

Editorial

Application of Machine Learning in Mining, Mineral Processing and Extractive Metallurgy

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Machine learning (ML) is one of the most active areas of artificial intelligence, and after several decades of methodological development, it is now being applied in practically every industry. Mining, mineral processing, and extractive metallurgy are no exception. These sectors operate large, capital-intensive, and tightly coupled production chains in which the underlying processes are strongly nonlinear, only partially observable, and subject to considerable heterogeneity in feed properties and operating conditions. In such environments, the application of ML—and of deep learning in particular—offers substantial benefits: the predictive modelling of processes, which improves the anticipation of their behaviour; the variability of their outputs, and their controllability; the real-time analysis of operational variables to optimise plant performance; the predictive maintenance of equipment and components; and the optimisation of energy and water use.

At the same time, applying ML in these domains poses well-known difficulties. Datasets are frequently scarce or unevenly sampled, abnormal events and conditions are hard to identify and characterise, and many of the variables that matter the most cannot be measured directly inside the equipment. Addressing these challenges generally requires the creative combination of different learning paradigms, the incorporation of phenomenological knowledge into otherwise data-driven models, the development of reliable in-line sensors together with the continuous measurement of critical variables, and the adoption of interoperable data models and tools that can coexist with the control systems already in place in industrial plants. The value of any solution ultimately rests on its ability to deliver measurable, quantitative benefits in real operations.

This Special Issue was conceived to gather innovative applications of ML across mining value chain, together with evidence of their quantitative benefits in mining, mineral processing, and extractive metallurgy. The collection brings together six contributions—five original research articles and one review—organised here following the natural sequence of the production chain, from planning and ore characterisation through comminution, concentration, and hydrometallurgical extraction, to the management of tailings. The methods represented are equally varied, ranging from classical state estimation and probabilistic graphical models to label-specific feature selection and bio-inspired deep learning, and several contributions place particular emphasis on interpretability and on supporting real-time decision-making.

The volume opens upstream, at the mine site. Saavedra et al. (Contribution 1) review modern, data-driven approaches to ore blending, an operation that is essential for ensuring feed consistency and for stabilising downstream processing, yet remains difficult because of ore variability and operational constraints. Following a systematic (PRISMA-based) survey of the recent literature, the authors focus on the role of data science and ML in



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predicting key process variables and supporting real-time decisions, and they discuss the core obstacles of data quality, feature engineering, and model generalisation, alongside enabling technologies such as sensor integration, automation platforms, and real-time data acquisition. Their main contribution is to consolidate the state of the art and to underline that standardised, high-quality data are a prerequisite for robust digital solutions in upstream blending and, more broadly, in mineral processing.

Reliable characterisation of the ore underpins every subsequent decision. Dell'Aversana (Contribution 2) addresses the automated classification of minerals in thin sections under optical microscopy by means of Mycelial_Net, a deep learning architecture inspired by the adaptive, decentralised connectivity of fungal mycelial networks. The model dynamically adjusts not only its weights but also its topology during training and, when combined with residual networks (ResNets) acting as a feature extractor, it proves more robust and interpretable than conventional convolutional neural networks, particularly on low-resolution and noisy petrographic images. On a four-class igneous mineral dataset, validation accuracy rose from roughly 78% for the baseline network to over 95%, with more balanced performance across the previously underperforming classes, illustrating the promise of adaptive, biologically inspired architectures for digital petrography.

Moving into the plant, comminution is the most energy-intensive and one of the most variable stages of the beneficiation plant. Saldana et al. (Contribution 3) develop and validate a stochastic model of semi-autogenous (SAG) milling based on discrete Bayesian networks that represents the causal relationships governing mill production and power under uncertainty or partial knowledge of the explanatory variables. Using operational data from a Chilean copper operation, the authors combine expert-guided structure learning with Bayesian parameter estimation and—although the model attains high predictive indicators—they rightly stress that its primary purpose is explainable causal inference and probabilistic scenario evaluation rather than exact regression. The sensitivity analysis identifies water feed and the percentage of solids as the main drivers of throughput, and rotational speed and pressure as the main drivers of power, offering an interpretable and uncertainty-aware tool to support process control.

Concentration by flotation presents a different kind of challenge, in which expert knowledge usually compensates for limited data. Dong et al. (Contribution 4) tackle the design of the copper flotation backbone process, formulated as a multilabel classification problem in which historical databases provide only a small number of training samples. They propose a correlation- and knowledge-based joint feature selection method that uses label correlations to prioritise the most relevant features to strongly related labels, while the knowledge of domain in copper flotation further refines the selection. By integrating data with process knowledge in the proposed methodology, the method reduces its dependence on the size of the training set and achieves higher accuracy and computational efficiency than conventional multilabel feature selection algorithms.

Extractive metallurgy raises the recurring problem of observing variables that are not accessible for direct measurement. Bárzaga-Martell et al. (Contribution 5) study copper heap leaching, where material variability, the uneven distribution of the leaching solution, and environmental factors complicate monitoring and control, and where the key internal variables can seldom be instrumented. The authors design and compare two state observers—an Extended Kalman Filter and an Unscented Kalman Filter—to estimate the moisture content, the copper grade in the ore, and the acid consumption from measurements of acid and copper concentrations. Both virtual sensors yield accurate estimates in simulation, and the approach offers a cost-effective route to recovering unmeasurable variables in real time, thereby improving the understanding of the internal dynamics of the heap and, ultimately, metal recovery and acid usage.

The mining value chain usually closes with the management of mine waste. Cao et al. (Contribution 6) propose an ML application to predict the compressive strength of cemented tailings fills from six input parameters, such as curing, mix design, and additives. Comparing adaptive boosting, random forests, support vector machines and artificial neural networks, they find that adaptive boosting delivers the best accuracy, and—importantly for practice—they embed the resulting model in a software tool that allows backfill engineers to estimate strength quickly, saving time and cost in the design of more eco-efficient mixtures.

Taken together, these six contributions show that ML is being applied across the entire mining value chain, from the planning and characterisation of the ore to comminution, flotation, leaching, and the disposal of tailings. Several common threads run through them. The first is the pervasive need to operate under uncertainty and data scarcity, which motivates probabilistic models, careful feature selection, and review-level attention to data quality. The second is the integration of phenomenological, expert, or domain knowledge with data-driven learning, whether through physically grounded state observers, knowledge-guided feature selection, or expert-informed network structures. The third is the construction of virtual sensors and soft estimators for variables that cannot be measured directly. And the fourth, equally salient, is a concern for interpretability and for delivering tools—explainable models, sensitivity analyses, and usable software—that operators can trust and act upon.

These same threads point to the work that remains. Realising the full benefits of ML in mining, mineral processing, and extractive metallurgy will require continued progress on reliable in-line sensors and the continuous measurement of critical variables, on interoperable data models and tools that integrate naturally, with existing plant control systems, and on hybrid schemes that couple machine learning with phenomenological models to make learning more efficient where the data are limited. Above all, it will require moving from simulation and offline validation toward demonstrations of quantitative benefit in real operations. The contributions collected here are encouraging steps in that direction, and we hope that they will stimulate further research at the intersection of machine learning and the minerals industry.

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List of Contributions

1. Saavedra, M.; Risso, N.; Momayez, M.; Nunes, R.; Tenorio, V.; Zhang, J. Blending Characterization for Effective Management in Mining Operations. *Minerals* **2025**, *15*, 891. <https://doi.org/10.3390/min15090891>.
2. Dell'Aversana, P. Mycelial_Net: A Bio-Inspired Deep Learning Framework for Mineral Classification in Thin Section Microscopy. *Minerals* **2025**, *15*, 1112. <https://doi.org/10.3390/min15111112>.
3. Saldana, M.; Gálvez, E.; Sales-Cruz, M.; Salinas-Rodríguez, E.; Castillo, J.; Navarra, A.; Toro, N.; Arias, D.; Cisternas, L.A. A Stochastic Model Approach for Modeling SAG Mill Production and Power Through Bayesian Networks: A Case Study of the Chilean Copper Mining Industry. *Minerals* **2026**, *16*, 60. <https://doi.org/10.3390/min16010060>.

4. Dong, H.; Wang, F.; He, D.; Liu, Y. Correlation and Knowledge-Based Joint Feature Selection for Copper Flotation Backbone Process Design. *Minerals* **2025**, *15*, 353. <https://doi.org/10.3390/min15040353>.
5. Bázquez-Martell, L.; Diaz-Quezada, S.; Estay, H.; Ruiz-del-Solar, J. Estimation of Copper Grade, Acid Consumption, and Moisture Content in Heap Leaching Using Extended and Unscented Kalman Filters. *Minerals* **2025**, *15*, 521. <https://doi.org/10.3390/min15050521>.
6. Cao, H.; Wang, A.; Yilmaz, E.; Cao, S. Machine Learning Algorithm-Based Prediction Model and Software Implementation for Strength Efficiency of Cemented Tailings Fills. *Minerals* **2025**, *15*, 405. <https://doi.org/10.3390/min15040405>.

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