Ensemble methods for landslide susceptibility mapping: A review of machine learning and hybrid approaches

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Abstract: The assessment of landslide susceptibility holds significant importance in disaster risk reduction. This study comprehensively examines the current research on landslide susceptibility from two aspects: the steps involved in landslide susceptibility assessment and modeling methods. Initially, we retrieved pertinent research articles, published between 2014 and 2023, and focused on "Landslide SensitivityAssessment" from the Web of Science database. Subsequently, we identified frequently occurring keywords in landslide susceptibility assessment studies employing ensemble learning methods during the past decade and created analytical charts. The standard methods for landslide inventory, evaluation indicators, and validation techniques were introduced along with their advantages and limitations. The shortcomings of eachmethod were identified, and potential future research directions were outlined. Finally, a detailed analysis of the use of ensemble methods in landslide susceptibility assessment was conducted; this is presented in several sections. The findings indicate that the advancement of ensemble learning methods has facilitated the development of landslide susceptibility assessment, rendering the landslide modeling process more efficient and accurate. In turn, this has enhanced the intelligence of models in landslide susceptibility research. The results of this study can help researchers understand the current conditions of landslide susceptibility research and provide a reference for subsequent research in this field.

Keywords: Landslide susceptibility mapping; Machine learning; Deep learning; Physical models; Ensemble methods

1. Introduction

As global engineering projects continue to expand and the frequency of extreme weather events increases, the hidden dangers of landslides are gradually becoming apparent, with landslides posing a potential threat on every continent (Zeng et al. 2022a, Ma et al. 2023). The widespread distribution, strong concealment, and high frequency of landslides present challenges for disaster monitoring and prevention (Jiang et al. 2020; Rolain et al. 2023; Zhang et al. 2023). In response to this issue, regional landslide susceptibility analysis (LSA) has emerged as a crucial tool for identifying areas prone to landslides and evaluating the spatial likelihood of landslide occurrence. While LSA is essential for understanding potential failure zones, it must be distinguished from hazard and risk assessments, which incorporate temporal probability and consequences." (Akıncı and Akıncı 2023; Bhuyan et al. 2023; Ikram et al. 2023).Landslides, which are one of the most life-threatening and property-endangering natural disasters, occur frequently on a global scale, resulting in significant losses to society (Wu et al. 2022, Yu et al. 2022, Zhang et al. 2024a). Therefore, employing advanced techniques and models for spatial landslide prediction is paramount for issuing timely warnings and implementing effective measures to mitigate the catastrophic consequences that landslide disasters can have (Guo et al. 2021, He et al. 2021, Li et al. 2023a).

In the existing literature, terms such as "landslide susceptibility prediction (LSP)," "landslide susceptibility mapping (LSM)," and "landslide sensitivity analysis" have occasionally been used interchangeably. However, these terms carry distinct connotations. In this review, we adopt the widely accepted term "landslide susceptibility analysis (LSA)" to refer to the process of evaluating the spatial likelihood of landslide occurrence based on environmental conditions. For describing the output of such assessments in the form of spatial distribution maps, we use "landslide susceptibility mapping (LSM)".

The susceptibility zoning of landslides is a predictive method to assess the probability of landslide occurrence based on various influencing factors recorded after a landslide event (Chowdhuri et al. 2021; Kavzoglu et al. 2021; Nguyen and Kim 2021; Arabameri et al. 2022).Susceptibility zoning is a practical approach for landslide prediction. Methods for landslide susceptibility assessment can be categorized into qualitative (knowledge-driven or heuristic) or quantitative (data-driven and physics-based) methods. Qualitative methods, such as geomorphological analysis and heuristic approaches, remain important tools, especially in regions with limited data availability. Although quantitative methods are generally preferred for their objectivity and reproducibility, qualitative approaches can offer valuable insights in complex terrains or where datasets are scarce.Physics-based quantitative methods include infinite slope models, limit equilibrium approaches, and advanced numerical simulations that integrate geologic and hydrologic modules. These methods estimate slope stability based on physical laws and material properties. While detailed and accurate at local scales, their application at regional scales often requires simplifications due to data limitations.These models can estimate slope stability as a function of soil mechanics and hydrologic measurements (He et al. 2021, Gong et al. 2022, Pham et al. 2022a, Zeng et al. 2022a).

Unlike qualitative methods, quantitative methods rely on statistical, physical, or numerical equations. Quantitative methods can be further divided into Physics-based, statistical, and recently emerging machine learning methods. Physics-based methods simulate a physical processes to capture the processes leading to slope instability (Pradhan et al. 2019; Zhang et al. 2024b). In contrast, statistical methods use a data-driven approach to simulate landslide processes. Machine learning methods have gained widespread attention from scholars due to their real-time and efficient performance.

Although machine learning has provided a fresh perspective for susceptibility assessment, most studies only use a singular model for predictions (Pham et al. 2017a, Arabameri et al. 2020). Due to the limited training data and the complexity of landslide prediction, a model based on a single learning algorithm may need to carefully consider the optimal fitting function or true distribution of the sample set within the hypothesis space, thereby affecting the prediction accuracy. Therefore,The mapping of landslide susceptibility using machine learning techniques has shifted toward the integration of multiple machine learning models in recent years, resulting in higher accuracy compared to basic classifiers (Zeng et al. 2023a, Achu et al. 2023, Zhang et al. 2024c). The use of hybrid ensemble models no longer relies solely on a singular approach, and these models have gained popularity due to their superior performance in accuracy and outcome quality. In hybrid ensemble modeling, multiple classifiers are combined to enhance the overall performance and learning precision of the model. Although this approach was initially introduced in the early 1990s, it has garnered significant attention from researchers in recent years, particularly in natural disaster modeling. By leveraging the strengths of various machine learning techniques, hybrid ensemble models can achieve more reliable predictive performance. However, these models primarily identify statistical patterns rather than uncovering the physical mechanisms behind landslides, unless interpretability is specifically addressed

In recent years, landslide susceptibility mapping (LSM) has played an increasingly important role in natural disaster risk assessment. Although numerous studies have explored the application of single machine learning models in LSM, systematic reviews focusing on ensemble learning techniques remain relatively scarce. The innovation of this paper lies in its comprehensive analysis of the latest advances and application potential of ensemble learning techniques in LSM. By comparing the performance of single models and ensemble models, this paper highlights the significant advantages of ensemble learning in improving prediction accuracy, enhancing model robustness, and reducing the risk of overfitting. Furthermore, this paper delves into the specific application scenarios and optimization methods or different ensemble strategies in LSM, providing new insights and directions for future research. This systematic review both fills gap in research and offers reliable technical support for landslide disaster risk management.

2. Trends

Ensemble machine learning algorithms address the issues of overfitting or underfitting by combining the predictions of multiple machine learning models. This, in turn, reduces the variance of the model and improves its bias, allowing for better handling of complex data distributions and enhancing the robustness and stability of the ensemble model.

Figure 1 shows the relative usage frequency of different ensemble methods over time based on chronological bibliometric data. Over the years, the proportion of heterogeneous methods has increased, while the proportion of homogeneous methods showed a declining trend before 2021. Although there has been a recent upturn in the proportion of homogeneous methods, the proportion of these methods remains lower than that of heterogeneous methods.

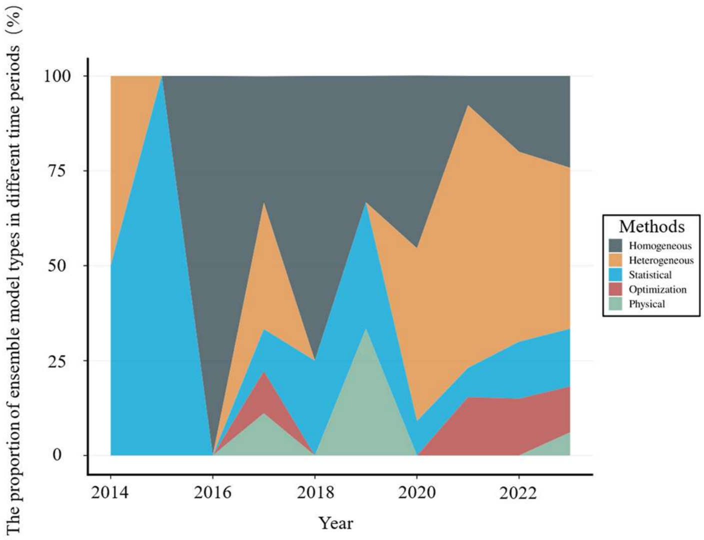

Fig.1 Relative usage frequency of different types of ensemble models in the past decade

Fifty-six keywords appeared more than twice in the analyzed publications. The most frequently used keywords are shown in Figure 2, with detailed descriptions provided in Table 1. Table1 gives a more detailed account of the temporal trends in the 11 most commonly used keywords. We analyzed these 11 most common keywords based on their chronological order. Among the most frequently used keywords are those that summarize the most commonly used classification techniques in susceptibility assessment, including terms like "Landslide susceptibility," "Machine learning,” "Rainfall," "Ensemble learning," "Big data," "One-sided selection," "Slope unit," "Information value," "Random forest," "Landslides," "GIS,"(Geographic Information System) "Ensemble model," "Remote sensing," "Modified frequency ratio," "AdaBoost," "MultiBoost," "InSAR," and "Classification."

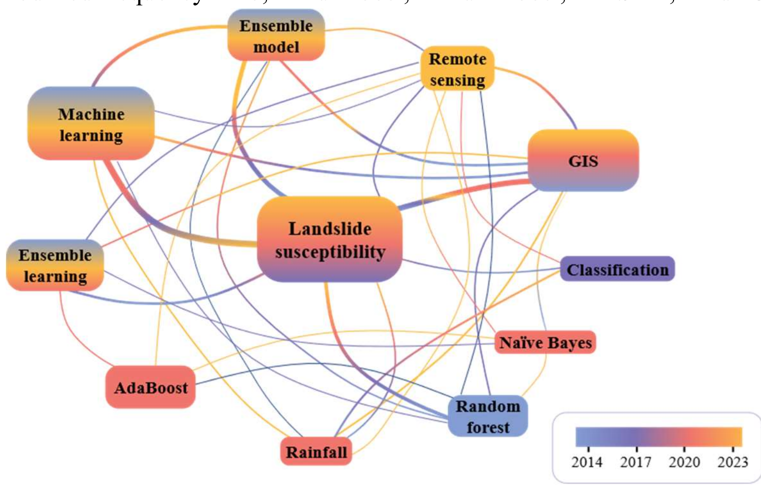

Fig.2 Temporal co-occurrence network of the most commonly used keywords. The line thickness represents the strength of connection between the keywords in the publication. Following the legend, the colors of the boxes and lines represent the chronological usage density of each word

Table 1 Frequency of predominant keywords used in the 132 analyzed publications

Keywords	Total occurrence 2014–2023		Occurrence 2014–2017		Occurrence 2018–2020		Occurrence 2021–2023	
	Count	Rank	Count	Rank	Count	Rank	Count	Rank
Landslide susceptibility	65	1^{st}	5	2^{nd}	10↑	1^{st}	50↑	1^{st}
Machine learning	37	2^{nd}	0	8^{th}	5↑	3^{rd}	32↑	2^{nd}
GIS	29	3^{rd}	12	1^{st}	5↓	4^{th}	12↑	4^{th}
Classification	19	4^{th}	0	9^{th}	3↑	6^{th}	16↑	3^{rd}
Ensemble model	19	5^{th}	4	4^{th}	6↑	2^{nd}	9↑	5^{th}
Random forest	11	6^{th}	1	6^{th}	2↑	7^{th}	8↑	6^{th}
Remote sensing	9	7^{th}	5	3^{rd}	1↓	10^{th}	3↑	9^{th}
Rainfall	9	8^{th}	0	10^{th}	2↑	8^{th}	7↑	7^{th}
Ensemble learning	7	9^{th}	0	11^{th}	2↑	9^{th}	5↑	8^{th}
AdaBoost	7	10^{th}	1	7^{th}	4↑	5^{th}	2↓	10^{th}
Naïve Bayes	4	11^{th}	2	5^{th}	0↓	11^{th}	2↑	11^{th}

As shown in Table 1, terms such as "Landslide susceptibility," "Machine learning," and "Ensemble model" have seen a continuous increase in usage over the study period. This trend may be related to the growing prevalence of artificial intelligence and ensemble models. As an example, "Machine learning" did not appear as a keyword from 2014 to 2017, but it became the third most cited keyword from 2018 to 2020. During this period, innovative techniques like "Ensemble model" and "AdaBoost" frequently appeared as keywords, indicating a growing interest among scholars in ensemble techniques. Subsequently, the frequency of terms like "Machine learning" and "Classification" has increased in recent years.

3. Data preparation

In the initial stage of landslide susceptibility assessment, researchers often relied on empirical methods, which involved observing past landslide events and geologic conditions to determine areas prone to landslides based on experience (Sharma et al. 2024). Qualitative parameters were incorporated into landslide susceptibility assessment for qualitative analysis with the introduction of qualitative and quantitative approaches. In terms of quantitative analysis, advances in computer technology have allowed for the analysis of geological, hydrological, and topographical data to achieve more accurate and comprehensive landslide susceptibility assessment (Gui et al. 2023a).

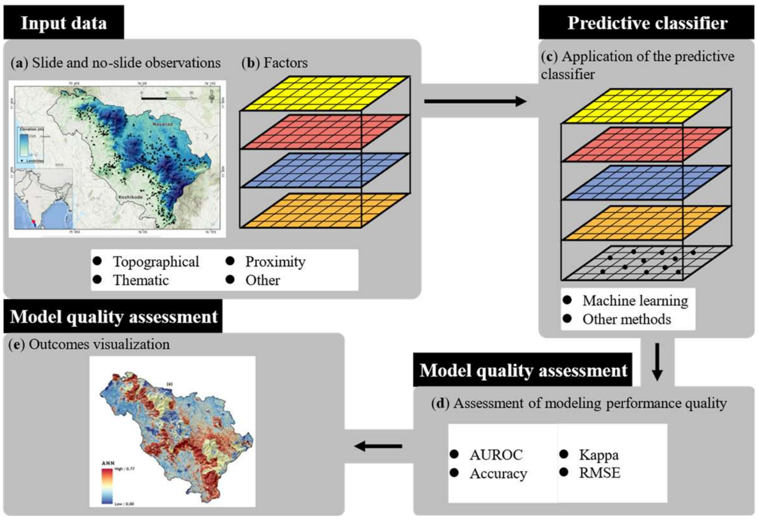

Fig.3 Process of standard machine learning and statistical landslide susceptibility modeling. The susceptibility assessment diagram depicted in Figure 3 originates from Achu (Achu et al. 2023)

The process of LSM assessment typically involves the following steps (Figure 3):

(a) Acquisition of landslide inventory: This step involves collecting data on past landslides in the study area. Non-landslide sampling points are also identified to create a balanced dataset for modeling. The landslide inventory is then split into test and training samples for model validation (Dung et al. 2021; Liu et al. 2021; Hang et al. 2022).

(b) Identification and acquisition of relevant environmental ground features: In this step, relevant environmental ground features that are known to influence slope stability are identified and acquired. These features are then used as predictors in the modeling process (Chen et al. 2021b). A modeling unit (e.g., pixels or slope unit) is also defined to analyze these features within a specific spatial context.

(c) Selection and application of classification technique: Various classification techniques are available for landslide susceptibility modeling. In this step, an appropriate classification technique is selected based on the characteristics of the dataset and the research objectives. Common techniques include logistic regression, decision trees, support vector machines, and random forests (Umar et al. 2014, Roy et al. 2019, Chen et al. 2021b). The selected technique is then applied to train the model using the training samples.

(d) Quality estimation of modeling performance: Once the model is trained, its performance must be evaluated by comparing the predicted results with the actual landslide occurrences in the test samples. Various statistical measures such as accuracy, sensitivity, specificity, and area under the curve (AUC) (Althuwaynee et al. 2014, Pham et al. 2017b, Chen et al. 2018) can be used to assess the quality and reliability of the model.

(e) Generation of the landslide susceptibility map: Finally, a landslide susceptibility map is generated based on the modeling results and the selected classification technique. This map categorizes the study area into different susceptibility zones, indicating the areas with high, moderate, and low likelihood of landslide occurrence (Jebur et al. 2015; Youssef et al. 2015; Tien Bui et al. 2016).

The study of landslides using ensemble techniques involves many essential elements, including landslide conditioning factors (LCFs), landslide datasets and inventory, ensemble models, and evaluation techniques. Each element influences the outcome of the landslide study differently.

3.1. Landslide inventory

Currently, there are many data sources used to prepare landslide inventories, including historical data, field survey data, satellite imagery, Google Earth imagery, and aerial photographs (Dai et al. 2023; He et al. 2024; Saha et al. 2024; Xue et al. 2024). These data are used for model training and testing. To ensure high prediction accuracy, the data must be rational and suitable. Therefore, we discuss several methods of data collection in this article point by point.

Historical data refer to a collection of data that record and organize past landslide events. In landslide susceptibility assessment, these historical data are crucial for understanding the frequency, scale, impact range, and possible causes of landslide activity in a region (Matougui et al. 2023; Tong et al. 2023; Yang et al. 2023). Therefore, when using historical data for assessment, attention should be paid to the completeness, accuracy, and timeliness of the data. In addition, to ensure the credibility and accuracy of the assessment results, historical data should be combined with other data sources and professional knowledge for comprehensive analysis.

Field investigations are crucial for gathering and verifying landslide data for landslide susceptibility assessment (Chen and Song 2023; Tang et al. 2023; Yu et al. 2023). The credibility of the landslide dataset can be enhanced by conducting on-site inspections of affected areas and identifying and measuring every potential slope failure. Field investigations typically involve physical examinations and detailed studies, providing data to supplement or correct data generated by other methods. However, field investigations face challenges in terms of time and resources; some landslides may not be directly accessible, and human error may introduce uncertainties in the measurement results.

In landslide susceptibility assessment, aerial photo interpretation is a commonly used method. This method involves using aerial imagery, typically high-resolution images obtained through aerial methods or satellites, to identify potential landslide signs and impact areas. The interpretation of aerial photos allows for rapid data acquisition over large areas without physically entering the field (Gui et al. 2023b). Aerial photo interpretation can help identify potential signs of slope failure (e.g., exposed rocks and land displacement), thereby providing an initial assessment of landslide risk (Zeng et al. 2023b). However, aerial photo interpretation typically requires specialized skills and tools and may be limited by weather conditions and obstructions. While this method can provide helpful information, the results are more reliable when combined with other data sources—such as field survey results—which, despite their limitations, offer critical ground-truth validation.

The interpretation of Google Earth imagery is also a common method applied in landslide susceptibility assessment. Google Earth provides high-resolution satellite images and aerial photographs, allowing researchers to remotely browse details of the Earth's surface. Potential landslide signs and affected areas can be identified through Google Earth. The advantage of this method lies in the ability to quickly obtain extensive data without the need for on-site inspection. Google Earth imagery interpretation can serve as a preliminary tool for landslide risk assessment, providing helpful information to guide further research or inform preventive measures. However, similar to aerial photo interpretation, interpreting Google Earth imagery requires specialized skills and tools and may be subject to limitations related to image resolution and occlusions. The assessment results typically need to be combined with other data such as field survey results to ensure the accuracy and reliability of the assessment.

In recent decades, technological developments have led to a continuous increase in the number of satellites, promoting the formation of a complete network for acquiring high-resolution images of the Earth's surface. As an essential data source and analysis tool, satellite images have the advantages of high resolution and comprehensive coverage. Thus, satellite imagery can provide extensive ground information for identifying potential landslide risk areas and signs. The analysis and comparison of data collected at various times allow the compilation of a comprehensive landslide inventory. Although satellite images have many advantages, some challenges in landslide susceptibility assessment remain, including limitations related to image resolution, cloud cover, and terrain occlusion, which may affect the accuracy and reliability of the data.

Accurate prediction of landslide susceptibility necessitates precise datasets and landslide inventory maps. Historical data and on-site surveys are paramount in the formulation of landslide inventories. Based on varying data sources, datasets with different resolutions can be generated for the research area of interest, with accuracies ranging from 0.5 to 100 m (Gui et al. 2023b; Hong 2023; Zheng et al. 2023). This variance primarily hinges upon the size of the study area. Thanh et al.(2022) used QGIS 3.6 and inverse-distance weighted interpolation to obtain a digital elevation model with a resolution of 10 m × 10 m for the study area. With advancements in satellite imagery and remote sensing technologies, more high-resolution datasets are being employed in landslide research. Lima et al.(2023) employed high-precision satellite imagery with a resolution of 0.5 m and documented over 2000 landslides within a 421-km^2 area. Landslide susceptibility assessment aims to generate maps of landslide susceptibility using existing landslide data, presuming that conditions similar to those of past landslides could lead to new landslides or the reactivation of previous ones.

Most studies use existing landslide data to generate susceptibility maps. However, overlooking insufficient or absent data may lead to discrepancies in the assessment outcomes. Rabby et al.(2023) proposed an objective approach based on Mahala nobis distance to identify the threshold of missing data in sampling. Compared to conventional approaches, this method demonstrates advantages in regions where landslide inventory lacks comprehensive representativeness. In response to the issue of uncertain effectiveness when applying landslide inventories to landslide susceptibility prediction, Bornaetxea et al.(2023) proposed a simplified approach to explore, describe, and compare various landslide inventories within specific study areas with the goal of assessing their suitability for LSM.

In landslide susceptibility assessment, the partitioning of the dataset is quite crucial, directly affecting the generalization ability and performance of the model. The evaluation outcomes of models under different dataset partitions also vary. Xing et al. (2023) explored the influence of continuous landslide impact factor interval attribute classification and data-driven modeling; the authors conducted uncertainty analysis on the landslide susceptibility index while maintaining a 7:3 partition ratio. Although this 7:3 ratio is used in most studies, it is not the sole option. Wang et al.(2023) integrated landslides triggered by rainfall and earthquakes into a dataset that does not differentiate between landslide types; they then compared this dataset with a non-classified landslide dataset with a partition ratio of 3:1.

In landslide susceptibility modeling, the consideration of both landslide and non-landslide points is of paramount importance, with most studies adhering to a 1:1 ratio for modeling. However, Liu et al.(2023) delved into the evolution of landslide susceptibility under different ratios of landslide to non-landslide points, with the goal of discerning the requisite volume of non-landslide data for susceptibility modeling. They found that different quantities of non-landslide points generated varied learning opportunities for the assessment model in terms of both landslide and non-landslide occurrences (Gui et al. 2023b). Moreover, as the volume of non-slope point data increased, the scope of highly susceptible areas gradually decreased. Conversely, Chang et al.(2023) employed a method involving the random selection of varying quantities of non-landslide samples within non-landslide regions to construct landslide susceptibility models. Using this method, they computed susceptibility indices for diverse landslide types and employed maximum probability analysis (MPA) to mitigate uncertainties associated with non-landslide sample selection in susceptibility assessment.

3.2. LSM conditioning factors

LSM conditioning factors are also called "predictors" and "environmental" factors. These conditioning factors are typically used to characterize the topographical circumstances under which landslides occur (Pal et al. 2022; Pham et al. 2022b; Abdollahizad et al. 2023). When considering the selection of controlling factors, it is vital to consider their correlation with the availability of data in the study area and their ability to adequately describe the occurrence of landslides.

Xue et al.(2024) suggested that environmental information should represent the conditions existing before landslides, i.e., the geologic conditions that affect the stability of local slopes and lead to landslides. They also pointed out that through statistical analysis of the common landslide conditioning factors (LCFs) based on machine learning in recent years, more than 40 types of LCFs have been identified, which can be classified into four major categories: topography, hydrology, land cover, and lithology. To further demonstrate the time effect of the terrain humidity index on the sensitivity of landslides, Canoglu (2019) proposed the saturation degree index, which allows the evaluation factors to align with the landslide mechanism in the study area and helps incorporate the effects of water in the analysis of landslide sensitivity.

According to previous studies, in the assessment of landslide susceptibility, the LCFS is usually divided into four categories. Therefore, to facilitate statistical analysis, the LCFs are divided into four types in this review : (i) topographical (e.g., slope, aspect, and curvature); (ii) thematic (e.g., lithology, land cover, and land use); (iii) proximity variables (e.g., distance to river and distance to fault); and (iv) other (e.g., rainfall, population density, and TWI (Topographic Wetness Index)). Among the different types of LCFs, topographical parameters (e.g., elevation) are recognized as the most relevant for LSM. Figure 4 counts the frequency with which the impact factors used in the 132 articles mentioned above appear in these articles.

In this study, we selected 15 LCFs that are commonly applied in published research (Figure4). Although numerous LCFs are used in research, the selection criteria for these factors vary. The 15 factors chosen here are the most commonly used. A few of the analyzed research projects either do not employ LCFs or only employ one or two factors (Mali et al. 2021; Felsberg et al. 2022; Kainthura and Sharma 2022), while others incorporate over 15 factors (Konurhan et al. 2023).

When a limited number of LCFs are employed, researchers often need to rely on a more detailed analysis of landslide mechanisms to ensure accurate susceptibility assessment. Conversely, the inclusion of too many LCFs may lead to redundancy and introduce noise into the model, potentially degrading its predictive performance. Therefore, recent studies have suggested various techniques for factor selection or dimensionality reduction to eliminate collinear or less informative variables and enhance model reliability.Deng et al.(2022) conducted a multicollinearity analysis to select the LCFs to be used in the model calculation. Samia et al. (2020) adopted space-time clustering to quantify the path dependency between landslides, offering novel insights for landslide mitigation factors. Zhao et al. (2021) used a traditional statistical certainty factor model to extract the optimal LCFs and then imported them into machine learning models for LSP in Ning Qiang County, Shanxi Province, China, obtaining the optimal LSP accuracy.

In the initial stage of LSP modeling, most research relies on expert experience or published literature to select LCFs. With the extensive use of heuristic approaches, various methods for screening factors, including the information value model, certainty factor model, and analytic hierarchy process, have gained scientific merit. For recently developed advanced machine learning models, factor screening has become relatively straightforward. However, for LSP, the purpose of factor screening is to facilitate computation and enhance accuracy while also considering the potential loss of some landslide information if LCFs are screened and eliminated (Hoang et al. 2023). Although most studies employ only a single method for factor screening, the use of multiple or ensemble methods for computation can be a viable option worth considering.

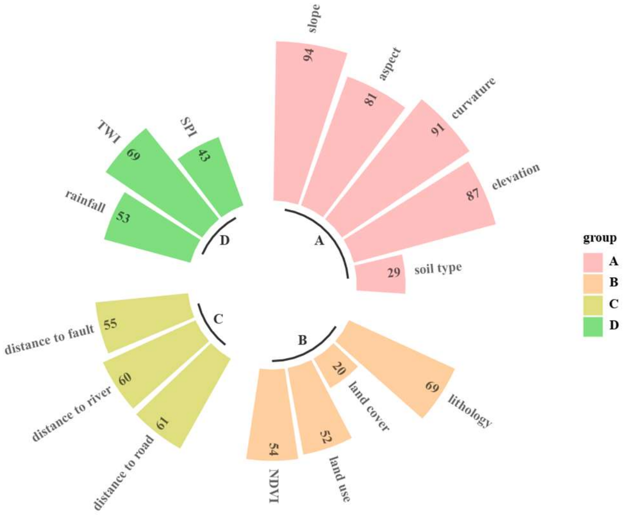

Fig.4 Most of the landslide conditioning factors used within the assessments reported in the selected publications. Legend: curvature (including possible multiple variations like planar and profile curvatures); NDVI, normalized difference vegetation index; TWI, topographic wetness index; SPI, stream power index. Groups A, B, C, and D represent topographical, thematic, proximity, and other factors, respectively.

Factors such as slope (present in 94% of the research), curvature (91%), elevation (87%), aspect (81%), and TWI (69%) were the five most frequently used factors. The top 10 factors were completed by lithology (69%), distance to road (61%), distance to river (60%), distance to fault (55%), and NDVI (54%).

3.3. Evaluation methods

Various metrics are used to evaluate ensemble models in LSM, including AUC, accuracy, Kappa, and RMSE (Zeng et al. 2023b). Among them, AUC is widely preferred for its threshold-independence, but it may be misleading in imbalanced datasets, which are common in LSM. Accuracy is simple but often overestimates performance due to class imbalance. Kappa and F1-score can provide more balanced assessments, while RMSE is useful when outputs are continuous but sensitive to outliers. Overall, relying on a single metric is insufficient—complementary use of multiple indicators is recommended for robust model evaluation.

3.3.1. Receiver Operating Characteristic (ROC) Curve

AUC, derived from the ROC curve, is frequently used in LSA due to its simplicity and threshold-independence. However, its effectiveness diminishes in highly imbalanced datasets—a common issue in landslide prediction—where it may misrepresent the model's true performance. Hence, complementary metrics such as Kappa or F1-score are recommended for a more balanced assessment.The. following are commonly used metrics for constructing·ROC curves.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{2}$$

$$\text{FPR=1-Specificity } = \frac{\text{FP}}{\text{TN+FP}} \tag{3}$$

where FP denotes false positives, which are erroneous positive outcomes; TN denotes true negatives, which are accurate negative results; FN indicates false negatives, which are inaccurate negative findings; and TP indicates true positives, which are precise positive detections.

The AUC value provides a summary of overall performance; AUC is the most popular method, and it is used in almost all of the included articles (Zeng et al. 2023b). A model can be considered accurate if it has an AUC value greater than 0.70 (Chen et al. 2017b). Table 3 provides a summary of the AUC values achieved by different categories of ensemble techniques.

Table 2 Top 15 most commonly used LCFs in the analyzed research studies

Ensemble Techniques	0.70–0.80	0.80–0.90	>0.90
Homogeneous	3	18	9
Heterogeneous	2	15	32
Statistical	1	10	4
Optimization	2	3	7
Physical	1	1	2

Heterogeneous ensemble techniques are the most commonly used ensemble techniques in landslide susceptibility assessment. The AUC values exceed 0.9 for approximately 30% of homogeneous ensemble learning methods, 65% of heterogeneous ensemble learning methods, 26.7% of statistical ensemble techniques, and 58.3% of optimization ensemble techniques. The AUC values in Table 3 indicate that these ensemble techniques can accurately generate landslide susceptibility maps.

3.3.2. Accuracy

Accuracy is widely used in landslide susceptibility assessments but may present overly optimistic results in imbalanced datasets, where non-landslide samples dominate. In such cases, the metric may reflect the model's bias toward the majority class rather than its ability to discriminate landslide occurrences. Therefore, relying solely on accuracy can obscure model limitations, and complementary metrics such as AUC or Kappa are recommended to ensure more reliable evaluation.3.3.3. Cohen's Kappa Coefficient

Cohen's Kappa coefficient, often referred to simply as Kappa or κ, is a statistical measure used to assess inter-rater agreement or reliability between two raters or observers. It was introduced by Jacob Cohen in 1960.

Kappa accounts for the possibility of agreement occurring by chance and provides a more robust measure of agreement than simple percent agreement, especially when dealing with categorical data or when there is a possibility of chance agreement. It is particularly useful in psychology, medicine, sociology, and natural language processing.

Cohen's Kappa is widely used in various fields to evaluate agreement between raters or observers when dealing with categorical data. For example, Kappa is often used to assess the reliability of diagnostic tests, evaluate the consistency of human judgments, and measure the agreement between annotators in natural language processing tasks.

3.3.4. RMSE

RMSE is a prevalent metric used to gauge the disparities between model predictions and actual observations; thus, it can be used to assess the fitting adequacy of the model on given data (Alqadhi et al. 2024). Because it penalizes large errors more heavily, RMSE is often used to assess model fitting quality. However, its high sensitivity to outliers can be problematic in landslide susceptibility mapping, where data distributions are often uneven and noise-prone. Consequently, while RMSE can complement classification-based metrics like AUC or Kappa, relying solely on it may obscure the model's actual predictive performance in spatial classification tasks.

4. Ensemble techniques in LSM

4.1. Ensemble methods between machine earning algorithms

As shown in Figure 1, in the past decade, numerous research studies on landslide susceptibility assessment have used a combination of machine learning algorithms as integrated learning models.

Machine learning focuses on developing algorithms and models that can learn from data and make predictions or decisions without being explicitly programmed (Qasimi et al. 2023). Machine learning is a subset of artificial intelligence, and it has revolutionized various industries and applications. This certainly includes the study of landslide susceptibility assessment, where machine learning techniques have had a significant impact. Traditional landslide susceptibility assessment methods rely on expert experience and manual rules, which may be subjective and limited in scope (Gopinath et al. 2023). However, by learning and modeling from large amounts of data, machine learning techniques can automatically uncover patterns and rules hidden within the data, thereby enhancing the accuracy and reliability of the assessment.

Machine learning techniques can analyze factors such as geology, topography, and climate to extract features for predicting landslide probability. These techniques can handle large amounts of data, identify complex relationships between relevant factors, and generate prediction models. Such models can be trained and optimized through supervised, unsupervised, or deep learning methods. Machine learning techniques can also handle multiple data sources, including remote sensing imagery, ground observations, and historical data, to comprehensively consider the influences of multiple factors, thereby improving the accuracy and comprehensiveness of landslide susceptibility assessments. Moreover, machine learning techniques can process and analyze new data in real time, allowing for timely updates and improvements to assessment results.

However, as landslide susceptibility research expands and the number of evaluation units increases, single algorithms may become prone to issues of overfitting or underfitting. Additionally, a single algorithm may perform poorly when dealing with complex data. Thus, researchers have applied ensemble techniques to combine two or more algorithms and create integrated algorithm models. Remarkable evaluation results have been achieved by integrating two or more machine learning algorithms. The following sections discuss the two most prevalent methods in machine learning ensemble methods.

4.1.1. Homogeneous Ensemble Algorithms

A homogeneous ensemble algorithm is a method of constructing an ensemble model by combining basic models of the same type (Zheng et al. 2023). Its origins can be traced back to the 1990s, when researchers realized that individual basic models may have specific limitations in addressing complex machine learning problems, leading to the idea of using multiple basic models to address these issues.

The earliest homogeneous ensemble algorithm can be traced back to 1994, when Leo Breiman and Adele Cutler proposed the random forest algorithm. By constructing an ensemble of multiple decision trees, random forests improve predictive performance by using the predictions of multiple trees for voting or averaging, thereby obtaining the final prediction. Subsequently, in 1999, Jerome H. Friedman proposed the gradient boosting tree algorithm, which iteratively trains multiple decision trees and gradually improves predictive performance by correcting the model's errors from the previous iteration.

The core concept behind the homogeneous ensemble algorithm is based on the notion of collective intelligence, wherein the performance of a single model can be improved by combining the predictive abilities of multiple models. The effectiveness of this collective intelligence has been widely validated in practical problems, leading to significant breakthroughs in machine learning research worldwide.

Due to the success of homogeneous ensemble algorithms, researchers have continuously explored various homogeneous ensemble methods in recent years. Commonly used homogeneous ensemble methods in landslide susceptibility assessment include bagging, AdaBoost, random forest, rotation forest, boosting, voting, and stacking. It is important to note that some ensemble methods can function as heterogeneous ensemble algorithms in specific scenarios, as discussed in the following subsection. This section solely focuses on the use of homogeneous ensemble methods.

Homogeneous ensemble algorithms use only a single type of base classifier when constructing a new ensemble model. Pham et al. (2017) employed the multi-layer perceptron neural network as the base classifier and combined it with ensemble methods (AdaBoost, Bagging, Dagging, MultiBoost, Rotation Forest, and Random SubSpace) for classification. Shortly after, Shirzadi et al. (2017) used RS(Random Subspace) to generate subsets from the training data and used each of these subsets to construct a classifier based on the relatively new algorithm NBT(Naïve Bayesian Tree). NBT is a decision tree-based algorithm that incorporates Bayesian theory to construct classification trees. RS is a relatively new ensemble framework that has the ability to enhance predictive model performance. Hence, it is evident that combining these advanced machine learning algorithms and novel ensemble frameworks can potentially yield better predictive outcomes compared to using a single model.

Table 4 presents the proportions of basic classifiers employed within homogeneous ensemble models. Hu et al. (2021) used the C4.5 decision tree and artificial neural network (ANN), two renowned machine learning classifiers, as the foundation for an evaluation model through various ensemble techniques and base learners. Subsequently, Miao et al. (2023) conducted LSM using the boosting-C5.0 decision tree model. These studies reflect the evolution of machine learning algorithms and their effects on model performance. Wu and Wang (2023) addressed the issue of imbalanced landslide and non-landslide sample data by adopting the Easy-Ensemble technique and then integrated the processed data into an ensemble framework for further computation. Such approaches undoubtedly enhance the overall framework structure of ensemble models.

Additionally, many researchers such as Mali et al. (2021) have used ensemble techniques to develop and evaluate novel feature selection methods for identifying the causal factors of slope failure and assessing their predictive potential. Wu and Lin (2022) established four event-based landslide susceptibility ensemble models by computing the ensemble of susceptibility indices, including their mean, median, and weighted mean, and the committee average of binary susceptibility values, resulting in superior evaluation performance compared to individual models. These methods provide valuable insights into conducting landslide susceptibility assessments.

To evaluate the effectiveness of homogenous ensemble models, some scholars have compared ensemble models with single-base classifier models. For instance, Miao et al. (2023) compared the performance of the Boosting-C5.0 model with those of C5.0, ANN, and support vector machine (SVM) models and found that Boosting-C5.0 outperformed other single-base classifiers. In contrast, some researchers have validated model accuracy using different ensemble frameworks. For example, Minh et al. (2023) combined several ensemble methods (Bagging and Decorate) with a radial basis function classifier (RBFC) to predict landslide susceptibility in the Trung Khanh district of Cao Bang Province, Vietnam. They found that the Bagging-RBFC model performs better compared to other ensemble frameworks under RBFC. Li et al. (2022) selected the J48 decision tree, ANN, and ensemble techniques such as AdaBoost and Bagging for comparison, affirming models superior performance over other ensemble models. One of the most intuitive methods for evaluating the quality of a model is to compare it with other conventional models, including the analysis of merits and drawbacks. For instance, Pham et al. (2016) developed rotation forest fuzzy rule-based classifier ensemble (RFCE), an ensemble method for the spatial prediction of landslides. However, when examining its advantages, Pham also acknowledged the limitations of the model. Therefore, the best method for evaluating a model is determined by the characteristics of the research itself; rather than relying on a fixed evaluation approach, any method that is reasonable and well-founded can be appropriate.

Table 3 Literature on landslide susceptibility mapping based on homogeneous ensemble

Author	Year	Ensemble Method
Pham et al.	2017	AdaBoost, Bagging, Dagging, MultiBoost, Rotation Forest, and Random SubSpace
Shirzadi et al.	2017	NBT and RS
Hu et al.	2021	Bag-C4.5, Boost-C4.5, Bag-ANN, Boost-ANN, and Stacking C4.5-ANN
Miao et al.	2023	Boosting-C5.0
Wu et al.	2023	Bagging, Boosting, Stacking
Minh et al.	2023	Dagging, Bagging
Li et al.	2022	RS-J48T
Pham et al.	2016	RFCE

4.1.2. Heterogeneous Ensemble Algorithms

Similar to homogeneous ensemble algorithms, heterogeneous ensemble algorithms are standard ensemble algorithms in machine learning. A heterogeneous ensemble model refers to an ensemble model composed of different types of base learners, which can be different algorithms or different configurations of the same algorithm. Heterogeneous ensembles use the advantages and characteristics of different base learners to improve the performance and generalization ability of the model.

Table 5 presents the proportions of basic classifiers or ensemble frameworks employed within the heterogeneous ensemble model. In this study, heterogeneous ensembles of machine learning algorithms can be roughly divided into two types. One type combines two or more base classifiers using an ensemble framework. These differ from homogeneous ensemble models in their inclusion of more than one type of base classifier. For example, if the base classifier and meta-classifier use the same algorithm in the stacking algorithm, the model can be considered to be a homogeneous ensemble algorithm. Otherwise, it is a heterogeneous ensemble algorithm. The second type of algorithm couples two or more machine learning algorithms to create a new ensemble algorithm.

4.1.2.1. Application of heterogeneous ensemble frameworks

Due to the extensive development of integrated frameworks in homogeneous ensemble models, the application of such frameworks in heterogeneous ensemble models has also been evaluated in recent years. Two typical strategies for heterogeneous ensembles are averaging and stacking. The averaging method constructs multiple similar yet independent base models and averages their prediction results to obtain the final prediction. After evaluating several machine learning models, Kumar et al.(2023) employed the averaging strategy to find the optimal ensemble model by combining them pairwise. The advantage of the averaging method lies in its ability to reduce the risk of overfitting in individual models, enhancing their generalization capability. By combining the prediction results of multiple models, the averaging method can mitigate the influence of sample noise and balance the biases and variances among different models, thus improving the overall predictive ability.

The core concept of the stacking strategy is to train a meta model to combine the predictions of multiple base models. The advantage of stacking lies in its ability to fully leverage the strengths of different models, resulting in better performance compared to simple voting methods. By combining information from multiple base models in a meta model, stacking effectively reduces the risk of overfitting and improves the generalization capability of the model. Song et al. (2020) proposed a stacking ensemble learning framework combined with embedded feature selection; they used four tree-based classifiers as base learners and logistic regression as the meta-learner in a two-layer structure. When constructing the stacking ensemble model, Hu et al. (2020) used different numbers of base classifiers to build the model and evaluated the model accuracy for comparison. The results indicate that more base classifiers do not necessarily lead to higher accuracy. An excessive number of base classifiers may result in longer computational processes, and the influence of some poorly performing models on the overall results must be addressed. However, the improvement relative to a single model is still considerable.

4.1.2.2. Ensemble machine learning algorithms

The coupling of machine learning algorithms refers to combining different machine learning algorithms to address complex problems or enhance predictive performance. This approach can operate at various levels, including model ensembling, feature engineering, hyperparameter optimization, and model selection. Regarding model ensembling, integrating multiple diverse learners through ensemble learning reduces model variance and enhances model generalization, thereby yielding more reliable predictive outcomes (Abdollahizad et al. 2023). The specific explanation of this aspect has been elaborated in the previous section and will not be reiterated here. The interplay of machine learning algorithms can be harnessed for various tasks including feature selection, transformation, and composition, with the goal of enhancing model performance. Feature engineering involves manipulating raw data to extract valuable information or create novel features. In landslide susceptibility assessment, the crux of feature engineering lies in effectively transforming the raw data into landslide conditioning factors. When optimizing hyperparameters using integrated machine learning algorithms, different machine learning algorithms have their own hyperparameters, and adjusting these hyperparameters can significantly affect model performance. Scholars are dedicated to coupling different optimization algorithms (e.g., grid search, random search, and Bayesian optimization) to search the hyperparameter space and more effectively enhance model performance. Different machine learning algorithms can also be integrated for model selection, achieving better performance on different problems. For example, ensemble learning methods can be used to simultaneously compare and combine multiple models, thereby generating more robust and accurate prediction results. Ensemble machine learning algorithms are often used to address issues related to model selection.

The interplay among machine learning algorithms is frequently leveraged to address model selection challenges. Chen et al. (2017) examined three renowned machine learning models, namely Max-Ent, SVM, and ANN. They compared the performance of paired combinations against individual models and found that the ensemble modeling of ANN-SVM outperformed all other models. This implies that models with extensive mathematical foundations may mutually reinforce each other bilaterally; however, the specific mechanisms and factors involved require further investigation.

ANN is a type of deep learning algorithm. Deep learning is a branch of machine learning. Its core idea is to learn the features and representations of data through multi-layer neural networks. The application of deep learning algorithms in ensemble algorithms is not uncommon. Aslam et al. (2023) compared the CNN(Convolutional Neural Network) architecture and ResNet with the most popular machine learning and deep learning techniques. They used several common metrics to validate the CNN architecture and ResNet, verifying the significant improvement of the CNN model relative to traditional techniques in landslide management and prevention. Kavzoglu et al. (2021) explored solutions to the problem of model variance and limited generalization ability. The authors proposed an ensemble deep learning architecture based on shared blocks to improve the predictive capability of a single deep learning model. To this end, a combination of CNN, recurrent neural network (RNN), and long short-term memory (LSTM) deep learning models and their ensemble form (CNN-RNN-LSTM) were used to model the landslide sensitivity of a province in Turkey. The results showed that the ensemble deep learning model has higher predictive accuracy compared to a single deep learning model.

Deep learning algorithms have greatly aided advances in model precision. However, integrated deep learning algorithms do not necessarily outperform integrated machine learning algorithms. Although deep learning algorithms have clear advantages in performance and adaptability compared to general machine learning algorithms, they also come with drawbacks such as training difficulties, large data requirements, and poor interpretability. Ali et al. (2022) combined a random forest algorithm with various machine learning algorithms and found that the RFT-LMT model (Random Forest-Logistic Model Tree)exhibited the best performance. Thus, deep learning algorithms are not universally suitable in all environments.

Compliance and interpretability requirements are essential in some industries and applications such as finance and healthcare. For landslide susceptibility assessment, interpretable algorithms must be introduced to gain insights into the basic decision mechanisms of LSM. Due to the reliability of interpretable algorithms compared to non-interpretable algorithms, the application of interpretable algorithms in landslide susceptibility assessment is a promising research direction.

4.2. Ensemble models based on statistical algorithms

Statistical models, which aim to elucidate and forecast the characteristics and relationships within data, play a pivotal role in statistics. The development of statistical models stems from exploring underlying patterns within data and comprehending latent mechanisms behind phenomena. The roots of statistical models can be traced back to the 17th century, when the early development of probability theory laid the foundation for the field of statistics. With the ever-increasing data volume and emergence of data science, statistical models have become increasingly crucial. By constructing models to depict and interpret the relationships between data, statistical models not only aid in understanding the mechanisms underlying phenomena but also facilitate prediction and decision support.

In the current era driven by data, statistical models are making continual advances. With the maturation of technologies such as machine learning and deep learning, the shape and application of statistical models are constantly evolving and expanding. In the field of landslide susceptibility assessment, researchers are exploring the integration of statistical models with other models. Aghdam et al. (2016) proposed a hybrid model combining statistical indices (Wi) and an adaptive neuro-fuzzy inference system (ANFIS) in the geographic information system for LSM. In this approach, the Wi model, which is based on statistical algorithms, is used to determine the weights of each landslide-related factor. Depending on the type of statistical model employed, integrating statistical models with other models can involve coupling with machine learning models or coupling two or more statistical models together.

Integrating statistical models and machine learning models is increasingly gaining attention in the fields of statistics and machine learning. Although both statistical and machine learning models aim to model and predict data, they have different foundations and assumptions in methodology and theory. By integrating methods and models from these two domains, we can fully leverage their respective strengths and enhance the ability to model and predict. Three methods are commonly employed for the integration of statistical models and machine learning models: ensemble models, stacking models, and fusion models.

The concept of ensemble modeling refers to the combination of statistical models and machine learning models to construct a composite model. For instance, in linear regression models, decision tree models are integrated as sub-models to incorporate both linear and non-linear relationships.

Stacked models involve hierarchically combining different models. Initially, multiple base models are used for prediction, and the predictions from the base models are then fed as inputs to the top-level model for the final prediction.

Fusion models entail synthesizing the predictions from statistical and machine learning models through model fusion techniques. Standard fusion methods include weighted averaging, voting, and stacking.

For landslide susceptibility assessment, voting and stacking methods are commonly used. In terms of stacked models, Zhang et al. (2024) combined the FR and RF models by inputting the variable factors obtained from the FR model into the RF model for learning. They then used the ensemble model to evaluate the landslide susceptibility and obtain the landslide susceptibility index. Saha et al. (2021) applied conditional probability statistical techniques to the boosted regression tree (BRT) algorithm. They obtained factor weights from the CP model and integrated them with the BRT model. In terms of fusion models, Chang et al. (2023) used MPA to reduce the uncertainty in non-landslide sample selection in LSP. They calculated landslide susceptibility and categorized susceptibility into extremely high, high, medium, low, and deficient low landslide susceptibility levels. They selected the optimal landslide susceptibility level with the highest probability for each slope unit. Whether it is the information flow and complementary advantages between different models, the reduction in prediction errors, or overall performance improvement achieved by integrating different models, statistical algorithms have demonstrated stable performance when integrated with machine learning algorithms. However, this integration approach is not applicable in all cases. For example, Xue et al. (2022) assessed landslide susceptibility using a back propagation neural network (BPNN) model coupled with frequency ratio (FR) and information value (IV) models and compared the results to the mapping results of a single BPNN model. They found that the statistical models were not more accurate than heuristic models. In that study, the AUC value of the statistical ensemble model was 0.4 percentage points lower than that of the heuristic ensemble model. However, it was 5.4 percentage points higher than that of the single BPNN model.

Table 4 Literature on landslide susceptibility mapping based on heterogeneous ensemble models

Author	Year	Ensemble Method
Kumar et al.	2023	Averaging
Song et al.	2020	Stacking
Hu et al.	2020	Stacking
Chen et al.	2017	ANN-SVM-MaxEnt
Aslam et al.	2022	CNN-ML/DL
Kavzoglu et al.	2021	Ensemble DL models
Ali et al.	2022	RFT-SVM/ANN/NB/LMT
Aghdam et al.	2016	Wi-ANFIS
Chang et al.	2023	MPA-LR/SVM
Xue et al.	2022	FR-BPNN/IV-BPNN

4.3. Ensemble models based on optimization algorithms

Optimization algorithms are a class of algorithms used to solve optimization problems. Optimization problems are widely present in various fields such as engineering, economics, and physics (Deng et al. 2022). The goal of optimization algorithms is to find the minimum or maximum value of a function to reach the optimal solution. The development of optimization algorithms can be traced back to the early 1920s when mathematical programming theory emerged. This theory primarily focuses on linear programming problems, which involve optimizing linear objective functions under linear constraints. However, linear programming can only be applied to simple problems, and it cannot handle complex nonlinear problems. In the late 1950s and early 1960s, with advances in computer technology, people began to explore numerical methods to solve more complex optimization problems. These numerical methods are primarily based on iteration to adjust the values of parameters or variables to approximate the optimal solution. Well-known algorithms such as gradient descent and steepest descent have been widely applied to function optimization problems. Over time, optimization algorithms have seen further development and expansion. In the 1960s and 1970s, solution methods for nonlinear integer problems emerged, and dynamic programming gradually matured. In the 1980s and 1990s, heuristic algorithms such as genetic algorithms, ant colony algorithms, and simulated annealing were also introduced for solving optimization problems.

In this section, it is necessary to clarify that the optimization algorithms mentioned here do not belong to the category of machine learning algorithms. Although some optimization algorithms are used to solve optimization problems, they are not widely classified as machine learning algorithms. These algorithms typically focus on finding optimal solutions without involving data learning and pattern recognition. For example, common optimization algorithms like genetic algorithm, simulated annealing, and ant colony optimization perform well in optimization problems and are generally considered distinct from traditional machine learning algorithms. Although there may be occasional intersections and mutual influence between optimization and machine learning algorithms, they have different theoretical foundations, application areas, and objectives. Therefore, although certain optimization algorithms are beneficial, they are not strictly classified as machine learning algorithms. The coupling between the mentioned optimization algorithms and machine learning algorithms here is also complementary to the coupling of machine learning algorithms with other algorithms.

In recent years, the rise of machine learning has provided new opportunities and challenges for developing optimization algorithms. The alignment between optimization algorithms and machine learning algorithms is not arbitrary. Optimization problems are a prevalent class of problems across various fields. From resource allocation problems in economics to design problems in engineering, they can be abstracted as optimization problems. Machine learning, as a method for addressing intricate problems, primarily achieves optimal predictive performance by refining model parameters. Optimization algorithms are specialized algorithms used to solve optimization problems such as gradient descent, Newton's method, and genetic algorithms. The parameter optimization problems in machine learning can also be addressed using these optimization algorithms. Therefore, combining optimization algorithms with machine learning algorithms can improve the efficiency and performance of model training. The increasing demands for model performance and efficiency in practical applications have driven the integrated development of optimization and machine learning algorithms. Integrating optimization algorithms makes it possible to swiftly identify the optimal model parameter configurations, thereby enhancing the generalization capability and practical performance of the model.

Based on the literature mentioned in this article, the integration of optimization algorithms and machine learning algorithms can be roughly categorized into parameter optimization, hyperparameter optimization, model selection, adaptive learning, and combining heuristic algorithms.

When training machine learning models, adjusting model parameters using optimization algorithms aims to improve the model fitting to the training data and ensure accurate predictions on unknown data. Razavi-Termeh et al. (2021) used ant colony optimization and differential evolution for the optimization of model parameters in an ANFIS. Meanwhile, Chen et al. (2021) employed a teaching-learning-based optimization algorithm along with the silkworm and gardener bird optimization algorithm for the optimization of an ANFIS model for LSM. Integrating optimization algorithms with machine learning algorithms is the most common and direct approach to parameter optimization.

In addition to the parameters obtained through training, machine learning models involve manually set hyperparameters such as learning rate and regularization parameters. Xiong et al. (2021) proposed an integrated model based on an ant colony optimization (ACO) strategy and a deep belief network (DBN). In this model, the ACO is used to search for the optimal values of hyperparameters such as batch size, initial learning rate, and dropout rate in the DBN. The integrated model demonstrates better rationality, scientific rigor, and interpretability. A comprehensive comparison of various indicators and landslide density has identified the crucial role of DBN hyperparameters in landslide susceptibility assessment. Wang et al. (2022) introduced a particle swarm optimization algorithm to determine DBN hyperparameters. To maximize the computational performance of these algorithms, Ikram proposed a new approach using the cuckoo optimization algorithm and the SailFish optimizer as meta-heuristic methods for developing ANNs in the Kurdistan region of Iran. Optimization algorithms can search for the optimal combination of hyperparameters, enhancing the performance and generalization capabilities of the model.

By evaluating performance metrics, the best machine learning model or model configuration can be chosen. This ensemble approach involves evaluating and comparing performance among multiple candidate models to select the best model or model combination. Optimization algorithms can help find the optimal model parameter configuration in this process. Xing et al. (2021) integrated the three fundamental machine learning models (back propagation, SVM, and random forest) through an objective function that calculates the RMSE between the predicted and observed results. A gray wolf optimization algorithm was then employed to compute the weight coefficients between the models. For the ensemble model, the weight coefficients could be allocated based on the results computed by the model; meanwhile, feature selection on conditional factors could be carried out using the optimization algorithm. AI-Shabeeb used five machine learning models based on genetic algorithms. In the initial modeling stage, the best features of each model among the five were selected. Once the significant variables were identified, they were used as input predictor factors for the model.

Some advanced optimization algorithms can adaptively adjust learning rates or other parameters during the training process of machine learning models to improve convergence speed and reduce oscillations during optimization. For example, AdaGrad and Adam, as self-adaptive learning rate algorithms, dynamically adjust update strategies for different parameters, thereby improving optimization efficiency and enhancing training stability. In addition to traditional methods like gradient descent, heuristic algorithms such as genetic algorithms and simulated annealing can also be used for parameter search and optimization in machine learning models. These algorithms are often employed to address complex non-convex optimization problems or to find better parameter configurations in cases with extensive search space.

4.4. Ensemble models based on physical models

A physical model refers to a method of modeling natural phenomena using physical laws and equations to describe and predict them. Based on known physical principles, experimental data, and theoretical assumptions, a physical model simplifies complex phenomena into mathematical expressions or computational models for analysis, prediction, and interpretation. With advances in computer technology, the concept of physical models has gradually expanded into computational physics and computational science. Through numerical simulation and computational experiments, individuals can construct more intricate and realistic physical models to address complex issues in the real world.

Compared to singular machine learning and statistical models, physical models demonstrate lesser efficiency and generality in handling data. However, the predictive outcomes of physical models typically possess higher interpretability and do not appear constrained when tackling abnormal data and sample imbalances. Recognizing these characteristics of the various models, researchers have introduced ensemble models based on physical models. In landslide susceptibility assessment, there are examples of integrating physical models with machine learning models. In response to the sharp increase in geologic disasters caused by extreme localized heavy rainfall events in South Korea, Park et al. (2019) devised a landslide early warning method by harnessing the advantages of statistical and physical hazard assessment methods. Building upon this foundation, they developed a landslide early warning model based on a sequential evaluation approach. This model transforms raw rainfall data to generate maps of landslide early warning level based on geographic information systems. This method has certain advantages for spatiotemporal landslide early warning. With the continuous advances in visualization and cloud computing, future integrated algorithms will emphasize the intuitive presentation and real-time monitoring of results. Through virtual reality and online platforms, integrated algorithms can achieve real-time monitoring and interactive display of geologic disaster processes, providing decision-makers and the public with intuitive and convenient information services. Gunther et al. (2009) conducted a physics-based stability assessment of slopes and performed a binary landslide susceptibility analysis using landslide inventory data and thematic ground condition factors. Both models demonstrate reasonable success rates when evaluated with existing inventory data. Attempts have been made to combine various models to create maps illustrating terrain instability and landslide susceptibility. The development of integrated algorithms should focus on the integration and interactivity of multi-source data. The effective integration of different data types (e.g., remote sensing data, sensor data, and geologic survey data) along with cross-validation and complementarity among models will further enhance the effective application of integrated algorithms in early landslide warning.

4.5 Applicability and Selection Challenges of Ensemble Techniques

Due to the diversity of landslide susceptibility maps and the varying spatial and temporal scales of study areas, it remains challenging to establish unified standards for selecting appropriate ensemble methods. The applicability of a given ensemble technique often depends on regional characteristics, data quality, and modeling objectives. Consequently, future studies should emphasize systematic comparisons and contextual evaluations to guide method selection.

5. Conclusions

Landslides are a common natural disaster that seriously threaten the lives and property of humans. To reduce casualties and property losses, it is necessary to predict and provide early warning before landslides occur. LSM provides suggestions for mitigating these issues by mapping the spatial probability of landslide occurrence. The widespread use of ensemble learning techniques in LSM has increased prediction accuracy. This article reviews the ensemble learning methods used in this field; the main conclusions and suggestions for future work are provided as follows:

Generally speaking, traditional machine learning methods can produce reliable susceptibility maps for landslides. In contrast, ensemble learning methods can generate more advanced models to further improve mapping accuracy, which is particularly evident for large sample sizes.

Each different type of integrated techniques has specific advantages. The advantage of homogeneous integration methods lies in their ability to reduce the risk of overfitting of individual models and enhance model robustness by combining multiple models of the same type, thereby improving overall predictive performance. Additionally, homogeneous integration methods can effectively enhance performance and accuracy when dealing with large datasets. The advantage of heterogeneous integration methods lies in their ability to combine various types of models, leveraging the strengths of each model to enhance overall predictive performance. This approach effectively handles complex and diverse datasets, providing more comprehensive predictive results by integrating different model characteristics. The advantage of integration techniques based on optimization algorithms is that they can adjust the weights and combination methods of individual base learners through optimization algorithms while quickly finding suitable model parameters to maximize overall performance. This method can be flexibly applied to different datasets and problems, thereby improving prediction accuracy and robustness. The advantage of integration techniques based on statistical methods is their ability to use statistical principles to combine multiple models, thereby improving overall predictive performance. This method can reduce errors and improve prediction accuracy by weighting or combining model predictions. Statistical methods can also interpret the relationships between models and assess confidence, aiding in understanding and explaining prediction results. The advantage of integration techniques based on physical methods is their ability to use principles of physics or domain knowledge to design and combine multiple models, thereby improving overall predictive performance. By combining multiple physical models, this method can enhance prediction accuracy and interpretability.

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