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Mini Review

The Integration of Artificial Intelligence (AI) and Machine Learning (ML) in Mineral Processing: A Mini Review

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Abstract

The mineral processing industry, a cornerstone of the global economy, is undergoing a rapid transformation driven by the integration of Artificial Intelligence (AI) and Machine Learning (ML). This mini-review summarizes recent advances and current trends in AI/ML applications across key domains of mineral processing, including ore characterization and sorting, process modelling and optimization, and predictive maintenance. Particular emphasis is placed on how data-driven techniques contribute to enhanced mineral recovery, reduced energy and water consumption, and improved workplace safety. The discussion highlights the transition from theoretical potential to demonstrated industrial value, while identifying persistent barriers—such as data quality, model interpretability, and workforce skill gaps. Finally, future research directions are outlined, focusing on deep learning, hybrid AI–physical modelling, and reinforcement learning for plant-wide optimization and autonomous operation.

Keywords: Artificial Intelligence; Machine Learning; Mineral Processing; Process Optimization; Predictive Maintenance; Flotation; Comminution

Introduction

The mineral processing industry is a critical component of global economic development and sustainable resource management, particularly in the era of electrified mobility and renewable-energy technologies. However, the sector faces twin challenges: declining ore grades and increasing pressure to minimize its environmental footprint, including water and energy use [1,2]. These challenges expose the limitations of traditional process-control strategies, which often struggle to manage the inherent complexity, non-linearity, and variability of mineral processing circuits [3].

The emergence of the Fourth Industrial Revolution (Industry 4.0) has created the technological foundation needed to address such long-standing inefficiencies [4]. The proliferation of advanced sensor networks, low-cost connectivity, and scalable computing infrastructure has resulted in an unprecedented flow of data from the plant floor. Modern mineral processing facilities are equipped with vision systems, online analysers (e.g., prompt gamma neutron activation analysis, laser-induced breakdown spectroscopy), vibration sensors, and other smart instruments that collectively generate large volumes of multidimensional, high-frequency data [1-5]. Yet this data deluge introduces its own challenge: the information complexity far exceeds human analytical capacity, making it difficult to translate raw data into actionable insights [6].

Within this context, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as pivotal technologies, marking a paradigm shift from reactive control to predictive and prescriptive analytics [7]. These methods can identify complex, non-linear correlations within multivariate process data that are typically imperceptible to human operators [8]. Early applications of AI in mining and metallurgy-primarily in the form of rule-based expert systems-date back several decades [9], but progress was limited by computational constraints and data scarcity. Today, the convergence of big data, high-performance computing, and advanced algorithms has transformed AI from a theoretical concept into a practical enabler of operational excellence [10,11].

This mini-review synthesizes current progress in integrating AI and ML into mineral processing operations. It explores transformative applications in ore characterization, process optimization, and predictive maintenance, evaluates barriers to large-scale implementation, and identifies future research directions that may accelerate the transition toward intelligent, autonomous mineral processing plants.

Key Application Areas

The application of AI and ML in mineral processing is diverse, extending beyond proof-of-concept studies to deliver measurable improvements in process performance, efficiency, and safety. This section highlights three critical domains in which AI/ML integration has demonstrated substantial industrial impact-from ore characterization and sorting to process optimization and predictive maintenance.

Ore Characterization and Sorting

The heterogeneity of run-of-mine ore is a primary source of process variability, causing downstream fluctuations in grade, throughput, and recovery. Conventional ore characterization methods, such as laboratory assays, provide delayed and discontinuous feedback, limiting real-time control. AI, particularly computer vision and deep learning, is transforming this space.

Convolutional Neural Networks (CNNs) can now analyse high-resolution images from conveyor-belt cameras or drone-based inspections to perform near-real-time lithological classification and grade estimation [12,13]. These networks identify and quantify mineralogical features based on visual cues such as colour, texture, and reflectance [14]. Such capabilities underpin modern sensor-based sorting systems, which use AI-driven insights to trigger pneumatic or mechanical separation mechanisms, rejecting barren material prior to energy-intensive comminution [15]. This pre-concentration step reduces energy and water consumption per unit of valuable metal produced while stabilizing feed quality for downstream processes [16]. Furthermore, integrating hyperspectral and laser-induced breakdown spectroscopy (LIBS) data with ML algorithms-such as principal component analysis (PCA) and clustering-enables a richer geochemical understanding of ore variability in real time, enhancing sorting selectivity and efficiency [17].

Process Modelling and Optimization

Core mineral processing operations, particularly comminution and flotation, exhibit strong non-linearities, multivariable dependencies, and time delays, making them challenging to control through traditional Proportional–Integral–Derivative (PID) or Linear Model-Predictive Control (MPC) systems. ML techniques excel in such environments by learning complex input–output relationships directly from operational data, providing predictive models that capture interactions among feed characteristics, reagent dosage, and key Performance Indicators (KPIs) such as grade, recovery, and particle size distribution [18,19].

Comminution: In crushing and grinding circuits, ML models such as Gradient Boosting Machines (GBMs) and Artificial Neural Networks (ANNs) are used to predict product size and optimize mill load and power consumption. By integrating sensor data from acoustic emissions, bearing pressure, and motor power, these models can recommend setpoints for feed rate and mill speed to maximize throughput while minimizing overgrinding and mechanical wear [20,21].

Flotation: Froth flotation has become one of the most prominent application areas for AI. ML algorithms trained on froth image features-such as bubble size distribution, froth velocity, and texture stability-use CNNs to infer process performance parameters like concentrate grade and recovery [22,23]. Supervised learning models then relate these image features to control variables (air flow, froth depth, reagent dosage), allowing for dynamic, closed-loop control [24].

Beyond supervised learning, Reinforcement Learning (RL) has emerged as a transformative technology enabling autonomous process control. RL agents interact continuously with a simulated or real process environment to learn optimal control policies that maximize a long-term reward, such as cumulative metal recovery or energy efficiency [25,26]. Successful implementations often adopt hybrid architectures that combine deep learning for feature extraction with physics-informed or regression models for interpretable prediction [11].

Predictive and Prescriptive Maintenance

Unplanned downtime of critical assets-such as SAG mills, crushers, and slurry pumps-remains a major contributor to production losses and maintenance costs. The transition from preventive (time-based) to predictive (condition-based) maintenance represents a major shift toward data-driven reliability management.

By analysing time-series data from vibration, temperature, acoustic, and motor-current sensors, ML models can detect early signs of mechanical degradation long before catastrophic failure occurs [27,28]. This approach allows maintenance activities to be scheduled based on asset condition rather than fixed intervals, improving equipment availability and operational safety [29]. Advanced anomaly-detection algorithms (e.g., autoencoders, isolation forests, one-class SVMs) identify deviations from normal behaviour, while regression and survival models forecast remaining useful life (RUL) of components such as mill liners or pump impellers [30].

The next stage-prescriptive maintenance-extends predictive capabilities by recommending specific actions to prevent or mitigate failures. This is supported by digital twin technology, which creates dynamic, virtual replicas of physical assets. When coupled with real-time sensor feeds, digital twins enable simulation of alternative maintenance strategies and performance outcomes, guiding operators toward cost-optimal decisions [31,32]. Industrial implementations have shown that AI-driven maintenance frameworks can improve overall equipment effectiveness (OEE) by up to 20 % and reduce unplanned downtime by over 50 % [33].

Proposed AI Tools for Advanced Mineral Processing

The implementation of AI in mineral processing has advanced from conceptual demonstrations to robust, plant-scale applications through an array of specialized software, hardware, and data-management tools. Table 1 summarizes the principal AI subfields, key technologies, and their relevance to specific mineral-processing functions. The classification is organized to reflect the data flow across a typical plant-from ore feed and processing control to asset management and system-wide integration.

Table 1: Representative AI Tools and Technologies in Mineral Processing.

Application area	AI Sub-Field	Specific AI Tools & Technologies	Function and Relevance to Mineral Processing
Ore characterization and sorting	Computer Vision (CV)	CNN architectures (e.g., ResNet, U-Net)	Perform pixel-level classification of ore images for identifying mineral phases and particle boundaries on conveyor belts.
	Hyperspectral Data Analysis	PCA, k-Means Clustering, Support Vector Machines (SVM)	Analyze hyperspectral or LIBS data cubes for non-contact, real-time geochemical assay and mineral identification.
	Sensor Fusion and Control	Reinforcement Learning (RL) Agents	Optimize actuation of air jets or diverter arms based on live sensor data to maximize grade and recovery.
Process modelling and optimization	Machine Learning (ML)	Tree-based models (e.g., XGBoost, Random Forest)	Build non-linear predictive models of grade, recovery, and throughput from operational plant data.
	Deep Learning	Recurrent Neural Networks (RNNs/LSTMs)	Model long-delay time-series data in flotation or thickener circuits to forecast process states.
	Autonomous Control	Deep Reinforcement Learning (DRL) frameworks (e.g., OpenAI Spinning Up, Google Dopamine)	Develop agents that autonomously learn optimal control policies for multivariate processes (e.g., reagent dosing, mill speed).
	Hybrid Modelling	Physics-Informed Neural Networks (PINNs)	Integrate first-principles physical laws (e.g., mass and energy balances) with ML models to enhance interpretability and robustness.
Predictive and prescriptive maintenance	Anomaly Detection	Isolation Forest, Autoencoders, One-Class SVM	Detect abnormal vibration, temperature, or acoustic patterns that precede equipment failure.
	Prognostics	Survival Analysis Models (e.g., Cox Proportional Hazards, Random Survival Forests)	Estimate Remaining Useful Life (RUL) of critical components such as mill liners or gearboxes.
	Digital Twin Technology	Commercial Platforms (e.g., Siemens Process Simulate, ANSYS Twin Builder, Dassault 3DEXPERIENCE)	Create virtual replicas of assets or circuits to simulate alternative operational or maintenance strategies.
Cross-cutting Enablers	Data Infrastructure	Cloud Platforms (e.g., AWS IoT SiteWise, Azure Digital Twins, Google Cloud AI Platform)	Enable ingestion, storage, and processing of high-frequency sensor data essential for all AI applications.
	Model Operationalization (MLOps)	MLflow, Kubeflow, Azure ML	Manage end-to-end ML life cycles, including training, deployment, monitoring, and retraining of production models.
	Explainable AI (XAI)	SHAP, LIME	Provide interpretability for complex CNN and DRL models, increasing operator trust and regulatory acceptance.

Illustrative Case Examples

(a) Intelligent Ore Sorter using CNNs: A U-Net convolutional architecture processes high-resolution belt images in real time. Each rock fragment is segmented and classified as “ore” or “waste” and the output mask triggers pneumatic actuators within milliseconds. This results in accurate rejection of barren material, improving energy efficiency and feed consistency.

(b) Froth Flotation Optimizer with XG Boost and Deep Q-Learning: An XG Boost model predicts concentrate grade several minutes ahead based on froth image features, chemical assays, and air-flow data. Its output informs a Deep Q-Network (DQN) agent trained to maximize a composite reward function-e.g., (Grade × Recovery) – Reagent Cost-thereby enabling autonomous reagent-dosage control.

(c) Mill-Liner Wear Prognostics with a Digital Twin: Sensor data (vibration and acoustic) feed a Random Survival Forest model that estimates liner failure probability. These predictions are visualized in a digital twin of the SAG mill, allowing maintenance planners to simulate the trade-off between continued operation and immediate liner replacement, thereby supporting prescriptive, cost-optimal decisions.

Discussion

The ecosystem of AI tools in mineral processing demonstrates a clear trend toward integration-across data collection, model development, and real-time decision support. Cloud and edge computing platforms provide the scalability necessary for industrial deployment, while MLOps frameworks ensure reproducibility and continuous model improvement. Equally critical are explainability techniques such as SHAP and LIME, which help translate opaque model outputs into interpretable insights for engineers and operators, fostering confidence and compliance in AI-assisted control environments [35,36].

Challenges and Future Directions

Despite remarkable progress, the widespread adoption of AI and ML in mineral processing remains constrained by several technical, organizational, and human-centric challenges. These barriers must be systematically addressed to unlock the full potential of intelligent, autonomous mineral processing systems.

Data Quality, Availability, and Standardization

High-quality, representative data are the foundation of any AI system. However, mineral processing data are often heterogeneous, sparse, and noisy, reflecting diverse sensors, process configurations, and measurement frequencies. The lack of standardized data architectures and ontologies hampers interoperability between sites and vendors [34]. Moreover, labelled datasets-essential for supervised learning-remain scarce because of limited historical records and confidentiality restrictions within mining companies.

Future work should prioritize the creation of open, anonymized benchmark datasets and the adoption of Industrial Data Space (IDS) principles to enable secure data sharing and model transferability.

Model Interpretability and Operator Trust

The "black-box" nature of advanced AI models-especially deep neural networks and reinforcement-learning agents-often undermines user confidence. In critical process industries such as mining, operators must understand why an algorithm recommends a certain action before implementing it in production. Explainable AI (XAI) methods, including Shapley Additive explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), have emerged as effective tools to improve transparency [35,36]. Developing domain-specific XAI frameworks that can relate model behaviour to physical and chemical process parameters will be key to integrating AI into day-to-day operations.

Workforce Skills and Cultural Transformation

Bridging the skills gap is another critical requirement for successful AI integration. Most metallurgical and process-engineering curricula still emphasize traditional control and design methods rather than data-centric thinking. Consequently, there is a growing need for interdisciplinary training programs that combine mineral-processing expertise with data science, machine learning, and automation [37]. Equally important is cultivating a culture of collaboration between domain experts and data scientists. Embedding AI specialists within operational teams can accelerate adoption and ensure that algorithms address real industrial challenges rather than abstract optimization goals.

Toward Hybrid and Autonomous Operations

Future research is expected to focus on hybrid modelling, where first-principles (mechanistic) equations are coupled with data-driven approaches to exploit their complementary strengths [38]. These physics-informed models promise improved generalizability across ore types and plant configurations. Furthermore, deep reinforcement learning (DRL) presents a compelling path toward plant-wide optimization and fully autonomous control loops [39]. Transfer learning and domain adaptation techniques will also play a major role in scaling ML solutions across geographically and geologically diverse operations [40]. Finally, the ongoing evolution of IoT, cloud computing, and edge analytics will expand the real-time data infrastructure required to support these advanced AI frameworks, enhancing connectivity and decision-making across the entire mining value chain [41].

Conclusion

Artificial Intelligence (AI) and Machine Learning (ML) are reshaping the mineral processing industry, shifting it from empirical and experience-based operation toward data-driven, adaptive, and increasingly autonomous systems. Their integration across key domains-ore characterization, process optimization, and maintenance-has demonstrated tangible benefits in productivity, resource efficiency, and safety. AI-driven approaches enable a deeper understanding of process dynamics, facilitate real-time optimization, and support predictive and prescriptive decision-making. These advancements not only enhance recovery and reduce energy and water consumption but also contribute to sustainability objectives by lowering environmental impact and operational risk.

Despite the substantial progress, the transition from isolated pilot applications to fully autonomous, AI-empowered plants is still in its early stages. Persistent barriers-including limited data availability, model interpretability, and workforce readiness-require targeted research and strategic organizational adaptation. In this context, explainable AI, hybrid modelling, and reinforcement learning are expected to play pivotal roles in bridging the gap between theoretical promise and industrial practice.

Ultimately, the future of mineral processing will be defined by the ability to integrate AI technologies seamlessly with existing process-control frameworks and domain expertise. By fostering collaboration between metallurgists, control engineers, and data scientists, the industry can accelerate the realization of intelligent, sustainable, and resilient mineral processing operations capable of meeting the demands of a rapidly evolving global economy.

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