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Review article: Deep Learning for Potential Landslide Identification: Data, Models, Applications, Challenges, and Opportunities

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Abstract.
As global climate change and human activities escalate, the frequency and severity of landslide hazards have been increasing. Early identification, as an important prerequisite for monitoring, evaluation, and prevention, has become increasingly critical. Deep learning, as a powerful tool for data processing and analysis, has shown significant potential in advancing landslide identification, particularly in the automated processing and analysis of remote sensing, geological, and terrain data. This review provides an overview of recent advancements in the utilization of deep learning for potential landslide identification. First, the sources and characteristics of landslide data are summarized, including satellite observation data, airborne remote sensing data, and ground-based observation data. Next, several commonly used deep learning models are classified based on their roles in potential landslide identification, such as image analysis and processing, time series analysis. Then, the role of deep learning in identifying rainfall-induced landslides, earthquake-induced landslides, human activity-induced landslides, and multi factor-induced landslides is summarized. Although deep learning has shown certain successes in landslide identification, it still faces several challenges, such as data imbalance, insufficient generalization capabilities of the models, and the complexity of landslide mechanism research. Finally, the future directions in the field are discussed. It is suggested that by combining knowledge-driven and data-driven methods for potential landslide identification, deep learning holds broad prospects for future applications in this field.

1 Introduction

Landslides are geological hazards induced by either natural forces or human activities, typically involving the interplay of various factors such as geology, meteorology, hydrology, and topography. Every year, landslides cause significant global losses, particularly in regions with heavy rainfall, frequent earthquakes, and complex geological conditions, representing a major threat to human life, property, and infrastructure.

According to data released by the United Nations International Strategy for Disaster Reduction (UNISDR), more than 1,000 landslide-related disaster events occur annually, causing thousands of fatalities and substantial economic losses. As global climate change progresses, the frequency of extreme weather events increases, leading to a growing risk of landslides.

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Potential landslides refer to slopes prone to instability that may fail and trigger disasters within a certain time frame. Potential landslides represent the precursor stage of landslide occurrence (Lin et al., 2024). If potential landslides are not identified and addressed promptly, the slope may eventually become unstable and develop into a landslide due to changes in internal stress conditions and external triggering factors.

Due to the relativity and dynamic nature of potential landslides, the identification work becomes extremely complicated. On the one hand, it is not possible to determine that a landslide will definitely occur just because there are signs of deformation on the slope. Multiple factors need to be comprehensively considered to assess the possibility of its instability. On the other hand, the uncertainty of external factors increases the difficulty of judgment. Sudden events such as heavy rainfall and earthquakes may instantly change the stress state of the slope and trigger signs of deformation. Given the dynamic characteristics of potentials, it is also essential to conduct long-term monitoring of the landslides with potential hazards after identification.

Conventional methods for landslide identification and monitoring, such as field surveys, geological analysis, and radar interferometry, can identify potential landslide areas to a certain extent. However, these methods often have problems such as high costs, significant time consumption, and difficulties in data collection, and their applications are limited in extensive areas. In addition, conventional machine learning requires tedious feature selection and lacks autonomy in feature extraction. As a result, it is difficult for these traditional methods to extract available information from big data and they are unable to represent complex monitoring processes (Sheng et al., 2023). For the above reasons, how to effectively identify and monitor areas with potential landslides has become an important topic in the current prevention and control of geological hazards.

Over the past few years, deep learning has stood out in the application of landslide hazards (Aslam et al., 2021; Nava et al., 2023; Wang et al., 2023a; Zhou et al., 2023). Deep learning is a branch of machine learning, consisting of consecutive operations (Janiesch et al., 2021). These operations gradually extract complex features by using the results of previous operations as inputs. Through the training of large-scale and multi-source data, deep learning models are able to automatically extract features, capture complex nonlinear relationships, and conduct pattern recognition in high-dimensional data, which shows great potential in the identification of potential landslides (Nava et al., 2021; Yang et al., 2024c).

In this review, we aim to summarize the applications of deep learning in the field of potential landslide identification, including data, models, applications, challenges, and future directions.

(1) We classify commonly used heterogeneous data into three categories for research. These data sources offer comprehensive data support for the application of deep learning in potential landslide identification.

(2) We introduce the roles of commonly used deep learning models in potential landslide identification, and compare the advantages and disadvantages among different models.

(3) We analyze the performance of deep learning models in different scenarios through case studies, discussing the adaptability of deep learning in potential landslide identification.

(4) We summarize the main challenges currently faced by the application of deep learning in potential landslide identification, and highlight new opportunities and promising future directions.

The remainder of this paper is organized as follows. Section 2 introduces seven main data sources. Section 3 summarizes five roles of deep learning models in potential landslide identification. Section 4 investigates the application of deep learning

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models in four typical landslides and provides a comprehensive summary. Section 5 analyzes the current challenges in potential landslide identification. Section 6 discusses future research directions. Section 7 provides the concluding remarks.

2 Deep Learning for Potential Landslide Identification: Data Source

Accurate identification of potential landslides is the primary step in effectively preventing and mitigating the impacts of landslide hazards. Data sources are the cornerstone of achieving this objective. Different types of data provide indispensable information for potential landslide identification from various perspectives, and drive ongoing advancements in related research and practices.

In potential landslide identification, the richness and reliability of data sources directly determine the accuracy and effectiveness of research. Data sources not only provide fundamental information to outline the landslide environments, but also enable dynamic monitoring and precise analysis. This section will comprehensively review the critical roles played by three main types of data sources: satellite observation data, airborne remote sensing data, and ground-based observation data (see Fig. 1).

2.1 Satellite Observation Data

Since the launch of Landsat-1, the first earth observation satellite for studying and monitoring the Earth's surface on July 23, 1972, satellite data has become widely accessible, extending beyond single-purpose analyses or results (Wulder et al., 2022). With the continuous development of satellite observation, its immense potential for application in landslide research has become evident (Liu et al., 2021d). Currently, satellite observation data primarily refers to data obtained through space-borne synthetic aperture radar (SAR) and optical remote sensing.

2.1.1 Space-borne SAR

SAR is an active microwave remote sensing system (Franceschetti and Lanari, 2018). It is not only capable of acquiring data on demand by actively emitting microwave signals but also facilitates partial penetration of vegetation cover through its longer wavelength bands (such as the L-band), thereby allowing the retrieval of surface deformation information beneath vegetated areas. The time series data provided by SAR can serve as input for deep learning models, allowing these models to be trained to identify long-term patterns of terrain change. Continuous monitoring of potential landslide areas is crucial, and SAR is widely employed in high-risk environments.

Interferometric synthetic aperture radar (InSAR) has been developed based on. It obtains surface elevation information by performing coherent processing on two sets of SAR images observed in the same area (Dai et al., 2022; Ma et al., 2023b; Zeng et al., 2024).

In contrast, SAR mainly provide backscatter information of ground objects. Although some features of ground objects can be identified according to the scattering characteristics, their ability to obtain topographic elevation information is relatively weak. InSAR, on the other hand, can directly generate topographic elevation data, which is of great significance for analyzing

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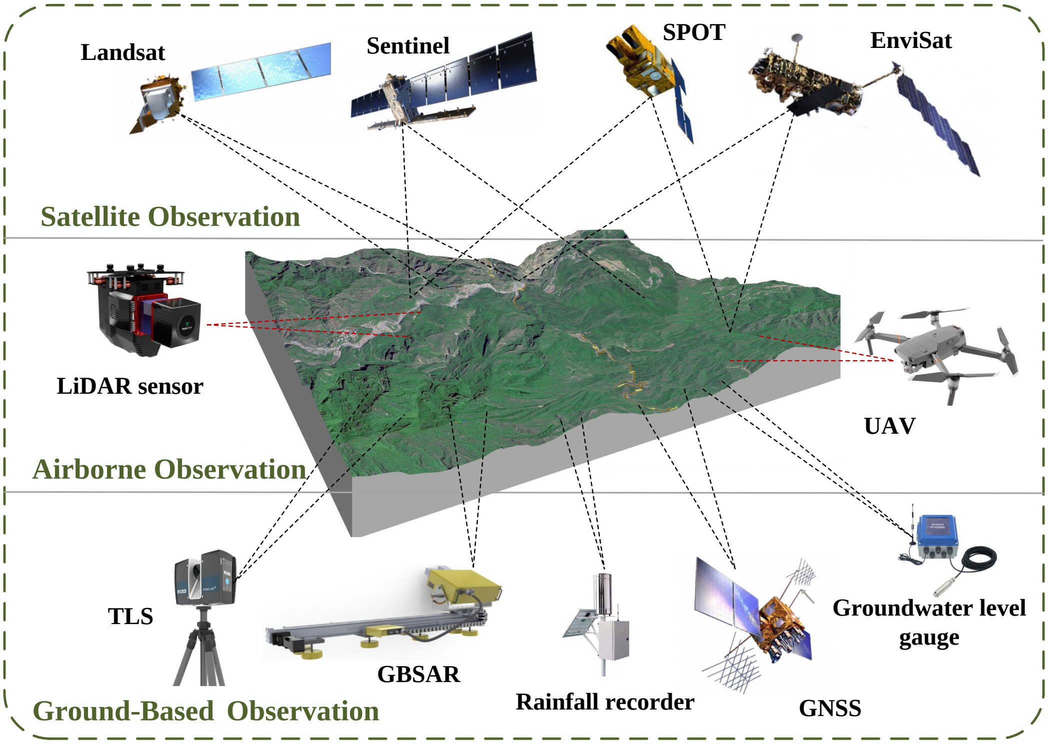

Figure 1. Data sources for potential landslide identification.

the topography and geomorphology in the identification of potential landslides, and determining key elements such as the topographic undulation and slope of potential landslide areas.

When screening for potential landslides over a large area, InSAR has higher efficiency (Dun et al., 2021; Tang et al., 2025; Zhang et al., 2021). When monitoring large potential landslide areas such as mountainous regions, InSAR can quickly obtain topographic deformation information over a large area, promptly detect potential areas with potential landslides, and reduce the workload and blind spots of manual inspections.

At present, InSAR is widely employed to generate ground deformation velocity maps and time-series data, which reveal the dynamic evolution of landslide-prone areas.

Differential interferometric synthetic aperture radar (D-InSAR) is an advancement of InSAR that eliminates topographic phase through differential processing, focusing specifically on deformation information extraction (Shen et al., 2022). The emergence of D-InSAR not only enables the transition from mixed deformation-topography signals to pure deformation signal extraction but also extends its applicability from detecting discrete deformation events to identifying slow-moving landslide processes, significantly enhancing the reliability of landslide monitoring.

2.1.2 Optical Remote Sensing

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Optical remote sensing refers to the acquisition of surface information through sensors that measure reflected solar radiation. Its application in geological hazard investigations dates back to the 1970s.

Optical remote sensing offers high resolution, currently capable of achieving spatial resolutions as fine as 0.3 meters or better. In potential landslide identification, it not only facilitates the retrieval of detailed surface textures and color characteristics using rich spectral data but also enables the direct identification of morphological features and object contours via visual interpretation of imagery (Cheng and Han, 2016; Li et al., 2022b).

Landslide formation typically follows a progressive process from deformation to failure, accompanied by precursor indicators such as tensile cracks, stepped scarps, and localized collapses. These indicators exhibit distinct spectral signatures in optical imagery compared to their surroundings, enabling both manual interpretation and automated detection.

In vegetated mountainous regions, surface vegetation often undergoes detectable changes before a landslide event. Optical remote sensing leverages multispectral data, particularly red and near-infrared bands, to monitor vegetation health and identify potential landslide zones. Furthermore, the calculation of the normalized difference vegetation index (NDVI) facilitates the evaluation of vegetation health in potential landslide regions, providing critical insights into potential landslide precursors (Verrelst et al., 2015).

2.2 Airborne Remote Sensing Data

Airborne remote sensing data, typically acquired by manned aircrafts, provide high-resolution imagery of localized areas. Advanced airborne platforms equipped with oblique photogrammetry and, more recently, close-range photogrammetry technologies enable millimeter-level accuracy in 3D photogrammetry, facilitating the observation of subtle surface deformations, rock mass structures, and the construction of highly detailed 3D models of terrain and above-ground infrastructure (Macciotta and Hendry, 2021; Xu et al., 2023). Among these technologies, airborne photogrammetry and airborne radar are the most commonly used.

2.2.1 Airborne Light Detection and Ranging (LiDAR)

LiDAR has been used for landslide and other geological hazard investigations in many regions since the late 1990s. As an active remote sensing system, LiDAR can laterally scan a range of 60° and capture 400,000 points per second, enabling large-scale 3D scanning of terrain, structures, and vegetation within a short period (Mallet and Bretar, 2009). It offers centimeter-level accuracy in both horizontal and vertical dimensions.

Airborne LiDAR is irreplaceable in capturing 3D details and penetrating vegetation, particularly in densely vegetated areas where conventional aerial photography faces significant limitations. Airborne LiDAR not only acquires high- resolution digital surface models (DSMs) from laser point cloud data but also generates high-accuracy DEMs by removing vegetation contributions (Fang et al., 2022; Jaboyedoff et al., 2012; Yan et al., 2023), thereby revealing concealed hazard features such as mountain fractures, loose deposits, and landslide masses under vegetation cover.

Point cloud data obtained from airborne LiDAR can monitor dynamic changes in mountainous terrain by detecting deformations such as subsidence, displacement, and uplift, while also facilitating the construction of 3D landslide models to

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simulate sliding directions and impact areas. Through intuitive visualization of slope morphology and structure from multiple perspectives, LiDAR enables researchers to conduct a comprehensive assessment of slope conditions and identify subtle hazard features that may not be easily discernible in 2D imagery.

2.2.2 Unmanned Aerial Vehicle (UAV)

UAV aerial photogrammetry provides outstanding maneuverability and high-precision measurements. Traversing over steep slopes and valleys, UAVs are able to monitor areas that are often inaccessible to satellites and manned aerial platforms (Niethammer et al., 2012), thus addressing critical observational limitations.

In large-scale and topographically complex regions, UAVs can perform efficient aerial inspections, overcoming the limitations of ground-based inspections in inaccessible or visually obstructed regions. By rapidly scanning mountain slopes, embankments, and gullies, UAVs provide a comprehensive understanding of the geological conditions and enable timely identification of macro-scale geomorphic anomalies. However, given cost-effectiveness constraints, UAVs are currently more commonly used for periodic and continuous monitoring in localized areas. They are particularly well-suited for rapid and dynamic monitoring of landslides in high-priority zones.

With the rapid advancement of UAVs, centimeter-level vertical and oblique aerial photogrammetry is now achievable (Fan et al., 2020). The high-definition cameras mounted on UAVs are able to capture the subtle cracks on the surface of the mountain. These cracks may be early signs of a landslide (Sun et al., 2024a). By conducting a comparative analysis of the images taken at different times, the development and changes of the cracks can be monitored, including the increase in the length, width and depth of the cracks, as well as the changes in the crack orientation. In some mountainous areas or valleys, there may be a large number of loose accumulations. These accumulations may trigger landslides under specific conditions. Aerial photography by UAVs can clearly identify information such as the distribution range, accumulation quantity and accumulation shape of these loose accumulations, and assess their potential threats to the surrounding environment.

When equipped with LiDAR sensors, UAVs can effectively remove vegetation from the data. Then, assisting researchers to reveal landslide boundaries, crack patterns, and other deformation features hidden beneath vegetation cover. This integrated approach combines the strengths of photogrammetry and LiDAR, allowing for rapid deployment and targeted area monitoring while mitigating the challenges posed by vegetation cover in landslide detection and assessment.

After extreme weather events such as heavy rainstorms or geological events like earthquakes occur, the stability of the mountain may be affected, making it prone to triggering geological hazards. UAVs even can quickly conduct aerial monitoring of the relevant areas after extreme weather.

2.3 Ground-based Observation Data

Satellite observation and airborne remote sensing are mainly employed for identifying potential landslides based on surface morphology. However, due to the influence of various factors, the identification results may not always be fully accurate, leading to potential misjudgments. Therefore, the potential landslide points identified through remote sensing still necessitate field investigations by researchers for verification, differentiation, confirmation, or exclusion of hazards. In some cases, additional

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on-site observation and monitoring methods are needed for accurate assessment. Commonly used ground-based monitoring methods include ground-based SAR, 3D laser scanners and various sensor devices deployed or installed on the ground.

2.3.1 Ground-based Synthetic Aperture Radar (GB-SAR)

GB-SAR is an active ground-based microwave remote sensing system that has been developed over the past decade. Compared to spaceborne SAR, GB-SAR allows adjustment of radar wave incidence angles and azimuths, preventing phase decorrelation issues caused by terrain obstructions in satellite SAR, making it particularly suitable for monitoring steep slopes, canyons, and other areas with limited satellite line-of-sight (Noferini et al., 2007).

GB-SAR effectively integrates the principles of SAR imaging with electromagnetic wave interferometry. By leveraging precise measurements of sensor system parameters, attitude parameters, and geometric relationships between orbits, GB-SAR quantifies spatial positions and subtle changes at specific surface points, allowing for the measurement of surface deformations with millimeter or even sub-millimeter precision.

During landslide movement, the ground experiences noticeable subsidence, displacement, or cracking. GB-SAR can be configured for high-resolution, continuous observation to capture instantaneous deformations during the landslide creep phase and generate corresponding displacement maps (Liu et al., 2021a; Xiao et al., 2021). This capability facilitates the distinction between evolutionary stages of landslides and further analysis of the dynamics of landslide activity.

For small-scale regional monitoring, GB-SAR can establish customized geometric configurations specifically designed for target areas. Utilizing mobile rail systems or multi-antenna setups, GB-SAR reconstructs 3D deformation vector fields of landslide masses, identifying sliding directions and potential failure surfaces.

2.3.2 Terrestrial Laser Scanning (TLS)

TLS emerged in the mid-1990s. It plays a unique role in local refined monitoring by emitting laser pulses and measuring their reflection time (Stumvoll et al., 2021; Teza et al., 2007).

The landslide often manifests as a sharp change in the ground surface. TLS can provide data with sufficient accuracy, assisting researchers in identifying the features of these landslides. By combining topographic analysis, the location of the landslide surface can be accurately determined. TLS scanner can also help identify the landslide mass, that is, the flow path of the landslide materials. Through analyzing the point cloud data, the movement path of the landslide area, the soil accumulation area, and the accumulation location of the landslide materials can be extracted, providing detailed information for the analysis and assessment of potential landslides.

By quickly and massively collecting spatial point position information, TLS can automatically splice and rapidly obtain the appearance of the measured object. It can be used to construct high-precision surface models and appearance models of buildings and structures. The 3D model can display the shape and structure of the mountain and the detailed features of the ground surface from different angles and in all directions (Zhou et al., 2024), enabling geological experts and engineers to have a more intuitive understanding of the overall situation of the landslide area. For example, the cracks in the mountain, the loose

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accumulations, and the degree of weathering of the rocks can be clearly seen, providing richer information for the identification of potential landslide hazards.

Currently, TLS is commonly used in critical areas requiring localized precision. For historical landslide masses, it captures reactivation indicators such as rear tensile cracks and frontal bulging, with data input into anomaly detection models to identify reactivation signals.

2.3.3 Ground-based Sensor Devices

Compared to the aforementioned data sources, ground-based sensors offer key advantages, including high precision, real-time capabilities, and multi-parameter fusion (Dai et al., 2023). They can address the limitations of remote sensing and provide critical ground-based dynamic information for potential landslide identification.

Ground-based sensing devices are highly diverse, and the data they acquire directly reflect the state of landslide masses. These datasets provide foundational inputs for deep learning models, enabling multi-dimensional analysis and interpretation of potential landslide conditions. For example, ground sensors (e.g., GNSS receivers and crack meters) can collect parameters like displacement and tilt angle at frequencies ranging from minutes to seconds, capturing transient, anomalous signals just prior to landslide events, thereby filling the temporal resolution gap in remote sensing (Jiang et al., 2022). By integrating time series data with SAR imagery, deep learning models can be trained to uncover correlation patterns between surface deformations and subsurface parameters. Instruments such as piezometers and soil pressure gauges can directly monitor key parameters like pore water pressure and soil stress on the sliding surface. By combining the obtained subsurface data with geomechanical equations, the position of the sliding surface or geotechnical strength parameters can be inverted.

3 Deep Learning for Potential Landslide Identification: Models

Potential landslide identification relies heavily on extensive data analysis, and the key is how to efficiently and accurately extract features that are helpful for identifying landslide occurrences. Conventional landslide identification methods often rely on human expertise or rules, often necessitating expert knowledge for identifying relevant features. With continuous exploration, deep learning, through its powerful feature learning capabilities, enables the automatic extraction of meaningful features from raw data, significantly reducing manual intervention. Especially when dealing with high-dimensional and complex landslide data, deep learning models can extract deep features related to landslides from raw data in a data-driven manner, without the need for manual feature design.

The choice of deep learning models typically depends on the type of data and the task requirements. Although each model typically has multiple effects, its internal architecture results in different focal points when it comes to automated feature extraction. This section analyzes several commonly used deep learning models from five perspectives: image analysis and processing, time series analysis, data generation, data cleaning, and data fusion.

3.1 Models for Image Analysis and Processing in Potential Landslide Identification

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Image data plays a critical role in potential landslide identification, especially through remote sensing, satellite, and UAV imagery. These images enable the acquisition of large-scale terrain data, encompassing complex geographical features, vegetation coverage, and ground fissures, which often serve as potential precursors to landslide occurrences. The adoption of deep learning has facilitated a shift from conventional manual visual interpretation to automated high-precision segmentation.

Convolutional neural networks (CNNs) represent the fundamental architecture in image processing. A CNN primarily comprises convolutional layers, pooling layers, and fully connected layers, each performing predefined functions on its input data (Kattenborn et al., 2021; Liu et al., 2022a).

The convolutional layer, as the core component of CNNs, contains multiple kernels that progressively extract more detailed feature representations (Hussain et al., 2019; Shi et al., 2020; Yao et al., 2021). Meanwhile, the shared-weight strategy inherent in convolutional layers allows for network training with fewer parameters than fully connected architectures. Convolutional kernels of different sizes facilitate multi-scale feature extraction. Small kernels focus on fine details, such as small cracks and the texture of localized soil loosening, while large kernels emphasize capturing overall shapes, such as the general outline of landslides and the macroscopic morphology of mountain bodies. Pooling layers, typically positioned after convolutional layers, serve to reduce the size of feature representations and enhancing the model's resistance to overfitting when handling diverse data. Common pooling methods include max pooling and average pooling, which enhance robustness to minor transformations such as translation and rotation, ensuring a degree of invariance in the features extracted by CNNs. Pooling operations downsample the convolved feature maps, reducing computational complexity while reinforcing feature robustness. Through the hierarchical stacking of multiple convolutional and pooling layers, CNNs incrementally extract more abstract and semantically rich features (Mao et al., 2024). The final fully connected layer flattens the pooled feature maps and performs classification, outputting results that distinguish potential landslide areas from non-landslide areas or enable further analysis of landslide types (Wu et al., 2024).

The layers of a CNN can be combined in various ways, forming distinct CNN architectures. These architectures are primarily determined by task requirements, which may include image classification, multi-class segmentation, or object localization within a scene.

Conventional CNNs typically consist of multiple stacked convolutional layers, pooling layers, and fully connected layers. However, increasing network depth introduces challenges such as vanishing gradients and degradation arise, resulting in model performance deterioration.

ResNet addresses these limitations by integrating residual blocks into the foundational CNN framework (Qi et al., 2020; Yang et al., 2022). These residual blocks utilize shortcut connections that preserve original feature information. This framework facilitates the construction of ultra-deep networks capable of extracting high-level semantic features for landslide detection, thereby enhancing adaptability to complex terrain classification tasks (Ullo et al., 2021). Models with higher parameter counts generally exhibit greater representational capacity but are prone to overfitting, while demanding higher computational resources and temporal costs for both training and inference. For instance, ResNet-152 contains orders of magnitude more parameters than ResNet-50, yet the latter is often preferable in computationally constrained environments due to its balanced efficiency and performance.

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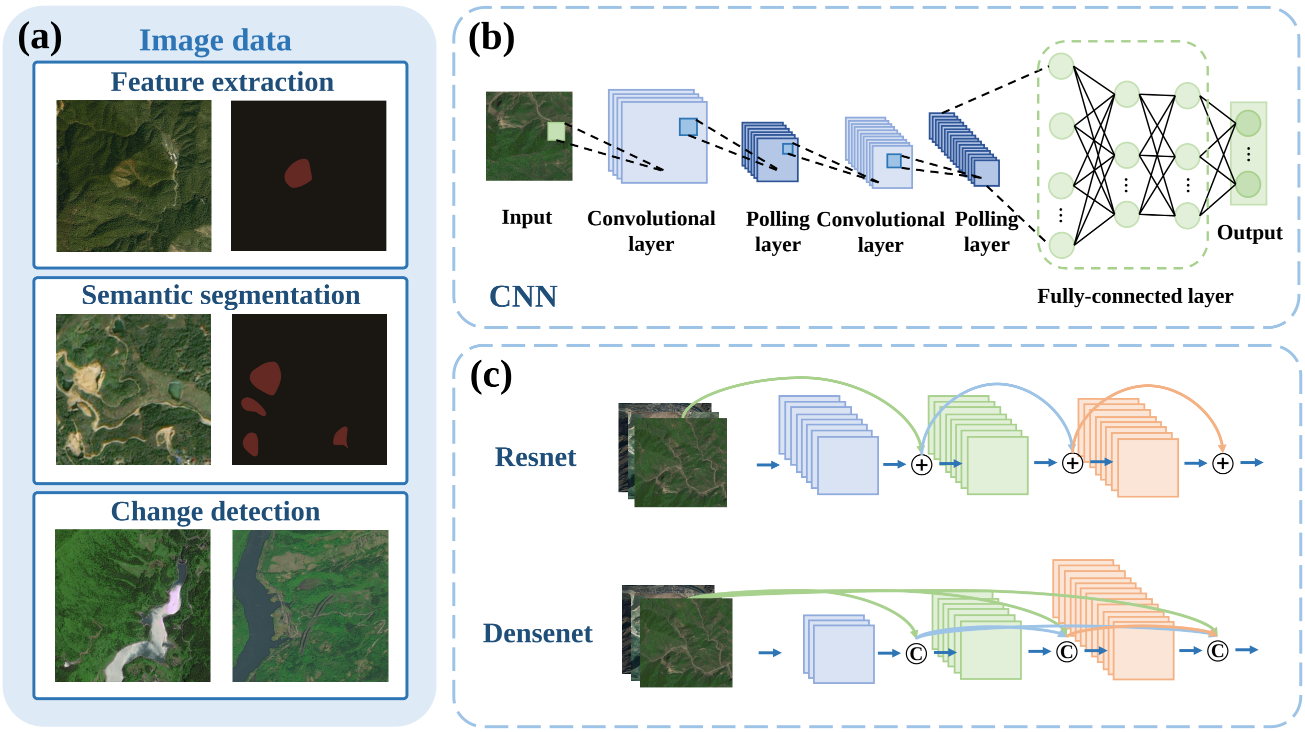

Figure 2. The role of deep learning models in image analysis and processing. (a) Three commonly used applications of CNNs in image processing for potential landslide identification. (b) Schematic of a basic CNN architecture. A conventional CNN typically comprises stacked convolutional layers, pooling layers, and fully connected layers. (c) Comparative schematic of ResNet and DenseNet architectures. In contrast to ResNet, which combines features through summation before passing them to subsequent layers, DenseNet integrates features via channel-wise concatenation.

DenseNet is a further innovation of ResNet (Huang et al., 2017). Both of these neural networks are based on a similar idea, which is to establish a "shortcut" between different layers. However, the structure of DenseNet is simpler and more effective, with fewer parameters. In ResNet, each layer is only connected to the previous layer, while in DenseNet, each layer is directly connected to all previous layers, and each layer can obtain gradients from the loss function. This can optimize the information flow and gradients of the entire network, making it easier to train and performing better on small datasets. The structure of DenseNet can achieve better feature reuse and reduce the number of parameters. Moreover, the layers of DenseNet are narrower than those of other deep learning networks (Liu et al., 2021c), making it reduce redundancy by learning with fewer feature maps. This architecture is suitable for the extraction of multi-scale landslide features under complex terrains, even with limited landslide training samples.

With the rapid expansion of deep learning methods based on CNNs, semantic segmentation models have increasingly become the standard in landslide detection. Numerous advanced semantic segmentation networks have been proposed and validated for

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automatic landslide detection, significantly enhancing the efficiency and accuracy of large-scale detection. U-Net is a typical example (Ronneberger et al., 2015), which features a U-shaped architecture. U-Net employs an encoder-decoder structure, where the encoder is similar to conventional CNNs, progressively reducing image resolution and extracting features through convolution and pooling operations; the decoder then restores the image resolution through transposed convolution or upsampling operations (Dong et al., 2022; Nava et al., 2022). Skip connections bridge low-level detail features with deep semantic features, thereby refining segmentation precision.

When dealing with complex features in landslide-prone areas, DeepLab is a more suitable choice (Sandric et al., 2024). Built upon deep convolutional neural networks, DeepLab employs dilated convolutions to expand the receptive field and integrates an atrous spatial pyramid pooling (ASPP) module to capture multi-scale contextual information.

In contrast, the U-Net architecture is relatively simpler and better suited for small targets and high-resolution imagery, such as landslide crack segmentation or fine annotation of high-resolution UAV images. DeepLab, on the other hand, is more effective for large-scale landslide area detection and multispectral remote sensing image classification (see Fig. 2).

After achieving semantic segmentation to obtain the accurate extent of a landslide and the classification of ground objects, change detection is employed to monitor the changes in the landslide area over time. By comparing the segmentation results of multiple temporal phases or directly analyzing the feature differences, the dynamic evolution of potential hazards can be quantifie (Amankwah et al., 2022).

Wang (2023) demonstrates that 3D CNNs can directly process these 3D tensors. These models capture spatial and temporal features using convolutional kernels while transforming multi-temporal image sequences into change hotspot maps or temporal variation curves as output.

Some studies even have integrated attention mechanisms into conventional CNN architectures to enhance the analysis of multi-temporal remote sensing imagery, thereby enabling the identification of landslide hazard evolution over time.

3.2 Models for Time Series Analysis in Potential Landslide Identification

The occurrence of a landslide is a gradual accumulation process, usually influenced by a variety of factors. We refer to data that reflect the changing states of a landslide body over time as time series data. Time series data analysis aims to excavate the information hidden in the time series data to help identify potential landslides. Different from conventional time series data analysis methods, using deep learning models an automatically reveal the dynamic change trends and periodic patterns in the data, providing more accurate information for landslide prediction.

Recurrent neural networks (RNNs) are a class of deep learning models specialized in processing sequential data, capable of capturing temporal dependencies within input sequences (Ngo et al., 2021; Zaremba et al., 2014). Unlike conventional feedforward neural networks, in an RNN, each neuron not only receives the current input but also the output of the previous time step as additional input. This structure endows the RNN with a memory mechanism.

The architecture contains three primary components working in coordination:(1) The input layer means that one data point is input at each time step. (2) The hidden layer contains recurrent connections, which enable the information from the previous

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time step to be passed to the current time step, and the output serves as the input for the next time step simultaneously. (3) The output layer generates the output under the control of the state of the hidden layer (Cho et al., 2014; Zhao et al., 2021b).

During the training process, the RNN will process the data at each time step in sequence, continuously updating the hidden state. By combining the input of the current time step with the hidden state of the previous moment for calculation to gain an understanding of the data at the current moment, this structure enables the RNN to capture the temporal evolution patterns of landslide-related factors.

Due to conventional RNNs struggle to model long-term dependencies and limit their applicability to short-term temporal sequences, long short-term memory networks (LSTM) were developed (Wang et al., 2023b).

LSTM is an enhancement of RNNs, primarily processing long sequence data. Compared to standard RNNs, the hidden layer architecture of LSTM is much more complex. By incorporating memory cells and gating mechanisms, LSTM selectively propagates critical information across multiple time steps, thereby effectively capturing long-range temporal dependencies (Landi et al., 2021; Yu et al., 2019).

The basic unit of an LSTM consists of three primary gates: (1) the input gate, which determines what new information should be added to the cell state; (2) the forget gate, which decides what old information should be discarded; and (3) the output gate, which selects the information to be output from the cell state as the hidden state at the current time step (Sherstinsky, 2020; Smagulova and James, 2019; Staudemeyer and Morris, 2019). The output hidden state, after a nonlinear transformation, can be used for prediction or as the input for the next time step (Yang et al., 2019).

This structure allows the LSTM to retain key information over long sequences while selectively forgetting irrelevant information according to the requirements. Through learning from historical data, the LSTM can predict the likelihood of landslides occurring, as well as the possible scale and impact range of landslides under different future conditions.

Due to the ability to self-update weights and significantly improve network accuracy, LSTMs can also be used as a complex nonlinear component in the construction of larger deep neural networks. The model does not require separating trend and periodic components from the original deformation data, yet it can compensate for deformation trend predictions caused by unexpected interruptions in monitoring data. These properties make LSTMs particularly suited for high-accuracy research and analytical scenarios requiring large-scale datasets (Gidon et al., 2023; Xu and Niu, 2018).

Gated recurrent unit (GRU) is a simplified version of LSTM(Chung et al., 2014; Zhang et al., 2022b), which has fewer parameters. Due to their higher computational efficiency, GRU has potential advantages in real-time data processing scenarios in landslide monitoring.

GRU mainly consists of the update gate and reset gate. The update gate is used to control how much of the previous information should be preserved at the current time step, while the reset gate is used to determine whether to ignore the hidden state of the previous time step, enabling the model to adaptively learn information across different temporal scales. This dual-gate mechanism enables adaptive learning of multi-scale temporal patterns.

Compared with the LSTM, the GRU has fewer parameters and higher computational efficiency, giving it an advantage in some landslide monitoring scenarios where real-time performance is critical.

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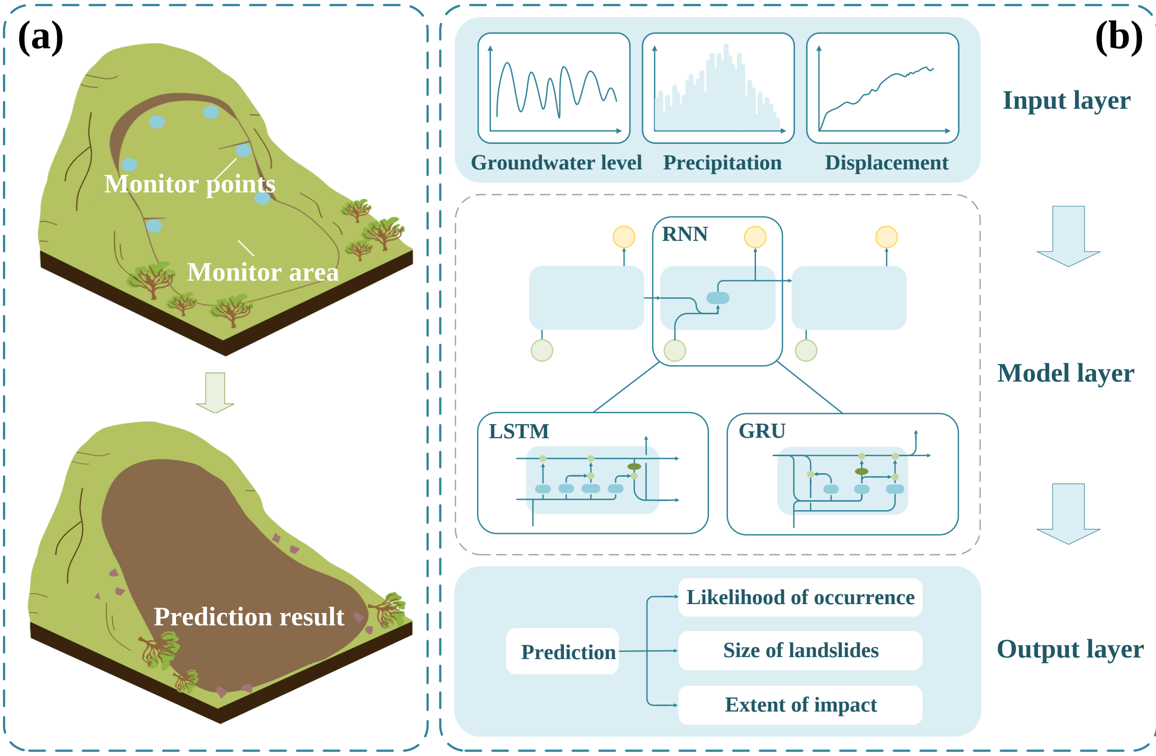

Figure 3. The role of deep learning models in time series analysis. (a) In potential landslide identification, time series data can be obtained through monitoring. (b) RNNs, LSTMs, and GRUs provide more accurate information for landslide prediction by processing time series data.

GRU is capable of effectively handling time series data with long-term dependencies, making it suitable for long-term prediction of landslide hazards. Moreover, by learning temporal patterns in historical data, GRU can identify critical conditions for landslide occurrence in advance. GRU particularly well-suited for applications involving real-time analysis of on-site monitoring data, where rapid detection of imminent landslide risks is essential and data volume is relatively limited.

Transformer was originally designed to handle sequential data in natural language processing, which was first introduced by Vaswani in 2017 (Vaswani et al., 2017). Unlike conventional recurrent and convolutional structures, the Transformer employs employs a self-attention mechanism to directly model the entire sequence.

Since the Transformer has the ability to adaptively learn latent features and patterns within the data, when it comes to processing landslide time series data, it can automatically tweak the model parameters to accommodate diverse landslide scenarios and temporal data variability (Wang et al., 2024a; Zerveas et al., 2021).

Transformer also can analyze positional relationships across the entire sequence, better capturing complex dependencies in long sequences, making it especially suitable for handling large-scale, long-term sequential datasets.

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In contrast, RNN-based models exhibit a relatively simple architecture (Li et al., 2021a; Wang et al., 2020b). Their mechanisms are conceptually intuitive, making them more interpretable (see Fig. 3). On the other hand, Transformers are more complex in structure with numerous parameters, necessitating substantial computational resources during early training to process large-scale data, while being susceptible to overfitting on small datasets. Understanding how the model extracts features and makes decisions is not straightforward from large amounts of landslide data, posing challenges for its interpretability and practical deployment.

3.3 Models for Data Generation in Potential Landslide Identification

Data generation refers to modeling the underlying data distribution of data to generate entirely new samples independent of the original dataset (Kingma et al., 2014; Moreno-Barea et al., 2020; Shorten and Khoshgoftaar, 2019), thereby enriching the dataset. In potential landslide identification, data generation mitigates challenges of data scarcity and imbalanced class distributions, thereby enhancing the generalization capability of predictive models.

Deep generative models are the leading deep learning approach for synthetic data generation (Alam et al., 2018; Karras et al., 2020; Ma et al., 2024; Xu et al., 2015). They operate on principles similar to those of deep learning, utilizing deep neural networks to learn data representations and optimizing the learning process through objective functions.

A fundamental characteristic of deep generative models lies in their probabilistic nature. These models learn an approximate probability distribution from observed samples and subsequently generate novel samples that maintain statistical consistency with the original dataset. Unlike conventional discriminative models, generative models not only classify data but also learn the underlying distribution and generate new data points. Commonly used deep generative models include generative adversarial networks (GANs), variational autoencoders (VAEs, a variant of autoencoders), and diffusion models.

GAN is a suitable choice to generate highly realistic and diverse new images (Goodfellow et al., 2014; Tran et al., 2021). Instead of explicitly modeling data distributions, GANs implicitly learn distributions through adversarial training between generator and discriminator networks.

During data generation, the generator network in a GAN synthesizes images or data resembling real samples by processing input noise vectors (Gui et al., 2021; Saxena and Cao, 2021). The discriminator, on the other hand, is used to distinguish between the generated data and the real data.These two components are continuously optimized through adversarial training. Eventually, the generator is able to produce high-quality synthetic data, which is highly similar to the real data in terms of features.

With this adversarial structure (Al-Najjar et al., 2021), GANs can generate high-quality data that closely matches the distribution of real data in an unsupervised learning context, making them well-suited for high-resolution image synthesis.

With the proposal and development of GANs, researchers have introduced various enhanced structures that are more effectively applied to potential landslide identification. For example, the conditional GAN (CGAN) (Kim and Lee, 2020; Loey et al., 2020), Pix2Pix (Qu et al., 2019), and Wasserstein GAN (WGAN) (Wang et al., 2019).

In the case of GANs, although the generated high-quality images may visually resemble real potential landslide regions, mode collapse can lead to a lack of diversity in the generated data, failing to cover all possible types of hazards (Fang et al.,

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2020). If certain types of potential landslides are underrepresented in the training dataset, GANs may struggle to generate those types effectively, thereby limiting the effectiveness of data augmentation. Given that the inherently unstable training process of the GANs may require more hyperparameter tuning and computational resources, this model will pose additional challenges in scenarios with limited data availability (Al-Najjar and Pradhan, 2021; Feng et al., 2024).

As a variant of the autoencoders (AEs), the variational autoencoder (VAE) introduces the idea of probabilistic generation (Kingma et al., 2013). VAE constrains the latent space through variational inference, thus enabling the generation, reconstruction, and transformation of sample data.

Compared to GANs, the samples generated by the VAE may have better diversity (Cai et al., 2024; Islam et al., 2021; Oliveira et al., 2022), because the structured constraints of its latent space are helpful for generating samples with continuous changes. This is beneficial for simulating potential landslides under different geological conditions.

The encoder of the VAE maps the input data to a low-dimensional latent space, where each vector represents the underlying features of the input. The decoder then reconstructs the original data based on the vectors in the latent space. Different from conventional AEs, the output of the VAE encoder includes two parameters: the mean value and the standard deviation. These two parameters define the probability distribution in the latent space, which is usually assumed to be a Gaussian distribution. The decoder samples a latent variable from this probability distribution and reconstructs it into output data, thus generating data with inherent randomness and diversity. Therefore, the VAE can extract latent features from landslide data and generate new landslide data based on these features.

By learning from extensive landslide datasets, VAEs capture critical geomorphological features and patterns, enabling the generation of novel samples that preserve these characteristics. This capability enables innovative applications in potential landslide analysis. This is crucial for exploring landslide scenarios under different feature combinations and identifying potential landslide patterns. Compared to GANs, VAEs exhibit superior sample diversity and training stability though the generated samples often lack the fine-grained details produced by GANs, particularly in high-resolution geospatial contexts. Moreover, VAEs may still face challenges in handling highly imbalanced data, as the generated samples tend to favor majority classes, which can limit its effectiveness in augmenting minority class data.

When computational resources and time are sufficient, and high-quality data generation with exceptional diversity is prioritized, diffusion models are the recommended choice (Croitoru et al., 2023; Yang et al., 2023a; Zhu et al., 2023a).

Diffusion models fundamentally learn the distribution of data. During training, the model applies a forward diffusion process that gradually adds noise to the original data until it approximates a Gaussian distribution. Then, in the reverse diffusion process, the model learns to iteratively refine its reconstruction of the original data distribution from the noisy data. After being fully trained, the model is able to capture the latent distribution patterns of the data, and thus can sample based on the learned distribution to generate new data (Ho et al., 2022). That is to say, by grasping the inherent laws and features of the data, the model has the ability to generate data that conforms to the distribution of the data.

Denoising diffusion probabilistic model (DDPM) is a classic implementation of the diffusion models, which lays the probabilistic framework for the diffusion models (Choi et al., 2021; Ho et al., 2020; Jing et al., 2023; Perera et al., 2023). The generation quality is optimized through variational inference and noise scheduling. Denoising diffusion implicit model (DDIM) has

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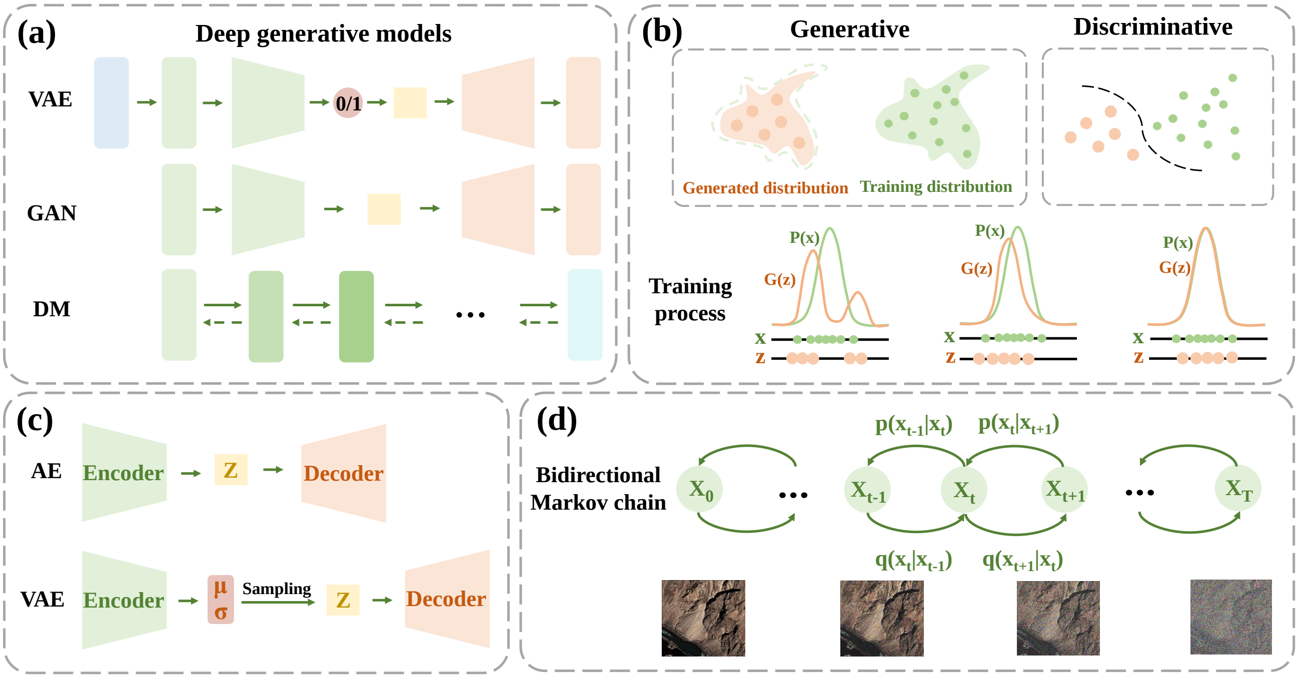

Figure 4. The role of deep learning models in data generation. (a) Comparative schematic of three commonly used deep generative model architectures. GAN: adversarial training. VAE: maximize variational lower bound. Diffusion models: gradually add Gaussian noise and then reverse. (b) Schematic of the adversarial training workflow for GAN-based data generation. (c) Comparative architecture of AE and its variational counterpart, VAE. (d) Schematic of a diffusion model applied to denoise potential landslide data.

made improvements on the basis of DDPM (Song et al., 2020). It uses non-Markov chain reparameterization and deterministic sampling, and greatly improves the efficiency with almost no loss of quality.

Notably, DDIMs utilize the same training framework as DDPMs. If certain parameters of DDIMs are assigned particular values, its generation process becomes equivalent to DDPMs. Thus, DDIMs function as an accelerated sampling variant of DDPMs. The critical distinction lies in their sampling mechanisms. DDPMs employ stochastic and Markovian sampling, whereas DDIMs enhance efficiency through non-Markovian deterministic sampling, though this comes at the expense of reduced sample diversity.

Although diffusion models demonstrate strong capabilities in generating high-quality images and handling noise, they generate superior-quality data and ensure greater training stability compared to GANs and VAEs. However, diffusion models have not yet been widely applied directly to the identification of potential landslides and remain in the exploratory stage (see Fig. 4). We believe that as generative models advance in the field of geospatial remote sensing, they hold vast potential for application and could play a pivotal role in future landslide risk analysis and monitoring systems.

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3.4 Models for Data Cleaning in Potential Landslide Identification

In potential landslide identification, data cleaning, particularly anomaly detection, is a critical issue (Deijns et al., 2020; Jiang et al., 2020). It can distinguish between normal fluctuations and true anomalies, identifying early signs such as subtle changes in the mountain's state or abnormal trends in surface displacement, thus enabling more accurate landslide hazard assessment. With the rapid development of deep learning, the applications in data cleaning have become increasingly widespread, enabling models to automatically learn latent data patterns and identify potential anomalies.

AEs and their variational counterparts are highly effective in unsupervised data cleaning. These models autonomously learn normal geomechanical patterns from data and flag deviations, achieving effective hazard identification even when labeled anomaly samples are scarce.

The AE is a typical unsupervised learning model consisting of an encoder and a decoder The encoder compresses the input data into low-dimensional features, and then the decoder reconstructs the input. During the training process, the autoencoder learns the intrinsic features and patterns of normal landslide data, so that for normal data, the reconstruction error is small. When abnormal landslide data is input, due to the difference between its features and the distribution of normal data, the reconstruction error will be large.

When performing anomaly detection, a suitable reconstruction error threshold is set. When the reconstruction error of the test data exceeds this threshold, it can be determined as abnormal data. In the anomaly detection of landslide displacement data monitored by sensors, if the error of the displacement data after being reconstructed by AEs during a certain period is significantly higher than the normal level, it may indicate that there is an abnormal situation of potential landslides during this period.

As previously introduced, VAE is an extension of AE. Compared to conventional autoencoders, VAE introduces randomness into the latent space, making it more effective in handling data uncertainty (Li et al., 2020; Park et al., 2018). During training, VAEs learn the latent distribution of the data and can generate new samples resembling the training set. When input samples deviate significantly from this learned distribution, the VAE fails to reconstruct them accurately, thereby flagging anomalies through elevated reconstruction errors. For landslide monitoring, if a VAE is trained on imagery of stable slopes, it internalizes stable terrain features. When an image significantly differs from the stable region, the model will produce a high reconstruction error, indicating the presence of anomalous data.

In contrast, AEs are well-suited for univariate anomaly detection, particularly for landslide precursor detection, while VAEs capture latent space distributions and are more effective for multivariate anomaly detection.

GANs can also be utilized in data cleaning (Kang et al., 2024; Xia et al., 2022). In data cleaning, the discriminator is trained to distinguish between generated data and real data. When new test data is input, if the discriminator struggles to determine whether it is real or generated data, the test data may significantly deviate from the distribution of normal data, indicating a potential anomaly. In landslide monitoring, data may be influenced by various factors, GANs demonstrate robustness by filtering out such interference, thereby enhancing data cleaning accuracy (Radoi, 2022).

AnoGAN extends conventional GANs by directly incorporating data cleaning as one of its primary objectives (Lin et al., 2023; Thomine et al., 2023). It introduces an additional encoder during training, which maps input data to the latent space. The difference between this latent vector and the latent vector of normal samples generated by the generator serves as the basis for data cleaning.

RNNs, LSTMs, and GRUs are also effective for identifying anomalous patterns in sequential data (Zhang et al., 2022a). In potential landslide identification, these models process time series inputs to learn normal temporal dynamics and trends. When new data deviates significantly from the normal patterns learned by the model, such deviations can be flagged as anomalies. However, these models are primarily used for time series data, performing data cleaning by predicting future values of the sequence. For instance, if displacement measurements exhibit abrupt deviations while rainfall remains within historical norms, the model detects such discrepancies by comparing observed values with predictions based on learned temporal dependencies.

3.5 Models for Data Fusion in Potential Landslide Identification

In practical applications, the identification of potential landslide hazards is a complex task that influences by multiple factors (Zhang et al., 2018). These factors are often reflected through different data sources. We can roughly divide heterogeneous data into four categories: image data, time series data, structured data, and textual data. Data fusion is essential for the accurate identification of potential landslides. In order to better identify potential landslides, data fusion is essential.

Since the features, scales, and resolutions of heterogeneous data are all different, currently, the powerful feature learning ability of deep learning models is often utilized to automatically capture the nonlinear relationships and high-order interaction information among these heterogeneous data.

Due to the complex non-Euclidean structural characteristics of the geological environment, topographic data and their spatial relationships related to landslide hazards, conventional methods such as CNNs have difficulty in handling these relationships. As a neural network architecture for processing graph-structured data, graph neural networks (GNNs) can effectively model such spatial relationships (Ying et al., 2018; Zeng et al., 2022). They can treat the nodes in the geographical space (such as different geographical location points) and their connection relationships (such as the distance between adjacent nodes, terrain undulations, etc.) as the structure of a graph for processing.

When dealing with heterogeneous data, GNNs support feature interaction between different types of nodes through the message passing mechanism, thereby eliminating redundancy and mutual exclusivity among data sources and enabling dynamic fusion of multi-modal features (Zhang et al., 2024d; Zhao et al., 2024b). By passing and aggregating information across nodes, GNNs can also conduct a detailed analysis of various heterogeneous data in local areas. This capability allows GNNs to capture subtle geological structural changes and detect localized anomalies in monitoring data, providing advantages for analyzing local features and early signs of potential landslide movements.

By learning a large amount of landslide potential cases, GNNs can discover the general patterns and rules of landslides, thus having good generalization ability. When facing new and unseen regions or data, GNNs can predict and assess the potential landslides in those regions based on the knowledge they have already learned.

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According to the differences in message passing and aggregation methods, GNNs have derived various variants. For example, graph convolutional network (GCN) is generated by generalizing the convolutional operation to graph-structured data (Sharma et al., 2022; Wang et al., 2020a), and graph attention network (GAT) dynamically weights the importance of neighboring nodes by introducing the attention mechanism (Yuan et al., 2022; Zhou and Li, 2021). The emergence of these new architectures makes GNN variants more targeted than conventional GNNs and suitable for modeling heterogeneous relationships. Currently, they are often used for weighted analysis of the impacts of different geographical factors on landslides.

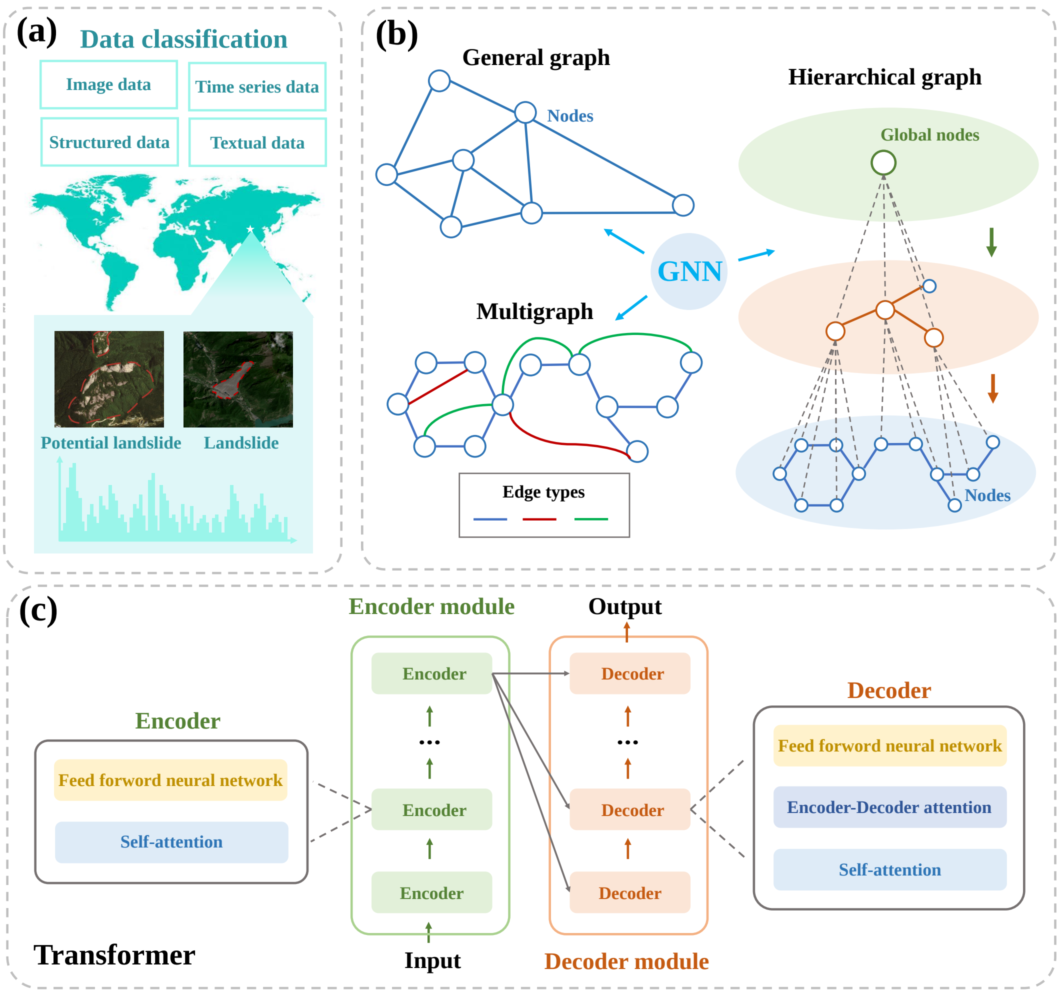

Figure 5. The role of deep learning models in data fusion. (a) Classification of heterogeneous data for potential landslide identification. (b) Schematic of general graph and more complex graphs. (c) Schematic of the fundamental Transformer architecture.

As previously discussed, Transformer has become a universal architecture for processing sequential and multimodal data, owing to its self-attention mechanism and modular design.

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Transformer is also composed of stacked encoders and decoders (see Fig. 5). However, unlike other architectures, the Transformer architecture introduces the self-attention mechanism (Zhao et al., 2021a), which is a crucial innovation. This enables the Transformer to automatically calculate a weight vector for each position in the input sequence based on the relationship between this position and other positions, so as to represent the importance of this position in the entire sequence. Such a weight vector can be regarded as the "attention distribution" of each position in the input sequence, that is, the model determines which positions in the sequence to focus on. By considering all positions in the input sequence simultaneously, Transformer is able to calculate the correlations between each position and other positions in the sequence in parallel (Esser et al., 2021; Huang and Chen, 2023; Zerveas et al., 2021), rather than processing them step by step like CNNs or RNNs.

Transformer can also convert multimodal dFor different types of data, it transforms them into vector representations via different embedding layers.ata into a unified vector representation through different embedding layers. Subsequently, through the use of the self-attention mechanism and multilayer neural networks, these vectors are fused and feature representations are extracted, enabling the model to process and integrate data from various modalities within the same model framework (Lv et al., 2023; Tang et al., 2022).

4 Deep Learning for Potential Landslide Identification: Applications

Potential landslide identification can be broadly categorized into two types. The first involves conducting a thorough investigation and assessment of the region following a significant rainfall or earthquake event, prior to the occurrence of a landslide. Remote sensing imagery is typically employed to observe and analyze various factors, including changes in topography, the expansion of surface cracks, and abnormal vegetation patterns, in order to identify potential landslides. This allows for the implementation of appropriate preventive and mitigation measures to avoid larger-scale landslides in the future.

The second type involves analyzing previously occurred landslides to establish the relationship between triggering factors and landslide events, as well as to summarize the characteristics and patterns of landslides. Subsequently, retrospective analysis is performed to determine whether other potential landslides exist in the region. Meanwhile, continuous monitoring and evaluation of these potential landslide areas are conducted to prevent secondary landslides, while also providing valuable experience and a scientific basis for future landslide prediction.

The purpose of classifying landslides is to investigate the various patterns underlying landslides triggered by different causes. Given that different types of landslides exhibit varying triggering mechanisms and conditions, the focus of identification should vary accordingly, prioritizing cost minimization while ensuring the accuracy of landslide identification.

In this section, we focus on the analysis of the second type of potential landslides. Based on triggering factors, landslides can be classified into four categories: rainfall-induced landslides, earthquake-induced landslides, human activity-induced landslides, and multi factor-induced landslides. For each category of landslide, we provide a brief outline of its characteristics, discuss the applications of deep learning to different types of landslides, and examine the selection of monitoring methods for each category.

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4.1 Application of Deep Learning in the Identification of Rainfall-induced Landslides

Rainfall stands as the predominant global trigger for landslides. Intense and short-duration rainfall events (lasting from a few hours to several days) often induce shallow landslides (Ma and Wang, 2024), whereas prolonged rainfall (lasting from several weeks to months) can lead to deeper and larger landslides, with depths ranging from 5 to 20 meters (Casagli et al., 2023). Consequently, rainfall intensity, cumulative precipitation, and rainfall duration constitute critical triggering parameters for rainfall-induced landslides (Mondini et al., 2023).

Sustained or intense rainfall elevates slope unit weight and moisture content, alters pore water pressure regimes, and reduces shear strength via the principle of effective stress, thereby initiating surface instability. This hydro-mechanical coupling establishes a pronounced positive correlation between rainfall patterns and slope deformation (Li et al., 2022a).

Temporally, landslides exhibit both abrupt failure and delayed responses to rainfall. Pre-existing fractures act as preferential pathways for rainwater infiltration, yet the time required for percolation to reach slip zones introduces a hysteresis effect in slope deformation relative to precipitation events (Jiang et al., 2023; Liu et al., 2022b). During wet seasons, intense rainfall elevates groundwater tables, inducing fully saturated conditions in slope materials. This saturation amplifies shear strain rates, triggering rapid acceleration of landslide movement. Post-rainfall, groundwater levels remain elevated for extended periods (weeks to months), resulting in sustained but decelerated sliding velocities rather than complete stabilization. Consequently, despite concentrated rainfall during wet seasons, numerous landslides occur in subsequent dry periods (Ren et al., 2023), highlighting the delayed destabilization governed by lingering pore pressure dynamics. The hysteresis phase reflects progressive energy accumulation toward critical thresholds, while abrupt failure signifies rapid energy release during instability. This transition is typically characterized by a near-instantaneous shift from stable to unstable states when pore water pressures or soil moisture content exceed critical thresholds, with minimal intermediate deformation phases.

The spatial clustering of rainfall-induced landslides fundamentally arises from the coupling of moisture transport efficiency and geotechnical strength degradation within specific geomorphic units (Wicki et al., 2020; Yu et al., 2021). Spatially, such landslides are concentrated in high-rainfall zones and permeable lithologies, where hydro-mechanical feedback dominates slope destabilization. High-rainfall zones, characterized by frequent and intense precipitation, impose dual hydrological stresses on slopes: surface runoff erodes toe regions, while infiltration elevates pore pressures, collectively acting as external drivers of failure. Highly permeable strata, characterized by high porosity or interconnected fractures, accelerate water migration. Combined with high permeability, these properties regulate water retention time within the slope and control the efficiency of pressure transmission, forming an internal transport network that facilitates landslide progression. The superposition of these mechanisms drives slope stability beyond critical thresholds over short timescales, culminating in abrupt failure.

What determines the critical threshold for rainfall-induced landslides? First, it is essential to define the critical threshold as the minimum amount of rainfall required to trigger a landslide under specific geological and topographic conditions (Naidu et al., 2018; Segoni et al., 2018b). This threshold is typically classified into two types: empirical thresholds, which are derived from statistical relationships between historical landslide events and rainfall data, and physically based thresholds, which incorporate hydromechanical models. Both approaches assume rainfall as the primary destabilizing driver. Monitoring systems

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thus integrate rain gauge and remote sensing to assess proximity to critical saturation thresholds (Li et al., 2023a; Piciullo et al., 2018). Moreover, the relationship between rainfall and landslides is often nonlinear and influenced by multiple factors. Deep learning models enable data-driven determination of context-specific critical rainfall values across diverse geological and topographical settings (Sala et al., 2021; Segoni et al., 2018a). For example, Badakhshan et al. (2025) incorporated the role of soil strength. Soares et al. (2022) utilized the U-Net model, reveals that the inclusion of a normalized vegetation index layer enhances model balance and significantly improves segmentation accuracy.

Following the development of rainfall threshold models, real-time monitoring of historically rainfall-induced landslides is imperative. First, continuous surveillance enables early detection of subtle deformations and precursory anomalies (Guzzetti et al., 2020; Zhu et al., 2023b), facilitating timely reactivation warnings to mitigate secondary hazards to lives and infrastructure. Second, by continuously monitoring rainfall, soil moisture, and groundwater levels, we can support dynamic recalibration of threshold parameters. This data assimilation enhances model adaptability to evolving hydrogeological conditions, ensuring operational relevance across heterogeneous terrains.

4.2 Application of Deep Learning in the Identification of Earthquake-induced Landslides

Earthquakes not only trigger landslides during the seismic phase but also increase the susceptibility of post-earthquake landslides by weakening slope materials or forming co-seismic landslide deposits (Zhang et al., 2024a; Zhao et al., 2024a). On the one hand, the seismic vibrations can loosen the structure of the rock and soil mass on the slope, reducing the cementation between particles. The originally intact rock mass may develop cracks, and the density of the soil decreases, thus reducing the overall stability of the slope and making it more prone to landslides after the earthquake. On the other hand, the landslides that have occurred during the earthquake process will generate a large amount of deposits. These co-seismic landslide deposits are usually accumulated at positions such as the lower part of the slope or in valleys. They are in a relatively unstable state themselves, providing a material basis for subsequent re-sliding (Fan et al., 2019; Yao et al., 2024).

So, what is the temporal relationship between earthquake-induced landslides and seismic events? When an earthquake occurs, landslides may be triggered instantaneously by seismic ground motion, typically within seconds to minutes after the earthquake. Such landslides are mainly triggered by the peak ground acceleration (PGA) or peak ground velocity (PGV) of the seismic ground motion (Kargel et al., 2016; Zhao et al., 2023). When these values reach a certain level, they are sufficient to enable the rock and soil masses on the slope to overcome the frictional force and shear strength, thus leading to the occurrence of landslides.

Earthquake-induced landslides are typically concentrated in areas of high seismic intensity, particularly on steep slopes or within loose accumulations (Li et al., 2024). A fault is a place where the rocks in the earth's crust break and undergo relative displacement. Its existence destroys the continuity and integrity of the rock mass, making it more prone to deformation and damage under the action of seismic forces. On the hanging wall of a reverse fault, the compressive force usually causes the rock blocks to break, and mountain landslides are likely to occur during seismic events. In contrast, on the footwall of a normal fault, the tensile force may cause the rock blocks to fracture and loosen, thus increasing the risk of mountain landslides.

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The Newmark model is a commonly used basic model in the research of earthquake-induced landslides. Based on a simplified assumption, it regards the rock and soil masses on the slope as rigid blocks. When these rigid blocks are affected by seismic vibrations, they slide on the slope surface. By calculating the cumulative downhill displacement of the rigid blocks caused by the continuous increase of seismic vibrations, the stability of the slope under the action of an earthquake is measured. In other words, the greater the cumulative downslope displacement, the more unstable the slope is during the earthquake, and the higher the likelihood of a landslide occurring. However, Newmark's model exhibits critical limitations: (1) Dependence on oversimplified soil or rock strength assumptions and (2) Inadequate integration of high-resolution seismic motion data. Deep learning models address these gaps by processing massive real-time datasets, filtering noise from obscured remote sensing imagery (Wang et al., 2024b), and fusing seismic parameters with multispectral satellite data through cross-modal architectures (Dahal et al., 2024).

Within hours to days post-main shock, aftershocks can further destabilize already loosened slope structures, triggering secondary landslides clustered near co-seismic failure zones or aftershock epicenters (Sun et al., 2024b; Zhang et al., 2024c). These landslides are often concentrated around the mainshock-induced landslide bodies or the epicentral region of aftershocks, potentially forming disaster chains (e.g., landslides blocking rivers, leading to the formation and subsequent failure of landslide dams, which may trigger flooding). Even years post-earthquake, relic landslide deposits may reactivate through gradual creep or extreme climatic forcing, necessitating long-term spatiotemporal monitoring and dynamic risk reassessment (Jones et al., 2021; Li et al., 2021b). Moreover, earthquake-induced landslides are often associated with complex 3D topographic changes, which are difficult to capture using conventional 2D analyses. Deep learning frameworks enable precise reconstruction of landslide geometries by processing LiDAR-derived or UAV-derived 3D point clouds, capturing volumetric deformation patterns critical for mechanistic modeling.

Current applications of deep learning in earthquake-induced landslides primarily focus on semantic segmentation and change detection (Chowdhuri et al., 2022; Huang et al., 2023b; Liu et al., 2020a; Yang et al., 2024b). Liu et al. (2021b) employed graph isomorphism networks (GIN) to model long-range dependencies among high-level features extracted by ResNet-50. Zi et al. (2021) utilized a hybrid architecture combining graph attention networks (GATs) and channel self-attention mechanisms enhances the modeling of feature interdependencies from ResNet-50. Yang et al. (2023b) incorporated a spatial attention module to capture contextual dependencies and extract rich non-local spatial features, proposing a novel semantic segmentation network, EGCN, to enhance landslide recognition accuracy.

Both physics-based and data-driven model calibration rely on earthquake-induced landslides inventories (Bhuyan et al., 2023; Tanyaş et al., 2017). Despite increased inventory availability, persistent issues of representativeness and completeness limit model generalizability and mechanistic fidelity.

4.3 Application of Deep Learning in the Identification of Human Activity-induced Landslides

Human activity-induced landslides typically arise unintentionally during construction activities, where initial slope equilibrium is disrupted by slope toe excavation or water infiltration into exposed fractures (Zhao et al., 2022). Compared to natural landslides, human activity-induced failures are often more controllable, underscoring the critical importance of pre-

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disaster identification for risk mitigation. These landslides are characterized by localized micro-deformation and subsurface disturbances, necessitating integrated monitoring systems that combine high-resolution remote sensing data with ground-based sensors for early anomaly detection.

Current predominant anthropogenic triggers include mining and loading (Ma et al., 2023a; Xu et al., 2022). These activities induce severe surficial damage, with stratigraphic movement and surface deformation leading to the formation of ground fissures. Such fissures compromise surface ecosystems and vegetation, while also penetrating subsurface mining cavities, posing grave risks to operational safety. Consequently, deep learning models are essential for automated ground fracture extraction to enable real-time hazard mapping and preventive interventions (Huangfu et al., 2024).

Moreover, the triggers of human activity-induced landslides are not only related to natural conditions but also closely associated with dynamic human activities. Consequently, their analysis necessitates the integration of multimodal and cross-scale data to capture coupled environmental and behavioral drivers (see Fig. 6). In engineering operations such as mining or road construction, factors including proximity to potential landslide zones, excavation depth, and slope angles must be rigorously evaluated through geohazard risk assessments. During excavation phases, geotechnical investigations are imperative to identify weak lithological strata or fracture-dense zones predisposed to instability. Continuous slope stability monitoring requires deploying IoT-enabled sensors to track temporal variations in surface fissure dimensions and subsurface displacement vectors. Monitoring data from these sensors can be integrated into deep learning models for multimodal analytics, enabling dynamic risk prediction and adaptive mitigation planning.

To mitigate misclassification between anthropogenic signatures and natural terrain, integrating multispectral data with topographic elevation data enhances discriminative capacity (Meng et al., 2021; Selamat et al., 2023). For instance, in mountainous regions, DEMs revealing artificially excavated steep slopes combined with fractured geological strata from structural maps provide preliminary evidence of human influence on landslide susceptibility (Lian et al., 2024).

In fact, landslides triggered solely by human activities are relatively rare. Single human activities are typically insufficient to independently trigger landslides, with natural factors often acting in conjunction with human activities. Furthermore, the prohibitive cost of acquiring subsurface disturbance data results in sparse historical landslide samples for specific engineering scenarios, limiting data-driven model training.

4.4 Application of Deep Learning in the Identification of Multi factor-induced Landslides

Multi factor-induced landslides result from the synergistic interaction of multiple natural and anthropogenic factors (Hao et al., 2023). Their triggering mechanisms involve the dynamic spatiotemporal coupling of these factors, driving progressive destabilization of geomaterials through cumulative strength degradation. The formation of such landslides may involve various types of movements, including collapse, creep, and flow phenomena. They often exhibit characteristics such as complexity, nonlinearity, and suddenness. Therefore, their identification is markedly more complex compared to landslides triggered by singular factors.

Unlike simpler landslide types, identifying composite landslides necessitates multimodal data fusion to holistically assess predisposing conditions (Li, 2025; Yin et al., 2023). It further requires disentangling the nonlinear superposition effects of

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multiple factors and quantifying their relative contributions to failure initiation. For instance, Dou et al. (2019) analyzed how earthquake intensity and rainfall metrics jointly modulate landslide susceptibility, deriving failure probabilities under varying parameter combinations. In multi factor-induced landslides, earthquakes and rainfall often interact with other factors. For instance, during heavy rainfall, the rate of landslide formation after an earthquake may be higher, possibly driven by the removal of excessively steep slopes, changes in vegetation and groundwater, and alterations in the mechanical properties of the bedrock and weathered layers in the earthquake-induced landslides canopy. This necessitates systematic investigation of multi-hazard coupling effects to quantify emergent risks.

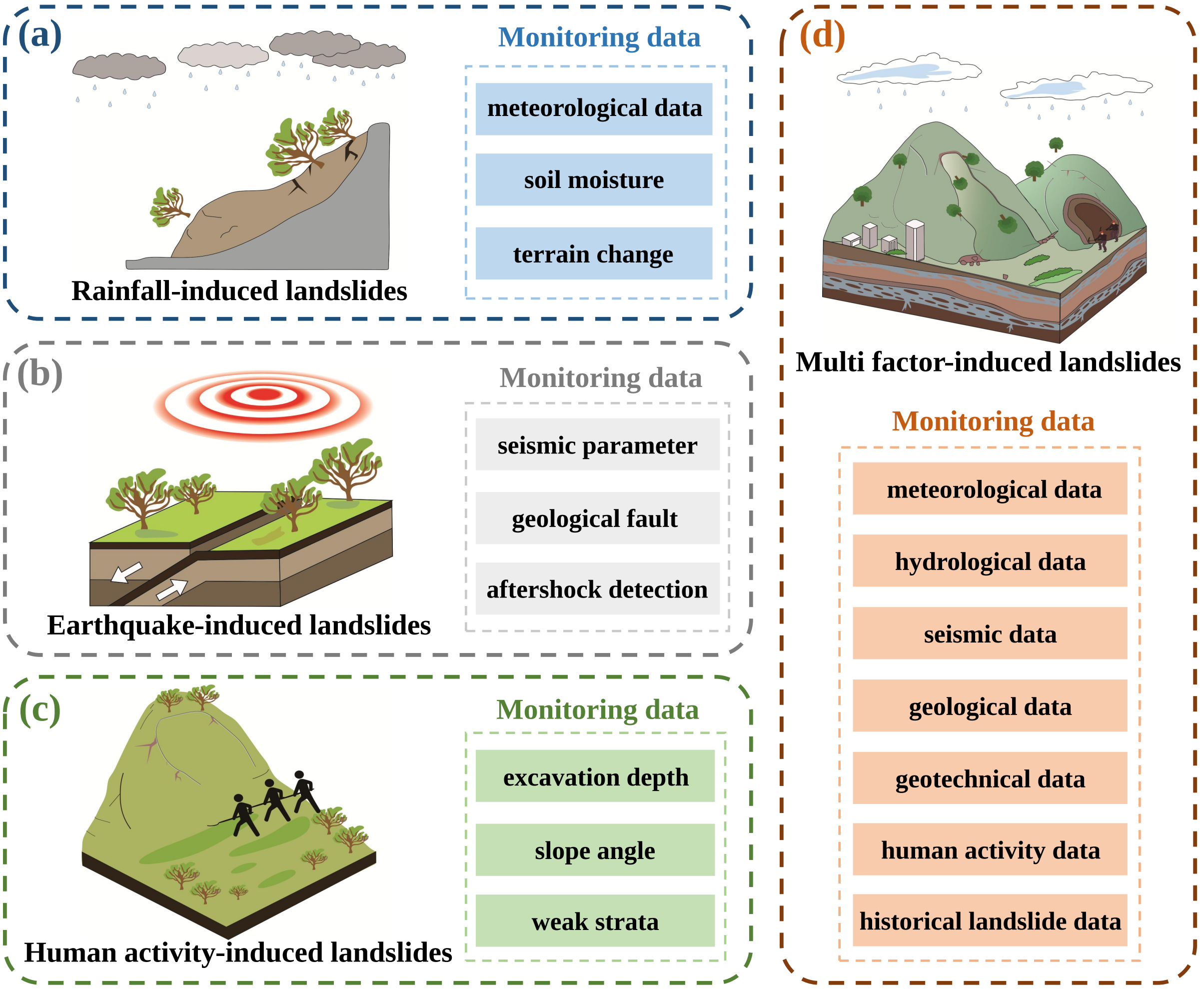

Figure 6. Selection of monitoring data for different types of landslides (a) Rain-induced landslides. (b) Earthquake-induced landslides. (c) Human activity-induced landslides. (d) Multi factor-induced landslides.

In addition to the approach of constructing physics-based models that account for multiple factors, GNNs can be employed. These models represent landslide-prone areas as graph nodes, dynamically updating node states through spatiotemporal edges

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(Lei et al., 2025). Furthermore, cross-attention mechanisms can be integrated into the model to capture spatiotemporal dependencies among contributing factors. Alternatively, gated fusion units may be incorporated to dynamically adjust the weights of multi-modal features (Yang et al., 2024a).

With the accumulation of new data and the dynamic variations in multi factor-induced landslides, regular model updates are critical to ensuring identification accuracy and adaptability. Existing studies predominantly apply these methods based on comprehensive historical landslide datasets and employ batch learning theory for identification. However, when new data becomes available, the model must be retrained from scratch. This approach is not only highly inefficient but also fails to account for the connections between newly observed and historical landslides. To address this limitation, incremental learning methods offer a promising solution. These methods enable gradual parameter optimization through new data without retraining the existing model (Huang et al., 2022). Compared to conventional deep learning models, those integrated with incremental learning can more effectively leverage historical landslide data and adaptively learn from newly incorporated data, thereby better accommodating the dynamic nature of landslides.

4.5 Summary on the Applications of Deep Learning for Potential Landslide Identification

In general, the process of the applications of deep learning for potential landslide identification involves data collection, preprocessing, model construction, training, and validation, followed by deploying the trained model to identify potential landslides. Variations arise in data sources, trigger mechanisms, and model handling approaches specific to each landslide type. For rainfall-induced landslides, the model prioritizes rainfall-related data, with particular emphasis on simulating rainfall infiltration effects. Earthquake-induced landslides require prioritization of seismic data, including earthquake magnitude and post-seismic geological alterations. Human activity-induced landslides demand focused analysis of the relationship between engineering activities and geological changes. In contrast, multi factor-induced landslides necessitate models that integrate multiple triggering mechanisms and perform a comprehensive assessment of the cumulative effects of diverse contributing factors.

Whether landslides are triggered by rainfall or earthquakes, gravity remains the dominant driving force (She et al., 2024). The primary role of triggering factors lies in reducing slope stability or amplifying gravitational effects. Before and during landslide occurrence, deformation of slope geomaterials constitutes the most observable phenomenon (Zhou et al., 2025). This deformation often manifests as the formation and expansion of cracks.

Since landslide deformation is a dynamic process, ranging from initial minor changes to eventual large-scale sliding, each stage exhibits distinct characteristics. Therefore, landslides can be classified into distinct stages based on their deformation characteristics, enabling more accurate identification of impending disaster warning signals (Zhang et al., 2024b). Here, we categorize landslide evolution into three phases: (1) Creep deformation stage, (2) Intermediate development stage, and (3) Progressive failure stage (see Fig. 7).

In the creep deformation stage, the slope gradually deforms under the influence of various factors, though surface manifestations may not be readily observable. Small, discontinuous cracks with limited width may emerge on the slope surface or crest. High-precision measuring instruments can detect localized minor displacements or deformations (Zhan et al., 2024).

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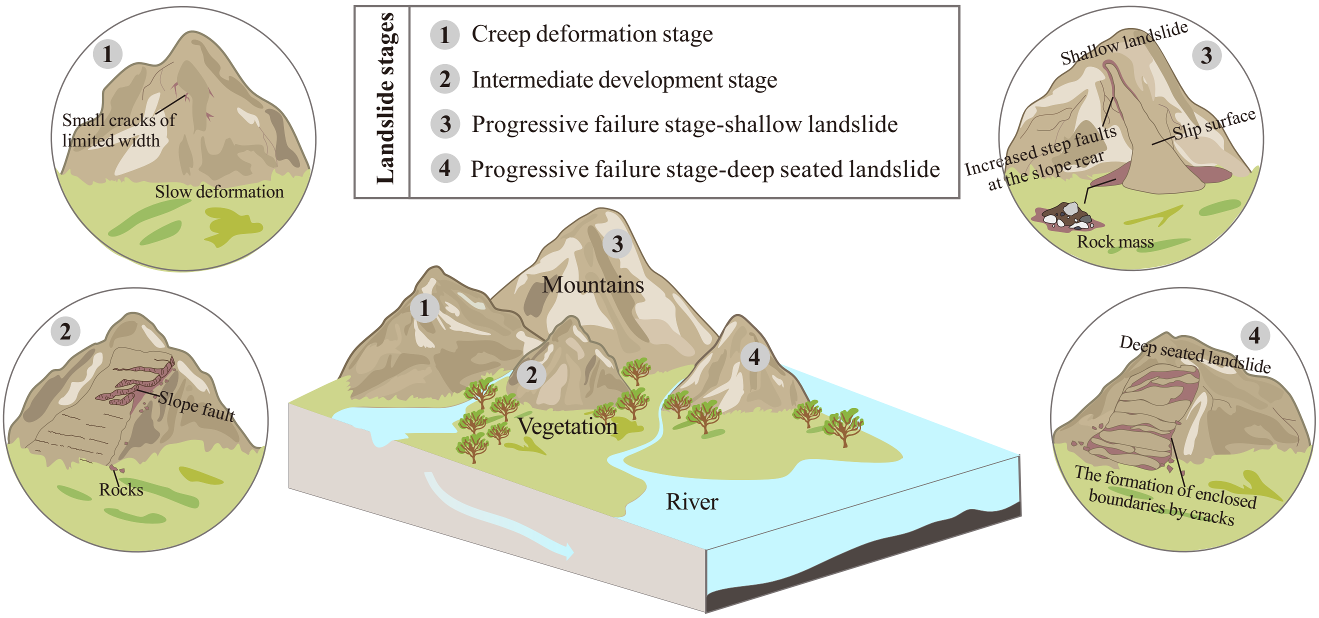

Figure 7. The development of landslides is divided into three stages with distinctive identification markers.

Vegetation on the slope may exhibit tilting or leaning patterns, with tree orientations potentially aligning in consistent directions. In the intermediate development stage, slope deformation progresses at a relatively stable rate. Initially observed surface cracks gradually widen and elongate, eventually interconnecting to form larger fracture networks. Crack widths may expand from a few centimeters to tens of centimeters or more, accompanied by displacement between soil or rock blocks. Monitoring systems can record slope displacements at a relatively constant rate. Slope deformation disrupts pre-existing groundwater flow paths, resulting in alterations to groundwater levels, volume, or quality within the landslide mass and surrounding areas. The progressive collapse stage predominantly reflects pre-sliding slope deformation characteristics and is critical for identifying imminent landslides (Cascini et al., 2022; Chen et al., 2024a). In progressive landslides, the potential sliding surface gradually evolves into a continuous failure plane. In sudden landslides, due to their abrupt evolutionary process, no distinct sliding surface is evident, making it necessary to rely on other indicators for identification. Physical phenomena such as crack widening and deepening, formation of enclosed boundaries by cracks and drainage holes, increased displacement at the rear edge of the slope, bulging at the slope's toe, increased seepage at the slope foot, an increase in slope angle, and reverse tilting of the slope collectively aid in identifying potential landslides.

Theoretically, the unique identification markers of each stage can serve as input features for deep learning models, enabling direct classification of landslides into distinct stages. This facilitates the implementation of more targeted mitigation measures for each stage. Since slope changes ultimately result from displacement variations, we propose that a landslide identification method based on deformation characteristics as indicative factors holds great potential.

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After classifying landslide stages based on deformation characteristics, different mitigation strategies should be applied to each phase. In the creep deformation stage, the focus should be placed on landslide triggering factors, with risk reduction measures such as drainage systems and slope cutting. In the intermediate development stage, monitoring should be intensified alongside temporary reinforcement measures. In the progressive collapse stage, emergency evacuation and stabilization of the potential landslide mass must be prioritized.

5 Deep Learning for Potential Landslide Identification: Challenges

5.1 Data Quality and Availability

In potential landslide identification, the performance of deep learning models is critically dependent on both data quality and availability (Alzubaidi et al., 2023; Gaidzik and Ramírez-Herrera, 2021; Whang et al., 2023). Low-quality or unreliable data directly impair the models' feature extraction capabilities, while insufficient data availability constrains their generalization capacity and real-time monitoring efficacy (Azarafza et al., 2021; Xiao and Zhang, 2023).

In reality, the collection of landslide inventories faces many difficulties and it is hard to obtain them comprehensively and accurately. Thus, data scarcity is a common problem in the identification of potential landslide, especially in remote areas or regions with limited data accessibility. In such cases, deep learning models may suffer from overfitting or insufficient generalization ability due to a lack of samples (Kong et al., 2025; Lee et al., 2018). Although there are large-scale datasets such as the CAS landslide dataset, they are still insufficient compared with the data requirements of deep learning models (Xu et al., 2024).

In the natural environment, non-landslide states are the norm, while the landslide state is relatively rare. This leads to the data collected mainly consisting of normal geological conditions, with much less data representing potential landslides. Such a severe skewness in the class distribution results in a serious imbalance in the data, that is, there is a huge difference in quantity between the minority class (landslide samples) and the majority class (non-landslide samples) (Jiang et al., 2024). Gupta and Shukla (2023) demonstrated that this data imbalance can cause learning algorithms to be biased towards the majority class, perform poorly on the minority class. This bias impedes the predictive ability of the learning algorithms, and ultimately lead to the final model's poor performance in identifying and predicting the minority class of landslide samples.

Even if some landslide inventory data have been collected, it is often difficult for these data to represent the real landslide situations within the study area. There may be issues such as omissions and biases, which greatly reduce the credibility of the results derived from these data (Woodard and Mirus, 2025; Zêzere et al., 2017).

The presence of irrelevant input dimensions within the data necessitates larger training datasets for deep learning models to achieve satisfactory generalization performance. This can be attributed to the models' tendency to overfit to noise or spurious patterns within extraneous features, thereby failing to capture task-relevant characteristics. Such overfitting diminishes adaptability to unseen data, reduces prediction accuracy, and ultimately degrades data efficiency (D'Amario et al., 2022). As a result, deep learning models may exhibit inaccurate recognition or even failure when confronted with novel, complex scenarios outside the training distribution.

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Different types of features vary in terms of data format, dimensions, and semantics, posing a key challenge in achieving high-level feature fusion for complementary and synergistic information integration (Liu et al., 2023b). For example, different sensor data exhibit significant differences in physical meaning and data structure (Ghorbanzadeh et al., 2022). Optical imagery (RGB matrices) reflects surface coverage but is susceptible to cloud interference. SAR data (complex phase) can capture deformation information but contains speckle noise. LiDAR point clouds (3D coordinates) provide high-precision terrain data but have limited coverage. Ground sensors (temporal scalars) enable real-time monitoring of subsurface parameters but are spatially sparse. Direct fusion of such multi-modal data induces feature space incompatibility, hindering cross-modal correlation extraction (Cai et al., 2021; Jin et al., 2022).Zhang et al. (2023) highlights that even remote sensing data exhibits high heterogeneity in imaging mechanisms, illumination conditions, and spectral characteristics.

Furthermore, multiple types of heterogeneous data will increase model complexity, potentially leading to prolonged training times, excessive computational demands, and overfitting risks. Simple combination of low-level detail features with high-level semantic features may introduce contextual noise, compromising feature robustness and semantic coherence (Ji et al., 2020). When designing densely connected convolutional networks, a balance must be struck between model complexity and generalization capacity to mitigate overfitting on training data and ensure robust performance on unseen scenarios (see Fig. 8).

5.2 Limitations of Deep Learning Models

Although deep learning models have achieved success in landslide identification, they also have certain problems of their own. The most critical challenge is interpretability (Li et al., 2025). This means that it is difficult to explain how these models achieve these results.

Deep learning models typically contain a large number of parameters and layers, which makes it difficult to intuitively interpret their internal weights and feature expressions. It is unclear whether the model makes judgments based on key geological features (e.g., slope gradient, lithological structure, fracture distribution), or relies on irrelevant factors (e.g., vegetation color or image noise). In the identification of potential landslides, the most common situation is that the model may misjudge the shadow or cloud cover in a certain area as potential landslides, but it is impossible to trace the specific reasons. When combining multimodal data for landslide identification, it is also challenging to explain how the model weights different data sources.

The abstract features extracted by the models also lack correspondence to interpretable geological indicators Even if the model can identify potential landslides through the texture patterns of remote sensing images, it cannot explain whether these patterns correspond to the actual geomechanical parameters.

Since the probability values output by the model lack physical significance, they cannot reflect geological uncertainties. In practical applications, it often happens that the model's prediction of high-risk areas may not distinguish between the "uncertainty caused by data absence" and the "risk of the geological conditions themselves". Even geological experts struggle to verify the rationality of these features, thereby hindering the adoption of model results in practical engineering applications.

In addition, there is also a certain contradiction between the data-driven feature learning exhibited by deep learning models and the complexity of the real world. This is because the models tend to capture the statistical patterns on the surface of

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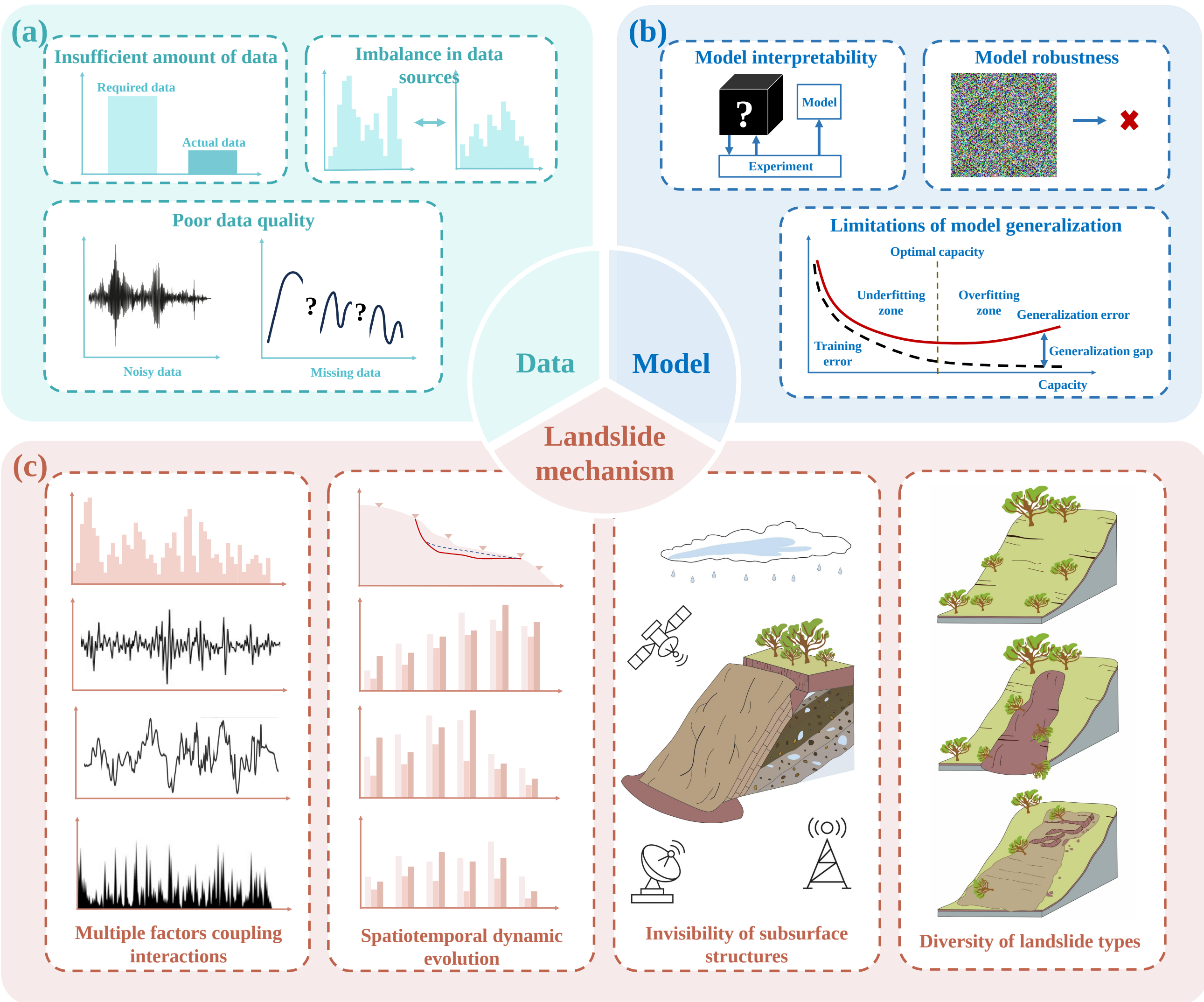

Figure 8. Challenges of deep learning in potential landslide identification. (a) Data quality and availability. (b) Limitations of deep learning models. (c) Complexity of landslide mechanisms.

the data rather than the physical mechanisms that are universal across different fields. However, the natural environment is characterized by infinite diversity, dynamism, and uncertainty. In the identification of potential landslides, this may lead to the need for repeatedly investing a large amount of annotation costs when deploying across regions and different sensors.

5.3 Complexity of Landslide Mechanisms

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5.3.1 Multiple Factors Coupling Interactions

The formation of landslides involves the dynamic coupling of multiple factors such as geological structures, geotechnical mechanics, hydrological conditions, topography, meteorological factors, vegetation coverage, and human activities (Scheingross et al., 2020). Therefore, the triggering mechanisms encompass multiscale processes spanning microscopic interparticle friction to macroscopic slope instability, and transient dynamic responses to long-term temporal evolution (Yi et al., 2022).

For example, the type of geotechnical material and structural surfaces in geological conditions affect soil stability, while hydrological factors such as rainfall infiltration and groundwater fluctuations alter soil mass properties, critically weakening shear strength due to pore pressure variations. Extreme meteorological events can alter slope stress regimes, while topographic parameters define geomorphic susceptibility thresholds. Human activities can also impact the stability of the slope. The interactions of these factors are highly nonlinear and temporally variable, making them difficult to describe with simple mathematical relationships.

This implies that changes in individual factors may induce cascading effects rather than linear responses. For example, rainfall-triggered failures exhibit threshold-dependent behavior governed by coupled hydro-mechanical processes. When rainfall intensity or duration surpasses critical thresholds, a rapid rise in the groundwater table increases pore water pressure, thereby reducing effective stress and weakening shear strength according to the principle of effective stress. This hydro-mechanical feedback often culminates in abrupt slope failure.

5.3.2 Spatiotemporal Dynamic Evolution

The inducing factors of landslides are not only extremely complex in spatial distribution but also highly dynamic in terms of time (Gao et al., 2023). This variability makes the research process of the landslide mechanism more difficult.

From the perspective of temporal dynamics, landslide formation is not instantaneous but evolves through prolonged stages. From initial deformation to eventual collapse, dynamic changes persist throughout the process, with distinct mechanisms governing each phase.

The early stage of a landslide is typically characterized by minor surface deformations or cracks, many of which remain imperceptible. The absence of conspicuous surface indicators results in the frequent omission of initial deformations, thereby heightening instability risks in later phases.

During the intermediate stage, accelerated deformation and pronounced surface fracturing emerge. At this stage, landslide dynamics grow increasingly complex, influenced by competing mechanical mechanisms. The evolving stress and strain fields complicate precise quantification of failure magnitude and velocity.

The terminal stage involves abrupt destabilization and catastrophic collapse, resulting in extensive surface disruption and mass displacement. Nonlinear dynamics dominate this phase, where rapid progression severely limits the feasibility of timely mitigation efforts.

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Since the numerical simulation of long-term creep requires a long time step, while the dynamic process of short-term abrupt changes requires a time resolution in the microsecond level, it is difficult to establish a unified model for these two situations. This will further intensify the conflict of time scales.

In terms of spatial heterogeneity, the influence scope of landslides usually involves geological structures ranging from the microscopic structure of geotechnical particles to the regional scale. Moreover, there are differences in the stratum structure, slope morphology, vegetation coverage, water content, which makes the effects of the same inducing factor vary in different regions. For example, in loose soil layers, heavy rainfall may lead to shallow landslides, while on rocky slopes with well-developed joints, earthquakes or water level fluctuations may trigger deep-seated landslides.

Through the interaction of factors at different temporal and spatial scales, positive or negative feedback affects the evolutionary trend of landslides, making the triggering, evolution and reactivation of landslides more complex and increasing the uncertainty of prediction (Haifeng et al., 2022; Li et al., 2023b).

5.3.3 Invisibility of Subsurface Structures

Landslide occurrence is intrinsically linked to subsurface structures. However, due to their invisibility, obtaining comprehensive geological information directly is challenging, adding significant complexity to the study of landslide mechanisms (Li et al., 2021c; Yan et al., 2020).

The occurrence of landslides is not merely linked to surficial phenomena but more critically governed by subsurface geological structures and hydrogeological characteristics. Subterranean features such as faults and folds directly influence the mechanical properties and stability of rock and soil masses. However, the inherent opacity of subsurface systems limits the accuracy of delineating these structures' spatial distribution, scale, and orientation through surface surveys or sparse borehole sampling, often yielding fragmented insights. Groundwater dynamics play a critical role in modulating slope stability. Fluctuations in the water table alter pore water pressure and effective stress within geomaterials, leading to a reduction in shear strength according to the principle of effective stress. Yet, direct monitoring of hydraulic head variations is inherently challenging, particularly in heterogeneous subsurface environments where localized aquifers exhibit divergent responses to hydrological forcing. Despite advancements in geophysical imaging and hydrological monitoring, the structural anisotropy and permeability heterogeneity of subsurface formations perpetuate ambiguities in mechanistic interpretations, risking oversights in landslide hazard assessments.

The invisibility of subsurface structures makes it difficult to monitor the specific processes and critical points of these dynamic changes in real time. Consequently, researchers can only infer these processes based on surface manifestations or limited monitoring data. This results in ambiguity and uncertainty in the analysis and interpretation of acquired indirect data. Even when model outputs exhibit qualitative agreement with field observations, the validity of underlying assumptions and parameterizations cannot be definitively verified.

5.3.4 Diversity of Landslide Types

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Landslides exhibit considerable typological variation, with distinct instability mechanisms and evolutionary pathways governed by geological settings, triggering factors, and kinematic behaviors. Based on material composition, landslides can be classified into rock landslides, soil landslides, debris flow landslides, and composite landslides, each exhibiting distinct variations in physical properties as well as failure modes (McColl and Cook, 2024; Yu et al., 2024). For instance, rock landslides dominated by brittle fracture differ fundamentally from soil landslides governed by plastic shear. Kinematic categorization further distinguishes translational sliding, toppling, creep, and flow-like movements, each involving divergent mechanical processes and triggering thresholds (Shu et al., 2021).

Due to the diversity of landslide types, with each type having different characteristics and influencing factors, it is very difficult to establish a universal research model for the mechanism of landslides. For different types of landslides, corresponding models need to be established according to their specific characteristics and main influencing factors (Milledge et al., 2022). This not only requires a large amount of on-site observation data and experimental research to determine the model parameters, but also requires consideration of the applicability and limitations of the models.

Furthermore, cross-typological interactions among landslides amplify predictive challenges. For example, collapsed debris may transition into debris flows, a process that is governed by hydromechanical coupling and granular-fluid dynamics. Such multi-typological and multi-process couplings resist comprehensive characterization via single-theory frameworks. Instead, they necessitate multi-scale numerical simulations to accurately reproduce the entire process. Consequently, the diversity of landslide phenomena requires interdisciplinary integration across solid mechanics, fluid dynamics, and multi-physics couplings. This task substantially increases the dimensionality and complexity of mechanistic studies, demanding hybrid modeling frameworks and cross-domain validation protocols.

6 Deep Learning for Potential Landslide Identification: Opportunities

6.1 Multi-source Data Fusion

Different methods specialize in identifying specific types of landslides, and no single method is capable of addressing all potential landslide types. Therefore, research on potential landslide identification should gradually shift from using single-source data toward multi-temporal, multi-source integrated analysis (Chen et al., 2023b; Ge et al., 2022; Xu et al., 2021). By seamlessly integrating various methods, it is possible to maximize the identification of potential landslide and effectively address the challenges of identification.

A single data source can hardly cover all the key elements. In contrast, multi-source data can comprehensively cover complex influencing factors by integrating various data sources, thus enhancing the integrity of information. For example, topographic and geological data can be used to reveal the stability of the slope structure, remote sensing data can capture surface deformations and vegetation anomalies, meteorological and hydrological data can identify the external dynamic conditions that trigger landslides, and ground monitoring data can provide high-precision real-time dynamic information. By integrating these data, a complete feature system including landslides causing factors, landslide-prone environment, and inducing factors can be constructed, avoiding the one-sidedness of information caused by a single data source.

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In the identification of potential landslides, multi-source data fusion specifically refers to the integration of raw data from different sources before feature extraction. Since different data sources have their own advantages in terms of resolution, coverage, and observation scale, the fused data can complement and verify each other (Liu et al., 2020b; Wang et al., 2021). For example, by integrating satellites and UAVs (Xia et al., 2021), the combination of high and low resolution data can be achieved. This enables the macroscopic screening of potential hazard areas and the microscopic identification of subtle surface cracks. By fusing the static stratum data from geological surveys with the time-series data of surface deformation monitored by InSAR, the combination of static and dynamic data is realized, which can distinguish between stable slopes and areas with potential creeping deformation. By combining surface cracks with abnormal vegetation indices, the combination of direct and indirect indicators is achieved, allowing for a more accurate positioning of potential slip surfaces. This complementarity reduces the noise interference and errors of single-source data. Through the cross-validation of multi-source data, the risk of misjudgment caused by insufficient sensor accuracy or data loss can be reduced.

The combination of multi-source data fusion and deep learning is essentially a deep coupling of data advantages and model advantages (Chen et al., 2023a; Zheng et al., 2021). The former fills information gaps and reduces uncertainties by integrating diverse heterogeneous data, while the latter unleashes the potential of data through automated feature engineering and nonlinear modeling. This integration not only improves the accuracy of potential landslide identification but also drives the paradigm shift of geological hazard monitoring from experience-driven to data intelligence-driven. In the future, with the development of cross-modal pre-trained models and edge intelligence technologies, the collaboration between multi-source data fusion and deep learning will demonstrate greater application value in fields such as real-time early warning and hazard simulation, becoming a core technological engine for building an integrated "aerial-space-ground-subsurface" monitoring system.

6.2 Model Ensemble

Model performance depends significantly on the nature of tasks, data characteristics, and specific requirements. Each deep learning model excels in specific tasks or data types but may underperforming in others. Model ensemble offers an effective approach to model optimization.

Although a single deep learning model can capture features in specific dimensions, it is often limited by data noise, model bias, or scene heterogeneity, and frequently faces problems such as insufficient generalization ability, overfitting, or one-sided decision-making (Kavzoglu et al., 2021; Lv et al., 2022). In the identification of potential landslides, model ensemble essentially achieves a synergistic effect through the aggregation of diversity. While avoiding the limitations and vulnerabilities of individual models, it also unleashes the complementary potential of multiple models through designed mechanisms (Zhou et al., 2022).

Various feature integrations can be carried out during the identification process. This method processes different data features through different models and integrates them at the final stage to obtain more comprehensive identification results. The combination of heterogeneous models is a more commonly used approach, which refers to combining various types of models to improve the accuracy of potential landslide identification. Each model can exert its advantages in different feature spaces (Fang et al., 2021), thus forming a powerful predictive combination. For example, when landslide identification requires the

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joint analysis of spatial and temporal features, the CNN-LSTM hybrid model is a widely adopted solution (Gao et al., 2024). This integration leverages the spatial perception capability of CNNs and the temporal dependency modeling of LSTMs, making it particularly suitable for rainfall-terrain coupled landslide prediction. Hybrid architectures can further integrate multiple models. For example, Guo et al. (2024) utilized a stacked approach integrating a 1D-CNN, RNN, and LSTM network can form a CRNN-LSTM ensemble model.

In the identification of landslides, model ensemble is not simply a technical superposition, but a systematic solution to problems. By addressing core issues such as the insufficient generalization ability of a single model, one-sided features, and the deficiencies in small sample scenarios, this approach transforms the local advantages of multiple models into a system-level global optimum. Ultimately, it achieves comprehensive breakthroughs in identification accuracy and engineering adaptability.

6.3 Knowledge-data Dually Driven Paradigm for Potential Landslide Identification

Conventional knowledge-driven methods, grounded in physical mechanics, rely on precise prior knowledge of geological structures and hydrological conditions. However, landslides are influenced by complex, coupled multi-factor interactions, characterized by high parameter uncertainty, making it challenging to comprehensively address such scenarios (Roy and Saha, 2019). Purely data-driven approaches, though capable of extracting patterns from massive datasets, lack physical interpretability, are susceptible to noise interference, and struggle to establish causal relationships in prediction outcomes (Qi et al., 2024).

Building upon future disaster prevention concepts, such as "digital twin" and "smart Earth", we propose a knowledge-data dually driven paradigm for potential landslide identification (Chen et al., 2024b; Das et al., 2024; Huang et al., 2023a; Riahi et al., 2022; Sukor et al., 2019; Zhao et al., 2024c). The core concept involves leverage knowledge analysis to gain a deeper understanding of landslide triggering mechanisms and mechanical behaviors, while combine data-driven methods to extract potential landslide features and patterns from monitoring data and historical records. This synergy establishes a closed-loop "theory-practice" verification mechanism, thereby advancing the transformation of geological hazard mitigation from passive response to proactive prevention.

In the first stage, multi-source data are systematically collected, organized, and integrated into a comprehensive dataset through feature extraction and spatiotemporal alignment (see Fig. 9).

In potential landslide identification, data sources are highly diverse. Thus, the initial step involves systematically collecting heterogeneous data and centralizing their management. This approach mitigates the limitations of single-source data, facilitating a more comprehensive and robust characterization of potential landslides. These data include high-dimensional feature information essential for data-driven models, as well as key parameters necessary for knowledge-based analytical frameworks.

Furthermore, since multi-source data may differ in acquisition time and spatial coverage, spatiotemporal alignment is required to ensure interoperability and facilitate synergistic analysis. The collected data shoule be preprocessed, including cleaning (removal of errors and outliers), standardization (unit homogenization), and classification (based on data type or region). These steps ensure that the data retain inherent physical significance and maintain consistent scales before being input into models, thereby establishing a reliable foundation for subsequent knowledge-data integration.

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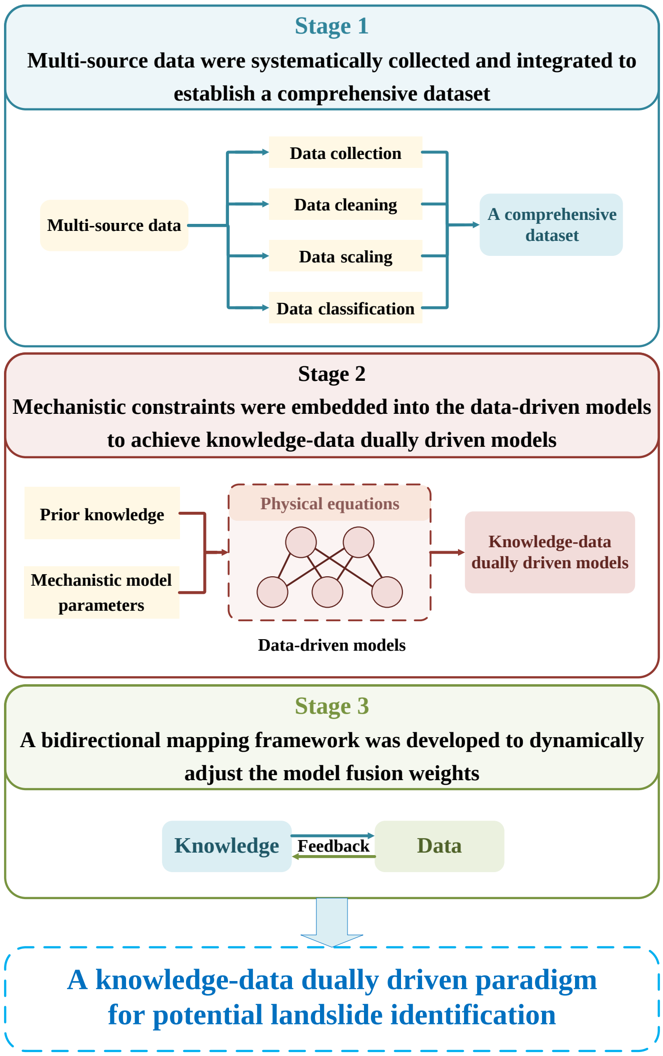

Figure 9. Flowchart of knowledge-data dually driven paradigm for potential landslide identification.

If the objective extends beyond identifying landslide locations to distinguishing their types and scales, the dataset must encompass information that captures these characteristics. During dataset construction, feature extraction and annotation methods should be chosen to emphasize these distinctions. For instance, combining texture analysis of remote sensing imagery with slope and aspect analysis of terrain data enables the extraction of features correlated with landslide types and magnitudes. Explicit annotations indicating each sample's landslide type and scale are incorporated during labeling.

In the second stage, mechanistic constraints are integrated into the data-driven model to achieve knowledge-data dually driven fusion.

Before model construction, prior knowledge can be derived from external sources, including domain expertise, historical data, and physical principles. Alternatively, mechanistic models may be employed to preprocess raw monitoring data. The outputs of mechanistic models or prior knowledge serve as a foundation for initializing parameters in data-driven models (Cui et al., 2024; Liu et al., 2023a; Ma and Mei, 2025). This is because, in data-driven models, the selection of initial parameter values significantly impacts on both the training process and final model performance. Incorporating prior knowledge helps define more reasonable initial parameter ranges, enabling the model to converge toward near-optimal solutions earlier in the training phase.

Knowledge embedding involves translating landslide physics into model constraints to guide the training and optimization of data-driven models (Dahal and Lombardo, 2025; Liu et al., 2024). At the architectural level, layers derived from physical equations can be structurally integrated into the network design. These physical equations can even be directly encoded as network layers, forming differentiable physics-informed computational modules. Differentiability is essential to ensure that these physics-based layers function as effective computational modules within the network. This requirement stems from the fact that training relies on optimization algorithms, which adjust model parameters by computing gradients of the loss function with respect to those parameters. Only differentiable physics-encoded layers allow gradient computation during backpropagation, enabling the model to learn parameters consistent with physical laws. At the loss function level, physical equations can be directly embedded into the neural network's loss function to enforce predictions that adhere to physical principles. As the model seeks to minimize the loss function, it iteratively adjusts its parameters to align predictions with the constraints imposed by these physical equations.

In the third phase, a bidirectional mapping framework for knowledge-data dually driven is established to facilitate dynamic collaborative optimization.

The model's performance is periodically evaluated using real-time monitoring data, enabling the reverse calibration of knowledge analysis parameters to achieve bidirectional feedback. Through this feedback mechanism, knowledge-data dually driven models undergo mutual verification and iterative refinement.

In practical applications, model validation can be performed using historical or field monitoring data to evaluate predictive accuracy. While optimizing model parameters for region-specific geological conditions, fusion weights are dynamically adjusted based on different stages of landslide evolution. During the initial phase of a landslide, knowledge analysis is more effective in identifying underlying factors and developmental trends, justifying a higher fusion weight for knowledge components. Conversely, during the acceleration or sliding phases, real-time monitoring data becomes crucial, and data-driven models excel at capturing dynamic changes, requiring a higher weight for data-driven components. This dynamic weight adjustment knowledge maximizes the integration of mechanistic and data-driven approaches, enhancing the model's ability to identify landslide risks across different evolutionary stages.

The knowledge-data dually driven paradigm, operating through an iterative "theory-guided data assimilation and data-informed theoretical refinement" mechanism, has advanced potential landslide identification from empirical reliance to scientifically quantifiable methodologies.

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Furthermore, the spatial analysis capabilities of geographic information system (GIS) were integrated into the practical identification workflow, enabling the study area to be partitioned into distinct landslide risk categories.This risk stratification considers the combined influence of region-specific factors, ensuring scientifically robust and practically viable classifications.

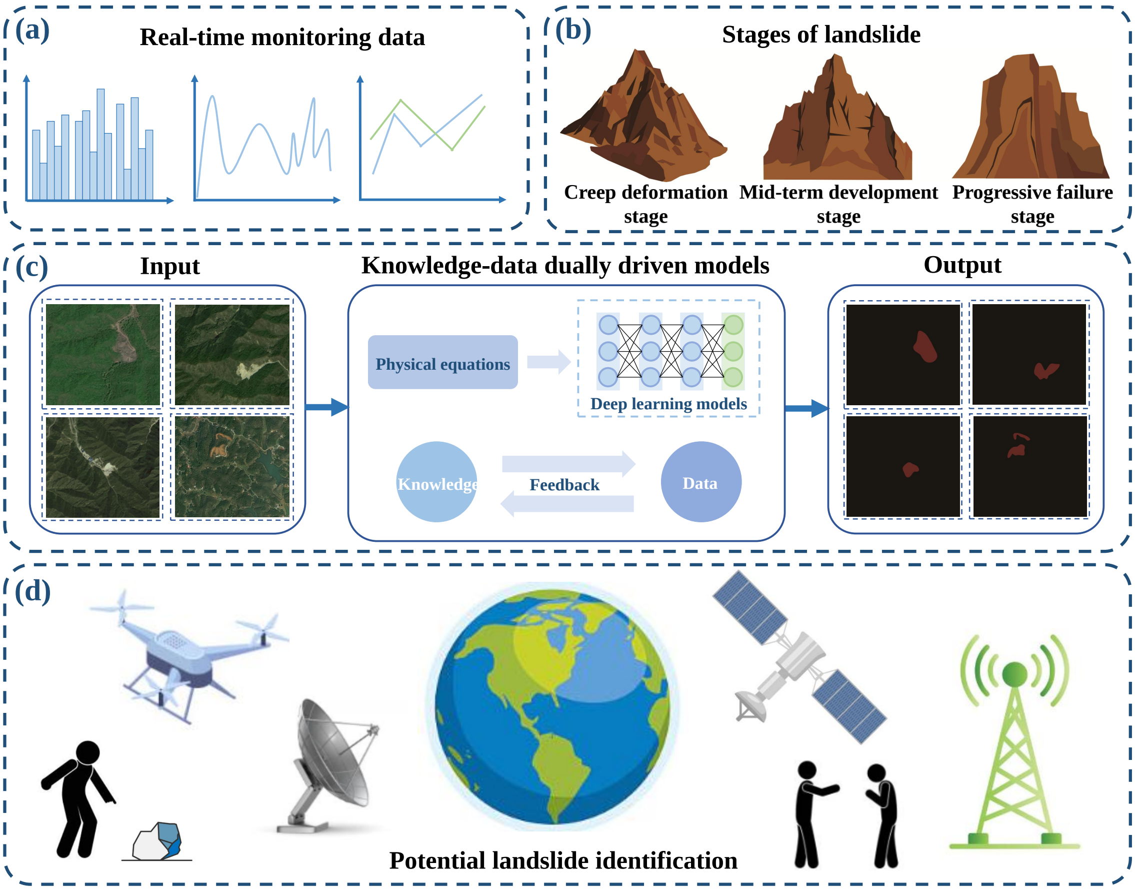

Figure 10. The process of potential landslide identification using a knowledge-data dually driven paradigm (a) Collection, organization, and analysis of real-time monitoring data. (b) Identification signals for different stages of landslides. (c) Construction and application of knowledge-data dually driven models. (d) Identification of potential landslides.

In high-risk areas, detailed investigations can be carried out using spatial remote sensing technologies, including high-resolution optical satellite image change detection and InSAR deformation analysis. Multi-temporal high-resolution optical satellite imagery is analyzed using image change detection algorithms to identify anomalous surface alterations. SAR enables precise measurement of millimeter-scale surface displacements, facilitating early detection of slope deformation precursors. Then, UAVs and airborne LiDAR can then be employed for further identification of high-risk areas. High-resolution imagery can be acquired through UAV-mounted sensors. Image interpretation and analysis facilitate the identification of potential land-

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slide indicators, including irregular slope geometries, soil loosening patterns, and anomalous vegetation growth. LiDAR enables the rapid acquisition of high-precision 3D point cloud data, which accurately captures topographic changes and penetrates vegetation canopies to reveal concealed ground surfaces, aiding in the detection of vegetation-obscured landslide precursors. Ground-based observations are subsequently integrated to validate findings and acquire real-time dynamic information of landslide bodies. A comprehensive assessment, combining expert knowledge with field-derived practical experience, is conducted to finalize the screening and confirmation of potential landslides. Critical parameters including location, scale, hazard level, and potential sliding direction are determined, providing an empirical foundation for subsequent landslide mitigation strategies (see Fig. 10).

7 Conclusions

In this review, we summarized the latest advancement in the applications of deep learning models for potential landslide identification, as well as the challenges and opportunities for the future. First, we examined seven major heterogeneous data sources available for potential landslide identification. Next, we introduced the five common roles of deep learning models in potential landslide identification. Then, we reviewed the applications of deep learning in the analysis of four typical landslides and discussed the common-used monitoring methods. Finally, we analyzed the current challenges and future research directions.

Several key conclusions are drawn. (1) Single data source often fail to ensure the accuracy of identification, whereas multi-source data fusion can address this issue to some extent. (2) Deep learning models have been widely applied in potential landslide identification, but they still face challenges in terms of interpretability and complexity. Future research should focus on further enhancing the structure and algorithms of deep learning models. (3) Knowledge-data dually driven paradigm for potential landslide identification can improve its accuracy on both theoretical and practical levels.

Author contributions. Pan Jiang and Gang Mei conceived the review topic and designed the systematic literature framework, defining key research domains for potential landslide identification. Pan Jiang conducted the comprehensive literature search and categorized them into thematic sections. Zhenjing Ma provided senior supervision, refining the logical structure. Gang Mei conducted the final review and editing, enhancing clarity and coherence. All authors approved the submitted version and agree to be accountable for all aspects of the work.

Competing interests. All authors declare they have no financial interests, and the authors have no relevant financial or non-financial interests to disclose.

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