Proceedings of the 21st ICSMGE, Vienna, Austria, 14 – 19 June 2026. Pistrol, Adam & Schweiger (eds.)
Published by: ÖGG, Austrian Society for Geomechanics, Salzburg, Austria, ISBN 978-3-9503898-4-5
https://doi.org/10.53243/ICSMGE2026-505

Integration of machine learning and physics-based approaches to analyse the stability of flooded mine shafts during geothermal heat extraction.

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ABSTRACT: Geothermal energy harvesting from underground mines has gained considerable attention over the years, offering a new purpose for many mines once they are decommissioned. When a mining operation ends, either permanently or temporarily, some underground mines may flood, filling with mine water which could be ideal candidates for geothermal heat extraction from mine water. However, during heat extraction, thermal and mechanical stresses in the rock mass can impact the stability of the mine shaft, affecting continuous operations. This study aims to integrate Machine Learning (ML) and physics-based modelling to improve stability analysis of mine shafts during geothermal heat extraction, aiming to develop a shaft stability classification. A training dataset combining geomechanical principles was developed and four supervised ML models were trained to predict the shaft risk category based on the input features. The models were tested with field data from literature, and the results highlight that ML hybrid models can be used as a preliminary assessing tool enabling early screening of sites with favourable stability conditions.

KEYWORDS: Geothermal Energy, Hybrid Models, Machine Learning, Mine shafts, Mine water.

1 INTRODUCTION

The transition toward sustainable and renewable energy sources has become a global necessity (Gielen et al. 2019). Among various emerging technologies, mine-based geothermal systems have gained increasing attention due to their potential to harness low-grade geothermal energy from abandoned and flooded mine workings (Chu et al. 2021). These flooded shafts are typically considered environmental and safety liabilities. The behaviour of flooded mineshafts during mine water heat recovery is not yet fully understood, especially when water with changing temperatures is reinjected into the system (Ng et al. 2019). Therefore, it is important to view these mineshafts as potential sources of renewable energy and thermal energy storage, while also carefully analysing their structural stability under different thermal conditions.

Mine shafts can be converted into geothermal systems using either open-loop (Figure 1(a)) or closed-loop (Figure 1(b)) configurations, each with distinct advantages and limitations (Hall et al. 2011; Loredo et al. 2016). Closed-loop systems, where heat is transferred via a sealed water-antifreeze loop in contact with stationary mine water, are suitable for sites with contaminated water (Hall et al. 2011; Loredo et al. 2016; Lund et al. 2004). In contrast, open-loop systems, which pump mine water to the surface for heat extraction before reinjection or discharge, offer higher energy yields but involve greater challenges in water treatment, legal compliance, and shaft stability due to continuous temperature and flow changes (Chu et al. 2021; Loredo et al. 2016; Hall et al. 2011). Their efficiency depends heavily on mine water quality and quantity.

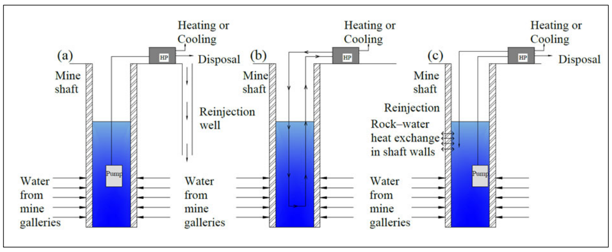

Figure 1. Geothermal heat pump loop configurations using flooded mine shafts (a) Open loop (b) Closed loop (c) Standing column (adapted from (Ng et al. 2019)).

Loop design also influences system performance: U-tube loops are easy to install but less efficient, while helical coils provide a larger surface area for improved heat transfer (Javadi et al. 2019). Coaxial loops can reduce drilling costs and simplify installation due to their smaller borehole diameter for the same flow rate. Standing column systems (Figure 1(c)), which circulate groundwater within the shaft, offer high thermal output but require reliable water quality and moderate flow rates to prevent clogging or fouling (Nguyen et al. 2012).

Despite growing interest in mine water geothermal systems, there is a lack of research focused on the stability of long abandoned and repurposed mine shafts, particularly in the context of their use for thermal energy recovery. Most existing studies overlook the need for a simple, performance-based design framework that can assess the structural behaviour of these shafts under changing thermal and hydraulic conditions. This study aims to address this gap by investigating the stability of flooded mine shafts and proposing a physics-inspired ML approach to support more reliable and data-driven design and decision-making for their safe and effective reuse.

2 BACKGROUND

2.1 *Factors affecting mine shaft stability*

Mine shaft stability is primarily governed by in-situ stress conditions, rock mass anisotropy, and geological complexity. Circular shafts lined with concrete are widely used due to their capacity to withstand uniform external pressures and their durability, including fire and airflow resistance. Key design considerations include lining thickness, rock and hydrostatic pressures, shaft diameter, and the physical properties of support materials. Thick-walled cylinder models are typically used for analysis (Chan and Beus 1985).

In elastic rock, support may not be required, but in plastic conditions, linings are essential to control ground movement and prevent failure (Ozturk and Guler 2016). Long-term deterioration due to weathering, chemical degradation, corrosion, and thermal cycling can weaken shaft linings, particularly in flooded or acidic environments (Salmi et al. 2019). Monitoring tools such as extensometers and pressure cells are used to evaluate deformation during construction and operation. Walton et al. (2018) used extensometer data to study the stability of various shaft geometries, noting that radial deformation tends to decrease with distance from the shaft wall.

2.2 *Evaluation of mine shaft stability for potential reuse*

Repurposing mine shafts for geothermal or energy-storage applications requires accurate stability assessment supported by empirical, analytical, numerical, and data-driven techniques. Traditional analytical tools, such as elastic theory, thick-walled cylinder models, and failure criteria like Mohr-Coulomb and Hoek-Brown assist with early stress evaluation, while empirical systems (RMR, Q-system, GSI) support preliminary classification when data are limited. Advanced numerical methods, including FEM, FDM, BEM, DEM, and hybrid simulations, model complex mechanical and hydrogeological interactions; however, these methods can be computationally expensive and challenging to implement for large parameter spaces or long-term behaviour.

Hybrid physics-ML approaches overcome the limitations of purely data-driven and purely physics-based models. While ML models rely heavily on large datasets and lack physical interpretability, and physics-based models struggle with nonlinear, site-specific behaviour, the hybrid method integrates both strengths. This reduces computational effort, improves generalisation, and more accurately captures the mechanisms governing shaft stability, enabling safer and more reliable repurposing of mine shafts for geothermal and energy-storage applications.

3 METHODOLOGY AND MODEL DEVELOPMENT

3.1 *Data generation and analysis*

A physics-based synthetic dataset was created for circular mine shafts, grouping configurations into Low, Medium, and High risk categories. The dataset incorporates intact rock strength (σ_{ci} (MPa)), GSI, unit weight of rock (γ_{rock}(kN/m³)), Hoek–Brown constant (m_i), shaft radius (r_{shaft}(m)), lining thickness (t_{lining}(m)), concrete uniaxial compressive strength (UCS) (f_c (MPa)), degradation rates above (α_{above}) and below (α_{below}) the water table, rock relaxation (ΔP_{relax}(MPa)), water table depth (H_{water}(m)), shaft depth (H (m)), and shaft age (Age_{shaft}(years). Figure 2 presents the histograms of these parameters (a) - (m) respectively, along with the Factor of Safety (FOS) distribution (n), highlighting the variability and balanced representation of conditions used for training the ML models in this study.

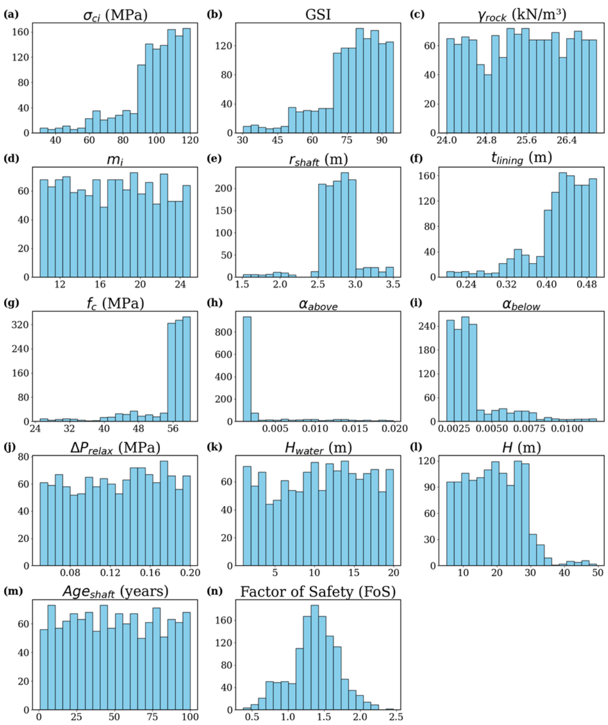

Figure 2. Histograms of shaft parameters and FOS (a) Intact rock UCS (b) GSI (c) Unit weight of rock (d) Hoek–Brown constant (e) Shaft radius (f) Lining thickness (g) Concrete UCS (h) Degradation rates above (i) Degradation rates below (j) Rock relaxation (k) Water table depth (l) Shaft depth (m) Shaft age (n) FOS

These parameters collectively capture geometric dimensions, material strength, rock mass quality, environmental influences, and deterioration effects over time. A time-dependent model simulated concrete lining degradation and changing stress conditions over the lifespan of the shaft, accounting for soil pressure, hydrostatic pressure, seepage, and stress relaxation. Final FOS values, based on hoop stress and degraded tensile strength, were used to classify risk, where FOS > 1.8 was labelled as low risk, 1.2 < FOS ≤ 1.8 as medium risk, and FOS ≤ 1.2 as high risk.

3.2 *Model development*

The use of synthetic data was necessary to enable preliminary investigations, allowing us to explore model development, test performance, and examine potential patterns under controlled scenarios. Synthetic datasets provide flexibility to simulate a wide range of conditions that may not yet be captured in real-world datasets. Four supervised ML models were trained to predict the shaft risk category based on the input features, multinomial logistic regression, Random Forest, XGBoost, and a feedforward Artificial Neural Network (ANN). The model was trained using the scaled features and the multinomial loss function for predicting three classes. The model coefficients were examined to see how each feature contributes to the log-odds. This provides a clear baseline.

The Random Forest model with 200 estimators was used to identify non-linear patterns and to calculate impurity-based feature importance. XGBoost, a powerful gradient-boosting algorithm with effective predictive power, was trained on multi-class log loss and evaluated on frequency-based and gain-based feature importance. To enable better interpretation of XGBoost predictions, SHapley Additive explanations (SHAP) values were also computed to quantify the marginal contribution of every feature to all classes. All models were trained on the same synthetic dataset using standardised input features. Performance was evaluated using classification accuracy, confusion matrices, and consistency across training and validation datasets. The complete integrated workflow is summarized in Figure 3.

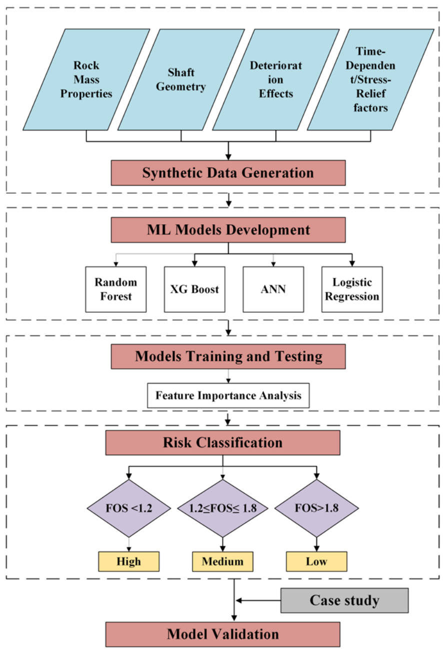

Figure 3. Workflow of the data-driven framework developed for evaluating mine-shaft structural stability.

4 RESULTS AND ANALYSIS

4.1 *Correlation analysis between input parameters and FOS.*

Correlation analysis between the calculated FOS and input parameters showed significant relationships (Figure 4). FOS was positively related to parameters such as intact rock strength (Figure 4 (a)), GSI (Figure 4 (b)), lining thickness (Figure 4 (f)) and concrete UCS (Figure 4 (g)) demonstrating their role in enhancing structural stability.

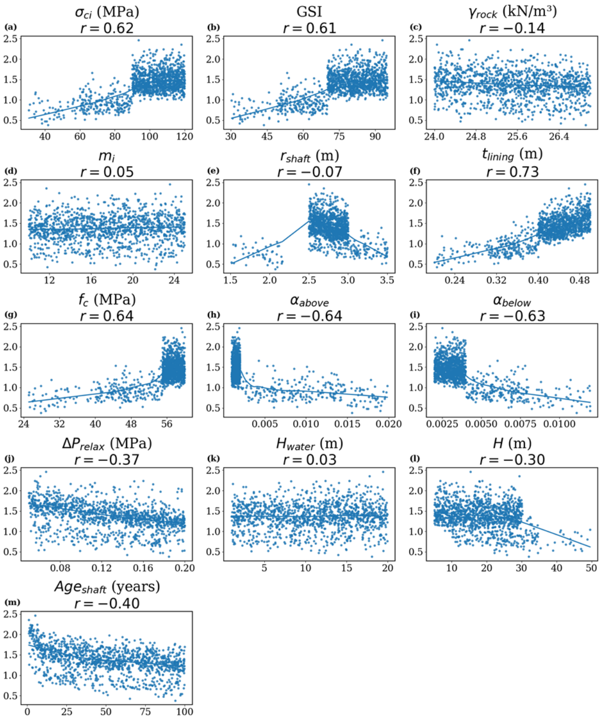

Figure 4. Regression plots between parameters and FOS (Pearson's r) (a) Intact rock UCS (b) GSI (c) Unit weight of rock (d) Hoek–Brown constant (e) Shaft radius (f) Lining thickness (g) Concrete UCS (h) Degradation rates above (i) Degradation rates below (j) Rock relaxation (k) Water table depth (l) Shaft depth (m) Shaft age

Degradation rates, those above (Figure 4(h)) and below (Figure 4(i)) the water table showed a strong negative correlation with FOS, highlighting the adverse impacts of long-term environmental and chemical degradation. This emphasises the need to take material durability and groundwater interaction into account when evaluating the long-term potential for repurposing of abandoned shafts.

The analysis indicates that shaft age, depth, and rock stress relaxation negatively affect stability. Older shafts experience material degradation, corrosion, or wear, reducing load-bearing capacity. Greater depths increase in-situ stresses and hydrostatic pressures, accelerating lining deterioration and rock deformation. Stress relaxation leads to loss of confinement, crack propagation, and potential instability. Conversely, the Hoek-Brown constant, water table height, and rock unit weight showed negligible influence within the analysed dataset.

4.2 *Comparative performance of machine learning models*

The classification models developed for predicting shaft risk categories achieved consistently high accuracy, particularly for the medium risk class, which was correctly identified in over 150 cases by all models. Predictions for the High category are generally accurate, although Random Forest (Figure 5(a)) and XGBoost (Figure 5(b)) exhibit slightly higher misclassification into the Medium category compared to Logistic Regression (Figure 5(c)) and ANN (Figure 5(d)). The Low category shows the weakest predictive performance across models, with frequent misclassification into Medium, suggesting possible class imbalance or overlapping feature space. Furthermore, ANN and Logistic Regression provide slightly better separation between High and Medium categories, whereas Random Forest and XGBoost show marginally greater confusion between these classes.

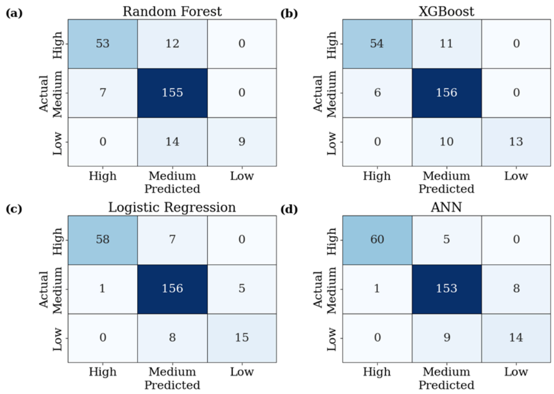

Figure 5. Confusion matrices for the test data of ML models used for shaft stability classification (a) Random Forest (b) XGBoost (c) Logistic Regression (d) ANN

4.3 *Feature importance across machine learning models*

Feature importance analysis Figure 6 was performed for each ML model to evaluate the contribution of individual input parameters to predictive performance. The Random Forest model identified shaft age, lining thickness, and concrete UCS as the most influential factors in classifying shaft stability. The XGBoost model similarly highlighted these parameters but also emphasised the importance of rock relaxation. Both Logistic Regression and the Artificial Neural Network indicated that lining thickness, rock relaxation, shaft radius and shaft age were the primary parameters driving their predictions.

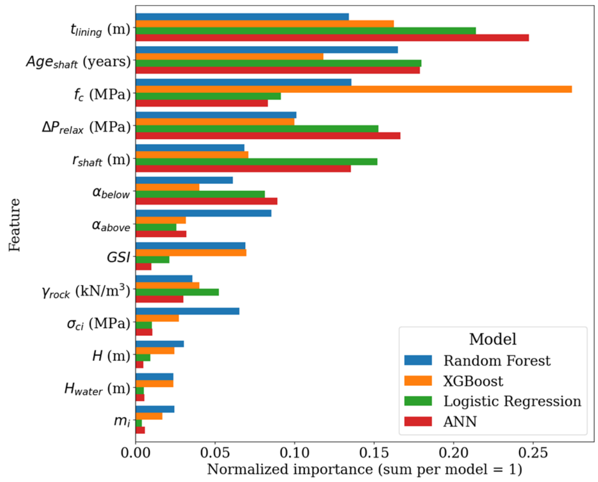

Figure 6. Normalized feature importance of parameters

5 VALIDATION AND DISCUSSION

To evaluate the applicability and reliability of the developed shaft risk classification models, it is essential to test the developed models with real-world data. This is because it corrects the biases and simplifications of physics-based synthetic data, ensuring the model reflects true real-world behaviour rather than the assumptions of the simulation.

The model was validated using a real-world case study from Kaya and Tarakçi (2021), involving a 220 m-deep service shaft with a 2.6 m diameter and groundwater approximately

10 m below the surface. Parameters were also sourced from Sun et al. (2018), who analyzed deformation mechanisms and shaft lining stress in alternating hard and soft rock at the 1008 m deep, 6 m diameter auxiliary shaft of AN JU Mine, China, using three-dimensional numerical modelling.

In preparing the validation dataset, key geotechnical parameters, intact rock strength, GSI, unit weight of rock, and the Hoek–Brown constant were sourced directly from the publication and applied without modification to preserve the realism of the ground conditions. Parameters not reported in the study, including shaft age, rock relaxation pressure, and degradation rates above and below the groundwater level, were estimated based on typical ranges reported in the literature to fulfil the model input requirements.

The trained models, Random Forest, XGBoost, Logistic Regression, and ANN, were each tested against this field-based dataset. The confusion matrices (Figure 7) reveal significant variations in model performance. Both Random Forest (Figure 7(a)) and XGBoost ((Figure 7(b)) accurately classified all 12 'High' instances, while Logistic Regression (Figure 7(c)) and ANN (Figure 7(d)) incorrectly labeled 2 of these as 'Medium'. Therefore, Random Forest and XGBoost appear to be the most dependable models in this situation, whereas Logistic Regression and ANN might need additional tuning to minimize the misclassification between 'High' and 'Medium' categories.

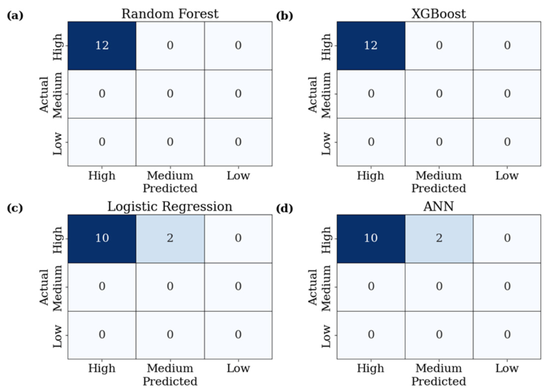

Figure 7. Confusion matrices comparing classification performance of four ML models on validation dataset (a) Random Forest (b) XGBoost (c) Logistic Regression (d) ANN

For engineers and regulators looking to repurpose water-filled abandoned mine shafts for geothermal energy extraction, hybrid physics-based and data-driven models provide critical support by predicting shaft stability, degradation, and failure risk. They enable rapid screening of suitable shafts using geotechnical, hydrogeological, thermal, and structural parameters, build confidence in feasibility and safety, and when combined with real-time monitoring allow continuous risk assessment and early-warning systems. These models also offer quantitative guidance for design decisions, including reinforcement, pumping strategies, heat-exchanger placement, and cost-effective installation.

6 CONCLUSIONS

A data-driven framework was developed to assess the structural integrity of abandoned mine shafts for geothermal heat extraction, incorporating synthetic data that reflects geomechanical degradation and seepage effects. The main conclusions of the study are:

- Lining thickness, shaft age, concrete UCS, shaft radius and rock relaxation emerged as the most influential factors in shaft stability from all the predictive models.
- Random Forest and XGBoost models give high performance whereas Logistic Regression and ANN need need additional tuning to minimize the misclassification between 'High' and 'Medium' categories.
- Field data validation confirmed the reliability and scalability of the framework for forecasting long-term shaft stability in geothermal applications.

Therefore, the proposed approach offers a reliable and scalable tool for long-term shaft integrity analysis.

7 LIMITATIONS AND FUTURE WORK

This study uses a hybrid physics-ML approach, combining geomechanical principles with hydrostatic loading, seepage, and rock relaxation, across diverse geological and design scenarios. Limitations include simplified lining-rock interactions, empirical degradation assumptions, and exclusion of full 3D effects. Initial validation was promising, but wider testing and inclusion of additional parameters and field data are needed to enhance accuracy and applicability.

8 ACKNOWLEDGEMENTS

This work was supported by the Australian Research Council (ARC) under the Discovery Early Career Researcher Award (DECRA) scheme DE240100204.

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