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Machine Learning (ML) Approaches in Landslide Prediction: A Systematic Review and Implications for Environmental Risk Management and Science Education

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Abstract: *This study systematically reviewed the application of machine learning (ML) models in landslide prediction, synthesizing advances, limitations, and emerging directions. Using the PRISMA framework, eight studies published between 2019 and 2024 were selected from major databases following rigorous inclusion criteria. Results revealed that ML models varied from standalone to ensemble, hybrid, and optimized approaches, with ensemble and hybrid frameworks often demonstrating superior reliability across diverse geospatial contexts. Performance metrics such as training and validation AUC, accuracy, and recall indicated generally strong predictive capacity, though inconsistencies in reporting limited cross-study comparability. Conditioning factors and preprocessing strategies were highly variable, reflecting both regional specificity and methodological divergence, while validation techniques ranged from random splits to cross-validation. Key challenges included imbalanced datasets, a lack of standardized metrics, and limited integration of geophysical and environmental factors, which constrained model transferability and generalizability. Emerging technologies such as explainable AI, transfer learning, advanced GIS integration, and multi-temporal remote sensing were identified as promising avenues to address these gaps. Overall, the findings highlight the capacity of ML to advance landslide susceptibility mapping while underscoring the need for methodological standardization and cross-regional datasets, with broader implications for disaster risk reduction, sustainability, and science education.*
Keywords: *environmental risk management, landslide prediction, machine learning, science education, systematic review*

INTRODUCTION

Landslides represent significant geological hazards characterized by the movement of rock, soil, and debris down slopes, often initiated by factors such as rainfall, earthquakes, volcanic activity, and human actions, including deforestation and construction [1-4]. They result in immediate losses and impose long-term social, economic, and environmental costs by disrupting ecosystems, settlements, and land-use systems. As a result, significant research has focused on elucidating the drivers, distribution, and prediction of these phenomena to mitigate risk and guide sustainable development [5-8].

Landslides in the Philippines commonly occur in mountainous and urbanizing areas, where the intersection of exposure and development pressures coincides with significant rainfall. Case studies in Antipolo, Rizal [2] and Baguio City [3] demonstrate that slope instability and changes in land use increase susceptibility. Central and Eastern Visayas have experienced significant destructive events, such as the 2018 Naga City landslide [9] and the 2022 Toledo City slope failure [10], both of which were influenced by hydrometeorological and anthropogenic factors. Additional incidents reported in Talisay, Sudlon II, and Tisa exemplify rainfall-induced slope failures in peri-urban areas, highlighting the critical necessity for predictive tools that account for local environmental and socio-economic factors.

Prediction has thus become integral to disaster risk reduction, environmental planning, and climate adaptation. Conventional susceptibility and hazard models incorporate factors such as rainfall, topography, lithology, soils, and land use to identify vulnerable areas and inform interventions like slope stabilization, drainage systems, and resettlement [11-13]. Improvements in geographic information systems (GIS) and remote sensing have enhanced spatial analysis and enabled semi-automated mapping. Additionally, statistical methods such as logistic regression (LR) and bivariate techniques have historically established baselines for evaluating susceptibility [4, 14]. Nonetheless, these methods frequently encounter challenges in addressing nonlinear relationships and incorporating various environmental datasets [15-16].

Machine learning (ML) has recently gained prominence due to its ability to model complex, nonlinear interactions among multiple predictors. Methods including random forest (RFs), support vector machine (SVM), and adaptive neural-based fuzzy inference system (ANFIS) demonstrate enhanced efficacy in susceptibility mapping, especially when integrated with GIS and remote sensing [17-21]. Hybrid methods that combine various algorithms are being increasingly utilized to enhance predictive accuracy and minimize uncertainty [21]. However, gaps persist: restricted landslide inventories, inconsistent data preprocessing, and diverse validation methods impede comparability and generalization across studies [22-24]. The identified limitations highlight the necessity of systematic reviews to integrate findings and pinpoint avenues for methodological improvement.

This review synthesizes the use of ML models in landslide prediction, analyzing their strengths, limitations, and adaptability across different contexts. This underscores the impact of preprocessing, sampling, and validation decisions on predictive results. The review highlights the importance of advancing hazard science in relation to environmental management and science education. Enhanced predictive modeling contributes to ecosystem protection, resilient land-use planning, and disaster preparedness. Furthermore, incorporating this knowledge into curricula can promote environmental literacy, data-analytic reasoning, and innovation in geohazard research. The synthesis serves as a framework for student science investigatory projects (SIPs), especially in the physical and applied sciences, robotics and intelligent machines (RIMs), and technological innovations, by demonstrating the integration of data, algorithms, and field evidence to tackle significant environmental issues.

MATERIALS AND METHODS

This study employed a systematic review methodology to consolidate existing knowledge on machine learning (ML) models in landslide prediction. A systematic review was deemed appropriate as it ensures transparency, replicability, and rigor in synthesizing evidence. Guided by a systematic review protocol [25], the process involved collecting, coding, and evaluating studies to identify effective approaches for susceptibility mapping and disaster risk reduction.

Strict inclusion criteria were applied: studies published between 2019 and 2024, written in English, appearing in peer-reviewed journals, and explicitly addressing ML applications in landslide prediction. Only quantitative or quasi-experimental studies with sufficient data for comparison were considered, while reviews, qualitative research, abstracts, and theses were excluded to maintain relevance and quality. The search strategy covered Scopus, Crossref, Google Scholar, and Elsevier, employing Boolean combinations of keywords such as “machine learning models,” “landslide prediction,” and “landslide susceptibility.” Publish or Perish [26] supported retrieval, complemented by manual searches. Study selection followed the PRISMA protocol from meta-analytical studies [27-28]: from 1,678 identified articles, 1,556 were excluded as duplicates or irrelevant, 88 failed to meet criteria, and 34 were screened. After further exclusion, 20 full texts were assessed, 10 were discarded, and 8 qualified for the final synthesis.

Extracted data were analyzed thematically and comparatively. Key variables included locale, landslide count and type, and data split; ML model categories; performance metrics such as training and validation area under the curve (AUC), accuracy, and recall/sensitivity (SST); conditioning factors; preprocessing and validation techniques; and regional specificity. The review also synthesized challenges, research gaps, and emerging technologies, providing a comprehensive appraisal of current ML applications in landslide prediction.

RESULTS AND DISCUSSION

Characteristics of the Studies

The systematic review included eight studies and their characteristics, including locale, landslide count and type, and data split, are shown in Table 1.

Table 1. Characteristics of the studies included in the systematic review

Author	Locale	Landslide Count	Landslide Type	Data Split
Kulsoom et al. [29]	Pakistan	303	Debris flow, rockslide	70:30
Sahin [23]	Turkey	105	Shallow landslides	70:30
Song et al. [30]	China	>580,000 pts	Various	Training/testing
Chen et al. [17]	Greece	335	Various	Training/testing
Arabameri [31]	Iran	241	Various	4-fold cross validation
Chen and Song [21]	China	34,893	Shallow landslides	70:30
Tran et al. [24]	Vietnam	76	Shallow landslides	70:30
Lee et al. [12]	South Korea	151	Shallow landslides	70:30

Based on Table 1, there is variability in dataset size, landslide typology, and regional focus, emphasizing the complexities inherent in predictive modeling within geohazard research. Sample sizes varied from modest inventories, including 76 shallow landslides in Vietnam [24] and 105 in Turkey [23], to large datasets comprising over 35,000 cases in Sichuan Province [21] and nearly 580,000 in China [17]. Smaller datasets require meticulous model calibration to reduce overfitting, while large-scale datasets necessitate computationally efficient methods that can address heterogeneity and imbalance. Research on landslide typology has examined various processes, such as debris flows and rockslides in Pakistan [29], shallow landslides in Turkey [23], South Korea [12], Vietnam [24], and China [21], and mixed types in Iran [31] and Greece [17]. The distinctions suggest that the geomorphological characteristics of the study area likely influence predictive accuracy and model transferability.

The diversity of validation strategies and data partitioning methods employed is equally notable. The majority of studies used the standard 70:30 train-test split, which is a pragmatic option for datasets of moderate size, whereas larger datasets permitted more adaptable partitioning strategies [30]. Arabameri [31] employed k-fold cross-validation to enhance generalizability and mitigate bias in performance estimates. The methodological differences underscore the necessity of aligning validation techniques with the characteristics of the dataset, as improper partitioning may either exaggerate accuracy in smaller datasets or fail to capture variability in larger ones. The variation in sample sizes, landslide types, and validation strategies demonstrates the flexibility of machine learning techniques in landslide prediction. However, it also highlights that the scale, quality, and representativeness of the input data significantly influence the robustness and reliability of models.

Standalone Models for Landslide Prediction

After examining dataset characteristics, the next focus is on standalone ML models, which operate independently and provide a baseline for assessing predictive performance [24]. Table 2 presents the models and their description and application context.

Table 2. Standalone ML models in predicting landslides

Model	Description and Application Context	Reference
Logistic Regression (LR)	A foundational model used to establish baseline performance metrics.	[30]
Artificial Neural Network (ANN)	A foundational model used for baseline performance, often with various activation functions.	[12,17,29]
Hyperpipes (HP)	A straightforward and fast classification algorithm used as a base classifier.	[24]
Support Vector Machine (SVM)	A non-parametric kernel-based technique for classification.	[17]

Credal Decision Tree (CDT)	A decision tree model used to deal with classification problems; noted as an unstable classifier on its own.	[31]
Naive Bayes (NB)	A supervised learning method that employs the Bayes theorem.	[29]
K-Nearest Neighbor (KNN)	An unsupervised pattern detection algorithm.	[29]
Convolutional Neural Network (CNN)	A deep learning model used for feature extraction and pattern recognition.	[21]

As presented in Table 2, the standalone models underscore the variety of ML approaches utilized in landslide prediction, encompassing basic statistical classifiers and sophisticated deep learning frameworks. These models operate autonomously, establishing a fundamental benchmark for comparison with more intricate ensemble or hybrid methodologies. ANNs emerged as the most prevalent choice, recognized for their capacity to model nonlinear relationships between geo-environmental factors and the occurrence of landslides. Multi-layer architectures enable ANNs to capture complex interactions within datasets, thereby enhancing predictive accuracy in diverse contexts [12,17,29]. CNNs similarly enhanced these benefits by directly extracting spatial features from high-dimensional inputs, while optimization techniques improved performance in large-scale applications [21].

Additional standalone models fulfilled supplementary functions. LR established a benchmark for predictive performance in imbalanced datasets [30], whereas SVMs demonstrated competitive accuracy via kernel-based classification and feature selection methods [17]. Algorithms like NB and KNN provide efficient solutions in particular contexts, although they exhibit limitations in managing complex patterns [29]. Similarly, CDTs were utilized in susceptibility mapping; however, their inherent instability frequently required integration with ensemble methods [31]. HP was introduced as a rapid baseline classifier; however, it exhibited limited accuracy independently, highlighting the necessity for model improvement [24]. The results indicate that standalone models are essential for landslide susceptibility analysis, primarily serving as baseline comparisons and components for more sophisticated predictive frameworks.

Ensemble Models

Building on the standalone approaches, ensemble models integrate multiple algorithms to enhance robustness and predictive accuracy in landslide susceptibility mapping [24,31]. Table 3 showcases the ensemble methods applied in the reviewed studies.

Table 3. Ensemble ML models in predicting landslides

Model	Description and Application Context	Reference
AdaBoost-HP (ABHP)	Combines the HP algorithm with the AdaBoost ensemble technique.	[24]
Bagging-HP (BHP)	Combines the HP algorithm with the Bagging ensemble technique.	[24]
Dagging-HP	Combines the HP algorithm with the Dagging ensemble technique.	[24]
Decorate-HP	Combines the HP algorithm with the Decorate ensemble technique.	[24]
Real AdaBoost-HP (RABHP)	Combines the HP algorithm with the Real AdaBoost technique.	[24]
CDT-Bagging	Combines the CDT with Bagging to reduce model variance.	[31]
CDT-Multiboost	Combines the CDT with Multiboost to reduce variance and bias.	[31]
CDT-SubSpace	Combines the CDT with SubSpace to prevent overfitting.	[31]
Random Forest (RF)	A decision tree-based ensemble method known for high accuracy and robustness.	[23,29-30]
Gradient Boosting Machines (GBM)	An ensemble method that builds a strong learner from a series of weak prediction models.	[23]
Extreme Gradient Boosting (XGBoost)	A powerful decision tree-based ensemble method known for high performance.	[23,29]

LightGBM	A framework that implements a gradient boosting decision tree algorithm.	[30]

According to Table 2, various ensemble machine learning models are utilized in landslide susceptibility mapping, emphasizing their capacity to improve predictive accuracy through the reduction of variance and bias relative to individual classifiers. RF emerged as the most prevalent ensemble method, consistently exhibiting superior performance across various contexts. The dependence on numerous decision trees enhances its efficacy in managing complex and heterogeneous datasets, resulting in dependable and generalizable susceptibility maps [23,29-30]. XGBoost has become a widely utilized ensemble method, recognized for its computational efficiency and robust predictive performance. Research indicates that optimized versions of XGBoost enhance classification performance by emphasizing the most significant causative factors, highlighting its versatility in diverse landslide-prone settings [23,29]. GBM and its variant LightGBM were utilized, especially in scenarios necessitating effective management of imbalanced datasets, demonstrating enhanced recall and predictive stability [23,30].

In addition to tree-based boosting methods, various ensemble techniques have shown novel combinations to enhance the performance of less common classifiers. For example, HP was combined with AdaBoost, Bagging, Dagging, and Decorate to improve classification robustness [24], whereas CDTs were integrated with Bagging, Multiboost, and SubSpace to reduce overfitting and enhance model reliability [31]. These studies demonstrate that ensemble learning enhances the predictive capabilities of established models while also broadening the applicability of unconventional algorithms in landslide susceptibility mapping. Ensemble approaches emphasize the significance of integrating multiple learners to address complex nonlinearities in geospatial data effectively. RF and XGBoost are particularly noted for their reliability and frequent application in enhancing landslide hazard prediction.

Hybrid/Optimized Models

Beyond ensemble methods, hybrid and optimized models combine or refine algorithms to enhance accuracy and address data limitations. Table 4 presents the hybrid and optimized models applied in landslide susceptibility mapping.

Table 4. Hybrid/optimized ML models in predicting landslides

Model	Description and Application Context	Reference
ANN-PSO, SVM-PSO	Couple a base model (e.g., ANN, SVM) with a metaheuristic algorithm called particle swarm optimization (PSO) to fine-tune structural parameters.	[17]
CNN-BWO	Couples a CNN with beluga whale optimization (BWO) to enhance prediction accuracy.	[21]
CNN-COA	Couples a CNN with coati optimization algorithm (COA) to enhance prediction accuracy.	[21]

As presented in Table 5, hybrid and optimized models that enhance the capabilities of standalone and ensemble methods by integrating base learners with metaheuristic algorithms to refine parameters and improve prediction accuracy. ANN and SVM, when combined with PSO, have shown enhanced structural tuning and robustness in landslide susceptibility mapping [17]. CNNs optimized using BWO and COA improved predictive accuracy through hyperparameter refinement and enhanced spatial feature extraction [21]. These methods demonstrate that hybridization and optimization can address the shortcomings of traditional models, especially in managing complex, nonlinear relationships among causative factors, thus enhancing the reliability and resolution of susceptibility maps.

Performance Metrics of the Best Models

To assess the predictive reliability of the reviewed approaches, each study reported performance metrics for its best-performing model, offering a basis for comparing accuracy and robustness across methods. Table 5 highlights the performance metrics of the best model identified in each study.

Table 5. Performance metrics of the best model in each study

Best Model	Training AUC	Validation AUC	Accuracy (%)	Recall/SST	Reference
XGBoost	0.997	-	-	-	[29]

XGBoost_Opt	-	0.898	85.01	-	[23]
O_RF	-	0.932	90.70	0.705	[30]
ANN	0.969	0.800	-	-	[17]
CDT-Multiboost	0.995	0.993	97.30	0.967	[31]
CNN-COA	0.946	0.919	90.90	0.889	[21]
ABHP	0.933	0.922	84.38	0.768	[24]
ANN (Tan-sig)	0.968	0.879	90.00	92.38	[12]

As highlighted in Table 5, the performance metrics of the top models in each study validate the enhanced accuracy and robustness of machine learning methods for landslide susceptibility mapping. High AUC values in both training and validation datasets across studies indicate the models' strong discriminative ability, frequently surpassing 0.90. The CDT-Multiboost attained a validation AUC of 0.993 and an overall accuracy of 97.30%, demonstrating its effectiveness in reflecting the impact of various geo-environmental factors [31]. The CNN-COA model demonstrated robust performance, underscoring the advantages of integrating optimization algorithms with deep learning to improve predictive accuracy [21]. The oversampled RF (O_RF) demonstrated a validation AUC of 0.932 and an accuracy of 90.70%, indicating that the balancing of imbalanced datasets enhances recall and improves the detection of landslide-prone areas [30].

Alternative models, despite exhibiting marginally reduced validation performance, displayed significant strengths as well. XGBoost and its optimized variant demonstrated consistently high training and validation AUCs, with the optimized version attaining an AUC of 0.898 and an accuracy of 85.01% in Turkey, thereby confirming its adaptability across varying data conditions [23,29]. ANNs have demonstrated competitive performance, as evidenced by a training AUC of 0.969 [17] and validation AUC of 0.879 and an accuracy of 90.00% [12] through the use of optimized activation functions. Ensemble models, such as ABHP, demonstrated balanced performance, achieving a validation AUC of 0.922, thereby underscoring the advantages of integrating weak learners [24]. The results indicate that no single model consistently outperforms others; instead, model performance is contingent upon the characteristics of the dataset, optimization strategies, and feature selection. This highlights the necessity of customizing model selection and optimization to specific geohazard conditions to produce dependable susceptibility maps for disaster risk mitigation.

Conditioning Factors in Landslide Prediction

Given that model performance is highly context-dependent, the review also examined the conditioning factors used to capture the environmental and geological drivers of landslides. Table 6 shows the conditioning factors applied across the reviewed studies.

Table 6. Conditioning factors in predicting landslides

Factor	Specific Factor	References
Topographical	Slope	[12,17,21,23-24,29-31]
	Elevation	[12,17,21,23-24,29-31]
	Curvature plan and profile	[12,17,21,23-24,29-31]
	Slope aspect	[12,17,21,23-24,30-31]
	Topographic ruggedness index (TRI)	[12,21,23,29-30]
Hydrological	Proximity to stream or river	[12,17,23-24,29-31]
	Topographic wetness index (TWI)	[12,17,23-24,29-31]
	Precipitation or rainfall	[21,23-24,29-31]
	Stream power index (SPI)	[17,21,23,29,31]
	Drainage density	[23-24,31]
Geological	Lithology	[17,21,23-24,29-31]
	Proximity to fault	[17,21,24,29,31]
	Weathering	[12,24]
Anthropogenic	Proximity to road	[12,21,24,29,31]
	Land use or land cover	[12,21,23,3-31]
Other Factors	Seismic intensity or earthquake	[21,29-30]
	Soil type, depth, or texture	[12,31]

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According to Table 6, conditioning factors employed in landslide susceptibility modeling encompass topographical, hydrological, geological, anthropogenic, and various environmental domains, illustrating the intricate interaction of physical and human influences on slope instability. Topographical factors, including slope, elevation, curvature, aspect, and terrain roughness, were most commonly utilized and consistently recognized as key determinants of landslide occurrence. The parameters significantly affect slope stability by regulating gravitational forces, drainage patterns, and stress distributions, rendering them essential components in machine learning models [17, 29, 31]. Their prevalence in research underscores the importance of digital elevation data as a fundamental component of susceptibility assessments, especially when incorporated into high-resolution terrain models.

Geological factors are critical conditioning variables, particularly lithology and proximity to fault lines, which define the material and structural conditions that predispose slopes to failure. Weak rock units, including clay-rich formations and highly weathered profiles, are frequently associated with heightened susceptibility, whereas faults serve as structural weaknesses that increase the likelihood of failure [21,24]. Some studies have examined weathering processes, contributing to the understanding of the long-term degradation of slope materials, which diminishes shear strength and stability [12]. The findings emphasize the importance of integrating geological and tectonic datasets with topographic metrics to capture both static and dynamic influences on slope behavior effectively.

Hydrological conditioning factors further strengthened the influence of water in initiating landslides. Proximity to streams, rainfall and precipitation records, topographic wetness indices, and drainage density have been extensively utilized, with research consistently highlighting their significance in slope failure processes [23,30]. Rainfall is often identified as a triggering factor due to its ability to saturate soils, diminish cohesion, and elevate pore water pressure, which collectively contribute to the initiation of slope movement. Derived indices, including SPI and TWI, enhanced predictive performance by quantifying surface runoff and soil moisture dynamics [17,31]. The hydrological inputs highlight the importance of integrating both long-term climatic conditions and short-term rainfall events into susceptibility models to reflect temporal variability in slope responses accurately.

Human activities and external hazards introduce additional complexity, demonstrating how they disrupt natural slope equilibrium. Proximity to roads and changes in land use or land cover were often examined, highlighting the destabilizing impacts of construction, deforestation, and urbanization on slope systems [12,29]. Seismic intensity and soil characteristics are additional factors that contextualize regions where earthquakes or soil heterogeneity significantly influence slope failure [21,31]. Although utilized less often, these parameters underscore the complex nature of landslide conditioning, indicating that susceptibility cannot be comprehensively understood without accounting for both natural processes and human influences. These findings confirm that effective landslide prediction necessitates the integration of various conditioning factors, allowing ML models to encompass the complete range of geophysical and environmental influences on slope instability.

Regional Specificity in Landslide Prediction

Because conditioning factors and model performance vary with local environments, the review also examined regional specificity to understand how geographic and geomorphological contexts shape landslide prediction. Table 7 summarizes the regional settings of the reviewed studies.

Table 7. Conditioning factors in predicting landslides

Locale	Most Influential Factors Identified	Reference
Nam Dam, Vietnam	Distance from roads, elevation, river density	[24]
Taleghan-Alamut, Iran	Distance from roads, slope, lithology, rainfall	[31]
Sichuan, China	Annual maximum 24-hour rainfall, lithology, road density, slope angle	[21]
Mt. Umyeon, South Korea	Slope, sediment transport index (STI), TRI	[12]
Achaia, Greece	Lithological cover, slope angle	[17]
Ayancik, Turkey	Slope, elevation, TWI, STI, drainage density	[23]
Karakoram Highway, Pakistan	Proximity to road, slope, roughness, proximity to fault, precipitation, elevation	[29]

As summarized in Table 7, the factors conditioning landslides are notably context-dependent, differing based on local geomorphology, climate, and anthropogenic influences. Slope and elevation are consistently dominant predictors in most study areas, underscoring their fundamental role in slope stability [17,23-24,29]. Regional variations influenced the significance of various factors; for example, road density served as a key driver in Vietnam and Pakistan, where extensive infrastructure interacts with unstable terrain [24,29]. In contrast, rainfall became a predominant factor in Iran and China, both noted for their intense precipitation events [21,31]. Geological conditions significantly influenced susceptibility, especially in Greece and Iran, where lithological diversity and proximity to faults were prominent factors [17,31]. The findings indicate that although fundamental factors like slope are essential, it is necessary to include localized drivers, such as climatic, geological, or anthropogenic influences, for precise regional modeling.

Furthermore, regional studies emphasized the importance of customizing models to accurately reflect the distinct interactions between natural and human systems in each area. In mountainous regions like Pakistan's Karakoram Highway and Turkey's Ayancik district, various interacting factors, such as slope, roughness, precipitation, and proximity to roads, necessitated the use of ensemble or optimized models to address complexity [23,29]. Conversely, in urbanized locations such as Mt. Umyeon in South Korea, terrain indices such as TRI and STI were essential for analyzing shallow landslides induced by rainfall [12]. The Sichuan region of China focused on hydrological and seismic influences [21], whereas Greece and Iran underscored geological controls [17,31]. These examples emphasize the necessity of regional specificity in the development of effective landslide susceptibility models, emphasizing the selection of conditioning factors based on both their general relevance and their local importance in influencing hazard dynamics.

Preprocessing and Validation Techniques in Landslide Prediction

Data preprocessing and validation are critical for ensuring reliable landslide prediction models. Table 8 gleaned the key techniques employed across the reviewed studies.

Table 8. Preprocessing and validation techniques in predicting landslides

Technique	Description/Purpose	Reference
Data Partitioning	Randomly splitting data into training and validation subsets, typically at a 70:30 ratio. Ensures model is tested on unseen data to prevent overfitting.	[12,17,21,23-24,29-30]
Cross-validation	K-fold cross-validation is used to ensure model reliability by training and validating on different data folds.	[31]
Oversampling	Techniques like synthetic minority oversampling technology (SMOTE) are used to create synthetic samples for the minority class (landslides) to balance the dataset.	[30]
Undersampling	Randomly removing samples from the majority class (non-landslides) to create a balanced dataset.	[30]
Feature Selection	Identifies most predictive and least correlated features using methods like One-R, information gain ratio (IGR), SU (symmetrical uncertainty), RF, linear support vector machine (LSVM), or genetic algorithms (GA) to improve model efficiency and reliability.	[12,17,21,23-24,29,31]
Multicollinearity Analysis	Diagnoses high correlation between input variables using variance inflation factors (VIFs) and tolerance (TOL) measures to prevent model instability.	[12,17,23,30-31]
External Validation	Compares model output to real-world physical phenomena, such as using small baseline subste-interferometric synthetic aperture radar (SBAS-InSAR) to measure surface deformation.	[29]

Preprocessing and validation techniques and their critical importance in the development of robust and reliable landslide prediction models are gleaned in Table 8. Random data partitioning, commonly executed with a 70:30 training-to-testing ratio, was extensively utilized to mitigate overfitting and assess model performance on unseen data [23,29-30]. Cross-validation methods, especially k-fold techniques, enhanced model reliability through the systematic rotation of training and validation subsets [31]. In studies addressing class imbalance, oversampling and undersampling techniques, such as SMOTE, were utilized to mitigate the limited representation of landslide occurrences compared to stable areas [30]. The preprocessing strategies employed ensured that machine learning algorithms were trained on representative datasets, thereby enhancing generalizability across diverse geomorphological and climatic contexts [12,17,14].

Feature selection has become a vital preprocessing step, commonly employed to identify the most predictive variables and reduce multicollinearity [17,29]. Techniques, including RF importance measures, IGR, and genetic algorithms, enabled researchers to eliminate redundant or highly correlated features, thereby enhancing model efficiency and interpretability [21,23,31]. Complementary analyses of multicollinearity, employing VIFs and tolerance measures, were conducted to mitigate instability in model outputs [12,30]. These approaches ensured that landslide susceptibility maps were reliable and actionable, emphasizing the critical factors influencing slope instability in each study area.

Validation techniques have expanded from internal checks to encompass external comparisons with real-world measurements, including the use of SBAS-InSAR for the detection of surface deformation [29]. This external validation confirmed the model's accuracy and increased confidence in susceptibility predictions, aiding decision-making and mitigation planning. The findings indicate that effective landslide modeling depends on a combination of robust data partitioning, careful feature selection, and rigorous validation, which ensures that machine learning models are statistically sound and practically relevant across various terrains and environmental conditions [21,24].

Challenges in Landslide Prediction

Landslide prediction faces multiple technical and data-related challenges. Table 9 illustrates the primary challenges identified across the study in the systematic review.

Table 9. Limitations and challenges in predicting landslides

Category	Limitation/Challenge	Explanation
Data Limitations	Subjective non-landslide sampling	The selection of non-landslide samples lacks a standardized, objective protocol, which can introduce bias into the model.
	Imbalanced datasets	Landslide events are a minority class, which can lead to models with high overall accuracy but low recall, making them unreliable for practical use.
	Lack of time-variant data	Most current models are static, but landslide triggers like rainfall and seismic activity are dynamic over time.
	Data resolution	The spatial resolution of input data, such as digital elevation models (DEMs), can impact the accuracy of the model outputs.
Computational Limitations	High computational cost	Advanced hybrid and deep learning models require significant computational resources, which can be a drawback for time-sensitive applications.
	Hyperparameter tuning	The process of finding optimal parameters for complex models can be time-consuming and computationally expensive.
Model Limitations	Overfitting	Models can perform very well on training data but poorly on validation data, indicating a lack of generalizability.
	"Black box" nature	Complex models like deep learning are often difficult to interpret, which hinders a clear understanding of the physical processes.
	Lack of adaptability	Models trained for one specific region may not be easily adapted to a new area without significant recalibration.

Table 9 illustrates significant data limitations, including subjective sampling of non-landslide areas, imbalanced datasets, and the absence of time-variant information. Such issues may introduce bias into models and diminish their reliability, particularly given that landslides occur infrequently in comparison to stable terrain [17,24]. The spatial resolution of input data, including DEMs, significantly influences

model outputs, as coarse resolutions may neglect local slope variations essential for susceptibility assessment. To address these limitations, it is necessary to integrate high-resolution remote sensing, temporal monitoring, and standardized sampling protocols to ensure that datasets effectively capture both static and dynamic triggers of slope failure.
Constraints related to models and computations exacerbate the challenges. Hybrid CNN models and deep learning ensembles demonstrate high predictive performance; however, they frequently compromise interpretability, scalability, and computational efficiency [17]. Overfitting is a significant issue when models exhibit strong performance on training data yet demonstrate inadequate results on unseen validation datasets, thereby restricting their applicability to new regions. Additionally, hyperparameter tuning and significant processing requirements limit the operational viability of these models in resource-constrained environments. The environmental specificity of numerous predictive models limits their generalizability, as parameters optimized for one region, such as slope, lithology, rainfall, and human activities, may not apply to another area without recalibration [21,24]. These challenges highlight the necessity for balanced strategies that incorporate effective data collection, model transparency, and computational efficiency to improve the practical implementation of landslide susceptibility prediction.

Gaps and Emerging Technologies in Landslide Prediction
The review also identified key research gaps and emerging technologies in landslide prediction, highlighted in Table 10.

Table 10. Research gaps and emerging technologies in predicting landslides

Research Gap	Proposed Solution	Emergent Technology
Subjective non-landslide sampling	Develop and standardize objective protocols for selecting non-landslide samples.	Advanced statistical and sampling algorithms.
Static, grid-based mapping	Shift from grid-cell-based models to physically meaningful mapping units, such as slope units.	Terrain segmentation, advanced GIS analysis.
Lack of time-dependent modeling	Incorporate multi-temporal data on landslide triggers and conditioning factors to create dynamic susceptibility maps.	Advanced remote sensing (e.g., multi-temporal satellite imagery) and time-series data analysis.
Poor model generalizability	Use transfer learning techniques to adapt models from a well-studied region to a new area.	Transfer learning frameworks for machine learning.
Model opaqueness	Develop new, more robust, and interpretable deep learning architectures.	Explainable AI (XAI) and advanced deep learning model design.

As highlighted in Table 10, the review identified various research gaps and emerging technological opportunities in landslide prediction. Identified gaps encompass the subjective selection of non-landslide samples, dependence on static, grid-based mapping, restricted time-dependent modeling, inadequate model generalizability, and the lack of transparency in complex deep learning models. The identified limitations underscore the need for methodological refinement, the inclusion of additional input variables, and the implementation of advanced computational frameworks to enhance the accuracy, interpretability, and scalability of landslide susceptibility models [17,29].
Emerging technologies present potential solutions to these challenges. Advanced statistical and sampling algorithms standardize non-landslide selection, while terrain segmentation and enhanced GIS analysis facilitate the creation of more physically meaningful mapping units, surpassing simplistic grid-cell methodologies. The integration of multi-temporal remote sensing with time-series analyses mitigates the deficiency in dynamic modeling, while transfer learning frameworks facilitate the adaptation of models to new regions, thereby enhancing generalizability. Explainable AI (XAI) and advanced deep learning architectures can mitigate the “black-box” problem, offering interpretable insights into the drivers of slope instability. The integration of these technologies can address existing research gaps and improve predictive performance, operational applicability, and decision-making in landslide risk mitigation [12,23-24].

Implications for Environmental Risk Management

The review's findings have considerable implications for environmental risk management, particularly in areas prone to landslides. The identification of topographical, geological, hydrological, and anthropogenic factors as primary drivers of slope instability underscores the importance of incorporating multidisciplinary data into hazard assessment frameworks [1-4,17,32]. Environmental managers can utilize these insights to prioritize monitoring and mitigation efforts in high-risk areas, concentrating on locations where critical factors such as steep slopes, unstable lithology, and high precipitation intersect [11,13]. The regional specificity of influential factors, as indicated in Table 7, underscores the necessity for risk management strategies to be customized to local environmental and socio-economic contexts instead of depending exclusively on generic models [21,23,33].

The research emphasizes the significance of advanced modeling, preprocessing, and validation techniques in enhancing the reliability of landslide predictions. Methods including feature selection, random sampling, and cross-validation improve model accuracy and serve as effective tools for decision-making in disaster preparedness and mitigation [12,15,30-31,34]. Environmental managers may employ susceptibility maps generated from these models to guide infrastructure planning, land-use zoning, and early warning systems [35-36]. The integration of remote sensing, GIS, and time-series data enables the dynamic monitoring of environmental changes, facilitating proactive interventions that mitigate exposure and vulnerability to landslides [21,29].

The identified research gaps and emerging technologies in the study offer opportunities to enhance environmental risk management frameworks. Terrain segmentation, transfer learning, and explainable AI improve the generalizability and interpretability of predictive models, enabling managers to make data-driven decisions in previously unmonitored or resource-constrained areas [17-18,24]. Implementing these innovations enables agencies to improve immediate operational responses and long-term planning, ensuring that risk mitigation strategies are adaptable, scientifically based, and equipped to tackle the changing challenges presented by climate variability, urbanization, and other human-induced pressures [21,29,37-38].

Inputs for Science Education

The review's findings hold significant implications for science education, especially in promoting environmental literacy and understanding of geohazards. Students can contextualize the complex interactions between natural and human-induced processes by examining the topographical, geological, hydrological, and anthropogenic drivers of landslides [1-4]. This knowledge can be incorporated into curricular activities that promote critical thinking and civic engagement, including investigatory projects [39] and field-based learning on local hazards, such as earthquakes [40]. Highlighting the socio-environmental consequences of geological hazards, such as community displacement, infrastructure damage, and ecosystem disruption, fosters the development of informed and environmentally responsible individuals [41-42].

The incorporation of predictive modeling, machine learning, and artificial intelligence within educational settings presents opportunities to enhance scientific inquiry, data analysis, and innovation. Techniques including GIS-based mapping, hybrid modeling, and AI-assisted simulations can be integrated into investigatory projects and practical activities within physical and applied sciences, robotics, and intelligent systems [15,17,39,43-44]. These methods enable students to examine intricate datasets, investigate real-world environmental issues, and suggest data-informed solutions, thereby enhancing interdisciplinary understanding, technological proficiency, and problem-solving abilities [44-45]. Integrating these activities into the classroom promotes academic and civic engagement, especially in areas such as disaster risk reduction, climate change adaptation, and sustainable practices, thereby connecting theoretical knowledge with practical applications.

Addressing gaps in predictive modeling and utilizing emerging technologies enhances the significance of innovation, inquiry, and scientific reasoning within science education. Engagement with explainable AI, terrain segmentation, and high-resolution remote sensing offers students the opportunity to design experiments, simulate hazard prediction, and assess mitigation strategies [21,24,44]. The integration of various representations, interactive simulations, and game-based activities enhances conceptual understanding, critical thinking, and analytical reasoning [43,45-47]. These educational strategies equip learners to tackle complex, real-world problems by integrating scientific inquiry, data analysis, technology, and interdisciplinary knowledge, thereby promoting innovation, resilience, and environmental stewardship.

CONCLUSION

The review underscores that machine learning approaches for landslide prediction are most effective when they are adaptable, context-sensitive, and rigorously validated, reflecting the interplay of methodological choices, regional variability, and data complexity. The generalizability of models depends not only on their structure, whether standalone, ensemble, hybrid, or optimized, but also on the systematic integration of preprocessing and validation techniques that enhance robustness across diverse conditions. Furthermore, the review highlights that addressing current challenges and research gaps, including data limitations and model interpretability, requires the adoption of emerging technologies and interdisciplinary approaches, suggesting that future predictive frameworks should be flexible, scalable, and capable of informing proactive environmental risk management, with potential applications in science education to enhance student understanding of geohazards, data analysis, and technological problem-solving.

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