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Using Machine Learning to Model Mechanical Processes in Mining: Theory, Practice, and Legal Considerations

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Abstract

Artificial intelligence (AI) technologies, though critical for economic development, also pose risks of unpredictable outcomes and loss of control. Thus, a legal framework is necessary to regulate their use. International and state oversight is required to establish clear rules of conduct for all parties involved in AI relations, ensuring these technologies remain human-oriented and secure. In geological studies, AI can enhance the accuracy of predictions, such as improving the understanding of rock behavior during drilling. Machine learning methods, including linear regression and gradient boosting, have proven effective in predicting the mechanical properties of rocks, which helps optimize drilling operations and minimize risks like equipment damage. However, models must be fine-tuned to account for more complex dependencies, such as mineralogical characteristics. Despite the effectiveness of AI, challenges remain, including the need for high-quality data and the potential for overfitting in some methods. Incorporating AI studies into the geological code is crucial for effectively managing these technologies. By enhancing transparency, security, and accountability in AI systems, governments can mitigate risks while fostering innovation. In geology, AI's potential for reducing drilling costs and improving safety, as well as its application to other areas like mining and construction, will drive significant advancements in scientific and industrial fields.

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1. Introduction

Over the past half-century, the global community has entered an era of rapid development of research methods using machine learning (ML) and artificial intelligence (AI). Their use has opened new prospects for solving complex problems in various fields of science and technology, including the study of the Earth in general and geomechanical processes in rocks in particular. This trend is not accidental, since such technologies allow for a more accurate consideration of the discrete structure of rocks, mineralogical composition, texture, porosity, and other factors affecting their mechanical properties.[1,2]

Moreover, the use of AI allows for predicting the behavior of rocks in fracture problems based on their mineralogical composition and structural heterogeneity,[3-5] which significantly improves the accuracy of modeling compared to traditional approaches.[6]

Prediction of the mechanical behavior of rocks is one of the fundamental problems of geomechanics and engineering geology.[7-10] This is explained by the fact that these rocks, characterized by a complex mineralogical structure, a high degree of heterogeneity, and anisotropy, present significant challenges for accurate modeling.[11-14] At the same time, classical methods based on continuum mechanics often do not fully consider the discrete nature of rocks, which leads to limited accuracy of predictions when applied to real geotechnical problems.[15,16]

However, introducing any innovations into the research environment requires a serious assessment of the legal

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consequences associated with the regulation of mining and geological relations and the AI field.[17-26] The latter, as announced in the so-called Blietchley Declaration, poses a potentially catastrophic danger to humanity, so such fast-growing technologies must comply with the principles of human-centricity, reliability, safety, and responsibility in approaches to the use of AI. In addition, the AI Regulation (Artificial Intelligence Act), adopted on March 13, 2024, in the European Union (EU), is designed to ensure safety and respect for the rights of citizens when using AI.

Thus, the main objective of the presented study is to study the use of AI technologies for modeling the predicted properties and processes of rock destruction. The rationale for this choice is the theoretical and applied position, according to which such modern AI algorithms as ML and neural networks make it possible to consider complex and nonlinear dependencies between various physical and mechanical parameters of rocks, for example, mineralogical composition, density and porosity, as well as their behavior under mechanical loads. Unlike most known methods, AI-based approaches are able to adapt to changes in destruction conditions in real time, which allows for increasing the efficiency of drilling operations and reducing operating costs.[27-31]

The purpose of this paper is to consider legal caveats and compare the results of methods for modeling mechanical processes in rocks based on the synthesis of ML and AI methods. To achieve the set goal, the following tasks are envisaged:

- assessment of the state and prospects of legal support for the use of geological AI technologies;
- review of the use of models for predicting the strength of rocks based on data on the mineralogical composition, texture, porosity, and other characteristics;
- comparative analysis of individual ML methods (linear and polynomial regression) and ensemble learning methods (random forest, gradient boosting).

2. Literature review

The mechanical behavior of solids such as rocks is a challenging problem for mathematical modeling due to their discrete structure.[32-37] Rocks consist of many crystallites, grains, and fragments, which significantly complicates the prediction of their behavior under the influence of external forces such as the load from a drilling tool. Traditional continuum-based models cannot accurately account for the influence of microscopic features such as rock texture and microstructure, as well as the interaction between mineral grains. These features lead to inaccurate results when modeling fracture and deformation processes under real drilling conditions.[38-43]

The mineralogy and structural heterogeneity of rocks play a critical role in the drilling process. Different minerals have different effects on the mechanical properties of rocks, such as strength, fracturing, and wear. For example, rocks composed mainly of quartz have high strength, while clayey or carbonate rocks may be more susceptible to failure under the action of a drilling tool.[44-50] Structural heterogeneity, including differences in porosity, layering, and water saturation of rocks, also has a significant impact on the behavior of the material during drilling. These characteristics can cause unpredictable changes in the rate of rock failure, cuttings formation, and other aspects of the drilling process, which complicates the problems of prediction and optimization.[51–54]

To build effective drilling models using AI, various geological and physical-mechanical parameters of rocks are used. The main data required for the analysis include the mineralogical composition, density, porosity, and strength of rocks. The mineralogical composition affects the mechanical properties of rocks, such as shear strength and fracturing.[55,56] Density and porosity are key characteristics for predicting the behavior of rocks during drilling, since they determine the ability of the rock to penetrate fluid, as well as its resistance to fracture.[47-49] The strength of rocks, in turn, is closely related to their mechanical behavior under the influence of a drilling tool.[50-55]

Various ML models are used to analyze data and predict the mechanical behavior of rocks during drilling. One of the main methods is linear regression (LR) and polynomial regression (PR), which allows identifying relationships between various physical parameters and characteristics of rocks. Neural networks, deep neural networks (DNN), which are capable of processing complex data and identifying nonlinear relationships between input and output parameters, are also actively used. Ensemble methods, such as random forest (RF) and gadient boosting (GB), have also found wide applications, as they provide high accuracy of predictions by combining many weak models.[56-58]

AI algorithms are used to optimize drilling parameters such as drilling speed, drilling tool pressure, drilling fluid circulation rate, and other factors. AI can also predict changes in drilling conditions and adapt parameters in real time, which can improve the efficiency of drilling operations.[59,60]

To test the hypotheses formulated based on AI models, laboratory tests are conducted on rock samples. These tests use standard methods of destruction, such as compression and tension tests, as well as crack formation tests. These experiments not only test theoretical calculations, but also obtain new data for further training of AI models. Particular attention is paid to studying the dynamics of rock destruction

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under various loads, which is important for predicting their behavior during drilling.[61-65]

To evaluate the accuracy of AI models, test data obtained from experiments and data from real boreholes are used. These data include both geophysical parameters and information on the mechanical behavior of rocks during drilling.[66,67] Verification of the accuracy of predictions involves comparing the results obtained using AI with actual drilling data, which allows one to evaluate the effectiveness of the model and adjust it to improve the accuracy of predictions.[68-70]

The above information on various approaches to modeling mechanical processes in rocks indicates, firstly, significant scientific interest and relevance of the problem under consideration. Secondly, despite the fairly high number of publications, it should be recognized that most of them did not aim at a systematic review and comparative analysis of the results of modeling mechanical processes in rocks, carried out using the synthesis of ML and AI methods. Thirdly, as the analysis of sources showed, issues related to legal precautions when conducting geological AI research have not yet been raised in scientific papers.

3. Materials and methods

3.1 Methods of studying the legal basis for geological AI activities

In assessing the status and prospects of legal support for the use of geological AI technologies, general scientific and special research methods were used. In particular, the methods of deduction and induction, analysis and synthesis, and abstraction and generalization were chosen as the main methods of cognition used in jurisprudence. Special scientific research methods belonging to the methodological basis of legal science were used in the process of analyzing the provisions of legislation, legal facts, objects, and phenomena, as well as in presenting Section 1.

The introduction should briefly place the study in a broad context and highlight its importance. It should define the purpose of the work and its significance. The current state of the research, such as RF and GB.

3.2 Methodology for approximating the dependence of drilling speed on compressive strength

3.2.1 General provisions

The process of approximating the relationship between compressive strength and drilling speed for rocks is considered using LR, PR, RF, and GB models. These methods allow for modeling complex nonlinear relationships and predicting drilling speed depending on the physical characteristics of the rock, which is essential in engineering geology and drilling operations.[71,72]

The objective of this stage of the work is to create a predictive model for drilling speed based on the known compressive strength of the rocks.

3.2.2 Preparation of initial data

The data that models the rock composition includes the following six attributes: clay (%), quartz (%), feldspar (%), clay minerals (%), average particle size (μm), and heterogeneity index.

Based on these data, the compressive strength dependence is calculated. The formula for calculating compressive strength is as follows in Eq. (1):

$$\sigma(\text{МПа}) = \beta_1 \cdot \text{Clay} + \beta_2 \cdot \text{Quartz} + \beta_3 \cdot \text{Feldspar} + \beta_4 \cdot \text{Clay\_minerals} + \beta_5 \cdot \text{Average\_particle\_size} + \beta_6 \cdot \text{Homogeneity\_index} + \epsilon \quad (1)$$

where ϵ is a random error with a normal distribution.

3.3 Models

ML methods have been increasingly applied in geological prediction research. LR and PR are common ML methods that process the linear relationships of the rock characteristics.[73] RF and GB are ensemble ML methods that allow more efficient modeling of nonlinear relationships.[74,75]

3.3.1 LR

To begin with, an LR model is constructed, which assumes a linear relationship between compressive strength and drilling speed using Eq. (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \quad (2)$$

where y is the target variable (compressive strength), $x_1, x_2, \ldots, x_n$ are the features (minerals, particle size, heterogeneity index, *etc.*), β_0 is the free term, $\beta_1, \beta_2, \ldots, \beta_n$ are the regression coefficients, and ϵ is the model error.

3.3.2 PR

To improve the accuracy of the model, PR is used.[73] Polynomial features are created for the original variables, for example, for the quadratic and interaction terms as shown in Eq. (3):

$$X_{\text{poly}} = [1, x_1, x_2, x_3, x_1^2, x_2^2, x_3^2, x_1 x_2, x_1 x_3, x_2 x_3] \quad (3)$$

where X_{poly} are the new polynomial features, and x_1, x_2, x_3 are the original features.

3.3.3 RF

RF is an ensemble ML method that uses multiple decision trees to improve prediction accuracy. It is based on the bagging principle (bootstrap aggregating), which helps reduce model variability and overfitting problems.[74,75]

Let $D = \{(x_i, y_i)\}_{i=1}^{N}$ be a training set, where x_i are the features, and y_i is the target variable.

Decision M trees are trained where each tree T_j uses a subsample $D_j \subset D$.

For each decision tree $T_j(x)$ returns a prediction for the input x. In the case of a regression problem, the final prediction $\hat{y}(x)$ is obtained by averaging the predictions of all trees in Eq. (4):

$$\hat{y}(x) = \frac{1}{M}\sum_{j=1}^{M} T_j\,(x) \tag{4}$$

In the case of a classification problem, the final prediction $\hat{y}(x)$ is determined by a majority vote Eq. (5):

$$\hat{y}(x) = \text{mode}\big(T_1(x), T_2(x), \dots, T_M(x)\big) \tag{5}$$

where mode is the most frequent value among the predictions of all trees.

Using random subsamples to build trees and randomly selecting a subset of features for each node helps reduce overfitting because trees cannot depend heavily on the same information and do not "remember" the training data.

3.3.4 GB

GB is a method that builds a series of weak models (usually decision trees), where each subsequent model attempts to correct the errors of the previous ones. This is a method of alternating learning, where each model optimizes the error of the previous one.[76]

For a regression problem, the target variable y is predicted as the sum of the weak models' outputs in Eq. (6):

$$\hat{y}(x) = f_0(x) + \sum_{m=1}^{M} \nu_m\, f_m(x) \tag{6}$$

where $f_0(x)$ is the initial model (usually the mean value), $f_m(x)$ is the m-*th* weak model (decision tree), and ν_m is the coefficient that determines the weight of each step in the learning process.

For each new model $f_m(x)$, the gradient descent error is minimized using Eq. (7):

$$f_m(x) = \underset{f}{\text{argmin}} \sum_{i=1}^{N}\big[L\big(y_i, \hat{y}_{i,m-1}\big) + \gamma \cdot \Omega(f)\big] \tag{7}$$

where $L\big(y_i, \hat{y}_{i,m-1}\big)$ is the loss function (*e.g.*, the mean squared error for regression), $\Omega(f)$ is the regularizer that prevents the model from overfitting.

In each iteration, we update the prediction using the gradient of the loss function, which helps reduce the error. GB involves two key aspects to prevent overfitting: adding a regularization term $\Omega(f)$, which penalizes models with high complexity, and a coefficient ν, which controls how much each new model contributes to the overall prediction. Lower values ν reduce the chance of overfitting.[77]

3.4 Calculation of drilling speed

To improve the accuracy of the formula for the dependence of drilling speed on compressive strength, additional parameters can be considered,[78-80] such as:

(1) Rock strength: A linear decrease in drilling speed with increasing strength may not be sufficient. A logarithmic relationship or other nonlinear function often more accurately describes this relationship.

(2) Type of drilling equipment and operating mode: It is necessary to include parameters such as weight on the drill bit, rotation speed, and hydraulic parameters.

(3) Composition of drilling mud: Viscosity and density can significantly affect drilling efficiency.

To calculate the drilling speed, we use a function of the following Eq. (8):

$$v = v_{\max} \cdot e^{-k\cdot\sigma} + \epsilon \tag{8}$$

where v is the drilling speed (m/h), $v_{\max}$ is the maximum drilling speed at low strength, (m/h), σ is the compressive strength (MPa), k is the coefficient reflecting the influence of strength on speed (depends on drilling conditions), and ϵ is the random noise to account for errors and instabilities.

Eq. (8) allows one to realistically describe the decrease in drilling speed with increasing strength,[81,82] considering the nonlinear nature of the dependence.

3.5 Evaluation of the quality of the model

The quality of the model is assessed using the mean square error (MSE), which is calculated using Eq. (9):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

where y_i are the actual values, $\hat{y}_i$ are the predicted values that a model estimates or forecasts based on the given input data, and n are the number of observations.

3.6 Data visualization and models

To demonstrate the relationship between actual and predicted drilling speed values, a graph is created. It displays actual values as blue dots, allowing the original data to be visualized. For the predicted values, lines from two models are added: linear regression (orange line) and polynomial approximation (green line).

Each model has its own formula, which is also displayed on the graph. For example, for LR, this is an equation of the form $y = ax + b$, and for PR, it is $y = a_3x^3 + a_2x^2 + a_1x + a_0$. These formulas help to understand how the models describe dependence. The numerical values of the coefficients are calculated in advance and show the exact behavior of the function.

Comparing the lines to the actual data provides insight into the accuracy of the models. If the green line (polynomial) fits the points better, it indicates a nonlinear relationship that the linear model cannot describe. This approach makes the analysis more understandable and visual.

Python is used to plot the graph, and the data is visualized using libraries such as Matplotlib. Such analysis helps to identify the model that most accurately describes the experimental data.

4. Results and discussion

4.1 Results of modeling compressive strength

The data includes chemical composition and other characteristics of the material, as well as the compressive strength prediction obtained using various regression methods (LR, PR, RF and GB).

This study explores the use of machine learning to predict compressive strength and drilling speed of materials based on their physical properties. The dataset consists of synthetic data generated for various features that influence these material properties, such as clay, quartz, and feldspar content, particle size, and homogeneity index. ML models were employed to predict compressive strength and drilling speed based on these features, providing insight into material behavior under mechanical stress.

4.2 Programming language and environment

The entire analysis was performed using Python in a Google Colab environment. Google Colab provides an interactive and cloud-based platform for running Python code, which is particularly useful for data science and machine learning tasks. The platform supports Python, and by using Jupyter notebooks, we were able to easily implement, visualize, and share the ML models and their results.

4.2.1 Libraries and frameworks used

To perform the analysis, we utilized several powerful Python libraries, including:
Numpy: for numerical operations and generating random data.
Pandas: to structure the dataset and facilitate data manipulation.
Sklearn (scikit-learn): this library was used extensively for building and training ML models, including LR, PR, RF, and GB regression models. Additionally, it was used for splitting the dataset and evaluating the models.
Matplotliband seaborn: for data visualization, these libraries helped in plotting the results and visualizing model performance through graphs and charts.

4.2.2 Data generation and feature engineering

The synthetic dataset consists of 1,000 samples where each sample has several features (Table 1): clay content (%); quartz content (%); feldspar content (%); clay mineral content (%); average particle size (µm); homogeneity index.

Table 1: Example initial data.

Sample	Clay (%)	Quartz (%)	Feldspar (%)	Clay minerals (%)	Average particle size (µm)	Heterogeneity index	Compressive strength (MPa)
1	44.98	15.55	8.93	11.73	5.76	0.39	18.93
2	68.03	26.26	8.70	12.97	8.07	0.47	40.11
…	…	…	…	…	…	…	…
100	36.24	34.20	9.08	10.72	1.58	0.87	17.39

The target variable, compressive strength, was calculated as a weighted sum of these features, with each feature influencing the strength to a varying degree. The drilling speed was assumed to be inversely proportional to compressive strength.

4.3 Modeling compressive strength

LR (Fig. 1): The first model applied was linear regression, which assumes a linear relationship between the input features and the target variable. This model was implemented using:
(1) sklearn.linear_model.LinearRegression for fitting the linear model.
(2) sklearn.model_selection.train_test_split to split the data into training and testing sets.
(3) sklearn.metrics.mean_squared_error for evaluating model accuracy by calculating the MSE.

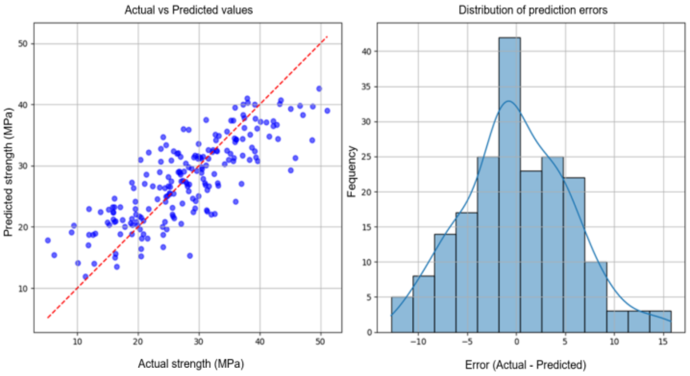

Fig. 1: Modeling of rock strength prediction using the LR method.

PR (Fig. 2): To capture more complex relationships, we extended the linear regression model by adding polynomial features (degree 2). This allowed the model to account for interactions between features. The polynomial features were generated using:
(1) sklearn.preprocessing.PolynomialFeatures to create higher-order terms of the features.
(2) sklearn.linear_model.LinearRegression for training the polynomial regression model.

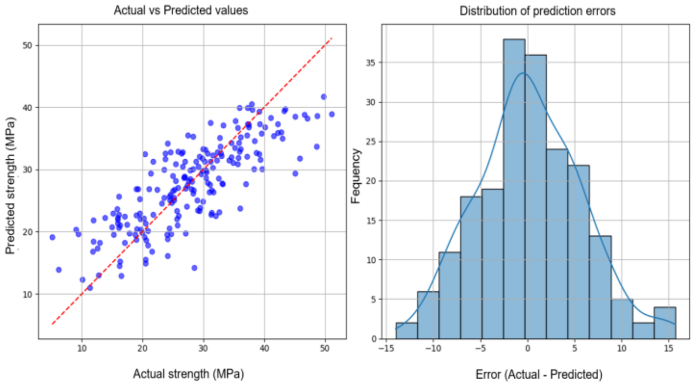

Fig. 2: Modeling of rock strength prediction using the PR method.

RF regression (Fig. 3): An ensemble method that builds multiple decision trees and averages their predictions. It's particularly useful for capturing non-linear relationships in the data. The RF was implemented with: sklearn.ensemble.RandomForestRegressor for creating and training the random forest model.

GB regression (Fig. 4): GB regression builds trees sequentially, each one trying to correct the errors of the previous one. This method is highly effective for complex data patterns. It was implemented using sklearn.ensemble.GradientBoostingRegressor for the boosting model.

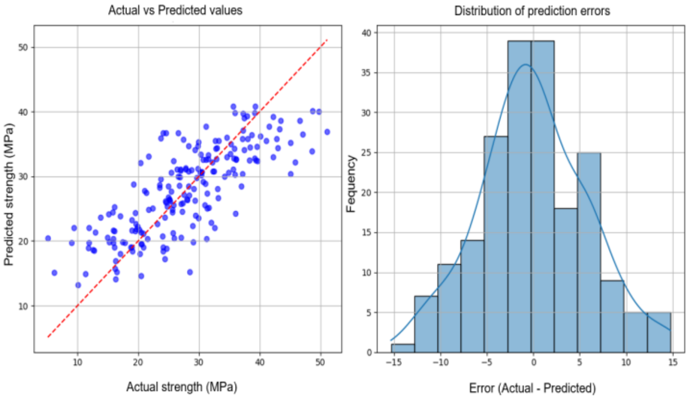

Fig: 3: Modeling of rock strength prediction using the RF regression method.

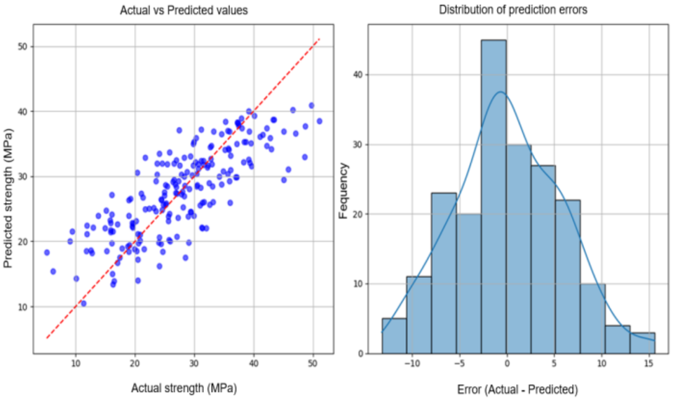

Fig. 4: Modeling of rock strength prediction using the GB regression method.

The comparison of actual and predicted strength for different regression methods is presented in Table 2.

4.4 Predicting drilling speed

For drilling speed, we used the predicted compressive strength from the models to build a secondary regression model. The linear regression model predicted drilling speed based on compressive strength, assuming an inverse relationship between the two (Fig. 5). This model was implemented using sklearn.linear_model.LinearRegression for predicting drilling speed.

Fig. 5 shows the relationship between compressive strength and drilling rates. To test the accuracy of the model, LR was used to predict drilling rates because of its simplicity and interpretability. LR provides a straightforward and interpretable relationship between compressive strength and drilling speed. The inverse relationship aligns well with theoretical expectations, and LR offers a simple yet effective baseline model for prediction. The relationship between compressive strength and drilling rates is presented in Table 3.

Table 2: Example of prediction results.

Model	Actual strength (MPa)	Predicted strength (MPa)	Discrepancy, %
LR			
1	21.32	28.57	-33.96
2	35.86	34.52	3.74
…	…	…	…
100	34.581	35.57	-2.86
PR			
1	21.32	29.35	-37.61
2	35.86	34.33	4.27
…	…	…	…
100	34.58	34.25	0.96
RF			
1	21.32	27.47	-28.80
2	35.86	34.27	4.43
…	…	…	…
100	34.58	36.00	-4.10
GB			
1	21.32	26.78	-25.61
2	35.86	34.14	4.80
…	…	…	…
100	34.58	36.54	-5.67

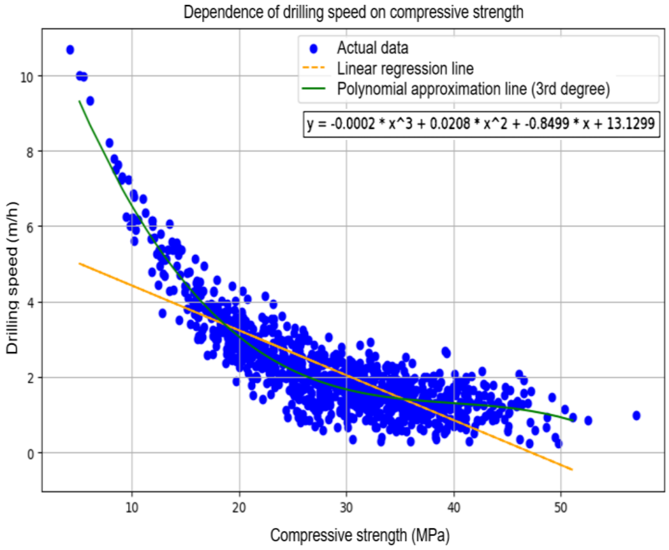

Fig. 5: Testing predicting drilling speed using LR.

Table 3: Relationship between compressive strength and drilling rates.

Compressive strength (MPa)	Actual speed (mph)	Predicted speed (mph)
18.93	1.93	2.08
40.11	0.08	0.34
…	…	…
17.39	0.81	0.50

4.5 Model evaluation and visualization

Each model was evaluated using MSE, a standard metric for regression tasks. matplotlib and seaborn were used for visualizing the predictions, including plotting actual vs.

predicted values and analyzing the error distribution. These visualizations helped assess model performance and interpret the results. The MSE values were 29.62 for LR, 30.14 for PR, 33.37 for RF, and 31.91 for GB (Table 4).

Table 4: Visual comparison of the MSE values.

Model	MSE
LR	29.62
PR	30.14
RF	33.37
GB	31.91

The model demonstrated adequate ability to predict drilling speed considering the relationship with compressive strength. Despite small deviations, the model effectively describes trends and can be improved by considering additional factors such as drilling equipment parameters and drilling fluid characteristics.

4.6 Analysis of simulation results

LR showed the slightest error among all the models tested. This indicates that the relationships between compressive strength and drilling speed are predominantly linear. However, small deviations in the predictions may indicate the simplification of complex nonlinear processes that this model does not consider.

Despite the inclusion of additional degrees of variables, PR showed a worse result than the linear model. This may be due to overfitting the given data or the absence of significant nonlinear patterns. This result indicates that complicating the model in this case is inappropriate.

The RF model showed the highest error, indicating that it is prone to overfitting and is overly sensitive to noise in the data. Despite the model's ability to handle complex nonlinear relationships, it was less effective for this dataset.

GB demonstrated a balanced approach, losing to linear regression in accuracy but showing the best results among ensemble methods, confirming its ability to adapt to complex data patterns without losing generalization ability.

Analysis of the modeling results revealed significant differences in the accuracy of the different approaches. Linear regression showed the best performance, providing the lowest mean squared error. This makes it the optimal choice for this data set, especially if the simplicity and interpretability of the model are essential.

Although GB is inferior to linear regression in accuracy, it demonstrates good results when working with more complex dependencies. This model will be especially effective with more complex data or further expansion with additional characteristics. Its use can be justified if the task requires considering nonlinear patterns.

On the other hand, RF has shown to be a less efficient option, with a higher error rate compared to other models. This is probably due to its tendency to overfit the available data, which reduces the generalization ability. Thus, its use in this case is limited.

The results of the analysis confirm the importance of choosing an appropriate modeling method based on the nature of the data and the objectives of the study.

4.7 Analysis of legal aspects of using AI in mining

AI technologies, as an object of legal regulation, have dualism of features that, on the one hand, are extremely important for economic growth and sustainable development and, on the other hand, have an unsafe potential for unpredictable achievements and the possibility of a person losing control over them. Therefore, this innovation cannot develop without any international and state supervision, which requires the presence of legally regulated rules of conduct for all interested participants in AI relations. In this situation, it is important to find a balance between the legal regulation of AI technologies and the need for their permanent development. In this regard, it is necessary to bring international cooperation to a new productive level that would allow overcoming AI risks and contribute to the fact that AI design, AI development, AI implementation, and AI use are carried out by the relevant entities in a safe way, that is, in a way in which AI technologies will be human-oriented, reliable, safe and provide for liability for negative consequences. Thus, the state AI policy should provide for measures that allow:

- detect, identify, classify and/or categorize AI risks;
- ensure an assessment of the content of the AI systems market;
- form a toolkit for checking and monitoring the security, transparency and accountability of AI subjects and AI objects;
- conduct a preliminary assessment of the potential impact of AI systems on security and fundamental human rights;
- create competent authorities that ensure registration, compliance assessment, appeal, control and supervision in the AI sphere;
- apply sanctions to AI system operators for violating regulatory requirements.

The field of geological study of the subsoil is no exception. Moreover, the methods of AI geology, as a component of Earth sciences, allow, among other things:

- to generate answers about the search for new promising mineral deposits automatically ;
- to carry out the accounting of geological information, its cataloging, scanning, digitization and promulgation;
- to provide AI algorithm with initial data in the form of materials from geochemical search methods, maps of gravitational and magnetic fields, space images, *etc*., processes drilling data, optimizes searches, and predicts mineral shortages, including critical minerals, in the long term.

At the same time, it should be noted that most stakeholders recognize the possibility of errors in decisions made by AI systems and seek to protect consumers from their consequences. Indeed, the use of an AI system can potentially lead to a negative and/or undesirable situation caused by an error in the AI algorithm. A natural production and legal reaction to this will be the problem of establishing the person who should be held liable for the damage caused. Moreover, the variability in this case is quite wide - the developer of the AI system, the legal entity using the AI system, and the official responsible for the use of the AI system. In this regard, for the legal regulation of geological AI relations, it is extremely important to designate the general boundaries of the use of AI systems. For example, high-risk AI systems, based on the requirements of the White Paper on AI, must be sufficiently transparent so that users can understand and control how the high-risk AI system produces its products. In our case, we are talking about the results of modeling mechanical processes in rocks. The information about the geological AI system should be disclosed:

- the level of accuracy, reliability, and safety;
- the circumstances of use under which the system may create risks to the safety and rights of the user;
- the general logic and choice of the system design;
- a description of the system training data.

In addition, legal regulation is required in the areas of liability insurance for damage caused by an error in an AI algorithm and certification of AI systems.

In general, if we approach the issue of legal regulation of geological AI relations systematically, then the most appropriate approach seems to be the formation of articles of a codified legislative act, first of all, according to the object composition of these relations, which can be represented by:

(1) Material resources - subsoil within the borders of the state, deposits, rocks;

(2) Information resources - geoinformation system, geological information fund, resources of primary and secondary geological information;

(3) Active resources - prospecting, evaluation, geological exploration, geophysical, and other types of geological activity.

Consequently, it is proposed to define the source of the right for geological AI study of the earth's crust as the corresponding section of the Geological Code, which will reflect the provisions regarding powers at various levels of management and implementation of geological operations using AI technologies, as well as objects of geological AI relations.

5. Conclusion

AI technologies, as an object of legal regulation, have a dichotomy of features that, on the one hand, are extremely important for economic growth and sustainable development. On the other hand, have an unsafe potential for unpredictable achievements and the possibility of a person losing control over them. Therefore, this innovation cannot develop without any international and state supervision, which requires the presence of legally regulated rules of conduct for all interested participants in AI relations.

The source of the right for geological AI study of the earth's crust should be the corresponding section of the Geological Code, which will reflect the provisions regarding powers at various levels of management and implementation of geological operations using AI technologies, as well as such objects of geological AI-relations as rocks, geological information, and geological activity.

AI modeling of rock mechanics opens new possibilities in increasing the accuracy and adaptability of forecasts during well drilling. Modern ML methods allow considering complex geophysical and mineralogical characteristics of rocks, such as their texture, mineralogical composition and water saturation, which significantly improves the understanding of their behavior during drilling. This contributes not only to more efficient management of the drilling process but also to minimizing the risks associated with equipment damage and loss of time.

ML methods demonstrated significant advantages in predicting mechanical properties of rocks. The analysis showed that linear regression is the most accurate model for the current data set, which is due to its ability to effectively account for key relationships between parameters, such as compressive strength and drilling speed. However, small deviations in predictions indicate that the model can be improved, for example, by including additional rock properties.

The GB method has shown promise for problems with more complex dependencies. It has shown a balanced trade-off between accuracy and complexity, making it suitable for advanced prediction scenarios such as analyzing the influence of textural and mineralogical characteristics. Its advantage is its ability to model nonlinear dependencies, which is especially useful when large data sets are available.

RF and PR methods showed less effective results. RF has a high error due to overfitting and excessive sensitivity to small changes in the data. PR slightly improved accuracy compared to LR, which indicates the weak role of nonlinear dependencies in this context. These methods require careful use and deep data analysis before using them.

Future work should focus on improving the quality and availability of data, especially for rare and complex rock types, to enhance the accuracy of AI models. Optimizing AI models for limited computational resources is also essential to ensure efficiency in practical applications. Integrating real-time data with machine learning methods could significantly improve prediction accuracy and enable dynamic optimization of drilling processes. Expanding the application of AI to other areas, such as mineral processing, rock mass stability prediction, and geotechnical engineering, could further increase efficiency and cost-effectiveness. Additionally, establishing clear legal and ethical frameworks for AI use in geological applications is crucial to balance innovation with safety and accountability.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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