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Machine Learning Innovations for Improving Mineral Recovery and Processing: A Comprehensive Review*

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Abstract: To overcome the limitations of traditional mineral processing and recovery methods, cutting-edge technologies, including Machine learning (ML), emerge as a paradigm shift in this sector, offering predictive insights, data analysis, and real-time monitoring capabilities. The emergence of ML algorithms, such as Artificial Neural Networks (ANN), Support Vector Machines, and others, trigger this paradigm. This review explores real-world examples and case studies to unveil the transformative potential of ML in mineral processing and recovery (exploration, mining, production). This attempt unveils that ML algorithms are extensively utilized in enhanced ore sorting and classification, predictive modeling, real-time process control and fault diagnosis, and automated mineral identification. Among these applications, predictive modeling for process optimization and enhanced ore sorting and classification stand out, with ANN being the most frequently employed algorithm. While challenges persist, such as limited data availability, non-normally distributed and non-linear data, and varying data dimensions and rates, the advantages of employing ML algorithms are undeniable. These advantages include enhanced operational efficiency, waste reduction, increased recovery rates, real-time monitoring, cost-effectiveness, time efficiency, and reduced energy consumption. This article aims to catalyze further research and promote the widespread adoption of ML for more efficient and sustainable mineral processing and recovery practices.

Keywords: Mineral recovery, conventional mineral processing, machine learning, artificial intelligence.

Introduction

Mineral resources, the bedrock of innovation and progress, play an indispensable role in shaping the modern world. These resources are the foundation of numerous industries, providing essential raw materials for manufacturing, construction, and energy production (McCoy and Auret, 2019; Dubinski, 2013). However, the journey of minerals from the earth's depths to industrial utility has long relied on traditional processing and recovery methods. Techniques like leaching, flotation, physical separation (gravity, magnetic, electrostatic), and commination have played critical roles in conventional mineral processing and recovery methods. These traditional techniques have inherent limitations. They can be resource-intensive, time-consuming, and subject to inefficiencies (McCoy and Auret, 2019). However, recently, the landscape of mineral processing and recovery has been transformed through the integration of computer-aided technologies. Software technologies such as simulation and modelling software (e.g., DES modelling using Arena), employed by Anani et al. (2017), have revolutionized the industry. These technologies have demonstrated remarkable success by enabling rapid and virtual simulations of exploration data (Anani et al., 2017). Nonetheless, a transformative integration has emerged within the mineral processing and recovery industries, paving the way for the emergence of a superior paradigm: machine learning (ML).

As a subset of artificial intelligence (AI), ML represents the frontier of transformation in the mining industry. Its applications span exploration and resource estimation, mine planning and design, mineral extraction, ore sorting and processing, environmental and health safety, and beyond (McCoy and Auret, 2019; Ghorbani et al., 2016; Anani et al., 2017; Porwel et al., 2003). ML algorithms such as Neural networks, support vector machines (SVM), random forests (RF), and reinforcement learning, among others, are being harnessed to optimize mineral recovery processes (McCoy and Auret, 2019). Although they offer game-changer promises in the field – precision, adaptability, resource efficiency, and cost reduction, some challenges persist, underscoring the dynamic nature of this ever evolving field.

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This review aims to illuminate the transformative potential of ML algorithms – how they have been and can be used to optimize operations and processes. It seeks to inspire further research, dialogue, and the widespread implementation of ML techniques, fostering more efficient and sustainable mineral processing and recovery practices.

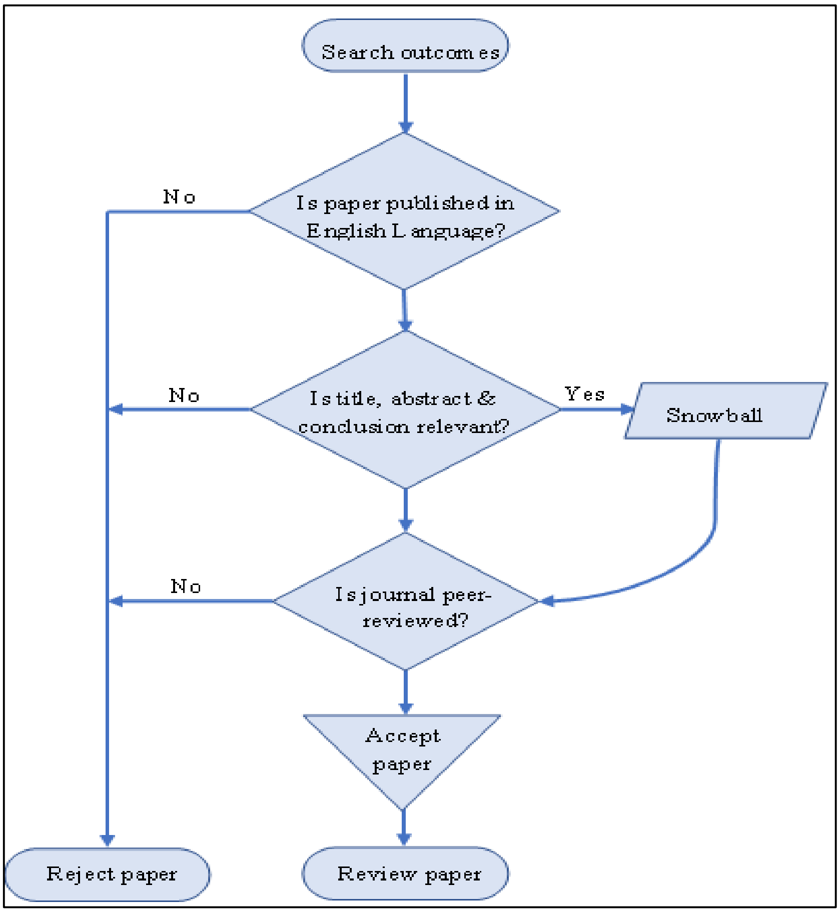

Fig. 1 Flowchart of papers review followed by this work.

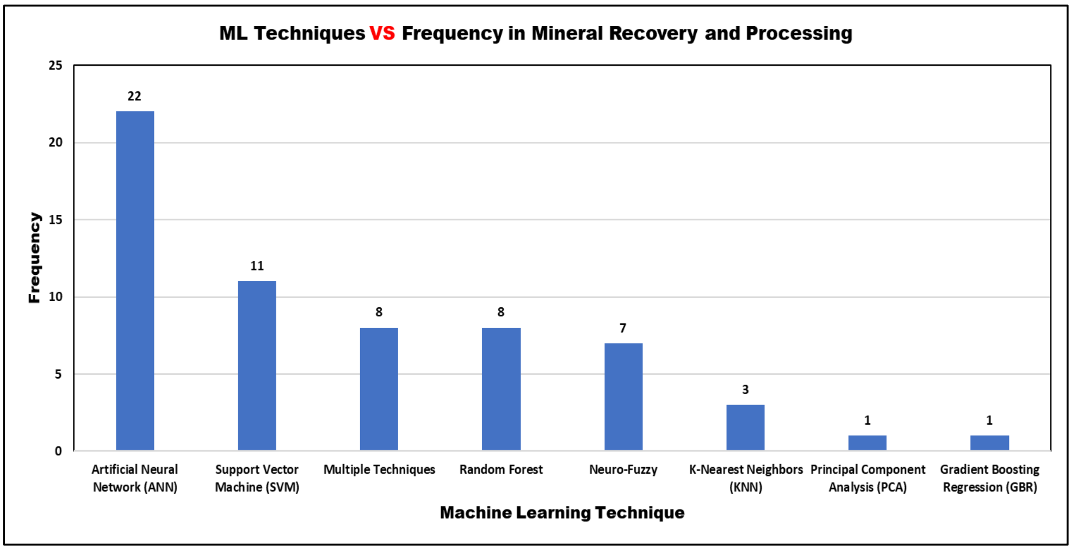

Fig. 2 Distribution of ML algorithms for mineral recovery and processing (2008 – 2025).

Review Methodology

Extensive literature searches and information extraction were conducted to identify relevant peer-reviewed publications indexed in major scientific research databases, including Google Scholar, Science Direct, Scopus, Academia, Springer, Pro Quest, Taylor & Francis, Research Gate, Wiley, Academia, PubMed, National Science Library of Chinese Academy of Sciences, Web of Science, Books, Journals, Dissertations, E-Books, E-Journals, E-Databases, CNKI, EBSCO, etc. The literature search involved searching relevant and specified keywords and phrases to narrow the search scope, encompassing terms such as "machine learning" and " mineral recovery and processing." Relevant documents were found by searching. Following Wee & Banister's (2016) strategy, the snowballing strategy involving both forward and backward searches was implemented, leading to the identification of supplementary papers. The outcome of this comprehensive search yielded an abundance of journals, conferences, and media publications about the application of ML in mineral recovery and processing. The search focus was narrowed exclusively to peer-reviewed journal articles in English, as depicted in Figure 1 following Dumakor-Dupey and Arya (2021). Papers falling within the accepted category successfully navigated all decision stages. This rigorous process culminated in an exhaustive content review of 31 accepted papers between 2008 to 2025. Figure 2 shows a summary of different ML models/algorithms used in mineral recovery and processing within the timeline of this review. Artificial neural network (ANN) is the most commonly used technique, followed by SVM. These methods are favored because they recognize patterns and model complex systems. They can model physical characteristics in complex systems without needing extensive experiments.

Overview of Machine Learning

ML is a subset of AI that focuses on the development of algorithms and statistical models that enable computer systems to learn from and make predictions or decisions based on data without being explicitly programmed (Goodfellow et al., 2016). ML algorithms can be categorized into supervised, unsupervised, and reinforcement learning, each catering to different learning tasks (Goodfellow et al., 2016). Supervised learning involves training a model on labeled data, where the algorithm learns to predict outcomes based on input features. On the other hand, unsupervised learning deals with unlabeled data, aiming to uncover underlying patterns or groupings in the data. Reinforcement learning focuses on training models to make sequential decisions by rewarding correct decisions and penalizing incorrect ones (Goodfellow et al., 2016). The choice of ML algorithm depends on the specific task and dataset in mineral processing. Some of the most commonly used ML algorithms in mineral processing and recovery include SVM, RF, ANN, K-Means Clustering, Convolutional Neural Networks, and Reinforcement Learning.

ML Approaches in Mineral Recovery and Processing

During mineral recovery and processing stages, ML offers its prowess in the following instances.

Predictive Modeling for Process Optimization

Process optimization in mineral recovery involves maximizing efficiency while minimizing energy consumption and resource waste (Flores and Leiva., 2021). Conventional process modeling relies on empirical equations and simulations, which often lack accuracy in complex mineral processing environments. ML models, such as ANN, have risen to prominence as essential instruments in domain of predictive modelling within mineral processing with desirable accuracy (Golmohammadi et al., 2013).

Golmohammadi et al. (2013) harnessed the potential of partial least squares and ANN algorithms to forecast the precipitation rate within the ferric Fe bioleaching process. Similarly, Leiva et al. (2017) employed an integration of ANN and linear, quadratic, and cubic regression methods to model copper recovery within heap leaching. Flores and Leiva. (2021) expanded the horizon by combining multiple ML algorithms, including RF, SVM, and ANN to predict copper recovery in heap leaching scenarios. Their findings yielded a notable conclusion, highlighting the superiority of ANN, particularly in capturing non-linear relationships within the studied model.

In another pertinent study, Shoppert et al. (2020) employed a multilayer perceptron rooted in ANN to uncover the dynamics of leaching conditions in fly ash desilication. Their objective was twofold: showcasing the potential for heightened SiO_2 extraction from fly ash desilication through NaOH leaching while concurrently mitigating NaOH loss via solid residue and preserving Al_2O_3 in the leaching process. Across the spectrum of predictive modelling in mineral leaching processes, ML stands as a watershed moment in the mineral industry, as illuminated by the studies of Flores and Leiva (2021), Golmohammadi et al. (2013), Xie et al. (2016), and Niu and Liu (2017).

Enhanced Ore Sorting and Classification

The traditional ore sorting and classification methods rely on physical properties and manual sorting, leading to inefficiencies and errors. However, the emergence of ML algorithms (e.g., SVM and RF) with image processing capabilities has played a significant role in the classification and sorting of ores. These algorithms measure key attributes of ores, including particle size, edge characteristics, and reflection properties (McCoy and Auret, 2019).

By employing a well-trained classifier and identifying the decision boundaries that delineate optimal-fit intervals corresponding to sieve-size categories, Andersson et al. (2012) successfully ascertained the size distribution by weight for crushed limestone rocks on conveyor belts with a high degree of accuracy. Nonetheless, the challenge of dealing with ore particles that are only partially visible has posed a significant obstacle in the application of this technology. However, Thurley and Ng (2008) tackled this challenge by employing discriminant analysis to distinguish between partially visible and fully visible particles. These investigations suggest that a reliable estimation of particle size distribution can be achieved, provided the product type is known.

Real-time Process Control and Fault Diagnosis

Several unplanned downtimes and inefficiencies in mineral processing plants result in financial losses and suboptimal recovery rates. ML algorithms emerged to continuously adapt to process parameters to maximize mineral recovery while minimizing operational costs and energy consumption (van Zijl et al., 2021). Although this area of application is growing, only a few research articles have employed ML algorithms and models in this aspect. However, Khoukhi and Khalid (2015) utilized fuzzy logic, ANN, and Genetic Algorithms for fault diagnosis. First, they applied the three-fault diagnosis scheme. Then, hybrids of these techniques are used to enhance the precision of fault diagnosis. The study concludes that the integration of the three approaches allows for gaining critical information about fault presence or its absence in the shortest possible time. Also, the works of van Zijl et al. (2021) in modern mineral processing plants utilize fault detection to minimize time spent under faulty conditions.

Tailings Management and Environmental Impact Reduction

Mine tailings pose significant environmental risks, requiring efficient monitoring and management. However, with the advent of ML algorithms, environmental risks are predicted in real-time and adequate safety measures are employed (Petropoulos et al., 2013). For instance, Petropoulos et al. (2013) integrated the SVM classifier with multi-temporal change detection of Landsat TM imagery to characterize and monitor tailing expansion in soil and plants (vegetation) with a reported accuracy of over 90%. With real-time monitoring and characterization of waste expansion rates, ML reduces the ecological footprint of mining operations.

Limitations of ML in Mineral Processing and Recovery

Despite the advantages offered by ML algorithms, such as their ability to effectively capture nonlinearities in the data without requiring prior knowledge of the underlying processes, several drawbacks exist. One prominent concern is the propensity for ANNs to over-fit the training data, potentially leading to poor generalization performance on unseen data. Additionally, the computational complexity associated with training large-scale models can pose practical challenges, particularly in real-time applications. Furthermore, some algorithms, like the ANNs, are often regarded as black-box models, meaning their internal workings are not readily interpretable by end-users. This lack of interpretability can hinder trust and understanding, limiting their adoption in certain contexts (van Zijl et al., 2021). Another limitation to ML applications in mineral processing and recovery is the domain Expertise and Large dataset requirement. Also, ML algorithms may require extensive model training and optimization to effectively classify properties relevant to mineral processing, such as ore size, edges, and reflection properties.

Future Research Directions

Future research should prioritize advancing ML applications in mineral recovery by refining hybrid models, optimizing automated feature selection, enhancing explainable AI (XAI), integrating big data, and promoting sustainable practices. The development of hybrid models that combine Deep Learning and Reinforcement Learning with domain-specific knowledge could significantly improve predictive accuracy and decision-making in mineral processing.

Automated feature selection methods require further refinement to identify optimal input parameters while minimizing model complexity. Increasing the interpretability of ML models through XAI will be essential to fostering trust and facilitating broader industry adoption. Additionally, leveraging big data from IoT and sensor networks will enhance real-time process monitoring, enabling more responsive and adaptive mineral recovery operations. Finally, future research should explore ML-driven approaches for improving sustainability in mineral processing, focusing on waste reduction, recycling, and energy efficiency to minimize the environmental impact of mining activities.

Conclusion

ML algorithms have emerged as essential tools in mineral recovery and processing, offering precise control, predictive capabilities, and automation. Their adoption leads to increased mineral recovery rates, reduced operational costs, and minimized potential environmental impact and health effects, thus reshaping the mining industry to be more sustainable, efficient, and productive. This paper reviews recent ML applications in mineral processing, focusing on research published in select journals from 2008 to 2025. According to this article, the most commonly used ML algorithms in mineral recovery and processing include ANN, SVM, and the integration of multiple techniques within the timeline considered in the review. These ML algorithms find widespread application in various types of data, including field, simulated, and historical data, enabling researchers and practitioners to analyze and optimize mineral processing operations effectively. The review identifies interesting techniques, challenges, complexities, and future opportunities within each application category. It also outlines several future directions intended to stimulate discussion among researchers in the field and guide newcomers interested in exploring ML methods for their applications.

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