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Review Article

Machine Learning for Environmental Hazard Assessment: Advances in Landslide Detection and Prediction

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Abstract

Landslides are among the most devastating natural hazards, causing significant human casualties and economic losses worldwide. With the growing impact of climate change on slope instability, the demand for accurate and scalable methods for landslide detection and prediction has intensified. This study systematically reviews and synthesizes recent advancements in applying machine learning and deep learning techniques for landslide hazard assessment, evaluating methodologies, challenges, and future directions. A systematic review was conducted using a detailed protocol, including a comprehensive literature search, defined inclusion and exclusion criteria, and structured data extraction. Studies were classified into three domains: landslide detection, susceptibility mapping, and temporal forecasting. Key performance indicators such as accuracy, precision, recall, F1-score, and area under the curve were synthesized to evaluate model performance. The findings reveal that traditional machine learning methods, notably Support Vector Machines and Random Forests, consistently achieve high accuracy. Deep learning architectures, particularly Convolutional Neural Networks and U-Net, outperform traditional approaches in segmentation accuracy and robustness across diverse spectral and topographic conditions. The integration of multimodal remote sensing data, such as optical imagery, LiDAR, and SAR, significantly improves model reliability by capturing complementary landslide characteristics. Despite these advancements, challenges including limited labelled data, class imbalance, and generalization issues persist. Addressing these limitations requires the development of advanced model architectures, data augmentation strategies, and the implementation of transfer learning and domain adaptation. In conclusion, machine learning and deep learning have substantially advanced landslide hazard assessment, yet further efforts are needed to enhance model scalability and operational applicability.

Keywords: Landslide Detection; Machine Learning; Deep Learning; Susceptibility Mapping; Remote Sensing Integration.

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Introduction

Landslides represent one of the most destructive natural hazards, causing profound impacts on human life, infrastructure, and economic activities worldwide. Over the past three decades, global landslides have been responsible for thousands of deaths and billions of dollars in damages annually, emphasizing their significance as a persistent geohazard [1, 2]. The implications of landslides extend beyond immediate loss, often triggering long-term socio-economic disruptions in affected regions. The urgency to address this issue has intensified with the observable patterns of climate change, which acts as a catalyst, increasing the frequency and severity of extreme weather events, such as intense rainfall and rapid temperature fluctuations. These climatic shifts exacerbate slope instability and thus elevate landslide risks, further amplifying the need for improved prediction, monitoring, and mitigation strategies [3].

Recent literature has emphasized the growing relevance of climate-induced landslide hazards, particularly as traditional risk assessment models struggle to accommodate the nonlinear, dynamic nature of environmental transformations. As pointed out by [3], excessive rainfall, snowmelt, and anthropogenic alterations significantly destabilize slopes, leading to an observable surge in mass wasting events. Moreover, the critical role of early warning systems, efficient hazard zoning, and real-time monitoring has been underscored as essential components of disaster risk reduction. Remote sensing technologies, offering large-scale, repeatable, and high-resolution observations, have substantially enhanced landslide detection and susceptibility mapping capabilities [3, 4] . Nevertheless, the complexities inherent to accurately capturing and predicting landslide behaviour across diverse terrains and climatic zones continue to present formidable challenges.

The primary research problem in landslide studies centres on the difficulty of accurately identifying, predicting, and assessing landslide occurrences under rapidly changing environmental conditions. Traditional approaches, typically grounded in expert-driven interpretations and statistical analyses, are often constrained by inherent subjectivity, high labour requirements, and limited scalability [5, 6]. While effective for localized assessments, these methods often lack robustness when extrapolated to larger or more heterogeneous regions. Their predictive capability is further limited by their inability to dynamically adapt to environmental variability induced by climatic or anthropogenic factors.

In response to these challenges, the research community has increasingly explored remote sensing-based techniques and advanced computational methods as general solutions. Remote sensing, through satellite imagery, LiDAR, synthetic aperture radar (SAR), and aerial photogrammetry, has revolutionized landslide mapping and monitoring. These technologies enable near-real-time observations of slope conditions, offering critical data for early warning and post-event assessment [3, 7]. Concurrently, the adoption of machine learning (ML) techniques has provided new avenues for enhancing predictive modelling by learning complex, nonlinear relationships between environmental variables and landslide occurrences. ML's data-driven nature, capacity to handle large and diverse datasets, and adaptability to complex patterns offer considerable advantages over traditional statistical methods.

Specifically, in recent years, researchers have leveraged various machine learning algorithms—such as Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Decision Trees (DT)—to improve the spatial and temporal forecasting of landslides. Deep learning models, particularly Convolutional Neural Networks (CNN) and U-Net architectures, have further advanced the field by enabling automated feature extraction from remote sensing imagery with superior accuracy [3, 8]. These methods allow for enhanced detection of landslide scars, susceptibility mapping, and dynamic risk assessments. However, despite these advancements, critical issues persist, such as overfitting, handling sample imbalance, generalizing across regions, and integrating heterogeneous data sources effectively.

Such challenges underscore the necessity for continuous methodological improvements and the development of more resilient, generalized models.

Several studies have directly addressed these methodological gaps by proposing ensemble learning methods, multimodal data integration frameworks, and transfer learning strategies. For instance, research integrating optical and radar data has demonstrated improved detection capabilities compared to single-sensor approaches [3]. Other works have highlighted the importance of balanced sampling, feature selection optimization, and hybrid modelling techniques combining multiple algorithms to enhance predictive performance and reduce bias [9]. These initiatives collectively represent significant steps toward overcoming the intrinsic limitations of earlier models. Nevertheless, despite the progress, there remains a notable gap in ensuring consistent model performance across different geological, climatic, and socio-environmental contexts, especially under the influence of rapidly changing environmental drivers.

An overview of closely related literature suggests that while machine learning methods have notably advanced landslide detection and prediction, current solutions often remain context-specific and lack broad generalization capabilities. The majority of existing studies have been constrained to specific case studies with homogeneous environmental characteristics, limiting their applicability elsewhere. Moreover, most models predominantly utilize supervised learning approaches, which are heavily dependent on the availability of high-quality labelled data—a resource often scarce in landslide-prone, remote, or data-poor regions. This reliance on extensive ground-truth data and the frequent absence of standardized performance evaluation frameworks point to a critical research gap.

Addressing these limitations, this study aims to systematically review and synthesize the developments in machine learning applications for landslide detection, susceptibility assessment, and prediction, focusing on the integration of remote sensing data and multimodal learning frameworks. The novelty of this work lies in its comprehensive evaluation of both traditional ML methods and emerging deep learning strategies, emphasizing comparative performance, robustness across different environments, and challenges related to data heterogeneity. It further proposes a critical analysis of future directions, highlighting the potential of multi-source data fusion, domain adaptation, and real-time monitoring systems. By consolidating insights from diverse studies, this review aspires to provide a foundational reference for researchers and practitioners aiming to advance landslide modelling methodologies and contribute toward more resilient and adaptive disaster risk reduction frameworks.

Systematic Review Protocol

This review adhered to a systematic protocol based on PRISMA guidelines. The literature search was conducted across three academic databases: Scopus, Web of Science, and Google Scholar. The following search string was used: "landslide AND (machine learning OR deep learning OR CNN OR SVM OR U-Net OR RNN OR LSTM) AND (remote sensing OR SAR OR LiDAR)". The search covered publications from 2013 to 2024, reflecting the surge of AI adoption in geospatial analysis.

A total of 412 articles were initially retrieved. After removing duplicates and applying inclusion criteria (peer-reviewed, English language, focused on ML/DL methods for landslide detection or prediction), 93 studies were retained for full-text review.

Inclusion Criteria:

- Studies applying supervised ML/DL for landslide detection, susceptibility, or forecasting

- Use of remote sensing data
- Reported performance metrics (accuracy, F1-score, AUC, etc.)

Exclusion Criteria:

- Purely geotechnical models without remote sensing
- Non-English publications
- Gray literature

Data extraction included: model types, input features, geographic location, dataset size, performance indicators, and modality used.

Overview of Machine Learning Techniques for Landslide Studies

Recent advancements in machine learning (ML) have significantly transformed landslide detection, susceptibility mapping, and hazard forecasting. Traditional ML algorithms, particularly Support Vector Machines (SVM), Random Forests (RF), and ensemble learning methods, have been extensively utilized for various landslide prediction tasks (**Figure 1**). Studies consistently report high-performance outcomes, with accuracy metrics often exceeding 85% and Area Under the Curve (AUC) values frequently above 0.86, demonstrating their effectiveness in different geographical and climatic conditions [10].

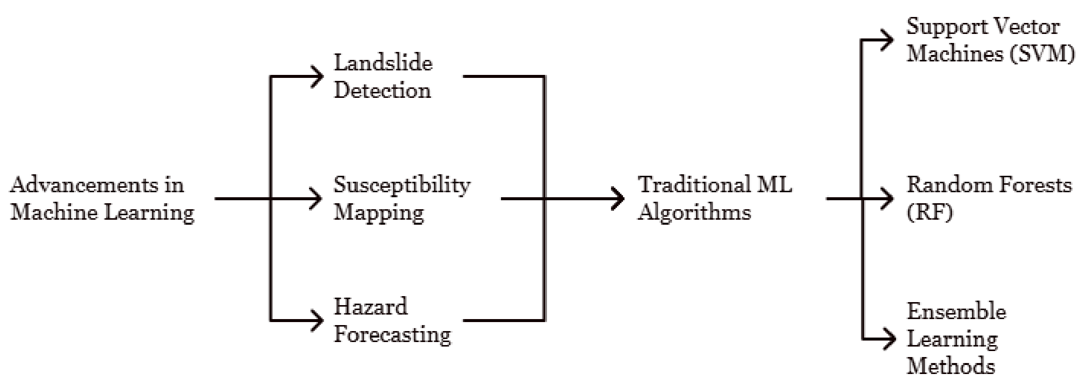

Figure 1. Recent advancements in machine learning (ML) for landslide studies

Support Vector Machines, known for their strong generalization capabilities in high-dimensional spaces, have been widely applied for pixel-based landslide classification tasks. RF models, leveraging ensemble learning from decision trees, offer robustness against overfitting and have become particularly popular due to their efficiency in handling nonlinear relationships among multiple environmental factors. Ensemble methods combining multiple classifiers, such as Gradient Boosting and AdaBoost, have shown improvements in sensitivity and specificity compared to single-model approaches [3, 11].

Table 1 presents a comparative analysis of major machine learning and deep learning models based on core performance indicators. Traditional ML models such as SVM and RF demonstrate high interpretability and relatively low computational complexity, making them ideal for rapid deployment in data-scarce settings. However, they rely on manual feature engineering and often exhibit limitations in capturing spatial complexities. In contrast, CNN and U-Net models show superior segmentation accuracy and generalization across varied terrains due to their ability to learn from raw image data. Nevertheless, these deep architectures require large labelled datasets, higher computational resources, and are more prone to overfitting without appropriate regularization strategies.

Table 1. Comparative Analysis of ML/DL Models for Landslide Detection and Prediction

Model	Accuracy	Data Demand	Interpretability	Generalizability	Computational Cost	Use Case
SVM	High	Moderate	High	Moderate	Low	Susceptibility mapping
Random Forest	High	Low	Moderate	Moderate	Low	Broad classification
CNN	Very High	High	Low	High	High	Scar detection, segmentation
U-Net	Very High	High	Low	Very High	Very High	Pixel-level segmentation
RNN / LSTM	Moderate	Very High	Low	Underexplored	High	Temporal landslide forecasting

Despite the success of these traditional methods, limitations remain, particularly regarding model sensitivity to class imbalance and their dependence on handcrafted feature extraction, which can limit adaptability under varying environmental and data conditions [10].

Advancements through Deep Learning Architectures

Deep learning (DL) architectures, particularly Convolutional Neural Networks (CNN) and U-Net models, have emerged as significant breakthroughs in landslide research, providing superior performance in feature extraction, spatial pattern recognition, and generalization as can be seen in **Figure 2**. Unlike conventional ML models that rely on manual feature engineering, DL models autonomously learn hierarchical feature representations, leading to improved accuracy and robustness.

Convolutional Neural Networks have been successfully applied for landslide scar detection and mapping from high-resolution optical imagery. Studies demonstrate that CNNs not only improve detection accuracy but also enhance the capability to capture complex landslide features over heterogeneous landscapes [12, 13]. U-Net, initially proposed for biomedical image segmentation, has been increasingly adopted for semantic segmentation tasks in landslide mapping. Its encoder-decoder structure with skip connections enables precise pixel-level classification, even under varying spectral conditions.

Research by Zhang et al. [14] shows that U-Net significantly outperformed traditional ML algorithms in both segmentation accuracy and generalization, achieving higher F1-scores and AUC values across diverse test areas. Similarly, Vega et al. [15] highlight U-Net's superior performance, noting its resilience to spectral variability and capacity to delineate landslide boundaries more accurately than conventional classifiers.

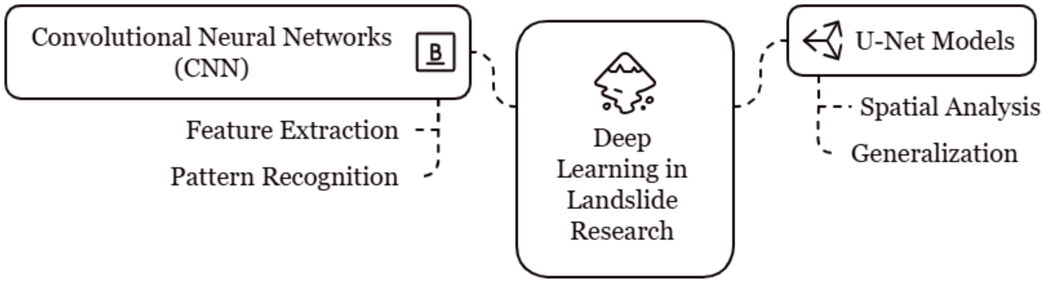

Figure 2. Deep Learning in Landslide Research

Integration of Remote Sensing Data Sources

Optical imagery, particularly from sensors like Landsat, Sentinel-2, and WorldView, remains the most common remote sensing data source for landslide studies (**Figure 3**). Its widespread availability, high spatial resolution, and rich spectral information have facilitated numerous ML applications. However, optical data alone often struggle under cloud cover or dense vegetation, limiting its effectiveness in certain environments.

Characteristic	Landsat	Sentinel-2	WorldView
Common Use	Yes	Yes	Yes
Availability	Widespread	Widespread	Limited
Spatial Resolution	High	High	High
Spectral Information	Rich	Rich	Rich

Figure 3. Comparison of Optical Imagery Sensors

To address these limitations, recent studies have integrated optical imagery with other remote sensing modalities, such as LiDAR and Synthetic Aperture Radar (SAR). LiDAR data, offering precise topographic information through high-resolution Digital Elevation Models (DEMs), enhance landslide susceptibility mapping by providing detailed slope, curvature, and elevation features [3]. SAR data, capable of penetrating clouds and providing information on surface deformation, complements optical imagery, particularly for temporal monitoring of landslide-prone areas.

The integration of these multimodal datasets has been shown to significantly improve model robustness and predictive accuracy. Mandlburger et al. [16] emphasized that models incorporating LiDAR-derived features with optical and SAR inputs achieved superior performance compared to single-sensor approaches, especially in complex terrains. The complementary nature of structural (LiDAR), spectral (optical), and deformation (SAR) information allows ML models to better capture diverse landslide characteristics, reducing uncertainties in predictions.

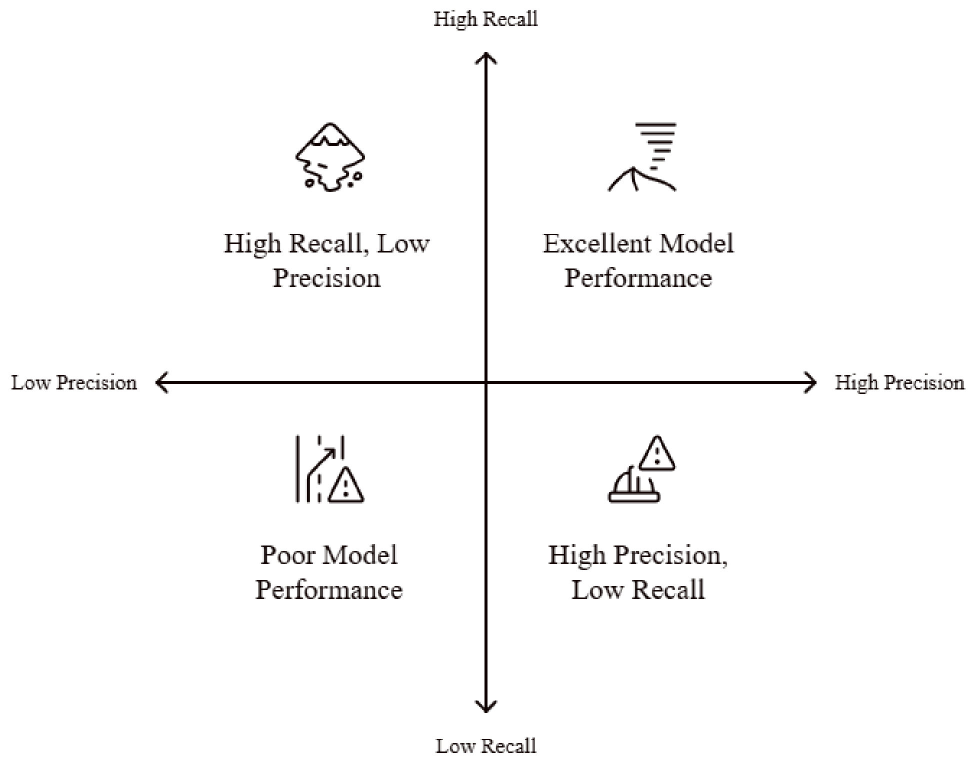

Figure 4. Performance Evaluation Metrics in Landslide Studies

Key Performance Metrics in Evaluated Studies

Based on **Figure 4**, performance evaluation in the reviewed studies was standardized around a core set of quantitative metrics, namely accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) [3]. These metrics provided comprehensive insights into the detection and classification capabilities of various models. Accuracy, measuring the overall proportion of correctly classified instances, remained consistently high, often exceeding 85% across both traditional machine learning and deep learning studies. Precision, which evaluates the proportion of true positive detections among all positive predictions, indicated model effectiveness in avoiding false positives, while recall, or sensitivity, measured the model's ability to identify all relevant positive instances, a critical aspect in landslide studies where missing events could lead to significant consequences. The F1-score, representing the harmonic mean of precision and recall, offered a balanced evaluation metric particularly valuable for addressing the imbalanced datasets common in landslide detection. AUC, capturing the trade-off between true positive and false positive rates, provided a threshold-independent assessment of model performance and frequently exceeded 0.86 in high-performing models [17]. Notably, studies employing multimodal data integration consistently reported improvements across all these metrics, with F1-scores and AUC values significantly higher than those achieved using optical imagery alone [18].

Detection, Susceptibility Mapping, and Temporal Forecasting Outcomes

In the detection category, ML and DL models demonstrated high competence in identifying landslides directly from remote sensing data (**Figure 5**). CNN-based approaches have demonstrated strong performance in mapping newly triggered landslides following earthquake and rainfall events, often achieving F1-scores exceeding 0.85. For instance, a comparative analysis by Oak et al. [19] evaluated four CNN-based semantic segmentation models—U-Net, LinkNet, PSPNet, and FPN—on satellite imagery from Bijie, China. The study found that the LinkNet model achieved the highest performance, with an accuracy of 0.974 and an F1-score of 0.857.

In another study [20], an improved Mask R-CNN model incorporating the Swin Transformer as a backbone network was employed to detect seismic landslides using UAV imagery from Wenchuan County, Sichuan Province, China. The model achieved an F1-score of 0.902 and demonstrated strong generalizability when applied to post-earthquake imagery from Haiti

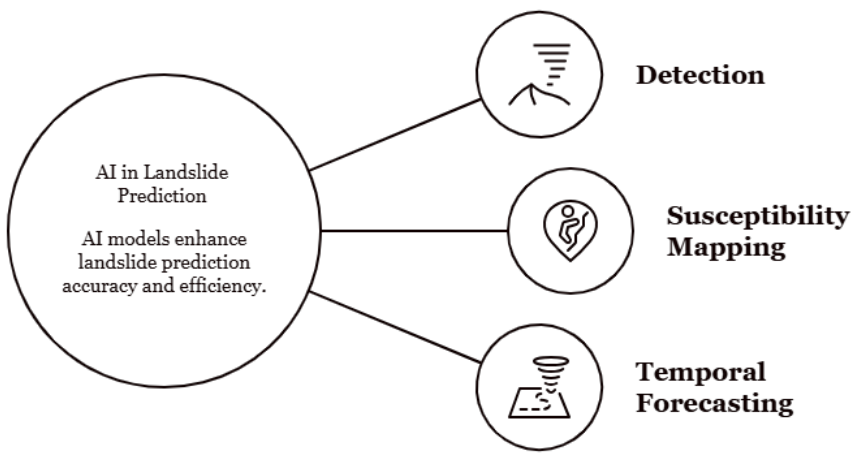

Figure 5. Exploring AI in Landslide Prediction

In temporal forecasting, although relatively fewer studies exist, promising developments have been noted with the application of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models, which can effectively handle temporal sequences such as rainfall trends and ground deformation signals [11]. These approaches can handle sequential data, enabling the prediction of landslide occurrences based on historical rainfall or deformation patterns. However, challenges remain due to the scarcity of temporally rich datasets and the difficulty of integrating diverse temporal predictors effectively [11].

Contributions of Multimodal Data Integration

The integration of multimodal datasets emerged as a critical advancement in landslide modelling. Studies combining optical imagery with LiDAR or SAR data consistently reported significant improvements in classification performance. LiDAR provides high-resolution elevation data that enable precise characterization of terrain features such as slope, curvature, and roughness—key factors in landslide initiation. When combined with optical imagery, which captures spectral characteristics of surface materials, the resulting models benefit from both spectral and topographic richness. For instance, Pereira et al. [21] demonstrated that integrating

LiDAR-derived Digital Terrain Models (DTMs) with optical data significantly improved landslide susceptibility mapping accuracy in mountainous regions. Their study highlighted that the model generated from LiDAR data achieved higher accuracy compared to models using Unmanned Aerial Vehicle (UAV) data, emphasizing the value of LiDAR in capturing detailed topographic information. SAR data, with its ability to penetrate cloud cover and provide surface deformation metrics through interferometric processing (InSAR), complements optical data by capturing precursory slope movements. Mondini et al. [22] reported that models incorporating Sentinel-1 SAR data alongside Sentinel-2 optical imagery achieved superior performance in early landslide detection, especially in humid tropical settings prone to cloud interference. Their systematic assessment of Sentinel-1 SAR C-band images demonstrated the potential of SAR data in detecting landslide events, particularly when optical data availability is limited.

Such integration helps mitigate the limitations inherent in single-source data: optical imagery captures surface characteristics, LiDAR provides structural terrain information, and SAR detects ground movements. Multimodal fusion thus enables a more holistic representation of landslide phenomena, improving detection under varied environmental conditions.

The success of multimodal approaches underscores the importance of data diversity for robust landslide modelling and highlights future opportunities for further leveraging emerging datasets, such as hyperspectral imagery and UAV-based photogrammetry.

To support a coherent comparison across studies, we propose a conceptual framework linking three key components of landslide modelling using AI:

1. Input Modalities: Optical (e.g., Sentinel-2), LiDAR, and SAR provide complementary spatial, structural, and deformation signals.
2. Algorithmic Approaches: Traditional ML (e.g., RF, SVM) vs. Deep Learning (e.g., CNN, U-Net, LSTM).
3. Performance Factors: Influenced by data availability, spatial resolution, class imbalance, generalizability, and computational constraints.

Deep Learning models generally benefit more from multimodal data fusion and are better suited for complex terrains, whereas ML models remain preferable in data-constrained or real-time operational contexts. Overfitting, model transferability, and segmentation accuracy vary based on this interaction.

Discussion

The findings of this systematic review affirm the significant progress made in applying machine learning (ML) and deep learning (DL) techniques for landslide detection, susceptibility mapping, and hazard forecasting. Nonetheless, despite notable achievements, critical challenges persist, impacting the reliability and generalizability of current models. A recurring limitation in landslide ML applications lies in the restricted availability of high-quality labelled data, often derived from manually interpreted landslide inventories [23]. The labour-intensive nature of inventory compilation and the occurrence of landslides as relatively rare events inherently result in small sample sizes and severely imbalanced datasets. This class imbalance—where non-landslide samples vastly outnumber landslide samples—complicates model training, often biasing predictions towards the majority class and diminishing the sensitivity to detect actual landslide events.

Moreover, the spatial and temporal variability of triggering factors such as rainfall, seismic activity, and land cover changes complicate the construction of robust predictive models. While ML/DL algorithms offer promising capabilities in capturing complex non-linear patterns, their performance heavily depends on the temporal granularity and completeness of input data. This is especially critical in hazard forecasting, where the goal is to anticipate potential landslide occurrences ahead of time rather than merely mapping their spatial susceptibility. Hence, the integration of time-series data and dynamic environmental variables becomes crucial in advancing from static susceptibility assessments to actionable, real-time hazard predictions.

The overfitting phenomenon remains a prominent concern across many studies. Models trained on limited, highly specific datasets may exhibit high apparent accuracy during internal validation but falter when applied to different regions or under varying environmental conditions [24]. This suggests that many models may inadvertently learn site-specific features rather than generalizable patterns associated with landslide mechanisms. Consequently, model robustness and transferability remain underdeveloped, presenting a significant barrier to widespread operational deployment.

Another challenge arises from the diverse nature of terrains where landslides occur. Variations in geological formations, vegetation cover, climatic conditions, and land use patterns imply that a model effective in one setting may perform poorly elsewhere without substantial retraining or adaptation. The difficulty in generalizing across such heterogeneous contexts underscores the necessity for methodological innovations that explicitly address environmental variability.

In response to these challenges, several future research directions emerge. One promising avenue involves the development of more sophisticated model architectures specifically designed to mitigate overfitting and enhance generalization capabilities. Techniques such as regularization, dropout layers, and ensemble methods offer mechanisms to prevent models from becoming overly specialized to training datasets. Equally important is the need for comprehensive comparative studies that benchmark diverse algorithms across standardized datasets and evaluation protocols, thus providing clearer insights into their relative strengths and weaknesses.

Data augmentation strategies also warrant further exploration. While data augmentation is a well-established technique in image-based machine learning, its application in geospatial landslide studies remains limited. Innovative approaches to artificially expand training datasets—such as generating synthetic landslide samples, perturbing input features, or utilizing generative adversarial networks (GANs)—could alleviate issues related to sample scarcity and improve model resilience. Although GANs have recently been explored for semantic segmentation tasks in geospatial applications, their potential in enhancing classification performance is equally compelling. Specifically, conditional GANs (cGANs) can be trained to generate realistic synthetic landslide and non-landslide examples conditioned on specific input features, thereby enriching the diversity of the training set. By addressing the severe class imbalance often seen in landslide datasets, such synthetic augmentation helps mitigate model bias toward the majority class. This, in turn, can lead to improved generalization and classification accuracy, particularly in detecting minority-class events like actual landslides. Moreover, the ability of GANs to preserve the statistical characteristics of complex spatial features makes them a powerful tool for producing high-fidelity training samples that reflect real-world variability in terrain, lithology, and triggering factors.

Transfer learning and domain adaptation represent another frontier with considerable potential. Transfer learning enables models trained on data-rich environments to adapt and perform effectively in data-poor regions by leveraging previously acquired feature representations [25]. Early applications of transfer learning in landslide detection suggest that pretrained networks, especially those originally trained on natural scene datasets, can be fine-tuned with relatively small amounts of site-specific data to achieve competitive performance. Domain adaptation techniques further enhance this by systematically aligning feature distributions between source and target domains, thus facilitating model transfer across disparate terrains without exhaustive retraining.

The integration of multimodal remote sensing data continues to demonstrate significant promise for advancing landslide modelling efforts. Studies consistently show that fusing optical imagery with LiDAR-derived topographic data and SAR-based deformation measurements enhances both spatial agreement and predictive accuracy [10]. This fusion exploits the complementary strengths of each data type: optical imagery captures land cover and surface reflectance characteristics; LiDAR offers precise elevation and slope information; and SAR detects subtle ground displacements indicative of incipient failure. Multimodal fusion thus enables a richer and more nuanced characterization of landslide conditions than any single sensor modality alone.

Nevertheless, effective multimodal data fusion requires addressing challenges related to data co-registration, resolution mismatches, and sensor-specific noise characteristics. Advanced techniques such as feature-level fusion, attention mechanisms in deep learning, and the use of encoder-decoder architectures specifically designed for multimodal inputs could further refine the integration process and maximize its benefits.

In sum, while machine learning and deep learning techniques have substantially enhanced the capacity for landslide detection and prediction, realizing their full potential demands sustained efforts to overcome persistent limitations. Robust model design, rigorous validation against independent datasets, strategic use of transfer learning and domain adaptation, and comprehensive multimodal data integration emerge as critical strategies for advancing the field. These directions not only promise improvements in model accuracy but also offer pathways toward more scalable, generalizable, and operationally deployable landslide early warning and risk management systems.

The urgency of these improvements is underscored by the increasing frequency and severity of landslide events driven by climate change [3]. As extreme rainfall events and rapid temperature fluctuations become more common, landslide hazards are expected to escalate, necessitating the availability of accurate and adaptable predictive tools. Thus, advancing machine learning methodologies for landslide modelling is not merely an academic pursuit but a pressing imperative for disaster risk reduction and resilience building at global, regional, and local scales.

Conclusion

This study systematically reviewed and synthesized recent advances in the application of machine learning (ML) and deep learning (DL) techniques for landslide detection, susceptibility mapping, hazard forecasting and temporal forecasting. The results demonstrated that traditional machine learning algorithms such as Support Vector Machines (SVM) and Random Forests (RF) continue to deliver strong predictive performance, often exceeding 85% in accuracy and achieving high AUC values. However, deep learning architectures, particularly Convolutional Neural Networks (CNN) and U-Net models, have shown superior capabilities in segmentation tasks, offering enhanced generalization across diverse spectral and environmental conditions.

Despite these advancements, persistent challenges were identified, notably limited labelled data, severe class imbalance, and difficulties in model generalization across varied terrains. These issues contribute to overfitting and restrict the operational deployment of current models. The discussion emphasized the need for more robust model architectures, improved data augmentation techniques, and the strategic application of transfer learning and domain adaptation methods to enhance reliability, particularly in data-scarce regions. Furthermore, the integration of multimodal data—combining optical imagery, LiDAR, and SAR—was highlighted as a critical advancement that significantly improves model robustness and spatial agreement.

The contributions of this study are twofold. First, it consolidates fragmented knowledge across multiple domains, providing a structured and comprehensive assessment of the field's current state. Second, it identifies key methodological gaps and proposes clear future research directions aimed at enhancing model performance, generalization, and applicability.

In light of the escalating landslide risks driven by climate change, improving the scalability and accuracy of ML-based landslide models is increasingly vital. Future research should prioritize developing transferable models, leveraging multimodal fusion techniques, and expanding global landslide databases. Advancing these areas will significantly strengthen early warning systems, risk management strategies, and ultimately contribute to reducing landslide-related losses worldwide.

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Conflict of Interest

The authors declare that they have no conflict of interest in relation to this paper review, whether financial, personal, authorship, or otherwise, that could affect its results presented in this paper.

Author Contribution Statement

Zulhelmi Zulhelmi: Conceptualization, Methodology, Writing- Reviewing and Editing. **Elizar Elizar:** Data curation, Writing- Original draft preparation, and Editing. **Nural Fajri:** Data curation and Visualization. **Aulia Rahman:** Visualization, Investigation, Writing-Reviewing and Editing.

Data Availability Statement

The manuscript contains no associated data.

Ethics Approval

Not required.

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