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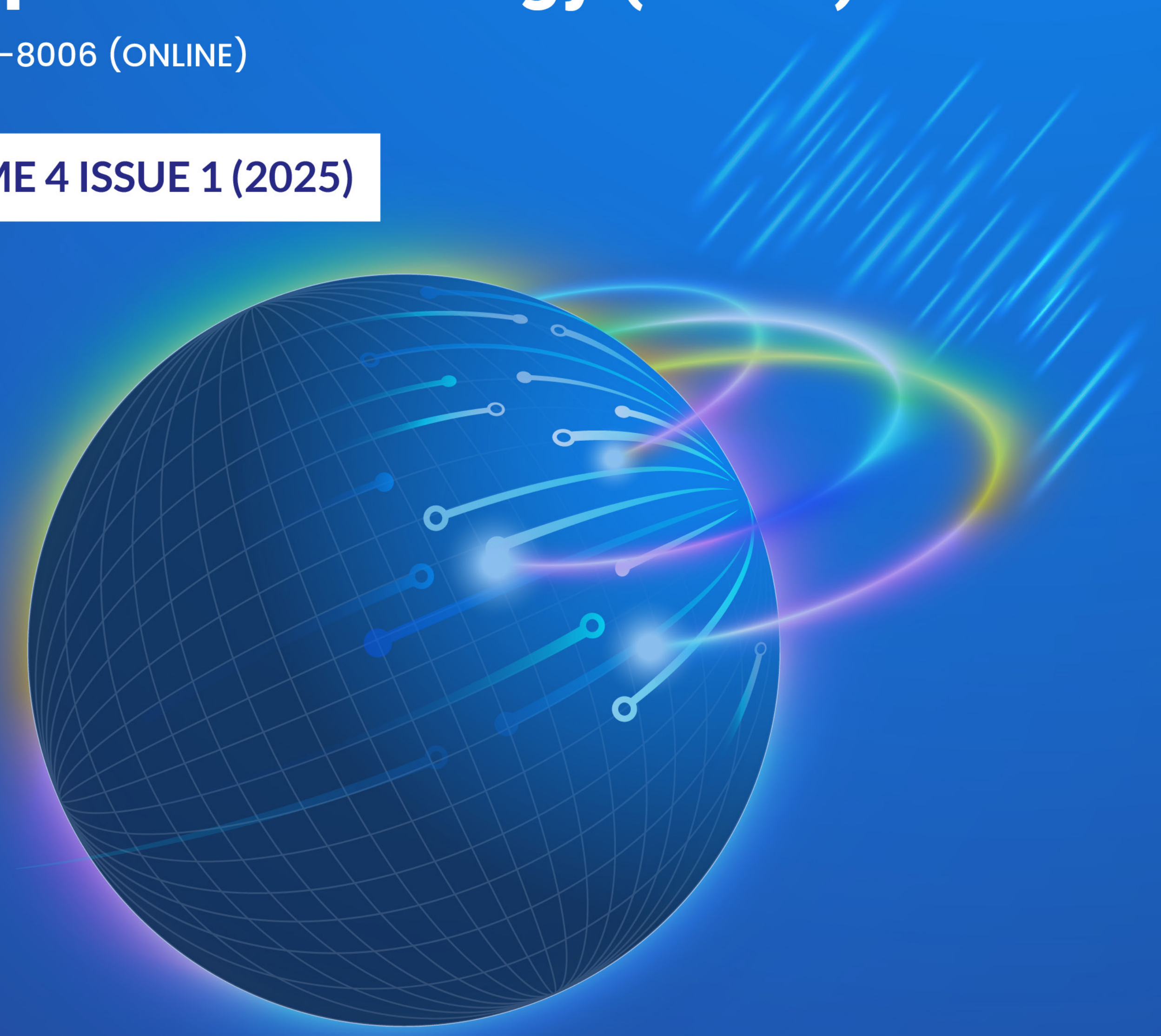

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Landslide Prediction and Mapping through Geospatial and Neural Network Approach

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ABSTRACT

Identifying landslides and creating susceptibility maps are crucial in providing planners, local officials, and decision-makers with essential tools for effective disaster management strategies. The accuracy of these maps is vital in minimizing potential loss of life and property. In order to develop comprehensive landslide susceptibility mappings, it is important to consider a range of factors that encompass both terrain characteristics and meteorological conditions. Numerous advanced algorithms have been explored in the literature to enhance the precision of these maps. This study utilizes a multi-layer perceptron neural network (MLPNN) with various activation functions, including ReLU, logistic, tanh, and identity, to compare model performance and establish the most accurate and reliable model for landslide susceptibility mapping. Nine conditioning factors were analyzed, including aspect, elevation, land use/land cover, normalized difference vegetation index (NDVI), rainfall, slope, soil type, earthquake, and lithology. The performance of the models was assessed using multiple metrics, including training score, testing score, kappa coefficient, specificity, sensitivity, and Area Under the Curve (AUC). The findings indicate that the MLPNN_logistic outperformed the other models, achieving kappa and AUC values of 0.504 and 0.757, respectively, in the development of susceptibility maps. As a result, the MLPNN_logistic model is identified as the most reliable and effective tool for landslide susceptibility mapping in this study, rendering it an optimal choice for predictive analyses in this field.

INTRODUCTION

Landslides represent one of the most catastrophic global geo-hazards, characterized by their complex geological nature and diverse occurrence across various geospatial environments and geomaterials. A landslide is defined as the mass movement of soil, rock, or debris down a slope, which involves shear displacement along one or multiple slip surfaces. These slip surfaces may range from clearly visible, such as a well-defined sliding plane, to those that are inferred based on the geologic and geomorphic conditions surrounding the area. According to the United Nations Development Program (UNDP), landslides rank as the second largest natural disaster worldwide, leading to significant human casualties and extensive property damage (Azarafza *et al.*, 2018; Pham *et al.*, 2020). The devastating impact of landslides underscores the urgent need to identify regions that are particularly prone to these events. Such identification is crucial for enhancing public safety and mitigating the adverse economic effects that can accompany landslide occurrences at both regional and national levels. In recent years, the study of landslide susceptibility zones has gained prominence in the field of hazard management. This area of research is dedicated to the development of precise and up-to-date landslide susceptibility maps, which are essential tools for various stakeholders, including government agencies, urban planners, decision-makers, and local landowners. By providing detailed insights into areas at risk, these maps empower authorities to create comprehensive emergency response plans designed to reduce the detrimental impacts of landslides on infrastructure, residential and commercial buildings, and the safety of human life. Furthermore, mapping landslide-susceptible areas is not merely a preventive measure but a strategic approach to managing the potential repercussions of landslides in vulnerable regions (Lee *et al.*, 2004; Feizizadeh *et al.*, 2014; Peethambaran *et al.*, 2020; Murthy *et al.*, 2023; Afroz *et al.*, 2022). The process of assessing landslide susceptibility, however, is inherently complex. It typically entails a thorough investigation into numerous underlying factors that contribute to susceptibility—such as topography, geology, hydrology, land use, and climatic conditions—to produce zonation maps that delineate susceptible regions with a high degree of spatial precision. Consequently, such rigorous assessments are critical for effective land use planning, risk reduction, and the formulation of policies aimed at safeguarding communities from the threats posed by landslides.

LITERATURE REVIEW

Numerous studies have been conducted for landslide susceptibility mapping by various researchers utilizing a wide range of statistical and machine-learning techniques documented in the literature. These approaches aim to identify areas prone to landslides by analyzing a combination of geospatial, environmental, and geotechnical factors. Statistical techniques, such as logistic regression, frequency ratio, and weights of evidence, have been extensively employed due to their simplicity and effectiveness in correlating landslide occurrences

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with causative factors. These models rely on historical landslide data to establish probabilistic relationships and are particularly useful for generating susceptibility maps in regions with abundant and reliable datasets. Khatun *et al.* (2022) employed a weighted overlay approach for landslide susceptibility mapping in Rangmati, Bangladesh, taking into account various conditioning factors such as soil texture, geology, lineament, slope, land use, and aspect. Arabameri *et al.* (2018) conducted a comparative study examining the analytic hierarchy process (AHP), frequency ratio (FR), index of entropy (IOE), and weight of evidence (WoE) methods for landslide risk zonation in Semnan Province, Iran, considering thirteen conditioning factors. In another study, Arabameri *et al.* (2018) compared evidential belief function (EBF), logistic regression (LR), and an ensemble of LR-EBF for landslide zonation in the same region. Bopche *et al.* (2022) utilized the weight of evidence method to create a landslide zonation map for Pune district, Maharashtra, considering ten conditioning factors. Tang *et al.* (2021) performed a comparative analysis between analytical hierarchy process information value (AHPIV) and logistic regression (LR) for landslide risk mapping in Zhushan County, China, incorporating thirteen conditioning factors. Kayastha *et al.* (2013) applied the analytical hierarchy process (AHP) for landslide zonation in the Tinau watershed, Nepal, focusing on geological, topographical, and hydrological factors. Regmi *et al.* (2014) compared the weight of evidence (WoE) and frequency ratio (FR) methods for landslide mapping in the Bhalubang-Shiwapur section of the Mahendra Highway in Western Nepal. Mondal *et al.* (2014) integrated the frequency ratio (FR) with the analytical hierarchy model (AHP) to develop a hybrid model for landslide zonation in the Shiv-Khola watershed, Darjeeling Himalaya, based on ten conditioning factors.

The advancement of machine learning techniques, including support vector machines (SVM), random forest (RF), artificial neural networks (ANN), and gradient boosting machines (GBM), has gathered significant attention in recent years due to their capacity to effectively manage complex, nonlinear relationships between input variables and landslide occurrences. These methodologies frequently demonstrate superior performance compared to traditional statistical models, particularly when applied to large and diverse datasets. Additionally, the emergence of hybrid models that combine statistical and machine learning approaches has proven beneficial, as they leverage the strengths of both paradigms. Kavzoglu *et al.* (2013) compared support vector machine (SVM) approaches, criteria decision analysis, and logistic regression for landslide susceptibility mapping in Trabzon Province, Turkey. Kavzoglu *et al.* (2022) conducted a comparative study examining the efficacy of extreme gradient boosting (XGBoost), random forest (RF), and natural gradient boosting (NGBoost) for landslide zonation mapping in Trabzon Province, Turkey. Park *et al.* (2012) performed a comparative analysis involving logistic regression, frequency ratio, artificial neural networks, and the analytical hierarchy process for landslide zonation in the Inje area of Korea. Additionally, Kavzoglu *et al.* (2015) investigated various methodologies including logistic regression (LR), weight of evidence (WoE), support vector regression (SVR), decision trees (DT), frequency ratio (FR), and statistical index for landslide susceptibility mapping in the Duzkoy district of Turkey. Colkesen *et al.* (2016) conducted a similar comparative study assessing the effectiveness of logistic regression, kernel-based Gaussian processes, and support vector machines for landslide susceptibility mapping in the Tonya district of Turkey. Pham *et al.* (2016) explored multiple methods, including rotation forest, random forest, bagging, naïve Bayes, AdaBoost, and MultiBoost, for landslide mapping in the Luc Yen district of Vietnam. Kalantar *et al.* (2017) compared logistic regression, support vector machines, and artificial neural networks for landslide zonation in Mazandaran Province, Iran. Park *et al.* (2019) conducted a comparative analysis of boosted regression trees and random forests for landslide zonation in the Woomyeon Mountain region of South Korea. Hong *et al.* (2020) examined ensemble methods, specifically Forest by Penalizing Attributes (FPA) in conjunction with Bagging and LogitBoost alternating decision trees (LADT) with Bagging, for landslide zonation in the Youfanggou district of China. Furthermore, support vector machines were utilized to analyze the predictive capability of conditioning factors within this context. Karakas *et al.* (2022) conducted a comparative study between multi-layer perceptron (MLP) and random forest methods for landslide zonation in Elazig, Turkey.

Recent studies in the literature predominantly focus on mitigating landslide risk by identifying zones susceptible to such events, primarily through the comparison of various statistical and machine learning models. These studies underscore the significance of selecting appropriate algorithms and feature sets to generate accurate susceptibility maps. Furthermore, a considerable number of researchers have examined the variation of hyperparameters in both standalone and ensemble models. However, a critical gap exists in the existing literature regarding the impact of hyperparameter variations on the performance of neural networks. This area has been inadequately addressed, leading to the potential for suboptimal models that may either overfit the training data or fail to effectively capture the underlying patterns within the dataset. Additionally, the absence of comprehensive analysis concerning hyperparameter settings complicates the assessment of different models' true capabilities or their suitability for specific datasets and geographical contexts. In response to this gap, the present study utilizes a multi-layer perceptron neural network (MLPNN) to investigate how variations in activation functions—namely 'relu', 'logistic', 'identity', and 'tanh'—influence model performance. This examination of hyperparameter variations aims to provide valuable insights into the robustness and stability of the models. Such analyses are essential for the development of reliable models that can be utilized effectively in real-world environments, where data availability and quality may vary significantly. The performance evaluation will be conducted utilizing ROC and kappa metrics, which will facilitate objective and comprehensive comparisons among the methods employed. This approach is expected to enhance the understanding of model behavior and contribute to the advancement of effective solutions in landslide risk management.

MATERIALS AND METHODS

Study Area

Sikkim, a small yet vital state nestled in the North-Eastern Himalayas of India, spans 7,096 square kilometers of striking and diverse landscapes. Featuring a young mountain system, the region boasts an array of geological wonders while also presenting challenges due to its susceptibility to landslides and seismic activity (Figure 1). The vibrant capital, Gangtok, serves as a central hub for exploring a remarkable range of elevations from 300 to 8,000 meters above sea level, with 66% of the state's terrain being mountainous and often capped with snow. The climate of Sikkim is uniquely varied, transitioning from tropical to alpine, which fosters an extraordinary ecosystem. Notably, rainfall in Gangtok is substantial at 3,494 mm, in stark contrast to the minimal 82 mm in Thangu. This climatic diversity supports a rich tapestry of life, contributing to Sikkim's multi-ethnic population and vibrant cultural heritage. As of 2011, the state represented less than 0.05% of India's total population, with a population density of 86 people per square kilometer. This blend of diversity and stunning natural beauty makes Sikkim an important area for ecological and cultural exploration.

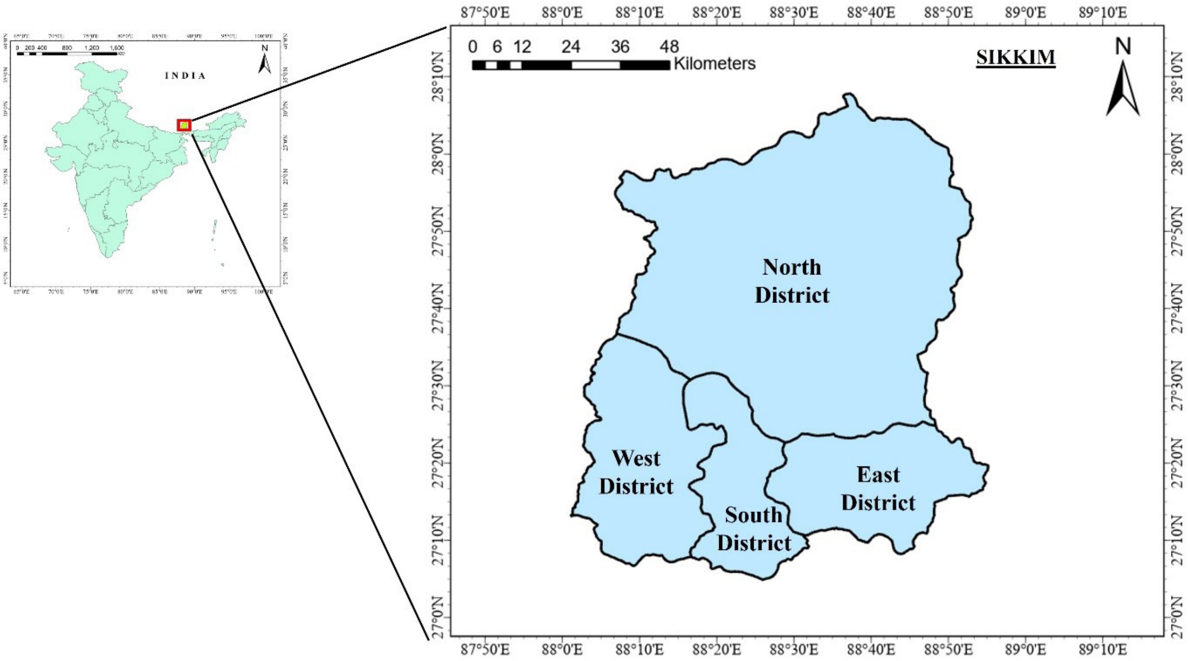


Figure 1: Study Area Map

However, the uneven population distribution in Gangtok has created a unique set of challenges for urban development and service delivery. The rapid growth of the population in a confined area has led to increased pressure on transportation systems, housing availability, and modern commercial development. As a result, addressing traffic congestion, housing shortages, and the emergence of informal settlements is a priority. It is essential for Gangtok to find sustainable solutions to balance development with environmental preservation. Geologically, the Sikkim Himalaya, particularly along the Teesta Valley, is defined by the Main Central Thrust (MCT) and Main Boundary Thrust (MBT) zones, which delineate various grades of Himalayan rocks. The central crystalline area in North Sikkim features high-grade gneisses, migmatites, and granitic intrusions, highlighting the region's complex geological history. Additionally, Sikkim's position in Zone IV on India's Seismic Zoning Map underscores the importance of earthquake preparedness and sustainable planning to ensure the safety and resilience of its communities.

Landslide Conditioning Factors (LCFs)

The study identified nine key conditioning factors essential for accurate landslide susceptibility mapping, along with an analysis of their spatial distribution (Figure 2). The slope map of the study area has been categorized into five distinct classes: 0-15° (very low), 15-25° (low), 25-35° (moderate), 35-45° (high), and 45-90° (very high). The aspect map has been classified into nine categories, including flat, north, northeast, east, southeast, south, southwest, west, and northwest. The elevation map is divided into three classes: (i) 222 – 2460 m, (ii) 2460 – 4227 m, and (iii) 4227 – 7899 m. The land use/land cover (LULC) map is classified into nine categories: (i) Water, (ii) Trees, (iii) Flooded vegetation, (iv) Crops, (v)

Built area, (vi) Bare ground, (vii) Snow/ice, (viii) Clouds, and (ix) Rangeland. The normalized difference vegetation index (NDVI) map is classified into five classes: (i) (-) 0.603 – 0.025, (ii) 0.026 – 0.125, (iii) 0.126 – 0.232, (iv) 0.233 – 0.465, and (v) 0.466 – 1. The rainfall map is divided into five categories: (i) 1000 - 1647 mm, (ii) 1648 - 2235 mm, (iii) 2236 - 2729 mm, (iv) 2730 - 3353 mm, and (v) 3354 - 4000 mm. The soil type map has been classified into five categories: (i) Humid Acrisols, (ii) Dystric Cambisols, (iii) Gleysols luvi Soils, (iv) Lithosols, and (v) Dystric Regosols. The lithology map has been classified into seven categories (i) Jurassic metamorphic and sedimentary rocks, (ii) Cretaceous and undivided igneous rocks, (iii) Mesozoic and Paleozoic intrusive and metamorphic rocks, (iv) undivided precambrian rocks, (v) undivided paleozoic rocks, (vi) Quaternary sediments and (vii) Tertiary and cretaceous sedimentary rocks. Lastly, the earthquake map is categorized into three magnitude classes: (i) 0.011 - 3.291, (ii) 3.292 - 6.018, and (iii) 6.019 - 11.794. These thematic maps were precisely prepared to enhance the analysis of landslide susceptibility by integrating them with landslide occurrence data, thereby enabling a more precise and comprehensive assessment.

Landslide Inventory

The landslide data utilized for this analysis has been obtained from Bhukosh, Geological Survey of India, encompassing a total of 693 data points, as depicted in Figure 3. These data points were imported into ArcGIS, where polygons were generated to establish a comprehensive dataset for further examination. To ensure the dataset's balance, an additional 695 non-landslide data points were randomly generated within ArcGIS, and corresponding polygons were created. By integrating the Landslide Conditioning Factors (LCFs) with both landslide and non-landslide data, a consolidated dataset comprising 12165 data points was developed. This dataset was then divided in a 70:30 ratio, with 70% allocated for training purposes and 30% for testing, to facilitate a thorough analysis.

The distribution and variability of each input variable related to landslides are presented in Figure 4. The figure demonstrates notable correlations among various features, highlighting significant relationships among them. The correlation coefficient of 0.61 between Land Use and Land Cover (LULC) and Elevation underscores how vegetation patterns and human activities vary with changes in altitude. Additionally, a moderate

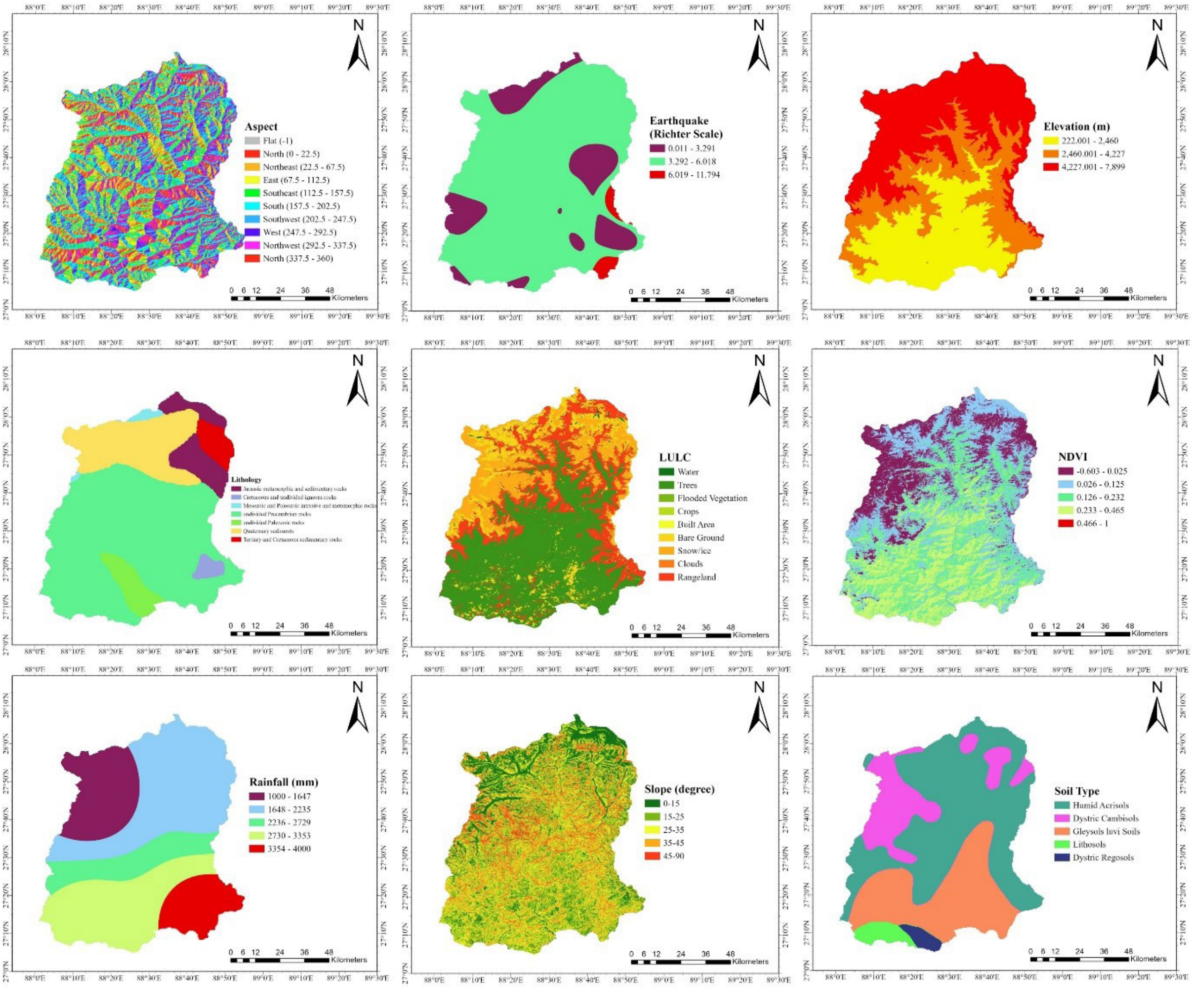


Figure 2: Landslide Conditioning Factors Map

correlation of 0.53 between the Normalized Difference Vegetation Index (NDVI) and Rainfall reveals the impact of precipitation on vegetation health and density. Furthermore, a correlation of 0.58 between Rainfall and Soil Type indicates that soil characteristics are influenced by rainfall distribution, which affects factors such as soil moisture and composition. Conversely, several features exhibit minimal correlation, suggesting weaker interdependence. For example, the weak correlation observed between Elevation and Soil Type suggests that soil properties are largely independent of altitude. Similarly, the correlation between Rainfall and Elevation is low, indicating that rainfall patterns do not strongly relate to elevation variations within the region. The relationship between NDVI and Elevation is also weak, indicating that vegetation density is not significantly affected by altitude in this study area. These insights into feature correlations are essential for comprehending the interplay of factors contributing to landslide susceptibility. Identifying highly correlated features can help reduce redundancy within models, while incorporating weakly correlated features ensures the diversity and independence of factors considered in the analysis.

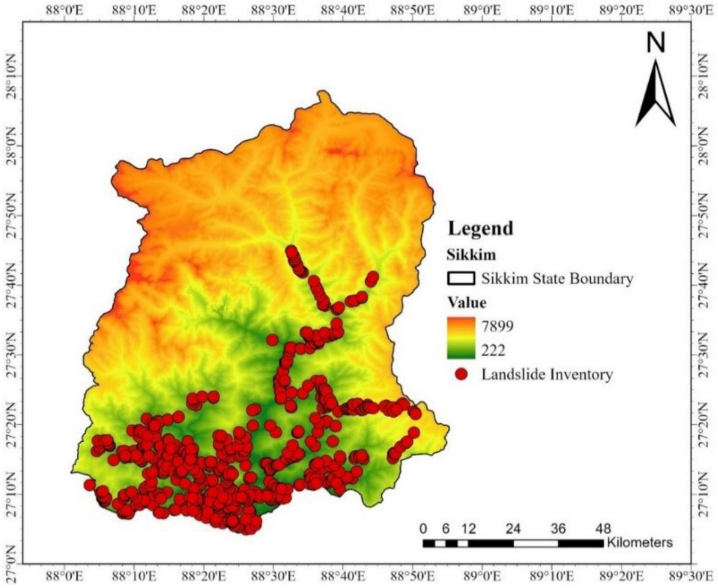


Figure 3: Landslide Inventory

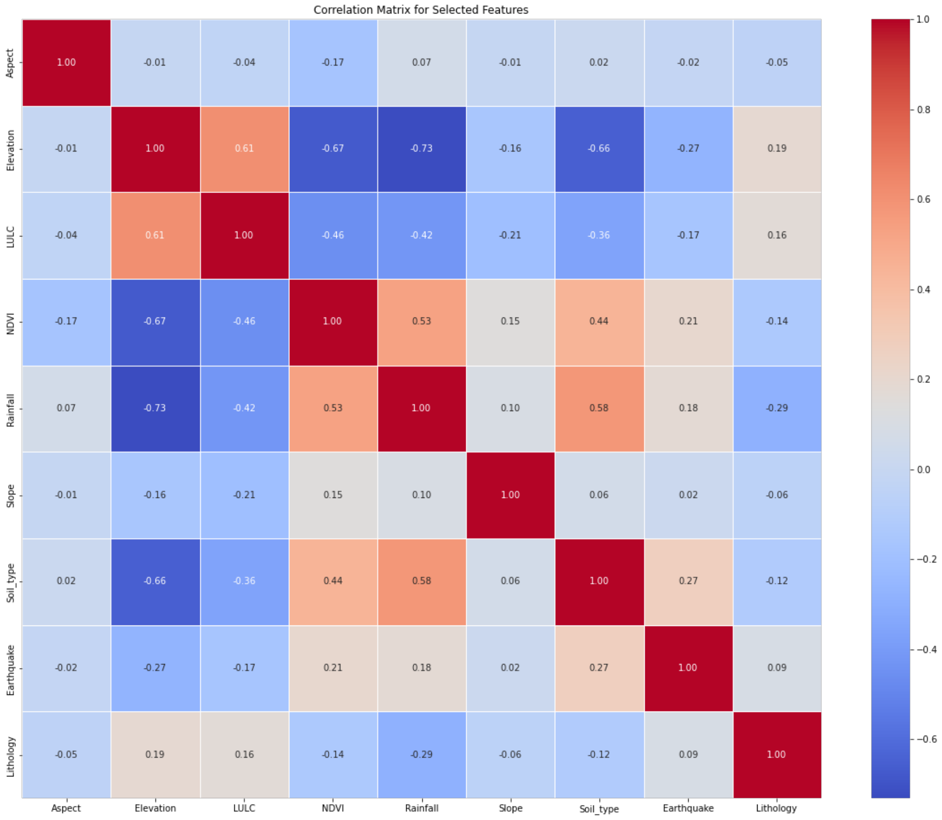


Figure 4: Correlation matrix of conditioning factors

Methodology

The methodology utilized in this study is presented in Figure 5, which outlines the systematic approach adopted to achieve reliable landslide susceptibility mapping. The research employs a Multi-Layer Perceptron Neural Network (MLPNN) to generate landslide susceptibility maps (LSMs) across a defined range of hyperparameters, detailed in Table 1. A significant focus of the study is the comparative analysis of various activation functions, specifically 'relu', 'logistic', 'tanh', and 'identity', and their effectiveness in producing LSMs. The choice of activation function is critical, as it influences the network's ability to learn complex, non-linear relationships inherent in the input data.

This is especially relevant in landslide susceptibility mapping, where the interactions among geological, hydrological, and environmental factors are often intricate and non-linear. By varying the activation functions and evaluating their impact on the model's predictive accuracy, this research aims to identify the most appropriate function for this particular application. Notably, the ReLU activation function is recognized for its computational efficiency and its effectiveness in overcoming the vanishing gradient problem, making it a widely used option in deep learning. Conversely, the sigmoid and tanh functions are more suitable for situations requiring probabilistic interpretations, as they constrain outputs within a defined range. The comparative analysis conducted in this study provides valuable insights into how different activation functions influence the overall performance of the MLPNN. This is assessed through key metrics, including kappa, sensitivity, specificity, and AUC. The findings contribute to an enhanced understanding of the model's capabilities and offer guidance for the refinement of methodologies in landslide susceptibility mapping.

Table 1: MLPNN hyperparameter settings

Hyperparameter	**Values**
solver	adam
activation	relu; logistic; tanh; identity
hidden layer	[50,50,50,50,50]
max_iter	500
learning_rate	adaptive
learning_rate	0.01

Furthermore, hyperparameters are essential in optimizing the model's performance. By systematically adjusting these parameters, we aim to prevent underfitting and overfitting, thereby enhancing the model's effectiveness with the training data. This careful calibration has enabled us to generate a series of Landslide Susceptibility Maps (LSMs), which were subsequently compared to identify the most effective model. These maps were visually represented and validated against ground-truth data as well as historical landslide occurrences, providing a comprehensive assessment of their reliability. The comparative analysis yields critical insights into how various activation functions can influence the model's performance and predictive accuracy. The methodology adopted in this study exemplifies a meticulous and systematic approach to landslide susceptibility mapping. By harnessing the capabilities of MLPNN and investigating a wide range of hyperparameters and activation functions, this research establishes a robust framework for the development of high-quality LSMs.

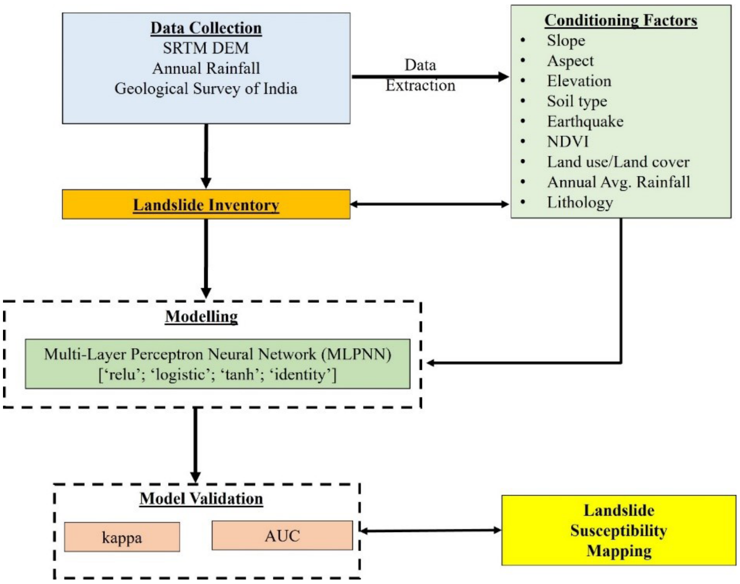


Figure 5: Methodology of the study

RESULTS AND DISCUSSION

The study utilized a Multi-Layer Perceptron Neural Network (MLPNN) to conduct a comparative analysis of various activation functions, specifically 'relu', 'logistic', 'tanh', and 'identity', in the context of generating landslide susceptibility maps. These activation functions were selected for their distinct characteristics and prevalent application in neural network methodologies, particularly for addressing non-linear classification challenges. The primary objective of the study was to identify the activation function that is most effective for landslide susceptibility mapping by examining its impact on the overall performance of the model. Optimal hyperparameters for each configuration—including the number of hidden layers, neurons per layer, learning rate, and maximum iterations—were rigorously determined through systematic experimentation, as detailed in Table 1. Careful fine-tuning of these hyperparameters was conducted to ensure that the MLPNN accurately captured the underlying patterns within the input data while preventing both overfitting and underfitting. To facilitate a fair and unbiased evaluation, the selected configurations were consistently applied across all activation functions. The model's performance was assessed using a range of metrics, including training score, testing score, specificity, sensitivity, kappa, and area under the curve (AUC). This comparative analysis of the resulting maps provided valuable insights into the influence of different activation functions on the model's accuracy, robustness, and overall capacity to effectively predict landslide-prone areas.

The ROC curves presented in Figure 6 detail the classification performance of the various models, with the AUC values underscoring their capacity to differentiate between classes. The AUC values for the models are as follows: 0.757 for MLPNN_logistic, 0.751 for MLPNN_relu, 0.750 for MLPNN_tanh, and 0.736 for MLPNN_identity. These results highlight the differing effectiveness of the activation functions in distinguishing between landslide-prone and stable areas. In addition to the AUC analysis, Figure 7 provides a comprehensive overview of the models performance across multiple metrics, including training scores, testing scores, sensitivity, specificity, and kappa coefficient. The MLPNN_relu model exhibited a commendable balance between training and testing performance, achieving scores of 0.742 and 0.740, respectively. Its high sensitivity of 0.908 indicates an excellent capacity for identifying landslide-prone areas; however, its specificity of 0.594 suggests a higher incidence of false positives. Conversely, the MLPNN_logistic model attained the highest kappa value of 0.504, signifying superior agreement between predicted and actual classifications. With a training score of 0.760, a testing score of 0.748, a sensitivity of 0.883, and a specificity of 0.631, the logistic activation function emerged as the most robust overall. The MLPNN_tanh function demonstrated consistent performance, with training and testing scores of 0.745 and 0.741, respectively. Its sensitivity of 0.875 and specificity of 0.624 render it a competitive option. While MLPNN_identity achieved the highest specificity of 0.673, indicating fewer false positives, it recorded the lowest sensitivity at 0.798, which hampers its effectiveness in identifying landslide-prone areas. The kappa value of 0.466 further reflects lower consistency compared to the other activation functions.

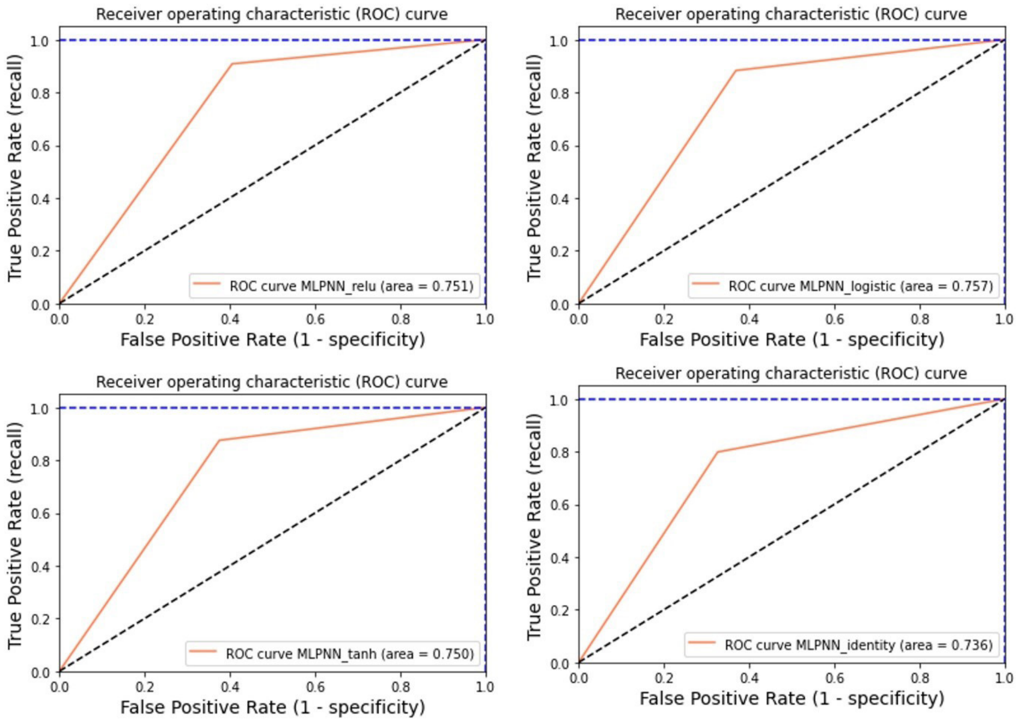
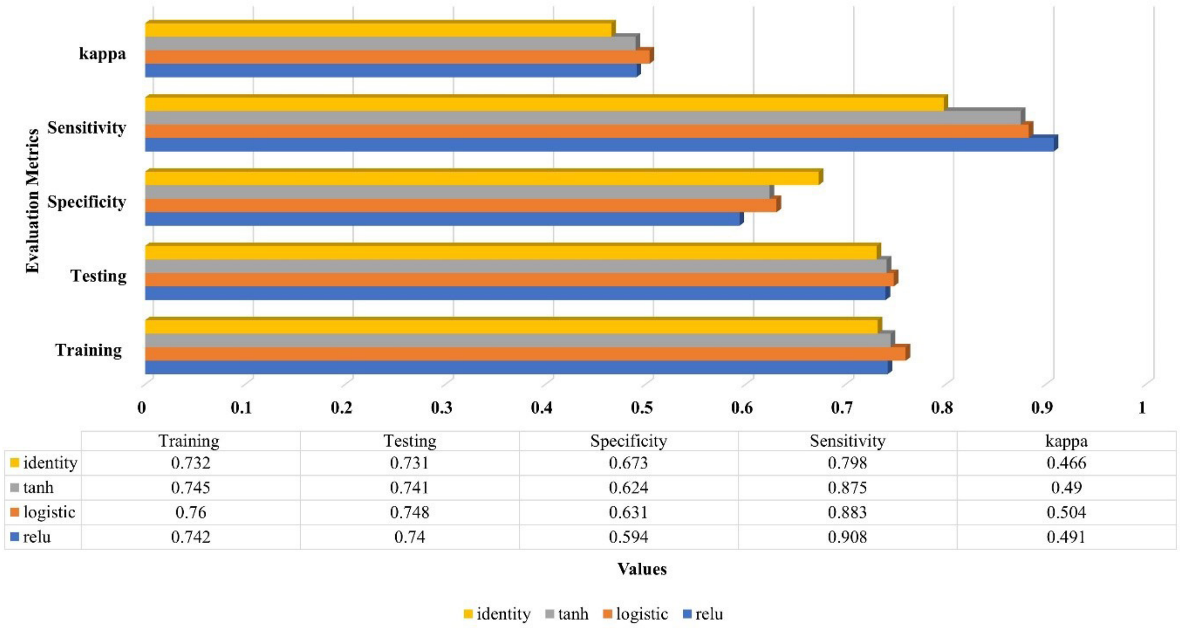


Figure 6: ROC curves of MLPNN models



	Training	Testing	Specificity	Sensitivity	kappa
identity	0.732	0.731	0.673	0.798	0.466
tanh	0.745	0.741	0.624	0.875	0.49
logistic	0.76	0.748	0.631	0.883	0.504
relu	0.742	0.74	0.594	0.908	0.491

Figure 7: Evaluation metrics

The evaluation metrics, along with the confusion matrices presented in Figure 8, offer a comprehensive analysis of the predictive accuracy of the models. These matrices detail the distribution of true positives, true negatives, false positives, and false negatives, thereby providing valuable insights into the classification performance of each model. The confusion matrix for MLPNN_identity indicates the highest number of misclassifications, totaling 979 instances. This finding suggests a relatively lower predictive accuracy, which is further reflected in its AUC score of 0.736. Similarly, MLPNN_relu shows 946 misclassifications, indicating limitations in its predictive capabilities despite its competitive AUC of 0.751 and commendable sensitivity. In comparison, MLPNN_tanh recorded 944 misclassifications, demonstrating slightly better performance than the ReLU activation function, yet still not achieving optimal classification results. Notably, MLPNN_logistic exhibited the lowest number of misclassifications at 918, showcasing superior classification abilities relative to the other activation functions. This outcome aligns with its highest AUC value of 0.757, further affirming its effectiveness in differentiating between classes. The reduced misclassification rate observed in MLPNN_logistic emphasizes its potential for practical applications, particularly in contexts where minimizing errors is crucial for reliable landslide susceptibility mapping.

The landslide susceptibility maps generated mentioned earlier are illustrated in Figure 9. These maps categorize the terrain into distinct susceptibility levels, serving as an essential tool for identifying high-risk areas and informing effective mitigation strategies. Figure 10 further quantifies the spatial distribution by depicting the percentage of the study area encompassed within each susceptibility classification—very low, low, moderate, high, and very high—across the various machine learning models. This analysis provides valuable insights into how different activation functions influence the classification of susceptibility zones. For the MLPNN_relu model, a significant portion of the study area, 26.79%, is predicted to fall into the "very high" susceptibility class, indicating notable areas of risk. In contrast, only 5.74% of the area is classified as "very low," which suggests a limited extent of minimal risk zones. This pattern illustrates the model's tendency to identify areas with heightened susceptibility. In the case of the MLPNN_logistic model, the "high" susceptibility class occupies the largest area at 25.96%, while the "very low" class covers the smallest area at 6.27%. This distribution indicates a more balanced classification approach compared to other models, with a focus on moderately high-risk zones. For the MLPNN_tanh model, the "low" susceptibility class is predominant, encompassing 27.46% of the area, whereas the "very low" class represents only 6.42%.

This outcome underscores the model's inclination to categorize a larger proportion of the terrain as having lower susceptibility, which may reflect a conservative classification strategy. Lastly, the MLPNN_identity model exhibits a distinctive distribution, with the "moderate" susceptibility class accounting for the largest share at 46.81%, and the "very low" class covering just 3.07% of the area. This model appears to categorize a substantial portion of the terrain into a mid-range risk category, offering a unique perspective on susceptibility zoning. The variations in area distribution among these models highlight the significant impact of activation functions and model parameters on the development of landslide susceptibility maps.

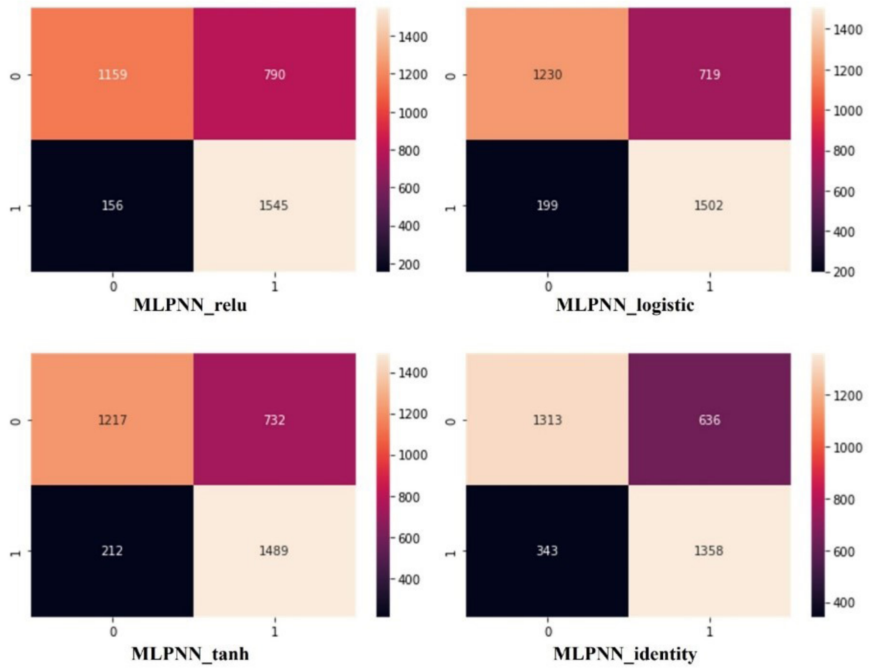


Figure 8: Confusion matrix of MLPNN models

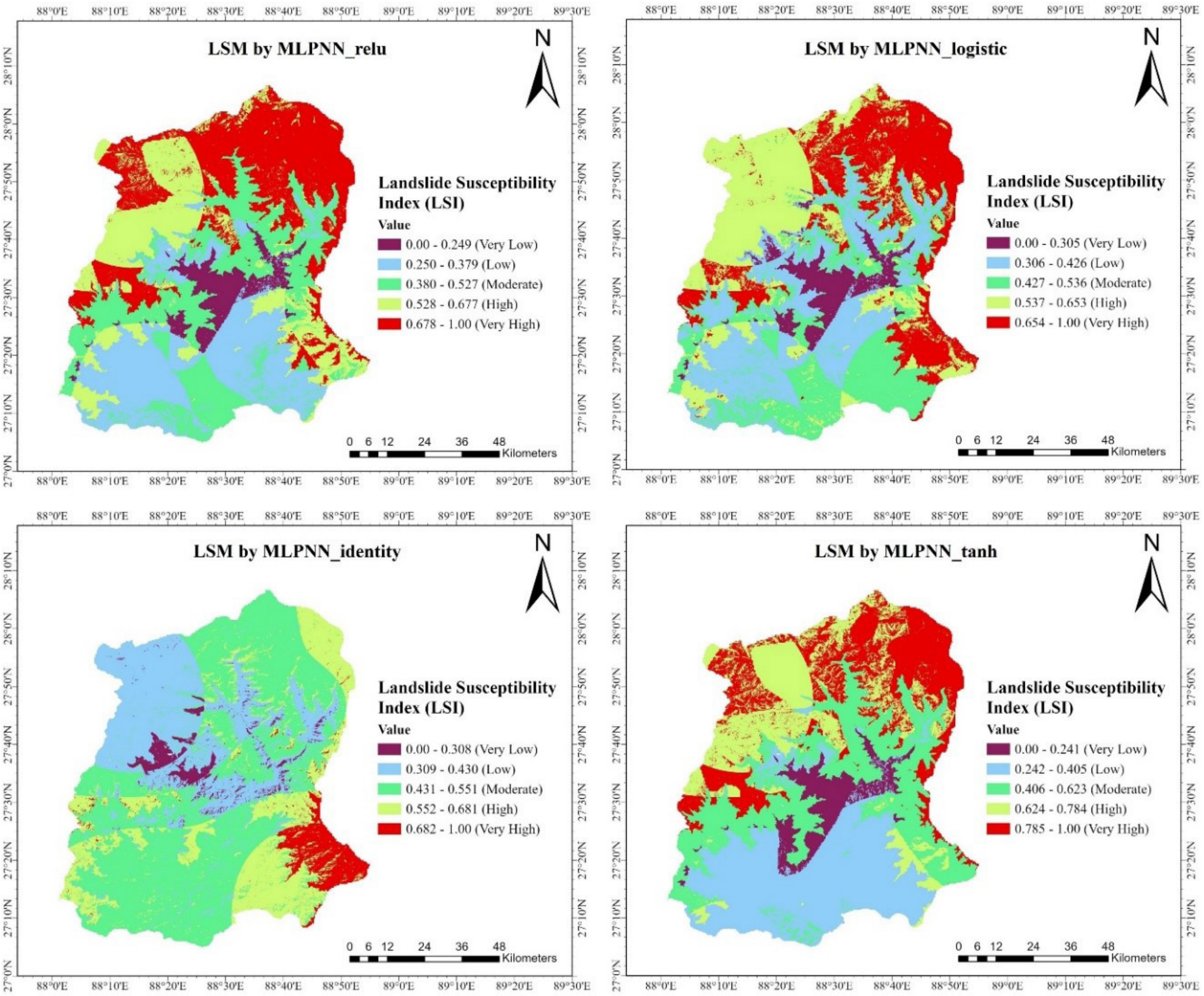


Figure 9: Generated LSM by MLPNN

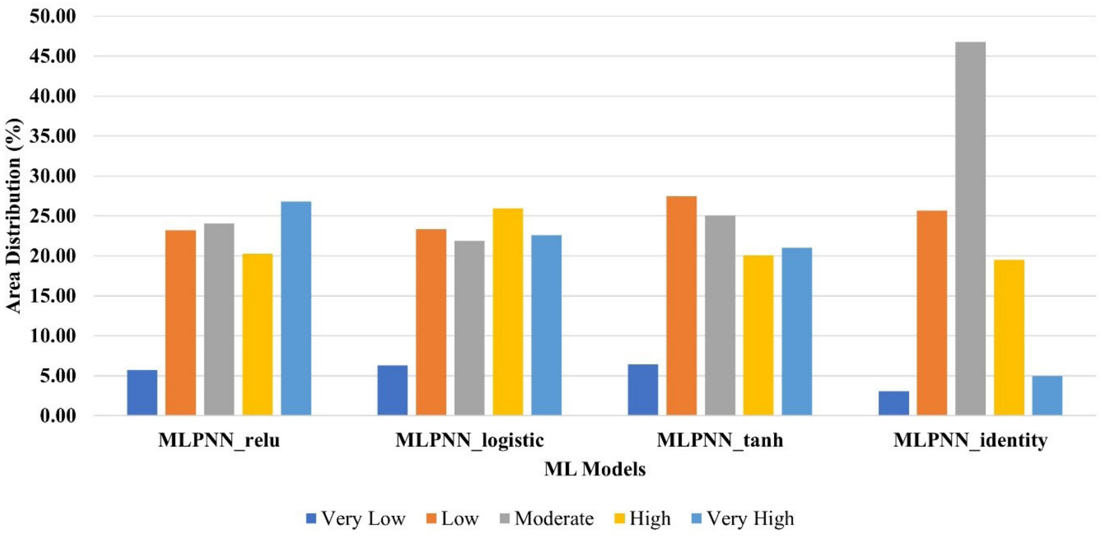


Figure 10: Area Distribution of study area by MLPNN

Overall, this analysis highlights MLPNN_logistic and MLPNN_relu as the most effective activation functions for producing accurate landslide susceptibility maps. Although logistic activation slightly surpassed ReLU in the overall metrics, ReLU's superior sensitivity makes it particularly advantageous for minimizing false negatives in identifying landslide-prone zones.

CONCLUSION

The identification of regions susceptible to landslides, along with the precise determination of their locations based on specified susceptibility levels, is essential for effective planning initiatives. Numerous methodologies have been proposed in the existing literature for the development of landslide susceptibility maps. This study assesses the efficacy of the Multilayer Perceptron Neural Network (MLPNN) in constructing accurate and reliable models for generating landslide susceptibility maps specifically for Sikkim, India. The research utilizes nine conditioning factors, which include aspect, elevation, land use/land cover, normalized difference vegetation index (NDVI), rainfall, slope, soil type, earthquake, and lithology. A comprehensive set of evaluation metrics has been employed to assess and compare the performance of the models. These metrics include training score, testing score, kappa coefficient, specificity, sensitivity, and Area Under the Curve (AUC). Such metrics provide a robust framework for analyzing the predictive accuracy and reliability of each model in classifying landslide susceptibility. The findings indicate that the MLPNN_logistic model outperformed other models based on the evaluation metrics. It achieved a kappa coefficient of 0.504, indicating a strong correlation between predicted and actual classifications while accounting for chance agreement. Additionally, the MLPNN_logistic recorded the highest AUC value of 0.757, demonstrating its exceptional capability to differentiate between classes and reliably predict landslide susceptibility.

Moreover, analysis of the confusion matrix revealed that the MLPNN_logistic model had the lowest number of misclassifications, totalling 918 incorrectly classified instances, thus establishing it as the most accurate among the evaluated models. These results underscore the MLPNN_logistic model's capability to minimize prediction errors and its robustness in managing complex datasets with multiple conditioning factors. In conclusion, the combination of a high kappa coefficient, superior AUC, and minimal misclassifications positions the MLPNN_logistic model as a reliable and effective tool for landslide susceptibility mapping, making it an optimal choice for predictive analyses in this domain.

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