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A REVIEW OF MACHINE LEARNING ALGORITHMS TO MINERAL EXPLORATION AND MAPPING

[1]Shakir Ullah*, [2]Sana Kashaf

[1]*College of Geophysics, Lab: Earth Exploration and Information Technology, Chengdu University of Technology 610059 China. shakirhayankhan365@gmail.com*
[2]*College of Material, Chemistry & Chemical Engineering, Chengdu University of Technology 610059 China. alikashaf107@gmail.com*
shakirhayankhan365@gmail.com

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Corresponding Author: * Shakir Ullah

Abstract
The current breakthroughs in smart mining offerings have brought a new wave of real-time data production and analyses, and the mining sector has leaped forward embracing machine learning (ML) to streamline their activities, enhance safety, and increase sustainability. This review examines 87 new publications, and a careful study of 42 significant papers to examine how ML is being used in several mining disciplines, including mineral exploration, ore grade modeling, process optimization, and environment management. The results point out the fact that the ML research is highly focused on the application of surface mining where numerous challenges and opportunities are built on complexity and abundance of data. Such techniques as deep neural networks (DNNs) and support vector machines (SVMs) are popular because they show good results in predictive maintenance, ore classification, and yield optimization, but techniques such as ensemble methods and reinforcement learning are becoming increasingly popular because they are more adaptable. Though the classic criteria of evaluation such as the robustness of regression tend to be widespread, more sophisticated tools such as the cross-validation and confusion matrices are on the rise. Data heterogeneity, model transparency, and data incorporation of real-time sensor data continue to remain a problem. The upcoming studies are recommended to focus on hybrid solutions that combine ML with physics-based models, exploit edge computing to get on-the-fly realizations, and resolve the ethical aspect of AI automation. All in all, the review highlights the revolutionary properties of ML in the mining field and the necessity of a more coordinated work of data scientists, engineers, and stakeholders to facilitate the development of efficient, smart, and sustainable mining trends.

INTRODUCTION

Recently, many studies have been using X-ray micro tomographic (μCT) images to statistically evaluate petrophysical characteristics. Rock imagery has become a cornerstone of the digital rock physics (DRP) method, providing a powerful tool to represent observed processes that are currently difficult or impossible to replicate in a traditional laboratory setting [1,2]. DRP simulations enable the calculation of key transport parameters, including permeability, porosity, and effective pore connectivity, as well as the visualization of multi-phase fluid dynamics, such as those occurring during water imbibition and Haines jump processes [5,6].

The mathematical framework of DRP serves as a virtual laboratory, allowing researchers to analyze the properties of heterogeneous granular materials with high precision. This approach leverages advanced computational techniques to process three-dimensional (3D) images, segment complex pore structures, and quantify physicochemical characteristics from high-resolution scans [3,4]. Recent advancements in imaging resolution and machine learning-based segmentation have further enhanced the accuracy of DRP models, enabling more reliable predictions of rock behavior under various subsurface conditions [7,8].

Moreover, DRP provides a non-destructive alternative to conventional core analysis, reducing experimental costs while offering insights into microscale phenomena that influence macroscopic rock properties [9,10]. By integrating μCT imaging with numerical simulations, researchers can better understand fluid-rock interactions, wettability effects, and multiphase flow dynamics critical factors in hydrocarbon recovery, carbon sequestration, and groundwater management [11, 12].

Despite its advantages, challenges remain in accurately reconstructing pore-scale geometries and validating DRP-derived parameters against experimental data [13, 14]. Future developments in high-performance computing and deep learning are expected to further bridge the gap between digital and physical rock analysis, enhancing the predictive capabilities of DRP in geoscience and engineering applications [15, 16].

1. Background

A virtual rock-physics experiment method needs to go through a number of crucial treatment phases in order being used. The first stage is to run a high geographic (and subsequently also temporal) definition computer tomography (CT) examination of the chosen solid sample. Effective phasing classification that can be challenging for a substantially uneven substance is necessary to subsequently enable the construction of a compelling digital rock model [5]. While simulating fluid flow somewhere at pore size, the fragmentation method is limited to the requirement to measure the binaries supercritical fluid dispersion (i.e., a binarization problem).

Leu et al. (2014) on the other hand, recently carried out vulnerability research wherein they demonstrated that even a minor distortion in the precision of the segmentation process may result in a sizable mistake in the computed permeation. DRP investigations require segmentation process as a necessary precursor, however there aren't many reliable, quick binarization methods that aren't skewed by human (subjective) user manipulations. In order to accurately describe a permeable space by removing the amplitudes of the complexities associated in figuring out the morphologies of pore connections, it is essential to select the right strategy for binarizing a picture [6].

2.1. High-Resolution Imaging and Segmentation Challenges

The first critical step in a virtual rock-physics experiment is acquiring high-resolution X-ray computed tomography (CT) scans of the rock sample. Modern micro-CT and nano-CT scanners provide three-dimensional (3D) representations of the pore structure at micrometer or even nanometer scales, capturing intricate details of the rock matrix and void spaces. However, the subsequent segmentation of these images into distinct phases (e.g., solid matrix vs. pore space) remains a major challenge, particularly for heterogeneous or poorly consolidated rocks where grayscale contrast between phases may be ambiguous.

Errors in segmentation can propagate through subsequent simulations, leading to significant inaccuracies in derived properties such as porosity, permeability, and elastic moduli. Leu et al. (2014) demonstrated that even minor misclassifications during segmentation could result in substantial deviations in computed permeability values, underscoring the need for robust and automated segmentation techniques. Traditional thresholding methods, while computationally efficient, often struggle with noise, partial volume effects, and complex pore geometries, necessitating more advanced machine learning or deep learning approaches for improved accuracy.

2.2. Binarization and Pore Network Representation

Following segmentation, the CT data must be binarized converted into a binary image where each voxel is classified as either pore space or solid matrix. This step is crucial because it defines the digital rock model used for fluid flow simulations (e.g., Lattice

Boltzmann Method or pore-network modeling). However, binarization introduces its own set of challenges:

Threshold Selection: Manual thresholding is subjective and prone to user bias, while automated methods (e.g., Otsu's method, entropy-based thresholding) may fail in heterogeneous samples.

Pore Connectivity Preservation: Over- or under-segmentation can artificially alter pore-throat sizes and connectivity, directly impacting permeability predictions.

Noise and Artifacts: Beam hardening, scattering, and reconstruction artifacts in CT scans can distort binarization, requiring pre-processing steps such as filtering or advanced reconstruction algorithms.

Recent advances in deep learning-based segmentation (e.g., convolutional neural networks, U-Net architectures) have shown promise in improving binarization accuracy by learning from labeled training datasets. However, these methods require extensive computational resources and high-quality ground-truth data, which may not always be available.

2.3. Implications for Digital Rock Physics (DRP) Simulations

The reliability of DRP simulations hinges on the fidelity of the digital rock model. Since permeability, capillary pressure, and electrical conductivity are highly sensitive to pore-space morphology, even small errors in binarization can lead to order-of-magnitude discrepancies in results. Thus, future research must focus on:

Developing standardized, automated segmentation protocols to minimize human bias. Integrating multi-scale imaging techniques (e.g., combining micro-CT with FIB-SEM) to capture both macro- and nano-pore structures. Hybrid machine learning and physics-based approaches to enhance segmentation accuracy while preserving geological realism. By addressing these challenges, virtual rock-physics experiments can become more predictive and widely applicable in fields such as reservoir engineering, carbon sequestration, and geothermal energy exploration

2. Rock Physics

We are far from being able to measure experimental principles for determining the behaviour of composite and simulations rock physics on timeframes from milliseconds to thousands of years, from subatomic to worlds. However, this constraint is beginning to gradually disappear thanks to the fourth research methodology of statistics innovation and discoveries [7]. Among the first commercial processes to be made accessible that used the data-intensive methodology is computational rock dynamics. Analysing in-situ characteristics and their alterations on the different temporal and spatial scales of peristaltic transport across a physiologically responding and compacting core specimens to the dimension and longevity of controlling a complete resource is possible with finely calculated trials with simulated stones. After SAXS/WAXS in situ experiments defined the sub-micron physics, it is now able to apply the knowledge to the following scale of studies, for which triaxial flow and deformation cells have been created to mimic in-situ conditions (Figure 1).

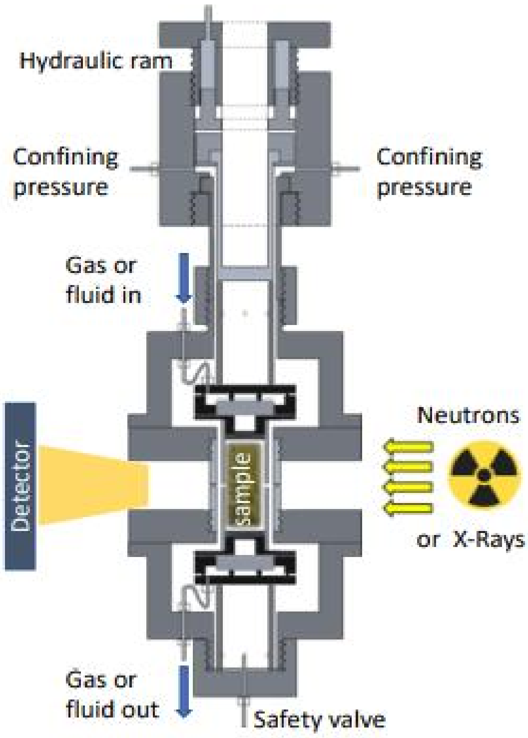

Figure 1: shows an illustration of a prototype X-ray and neutron tomography cell designed by T. Blach that was successfully tested in 2018 at the Institute Laue Langevin (ILL) in Grenoble, France, and the NIST Centre for Neutron Research in Gaithersburg, US. Details include the following: exchangeable windows (Ti, TiZr, Be, Al); cores (up to 20mm diameter and 100mm long); fluid pressure (up to approximately 100 MPa); hydraulic ram (up to approximately 100 MPa); temperature (up to about 300 oC, dual heaters); (CD4, He, CO2).

3. Permeability and porosity of oil reservoirs

In the research, numerous equations for predicting hydraulic properties were proposed. Nevertheless, the majority of such relationships are just useful for estimating penetration in boundary layers that are similar characteristics, poorly consolidated sands, and sandstone and shale [8-12]. For extremely heterogeneous aquifers, such as quadruple or dual permeability cracked carbonate rocks, it is exceedingly difficult to create a broadly applicable porosity/permeability relationship. Though permeable is a continuous quantity and its calculation requires an immediate result of economies of scale for increased reliability, the majority of the published algorithms incorporate unchanging rock characteristics data [9,11]. Dynamic data, meanwhile, can require longer effort and be more expensive [8,10-12]. In every E & P scheme in biomedical engineering, a precise estimate of the reservoir's mechanical properties is essential. Well data could be used to specify porosity with reasonable accuracy; however core analysis is the best way to determine permeability. In opposed to technological sampling techniques, coring requires a lot of time and money. Theoretically, determining porosity by using electrical measuring instruments entails resolving petrophysical formulae. A real practical association is difficult to establish or impossible to assess practically due to a number of issues. Whenever one assumes that the characterization of conventional heterogeneous repositories will include porous and permeable calcareous minerals with a challenging triple any dual permeability structure, the situation becomes more complicated. Even in the lab, creating a link between a physical variable and a log response is not simple. Several unfavorable factors, such as reservoir pressure, geology, fluid loss infiltration, and degradation to test pits, might affect the calculation of permeability unfavorably [8-12].

For heterogeneous aquifers such cracked carbonate media, several susceptibility white crystalline powder, including standard, authority, and stochastic, are illustrated [14-16]. An investigation on the petrophysical characteristics of cracked boundary layers with a fragment size that had a power balance was conducted by Bogdanov et al. in 2007 [14]. By combining the Darcy's formulas and obtaining the results from fissures and nearby interfacial properties, they investigated the susceptibility of rock formations computationally. These authors recommended two condensed factors to make it easier to provide a thorough explanation for a wide range of fractured characteristics, including fractured shape, opening, volume fraction, and density. Additionally, they proposed two widely used strategies for both intensive and slack fractured networks [14].

4. Rock typing and permeability prediction

5.1. Introduction to Rock Typing Methods

To execute suitable rock typing, various methods have been proposed, ranging from geological to petrophysical and machine learning-based approaches. Techniques such as the Lucia method [15] rely on geological characteristics, particularly pore geometry and texture, to classify carbonate reservoirs. This method is effective in distinguishing between grain-dominated and mud-dominated pore systems, which directly influence permeability.

Additionally, reservoir characterization techniques often integrate depositional and diagenetic properties, including porosity (ϕ), permeability (K), and capillary pressure (Pc). These parameters help define distinct rock types that exhibit similar fluid flow behaviors.

5.2. Petrophysical Rock Typing (PRT) and Hydraulic Flow Units (HFUs)

Petrophysical rock typing (PRT) involves classifying rocks based on their static and dynamic properties: Petrophysical Static Rock Typing (PSRT): Focuses on static properties such as capillary pressure (Pc), irreducible water saturation (Swc), and pore-throat size distribution. Petrophysical Dynamic Rock Typing (PDRT): Considers dynamic properties related to fluid flow, such as relative permeability and resistivity index.

A common challenge in reservoir characterization is the interchangeable use of **PRTs and Hydraulic Flow Units (HFUs). While PRTs focus on pore-scale properties, HFUs group rocks with similar fluid flow behavior, often derived from the Flow Zone Indicator (FZI) method. Kadkhodaie (2018) [17] provided a comprehensive review of different rock typing techniques, highlighting their applications in both academia and industry.

5.3. Integration of Machine Learning in Rock Typing and Permeability Prediction

Recent advancements in machine learning (ML) have enhanced rock typing and permeability prediction by establishing relationships between micro-scale rock properties and macro-scale measurements (e.g., porosity and permeability from routine core analysis (RCAL)) [18].

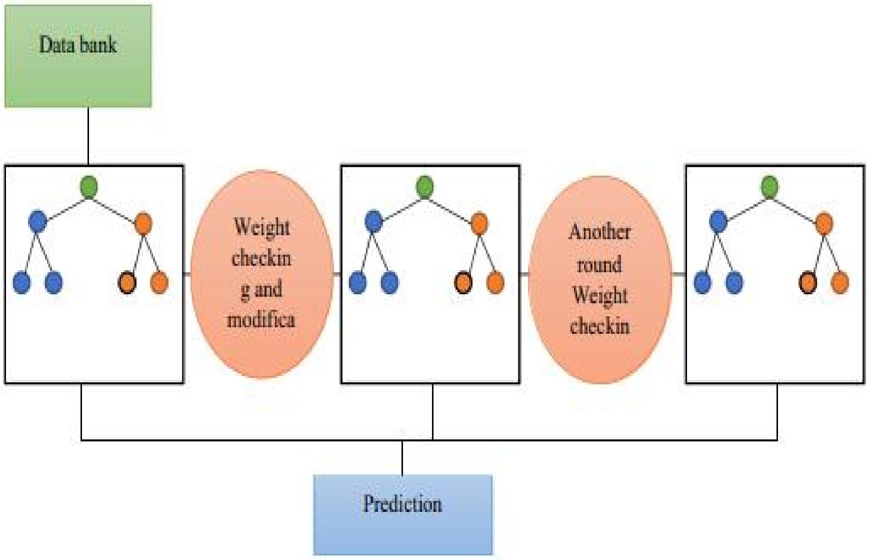

Figure 2: A common gradient boosting algorithm's design.

5. Machine Learning Techniques:

Machine learning techniques use fundamental connections, segmentation, or division of the fundamental well-log information to generate complicated relationship among variables. The majority of these programs have proven to be capable of producing extremely precise forecasts. Unfortunately, they typically don't really disclose the precise computations used in each forecast easily accessible. That restricts their ability to mine the well-log database more thoroughly, which is what they were intended to do. In certain circumstances, the hazy linkages seen between response variable causes organizations to function as "black boxes" [19]. When there are no underlying relationships between the response variable, accurate and truthful information techniques provide more openness, which in itself is excellent for several information extraction. The simplicity of the fundamental data-matching techniques, including proximity [20] and k-means clustering [21], limits the precision of the predictions they can make. Translucent open box (TOB) learning connectivity, a newly established, optimised identification (nearest neighbour) classifier [22], provides free, work perfectly, prediction performance along with massive data resource extraction functionality that seem to be perfect for forecasting rock properties specifications by well log analysis. For each regression model, the TOB optimized-data-matching algorithm provides a multi forecast approach. It is ideally adapted to making predictions and extracting data from typically non, dispersed, and clustering information with similar results among their characteristics, including those frequently connected to several well-log curves across various geological and noted that the purely.

That guided, non-parametric lesson plan matches comparable (closely related) datasets instead of relying on fundamental connections between the parameters. An advantage for in-depth data gathering of large datasets is that it is readily and openly programmed to offer all preliminary processes linked to every one of its forecasts. The TOB method is helped by the independence underlying relationships, accessibility, and two-stage prediction method to prevent clustering information. Several mutual information, supervised machine learning algorithms run into the issue of updated accordingly [23].

Chauhan et al., 2016 describes we identified the processing capacities of machine learning methods for X-ray micro tomographic stone pictures. In order to segment X-ray computers micro tomography mountain photographs and determine the open pores and pore diameter widths in the minerals, the study concentrated here on application of uncontrolled, guided, and group proposed techniques. The regulated generalized least neural network-based approach had the shortest waiting time, but the unstructured k-means approach did so. Visual examination of the pictures revealed multiphase configurations comprising substantial phases (minerals and finely grained minerals) and the pores component. The selected features chosen were proven to have a greater impact on accurateness of permeability measurements and average pore diameter. With empirical observations of 1772 percent collected just use a gas graduated cylinder, the mean standard permeability estimates of 15.9271.77 percent that was returned from all seven algorithms agrees quite well. Since it can distinguish a broad pattern, the regression analysis svm classification methodology outperforms feed backward neural network model among the supervised learning. In comparison to boastful approach, the enhancing strategy collapsed more quickly in the efficient classification procedures. In order to get an enhanced, the k-means methodology showed improvement than fuzzy c-means and self-organized mappings. [24].

Regenauer et al., (2019) describes the thorough understanding of fluid geological characteristics and related uncertainty is essential for exploratory geophysical and reservoirs organizational innovation. Researchers have created a fresh method that not only evaluates the dynamics of petrophysical characteristics under tectonic, toxicological, and industrial stresses but also evaluates uncertainty of those parameters in a stationary environment. We tackle this problem by merging computational modeling, observations, and geotechnical hypothesis in a novel multi-scale and computational fluid linear regression method. In order to offer a strong physics underpinning for the multiscaling methodologies given in accompanying studies for the bigger sizes, this work focuses on data unification from microscopic to laboratory level. [25].

Ahmadi and Chen (2019) compare various models for estimating the pore size distribution of oil wells using petrophysical records and a machine learning approach. To conduct a thorough assessment, a variety of machine learning techniques, along with the traditional convolutional neural network, simulated annealing, fuzzy decision tree, the imperialist competitive algorithm (ICA), particle swarm optimization (PSO), and a combination about those methods, are used. The machine learning methodology was introduced and pushed to the limit using information specimens were collected from crude oils in the northeastern Persian Gulf. The outcomes produced by other approaches applied in our previous research are compared with the results obtained from the machine learning models shown in their research and the pertinent real rock properties data. For the hybridization techniques, it is found that the mean absolute divergence between the technique predictions and the pertinent real numbers is below 1%. The findings of this study suggest that using hybridized machine learning techniques to estimate porosity and permeability can allow the creation of more accurate static subsurface simulations for use in simulations designs. [26].

Mohammadian et al., (2022) explained several specialties in the oil and gas sector, the concepts of permeability projection and petrophysical rock typing (PRT) are extremely important. The mix of computational intelligence techniques shown in this paper provides a fresh, comprehensible data-driven strategy to improving the precision of subsurface rock typing. A supervised machine learning system dubbed Extreme Gradient Boosting was trained using 128 core data from a heterogeneous carbonate reservoir in Iran, comprising porosity, permeability, connate water saturation (Swc), and diameter of holes at 35 percent mercury injection (R35) (XGB). The computation outcome, the revised production zone index (FZIM*), was utilized to calculate the permeability and R35 values with high accuracy (R^2 = 0.97 and 0.95, respectively) additionally, to determine the ideal number of PRTs, FZIM* was integrated including an uncontrolled machine learning technique (K-means clustering). Using this technique, 4 petrophysical rock types (PRTs) were identified, and the variety of their attributes were explored. The association among each model parameters and the outcome, but also every parameter's impact on the value of FZIM*, were then explained using shapely quantities and variation significance evaluation. Swc would have the least effect on FZIM, while Permittivity and R35 were shown to be the most important variables [27].

Wood (2020) explained that database schema is often not obtainable for everyone wells produced or comprehensive fluid portions, it is essential to predict the permeability (Ke), water saturation (Sw), and effective porosity (EP) of petroleum & energy reservoir segments using well event logs. For the purpose of evaluating information from numerous well-log graphs, a synthetic data matching algorithm is created. It offers the lithological units it examines precise rock properties metric projections and in-depth data analysis information. Dataset contains that mix conventional well logging lines with sedimentary sequence and sedimentary characteristics can be used to forecast Ke, Sw, and EP by expressing the well-log data in a uniform well-log formulation and assessing that structure using the data-matching method. The possibilities of the suggested method are illustrated by implementing it to a preprocessed networks of available composites well-log statistics and noted that the purely explanation (10 variables) for a 100-m segment across the Triassic reservoir of the Algerian Hassi R'Mel gas field (Algeria). ToB produces generalization ability that is helpful for differentiating potential forms at a standardized assessment level of collecting concentration (1 sample/10 cm) (RMSE for Ke 15 mD; for Sw 0.1; for EP 0.01). For the Hassi R'Mel well-log network, TOB offers much better predictive performance (RMSE for Ke 1.3 mD; for Sw 0.003; for EP 0.0006) at a high magnification monitoring frequency (1 sample/1 centimetre) for a 10-m zone of concern. For a thorough investigation of the posterior probability, the recommended data matching technique's attention to detail with each of the two projections is helpful. Information extraction like that [28].

6. Mineral Extraction by using Machine Learning:

These particular publications were chosen not because of their technique focus but because of their subject-area focus (i.e., mineral processing and related chemical, control, and process engineering principles) (e.g. publications focused on the development of new machine learning techniques independent of intended use in minerals engineering). The choice of these articles was driven by the discussion that will follow in this article on the value of domain expertise in the application of machine learning techniques. These periodicals typically have large readerships and scopes that specifically highlight the value of submitted research papers' industrial significance.

Searchable summaries

A spreadsheet with summaries of the publications that are cited in this review can be searched as supplemental material. These summaries are offered as a resource to the minerals processing industry in an effort to support machine learning research and applications to problems with practical industrial relevance. In this review, three application categories are used.

- Data-based modelling is frequently used as "soft sensors," which forecast measurements that are slow, challenging, or expensive using data from frequent plant measurements (such as temperatures, pressures, levels, flow rates, and spectra) (such as chemical composition, mineral grade, or mill load).
- Process monitoring, also known as fault identification and/or diagnosis. New measurements from the process are classified as normal or abnormal in fault detection, with the fundamental premise being that each abnormal measurement relates to a process fault. Finding the root of the discovered flaws is the process of fault diagnostics.
- Machine vision, a sort of data-based modelling that uses images or video as the input for the prediction of other measurements rather than process measurements.

Every technique or process that is described in a publication that has several, different steps is categorized and summarized on its own line in the spreadsheet.

Each publication (or section of a publication, in cases where a paper describes multiple techniques or techniques with multiple steps) is further classified in the spreadsheet according to the process of interest, the machine learning algorithm type used, the input and output data, and the necessary hyper parameters. Many machine learning methods need the specification of hyperparamaters, which are configurable factors that can significantly affect the implementation's success (McCoy & Auret, 2019).

7. Conclusion

The rapid advancements in smart mining technologies have enabled the real-time generation, collection, and sharing of vast amounts of data, fostering extensive machine learning (ML) research in the mining industry. This review systematically evaluated

87 papers published over the past decade, focusing on ML applications in mineral extraction, production optimization, and mine rehabilitation. Among these, 42 papers were rigorously analyzed to assess prevailing research trends, commonly used ML models, and evaluation methodologies.

The findings highlight that ML applications in mining have been predominantly concentrated in surface mining operations, with support vector machines (SVMs) emerging as the most frequently employed model, followed closely by deep neural networks (DNNs). Model performance evaluation primarily relied on standard error and linear regression metrics, indicating a preference for traditional statistical measures despite the increasing complexity of ML techniques.

However, several research gaps and future directions were identified. First, there remains a notable scarcity of ML applications in underground mining, where challenges such as limited data availability and harsh environmental conditions persist. Second, while deep learning models show promise in handling large-scale, high-dimensional mining data, their adoption is still in early stages compared to conventional ML techniques. Additionally, the lack of standardized benchmarking datasets and evaluation protocols across studies hinders the direct comparison of model performance. Future research should focus on (1) expanding ML applications to underrepresented areas such as underground mining and mine safety, (2) integrating multimodal data sources (e.g., geospatial, IoT sensors, and drone imagery) to enhance predictive accuracy, and (3) developing robust evaluation frameworks that account for real-world mining constraints, including data noise and computational efficiency. Furthermore, the adoption of explainable AI (XAI) techniques could improve the interpretability of ML models, fostering greater trust and usability among mining professionals.

In conclusion, while ML has demonstrated significant potential in transforming the mining sector, continued innovation, interdisciplinary collaboration, and industry-academia partnerships will be essential to fully realize its benefits in sustainable and intelligent mining operations.

8. References:

Blunt, M.J., et al. (2013). "Pore-scale imaging and modelling." Advances in Water Resources, 51, 197-216.

Wildenschild, D., Sheppard, A.P. (2013). "X-ray imaging and analysis techniques for quantifying pore-scale structure and processes in subsurface porous medium systems." Advances in Water Resources, 51, 217-246.

3. Andrä, H., et al. (2013). "Digital rock physics benchmarks—Part I: Imaging and segmentation." Computers & Geosciences, 50, 25-32.
4. Cnudde, V., Boone, M.N. (2013). "High-resolution X-ray computed tomography in geosciences: A review of the current technology and applications."Earth-Science Reviews, 123, 1-17.
5. Berg, S., et al. (2013). "Real-time 3D imaging of Haines jumps in porous media."PNAS, 110(10), 3755-3759.
6. Armstrong, R.T., et al. (2016). "Beyond Darcy's law: The role of phase topology and ganglion dynamics for two-fluid flow."Physical Review E, 94(4), 043113.
7. Iassonov, P., et al. (2009). "Segmentation of X-ray computed tomography images of porous materials: A crucial step for characterization and quantitative analysis of pore structures."Water Resources Research, 45(9).
8.] Andrä, H., et al. (2013). "Digital rock physics benchmarks Part I: Imaging and segmentation." Computers & Geosciences, 50, 25-32.
9. Leu, L., et al. (2014). "Sensitivity of digital rock-based permeability predictions to image processing and segmentation."Geophysical Research Letters, 41(7), 2499-2506.
10. Karimpouli, S., Tahmasebi, P. (2019). "Segmentation of digital rock images using deep convolutional autoencoder networks."Computers & Geosciences, 126, 142-150.
11. Saxena, N., et al. (2017). "Imaging and computational considerations for image computed permeability: Operating envelope of Digital Rock Physics."Advances in Water Resources, 107, 495-507.

Bultreys, T., et al. (2016). "Imaging and image-based fluid transport modeling at the pore scale in geological materials: A practical introduction to the current state-of-the-art."Earth-Science Reviews, 155, 93-128.

Bijeljic, B., et al. (2013). "Signature of non-Fickian solute transport in complex heterogeneous porous media."Physical Review Letters, 110(18), 184502.

AlRatrout, A., et al. (2018). "Automatic measurement of contact angle in pore-space images." Advances in Water Resources, 109, 158-169.

Schlüter, S., et al. (2014). "Pore-scale displacement mechanisms as a source of hysteresis for two-phase flow in porous media."Water Resources Research, 50(11), 8614-8629.

Berg, C.F., et al. (2017). "Robust determination of the pore-space morphology in sedimentary rocks."Transport in Porous Media, 118(1), 1-19.

Tembely, M., et al. (2021). "Machine learning for digital rock analysis: A review."Journal of Petroleum Science and Engineering, 200, 108260.

Wang, Y.D., et al. (2022). "Deep learning in pore scale imaging and modeling."Earth-Science Reviews, 227, 103944.

Berg, S., Ott, H., Klapp, S. A., Schwing, A., Neiteler, R., Brussee, N., ... & Stampanoni, M. (2013). Real-time 3D imaging of Haines jumps in porous media flow. *Proceedings of the National Academy of Sciences*, *110*(10), 3755-3759.

20. Khan, F., Enzmann, F., Kersten, M., Wiegmann, A., & Steiner, K. (2012). 3D simulation of the permeability tensor in a soil aggregate on basis of nanotomographic imaging and LBE solver. *Journal of soils and sediments*, *12*(1), 86-96.
21. Andrä, H., Combaret, N., Dvorkin, J., Glatt, E., Han, J., Kabel, M., ... & Zhan, X. (2013). Digital rock physics benchmarks Part I: Imaging and segmentation. *Computers & Geosciences*, *50*, 25-32.
22. Andrä, H., Combaret, N., Dvorkin, J., Glatt, E., Han, J., Kabel, M., ... & Zhan, X. (2013). Digital rock physics benchmarks Part II: Computing effective properties. *Computers & Geosciences*, *50*, 33-43.
23. Fusseis, F., Xiao, X., Schrank, C., & De Carlo, F. (2014). A brief guide to synchrotron radiation-based microtomography in (structural) geology and rock mechanics. *Journal of Structural Geology*, *65*, 1-16.
24. Leu, L., Berg, S., Enzmann, F., Armstrong, R. T., & Kersten, M. (2014). Fast X-ray micro-tomography of multiphase flow in berea sandstone: A sensitivity study on image processing. *Transport in Porous Media*, *105*(2), 451-469.
25. Bell, G., Hey, T., & Szalay, A. (2009). Beyond the data deluge. *Science*, *323*(5919), 1297-1298.
26. Newman, G. H., & Martin, J. C. (1977, October). Equipment and experimental methods for obtaining laboratory compression characteristics of reservoir rocks under various stress and pressure conditions. In *SPE Annual Fall Technical Conference and Exhibition*. OnePetro.

Dullien, F. A. (2012). *Porous media: fluid transport and pore structure*. Academic press.

Chan, S. K., Bindlish, R., O'Neill, P. E., Njoku, E., Jackson, T., Colliander, A., & Kerr, Y. (2016). Assessment of the SMAP passive soil moisture product. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(8), 4994-5007.

Thomas, D. C., & Pugh, V. J. (1989). A statistical analysis of the accuracy and reproductibility of standard core analysis. *Petrophysics*, *30*(2), 71-77.

Bogdanov, V.V. Mourzenko, J.F. Thovert, Effective permeability of fractured porous media with power-law distribution of fracture sizes, Phys. Rev. 76 (3) (2007) 15.

A.M. Saidi, Reservoir Engineering of Fractured Reservoirs, Total Edition Press, Paris, France, 1987.

T.D. Van Golf-Racht, Fundamentals of Fractured Reservoir Engineering, Elsevier, Netherland, 1982.

Jennings, J. W. & Lucia, F. J. Predicting permeability from well logs in carbonates with a link to geology for interwell permeability mapping (2001).

Skalinski, M. & Kenter, J. A. M. Carbonate petrophysical rock typing: Integrating geological attributes and petrophysical properties while linking with dynamic behaviour. Geol. Soc. Spec. Publ. 406(1), 229–259.

Kadkhodaie, A. & Kadkhodaie, R. A review of reservoir rock typing methods in carbonate reservoirs: Relation between geological, seismic, and reservoir rock types. Pet. Eng. Iran. J. Oil Gas Sci. Technol. 7(4), 13–35 (2018).

36. Davies, D. K. & Vessell, R. K. Flow unit characterization of a shallow shelf carbonate reservoir: North Robertson unit, West Texas. (1996).

37. Heinert, M., 2008. Artificial neural networks–how to open the black boxes. App. Art. Intell. Eng. Geo. (AIEG 2008) 5, 42–62.

38. Fix, E., Hodges Jr., J.L., 1951. Discriminatory Analysis, Nonparametric Discrimination: Consistency Properties. Technical report. USAF School of Aviation Medicine.

39. MacQueen, J. (1967). Classification and analysis of multivariate observations. In *5th Berkeley Symp. Math. Statist. Probability* (pp. 281-297).

40. Wood, D.A., 2018. A transparent Open-Box learning network provides insight to complex systems and a performance benchmark for more-opaque machine learning algorithms. Adv. Geo-Energy Res. 2 (2), 148–162.

41. Lever, J., Krywinski, M., Altman, N., 2016. Model selection and overfitting. Nat. Methods 13, 703–704.

42. Chauhan, S., Rühaak, W., Khan, F., Enzmann, F., Mielke, P., Kersten, M., & Sass, I. (2016). Processing of rock core microtomography images: Using seven different machine learning algorithms. *Computers & Geosciences*, *86*, 120-128.

Regenauer-Lieb, K., Blach, T., Singh, A., Halim, A., Clark, S., & Schrank, C. (2019). Rock physics for multiscale, multiphysics data assimilation from molecular to laboratory scale. *ASEG Extended Abstracts*, *2019*(1), 1-4.

Ahmadi, M. A., & Chen, Z. (2019). Comparison of machine learning methods for estimating permeability and porosity of oil reservoirs via petro-physical logs. *Petroleum*, *5*(3), 271-284.

Mohammadian, E., Kheirollahi, M., Liu, B., Ostadhassan, M., & Sabet, M. (2022). A case study of petrophysical rock typing and permeability prediction using machine learning in a heterogenous carbonate reservoir in Iran. *Scientific reports*, *12*(1), 1-15.

Wood, D. A. (2020). Predicting porosity, permeability and water saturation applying an optimized nearest-neighbour, machine-learning and data-mining network of well-log data. *Journal of Petroleum Science and Engineering*, *184*, 106587.

McCoy, J. T., & Auret, L. (2019). Machine learning applications in minerals processing: A review. *Minerals Engineering*, *132*, 95-109.