A comprehensive survey of artificial intelligence applications in predicting mining-induced subsidence, deformation, and landslides: Strengths, limitations, and future trends

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Abstract

Mining activities often cause mining-induced ground deformation, including subsidence and landslides, and related geo-environmental impacts, posing significant risks to infrastructure and safety. This study conducts a systematic assessment to identify, categorize, and evaluate AI-based methods (machine learning, deep learning, and hybrid models) for predicting and monitoring mining-induced ground deformation. The literature search was performed across major scientific databases, using predefined keywords and selection criteria, resulting in a final dataset of relevant peer-reviewed studies. The reviewed works were classified into three methodological groups: traditional machine learning, deep learning-based approaches, and hybrid methods. The results show that ML still dominates in terms of accuracy and explainability, DL has the potential to handle big data and real-time prediction, but requires large datasets and computational resources, and Hybrid combines the advantages of ML and DL to increase the efficiency of prediction and risk assessment. Besides, the study highlights the strengths and weaknesses of each approach and suggests future research directions. By systematically classifying and comparing AI-based prediction and monitoring approaches in terms of data requirements, accuracy, interpretability, and real-time capability, the presented results provide practical guidance for mine managers and engineers in selecting appropriate models for deformation risk assessment and in developing effective early warning systems for safer and more sustainable mining operations.

Keywords: Artificial intelligence, AI, Deformation, Landslides, Mine, Subsidence

1. Introduction

Mining-induced ground deformation, including subsidence, horizontal displacement, sinkholes, and landslides, represents one of the most significant geotechnical hazards in mining areas, posing serious risks to worker safety, infrastructure stability, and the surrounding environment [1,2]. These phenomena often result from the extraction of underground resources, which alter stress distributions in the rock mass and trigger progressive failure mechanisms [3]. In addition to safety concerns, mining-induced deformation can lead to long-term land degradation, disrupt local communities, and cause severe economic losses [4,5]. Accurate prediction of mining-induced ground deformation and its main manifestations (e.g., subsidence and landslides) is therefore critical for proactive mine planning, hazard mitigation, and sustainable resource management [6]. Over the past decades, various methods have been developed and applied for predicting and monitoring mining-induced ground deformation. These include widely used empirical prediction models, such as the Knothe influence

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function method [7,8] and the probability integral method (PIM) [9], as well as improved empirical and physical models, such as the improved probability integral method (IPIM) [10] and physics and geometry-based method [11], elastoplastic finite element model [12], 3-D finite element method [13]. In addition, geodetic and remote-sensing techniques, including InSAR, SBAS-InSAR [1,2,14], GPS [15,16], and GIS [17], are primarily used for deformation monitoring and data acquisition, providing essential input data for subsequent AI-based prediction models. Empirical models are straightforward and computationally efficient, but are often limited to specific geological conditions, reducing their transferability to other sites [18]. Numerical simulations can model complex mechanical processes with greater accuracy, yet they require detailed geotechnical parameters and significant computational resources [19]. Geodetic techniques, such as GPS, InSAR, and terrestrial laser scanning, provide high-precision measurements of ground displacement but are more effective for monitoring rather than long-term prediction [20]. These conventional approaches, while valuable, often struggle to address the highly non-linear, site-specific, and multi-factor nature of mining-induced deformation processes [21].

In recent years, artificial intelligence (AI) has emerged as a promising solution to these challenges. AI-based approaches, including machine learning (ML) and deep learning (DL), have demonstrated strong capabilities in modeling complex spatial-temporal relationships from large, heterogeneous datasets [22]. By integrating multi-source data such as remote sensing imagery, geological survey results, and in-situ monitoring records, AI models can learn patterns that are difficult to capture with conventional methods [23]. Moreover, AI techniques can adapt to changing conditions, enabling near real-time prediction and early warning systems [24]. Studies have shown that AI models not only improve prediction accuracy but also enhance robustness in data-sparse or noisy environments [25]. These advantages make AI-based prediction frameworks highly attractive for improving the safety, efficiency, and sustainability of mining operations.

There are a number of studies conducted to comprehensively evaluate the methods and technologies in predicting and monitoring subsidence or deformation due to mining. While [26] summarized existing knowledge on mining-induced subsidence, focusing on its causes, mechanisms, and associated geo-environmental impacts [27], provided a comprehensive analysis of existing methods and technologies for predicting and monitoring mining-induced subsidence, covering traditional surveying, remote sensing, numerical modeling, and emerging AI-based techniques. Similarly [28], summarized and evaluated the existing techniques used to monitor, calculate, and simulate ground subsidence caused by coal mining. Besides [29], presented the application of geographic information systems (GIS) in assessing and mapping mining-induced subsidence, summarizing how GIS integrates spatial data, monitoring results, and modeling outputs to visualize subsidence patterns. Focus on other methods [30], assessed current synthetic aperture radar (SAR)-based methods for detecting and monitoring rapid and large-gradient subsidence in coal mining areas [31]. Thoroughly assessed the applications of SAR and Interferometric SAR (InSAR) technologies in mining-related deformation studies. Using machine learning or deep learning approaches [32], performed an assessment on predicting land subsidence caused by coal mining, aiming to improve prediction accuracy compared to traditional empirical or numerical models. Moreover, several studies have evaluated the application of AI in mining operations, but have not focused on subsidence and deformation phenomena [33]. Provided a comprehensive overview of how AI techniques, including machine learning, deep learning, expert systems, fuzzy logic, and evolutionary algorithms, are applied to solve problems in mining and geological engineering. In addition [34], analyzed and synthesized the use of machine learning techniques across the full mining lifecycle exploration, exploitation, and reclamation.

Thus, although there are many comprehensive evaluation studies on displacement prediction in mining areas, some of them do not address methods for predicting and monitoring mining-induced ground deformation, including subsidence and landslides [27,28,30,32]. Some studies overlook or insufficiently incorporate artificial intelligence approaches, while others do not discuss AI at all, highlighting a lack of integration of advanced AI techniques in certain traditional or GIS-based methods [29,30]. Although AI methods have been evaluated broadly in mining contexts [33,34], there is a limited focus on applying AI specifically to the prediction and monitoring of subsidence and deformation phenomena that are critical for mining safety and management. Existing AI-based studies mainly focus on land subsidence related to coal mining, indicating potential gaps in extending AI applications to other manifestations of mining-induced ground deformation. To fill these gaps, this study was conducted to analyze in depth existing studies on AI applications for both predicting and monitoring mining-induced ground deformation, including subsidence and landslides, in mining areas. Based on this analysis, the strengths, limitations, and future research trends of AI-based approaches are systematically discussed.

2. Methodology

This study employed a systematic literature review approach to analyze the application of artificial intelligence techniques, including machine learning and deep learning, in the prediction of mining-induced deformation, including subsidence and landslides. Relevant research articles were collected from comprehensive academic databases and scientific search engines, primarily Google Scholar, Web of Science and Scopus, to ensure broad coverage of high-quality publications. To maintain rigor and relevance, the following inclusion criteria were applied:

- Publications written in English,
- Studies published from 2010 to the present, reflecting recent advancements in AI applications,
- Articles published in reputable, peer-reviewed journals,
- Focus on studies that apply AI methods, such as machine learning and deep learning, specifically directed at predicting or monitoring mining-induced ground deformation, including subsidence and landslides in mining contexts.

An initial search retrieved a total of 252 research articles related to mining-induced ground movement prediction and monitoring with AI techniques. After removing duplicates and non-relevant records, 114 articles remained for screening based on titles and abstracts.

Studies were excluded if: (1) they lacked direct application of AI or didn't involve predictive modeling (e.g., studies focused solely on descriptive analysis or non-AI modeling approaches); (2) Did not target mining-induced deformation, including subsidence and landslides; (3) Were conference abstracts, book chapters, or non-peer-reviewed materials; (4) Were not published in English or fell outside the 2010–2025 time frame.

Following this screening, 48 articles met all inclusion criteria and were selected for in-depth qualitative analysis, focusing on methodologies, datasets, AI model types, performance evaluation, and practical applications. The flowchart of research is shown in Figure 1.

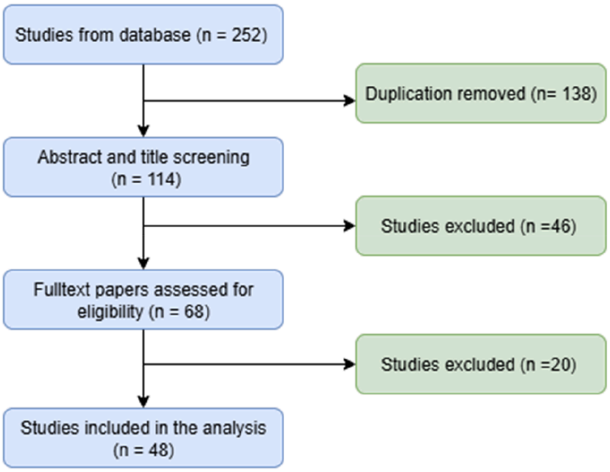

Fig. 1. Flowchart of research.

3. Application of artificial intelligence in the movement prediction of mining areas

In this study, subsidence and landslides are considered specific manifestations of mining-induced ground deformation; therefore, the reviewed AI-based studies are grouped according to these deformation types for clarity of comparison.

3.1. Application of machine learning in the movement prediction of mining areas

3.1.1. Deformation prediction of mining areas using machine learning

Predicting surface deformation in mining areas is critical for operational safety and environmental management, and recent research increasingly leverages data-driven methods to improve accuracy and timeliness. The attached summary synthesizes key approaches used across case studies, ranging from classical neural networks (BPNN, RBFNN, GRNN) and support-vector/regression-based methods to ensemble tree models (XGBoost) and hybrid workflows that average time-series data from remote sensing (SBAS-InSAR) as input for optimization algorithms and explainable-AI techniques (e.g., PSO-SVR, SHAP). Together, these studies demonstrate how dense monitoring data (prism, GPS, TLS, InSAR) plus machine-learning models form practical toolchains for both monitoring and short-to-medium-term prediction of mining-induced deformation.

In the study of [6], the authors evaluated the performance of three artificial neural network (ANN) techniques BPNN, RBFNN, and GRNN, for predicting open-pit mine wall deformation. Using a time-series dataset, the study found that RBFNN was the most effective model, outperforming the others by accurately handling the non-linear characteristics of rock mass deformation. The research concludes that ANNs are a robust and viable tool for deformation prediction, offering an improved alternative to traditional statistical methods for mine safety and management. Similarly [35], applied an RBFNN to predict rock mass deformation modulus using dilatometer and borehole data from the Bakhtiary dam site, Iran. Input variables included overburden thickness, RQD, UCS, discontinuity inclination, JRC, and filling thickness. The model achieved high accuracy, with UCS and RQD identified as the most influential parameters. Strengths include practical in-situ data use and sensitivity analysis; limitations involve site-specific applicability, shallow network architecture, and limited cross-validation. The superior performance of RBFNN observed in [6] for modeling complex, non-linear deformation patterns was further reinforced by [35], which successfully applied the same network architecture to estimate rock mass deformation modulus in a dam engineering context, and by [36], where RBFNN achieved top accuracy for multiple prism datasets in predicting open-cast mine surface deformation. The authors developed and evaluated four machine learning models to predict surface deformation in an open-cast mine using pit wall prism monitoring data. Displacement measurements from three prisms were used as inputs, and model performance was assessed using *MSE*, *RMSE*, *MAE*, and R^2. Results showed that BPNN performed best for Prism 1, while RBFNN achieved superior accuracy for Prisms 2 and 3. The study highlights the potential of neural network-based approaches to improve the accuracy and automation of deformation prediction in mining operations, thereby enhancing safety and operational efficiency.

In another study [18], proposed a machine learning-based model to predict slope deformation in an open-pit mine using real field monitoring data. The approach employed extreme gradient boosting (XGBoost), optimized via a grid search algorithm for parameter tuning. Key input variables included rainfall, temperature, and in-situ displacement measurements. The model showed higher prediction accuracy and stability compared to traditional statistical methods and other ML models like random forest and support vector regression. The demonstrated predictive strength of XGBoost in modeling slope deformation in this study is echoed in [21], where the algorithm, combined with SBAS-InSAR data and SHAP analysis, effectively quantified and explained the key factors driving subsidence over underground mines. They investigated surface subsidence over underground copper mines in southwest Poland using Sentinel-1 SBAS-InSAR data from 2014 to 2022. An XGBoost regression model was trained on geological and mining variables, and SHAP analysis was applied to interpret feature importance. The study found that overlying layer thickness, mined thickness, and time since mine closure were the dominant factors influencing subsidence velocity. The results highlight the effectiveness of integrating SAR time series, machine learning, and explainable AI in mining deformation assessment and management.

Also, to demonstrate the potential of advanced machine learning algorithms [19], compared four predictive approaches: multiple linear regression (MLR), ANN, random forest regression (RFR), and K-nearest neighbors (KNN) to estimate rock mass deformation modulus (*Em*) using rock mass rating (RMR_{89}) and point-load index (I_{50}) as key inputs. The models were trained and evaluated using performance metrics such as R^2, *MAE*, and *MSE*. Results showed that the ANN achieved the highest accuracy ($R^2 \approx 0.999$) and lowest errors, outperforming the other methods. The study concluded that ANN offers a highly accurate and efficient alternative to traditional in-situ testing for *Em* prediction, though validation on other sites is recommended. For the same purpose [37], proposed SVR-based models optimized with several swarm-intelligence algorithms to predict the deformation extent of roadway roofs during the non-support period. They train SVR models (hyperparameters tuned by GA, PSO, SSA, and a Grey Wolf Optimization variant) on seven site-specific input factors and evaluate performance using *RMSE*, *VAF*, and R^2. The Grey Wolf Optimization-enhanced SVR (GWO-e-SVR) achieved the best results (training $RMSE = 0.3126$, $R^2 = 0.8767$; testing $RMSE = 0.3245$, $R^2 = 0.8655$), showing good robustness on small samples. A sensitivity analysis highlights the strong spatio-temporal effect of non-support time on roof settlement, suggesting the model's utility for support design and reinforcement planning.

The reviewed evidence indicates that machine-learning approaches, particularly well-tuned neural networks and gradient-boosted trees, can achieve high predictive performance for mine deformation when trained on quality monitoring datasets, while optimization algorithms and explainability methods improve robustness and interpretability. Persistent limitations are site specificity, dependence on long, clean time-series, and limited cross-site validation; consequently, future work should prioritize hybrid physics-AI models, standardized benchmarking, uncertainty quantification, and operational validation to enhance generalizability and adoption in mine management.

3.1.2. Subsidence prediction of mining areas using machine learning

This section presents a comprehensive synthesis of recent research on subsidence prediction in mining areas using advanced data-driven approaches. The analyzed studies cover a range of machine learning and hybrid techniques such as artificial neural networks (ANN), gene expression programming (GEP), decision trees, support vector regression (SVR), extreme gradient boosting, and evolutionary optimization algorithms applied to diverse mining contexts worldwide. By integrating multi-source datasets, including in-situ measurements, geological parameters, and remote sensing data, these models address the non-linear and complex nature of subsidence processes. The section highlighted methodological innovations, performance comparisons, and the potential of AI-powered models to enhance the accuracy, efficiency, and interpretability of subsidence prediction for improved mine safety, environmental risk management, and sustainable land use planning. In the study [4], the authors investigated the use of an ANN to predict surface subsidence from underground mining. The main objective was to offer an effective alternative to traditional models. By training and testing an ANN model with real-world data from the Velenje Coal Mine, the study successfully demonstrated that ANNs can accurately forecast subsidence, highlighting their ability to model complex, non-linear processes. The paper's findings provide a new, practical tool for mine surveyors and engineers, enabling more accurate subsidence predictions for timely land management and infrastructure protection measures. Also used ANN [22], developed a mine-subsidence risk assessment framework that combines two analyses: analysis A uses an ANN to predict the likelihood of subsidence, and analysis B computes a subsidence risk index to grade the severity at each location. They apply the method to 227 sites across 37 abandoned mines (coal and metal), train and validate the ANN models, and then integrate outcomes from both analyses to assign a spatial subsidence-risk grade; an independent test set of 22 locations showed good agreement with observed ground conditions. The study demonstrates that ANN-based, data-driven mapping can automate and improve subsidence hazard identification and prioritization for monitoring and mitigation. To underscore the versatility and effectiveness of ANN-based approaches in mining subsidence research [38], applied this method to predict underground mining—induced surface subsidence at the Mong Duong coal mine (Quang Ninh, Vietnam). The ANN is trained on historical monitoring data and validated against observed displacement records, showing strong agreement and reliable prediction performance. The authors conclude the ANN-based approach is a practical, accurate tool for short-to-medium term subsidence prediction in underground mining contexts. They recommend its use to support risk mitigation and mine planning. Similarly [20], developed an ANN to predict ground-subsidence outcomes using a dataset of 247 subsidence cases from 27 abandoned mines in Korea. They trained the ANN on 229 cases to predict four outputs (subsidence type, final decision, filling method, local reinforcement), achieving very high in-sample correct-prediction rates. When tested on 18 independent cases, the model retained strong performance, demonstrating robust predictive ability. The authors conclude that the ANN framework can reliably predict subsidence-related decisions for unknown sites, while noting that further validation with more diverse data would strengthen generalization. In another study [39], applied an ANN with a recursive multi-step prediction scheme to predict surface subsidence at the Mong Dương underground mine. The model was trained on 12 monitoring cycles over 24 months, using the first nine cycles with K-fold cross-validation for tuning and the last three cycles for testing. Prediction errors grew with forecast horizon but remained small (absolute errors $\leq$ ~20 mm; relative errors at cycle 10 for four points: 0.9%, −1.7%, −1.7%, and 1.4%), indicating robust short-to-medium-term performance. The authors conclude that the recursive ANN framework is suitable for time-series subsidence monitoring in mining areas and can aid safety and operational planning. Also used the ANN algorithm [40], predicted ground subsidence due to underground mining over time using a multilayer feed-forward ANN with a back-propagation algorithm, applied to a case study at the Mong Duong underground coal mine in Vietnam. The method involves training a three-layer perceptron network with four hidden neurons, using inputs like distance from stope center, mined-out volume, point positions, and time cycles. Results show high accuracy ($RMS/MAE <$ 10% of maximum subsidence) when trained on more than eight monitoring cycles, but performance declines with fewer cycles or larger prediction intervals. The model is applicable for subsidence prediction along the main profile, supporting mining safety and land management. The role of ANN was also proven in the study by [41] to estimate subsidence. The authors integrated multiple ground subsidence hazard (GSH) maps of abandoned coal mines in Samcheok, Korea, using fuzzy logic ensemble techniques combined with GIS. They constructed spatial databases of various factors influencing subsidence, including topography, geology, mining conditions, and groundwater, and generated individual GSH maps using frequency ratio, logistic regression, and artificial neural network models. These maps were then integrated through fuzzy logic to produce a more accurate and reliable ensemble hazard map, which was validated against known subsidence occurrences. The ensemble approach improved prediction accuracy compared to single models, supporting better hazard assessment and management in abandoned mining areas.

Another evolutionary algorithm, gene expression programming, also utilized in predicting subsidence [23]. Developed a GEP-based symbolic regression model to predict maximum surface subsidence in longwall coal mining, deriving explicit algebraic prediction formulas from panel-scale data. They train and validate the GEP model on longwall panel datasets (Ulan region) using input variables such as panel width, cover depth, mining height, seam thickness, and related geometric factors, and perform sensitivity analysis to rank variable importance. The GEP model outperforms several conventional empirical methods in goodness-of-fit and provides compact, interpretable prediction expressions, with panel width and cover depth among the most influential predictors. The authors conclude that GEP is a promising, accurate tool for subsidence prediction and practical longwall planning. Similarly [32], proposed advanced hybrid machine learning models to predict land subsidence caused by coal mining, focusing on the longwall mining method. They developed and tested three hybrid models combining gene expression programming with optimization algorithms: biogeography-based optimization (BBO-GEP), Gray Wolf Optimizer (GWO-GEP), and Salp Swarm Algorithm (SSA-GEP). Using a comprehensive dataset from 14 coal mines with 11 geotechnical and mining parameters, their best model (BBO-GEP) achieved a high prediction accuracy with a correlation coefficient of 0.99. Sensitivity analysis highlighted mining depth as the most influential factor, providing a robust tool to aid environmental risk management and support sustainable mining practices. In 2023, the study of [42] developed hybrid machine learning models combining gene expression programming with optimization algorithms such as biogeography-based optimization (BBO), Gray Wolf Optimizer (GWO), and Salp Swarm Algorithm (SSA) to predict land subsidence caused by coal mining, particularly in longwall mining contexts. Using data from 14 coal mines with 11 geotechnical and mining-related parameters, the BBO-GEP model demonstrated the highest accuracy with a correlation coefficient of 0.99. Sensitivity analysis identified mining depth as the most influential factor affecting subsidence. This work provides a robust, optimized predictive tool for environmental risk management and sustainable mining decision-making. Using the same method [43], focused on predicting land subsidence caused by coal mining using hybrid machine learning models optimized with evolutionary algorithms. They developed three models combining gene expression programming with biogeography-based optimization (BBO), Gray Wolf Optimizer (GWO), and Salp Swarm Algorithm (SSA), tested on data from 14 coal mines with 11 geotechnical and mining parameters. The BBO-GEP model achieved the highest accuracy with a correlation coefficient of 0.99. Sensitivity analysis showed mining depth as the most influential factor, offering a robust predictive tool for environmental risk management and sustainable mining decisions.

Machine learning algorithms can be used in conjunction with remote sensing or multi-criteria analysis to indicate areas of potential subsidence [44]. Presented a machine learning approach to detect land subsidence caused by underground coal fires using multi-sensor satellite data (Landsat 8 OLI and Sentinel-1) in the Jharia Coalfield, India. The authors treat the coal fire–subsidence relationship as a binary classification problem and apply models like random forest to predict subsidence probability, validated by performance metrics. The results reveal significant subsidence near active mine benches and overburden dumps, with displacement trends forecasted using ARIMA, showing a 15–25% increase in subsidence. This integrated method supports improved monitoring and risk management of coal fire-induced land deformation. The article [45] utilized differential interferometric synthetic aperture radar (D-InSAR) technology to capture surface deformation data, which was then integrated into a particle swarm optimization-support vector regression (PSO-SVR) algorithm for predictive modeling. D-InSAR is used to capture surface deformation and subsidence trends over mining areas, while the PSO-SVR algorithm optimizes the predictive modeling of subsidence changes over time. This combined approach improves the accuracy and efficiency of subsidence monitoring, enabling better risk assessment and management in mining regions. The study demonstrates that the integrated model effectively tracks subsidence range and development trends with high precision. Additionally [46], developed a two-level modeling strategy to map risk related to land subsidence by combining multi-criteria decision-making (MCDM) techniques with artificial intelligence methods. The first level employs MCDM to integrate various factors influencing subsidence risk, producing a preliminary hazard map, while the second level uses AI models (such as machine learning algorithms) to refine predictions and improve classification accuracy. This approach leverages the strengths of both subjective expert knowledge and data-driven modeling to provide a comprehensive, accurate risk assessment framework. The study demonstrates effective identification of high-risk subsidence zones, supporting better land use planning and risk management in vulnerable areas.

To take advantage of the advantages of algorithms, some studies have been combined to solve the problem of settlement assessment in mining areas [25]. Developed a combined prediction model integrating a genetic algorithm (GA) with the extreme gradient boosting algorithm to accurately predict mining-induced maximum subsidence. The GA optimizes the hyperparameters of XGBoost, enhancing the model's accuracy and generalization ability when analyzing mining and geological factors such as mining depth, height, goaf area, and topsoil thickness. Tested on domestic mining datasets, the GA-XGBoost model outperforms several classic ensemble models, achieving an R^2 of 0.941, *RMSE* of 0.369, and *MAE* of 0.308, demonstrating its effectiveness for practical mining subsidence prediction and risk management. The model provides a valuable tool for optimizing mining plans and formulating subsidence control measures. Moreover [24], presented a novel approach for predicting mining-induced ground subsidence by combining survival analysis with an online sequential extreme learning machine (OSELM). The survival analysis is used to model the probability and timing of subsidence events, while OSELM, a fast incremental learning algorithm, predicts the subsidence magnitude dynamically as data becomes available. This hybrid approach effectively captures both the temporal occurrence and spatial extent of ground subsidence, offering improved prediction accuracy and adaptability for mining hazard management. The study demonstrates the model's practical application in coal mining areas with promising predictive performance.

The accuracy of using this method has been demonstrated in several studies [47]. Evaluated the suitability of a multilayer perceptron (MLP) neural network to approximate surface subsidence caused by rock-mass drainage. They tested multiple MLP configurations, selecting the optimal architecture based on mean-square error (*MSE*) and the correlation coefficient R, and found that a network with 24 hidden neurons performed best. Results showed considerable dispersion: both too few and too many hidden neurons worsened performance ($MSE\ \uparrow$, $R\ \downarrow$), and final residuals were presented as a histogram of calculated minus observed values. The authors conclude that MLPs can model drainage-induced subsidence but require careful architecture tuning to avoid degraded accuracy. In addition [48], applied decision-tree models to produce ground-subsidence hazard maps around abandoned underground coal mines by integrating spatial factors in a GIS framework. They trained CHAID and QUEST decision-tree classifiers on a historical subsidence inventory (50/50 train/validation) and compared their predictions to a frequency-ratio probabilistic model. CHAID gave the best performance ($AUC \approx 94\%$), QUEST performed slightly lower (~90%), and both outperformed the frequency-ratio method (~87%), indicating superior predictive power and interpretability of the decision-tree approach. The authors conclude that decision-tree ML is an effective, transparent tool for subsidence hazard mapping and prioritizing monitoring, while noting that further validation is needed before applying the models to other regions.

The analyzed publications demonstrate that AI-based and hybrid modeling approaches significantly outperform traditional empirical and statistical methods in predicting mining-induced subsidence. Techniques such as ANN, GEP, and XGBoost, especially when optimized with metaheuristic algorithms, offer high accuracy, adaptability to various data sources, and valuable insights through sensitivity analyses. The integration of remote sensing, GIS, and explainable AI further enhances spatial and temporal prediction capabilities, enabling proactive hazard mitigation and informed decision-making. However, challenges remain in ensuring model generalization across diverse geological settings, incorporating long-term monitoring data, and validating models at larger scales. Continued research in these areas will further solidify the role of AI in advancing predictive subsidence modeling and supporting sustainable mining practices.

3.1.3. Landslide prediction of mining areas using machine learning

Landslides in mining areas pose significant threats to safety, infrastructure, and environmental sustainability, particularly under extreme weather and complex geological conditions. Recent advancements in artificial intelligence and machine learning have enabled the development of predictive models that can accurately assess landslide susceptibility and risk. These approaches, ranging from gradient boosting regression trees (GBRT) and support vector machines (SVM) to explainable AI frameworks like GAMI-net, integrate multi-source datasets such as remote sensing imagery, field survey data, and geotechnical parameters. By capturing the non-linear interactions among factors like rainfall intensity, mining activity, and geological instability, these models offer improved accuracy, interpretability, and early-warning capability, thereby supporting more effective disaster prevention and risk management in mining operations. In the study of [49], the authors presented a landslide risk prediction model using the gradient boosting regression trees algorithm for open-pit mine dumps under heavy rainfall conditions. The model integrates machine learning techniques with slope stability analysis to accurately predict safety factors and landslide occurrence risk. Results demonstrate that the GBRT model outperforms other algorithms in prediction accuracy, enabling early warning and effective disaster prevention in energy mining operations. This work supports enhanced slope risk management by providing fast and reliable landslide risk assessment. Besides [50], proposed a new spatial landslide susceptibility prediction approach for karst mining areas using explainable artificial intelligence (XAI), specifically generalized additive models with structured interactions (GAMI-net). This method integrates remote sensing data, field surveys, GIS techniques, and interpretable machine learning to analyze landslide susceptibility and enhance model transparency. The GAMI-net model outperformed traditional models like random forest and SVM, achieving an AUC of 0.91, effectively revealing key factors such as coal mining, rock desertification, and heavy rainfall that contribute to landslide risk. Their approach not only provides accurate predictions but also valuable interpretability to support decision-making and landslide management in complex karst environments. In another study [51], applied machine learning methods to identify key predisposing factors contributing to open-pit landslides at the Sijiaying Iron Mine. The authors use a comprehensive dataset incorporating geomorphological, geological, and environmental variables, and employ interpretable machine learning models to analyze landslide susceptibility. Their approach highlights the most influential factors affecting slope stability and enhances prediction accuracy by revealing complex factor interactions. This research provides a valuable framework for landslide risk assessment and targeted mitigation strategies in mining areas. By the same approach [52], developed a landslide prediction model using support vector machine technology to forecast landslide occurrence and classify risk levels based on rainfall data. The model preprocesses rainfall datasets with normalization and uses radial basis function kernels for SVM training and testing to enhance prediction accuracy. Applied to the high-rainfall Cherapunjee region, the approach demonstrates efficient classification of landslide risk stages and improved early warning reliability. This research highlights SVM’s flexibility in handling non-linear relationships and its practical applicability to landslide-prone areas.

The analyzed studies demonstrate the effectiveness of AI-based models in predicting landslide risk in mining regions, with clear improvements over traditional methods in both accuracy and decision support. Techniques such as GBRT, SVM, and GAMI-net not only provide reliable forecasts but also enhance understanding of the driving factors behind slope instability. Their integration into mining safety management systems can facilitate proactive measures, targeted mitigation strategies, and optimized monitoring plans (see Table 1).

3.2. Application of deep learning in the movement prediction of mining areas

3.2.1. Deformation prediction of mining areas using deep learning

This section focuses on analyzing the application of deep learning techniques in predicting mining-induced deformation. Recent studies have demonstrated that advanced models, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, can effectively process and interpret large-scale interferometric synthetic aperture radar (InSAR) data. By automating complex tasks like phase unwrapping and integrating time-series surface deformation measurements, these methods improve the accuracy, efficiency, and scalability of subsidence detection and prediction in mining areas. In the study [53],

Table 1. Studies on machine learning applications.

References	Objective	Methods	Strengths	Limitations
Deformation				
[6]	Assess the accuracy of ANN as a viable technique for predicting deformation in open-pit mine walls.	Comparison of three supervised ANN techniques: BPNN, RBFNN, GRNN.	RBFNN showed the lowest error, handles nonlinear and complex deformation well, robust against faults and noise compared to traditional methods.	Results based on a specific dataset, may not generalize across all scenarios.
[35]	Develop a new RBFNN model to predict the deformation modulus of jointed rock masses based on dilatometer tests.	Developed an RBFNN using data from the Bakhtiary dam, Iran.	High prediction accuracy, sensitivity analysis highlights key parameters affecting deformation modulus.	Study limited to one location, affecting generalizability.
[18]	Propose an ensemble machine learning model to predict open-pit slope deformation and prevent collapses.	Ensemble of five learners: BPNN, SVM, RNN, ANFIS, RVM, trained with real GB-SAR field data.	High precision: ensemble outperformed individual learners in practical applications with real monitoring data.	Needs further validation for different geological conditions or mine types.
[36]	Predict surface deformation of pit walls using prism monitoring data.	Machine learning algorithms trained on prism displacement data from pit walls.	Real data input improves reliability and captures complex nonlinear relations for early warning and risk management.	Limited dataset and localized site; may miss external factors influencing deformation.
[21]	Identify factors influencing surface deformation from underground mining using SAR and explainable AI.	Random Forest applied to SAR data; SHAP method to interpret model outputs.	High-resolution SAR enables weather-independent monitoring, ML improves accuracy, SHAP offers model transparency and factor importance explanation.	Relies on data quality; limited geographical coverage; possible missing geological factors.
[19]	Develop and identify the most suitable AI model for the accurate prediction of rock mass deformation modulus.	Compared multiple AI models, including ANN and ANFIS, trained on geotechnical datasets.	Comprehensive comparison to select the best model; feature selection and optimization are used to enhance performance.	The study focused on specific datasets; prediction accuracy depends on data quality.
[37]	Predict deformation of roadway roofs during the non-support period using a hybrid SVR with swarm intelligence optimization.	Hybrid SVR model using Particle Swarm Optimization for parameter tuning.	Improved prediction accuracy and robustness over traditional SVR; practical for real-time monitoring.	Computational cost increased; external geological variability not fully modeled.
Subsidence				
[4]	Validate ANNs for surface subsidence prediction as alternatives to empirical/mechanical models.	Multi-layer feed-forward neural network with back-propagation.	Models complex nonlinear subsidence; computationally efficient; fewer assumptions than traditional models.	Accuracy depends on training data; it lacks physical interpretability.
[22]	Predict subsidence possibility and classify risk over abandoned mines to prioritize investigations.	Feed-forward ANN with resilient propagation training.	Uses multi-site real data; combines prediction and risk grading; practical for management.	Some input data is missing; only classification not magnitude or time-series output.
[38]	Predict land subsidence due to underground mining at Mong Duong, Vietnam using ANN.	ANN with four input features; k-fold cross-validation to optimize parameters.	Effective nonlinear modeling; good short-term prediction; locally tailored.	Accuracy drops with longer forecasts; dataset 2D and site-specific; generalization limited.
[47]	Evaluate ANN for subsidence due to rock mass drainage in mining areas	ANN trained on subsidence data with geotechnical/drainage inputs.	Models nonlinear relationships efficiently; a practical tool; handles multiple factors.	Depends on data quality; limited generalizability; ignores temporal dynamics.

(*continued on next page*)

Table 1. (continued)

References	Objective	Methods	Strengths	Limitations
[20]	Develop/validate ANN for subsidence over abandoned mines in Korea.	Feedforward ANN trained on data from 247 subsidence areas in 27 mines.	Uses real-world data; models nonlinear relationships; spatial prediction maps.	Limited to abandoned Korean mines; no temporal dynamics.
[39]	Develop a recursive multi-step ANN for surface subsidence prediction.	ANN trained on monitoring data; k-fold CV for optimization.	Enhances multi-horizon prediction, high correlation, and low errors.	Errors increase with forecast length, site-specific, and small monitoring points.
[40]	Investigate the use of an ANN to estimate ground subsidence caused by underground mining	Three-layer perceptron network with four neurons in the hidden layer and back-propagation for training	Suitable for predicting subsidence along the main profile; accuracy improves with > 8 cycles, RMS/MAE < 10% of max subsidence.	Accuracy depends on > 8 training cycles and the time interval between the predicted and last training cycle; lower cycles fail accuracy requirements.
[48]	Map subsidence hazard near abandoned coal mines using a decision tree in GIS.	Decision tree (CHAID/QUEST) on spatial data; compared with frequency ratio.	High accuracy; interpretable rules; GIS integration; handles heterogeneous factors.	Relies on input data quality; no temporal dynamics; ignores post-mining changes.
[23]	Develop a GEP model for maximum subsidence in longwall coal mining.	Multivariable symbolic regression via GEP, compared with empirical methods.	Captures nonlinear relationships; improved accuracy; sensitivity analysis.	Site-specific (Ulan mine); data-dependent; GEP complexity.
[44]	Detect subsidence from underground coal fires using multi-sensor satellite data and ML.	Multiple ML models (random forest, etc.) on satellite data.	High accuracy; complements other methods; integrates spatial data.	Data quantity/quality dependent; focused on surface subsidence; computationally intensive.
[41]	Integrate subsidence hazard maps for abandoned coal mines in Samcheok, Korea.	Combined geological/hydrological data with GIS mapping.	Provides detailed hazard maps; integrates multi-source data.	Limited to abandoned mines; no predictive modeling; site-specific.
[32]	Predict land subsidence due to coal mining.	Advanced ML models (e.g., GEP with optimization).	High accuracy; captures complex patterns.	Coal-specific; data-dependent; site-limited.
[43]	Predict subsidence in coal mining using ML and optimization	ML models with optimization algorithms.	High precision; handles complex data.	Site-specific; data-dependent.
[46]	Map land subsidence risk with a two-level modeling strategy.	Multi-criteria decision-making and AI techniques.	Robust risk assessment; integrates diverse factors.	Data quality-dependent; limited temporal dynamics.
[42]	Predict land subsidence in coal mining using ML models.	ML models with optimization techniques.	High accuracy; adaptable to complex data.	Site-specific; data-dependent; limited validation.
[45]	Monitor and predict coal mining subsidence dynamically.	Data source/Monitoring tool: D-InSAR and prediction algorithm: PSO-SVR for time-series analysis.	High precision; handles temporal data; real-time monitoring.	Data quality-dependent; site-specific; computationally intensive.
[25]	Develop a model to predict maximum ground subsidence in mining areas using a genetic algorithm (GA) combined with XGBoost.	Integrate GA to optimize XGBoost parameters, using mining and geological data as inputs to predict maximum subsidence.	High prediction accuracy; GA enhances XGBoost performance; robust for complex mining datasets.	Limited to maximum subsidence prediction; generalizability to other mining contexts needs validation; requires quality data and computational resources.
[24]	Predict subsidence with missing data reconstruction	Survival analysis + OS-ELM for dynamic prediction.	Handles missing data, online updating, and improved accuracy.	Relies on data quality; requires expertise; coal-focused.

Landslide				
[49]	Develop a fast landslide risk prediction model for open-pit mine dumps.	GBRT ML algorithm on slope/rainfall data.	High accuracy/speed; suitable for real-time monitoring; early warning.	Site-specific; data-dependent; focuses on dumps
[50]	Develop an explainable AI model for landslide susceptibility in karst mining areas.	ML with SHAP for interpretation; multi-source data.	Transparent factors; accurate for karst regions; integrates diverse data.	Site-specific; data availability issues; no temporal dynamics.
[51]	Detect predisposing factors for landslides in Sijiaying Iron Mine using ML.	Ensemble ML (RF + XGBoost soft voting); numerical simulation.	Robust prediction; integrates data acquisition and simulation.	Site-specific; computational demands; limited temporal scope.
[52]	Develop SVM-based landslide prediction model.	SVM on influencing factors; classification of occurrence probability.	Handles nonlinear data; accurate for small samples; efficient.	Limited dataset scope; no temporal/multi-source integration; parameter sensitivity.

authors presented a deep learning approach for detecting mining-induced deformation and performing phase unwrapping in large-scale interferograms. The method utilized convolutional neural networks (CNNs) to accurately identify deformation fringes in SAR interferometric images, thereby enhancing the interpretation of surface displacement caused by mining activities. This approach automates the traditionally complex and labor-intensive process of phase unwrapping, enhancing efficiency and accuracy in deformation monitoring. The results demonstrate the model's capability to effectively handle large datasets and complex deformation patterns for reliable subsidence assessment. Besides [54], integrates Small Baseline Subset (SBAS) InSAR measurements with a long short-term memory algorithm to retrieve and predict time-varying surface deformation in closed mines. SBAS-InSAR provides accurate deformation time series data, which the LSTM model uses to capture temporal dependencies for predicting future ground movement. The method effectively supports monitoring and predicting subsidence trends, facilitating safer mine closure management and hazard mitigation. This combined approach advances dynamic deformation analysis by enhancing prediction accuracy through the fusion of remote sensing and deep learning technologies. The analyzed results show that deep learning approaches, particularly CNNs and LSTM-based models, offer significant advantages for mining deformation monitoring, including handling complex patterns, automating labor-intensive processes, and delivering reliable predictions.

3.2.2. Subsidence prediction of mining areas using deep learning

Recent advancements in deep learning and geospatial technologies have significantly enhanced the ability to monitor and predict ground subsidence in mining areas. Integrating methods such as adaptive neuro-fuzzy inference systems (ANFIS), hybrid extreme gradient boosting, InSAR time-series analysis, and long short-term memory (LSTM) networks, researchers have developed robust models capable of capturing the complex spatial and temporal characteristics of subsidence. By leveraging multi-source data, including geological, geotechnical, operational, and remote sensing inputs, these approaches offer improved accuracy, cost-efficiency, and automation, providing essential tools for sustainable mining operations and risk mitigation. In the study of [55], the authors applied an adaptive neuro-fuzzy inference system (ANFIS) combined with GIS to map ground subsidence hazards around abandoned underground coal mines in Samcheok City, Korea. Five major causal factors, depth of drift, distance from drift, slope gradient, geology, and land use, were used as input variables for the ANFIS model. Two hazard maps generated with different membership functions showed high predictive accuracy of about 95%, validated against ground subsidence data not used in training. This demonstrates that ANFIS is an effective and reliable tool for quantitative ground subsidence hazard assessment in mining areas. Besides [56], conducted a comparative performance analysis of hybrid extreme gradient boosting models to predict rock layer subsidence in a subsea gold mine. The authors develop and test multiple hybrid XGBoost models enhanced with optimization techniques to improve prediction accuracy and generalization. Using geotechnical and mining data, the study evaluates the models' performance metrics, demonstrating that the hybrid approaches outperform conventional models in predicting subsidence. This research offers a robust and efficient tool for managing subsidence risk in complex subsea mining environments. Used another algorithm [57], used an advanced InSAR time series analysis method called ICOPS (improved combined scatterers with optimized point scatterers) to monitor land subsidence caused by open-pit mining in the Musan mining area, North Korea. This method combines persistent scatterers (PS) and distributed scatterers (DS) to enhance spatial coverage and measurement quality. Additionally, the study employs a deep learning algorithm (convolutional neural networks) in postprocessing to improve the reliability and accuracy of the subsidence detection. Results show significant subsidence rates exceeding 15 cm per year in dumping areas, highlighting the method's effectiveness for sustainable mine management and geotechnical risk mitigation. In another study [58], predicted ground subsidence during tunnel boring machine (TBM) operation in mixed-face ground conditions using real-time monitoring data and deep learning models. They developed two long short-term memory models: the first extracts features from TBM operational and geological data affecting surface settlement, while the second predicts longitudinal ground subsidence using those features. This method addresses limitations of traditional analytical and empirical approaches by incorporating TBM operational parameters such as cutterhead pressure and thrust force, leading to improved accuracy in settlement prediction. Their approach helps engineers anticipate and mitigate undesirable ground deformation during tunnelling in complex mixed soil and rock conditions. Additionally [59], proposed a novel spatiotemporal prediction model for ground subsidence using interferometric synthetic aperture radar (InSAR) technology, specifically integrating SBAS-InSAR for high-precision surface deformation monitoring. The model combines time-series InSAR data with a deep learning framework, likely involving convolutional and recurrent neural networks, to capture both spatial and temporal features of subsidence processes. Validated with observed data, the approach achieves highly accurate predictions with minimal error, improving upon traditional methods by reducing monitoring costs and enhancing prediction reliability. This integrated method supports precise, unmanned monitoring and prediction of ground subsidence, offering critical technical support for sustainable mining area development.

The assessed studies demonstrate that combining advanced deep learning algorithms with high-resolution monitoring technologies yields highly accurate and reliable subsidence predictions. These integrated approaches outperform traditional methods, enabling early detection of deformation, better hazard mapping, and informed decision-making for mine safety and land management.

3.2.3. Landslide prediction of mining areas using deep learning

Landslide prediction in open-pit mining is critical for protecting lives, infrastructure, and operations, and recent advances in deep learning enable more reliable early-warning systems. There are very few studies using DL technology to predict landslides in mining areas [60]. Proposed a comprehensive early warning system for rock slope landslides in open-pit mines using a hybrid data-driven model combining long short-term memory networks and seasonal autoregressive integrated moving average (SARIMA). The approach involves thorough noise reduction and decomposition of displacement data into trend and periodic components, which the LSTM-SARIMA model predicts separately with a combined accuracy of 96%. The model outperforms other machine learning methods, such as SVM, random forest, and XGBoost, in predicting slope displacement. Finally, the study introduces an improved tangent angle criterion on the predicted displacement-time curve to provide accurate and timely landslide warnings, demonstrating the system's practical effectiveness in the East China mining area. These results demonstrate the method's strong practical potential for landslide early-warning in mining regions (see Table 2).

Table 2. Studies on deep learning applications.

References	Objective	Methods	Strengths	Limitations
Deformation				
[53]	Develop DL-based methods for detecting and unwrapping mining-induced deformation from InSAR interferograms.	Two CNNs: DDNet for subsidence detection, PUNet for phase unwrapping on patches.	Automates InSAR processing; high accuracy on synthetic/real data; handles rapid deformation.	Requires computational resources; limited generalization; may overlook environmental factors.
[54]	Retrieve and predict deformation in closed mines using SBAS-InSAR and LSTM.	Data source/Monitoring tool: process Sentinel-1 data with SBAS-InSAR; prediction algorithm: train LSTM on time series for prediction.	Integrates RS and DL for monitoring/predicting; handles nonlinear patterns effectively.	Relies on quality time series; focused on closed mines; no physics-DL hybrids.
Subsidence				
[55]	Develop subsidence hazard mapping with ANFIS integrated in GIS.	ANFIS with GIS spatial inputs (geological factors); fuzzy logic + NN for nonlinear modeling.	Flexible for complex relationships; handles spatial data; robust via k-fold validation.	Sensitive to membership functions; needs high-quality data; computationally intensive.
[56]	Evaluate hybrid XGBoost models for predicting subsidence in subsea mining.	Hybrid XGBoost with optimization on mine datasets; comparative evaluation.	Enhances accuracy over single models; considers complex factors; aids model selection.	Specific to subsea gold mines; data-dependent; increased complexity.
[57]	Analyze open-pit mining subsidence using multitemporal InSAR and DL optimization.	Integrates scatterer interferometry with statistical/ML models for temporal analysis.	Improves detection accuracy; reduces noise; combines stats and ML	Limited generalizability; high complexity; misses some variables; requires expertise.
[58]	Predict subsidence during TBM operations in mixed-face ground using ANN.	ANN trained on real-time multi-sensor data from TBM excavation	Enables real-time predictions; captures nonlinear links; supports risk management.	Site-specific; relies on sensor data quality; challenges in extreme conditions.
[59]	Create spatiotemporal subsidence prediction model with InSAR and ConvLSTM.	Data source/Monitoring tool: process Sentinel-1 InSAR data (2016−2022); prediction algorithm: apply ConvLSTM for prediction.	High accuracy (R^2 ~0.95); captures patterns; aids safety/environmental management.	Tested on one area; resource-intensive; sensitive to InSAR data quality.
Landslide				
[60]	Develop an early warning system for landslides using a hybrid LSTM-SARIMA.	LSTM for displacement trend, SARIMA for periodic; compare with SVM, XGBoost, etc.	Leverages strengths for accurate prediction; improved warnings; outperforms alternatives	Complex implementation; dataset-specific; omits some factors; scalability concerns.

3.3. Application of the hybrid method in the prediction of deformation, subsidence and landslide in mining areas

This section provides a concise synthesis of recent advances in data-driven prediction and monitoring of mining-induced ground deformation and landslides, surveying machine-learning such as SVM, SVR, RF, XGBoost, GEP, deep-learning such as CNN, LSTM, neuro-fuzzy, and hybrid approaches, and their integration with remote-sensing (InSAR), geodetic (GPS, TLS, prism), and GIS datasets. Besides, it highlights methodological innovations such as model optimization, explainable-AI (SHAP/GAMI-net), and spatio-temporal decomposition and summarizes case studies that demonstrate enhanced accuracy and operational potential for early warning and risk management. In the study of [61], the authors proposed an intelligent prediction model for surface deformation of open-pit mine slopes based on a mayfly algorithm-optimized support vector machine (MA-SVM). This model aimed to address issues like large prediction errors, slow convergence, and poor generalization in traditional methods by optimizing SVM parameters via the mayfly algorithm, reducing uncertainty, and avoiding time-consuming parameter tuning. Using real deformation monitoring data from the Anjialing open-pit mine in China, the MA-SVM model demonstrated superior accuracy compared to SVM, genetic algorithm-SVM, and particle swarm optimization-SVM, achieving lower mean absolute and root mean square errors. The model is practical for early warning and effective prediction of slope deformation in mining operations, offering important support for ground stability management. Using another approach [62], proposed a land subsidence prediction model using recurrent neural networks (RNNs) that integrates temporal displacement data from InSAR monitoring with multiple influencing factors such as DEM, soil type, and building height. To improve accuracy beyond traditional methods, they construct a knowledge graph to capture spatial relationships between monitoring points and land subsidence data, enabling the model to jointly consider spatial and nonlinear temporal dependencies. Their approach outperforms previous models by effectively incorporating both spatial correlations among points and multiple subsidence-influencing factors, resulting in higher accuracy in predicting land subsidence displacement. This method offers a robust framework for more precise and comprehensive subsidence risk assessment and monitoring in mining-affected areas. Additionally [63], proposed an improved YOLO algorithm for the identification and precise location of mining landslides. This enhanced model optimizes detection accuracy by accurately extracting landslide features from images and converting detected landslide pixel coordinates into geodetic coordinates for precise localization. The results demonstrate the algorithm's effectiveness in detecting mining landslides, providing a valuable tool for real-time monitoring and risk management in mining areas. The study highlights the improved precision and applicability of the YOLO-based approach in a complex mining environment.

Besides deformation prediction, a hybrid algorithm is also used to determine the subsidence of the mining area. Predicting surface subsidence accurately is essential for safe and sustainable mine operations [64]. Employed a combination of SBAS-InSAR technology and a novel deep learning model integrating CNN, BiGRU, and attention mechanisms to achieve high-precision monitoring and prediction of surface subsidence in mining areas. SBAS-InSAR provides accurate time-series deformation data, while the CNN-BiGRU-attention model captures both spatial and temporal features of subsidence dynamics, enhancing prediction accuracy. Validated on real mining site data, this integrated approach effectively predicts subsidence trends, supporting sustainable mine management and hazard mitigation. The study demonstrates the superiority of combining advanced remote sensing with cutting-edge artificial intelligence for precise, real-time subsidence monitoring and prediction.

Additionally, this approach was utilized to identify landslides in mining regions [65]. Introduced an intelligent method for landslide detection and recognition based on the advanced deep learning model YOLOv11-seg. This model enhances both boundary detection accuracy and pixel-level segmentation of landslide areas, outperforming traditional methods by better handling complex terrain and occlusion challenges. The authors use data augmentation techniques to improve the model's robustness across different environments, achieving high precision, recall, and F1 scores in experiments. Overall, YOLOv11-seg provides a reliable and adaptable tool for intelligent landslide monitoring and risk assessment in diverse geological conditions.

The analyzed results show that AI-based techniques substantially improve the precision, automation, and interpretability of subsidence and landslide prediction in mining contexts, offering practical tools for monitoring, early warning, and mitigation of this phenomenon. The hybrid model can capture complex subsidence behaviors. Its demonstrated ability to anticipate trends supports earlier warnings, targeted mitigation, and more informed planning for safety and environmental protection (see Table 3).

4. Results and discussions

4.1. Distribution of AI-based studies by deformation type and method

Based on the systematic review in the document, which analyzed 42 selected articles (from an initial 252, after screening), the studies are categorized into machine learning, deep learning, and hybrid methods as shown in Table 4. The survey results indicate that subsidence-related studies dominate, accounting for approximately 57% of the total research. Deformation studies represent around 29%, while landslide-related works are the least common, at about 14%. This highlights subsidence as the primary geotechnical hazard in mining, driven by its widespread impact on infrastructure, environment, and safety (e.g., in coal/underground mines). Landslides receive the least focus, possibly due to their site-specific, event-driven nature and data scarcity. Regarding the AI methods used (Fig. 2), machine learning techniques remain the most prevalent, with around 69% of the studies employing them. Deep learning approaches are emerging but still less frequent, making up roughly 19% of the research. Hybrid methods, which combine ML and DL techniques, are the newest and least common, at approximately 12%. This distribution highlights the focus on predicting subsidence, which is a critical safety and environmental issue in mining operations. Machine learning's dominance reflects its broad applicability and the mature state of these algorithms, such as random forest, XGBoost, support vector machines, and artificial neural networks, which offer both good performance and interpretability with existing data. Deep learning shows great promise for processing complex, large-scale datasets like satellite imagery, such as InSAR-derived datasets and time-series monitoring data. Despite currently fewer studies, these methods are expected to grow rapidly, especially for real-time prediction and early warning systems for landslides and more subtle deformation patterns. Besides, hybrid AI approaches are gaining attention because they combine the strengths of traditional machine learning with deep learning's ability to capture complex spatiotemporal patterns. These methods hold potential to improve prediction accuracy and provide multidimensional prediction that spans both space and time.

Table 3. Studies on hybrid method applications.

References	Objective	Methods	Strengths	Limitations
Deformation				
[62]	Improve land subsidence displacement prediction using RNNs, incorporating spatial and temporal dependencies.	Graph-TAP model combining graph learning with GRU for spatial-temporal correlations.	Captures spatial relationships via graphs; uses GRU for temporal dynamics; superior to LSTM benchmarks.	Complex graph construction; needs testing for generalizability; resource-intensive.
[61]	Develop prediction model for open-pit mine slope deformation for stability and safety.	MA-SVM: mayfly algorithm optimizes SVM parameters using monitored data	Evolutionary optimization boosts accuracy; stable; practical for real-time; smaller dataset needs.	Limited to specific datasets; higher cost for large data; misses some external factors; data quality dependent
[63]	Improve YOLO for mining landslide identification and location for disaster monitoring.	Optimized YOLOv8 with attention mechanisms for detection on drone imagery.	Enhanced accuracy and speed; precise geolocation; robust in varied terrains.	Depends on imagery quality; high computational demand; limited multi-data integration info.
Subsidence				
[64]	Develop high-precision workflow for mining subsidence monitoring and prediction.	Hybrid CNN-BiGRU-attention model for spatial-temporal feature extraction and prediction.	Advanced RS-DL integration; high precision; enables risk management; effective on real data.	Computational complexity; needs diverse validation; misses some factors; requires expertise.
Landslide				
[65]	Develop intelligent landslide recognition for detection and segmentation in complex terrains	YOLOv11-seg optimized for feature extraction and boundary segmentation with data augmentation	High precision in boundaries/occlusions; outperforms traditions; generalizes well; efficient segmentation.	Training data dependent; resource-heavy; focuses on 2D; real-time challenges.

Table 4. The number of studies in each application in three methods.

Method	Defomation	Subsidence	Landslide	Total per method
Machine learning	[6,18,19,21,35–37]	[4,20,22–25,32,38–48]	[49–52]	29
Deep learning	[53,54]	[55–59]	[60]	8
Hybrid	[61–63]	[64]	[65]	5
Total per deformation type	12	24	6	42

In summary, the majority of AI research in mining-induced deformation concentrates on subsidence prediction using machine learning methods. The field is gradually shifting towards more sophisticated deep learning and hybrid approaches, expected to enhance safety management and sustainable mining practices through improved risk assessment and prediction capabilities.

4.2. Strengths and limitations of AI-based methods for mining-induced ground deformation

The above analysis results indicate that machine learning techniques such as random forest, support vector machines, artificial neural networks, and XGBoost have demonstrated high accuracy in handling complex, nonlinear geological data commonly collected from mines. They are relatively easier to apply and interpret compared to deep learning models, perform well on tabular and structured datasets, and have been successfully used across various mining sites with in-situ geological and geotechnical data. ML models are effective in capturing key influencing factors and provide good robustness when optimized with metaheuristic techniques. Besides, deep learning approaches excel at processing large-scale, complex, and unstructured datasets like satellite imagery (e.g., InSAR), time-series sensor data, and multidimensional geological information. Models such as convolutional neural networks, long short-term memory networks, and ConvLSTM are capable of automatically extracting intricate features, modeling spatiotemporal patterns, and delivering real-time predictions and early warnings for subtle deformation and landslide events. Hybrid methods combine the complementary strengths of ML and DL. By integrating traditional machine learning's interpretability with deep learning's automatic feature extraction and handling of complex data, hybrid models can improve prediction accuracy and spatiotemporal prediction capabilities. Optimizations with genetic algorithms, swarm intelligence, or other evolutionary strategies further enhance their performance in diverse mining conditions.

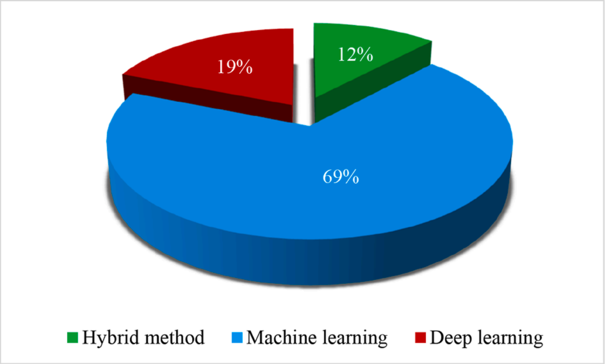

Fig. 2. Percentage distribution of studies that used AI technology in predicting mining-induced subsidence, deformation, and landslides.

In addition to the strengths, these methods also have some limitations. ML methods often depend heavily on the quality and completeness of data, and their performance can degrade when faced with large volumes of unstructured data or insufficient temporal resolution. Additionally, they may lack real-time prediction capability and struggle to generalize well beyond the specific mine or region on which they were trained. DL methods require large, diverse, and high-quality datasets for effective training. They are typically resource-intensive in terms of computational power and time, and their "black-box" nature can limit interpretability, making stakeholder acceptance and practical deployment more challenging. DL has been less extensively applied in mining deformation compared to ML due to these constraints. Hybrid models, while more powerful, are complex to design, tune, and validate. Their implementation demands significant computational resources and expertise, and the complexity may hinder model transparency and maintenance. Furthermore, hybrid approaches still face challenges in adapting across varying geological frameworks and scaling for operational use.

4.3. Advantages and limitations of the proposed classification framework

Beyond the evaluation of individual AI methods, it is necessary to assess the advantages and limitations of the classification framework proposed in this study. One of the main advantages of the framework is its structured and application-oriented organization, which classifies AI-based approaches according to algorithmic category (machine learning, deep learning, and hybrid methods) while simultaneously considering deformation types and data characteristics. This multidimensional structure supports a clearer interpretation of how different AI techniques are applied to specific mining-induced deformation scenarios, thereby facilitating method selection and practical implementation in monitoring, prediction, and early warning contexts.

Despite these advantages, the proposed classification framework has several limitations. First, it depends on the availability and quality of published studies, which may result in an imbalanced representation of deformation types, particularly for landslide-related applications. Second, some AI models exhibit overlapping characteristics across categories, especially in hybrid or customized implementations, which can complicate strict classification. In addition, differences in datasets, evaluation metrics, and validation strategies among the reviewed studies limit direct quantitative comparison of model performance. Therefore, the proposed framework should be regarded as a flexible analytical tool rather than a fixed or exhaustive taxonomy, and future updates will be required as AI techniques and data sources continue to evolve.

4.4. Comparison with existing review studies and added value of this work

Regarding the topic of this article, there have been several studies worldwide that have addressed it [27–30,33,34]. These studies have provided valuable syntheses of mining-induced ground deformation from different methodological perspectives; however, their scope and analytical depth vary considerably. Table 5 compares some aspects of the current study and previously published studies related to predicting deformation due to mining operations. The comparison between the present study and existing review papers is conducted using the following criteria in order to clearly identify differences in research scope, methodological emphasis, and practical relevance, as well as to highlight the added value of this work:

(1) Main focus: This criterion is used to distinguish whether a study primarily addresses traditional subsidence analysis, specific monitoring technologies, or adopts an integrated approach that emphasizes AI-based prediction and monitoring, thereby clarifying the central research objective of each review.
(2) Deformation scope: This criterion aims to assess whether existing reviews are limited to subsidence or consider multiple manifestations of mining-induced ground deformation, enabling evaluation of the comprehensiveness and hazard coverage of each study.
(3) Role of AI: This criterion is included to determine whether artificial intelligence is treated as a supplementary tool or as the core analytical framework, which is critical for assessing the novelty and methodological advancement of the present work.
(4) Methodological perspective: This criterion allows comparison of the dominant analytical perspectives, such as traditional empirical and physics-based methods, GIS, or SAR-based monitoring, versus AI-centered approaches, highlighting shifts in methodological paradigms within the field.
(5) Systematic classification framework: This criterion is used to examine whether a review provides a structured and unified framework for categorizing methods, which is essential for systematic comparison, model selection, and knowledge synthesis.
(6) Monitoring prediction integration: This criterion examines whether monitoring data (e.g., InSAR, GNSS, UAV) are merely described as observational tools or are explicitly incorporated as inputs to prediction models, enabling deformation prediction and early warning rather than purely descriptive analysis. The levels of monitoring–prediction integration describe how monitoring data are used in relation to prediction models, ranging from no linkage to conceptual or sequential use, and finally to the explicit incorporation of monitoring data as direct inputs for predicting and early warning.
(7) Application orientation: This criterion assesses the extent to which a study is oriented toward practical implementation, including decision support, real-time capability, and risk management, rather than purely methodological or conceptual discussions.

Based on Table 5, it can be seen that the current study shows outstanding differences and clear additional value compared to the six previously published review studies [27–30,33,34]. First, regarding the research focus, works [27–30] mainly focus on mining subsidence, with traditional approaches such as synthesis of predicting-monitoring methods, GIS, or SAR/InSAR specifically for

Table 5. Comparison between the present study (JSM) and representative review studies.

Key criterion	[27]	[28]	[29]	[30]	[33]	[34]	Present study
Main focus	Prediction and monitoring of mining-induced subsidence	Monitoring, calculation, and simulation of coal mining − induced subsidence	GIS-based assessment and mapping of subsidence	SAR-based monitoring of rapid subsidence	AI applications in mining and geological engineering (general)	Machine learning applications across mining stages	AI-based prediction and monitoring of mining-induced ground deformation
Deformation scope	Mainly subsidence	Subsidence only	Subsidence	Subsidence	Not focusing in depth on mining-induced subsidence/deformation	Not focusing in depth on mining-induced subsidence/deformation	Comprehensive (Subsidence, deformation, and landslides)
Role of AI	Supplementary, not central	Very limited or not addressed	Not addressed	Not addressed	High, but general-purpose	High, but general-purpose	Core predictive engine integrated with multi-source monitoring data
Methodological perspective	Traditional with limited AI	Traditional (monitoring-calculation-simulation)	GIS-oriented	SAR/InSAR-oriented	Broad AI overview	ML-oriented overview	AI-centered (ML-DL-Hybrid)
Systematic classification framework	No	No	No	No	No	Partial (ML by mining stages)	Yes (ML-DL-Hybrid)
Monitoring −prediction integration	Partial	Sequential description	No integration	No integration	No integration	No integration	Explicit integration for early warning
Application orientation	Methodological overview	Benchmark traditional review	Spatial assessment	Monitoring performance	General AI context	General ML context	Decision support and risk management

monitoring, while AI, if present, plays only a secondary role or is not mentioned. Studies [33,34] have a broader scope of AI in mining, but are general in nature, according to the mining sector or value chain, not directly focusing on mining-induced topographic deformation. In contrast, the current study clearly identifies AI as the central analytical framework, while combining both prediction and monitoring in the same overview. Secondly, regarding the scope of deformation, most previous studies have been limited to subsidence, while the present study systematically expands to include multiple forms of deformation caused by mining, including subsidence, ground deformation, and landslides. This allows this study to more fully cover real-world geotechnical hazards, especially in the context of complex mines and multi-geological conditions. The third key difference of the current study lies in its systematic classification framework and the level of integration between observation and prediction. Unlike previous studies that described observation and computation sequentially or separately, the current study proposes a unified classification framework based on ML-DL-Hybrid, while emphasizing the explicit integration of observational data (InSAR, GNSS, UAV, sensors) as direct input to the AI model for predicting and early warning. As a result, the application orientation of the current study shifts from methodological overview to decision support and risk management, something that previous studies have only addressed conceptually or not clearly defined.

In summary, compared to existing reviews, the outstanding added value of the current study lies not only in its updated AI but also in its systematic knowledge organization, broader risk scope, and clear orientation toward early warning and mine safety, thereby adding a perspective that was missing in previous review studies.

The comparative analysis demonstrates that, despite recent advances, significant challenges remain in translating AI-based approaches into robust and operational deformation-predicting systems. Based on these insights, future development trends and research directions are discussed below.

4.5. Future development trends and research directions

To overcome current limitations and maximize the potential of Artificial Intelligence in the mining sector, future research should focus on the following strategic directions, aiming to build upon and develop the models analyzed in this study:

4.5.1. Transitioning from pure data-driven to physics-based AI

While Hybrid models have shown high accuracy by combining multiple algorithms, the next trend should move toward integrating physical and geomechanical models (e.g., rock mechanics) directly into the AI training process. This integration will enable architectures like LSTM (strong in time-series) and CNN (strong in spatial features) to not only learn from data but also comply with mining mechanical principles. This approach will significantly enhance model generalization, reduce data dependency, and improve reliability under varying geological conditions.

4.5.2. Real-time monitoring and edge computing for early warning systems

Another important direction is the optimization of deep learning and hybrid models for real-time early warning systems. Future studies should focus on optimizing deep learning architectures, such as CNN for satellite/UAV imagery and LSTM for IoT sensor data, for deployment in real-time environments. By streamlining complex hybrid models through edge computing and cloud platforms, researchers can develop operational early warning systems that respond instantly to subtle or rapidly evolving deformation and landslide patterns.

4.5.3. Enhancing transparency through explainable AI-XAI

The “black-box” nature of deep learning remains a significant barrier. Future research must incorporate XAI techniques, such as SHAP (SHapley Additive exPlanations), LIME (local interpretable model-agnostic explanations), or attention-based models, to interpret the decision-making process of LSTM or CNN models. This is crucial for stakeholder trust and regulatory compliance, allowing mine managers to understand the core geological drivers behind the predicted deformations.

4.5.4. Develop a multi-hazard assessment framework and standardize data

Instead of isolated studies on subsidence or landslides, future frameworks should simultaneously address multiple mining-induced hazards. Developing unified prediction systems supported by standardized benchmarking datasets will allow for objective performance evaluation of machine learning, deep learning, and hybrid algorithms, enabling cross-site and cross-method comparisons across different mining scenarios and mineral types.

4.5.5. Multi-source data fusion and addressing data sparsity

The combination of multi-source monitoring data, including InSAR, UAV, GNSS, and in-situ sensors, is essential. Combined with data augmentation techniques, these multi-modal inputs will help CNN and other algorithms perform effectively even in cases of data sparsity, ensuring the detection of critical deformation patterns in landslide-prone areas.

4.5.6. Aligning AI with sustainable mining and environmental management

Finally, AI predictive tools must be aligned with sustainable mining practices. Future developments should emphasize solutions that support environmental impact mitigation, land reclamation planning, and long-term stability assessment. AI models should not only ensure operational safety but also become essential tools for post-mining landscape management and ecosystem restoration.

5. Conclusion

This study provides a structured and up-to-date review of artificial intelligence (AI) applications in predicting mining-induced ground deformation, including subsidence and landslides. Based on the systematic assessment of 42 peer-reviewed studies published between 2010 and 2025, the following key findings and future directions are established:

5.1. Scope and methodological coverage

The study comprehensively analyzes recent AI-based approaches for deformation prediction, focusing on data sources, AI model types (machine learning, deep learning, and hybrid models), evaluation metrics, and practical implementation aspects. The results highlight the rapid evolution of AI techniques in this research domain.

5.2. Performance of AI methodologies

Machine learning: Traditional ML models (e.g., ANN, SVM, RF, and XGBoost) demonstrate superior capability in handling complex non-linear relationships, often outperforming conventional empirical and statistical methods.

Deep learning: Advanced architectures such as CNN, LSTM, and ConvLSTM excel in extracting spatio-temporal features, particularly when integrated with remote sensing and continuous monitoring data (e.g., InSAR, GPS).

Hybrid models: The integration of AI with optimization algorithms, multi-sensor data fusion, and explainable AI (XAI) frameworks significantly enhances both prediction accuracy and model interpretability.

5.3. Identified challenges and limitations

Site specificity: Most current models are tailored to specific geological conditions, which limits their generalizability across different mining environments.

Data dependencies: There is a high reliance on large, high-quality datasets and a notable lack of extensive cross-validation in diverse scenarios.

5.4. Potential of hybrid AI frameworks

Hybrid models that integrate optimization techniques, multi-sensor data fusion, and explainable AI provide enhanced prediction accuracy and improved interpretability. Such frameworks represent a promising direction for supporting reliable and transparent deformation prediction in mining areas.

5.5. Future research directions

To advance the field toward more robust and operational early warning systems, future research should prioritize:

Innovative frameworks: Developing hybrid physics-informed AI models and multi-sensor data fusion techniques.

Transparency and reliability: Implementing explainable AI (XAI) and uncertainty quantification to improve stakeholder trust.

Standardization and open science: Creating standardized benchmark datasets and promoting open data to enhance model validation and generalization.

Operational integration: Focusing on real-time deployment to support proactive hazard mitigation and sustainable mine management.

In conclusion, although AI, particularly hybrid frameworks, exhibits transformative potential in predicting mining-induced deformation, its role in ensuring the safety and sustainability of mining operations depends on more extensive validation and seamless operational integration.

Ethical statement

The authors state that the research was conducted according to ethical standards.

Author contributions

Conceptualization: Minh Tuyet Dang (Minh T.D); **Methodology**: Long Quoc Nguyen (Long Q.N); **Data collection:** Dung Ba Nguyen (Dung B.N); **Data analysis**: Long Q.N: **Writing original manuscript (draft)**: Minh T.D, Long Q.N; **Reviewing original manuscript**: Minh T.D, Dung B.N; **Figures and charts:** Dung B.N; **Improving manuscript (revision stage)**: Minh T.D; **Other contributions**: Dung B.N. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

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