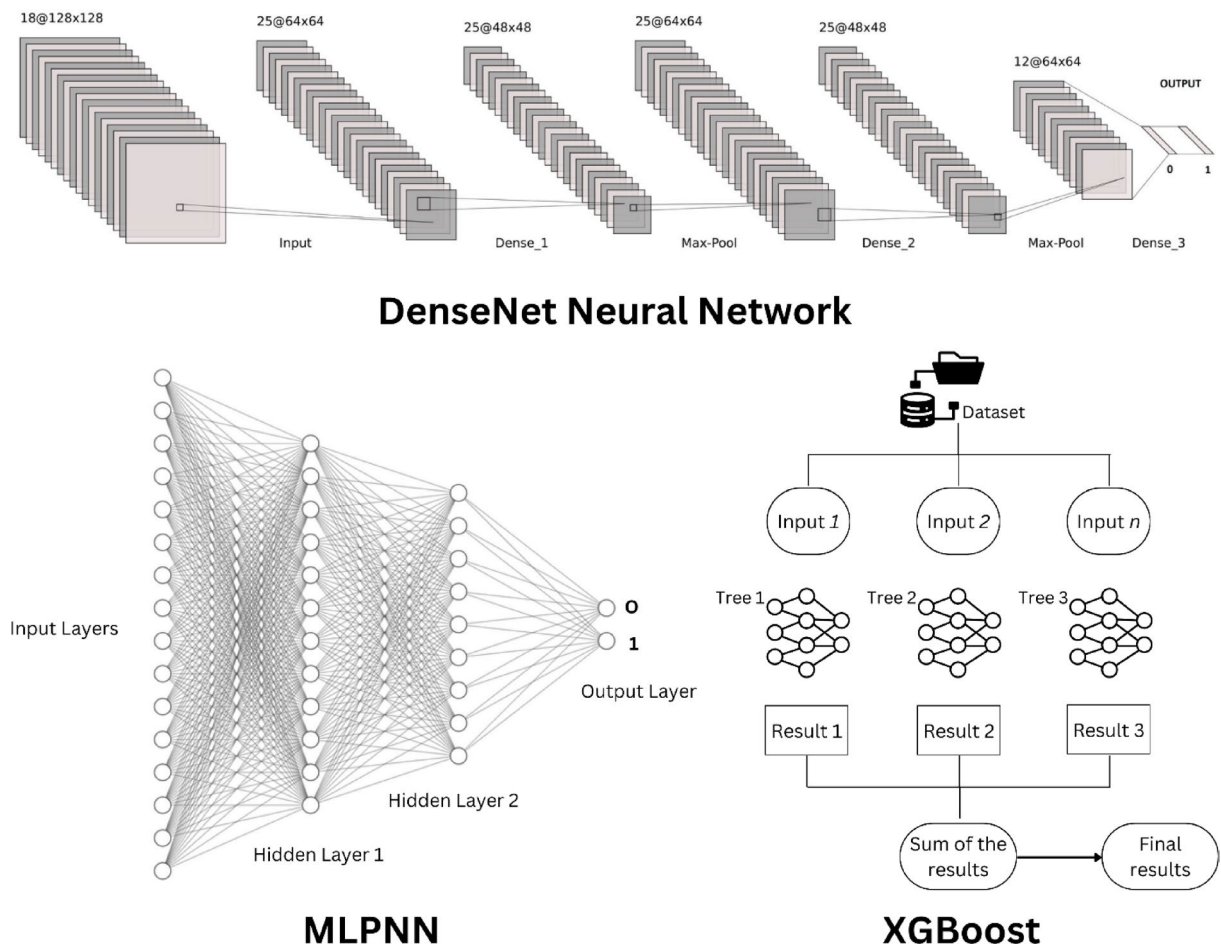


Fig. 3. Architecture of the 3 neural network algorithms.

gradient descent^{31,34,35}. In this study, the 'XGBoost regressor' was chosen. The objective function was set to 'reg: squarederror', utilizing mean squared error as the loss function to enhance prediction accuracy. The 'n_estimators' parameter was configured to 100, denoting the number of sequentially built decision trees, while the 'max_depth' hyperparameter was limited to 3 to prevent overfitting and maintain model precision.

(Objective Function)

$$Score = - \left(\frac{1}{2} \right) \sum \left(\frac{G_j^2}{(H_j + \lambda)} \right) + \gamma T$$

$\left(\frac{G_j^2}{(H_j + \lambda)} \right)$ sums up the scores for all the leaves in a tree; G_j : is the first order gradient statistic; H_j : This is the second order gradient statistic; λ is a regularization parameter that helps prevent overfitting by penalizing large weights;

$-\left(\frac{1}{2} \right)$ are factor scales the sum and ensures the score reflects the overall fit of the tree structure; γT adds a penalty for the number of leaves T in the tree, weighted by the regularization parameter γ .)

DenseNet, a new architecture in Convolutional Neural Networks (CNNs), features a unique connectivity pattern where each layer within a dense block is connected to all other layers³⁶. The design allows for the accessibility of feature maps from previous layers, promoting extensive reuse of features the model, making it more concise and less prone to overfitting, enhancing its ability to generalize unknown data precisely. DenseNet addresses challenges related to parameter depth and complexity by improving deep supervision and strengthening feature propagation. This results in optimized learning and a significant reduction in parameter number³⁷. DenseNet represents a significant advancement in deep learning, offering an efficient approach to handling complex data patterns and making accurate predictions³⁸. The Deep Learning Neural Network (DLNN) architecture for this study consists of three dense layers with neural depths of 25, 25, and 12 neurons, respectively, capturing hierarchical information from the input data. The 'relu' activation function is utilized for the first three hidden layers. The final output layer employs the 'sigmoid' activation function to convert outputs into probability distributions for evaluating landslide potential zones. The model is trained using the

'Adam' optimizer and the binary cross-entropy loss function of 53 epochs (after which the RMSE error started to increase), with a fine-tuned batch size of 64, ensuring optimal computational efficiency and model convergence.

Composite Function: In DenseNet, the output of the l -th layer is defined as:

$$H_l = F_l([H_0, H_1, \dots, H_{l-1}])$$

(H_1 is the output of the l -th layer. F_l is a composite function of three consecutive operations; $H_0, H_1, \dots, H_{l-1}$ represents the concatenation of the feature maps produced by layers 0 to $\{l - 1\}$.)

$$L = - \sum y_i \log(\hat{y}_i)$$

Following the successful development of three predictive maps using the MLPNN, XGBoost and DenseNet NN, a set of "Landslide Impendence Composite" maps are created. These composite maps are created using the "spatial ensemble" process, which combines the three LSMs spatially. The Impendence Composite map is created by generating two distinct sets of maps. These sets are based on the union and intersection of landslide-prone zones. The zones classified as 'High' and 'Very High' in the Landslide Susceptibility Mapping (LSM) are specifically considered when creating these composite maps to improve the overall accuracy of landslide predictions while also ensuring alignment with ground reality. The first set includes 3 union maps of 'High', 'Very High', and a combined map of 'High and Very High' zones. The second set is made up of 3 intersected 'High' and 'Very High', as well as a combined map of 'High and Very High' zones. These sets of 'High' and 'Very High' maps provide a highly accurate spatial threshold, indicating the maximum and minimum extent of potential landslides zones in the area.

The study procedure also includes an investigation of the 'combined 'High' and 'Very High' landslide impendence composite intersection' map. During the field verification, a new landslide event is identified based on the hazard zones predicted by these combined 'High' and 'Very High' landslide impendence composite intersection map on 23/09/2023. For the next phase of research, the Leaf map's satellite image¹⁵ is used in conjunction with the technology of Segment Anything Model (SAM), an automated detection algorithm to extract precise information about the surrounding buildings^{39,40}. The buildings which are extracted using SAM, underneath the newly constructed landslide are then identified and marked as vulnerable owing to their position. To have a deeper understanding of the problem, 3D models of these vulnerable buildings are created based on the data acquired during the field study, ensuring that they appropriately represent the ground reality.

Results and discussion

Multicollinearity analysis

This paper does a multicollinearity analysis on 18 chosen preconditioning parameters to evaluate their significance. The investigation findings, as provided in Table 1 indicate that the Variance Inflation Factor (VIF) spans from 1.011 to 2.770, while the Tolerance varies from 0.369 to 0.989. Based on the criteria stated by⁴¹ it can be inferred that there is no collinearity among the preconditioning components, given that the Variance Inflation Factor (VIF) is less than 5 and the Tolerance is more than 0.1. Of all the characteristics examined, the 'distance from the road' has the highest VIF score of 2.770, showing its considerable impact. In contrast, the 'Topographic Ruggedness Index' has the lowest VIF score of 1.011, indicating a lower level of effect as shown in Fig. 4.

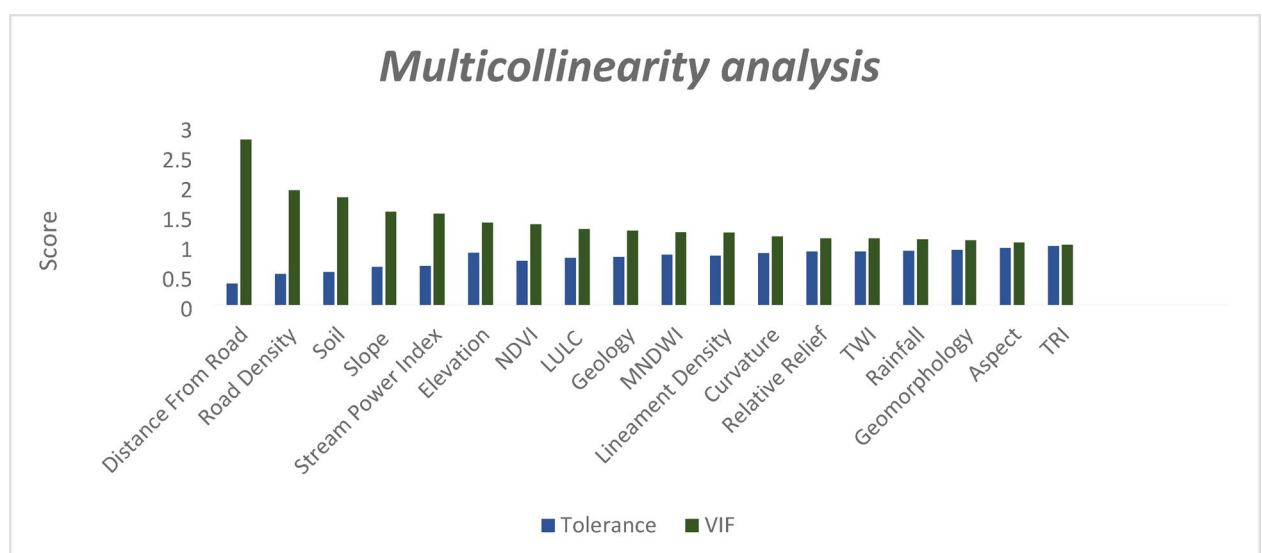


Fig. 4. Bar graph showing the VIF and tolerance value to assess multicollinearity analysis of the preconditioning factors.

Hence, the chosen 18 parameters that contribute to the preconditioning of landslides are considered suitable and accurate for forecasting the likelihood of landslides. This result is derived from the lack of collinearity between the elements, which guarantees that each factor contributes distinct and relevant information to the predictive model.

Assessment of landslide susceptibility models

This study uses 18 factors and three methods for Landslide Susceptibility Modeling. The models used are DenseNet NN, MLPNN, and XGBoost. The susceptibility maps produced by these models are categorized into five groups according on the probable severity of landslide occurrence as shown in Fig. 5. The categories, generated using the 'natural break' tool of ArcGIS, consist of 'Very High', 'High', 'Moderate', 'Low', and 'Very Low'. The accuracy of these models is computed inside a Python 3.5 environment. The DenseNet NN, MLPNN, and XGBoost algorithms achieve testing accuracies of 89.46%, 89.25%, and 88.41% correspondingly. The performance of the models was evaluated by analyzing the training and validation loss curves to monitor the Root Mean Square Error (RMSE) across epochs for both datasets (Fig. 6). The true positive rate was plotted against the false positive rate at various threshold settings on the Receiver Operating Characteristic (ROC) curve. The ROC-AUC values were determined to be 0.87 for DenseNet NN, 0.85 for MLPNN, and 0.84 for XGBoost algorithms. Furthermore, a Precision-Recall Curve was developed to examine the trade-off between precision and recall across different thresholds, and an F1 Score Curve was created to assess the F1 score at varying threshold values. The accuracy assessment scores (Fig. 6) for each classifier are provided in Table 2 (Fig. 7).

An ANOVA test was conducted to evaluate the statistical significance of the performance differences among the DenseNet NN, MLPNN, and XGBoost models. The test yielded an F-Statistic of 4.78 and a p-value of 0.009, indicating that the observed differences in model performance are statistically significant⁴².

Afterwards, an accuracy assessment of the three predicted landslide maps is carried out. This evaluation relies on validation data obtained from ground-based sources using Ground Control spots (GCP), as well as from inaccessible landslide spots extracted from satellite imagery provided by Google Earth Pro⁴³. The DenseNet neural network has the greatest accuracy rate of 86.05%, while the accuracy rates of 85.05% for XGBoost and 84.7% for MLPNN. This contrasting outcome between the model accuracy and ground truth-based AUC-ROC evaluations infer that though MLPNN exhibits greater model accuracy, the ground truth assessment favors the XGBoost model more than the MLPNN model, with a considerable difference between the two accuracy assessments.

Landslide impendence composite map

Landslide Impendence Composites is defined as the areas that fall into the 'Very High Susceptibility' and 'High Susceptibility' zones on all three Landslide Susceptibility Maps (LSMs), irrespective of the individual methodology used to prepare each LSM. The concept of a 'Landslide Impendence Composite' is a unique approach that is developed to identify with high landslide susceptibility. These regions are specifically categorized as being into the 'Very High Susceptibility' (VHS) and 'High Susceptibility' (HS) zones in all three Landslide Susceptibility Maps (LSMs), irrespective of the specific methods used to create each LSM. The process of generating Landslide Impendence Composite maps involves the integration of the VHS and HS zones from each LSM. This integration is achieved through the application of 'Set' theory, a branch of mathematical logic that studies set, or collections of objects. Specifically, the properties of 'Union' and 'Intersection' are utilized to merge the VHS and HS zones from each LSM. In this context, the union operation combines the VHS and HS zones from each LSM, while the intersection operation identifies the common areas among these zones. The resulting composite maps thus represents the combined landslide susceptibility of the area based on the three LSMs as in Fig. 8. The Landslide Impendence Composite map does not include areas that are classified as 'Moderate', 'Low', and 'Very Low' in

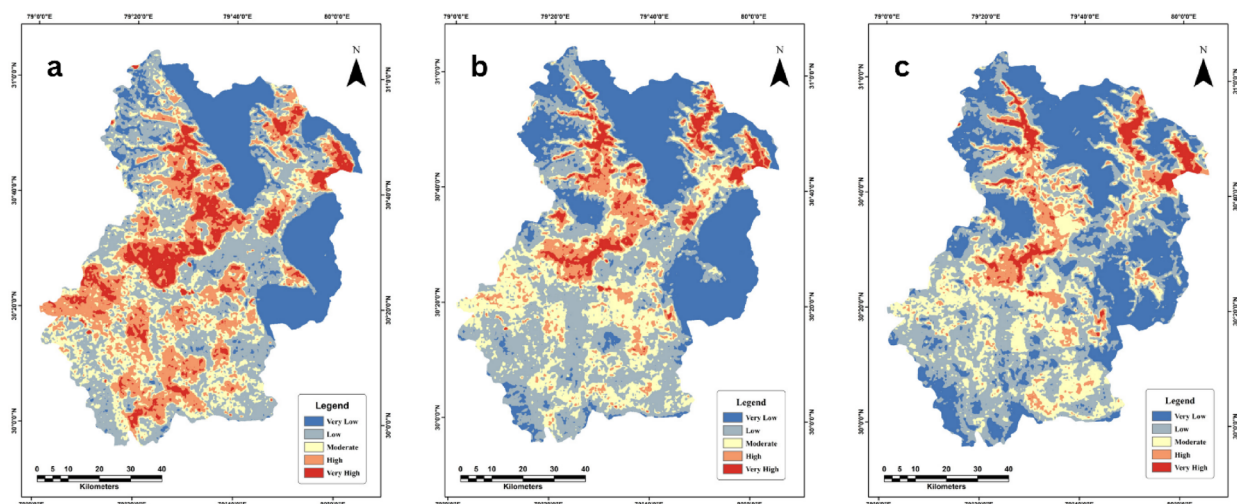


Fig. 5. Landslide Susceptibility Maps based on (a) DenseNet NN (b) MLPNN (c) XGBoost.

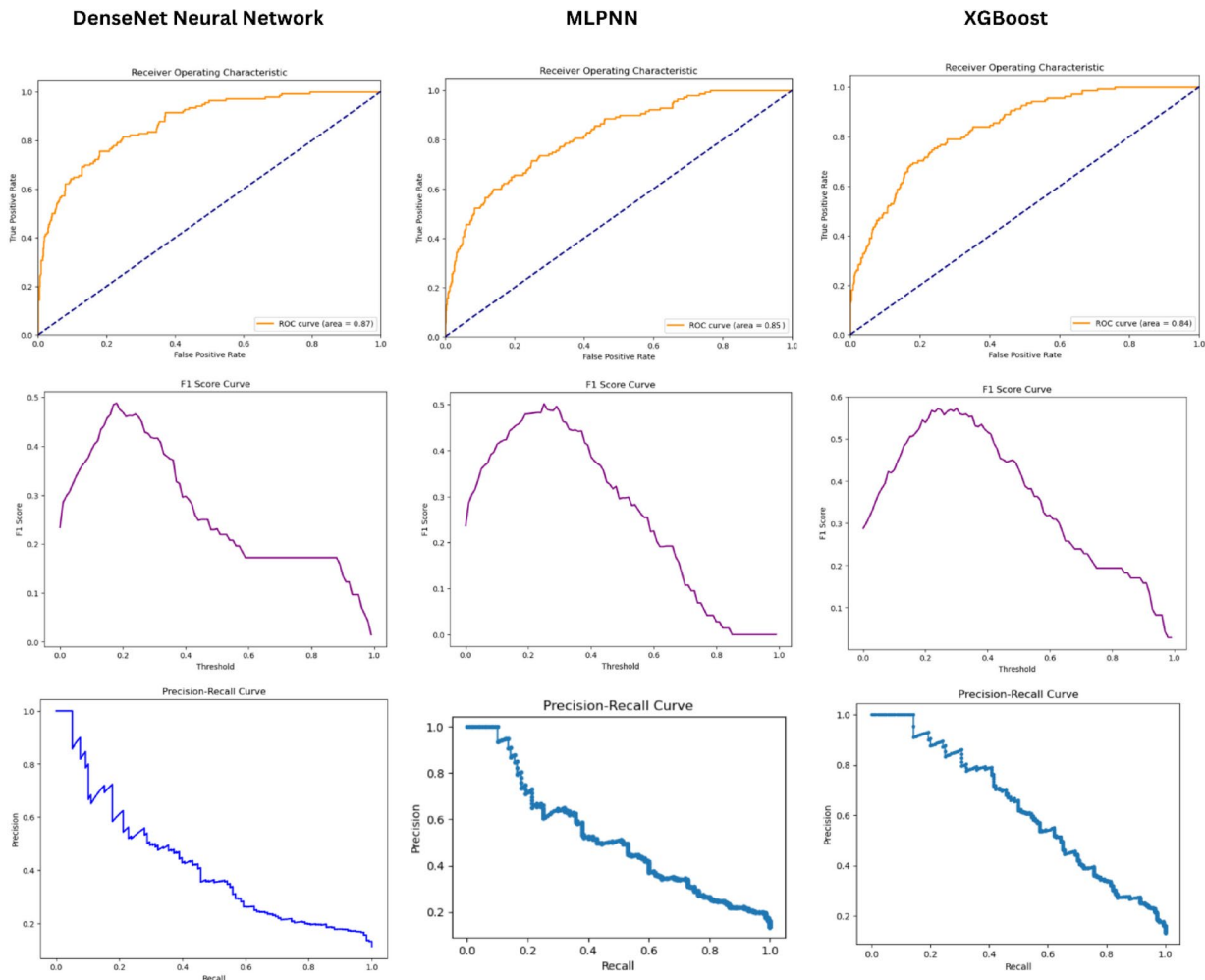


Fig. 6. Accuracy assessment of the 3 machine learning models based on statistical indices.

Classifier	Accuracy assessment score				
	Model accuracy	AUC-ROC	F1 Score	Precision	Recall
DenseNet NN	89.46%	0.87	0.85	0.82	0.83
MLPNN	89.25%	0.85	0.82	0.8	0.79
XGBoost	88.41%	0.84	0.82	0.81	0.82

Table 2. Accuracy assessment score of various statistical indices.

terms of landslide susceptibility. These locations are excluded from consideration, focusing emphasis towards the areas with the greatest possibility of landslide occurrences.

The technique of using a union and intersection approach to generate Landslide Impendence Composite maps provides a comprehensive and detailed understanding of landslide susceptibility. This technique distinguishes two unique but interrelated viewpoints on landslide hazards. On the one side, the ‘union’ operation finds the broadest possible danger zones, covering the maximum extent of probable landslides. The ‘intersection’ operation, on the other hand, identifies the places most likely to encounter landslides, indicating the smallest area with the greatest risk of landslide occurrences. According to the ‘intersection’ map, a landslide that occurred in mid-2024 had already been forecasted within the designated ‘Very High Susceptibility’ class of the “Intersected Landslide Impendence Composite Maps” which is in Video 1 (supplementary file). The details in the Fig. 9 depicts both the prediction map developed in 2023 and the precise location of the landslide that occurred in year 2024. Thus, it has effectively illustrated the accuracy of the prediction of ‘Intersected Landslide Impendence Composite Maps’.

This dual perspective provides a more efficient and realistic representation of on-the-ground situation, improving the accuracy and reliability of landslide risk assessments. Compared to individual Landslide Susceptibility Maps, this technique gives a deeper understanding of landslide hazards by integrating multiple perspectives. It not only indicates the high-risk locations, but also emphasizes the varied degrees of susceptibility

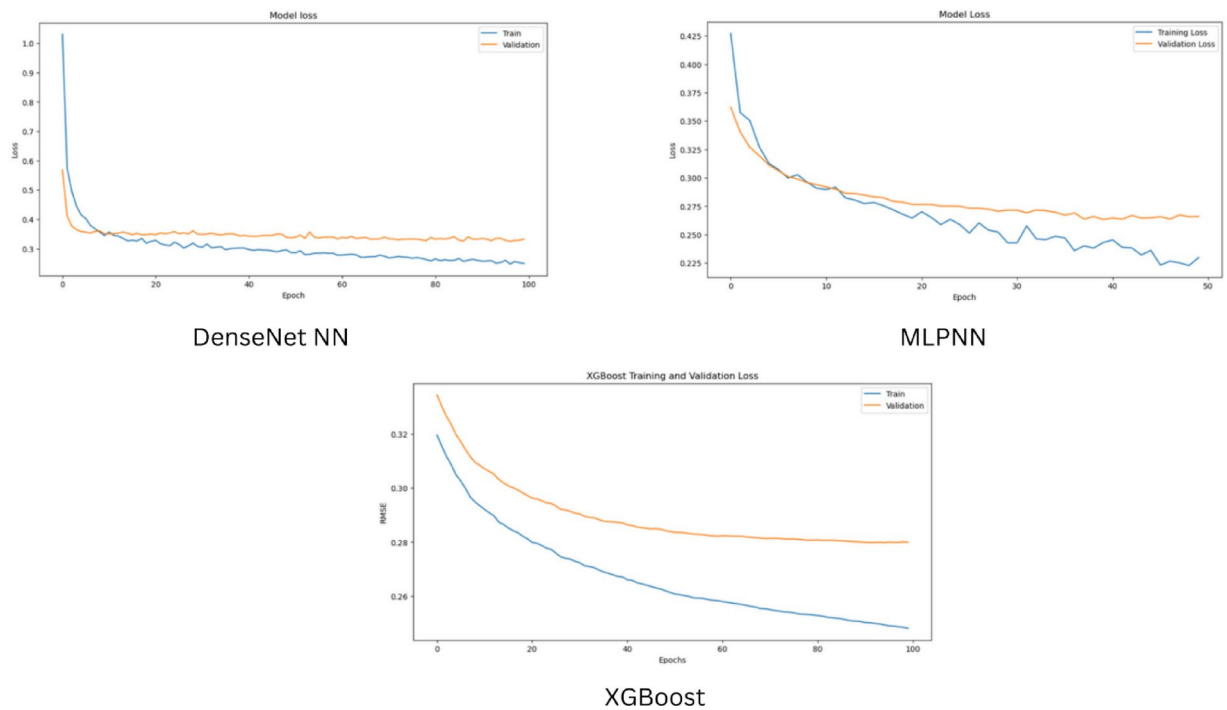


Fig. 7. Detailed RMSE loss curve of the 3 machine learning models respectively.

within areas. Therefore, the union and intersection approach for developing Landslide Impendence Composite maps is robust and effective tool for landslide risk management, which can be an effective approach that aligns best with ground reality.

Location of sample trigger point

A field verification has been conducted to investigate the locations of potential occurrences of landslide based on the outcome of “Combined Intersection Landslide Impendence Map”. While investigating, a fresh landslide crown has been identified in the Joshimath region of the study area which comes under VHS in the intersection map.

According to the local people the landslide has taken place on that area recently, and thus the crown of landslide has been identified. As the landslide is new, it is anticipated that it may be triggered multiple times with the arrival of the next monsoon season, posing a potential risk of mass destruction to the area beneath it as shown in Fig. 10.

From the satellite image in the Fig. 11, where the landslide crown is marked in red, it clearly illustrates that the landslide’s position as a potential threat to the built-up and infrastructural elements below.

Potential landside occurrence zone development

Following the detection of the landslide crown, a probable landslide occurrence buffer zone was demarcated to include the potentially vulnerable buildings situated beneath the landslide crown. As the slope of the region is northward, so a U-shaped buffer is created that has opened towards the gorges of Alakananda River down the slope. Further investigations revealed the existence of a fault line (lineament) under the surface of this buffer zone, as indicated in the Fig. 11. The detection of this fault line adds another degree of complexity to the potential risks associated with this area in Fig. 12, which is made in ArcGIS Pro 3.1 (<https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview>) It implies that the region is not just prone to landslides, but also to seismic activity, which could potentially trigger landslides. This underscores the potential risks associated with this area. Thus, the buffer zone is carefully designed to consider the geographical (Fault lines and Lineament Density) and topographical features (slope and aspect) of the region, ensuring a complete coverage of the potential landslide impact zone.

Building detection using segment analysis model (SAM)

In this research, the Segment Anything Model (SAM) was used to recognize buildings in the area around the landslide crown. The use of SAM has simplified the process by eliminating the need for manual digitization of buildings, thereby saving time and effort. The algorithm has shown to be very effective in accurately recognizing 94% of the 3000 structures in the region. SAM was executed using Google Colab⁴⁴. This model allows for improved visualization and understanding of building at risk, especially for buildings placed immediately under the landslide crown. To optimize computing performance and reduce time of processing, the building detection method was carried out in six batches shown in Fig. 13. After ‘Building’ detection the fine-tuning process is initiated to refine the detection. Buildings located above the landslide crown were classified as ‘Less

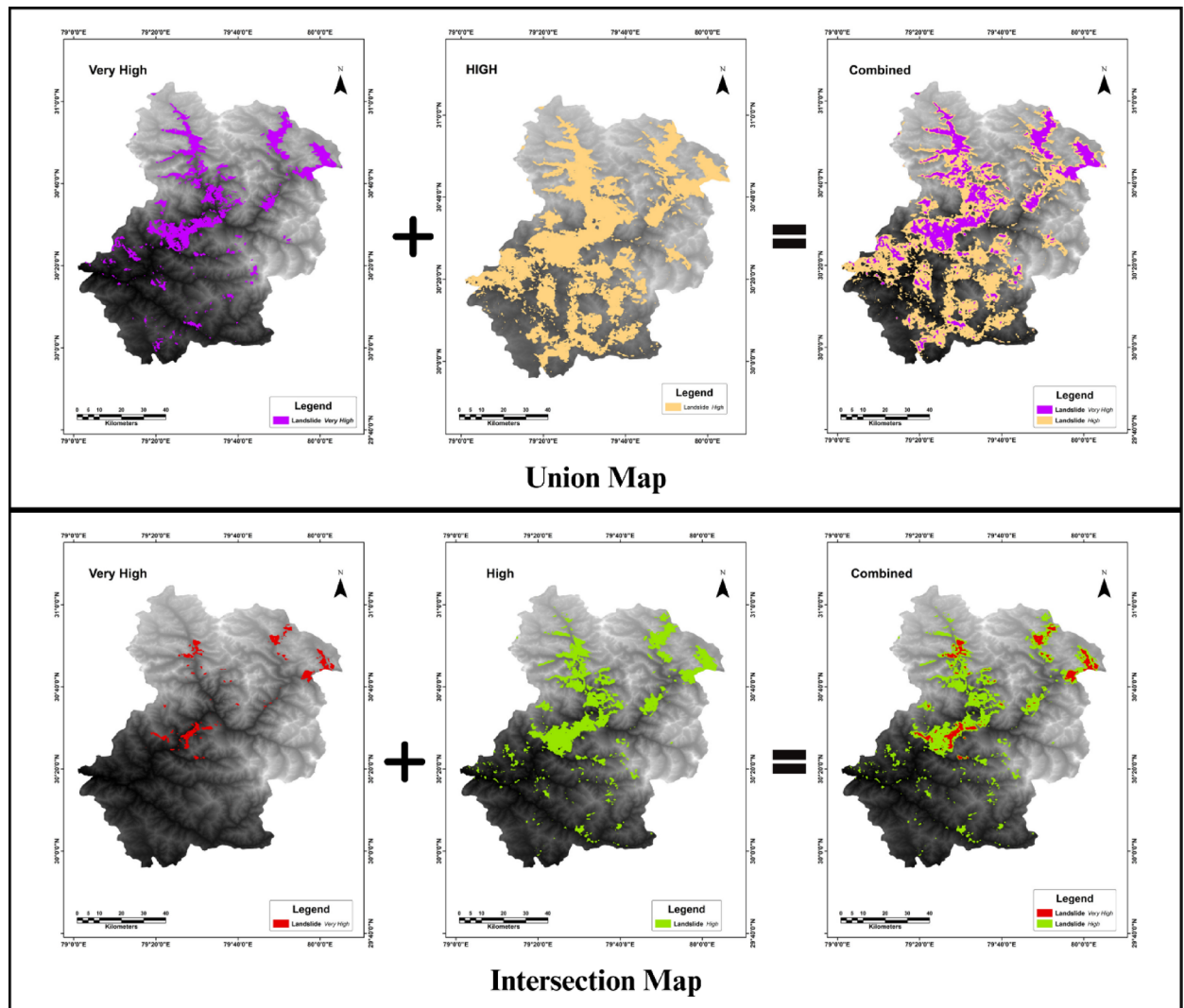


Fig. 8. Landslide impedance composite maps based on SET theory of Union and Interaction.

Risk', while those beneath the landslide, where there is a high probability of landslide occurrence, were classified as 'High Risk'. Some buildings were highlighted in red to indicate 'Buildings with cracks', a classification based on information gathered from a recent literature review⁴⁵.

To enhance understanding of the situation, 3D models of the buildings were developed using information collected from ground data during the field investigation. The primary purpose of these models was to accurately capture and visualize building heights. By incorporating this information into the 3D models, the structural integrity of the buildings was analyzed, and correlations between building heights and the presence of cracks were identified. A significant finding was revealed: buildings with two or more storeys exhibited the majority of the cracks. This insight would not have been apparent without the detailed and realistic representation provided by the 3D models. By visualizing the buildings in three dimensions, patterns and relationships that might have been overlooked in a traditional 2D analysis were discerned. So, these models give a more evident and realistic representation of the buildings' vulnerability to landslides.

Final output

The primary objective of this research is to predict landslide risk assessment within a micro area, aligning it with real-world conditions to identify buildings at risk of potential landslides. To achieve this goal, we followed a comprehensive methodology involving multiple technical phases which starts from generating landslide susceptibility maps using state of the art algorithms. The SET theory is applied on these LSMs for spatial ensemble of the algorithms to generate "Landslide Impedence Composite" maps (Fig. 8). Based on the "Combined Intersection" map (Fig. 8). A rigorous ground survey has been conducted in the study area. During this survey, a fresh landslide is identified, which falls within the 'very high susceptibility' zone predicted by the "Combined Intersection" map. Then the landslide crown is detected for further assessment of potentially vulnerable buildings. Further research, regarding sub surface geological element beneath the surface of the fresh landslide, also revealed that a fault line is under passing the region. Integrating all these factors a risk

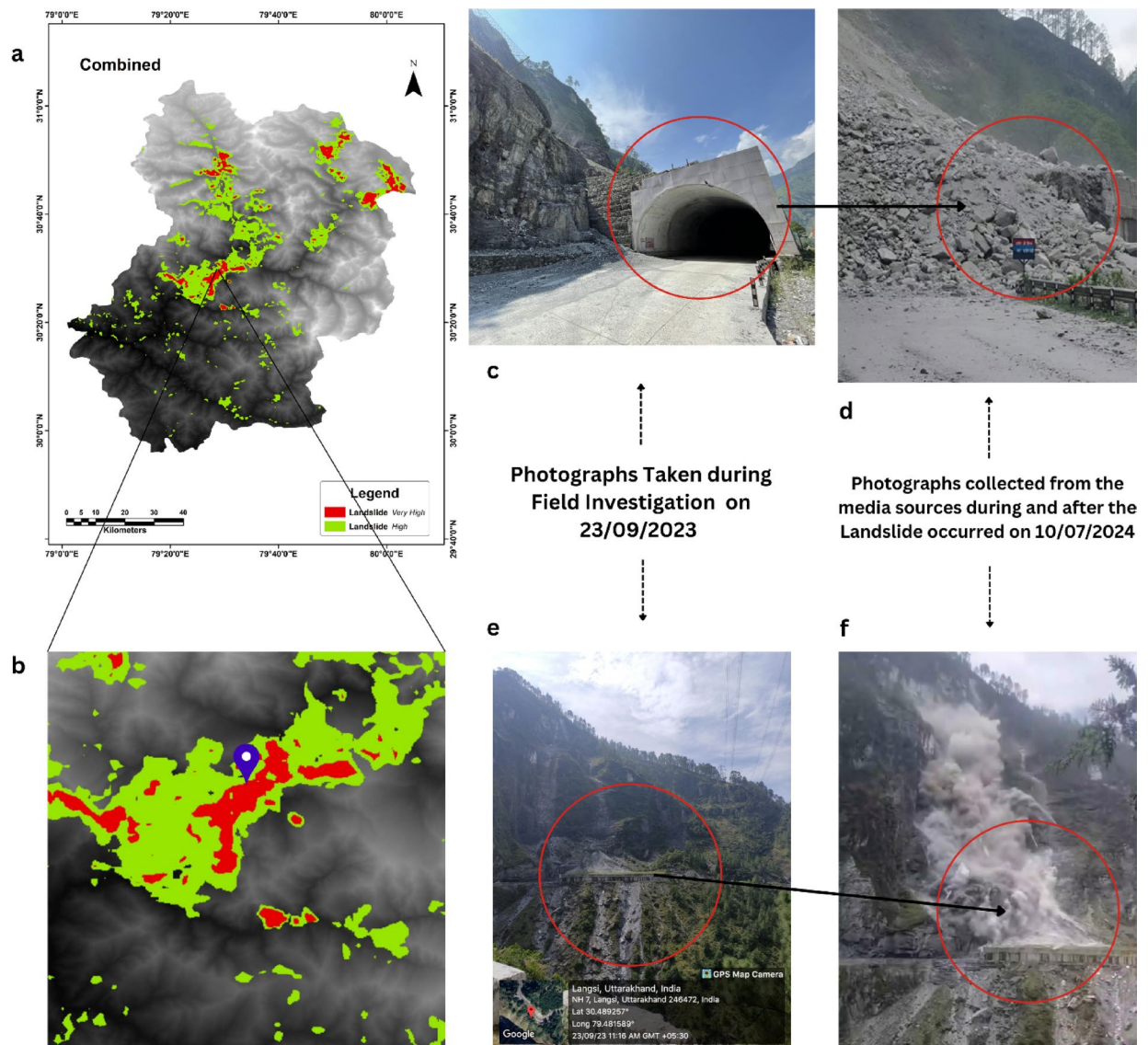


Fig. 9. (a) Intersected combined impedance composite map. (b) Zoomed (a) at the location of Patalganga Landslide. (c,e) Field photographs taken during filed verification of (a) map. (d,f) showing the Patalganga Landslide that has taken place.

zone is generated to mark the division between the vulnerable and non-vulnerable buildings. These buildings are detected using SAM algorithm and then fine-tuned. The ground information of the buildings is collected for generating 3D buildings, providing the visual representation of the actual scenario. Finally, a 3D building vulnerability map is generated using ArcGIS Pro 3.1, highlighting the buildings with cracks and the buildings with potential exposure to landslides as shown in Fig. 14. Furthermore, the 3D models allowed for the simulation and understanding of the spatial distribution of the buildings and their structural vulnerabilities. This enhanced visualization helped identify critical areas that require further attention and mitigation measures. The realistic results obtained from the 3D models provided valuable insights into the structural conditions, demonstrating the effectiveness of 3D modelling in accurately representing and analyzing complex structural data.

Conclusion

In this research, we deployed both deductive and inductive methodologies to carry out an in-depth investigation. Keeping in mind, that precise Landslide Susceptibility Mapping (LSM) is essential for effective risk assessment and disaster prevention, the primary aim is to achieve a better level of accuracy for the landslide prediction, that accurately correlates to the actual ground circumstances, so that further study can be conducted based on these LSM outcome. Recognizing the limitations of individual machine learning (ML) and deep learning algorithms, in spite of higher level of model accuracy, the adoption of a “Spatial Ensemble” technique emerges as a unique and important approach. Integrating results from multiple algorithms (DenseNet Neural Network, MLPNN, and XGBoost) based on landslide conditioning factors, the overall LSM prediction accuracy is enhanced. This

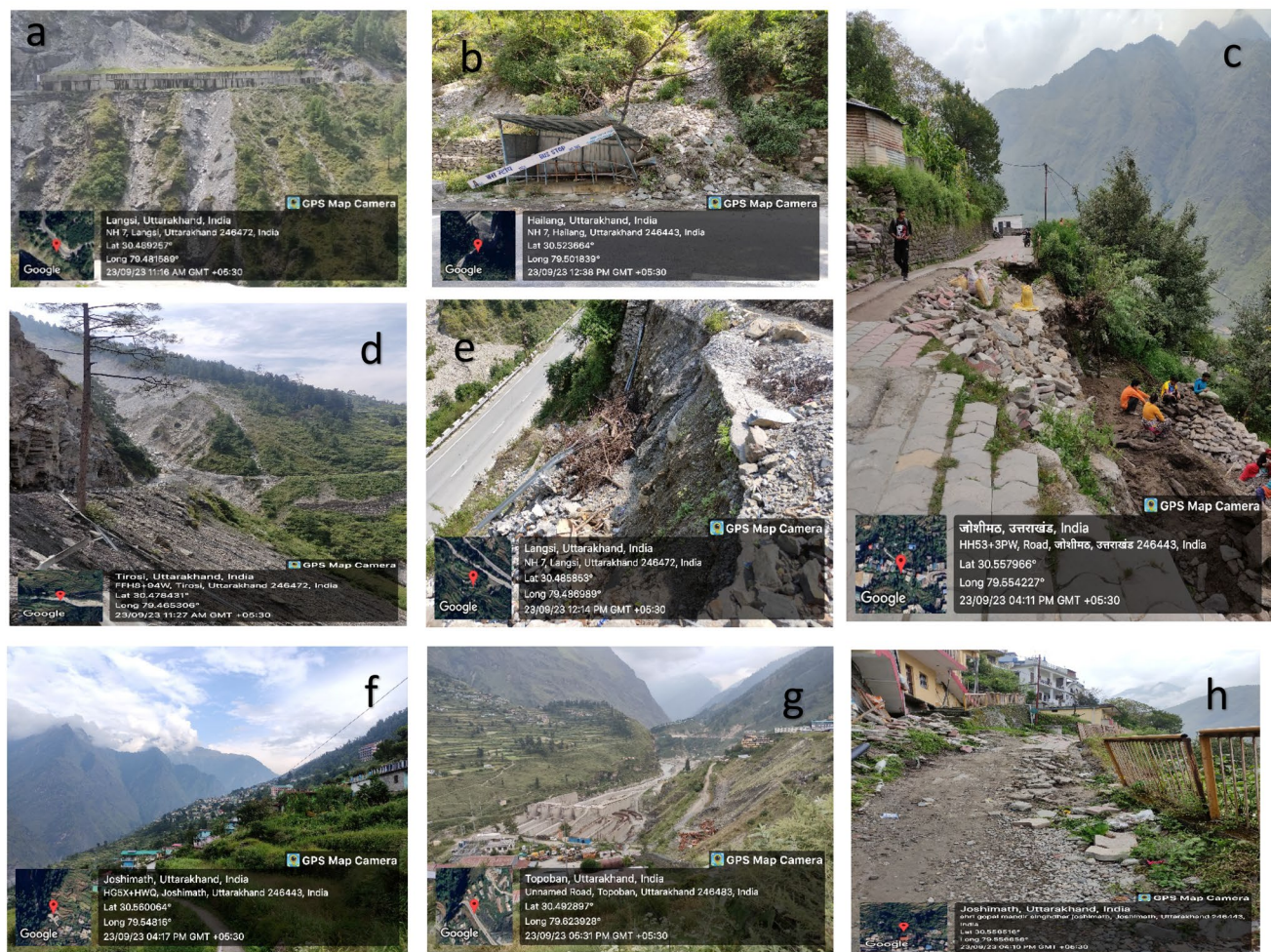


Fig. 10. Landslide risk zones identified by the researcher during field visit. (a,b,d,e,f,g) are previous landslide zone and also predicted by the author in Combined Intersected Landslide Impendence Map. (c,h) are new landslide triggered recently are identified during field investigation based on the above-mentioned map by the author.

ensemble approach leverages the strengths of individual algorithm while reducing their individual limitations, resulting in more robust and reliable landslide susceptibility assessments. From identifying new landslide on ground (from the outcome of LSM) to the application of sophisticated Segment Anything Model (SAM) for assessment of the potential vulnerability of the buildings, we introduced a unique meticulous approach that integrates computational modeling with rigorous field surveys to generate accurate conclusions. The validation process is not only strengthened by conducting a thorough literature review of recent work, which precisely identified structures with cracks in the same overlapping zone of landslide risk but also with the recent event of Patalganga landslide of 2024, that has been predicted in the combined intersected Landslide Impendence Composite map created in 2023. In addition, the existence of a fault line (Fig. 12) beneath the surface strengthened our process of validation. Most importantly, the area has a crucial bridge down the slope, that crosses the Alakananda River. If the landslide triggers, it would have crucial impacts on the transportation infrastructure. In the concluding section of this research, we also found it is essential to acknowledge the limitations and suggest future directions. The current study's impendence mapping is developed only with three models. Future research incorporating enhanced deep learning algorithms could provide more comprehensive insights into spatial ensemble techniques. Additionally, the deployment of more accurate Digital Elevation Models (DEM) and high-resolution satellite imagery will enhance the foundation of preconditioning factors. Machine learning-based rainfall prediction can significantly improve the accuracy of responses to triggering factors. There is always room for improvement in the spatial ensemble technique, and this paper serves as the foundational building block for further advancements in landslide risk assessment. Moving forward, we anticipate that these enhancements will lead to more robust and precise prediction models, ultimately contributing to better predictive capabilities and risk mitigation strategies. Thus, the advancements suggested here pave the way for a novel multidisciplinary research based on geospatial analysis and Artificial Intelligence (Deep Learning, ML and SAM) contributes essential insights to reduce disasters risk, highlighting the need of early mitigation strategies and resilient infrastructure development in the study area.

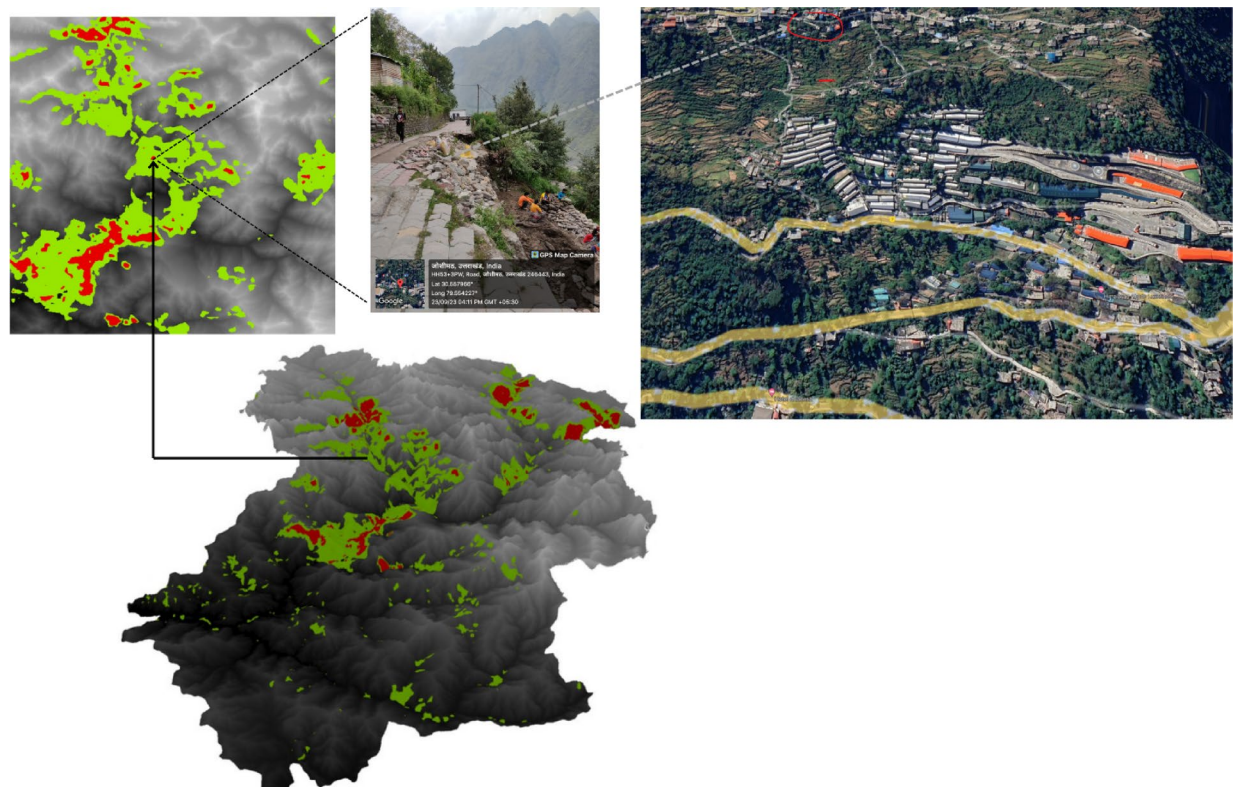


Fig. 11. Detailed location of the fresh landslide that has been identified during field verification.

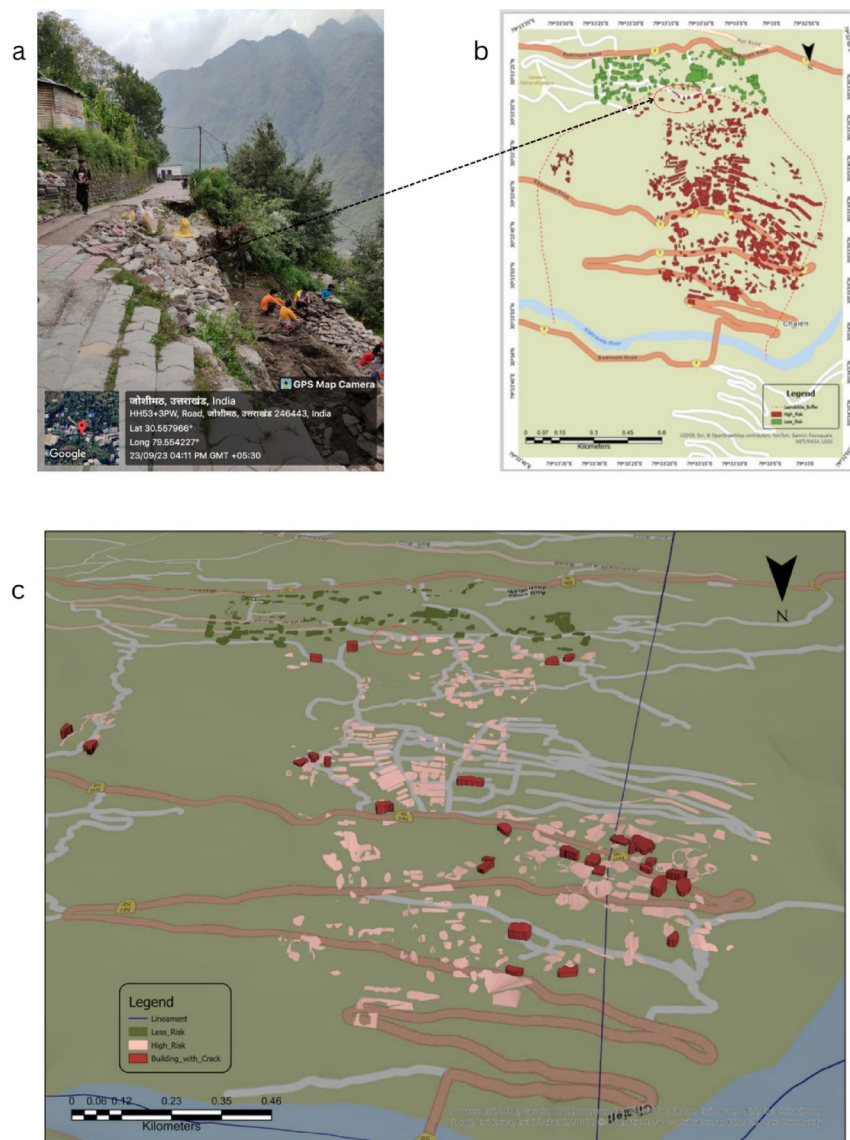


Fig. 12. (a) Field Photograph of location of new landslide. (b) Location of the landslide marked in red circle along with the buildings and landslide risk zone demarcation. (c) 3D visualization of the detailed scenario of the area along with the fault line beneath the area. Map is created using ArcGIS Pro 3.1 (<https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview>).

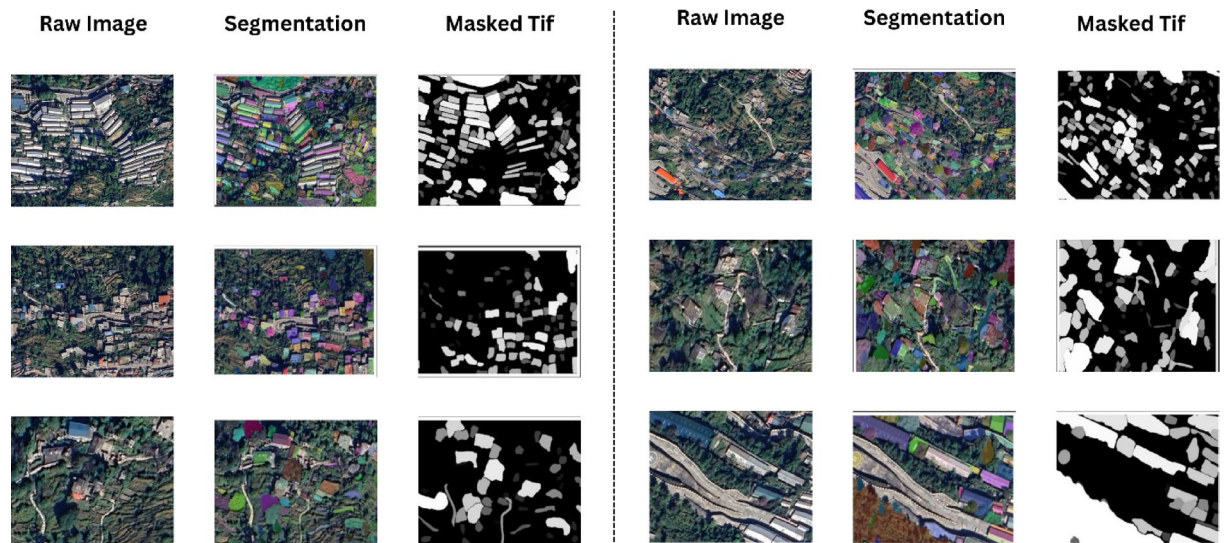


Fig. 13. Detailed procedure of segment anything model for auto detection of the buildings in the study area.



Fig. 14. 3D Map of the Buildings in safe zone (Green), Landslide risk zone demarcation (broken red line), Buildings vulnerable to landslide zone (Pink) and buildings with cracks (red). Map is created using ArcGIS Pro 3.1 (<https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview>).

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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References

- Stanley, T. & Kirschbaum, D. B. A heuristic approach to global landslide susceptibility mapping. *Nat. Hazards* **87**, 145–164 (2017).
- Das, S., Sarkar, S. & Kanungo, D. P. A critical review on landslide susceptibility zonation: Recent trends, techniques, and practices in Indian Himalaya. *Nat. Hazards* **115**, 23–72 (2023).
- Pardeshi, S. D., Autade, S. E. & Pardeshi, S. S. Landslide hazard assessment: Recent trends and techniques. *Springerplus* **2**, 523 (2013).
- Thiruganham, H. Deep Learning in Landslide Studies: A Review. in *Progress in Landslide Research and Technology, Volume 1 Issue 2*, 2022 (eds. Alcántara-Ayala, I. et al.) 247–255 (Springer International Publishing, Cham, 2023). https://doi.org/10.1007/978-3-031-18471-0_20.
- Huang, W. et al. Landslide susceptibility mapping and dynamic response along the Sichuan-Tibet transportation corridor using deep learning algorithms. *CATENA* **222**, 106866 (2023).
- Liu, S., Wang, L., Zhang, W., He, Y. & Pijush, S. A comprehensive review of machine learning-based methods in landslide susceptibility mapping. *Geol. J.* **58**, 2283–2301 (2023).
- Agboola, G., Beni, L. H., Elbayoumi, T. & Thompson, G. Optimizing landslide susceptibility mapping using machine learning and geospatial techniques. *Ecol. Inform.* **81**, 102583 (2024).
- Saha, S. et al. Application of RBF and MLP Neural Networks Integrating with Rotation Forest in Modeling Landslide Susceptibility of Sampheling, Bhutan. (Springer Singapore, 2022). https://doi.org/10.1007/978-981-16-7314-6_10.
- Hussain, M. A., Chen, Z., Zheng, Y., Zhou, Y. & Daud, H. Deep learning and machine learning models for landslide susceptibility mapping with remote sensing data. *Remote Sens.* **15** (2023).
- Hasan, N., Bao, Y., Shawon, A. & Huang, Y. DenseNet convolutional neural networks application for predicting COVID-19 using CT Image. *SN Comput. Sci.* **2**, 389 (2021).
- Saha, S. et al. Application of RBF and MLP neural networks integrating with rotation forest in modeling landslide susceptibility of sampheling, Bhutan. in *Impact of Climate Change, Land Use and Land Cover, and Socio-economic Dynamics on Landslides* (eds. Sarkar, R., Shaw, R. & Pradhan, B.) 221–245 (Springer Nature Singapore, Singapore, 2022). https://doi.org/10.1007/978-981-16-7314-6_10.
- Zhang, J. et al. Insights into geospatial heterogeneity of landslide susceptibility based on the SHAP-XGBoost model. *J. Environ. Manag.* **332**, 117357 (2023).
- Hong, H., Wang, D., Zhu, A. X. & Wang, Y. Landslide susceptibility mapping based on the reliability of landslide and non-landslide sample. *Expert Syst. Appl.* **243**, 122933 (2024).
- Oh, H.-J. & Lee, S. Cross-application used to validate landslide susceptibility maps using a probabilistic model from Korea. *Environ. Earth Sci.* **64**, 395–409 (2011).
- Wu, Q. Leafmap: A Python package for interactive mapping and geospatial analysis with minimal coding in a Jupyter environment. *J. Open Source Softw.* **6**, 3414 (2021).
- Kirillov, A. et al. Segment anything. *Proc. IEEE International Conference on Computer Vision* 3992–4003 (2023) <https://doi.org/10.1109/ICCV51070.2023.00371>.
- Sun, X. et al. Research Progress on Few-Shot Learning for Remote Sensing Image Interpretation. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **14**, 2387–2402 (2021).
- Alayrac, J. B. et al. Flamingo: A visual language model for few-shot learning. *Adv. Neural Inf. Process. Syst.* **35** (2022).
- Wang, D. et al. SAMRS: Scaling-up remote sensing segmentation dataset with segment anything model. in *Advances in Neural Information Processing Systems* (eds. Oh, A. et al.) vol. 36 8815–8827 (Curran Associates, Inc., 2023).
- Sangeeta & Maheshwari, B. K. Earthquake-induced landslide hazard assessment of Chamoli District, Uttarakhand using relative frequency ratio method. *Indian Geotech. J.* **49**, 108–123 (2019).
- Yin, A. Cenozoic tectonic evolution of the Himalayan orogen as constrained by along-strike variation of structural geometry, exhumation history, and foreland sedimentation. *Earth-Sci. Rev.* **76**, 1–131 (2006).
- Azarafza, M., Azarafza, M., Akgün, H., Atkinson, P. M. & Derakhshani, R. Deep learning-based landslide susceptibility mapping. *Sci. Rep.* **11**, 24112 (2021).
- Wang, Y., Fang, Z., Wang, M., Peng, L. & Hong, H. Comparative study of landslide susceptibility mapping with different recurrent neural networks. *Comput. Geosci.* **138**, 104445 (2020).
- Bookhagen, B. & Burbank, D. W. Toward a complete Himalayan hydrological budget: Spatiotemporal distribution of snowmelt and rainfall and their impact on river discharge. *J. Geophys. Res. Earth Surf.* **115** (2010).
- Google Earth. <https://earth.google.com/web/@0,-2.814,0a,22251752.77375655d,35y,0h,0t,0r/data=OgMKATA> (2024).
- Bhukosh. <https://bhukosh.gsi.gov.in/Bhukosh/Public> (2024).
- 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.* **12**, 639–655 (2021).
- Zhu, Y. & Newsam, S. DenseNet for dense flow. in *2017 IEEE International Conference on Image Processing (ICIP)* 790–794 (2017). <https://doi.org/10.1109/ICIP.2017.8296389>.
- Huang, G., Liu, Z. & Weinberger, K. Densely Connected Convolutional Networks. (2016).
- Sahin, E. K. Implementation of free and open-source semi-automatic feature engineering tool in landslide susceptibility mapping using the machine-learning algorithms RF, SVM, and XGBoost. *Stoch. Environ. Res. Risk Assess.* **37**, 1067–1092 (2023).
- Sahin, E. K. Assessing the predictive capability of ensemble tree methods for landslide susceptibility mapping using XGBoost, gradient boosting machine, and random forest. *SN Appl. Sci.* **2**, 1–17 (2020).
- Pham, B. T., Tien Bui, D., Prakash, I. & Dholakia, M. B. Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. *Catena* **149**, 52–63 (2017).
- Zeng, T. et al. Assessing the imperative of conditioning factor grading in machine learning-based landslide susceptibility modeling: A critical inquiry. *CATENA* **236**, 107732 (2024).
- Zhang, W., He, Y., Wang, L., Liu, S. & Meng, X. Landslide Susceptibility mapping using random forest and extreme gradient boosting: A case study of Fengjie, Chongqing. *Geol. J.* **58**, 2372–2387 (2023).
- Jennifer, J. J. Feature elimination and comparison of machine learning algorithms in landslide susceptibility mapping. *Environ. Earth Sci.* **81**, 1–23 (2022).
- Xiao, B. et al. PAM-DenseNet: A Deep convolutional neural network for computer-aided COVID-19 diagnosis. *IEEE Trans. Cybern.* **52**, 12163–12174 (2022).
- Zhang, K., Guo, Y., Wang, X., Yuan, J. & Ding, Q. Multiple feature reweight DenseNet for image classification. *IEEE Access* **7**, 9872–9880 (2019).

38. Huang, Z., Zhu, X., Ding, M. & Zhang, X. Medical image classification using a light-weighted hybrid neural network based on PCANet and DenseNet. *IEEE Access* **8**, 24697–24712 (2020).
39. Osco, L. P. et al. The segment anything model (SAM) for remote sensing applications: From zero to one shot. *Int. J. Appl. Earth Obs. Geoinf.* **124**, 103540 (2023).
40. Kim, J. & Kim, Y. Integrated framework for unsupervised building segmentation with segment anything model-based pseudo-labeling and weakly supervised learning. *Remote Sens.* **16** (2024).
41. Arabameri, A., Pourghasemi, H. R. & Yamani, M. Applying different scenarios for landslide spatial modeling using computational intelligence methods. *Environ. Earth Sci.* **76**, 832 (2017).
42. Dick, F. & Tevaearai, H. Significance and Limitations of the p Value. *Eur. J. Vasc. Endovasc. Surg.* **50**, 815. <https://doi.org/10.1016/j.ejvs.2015.07.026> (2015).
43. Torabi Haghighi, A. et al. Land degradation risk mapping using topographic, human-induced, and geo-environmental variables and machine learning algorithms, for the Pole-Doab watershed, Iran. *Environ. Earth Sci.* **80**, 1 (2020).
44. Google. Google Collab. <https://colab.google/> (2017).
45. Awasthi, S. et al. Analyzing Joshimath's sinking: Causes, consequences, and future prospects with remote sensing techniques. *Sci. Rep.* **14**, 10876 (2024).

Author contributions

SM: Conceived the idea, collected the data, ran the experiment, field verified, and wrote the manuscript. AKS: Checked the manuscript, overall supervised, and permitted to submit the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Informed consent

Informed consent has been obtained from all study participants and/or their legal guardians for the inclusion of identifying information and/or images in this manuscript. The consent includes permission for the publication of this information/images in an online open-access publication.

Additional information

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