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Review article

Application of artificial intelligence in three aspects of landslide risk assessment: A comprehensive review

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ABSTRACT

Landslides are one of the geological disasters with wide distribution, high impact and serious damage around the world. Landslide risk assessment can help us know the risk of landslides occurring, which is an effective way to prevent landslide disasters in advance. In recent decades, artificial intelligence (AI) has developed rapidly and has been used in a wide range of applications, especially for natural hazards. Based on the published literatures, this paper presents a detailed review of AI applications in landslide risk assessment. Three key areas where the application of AI is prominent are identified, including landslide detection, landslide susceptibility assessment, and prediction of landslide displacement. Machine learning (ML) containing deep learning (DL) has emerged as the primary technology which has been considered successfully due to its ability to quantify complex nonlinear relationships of soil structures and landslide predisposing factors. Among the algorithms, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two models that are most widely used with satisfactory results in landslide risk assessment. The generalization ability, sampling training strategies, and hyper-parameters optimization of these models are crucial and should be carefully considered. The challenges and opportunities of AI applications are also fully discussed to provide suggestions for future research in landslide risk assessment.

1. Introduction

Landslides (including the movement of rocks, soils or debris down a slope) are one of the most prevalent geological hazards in the world, posing significant threats and causing substantial losses to human society. According to the Global Fatal Landslide Database (GFLD), Fig. 1 shows the spatial distribution of the fatal landslides which has caused serious damage to human society (Froude and Petley, 2018). Unlike other engineering materials, soils and rocks are three-phased system with strong spatial variability and are sensitive to the change of moisture content and the environment conditions, and respond in a highly non-linear manner. These characteristics of soil structures make it difficult for us to prevent landslides effectively in advance. Therefore, research on landslide risk assessment is crucial for the advancement of human society.

Landslide risk assessment is defined as an assessment of the likelihood of landslides occurring and the potential hazards that could result. The potential hazards contain the injuries, the loss of life and damaged assets which could occur to a system like community or society in a given period (Guo et al., 2020a,b). This paper mainly discusses the monitoring, evolution and probabilistic analyses of landslides occurring which don't address the impact on towns, residents and socio-economics. Landslide risk assessment is divided into two categories: soft risk assessment approach and hard risk assessment approach (Lei et al., 2023). The former focuses on the risk of landslides in a region and the latter pays more attention to the risk of individual landslide (Chen and Chen, 2021; Lei et al., 2023).

In recent decades, studies have mainly focused on establishing knowledge-driven expert systems to assess the risk of landslides (Althuwaynee et al., 2012; Kayastha et al., 2013; Pourghasemi et al., 2012a,b; Tien Bui et al., 2012a). The results rely heavily on the personal experience of senior engineers with strong subjectivity. Moreover, the strong spatial variability of soils and rocks causes uncertainty and diversity of landslides in different regions (Li et al., 2016a; Liu and Leung, 2018).

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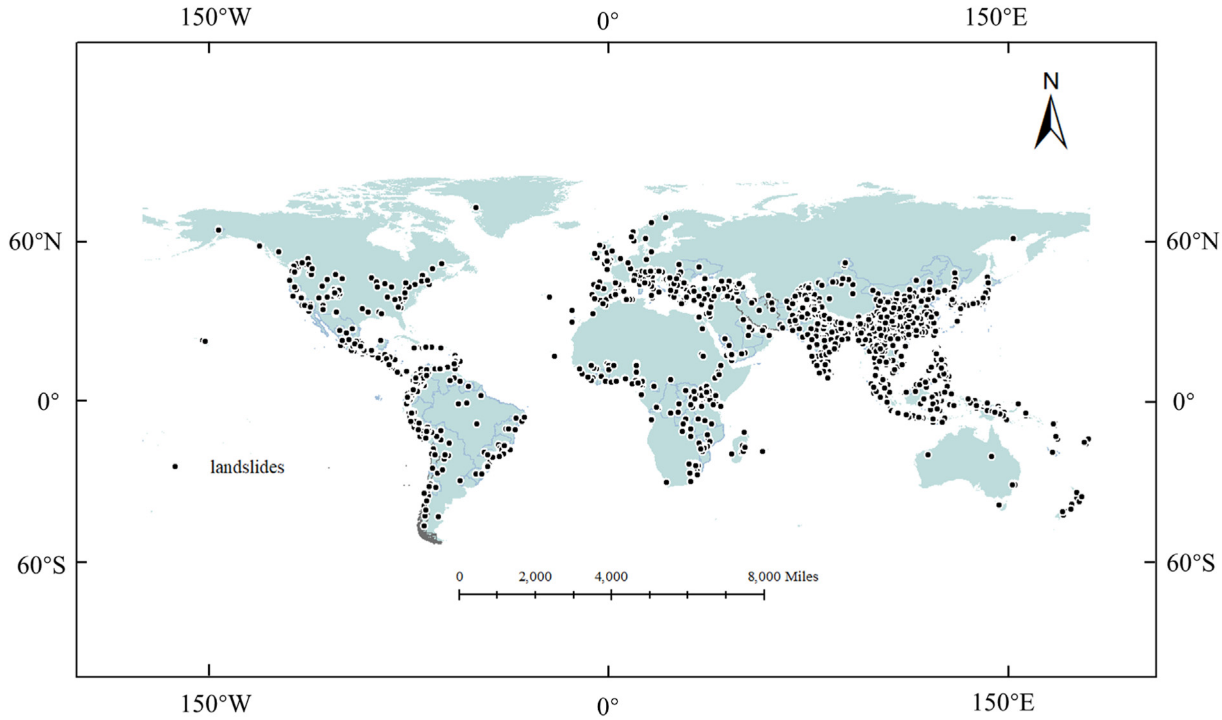

Fig. 1. Distribution of the NASA global fatal landslide database (modified from GFLD, https://svs.gsfc.nasa.gov/4710).

Thus, expert systems are only applicable in their designated survey area, which are highly dependent on manual labor and subjective experience of engineers. Semi-automated and automated operations which can represent the complex non-linear relationships of soil structures are in high demand.

Artificial intelligence (AI) is an advanced technology aiming to automate intellectual tasks that are normally performed by humans. It has an excellent ability to characterize the inherent nonlinear relationships between big data especially the geotechnical data (Baghbani et al., 2022). There are many branches of AI, including machine learning, natural language processing, cloud computing and others (Fig. 2). Currently, AI is widely used in many areas, such as facial recognition, autonomous driving and human-machine interaction (Fig. 2). The main aim of this paper is to investigate the applications of AI in landslide risk assessment. Research shows that the primary focus of AI applications in landslide risk assessment is machine learning (ML) containing deep learning (DL) (Dikshit et al., 2021). It is a data-driven method combining statistics with optimization theory.

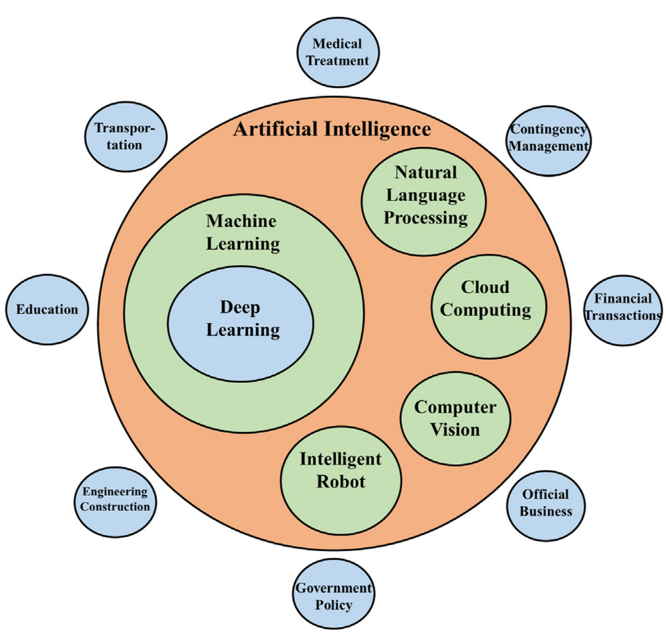

Fig. 2. The technologies of artificial intelligence and its main application fields.

This paper fully investigates the related studies of applications of AI in landslide risk assessment published in recent decades including reviews and research papers until 2024. This paper begins with the brief overview of the AI techniques mainly used in landslide risk assessment. The next section describes how AI techniques have been used in landslide risk assessment. It categorizes the topics into three parts including landslide detection, landslide susceptibility assessment and prediction of landslide displacement. Other applications like sampling strategies, hyper-parameters optimization and the development of graphical user interface (GUI) are also briefly introduced. In the next section, the challenges and future opportunities of AI techniques applied in landslide risk assessment are also provided. Finally, the overall conclusions are made to summarize the whole paper. The explainable AI combining with physical meaning and the generalization ability of the used models are crucial for future development.

2. Brief overview of AI techniques in landslide risk assessment

This section provides a brief overview of different AI techniques used in landslide risk assessment including ML, DL, hybrid models (HMs), performance testing of models and GUI. The former four are the methods and the GUI represents the useful tool mainly applied in landslide risk assessment.

2.1. Machine learning

ML is a data-driven method combining statistics with optimization theory. As shown in Fig. 3, it can be used for prediction and classification (Jordan and Mitchell, 2015). For supervised learning, the collected data are labeled before training, but for unsupervised learning, the data are all unlabeled (Jordan and Mitchell, 2015).

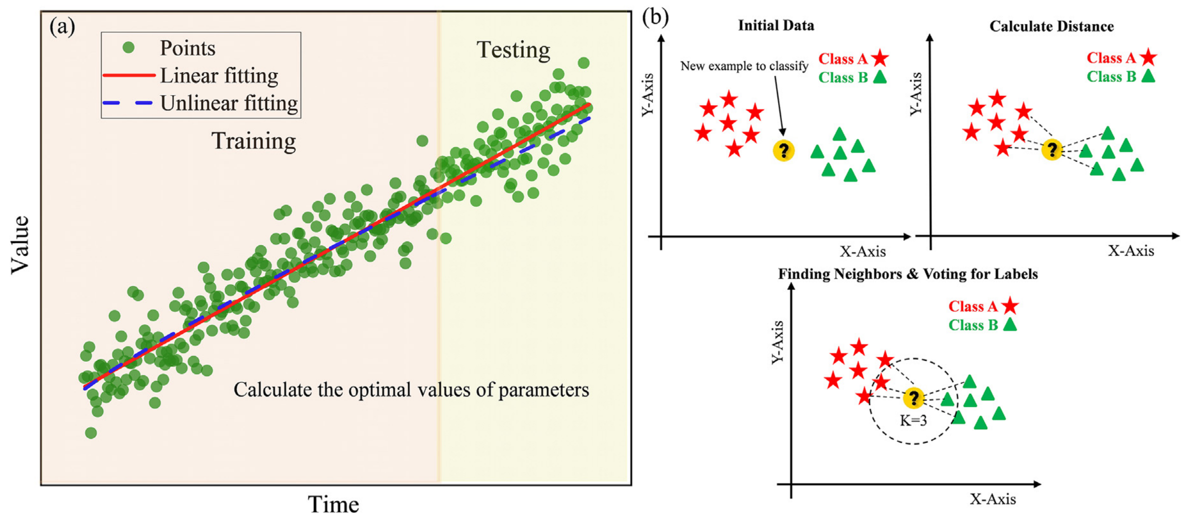

Fig. 3. The main objective of machine learning: (a) prediction of future trends based on historical data and (b) classification of the data according to specific laws.

Widely used ML models include linear regression, logistic regression (LR), support vector machine (SVM), K nearest neighbors (KNN), clustering, decision tree (DT), random forest (RF), naive bayes (NB), etc. The crucial step is to determine the optimal parameter values of the model. For the collected data, a training set is used for fitting the parameters, and a testing set is used for validating the efficiency of the outputs. The loss function is an important index to measure the performance of the model.

2.2. Deep learning

DL is an advanced ML approach that requires a larger amount of data (LeCun et al., 2015). DL framework is established with neural networks, and there are almost always more than three neuron layers (Fig. 4a–d). DL mainly has three steps (Fig. 4e). First, all the input data are subjected to a linear regression operation to obtain a series of results. Second, the

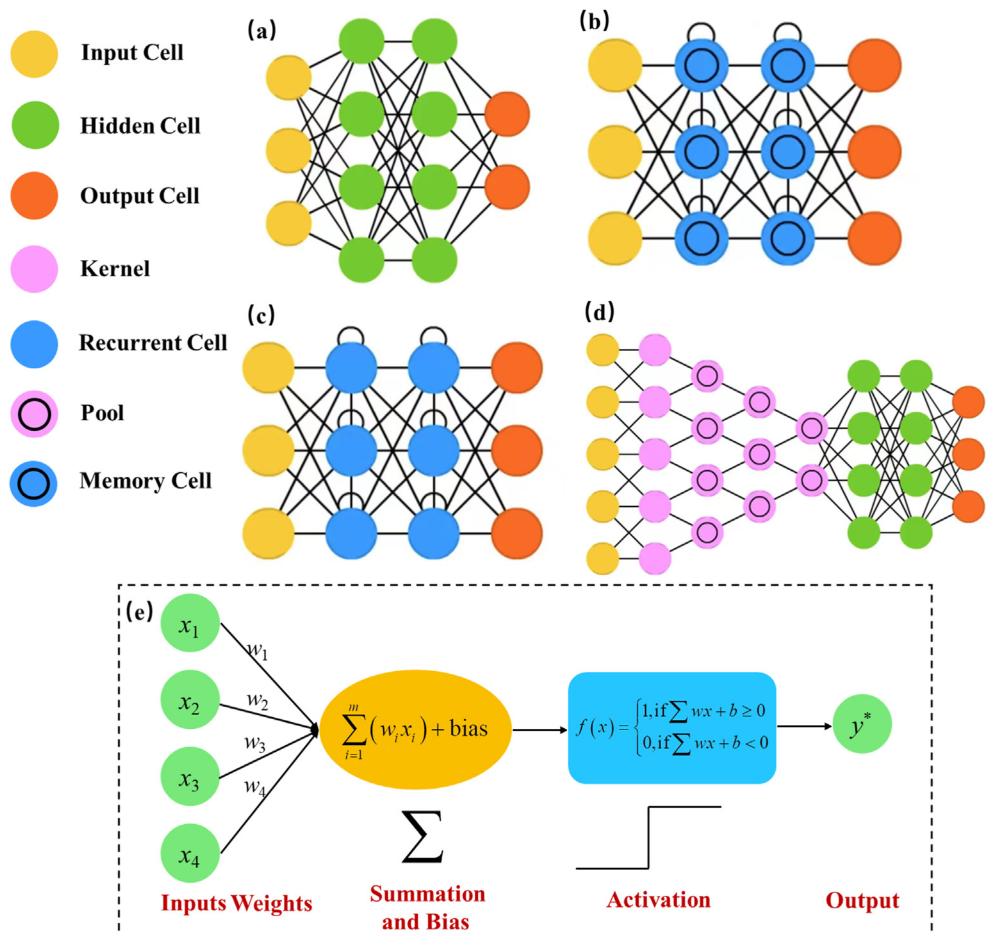

Fig. 4. Different deep learning models: (a) deep feedforward network; (b) long short-term memory; (c) recurrent neural network; (d) convolutional neural network and (e) working principle of one single neuron.

linear regression results are substituted into an activation function to obtain the outputs. The aim is to map the linear regression results to the specific interval of the activation function. Third, the outputs are used as inputs in the next layer of neurons. The calculation process is repeated to eliminate the invalid features, and then the final outputs can be obtained. Compared with ML, the framework of DL more closely resembles the complexity of the operating mechanism of the human neurological system.

Convolutional neural network (CNN) and recurrent neural network (RNN) are the two main DL frameworks that are most commonly used. CNN is mainly used in the fields of image recognition, object recognition and computer vision (Fig. 4d). RNN, on the other hand, is mainly used in fields such as natural language processing and time series analyses (Fig. 4c). In time series prediction, Long-short-term (LSTM) neural network's forgetting gate and memory gate effectively overcome the forgetting problem of RNN, which can memorize the historical information effectively (Fig. 4b).

Recently, transformer model consisting of encoders and decoders has been gradually widely used in geotechnical engineering. The architecture of transformer is shown in Fig. 5. The model based on the attention mechanism provides an effective solution for long-sequence time series prediction and natural language processing (Vaswani et al., 2017).

2.3. Hybrid model

HM integrates two or more ML models (Kadavi et al., 2018), fully combining the advantages of different models. It's also called ensemble learning including bagging, boosting and stacking, etc. For instance, the RF model is the simplest hybrid model and is composed of several decision trees which can solve the over-fitting problem of a single decision tree (Fig. 6). Some strategies like majority voting and averaging are used to obtain the optimal result (Fig. 6).

2.4. Performance testing of the model

The evaluation indexes are used to evaluate the performance of the ML models. In general, seventy percent or eighty percent of the dataset is used to train the model, and thirty percent or twenty percent of the dataset is used to validate the efficiency of the model. The commonly used evaluation indexes include accuracy, precision, recall, F1 score, intersection over union (IoU), root mean square error (RMSE), mean

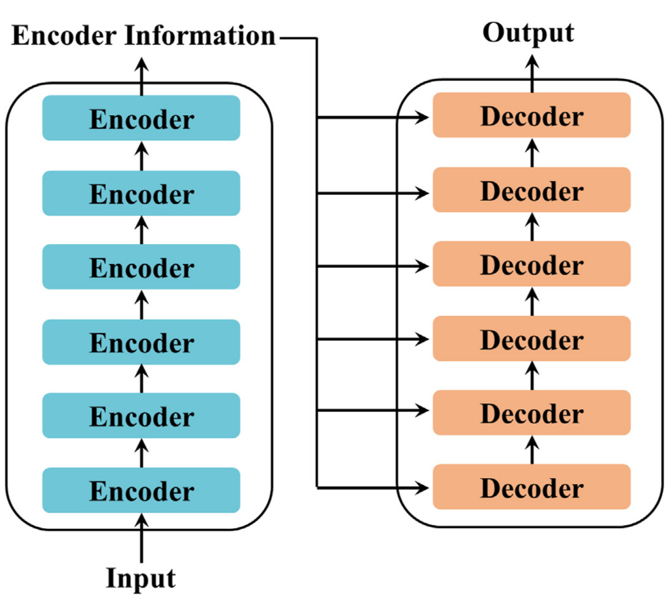

Fig. 5. The main architecture of the Transformer model (modified from Vaswani et al., 2017).

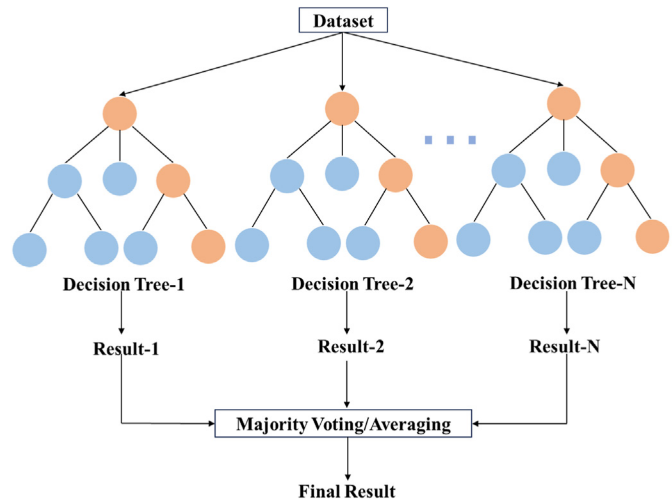

Fig. 6. The architecture of the simplest hybrid model named random forest.

absolute error (MAE), area under curve (AUC), etc. These indexes are defined in Eqs. (1)–(7) as shown below (Baghbani et al., 2022):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1 score} = 2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{4}$$

$$\text{IoU} = \frac{\text{Intersection Area}}{\text{Union Area}} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(P_i - O_i)^2} \tag{6}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \tag{7}$$

where TP is the true positive value, i.e. the data predicted to be true and actually true; FN is the false negative value, i.e. the data predicted to be false but actually true; FP is the false positive value, i.e. the data predicted to be true but actually false; TN is true negative value, i.e. the data predicted to be false but actually false; P_i represents the actual outputs; Q_i represents the prediction outputs. AUC is the area under the receiver operating characteristics curve (ROC).

The higher the accuracy, precision, recall, F1 score, IoU and AUC, and the lower the RMSE and MAE, the more effective the model is. IoU is an index mainly used in image recognition like object detection and semantic segmentation. Selecting reasonable evaluation indexes is crucial before model training. It's necessary to understand how these indexes behave overall, not individually.

2.5. Graphical user interface

GUIs are important tools that help normal users to implement complex algorithmic functions through a simple interface to make the landslide risk assessment. Generally speaking, a GUI encapsulates the complex mathematical models of ML and provides a visual platform for normal users. It enables normal users to easily apply relevant ML models to solve practical problems even if they do not understand the mathematical principles of the models. The development of a GUI is essential to realize the widespread application and popularization of AI techniques.

3. How AI techniques have been applied in landslide risk assessment

This section describes how AI techniques have been used in landslide risk assessment. Three key areas are identified and discussed including landslide detection, landslide susceptibility assessment and prediction of landslide displacement in this section. Other applications like sampling strategies, hyper-parameter optimization and GUIs are also discussed. Among these areas, landslide detection and landslide susceptibility assessment both belong to the soft risk assessment approach (regional) and prediction of landslide displacement belongs to the hard risk assessment approach (individual) (Lei et al., 2023).

ML is an algorithm that can learn from data without relying on rules-based programming. The statistical models used in the following sections are the formalization of relationships between variables in the form of mathematical equations which are distinguished from ML. Generally, ML is a subset of AI and DL is a subset of ML (Fig. 2). But in the following sections of the paper, ML and DL are distinguished. ML specifically refers to the conventional algorithms like SVM, LR, linear regression, DT, RF, AdaBoost, clustering, KNN, NB and others. DL refers to the neural network constructed by different frameworks like artificial neural network (ANN), CNN, RNN, graph neural network (GNN), LSTM and others.

Figure 7 shows the statistical results of the representative studies published in recent decades using AI techniques in landslide risk assessment for several main fields. Landslide susceptibility assessment has the highest number of studies followed by landslide displacement prediction, landslide detection and GUI. Landslide detection still relies heavily on visual interpretation by remote sensing techniques without the use of AI techniques. DL has been used as the main technique gradually replacing ML methods and statistical models. It still lacks advanced GUI tools that can be effectively used in this field.

3.1. Landslide detection

To prevent disasters caused by landslides, it is essential to identify slopes where landslides have previously occurred. Landslide detection involves the recognition and mapping of landslides in a region, providing information on the location, type, boundary, volume, and date of landslides. This is a critical prerequisite for determining landslide susceptibility.

Traditionally, landslide detection methods rely on the visual interpretation of remote sensing images and aerial photography, as supported by field surveys (Zhang et al., 2024). However, this approach is resource intensive, time-consuming, and subject to interpretation bias (Das et al., 2023; Wang et al., 2020b). Therefore, semi-automated or automated method by AI is crucial in generating landslide maps, which can effectively reduce the workload of manual landslide detection (Das et al., 2023; Liu et al., 2023a; Liu et al., 2023b, Liu et al., 2023c, Liu et al., 2024a; Lv et al., 2023; Zhang et al., 2024). Moreover, traditional landslide detection based on visual interpretation relies heavily on people's subjective judgment. This leads to inconsistent criteria for detecting landslides. The criteria for detecting landslides based on AI models are uniform and the results obtained are more objective than manual detection.

The application of AI, particularly image recognition technology, has emerged as a useful method in recognizing landslides using remote sensing and aerial photography data. The general flowchart of this approach is depicted in Fig. 8. This approach enables the accurate and efficient identification of landslides and reduces the dependence on human interpretation, improving the reliability and reproducibility of landslide detection.

3.1.1. ML in landslide detection

Initially, pixel-based ML models were utilized to detect landslides. These models focus on detecting landslides and non-landslides at the pixel level. Thus, complex features of geomorphological factors such as rivers, trees, mountains, and trenches are not considered (Fig. 9). In 2005, Nichol and Wong (2005) employed a pixel-based maximum likelihood classifier with satellite images, achieving approximately 70% detection of existing landslides. Borghuis et al. (2007) utilized both supervised and unsupervised pixel-based ML methods and successfully detected landslides. Various pixel-based methods have varying performance levels. For instance, pixel-based support vector machine models have outperformed other models, such as RF and maximum likelihood classifiers (Dikshit et al., 2021). Generally, pixel-based methods have been applied successfully in landslide detection and continue to be widely used as an effective semi-automated method at present (Liu et al., 2023a; Liu et al., 2023d; Liu et al., 2024b; Lv et al., 2023; Zhang et al., 2024).

In object-based ML approaches to landslide detection, the physical meaning of each complex geological feature consisting of landslides is considered (Fig. 9). Figure 10 shows the recognition results of different landslides and non-landslides at pixel-based and object-based level, respectively. Comparing with the pixel-based method, the object-based method may be more appropriate for identifying complex geological features and natural phenomena (Hölbling et al., 2012). For instance, not like the exposed landslides, the landslides covered with vegetation are usually difficult to recognize. To address this situation, (Li et al., 2015) proposed an object-based approach to detect forested landslides, reaching an accuracy of 89.11%. At present, object-based methods are widely

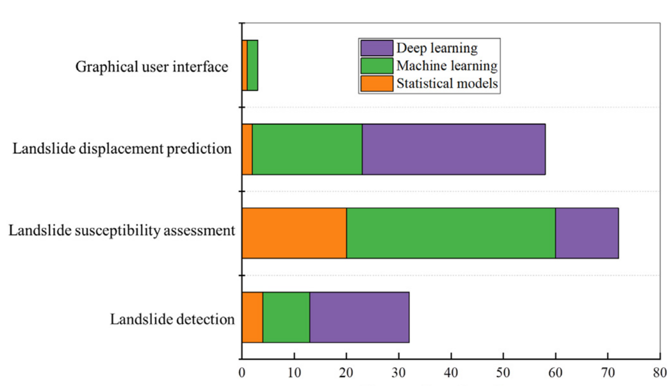

Fig. 7. Distribution of the use of AI techniques in landslide risk assessment in different application areas.

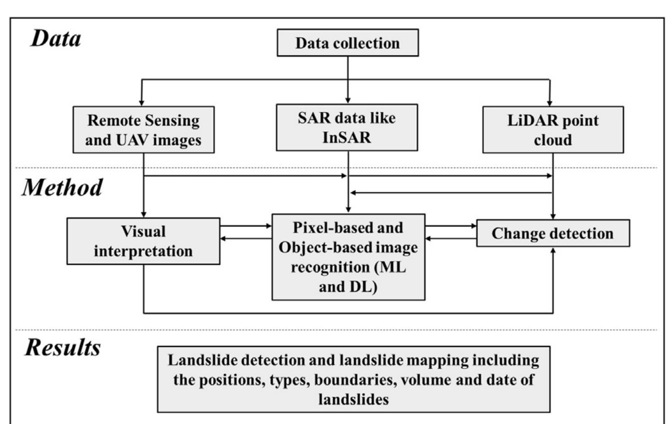

Fig. 8. General flowchart of landslide detection.

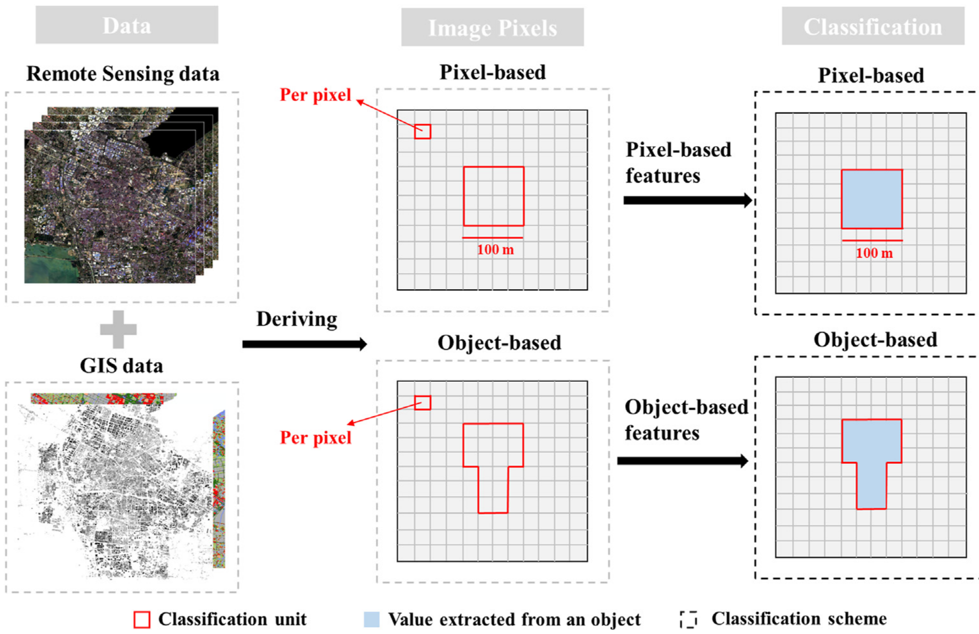

Fig. 9. The principle of pixel-based and object-based image recognition.

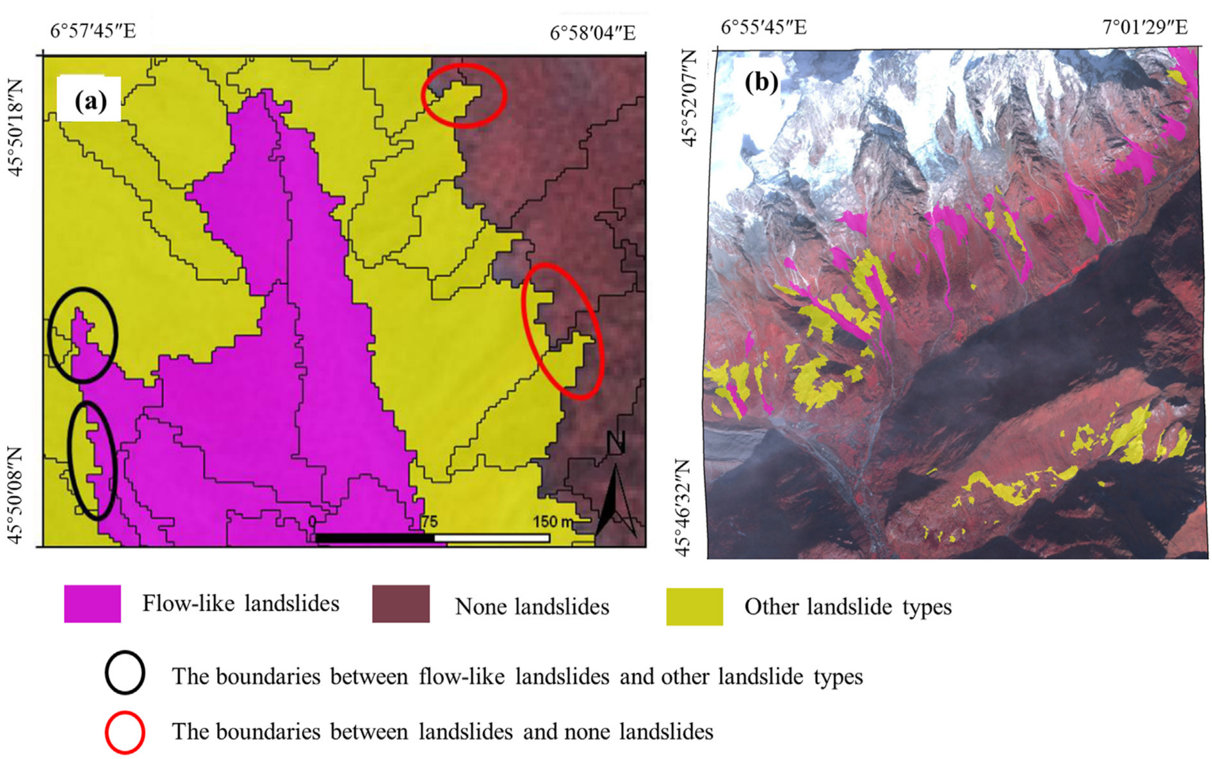

Fig. 10. The landslide recognition results in Aosta Valley, northwestern Italy: (a) pixel-based landslide recognition and (b) object-based landslide recognition (modified from Hölbling et al., 2012).

used for semi-automated landslide detection (Amatya et al., 2021; Bhuyan et al., 2023; Chandra et al., 2023; Comert et al., 2019; Feizizadeh et al., 2017; Sreelakshmi and Vinod Chandra, 2024).

The studies above mainly focused on analyzing the spectral information of satellite and UAV images from the same period. However, some slopes are potential landslides that lack obvious geological features such as cracks and surface exposure and are hard to directly recognize through visual interpretation. Essentially, the deformation of these kinds of slopes must be analyzed. The first useful way to obtain deformation information is to analyze and interpret satellite and UAV images from different periods. The core technology involves finding pixel differences between images. For instance, in 2015, Hoelbling et al. (2015) performed change detection of potential landslides covered with vegetation. In 2017, Feizizadeh et al. (2017) used an object-based method to analyze multi-temporal images to detect changes in landslides, reaching an accuracy of 94.74%. The second useful way to obtain deformation information is to use synthetic aperture radar data, such as those from InSAR (Hu et al., 2023; Chen et al., 2023; Confuorto et al., 2023; Li et al., 2024;

Li et al., 2023a; Xu et al., 2023; Yi et al., 2023a; Yi et al., 2023b). In 2018, Rosi et al. (2018) updated the landslide inventory in the Tuscany region by using InSAR with the persistent scatter interferometry technique to detect changes in landslides. In 2021, Liu et al. (2021) proposed a new InSAR-based procedure to detect landslides by integrating the geomorphological conditions from one period and changing the detection of landslides from different periods. The integration of spectral information and change detection can facilitate the recognition of landslides with higher accuracy, as it enables the mutual verification of the recognition results (Dai et al., 2023; Phakdimek et al., 2023).

3.1.2. DL in landslide detection

Recently, DL methods have been gradually used. Among the DL models, CNNs are the most widely used framework in landslide detection like U-net, Seg-Net and Yolo (Chandra et al., 2023; Han et al., 2023; Hu et al., 2023; Li et al., 2023c; Lu et al., 2023; Wang et al., 2020). The details of the operation process are shown in Fig. 11, and the following discusses the main development process of DL applications in landslide detection.

To verify the efficacy and superiority of DL models, in 2019, the performance of ML and DL in landslide detection were compared, and the results showed that DL methods don't significantly outperform ML methods because DL in landslide detection was still in its infancy (Ghorbanzadeh et al., 2019). The design of the framework of DL, such as the layer depth, input window size and training strategy, evidently influence the outputs (Ghorbanzadeh et al., 2019). For instance, RNN with different designs perform differently in the mapping of landslides (Wang et al., 2020a,b). A better understanding of DL models for landslide detection is in high demand and still needs further research.

Based on the above background, in 2019, Lei et al. (2019) proposed a novel approach integrating a fully convolutional network with pyramid pooling to detect landslides, and the experimental results showed that the methods were significantly improved and could outperform ML models, yielding higher precision and lower overall error. In 2020, Prakash et al. (2020) adapted a CNN using ResNet-34 blocks for feature extraction and proved that results with higher accuracy could be obtained using this method compared with those of ML methods. In 2022, Ghorbanzadeh et al. (2022) compared the performances of different object-based DL models and found that ResU-Net-OBIA performed better than the ResU-Net and OBIA approaches. In 2023, the Yolov7 algorithm based on the SE squeezed attention mechanism is verified to have higher generalization and can be used to detect landslides more accurately with fewer missed detections (Liu et al., 2023a). The research above all proves that a reasonable DL framework is crucial, which can help improve the results of landslide detection effectively with higher generalization ability and replace state-of-the-art approaches.

3.2. Landslide susceptibility assessment

Landslide susceptibility (LS) reflects the possibility of landslides occurring in a specific region. The process of landslide susceptibility mapping (LSM) involves considering various influencing factors, such as elevation, slope angle, lithology, soil type, aspect, distance to roads, distance to faults and distance to rivers, to analyze the likelihood of landslides as the input parameters. In general, steeper slopes, weaker soil shear strength, and closer proximity to rivers increase the LS of an area. Correlation analyses are supposed to be carried out between different influencing factors, with the strongly correlated influencing factors being eliminated and the weakly correlated influencing factors being retained. It's the critical standard for selecting input influencing factors for LSM.

Analyzing LS can aid policy-makers in taking effective measures to avoid disasters and reduce losses. The developments of LS studies are shown in Fig. 12. The conception was first proposed in the 1960s. Traditionally, LS has relied on statistical methods and expert systems, where senior engineers determine the parameter values of the model based on statistical results and practical experience. Currently, ML has become an efficient and objective approach to map LS. Figure 13 shows the primary flowchart of ML applied in LS. It has several advantages over traditional methods, such as higher objectivity and efficiency.

3.2.1. ML in landslide susceptibility assessment

In 2012, Mamdani fuzzy algorithms based on expert opinions were

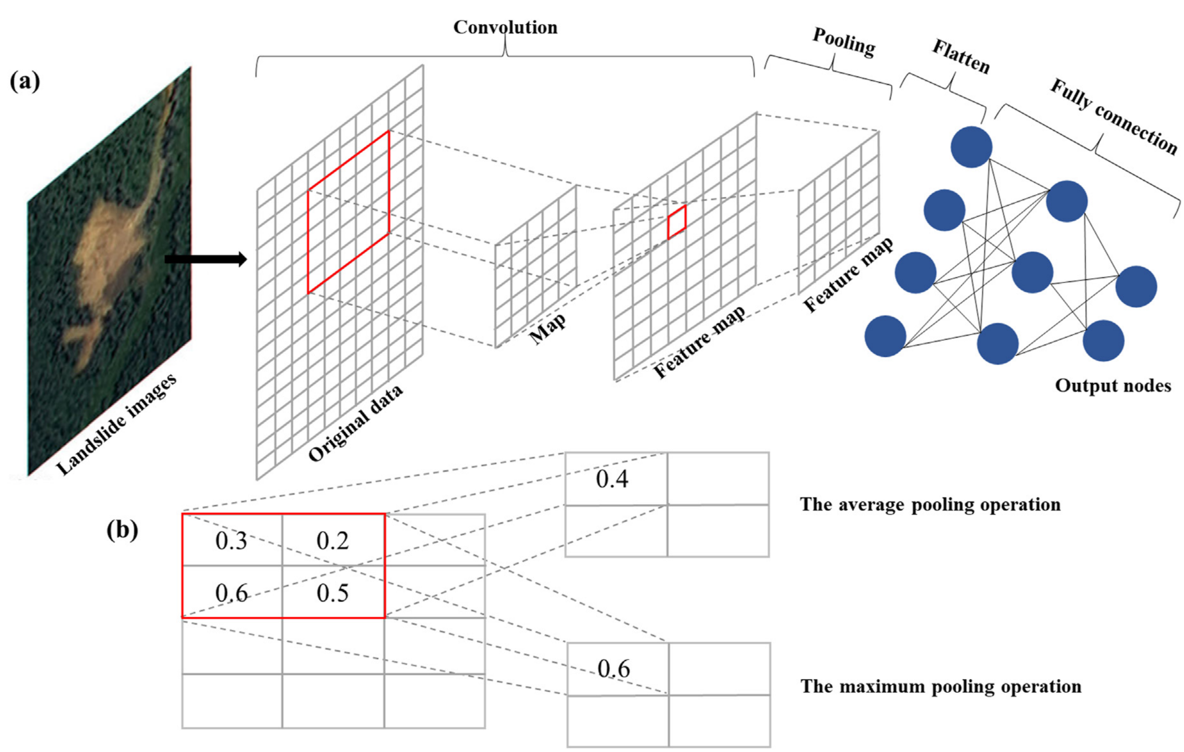

Fig. 11. Landslide recognition with a convolutional neural network: (a) process of the convolutional neural network and (b) two main pooling operations.

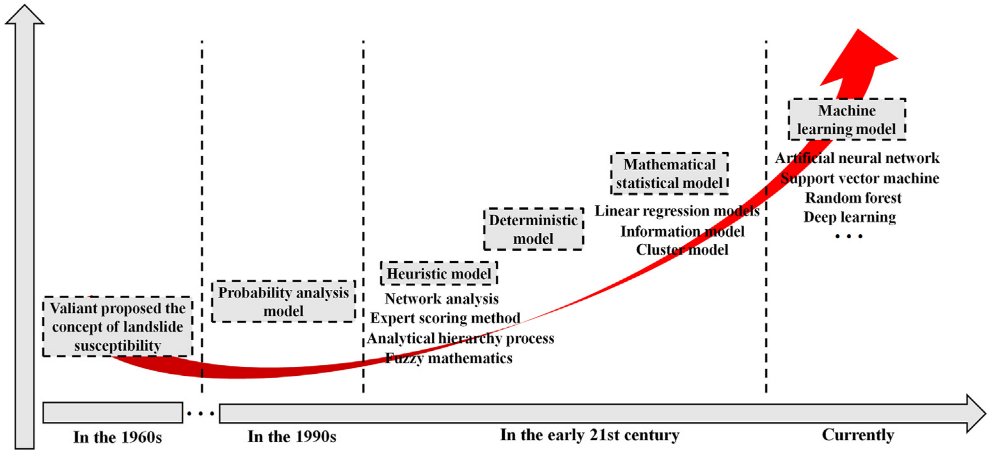

Fig. 12. The development of landslide susceptibility over time (modified from Dou et al., 2022).

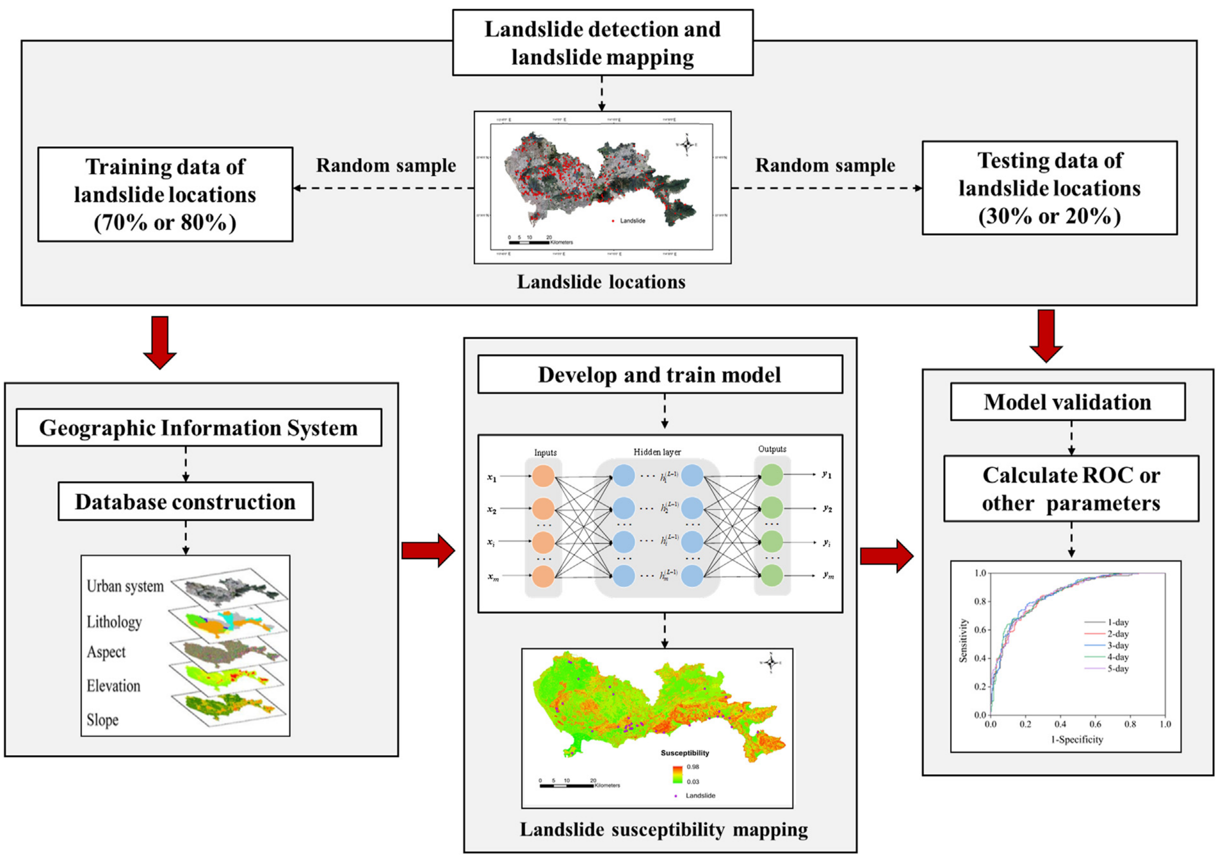

Fig. 13. The main process of landslide susceptibility mapping using machine learning.

used to successfully map LS in Sinop City, with an AUC value of 0.855, which indicates good fitness (Akgun et al., 2012). Althuwaynee et al. (2012) indicated that evidential belief functions can be effectively used in LSM. Tien Bui et al. (2012a) investigated the application of an adaptive neuro-fuzzy inference system for LSM and proved that the accuracy of the results can be quite satisfactory. In 2013, Kayastha et al. (2013) applied the analytical hierarchy process to LSM, and the analytical results were in good agreement with those of past landslides. The results were further validated by other research (Chang et al., 2023; Dou et al., 2019; Nath et al., 2024; Zhou et al., 2023). From the studies above, the evidential belief functions, fuzzy models and analytical hierarchy process can all perform well in the application of LSM.

To find the optimal models for LSM, most studies have focused on comparing the performance of these models. In 2012, Tien Bui et al. (2012b) compared the performance of evidential belief functions and fuzzy logic models and found that although both models perform well in terms of LSM, evidential belief functions are better, yielding higher accuracy. Pourghasemi et al. (2012a,b) found that fuzzy logic models perform better than the analytical hierarchy process in LSM. Of the three models above, evidential belief functions have the highest prediction capability. In addition to the models above, many researchers have also investigated other statistical models, such as the index of entropy, conditional probability models, frequency ratio, weights of evidence, certainty factor and index of entropy (Devkota et al., 2013; Ozdemir and

Altural, 2013; Pourghasemi et al., 2012a,b; Regmi et al., 2014). The results show that all the models above perform well and have similar accuracy in terms of LSM.

Some researchers compared ML models with statistical models and proved that ML models can obtain better results (Akgun, 2012; Ali et al., 2021; Felicísimo et al., 2013; Goetz et al., 2015; Huang et al., 2020; Pradhan, 2013). Thus, ML models have become the main research direction in LSM, and many studies have focused on comparisons between different ML models to obtain the optimal model. Fig. 14 shows the susceptibility mapping of landslides in Algeria using different ML models. Different models perform differently in terms of the final results. SVM, LR, NB, RF and other ML models were compared, and the results proved that all these ML models can perform LSM well; however, SVM, LR and RF are promising methods with better outputs (Chen et al., 2017; Guo et al., 2021; Pradhan, 2013; Tsangaratos and Ilia, 2016; Youssef et al., 2016; Youssef and Pourghasemi, 2021).

3.2.2. DL in landslide susceptibility assessment

DL has also increasingly been utilized in the field of LSM. In 2014, Conforti et al. (2014) used ANN for LSM in the Turbolo River catchment in southern Italy and found that the results were satisfactory. This study demonstrated the effectiveness of neural network models for LSM. In a recent study by Dou et al. (2020), DL models were applied to a case study in the Muong Lay district, and LSM outputs with good fitting to the testing set were obtained. Some researchers have become interested in whether DL models perform better than ML models. In 2020, Bui et al. (2020) compared DL models with ML models, such as SVM, DT and RF, for LSM. The results showed that the accuracies of the LSM results of the DL models were 3%–7% higher than those of other ML models. In 2021, Mandal et al. (2021) compared a CNN with ML models such as RF and bagging models and found that the CNN outperformed the other models and achieved higher precision. In summary, DL models have been proven to be better, i.e., higher LSM accuracy, compared with ML models (Jiang et al., 2023). The performances of different DL models are also compared in some studies (Ge et al., 2023; Kim and Lee, 2024). Currently, the two main DL frameworks used for LSM are CNNs and RNNs (Fan and Hua, 2009; Wang et al., 2020a,b; Yi et al., 2020; Mandal et al., 2021; Jiang et al., 2023).

3.2.3. HM in landslide susceptibility assessment

In addition to using single model, many studies have explored the use of HM to improve the LSM. Several studies demonstrated the superiority

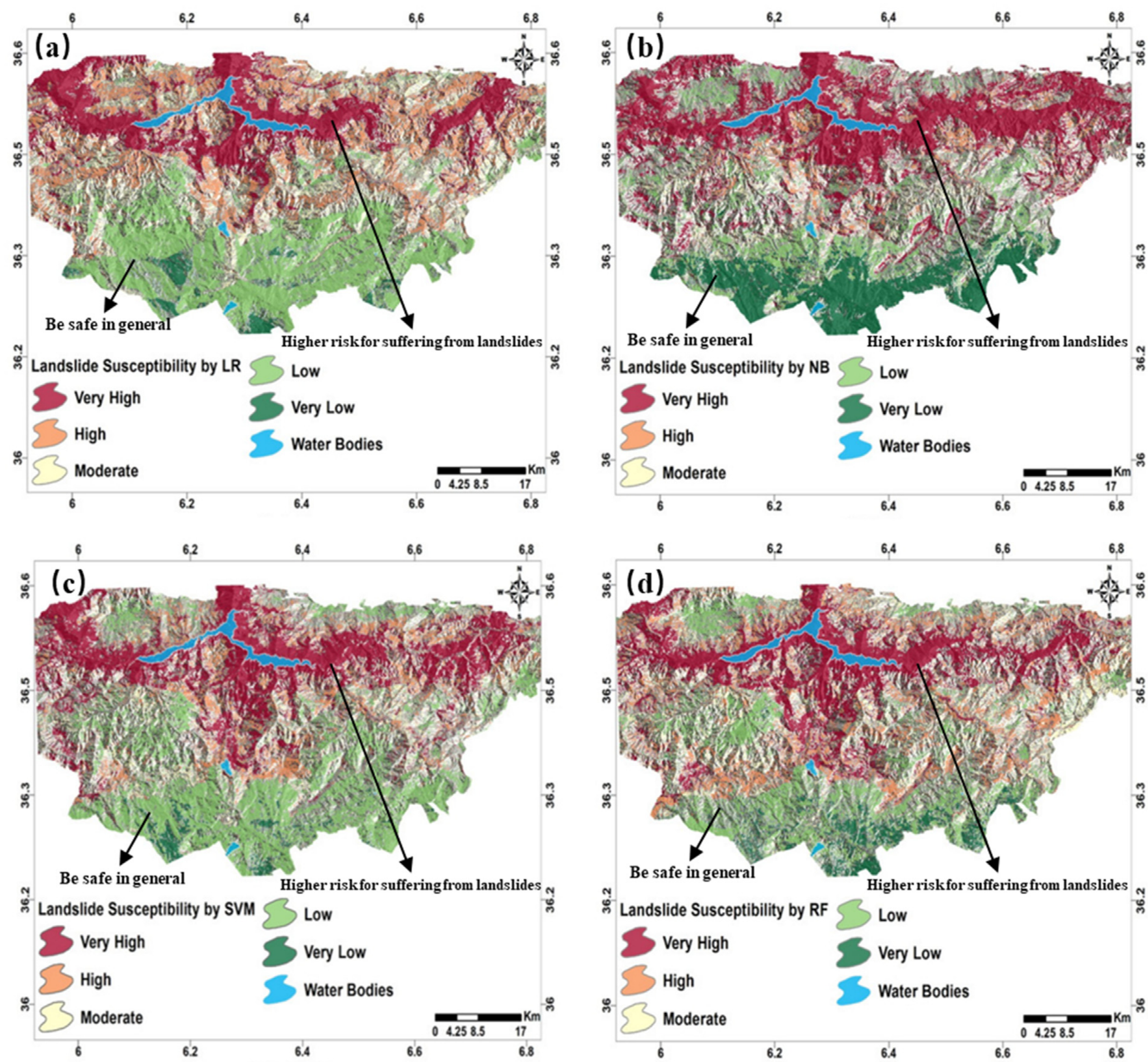

Fig. 14. The susceptibility mapping of landslides in Algeria using different machine learning models: (a) logistic regression; (b) naïve Bayes; (c) support vector machine and (d) random forest (modified from Merghadi et al., 2020).

of HM, including those by Pourghasemi et al. (2012), Chen et al. (2017), Goetz et al. (2015), Trinh et al. (2023), Youssef et al. (2016), Liu et al., 2024a, Yang et al. (2024a). In 2014, Althuwaynee et al. (2014) integrated evidential belief functions and the analytical hierarchy process for LSM and found that the novel model showed better performances than that of a single LR model. In 2020, Wang et al. (2020a) compared HM (an ensemble model of an SVM, an ANN and a gradient boosting DT) with single ML models and found that the AUC value of the HM was 0.11–0.35 higher than those of the ML models. Wang et al. (2020b) used an SVM with bagging, boosting, and stacking ensemble ML framework with data from a mountainous watershed in Japan to improve landslide assessment. This HM is proven to be better. (Di Napoli et al., 2020) found that the integration of different ML models can produce robust and more stable LSM outputs. Many studies also compared the performance of different HMs and proved that accuracy differences still exist (Balogun et al., 2021; Chen et al., 2019; Chen et al., 2016; Nguyen et al., 2019; Tien Bui et al., 2019).

3.3. Prediction of landslide displacement

Regional studies that focused on determining slopes with higher landslide risk were described above (soft risk assessment approach). The following section discussed studies related to mitigating potential hazards for these slopes (hard risk assessment approach). Predicting the evolution of these slopes is crucial for understanding the occurrence process of landslide disasters and forecasting them in advance.

The evolution of landslides, especially accumulation landslides, mainly contains three stages, i.e., the initial deformation stage, constant deformation stage and accelerative deformation stage. In the later period of the accelerative deformation stage, the tangent angle of deformation approaches 90°, and the risk of landslide failure reaches the maximum. The regulation shows that displacement is a very important factor in characterizing the evolution of landslides. To obtain the evolution of slopes with a high risk suffering from landslides, the main strategy is to monitor the displacement of these slopes with equipment, such as GNSS, displacement gauges, inclinometer and remote sensing, including InSAR and UAV, and then use ML models to predict the future displacement based on historical monitoring data (Zhang and Huang, 2009; Casagli et al., 2023; Xu et al., 2023). The development of landslide displacement prediction studies is shown in Fig. 15 and the main flowchart of landslide displacement prediction is shown in Fig. 16.

3.3.1. ML in the prediction of landslide displacement

In the 1980s and 1990s, the prediction of landslide displacement was mainly based on statistical models like fuzzy theory and gray system theory (Fig. 15). Since the 1990s, research has increasingly focused on nonlinearity, systematics and intelligence (Fig. 15). The field of AI, especially relevant ML models, has been introduced into the displacement prediction of landslides and has achieved good results (Fig. 15). For instance, in 2009, based on the time series of landslide displacement, Fan and Hua (2009) used phase space reconstruction and an SVM to effectively predict future landslide displacement. In 2013, Zhang et al. (2013) used exponential smoothing and nonlinear regression analysis to predict the displacement of landslides with high accuracy. Different ML models perform differently in landslide displacement prediction (Liu et al., 2012; Miao et al., 2010). Some studies compared the performance of the Gaussian process (GP), SVM and RBF networks and found that the GP models performed better than the other two models (Liu et al., 2012, 2014). As a result, to obtain better outputs, the selection of ML models

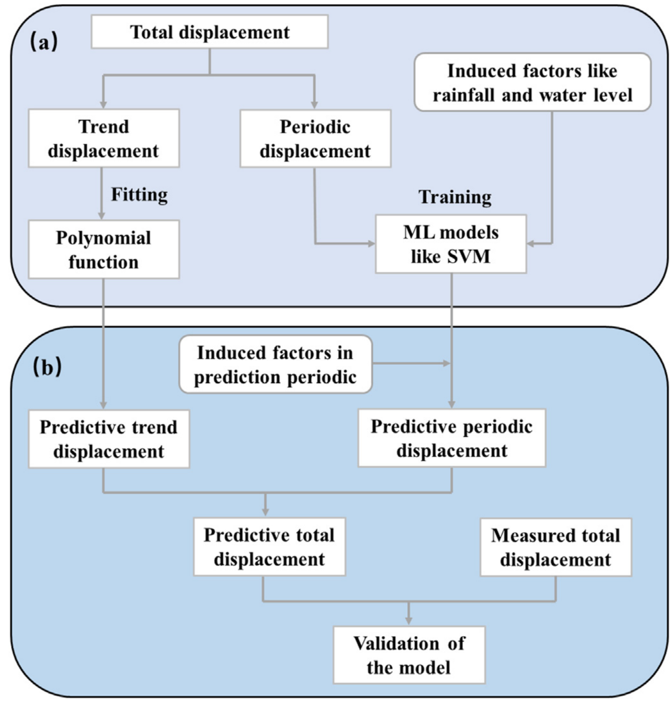

Fig. 16. Flowchart of landslide displacement prediction using machine learning: (a) model establishment and (b) model validation.

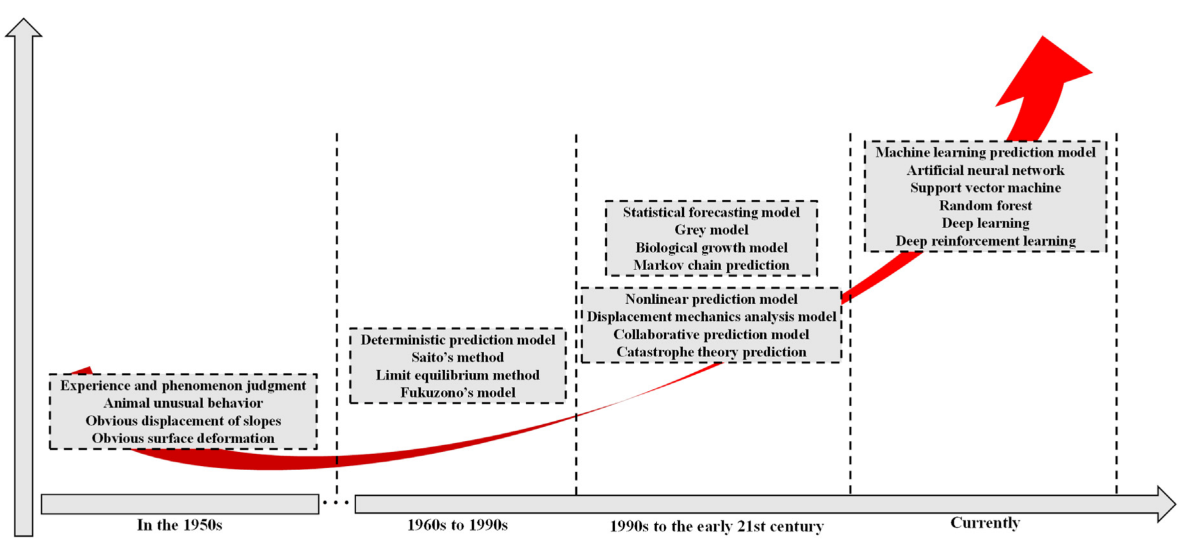

Fig. 15. The development of landslide displacement prediction over time (modified from Dou et al., 2022).

should be considered carefully for landslide displacement prediction.

For landslides, especially reservoir landslides, rainfall and fluctuations in the reservoir water level are two main factors that induce landslide disasters (Du et al., 2013; Zhang et al., 2019). Heavy rain or reservoir impoundment will significantly decrease the shear strength of rocks and soils (Fig. 17). However, the methods above only predict landslide displacement based on the time series of data and do not take the impact of induced factors into account. The risk of potential landslides will be greatly underestimated with these prediction results. To improve the prediction results, more research has begun to focus on considering the essential factors mentioned above. In 2013, Peng et al. (2013) used SVM to predict step-type landslide displacement. In this study, landslide displacement was split into two terms, the trend term and seasonal term (Fig. 17). The two terms were predicted separately, and then they were added to obtain the final output (Fig. 17). The trend term is related to the geological conditions of landslides, while the seasonal term has a high correlation with the influencing factors of water (Fig. 17). In 2014, Lian et al. (2014) proposed that the ensemble extreme learning machine performs well for predicting the accumulative displacement of landslides separated into trend terms and periodic terms. In 2018, Miao et al. (2018) used a support vector regression model to predict and separate landslide displacement into three terms: the trend term, periodic term and random term. This study clarified that the random term represents some uncertainties that will accelerate the evolution of landslides, such as anthropogenic activities and other social factors. In future research, to obtain prediction results with higher precision, the separation of landslide displacement into two or more terms is an indispensable step (Yang et al., 2019a; Zhang et al., 2021a; Zhang et al., 2021b).

3.3.2. DL in the prediction of landslide displacement

DL has also gradually been applied to the prediction of landslide displacement. In 2015, (Chen et al., 2015) used an RNN to predict the displacement of the Baishuihe landslide and found that the prediction accuracy was much higher than that of conventional ML models. In 2016, Jiang and Chen (2016) demonstrated the effectiveness of generalized regression neural networks on the prediction of landslide displacement. In 2022, Huang et al. (2022) used a modified CNN to accurately predict landslide displacement. The feasibility and superiority of DL models has also been validated by many other studies (Chen et al., 2016; Jiang et al., 2023b; Li et al., 2016b; Lian et al., 2016a,b; Lin et al., 2023; Nava et al., 2023; Yang et al., 2023; Yang et al., 2024b, Yang et al., 2024c; Zeng et al., 2023).

In 2018, Xu and Niu (2018) proposed an LSTM neural network to predict the displacement of landslides. This dynamic model can remember prior information and apply it to later outputs. In these studies, it was found that dynamic models perform better than static models. This conclusion was further validated in many other studies (Duan et al., 2023; Li et al., 2023a; Xie et al., 2019; Xing et al., 2019; Xing et al., 2020; Yang et al., 2019b). Moreover, for the same kinds of dynamic models, LSTM performs better than the Elman network, which means that different DL models perform differently even though they possess the same functions (Niu et al., 2021; Xu and Niu, 2018). LSTM has also been used to compare with RNNs and other DL models (Gao et al., 2022; Niu et al., 2021). The results showed that LSTM performs best and can be regarded as a main tool for landslide displacement prediction (Zhang et al., 2022; Duan et al., 2023; Li et al., 2023b). From the above, it seems that the Elman network is not an effective dynamic model. To address this problem, in 2019, Zhang et al. (2019) proposed an improved Elman

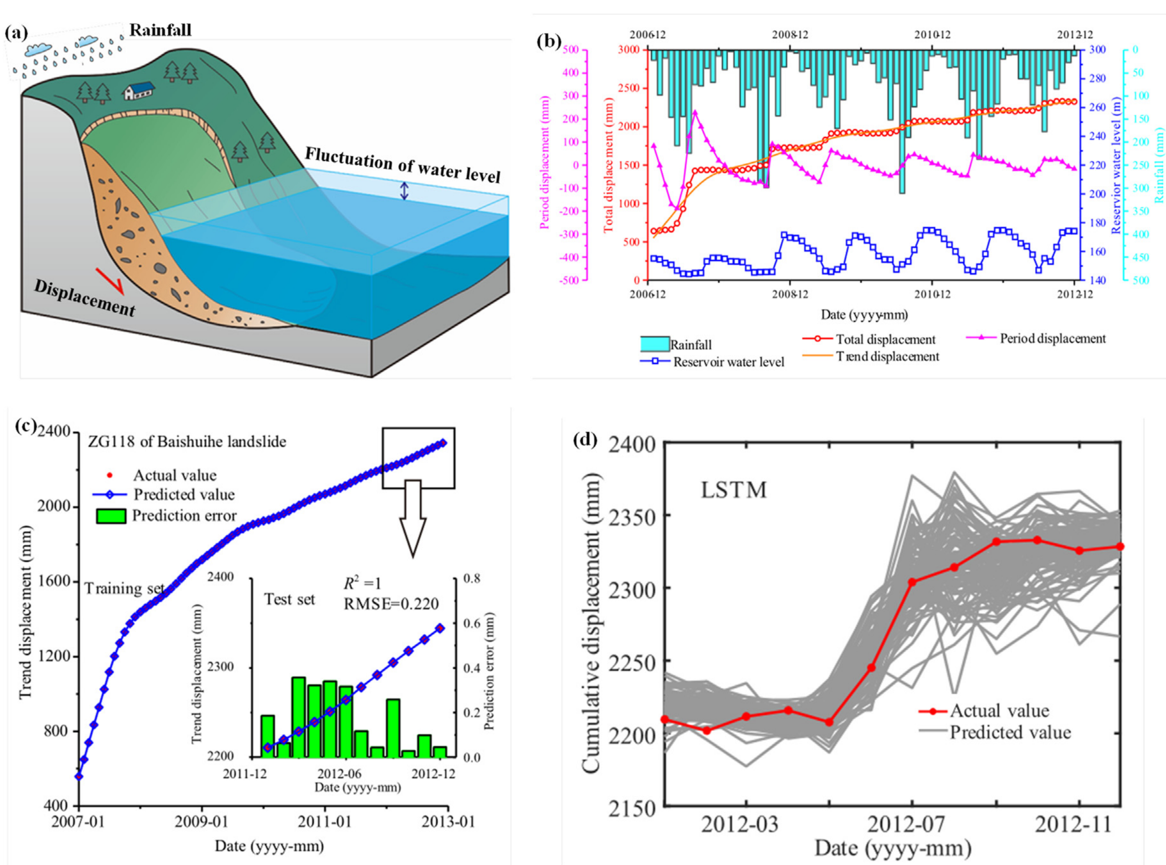

Fig. 17. Displacement prediction of the Baishuihe landslide: (a) landslide displacement induced by rainfall and water level; (b) monitoring data and displacement decomposition; (c) prediction results of trend displacement and (d) prediction results of cumulative displacement (modified from Wang et al., 2022).

network based on the piecewise time weighted gradient by considering the current and historical gradients simultaneously. The incorporation of slope stability models that account for the dynamic changes in slope gradients can result in more accurate modeling of real-world situations. This suggests that modifying original models can be an effective strategy for improving the precision of the final prediction results. Recently, Transformer model based on attention mechanism has also been utilized in landslide displacement prediction, which can perform obviously better than LSTM in the prediction of long-sequence time series (Xi et al., 2023).

3.3.3. HM in the prediction of landslide displacement

Some studies have combined the advantages of several models to improve the accuracy of landslide displacement prediction. In 2013, Zhao et al. (2013) integrated the BP neural network with a Markov chain for landslide displacement prediction. The former model is used to predict the displacement, and the latter model is used to analyze the range of prediction errors and adjust the parameters of the models to obtain minimal error values. This integrated model can effectively improve the accuracy of the prediction outputs.

SVM models have been proven to be useful algorithms with good performance in landslide displacement prediction. However, these models rely heavily on the optimal selection of parameters. The parameter values of SVM models will greatly influence the precision of the final output (Li and Kong, 2014). In this case, to compensate for the disadvantages of SVM, some models that are good at optimizing the model parameters can be integrated with the models to improve the performance. In 2014, Li and Kong (2014) integrated the genetic algorithm with SVM models for parameter optimization and found that the integrated models perform slightly better than single SVM model. The effectiveness of these models was further validated in many other studies (Wen et al., 2017; Zhu et al., 2018; Wang and Qiao, 2023).

Different HMs are also compared in some studies. In 2019, Liao et al. (2019) compared the performance of GWO-ELM models with GWO-SVM models for landslide prediction. The results showed that the former is apparently more precise than the latter. The selection of an appropriate HM is very important for the analysis results. In recent years, an increasing number of studies have been conducted to find the optimal HMs for different application cases (Dai et al., 2022; Gao et al., 2022; Guo et al., 2020a,b; Jiang et al., 2020; Jiang et al., 2022a; Lin et al., 2022; Lu et al., 2021; Luo et al., 2023; Wang et al., 2021; Zeng et al., 2022; Zhang et al., 2021a; Zhang et al., 2020, Zhang et al., 2021c, Zhang et al., 2021d).

3.4. Other applications

3.4.1. Sampling strategies

ML sampling strategies for landslide risk assessment are also very important for the final outputs (Guo et al., 2024). For the samples after feature extraction, which data types should be selected, which data will be used as the training set and which data will be used as the testing set, what is the basis for this selection strategy and how will it affect the results are all key questions that need to be further discussed.

In 2017, Kornejady et al. (2017) used the maximum entropy model for landslide susceptibility mapping of the Ziarat watershed in Iran. Two different sampling strategies, named the Mahalanobis distance and random sampling were used, and the analysis results were compared with each other. The results showed that the former performed obviously better. In 2020, Yi et al. (2020) compared the performance of ML models using different scales of the training set (small scale, medium scale and large scale) and found that small-scale datasets yield better performance than large-scale datasets. As the scale increases, the accuracy of the final output slightly decreases. In 2020, Dou et al. (2020) analyzed the influence of different types of samples on the outputs of ML and DL as shown in Fig. 18. The results showed that the sample type has a significant influence on the accuracy of conventional ML models. For DL models, especially CNNs, although the sample types are different, the outputs still have similar precision, which means that sample types are less consequential to the DL models. Currently, much research has focused on finding the optimal sampling strategies (Chang et al., 2023; Hong et al., 2024; Ke et al., 2023; Khabiri et al., 2023; Liu et al., 2023a; Ma et al., 2023; Trinh et al., 2023; Xing et al., 2023).

3.4.2. Hyper-parameter optimization

Hyper-parameters are parameters that need to be set before the ML process begins. For instance, the number of layers and nodes of a neural network and the number of trees in a RF are all very important hyper-parameters that need to be determined before calculations are performed. Hyper-parameters are closely linked with the design of the neural network framework and other ML models. Understanding the influence of hyper-parameters is essential in comprehending the working

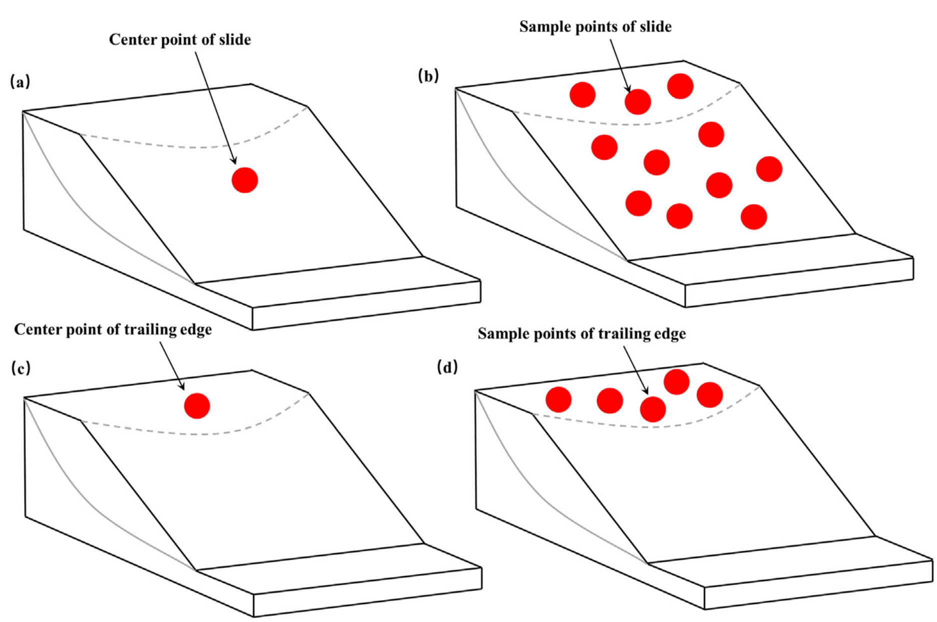

Fig. 18. Different sampling strategies: (a) centroid of a landslide body; (b) samples of a landslide body; (c) centroid of a landslide scarp and (d) samples of a landslide scarp (modified from Dou et al., 2020).

mechanism of ML, and it helps improve the final outputs.

In 2020, Sun et al. (2020) used a RF model for LSM, and a bayesian model was used to optimize the hyper-parameters of the RF models. The main aim is to obtain the optimal RF framework design to ensure an output with high accuracy. Based on former studies, in 2021, Sun et al. (2021) used a Bayesian model to optimize the hyper-parameters of RF and LR simultaneously and compared the performance of the two modified models. The results showed that both modified models perform better than the unmodified models, and the LR models optimized by Bayes perform much better than the modified RF models. The optimization of hyper-parameters can help us design better model frameworks. The optimization process is very useful to ensure the high precision of the final output.

3.4.3. Development of GUI

The development of GUIs is the final step in AI applications. A GUI encapsulates complex landslide detection, LSM and landslide displacement prediction ML models and provides a visual platform for normal users. GUI development is essential in realizing the popularization of AI technology for the mitigation of landslide disasters.

In 2017, Lagomarsino et al. (2017) used MATLAB to encapsulate a RF model and developed a GUI to obtain LSM. This GUI is a straightforward and easy application providing a useful tool for normal users. In 2021, Song et al. (2021) also encapsulated ML models to develop a GUI for LS assessment. This GUI contains more useful functions, including parameter initialization and determination of landslide boundary conditions.

GUI development for landslides is still in its infancy. Advanced GUIs containing functions such as landslide detection, LSM and landslide displacement prediction, which can be operated easily by normal users, are still in high demand in the field of landslide disaster mitigation.

4. Discussions

This section discusses the challenges and provides suggestions for the future development of AI applications in three aspects of landslide risk assessment. Table 1 suggests the main algorithms used for the three key areas and Fig. 19 summarizes the main challenges and opportunities ahead.

4.1. Challenges and opportunities for landslide detection

The main types of landslide detection methods are shown in Table 2. Some major problems still exist for landslide detection by AI. First, soil has strong spatial variability, i.e., soil parameters vary by location. Moreover, the geological conditions also vary greatly in different regions. These factors lead to obvious differences in the features of different landslides. This greatly increases the difficulty of landslide detection. Moreover, it still relies heavily on manual detection which is resource intensive, time-consuming and subject to interpretation bias. Credible general criteria for landslide detection is still lacking. The existing determination methods are mostly based on engineering experience and lack rigorous and systematic theoretical support. Second, although DL models can filter out invalid features from training data and retain the most useful features, there is still a lack of evidence to conclude that DL models have a higher capability of landslide detection than that of ML models. The application of DL models in this field is still in its infancy. How to design the framework of DL models appropriately to improve the model performance and the generalization ability is still ambiguous and requires more research. The future of landslide detection can be described as follows:

(1) The design of a DL model framework, which contains layers, nodes and hyper-parameters, is very important to ensure the efficiency and generalization of landslide detection results.
(2) Object-based DL models, especially object-based CNN models, will be the main useful method for landslide detection. The integration of object-based CNN models with other models and the appropriate modification of object-based CNN models will be the main research directions to improve the generalizability, precision and robustness of ML for landslide detection.
(3) The criteria applicable to determine different landslides in different regions are very useful in accurate landslide recognition. More general criteria are needed to consider the spatial variability of soil parameters and the specificity of landslide characteristics.
(4) The integration of spectral analysis and slope deformation information will be essential in landslide recognition. Integrated methods can play a role in mutual validation to ensure the precision of the detection results. Future research should focus on the proposal of better algorithms to improve the accuracy of image recognition and the interpretation precision of slope deformation to find potential landslides, especially landslides covered with vegetation.
(5) Few studies have focused on obtaining the rigorous boundaries, volume and types of landslides. Future research should focus on the proposal of useful and optimal algorithms to achieve this goal.
(6) It still lacks for advanced GUI tools for landslide detection. The development of related products is very important to realize the generalizability of AI technology for landslide detection.

Table 1
The main ML models summarized for the three application areas.

Field	Models with best performances
Landslide detection	Support vector machine, convolutional neural network, recurrent neural network and related hybrid models
Landslide susceptibility mapping	Support vector machine, logistic regression, random forest, convolutional neural network, recurrent neural network and related hybrid models
Landslide displacement prediction	Long short-term memory, transformer and related hybrid models

4.2. Challenges and opportunities for LSM

Compared with other ML models, LR, RF and SVM models perform better and have higher precision in LSM. HMs combine the advantages of different ML models and perform better than single ML models. DL models, especially CNN and RNN models, which have been widely used are the advanced technologies in LSM, perform better than conventional ML models. From the literature above, the future of landslide susceptibility mapping can be described as follows:

(1) Hyper-parameter and sampling strategies are also very important for the final accuracy in LSM. Different RF frameworks, different layers and different numbers of nodes in DL models have a significant influence on the final outputs. The appropriate framework design is essential. Different selections, scales and types of training sets also greatly influence the final outputs. Both hyper-parameter and sampling strategies should be considered simultaneously in LSM.
(2) DL models, especially CNN and RNN models, are the advanced technologies for LSM at present. Future research should focus on the optimization of these two models, including the appropriate selection of hyper-parameters and sampling strategies, integration with other advanced models and modifications to improve the robustness, generalizability and precision of the final outputs.
(3) The strategies for integrating different ML models, setting hyper-parameters and training sets still need further research. The kinds of strategies truly needed in different situations still lack discussion. Further studies for finding the optimal strategies are still needed.
(4) All the ML models described considered several influencing factors of landslides to analyze and obtain the LSM results. However, few studies clarified why these factors were selected over other

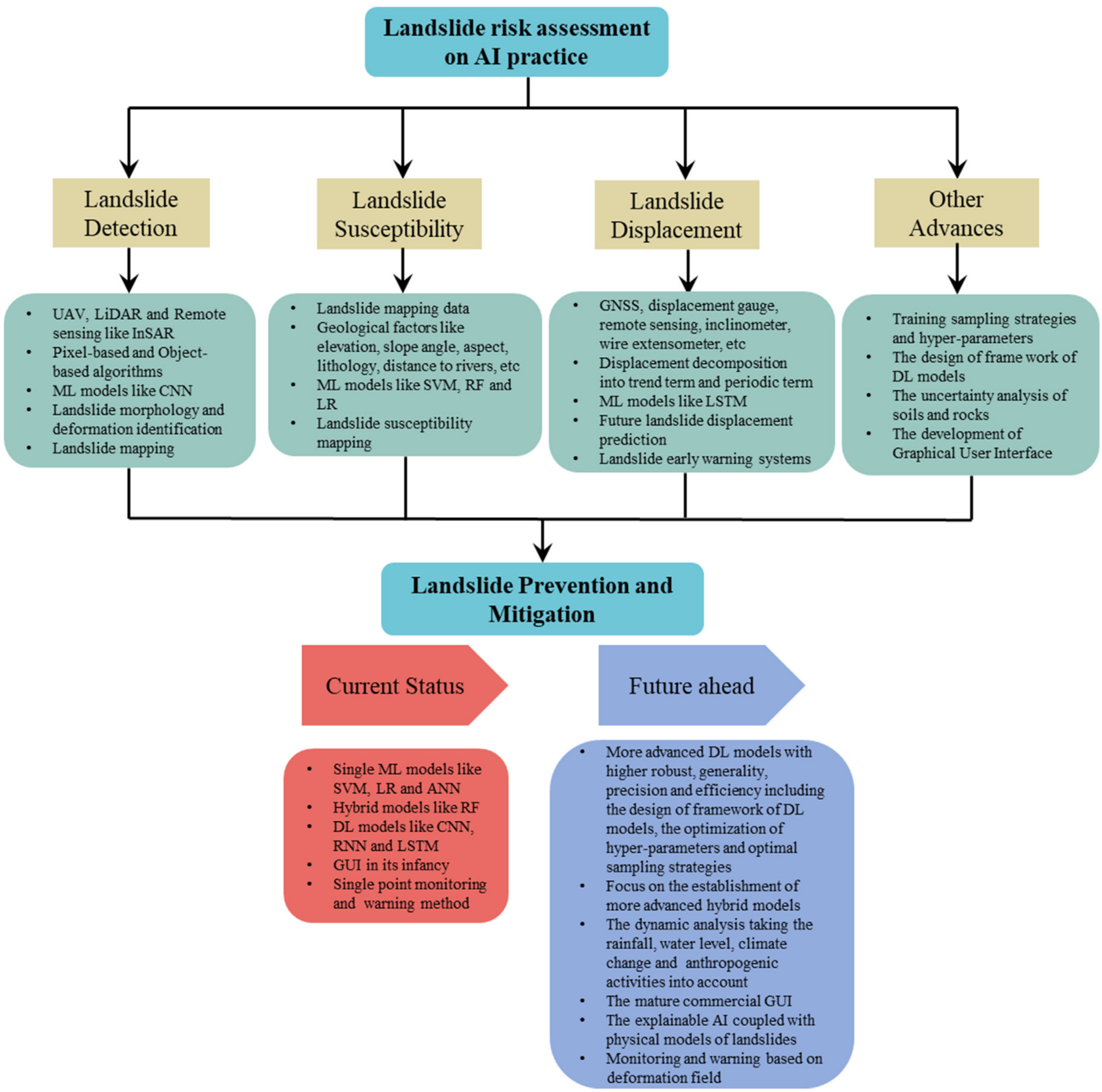

Fig. 19. The conclusions of current practices and future work.

factors and exactly how many influencing factors should be selected. Furthermore, the obtained LSM results are static and only have reference values for policy-making in a given period. For landslides, especially reservoir landslides, rainfall, fluctuations in the water level, earthquakes and anthropogenic factors will all cause changes in influencing factors such as the geological conditions, shear strength and water content of soil. It is very important to obtain a dynamic LSM that has long-term reference values for the government by taking the influencing factors into account. In addition to improving the accuracy, researchers should also focus on improving the computational efficiency of models, which is often overlooked.

(5) Advanced GUI tools are also rare for this field. The development of related products can help to realize the generalizability of AI technology to LSMs. For the calculation algorithms, in addition to accuracy, researchers should also improve the calculation efficiency of the models, which is rarely considered.

4.3. Challenges and opportunities for landslide displacement prediction

The current research mainly focuses on the prediction of single point landslide displacement by GNSS. The monitoring and prediction results can only reflect the deformation of the instrument installation position and cannot represent the overall deformation characteristics of a landslide. Sudden deformation rate changes of individual points do not mean that the overall deformation of a landslide follows this trend. This is very likely to lead to the misjudgment of landslide deformation and instability.

In recent years, non-contact monitoring techniques like InSAR, UAV and terrestrial laser scanning have been gradually used to get the superficial deformation of landslides for different periods (Jiang et al., 2021; Jiang et al., 2022b; Kulshrestha et al., 2022). The displacement prediction through the data obtained by non-contact monitoring techniques is still rarely considered and only a few studies have already discussed this research direction using DL (Kulshrestha et al., 2022).

As a result, the future of landslide displacement prediction can be described as follows:

(1) Most studies divided landslide displacement prediction into two parts, a trend term and a periodic term. The trend term is correlated with geological conditions, and the periodic term is determined by the periodic rainfall or fluctuation of the water level of

Table 2
Summary of landslide types and recognition methods.

Types	Recognition indicators	Main recognition methods
Exposed landslides without deformation	Presents a circular chair shape, with landslide rear wall, landslide sidewall and multilevel abutment, invisible deformation	Satellite and UAV images from one period; LiDAR point cloud
Exposed landslides with deformation	Presents a circular chair shape, with landslide rear wall, landslide sidewall and multilevel abutment, visible deformation	Satellite and UAV images from different periods; LiDAR cloud point from different periods; SAR images such as InSAR to interpret the deformation
Landslides covered with vegetation and without deformation	Cracks and small-scale collapse at the front edge, invisible deformation	Satellite and UAV images from one period; LiDAR cloud point to remove surface vegetation
Landslides covered with vegetation and with deformation	Cracks and small-scale collapse at the front edge, visible deformation	LiDAR cloud point from different periods; Satellite and UAV images from different periods; SAR images such as InSAR to interpret the deformation
Slopes with the possibility of landslide occurrence	No morphological or deformation information	Geophysical exploration and drilling

the reservoir. Actually, landslide displacement is not only influenced by these factors. Many uncertainty factors, such as earthquake and anthropogenic factors should also be considered. Thus, some scholars divided landslide displacement prediction into three parts: a trend term, a periodic term and an uncertainty term. It is still difficult to quantitatively analyze the uncertainty term, which needs to be considered carefully in further research.

(2) For the prediction of landslide displacement, LSTM neural network is a dynamic DL model that has been proven to be the most useful model and has been widely used in many studies in recent years. Future research should mainly focus on the optimization of DL models, especially LSTM, by integrating this model with other advanced models or modifying the framework of the model itself.

(3) The DL models like RNN and LSTM can't predict the long sequence time series well. Transformer model based on attention mechanism can solve these problems effectively to predict the evolution of landslide in long term. Informer performed better than the Transformer. It represents the main techniques used in the future.

(4) It is important to obtain the time series of the three-dimensional deformation field of a landslide in a reservoir area and then carry out the intelligent prediction of the future three-dimensional deformation field of the landslide based on ML and DL models. The predictions are not only limited to single point displacements, but also to superficial deformation obtained by non-contact monitoring techniques or deformation fields.

(5) There is a high demand for the development of useful GUI tools for normal users to directly predict the displacement of landslides. This GUI can be built in combination with the establishment of an early warning system for landslide disasters.

4.4. Other recommendations

Many studies have been conducted to enhance the performance of ML models for landslide analyses through DL, HMs, and hyper-parameter optimization. However, these approaches do not provide a clear understanding of the underlying mechanisms of landslides, which is necessary for informed decisions to prevent or mitigate landslide risks. To address this, the research should integrate ML models with physical models of landslides to create more explainable AI models (Guo et al., 2023). This would enable a deeper understanding of the mechanisms behind landslides and more effective policy-making. For the region with limited data, transfer learning can be used as a useful tool to solve these problems.

5. Conclusions

This paper reviewed hundreds of literatures related to applications of AI in landslide risk assessment. In recent years, there has been a sharp increase in number of research papers published on this topic. Three key prominent areas including landslide detection, landslide susceptibility mapping and prediction of landslide displacement were discussed where AI applications have been applied prominently.

Recently, DL methods have gradually replaced statistical methods and ML methods with better performance. CNNs and RNNs are two dominant DL methods used in the three areas. In landslide detection, CNNs are mainly used with satisfactory results; in landslide susceptibility assessment, both CNNs and RNNs are mainly used, and in landslide displacement prediction, RNNs are mainly used. RF, LR and SVM are also proved well in LSM. LSTM and Transformer are both reliable in landslide displacement prediction which can overcome the forgetting problem and predict the long-sequence time series. The method for construction of DL framework has a great impact on the final results.

HM combines the advantages of different models which can effectively improve the outputs. The selection of appropriate HM is critical for the future development of AI applications. The sampling training strategies, hyper-parameters optimization and the generalization ability of these models are also crucial. Advanced GUI tools in this field should be developed to realize the widespread use of relevant techniques by normal users.

Overall, the application of AI techniques in the three aspects of landslide risk assessment has yielded successful and promising results, which can describe the nonlinear relationships of soil and rock structures and predisposing factors. The explainable AI combining with physical meaning and transfer learning should be considered carefully in future research.

CRediT authorship contribution statement

Rongjie He: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Wengang Zhang:** Writing – review & editing, Resources, Formal analysis. **Jie Dou:** Writing – review & editing, Visualization, Formal analysis. **Nan Jiang:** Validation, Software, Investigation. **Huaixian Xiao:** Visualization, Investigation, Formal analysis. **Jiawen Zhou:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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