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ORIGINAL RESEARCH ARTICLE

AI Applications in Smart Mineral Processing: Ore Characterization, Sorting, and Efficiency

Ramdas Biradar[1], Babaso A. Shinde[2], Milind Manikrao Darade[3], Tushar Gaikwad[4], Seeram Srinivasa Rao[5], Aarti Puri[6,9], Ashwini G. Thokal[7], Govindrajan Murali[5], Anant Sidhappa Kurhade[8,9*]

[1] *School of Engineering and Technology, PCET's Pimpri Chinchwad University, Pune - 412106, Maharashtra, India*

[2] *Department of Artificial Intelligence and Data Science, Marathwada Mitramandal's Institute of Technology, Lohgaon, Pune - 411047, Affiliated to Savitribai Phule Pune University, Maharashtra, India*

[3] *Department of Civil Engineering, Dr. D. Y. Patil College of Engineering, Akurdi, Pune – 411044, Maharashtra, India*

[4] *Department of Engineering Chemistry, PCET's Pimpri Chinchwad College of Engineering and Research, Ravet, Pune - 412101, Maharashtra, India*

[5] *Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur (Dt) - 522502, Andhra Pradesh, India*

[6] *Department of First Year Engineering (Engineering Chemistry), Dr. D. Y. Patil Institute of Technology, Pimpri – 411018, Pune, Maharashtra, India*

[7] *Department of Chemical Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai – 400614, Maharashtra, India*

[8] *Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, 411018, Maharashtra, India*

[9] *Dnyaan Prasad Global University (DPGU), School of Technology and Research - Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri, Pune, 411018, Maharashtra, India*

***Corresponding author:** Anant Sidhappa Kurhade, a.kurhade@gmail.com

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ABSTRACT

Artificial intelligence (AI) is increasingly vital in modern mineral processing, where it addresses critical challenges such as falling ore grades, rising energy costs, and the demand for sustainable operations. Despite notable progress, most existing studies focus on individual applications like ore sorting or predictive maintenance and lack a holistic view of AI-enabled mineral processing systems. This review aims to bridge that gap by examining how AI tools can be integrated into a unified workflow that spans ore characterization, sorting, and real-time process optimization. Using a structured review of research articles, industrial case studies, and technical reports from 2015 to 2025, the study evaluates key AI techniques including machine learning, computer vision, digital twins, and predictive modelling. Findings indicate that AI has improved ore recovery by up to 30% in smart sorting systems and reduced equipment downtime by as much as 50% through predictive maintenance. These results demonstrate AI's ability to enhance both productivity and resource efficiency, though challenges related to data quality, system compatibility, and model interpretability persist. The review highlights the need for explainable AI, scalable digital twin architectures, and targeted workforce development to support wider adoption. Overall, the paper emphasizes the potential of AI to accelerate the transition toward intelligent, sustainable mining under the Mining 4.0 paradigm.

Keywords: Artificial Intelligence (AI), Mineral Processing, Ore Characterization, Intelligent Ore Sorting, Predictive Maintenance, Digital Twin Technology.

1. Introduction

Mineral processing is necessary to remove the gangue from the ore, to enable the recovery of the valuable constituents. Many such conventional monitoring methods are based on manual sampling, visual check and experience, which are not effective in providing efficiency and resources. The latest AI advances provide data-driven solutions across all facet of mineral processing, from mineral and metal deposit discovery (ore prospecting) to reserves evaluation, extraction and processing and much more. The injection of AI enables real-time intelligence, predictive control, and autonomous decision making into mining operations, and allows for enhanced productivity, sustainability, and profitability. The process of ore separation is the most critical in the mineral production process, which ultimately affects the utilization of raw ores to be obtained fully in the mining industry, especially when the problems of decreasing ore grades and more complex ore types are faced [1]. Contemporary mineral processing plants require advanced, data-driven techniques to control all the stages of unit processes, from characterization of the ore to the refined product recovery [2]. The use of artificial intelligence opens new avenues and supports automatic quality prediction and full traceability of the part and the process [3]. This technological advancement is motivated by the necessity to become more efficient, reduce the environmental impact and yet sustain the economic competitiveness of mining operations in the face of an international competitive environment [4]. Sensor-based sorting provides a method to overcome these challenges [5]. Data based methods which have been advocated as a means of improving mineral processing [6].

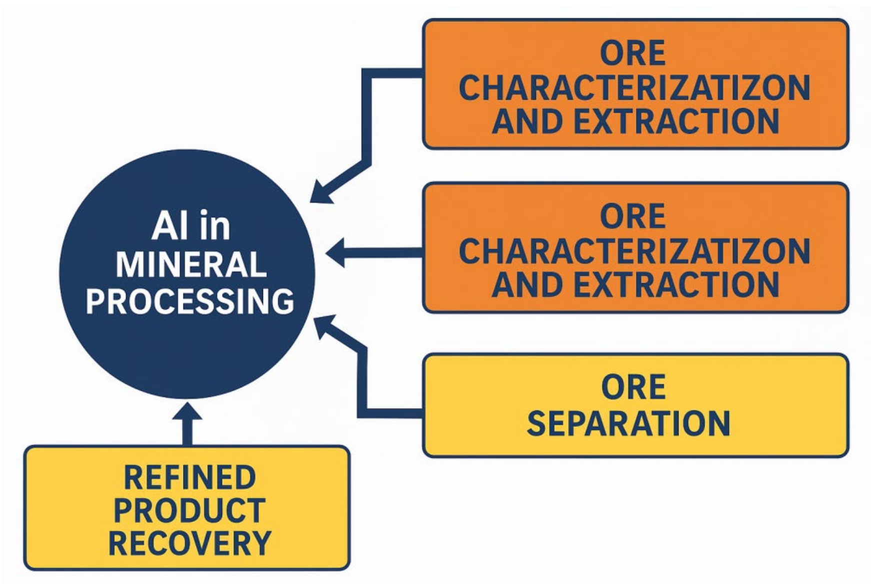

Figure 1. AI-Driven Workflow in Mineral Processing from Reserves Evaluation to Refining

The Figure 1 illustrates the end-to-end workflow of AI integration in mineral processing, beginning from reserves evaluation to final refining. It highlights how AI supports each stage—exploration, drilling, blasting, hauling, crushing, grinding, flotation, and refining—by enabling data-driven decision-making, predictive control, and system optimization. The diagram emphasizes AI's role in creating a continuous feedback loop for smarter and more efficient operations.

Through using AI algorithms, mining companies can obtain insights into the properties of ore at an unprecedented level, forecast the failure of equipment or the aging of machinery and instruments and optimize process parameters in a real-time manner [7]. The rise of Industry 4.0 technologies such as the cyber-physical system and Internet of Things has further helped in promoting the uptake of AI for mineral processing through facilitating integrated data collection [8]. Mining 4.0 may also potentially lead to increased efficiency, safety, environmental, and social acceptance of mineral extraction [9]. The incorporation of AI in mineral processing is not just an evolution, but a revolution, which is accelerating the journey towards intelligent, autonomous processing that, creates value from all possible ore deposits.

While earlier reviews have examined individual AI applications in areas such as ore sorting or predictive maintenance, this work uniquely synthesizes these developments into an integrated framework that bridges technical, operational, and sustainability perspectives across the entire mineral processing value chain.

2. Literature review

The abovementioned potential of AI application in mineral processing has led to a push of R&D efforts addressing different challenges along the value chain [10] [11]. The use of AI methods in the oil and gas industry to solve problems receives relevant attention [12]. Machine learning technology is applied to forecast the oilfield production characteristics, optimize development plans, and improve oil recovery [13]. For ore characterization, AI-based image analysis and spectroscopy allow for fast and reliable identification and quantification of minerals. Sensor-based ore sorting can be defined as the separation of o re p articles into batches according to their physical or chemical properties, as determined by in situ information, obtained from real-time, continuously operating sensors [14]. Neural networks, NLP, and generative models are some of the remarkable advancements that are influencing the industry [15]. AI algorithms can also help to optimize grinding, flotation and leaching processes, resulting in better metal recovery and less reagent use. Machine learning is utilized to develop predictive maintenance models to predict machine failures, avoid downtime and optimize maintenance intervals. Use of Data Mining in Drilling, Completion and surface facility engineering [16] Taken together, these advances add to the sustainability and efficiency of mineral processing technology. AI is a key technology to automate repetitive tasks, make better decisions, and boost productivity by reducing errors and providing business-relevant insight [17]. AI and ML have already seen deployments in various parts of the oil and gas upstream. This smart system reduces maintenance and risk costs [12]. Benefits such as the high memory space and fast numerical computing are implied by the technology [12]. AI enables the implementation of policies and practices that help the industry meet its current energy needs, without jeopardizing the environment for future generations [18]. Figure 2 presents the various AI applications across the mineral processing value chain, from ore characterization to resource optimization. This visual overview emphasizes how machine learning and computer vision are increasingly used not only in early-stage ore identification but also in downstream activities such as sorting and predictive maintenance. The figure also highlights the interconnectivity of these applications, supporting the review's focus on integrated, AI-driven processing workflows.

AI is used for areas that have enough data such as computer vision and natural language processing [19]. AI is also utilized for sensor fabrication [20]. AI has spread to engineering, urban planning and management [21]. AI based predictive maintenance reduces downtime and support the planning of maintenance operations, which can save cost at a large extend [22]. Process mining models are used to find ways to make the business more efficient. Nowadays the industrial processes are widely digitalized which allows to obtain a large amount of data that could and must be used for the improvement of processes and decision making [23]. AI at work is even loved by bosses who are hard to please [24]. Though we are yet to see a lot of empirical evidence of the impact of AI in the work place[1], it is an accepted wisdom that the use of intelligent machines will change the way businesses be conducted and how tasks are executed[25]. AI can help improve efficiency, safety, and productivity.

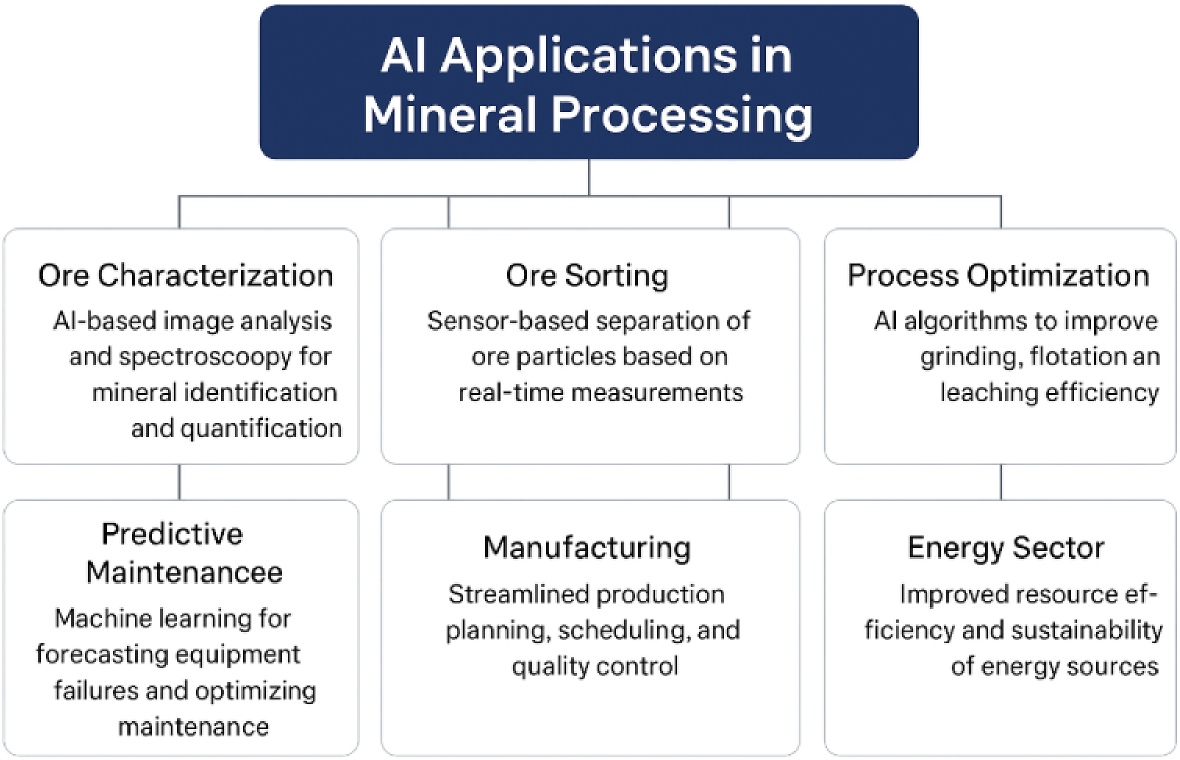

Figure 2. Key Applications of AI across the Mineral Processing Value Chain

The conventional engineering protocols of the oil and gas industry are finding it difficult to address the complexity of the industry [26]. Accordingly, the emergence of AI promises to provide innovative solutions to address these challenges of engineering operations efficiency, security and safety by taking advantages of the transformative tools and methods provided by AI [26]. The application of AI in mineral processing is both a promising and a challenging area. Data quality, data availability, choice of algorithm, and integration with existing systems are what volume editors are encouraged to look for when choosing ALPTS. Additionally, there's a demand for talent to build, launch and sustain AI-powered systems. These problems need to be address with caution. It is necessary to be aware of the deficiencies of AI models and try to counteract biases in data or in algorithms. The influence of AI on job opportunities and the necessity to invest in retraining and upskilling efforts to prepare the population for a smooth shift also require attention [27]. AI improves the efficiency, quality and dependability of renewable energy resources to ensure a sustainable energy future [28].

AI shows its influence on efficiency and cost-effectiveness of manufacturing business administration [29]. The capability of AI to address manufacturing systems globally helps decision-makers to uncover relationships and improvement measures, which leads to resource efficiency. AI can improve the quality of and consistency in renewable energy sources for a more sustainable energy future. Using AI-powered tools can facilitate better strategic planning, cross-functionality team working, and adaptive leadership for organizations [30]. AI may also be used to assist manufacturers to enhance supply chain resilience and to meet climate and sustainability objectives [31]. In the energy sector, big data and the creation of machine learning models and AI will be crucial in the future [32]. Most important, companies need to take care about certain issues, such as production process automation based on AI to re-design activities drastically [18, 33, 34]. To succeed in an industry, investments in AI tools have to be at the forefront. Even though the advantages were recognized, challenges, including privacy and interpretability of the model, continued to play a crucial role. To address these challenges, the emphasis is on explainable AI frameworks and strong cybersecurity solutions [35].

There are challenges to adopt AI in manufacturing operations, namely, high capital investment in hardware and software, talent acquisition/training to educate professionals with AI/ML technologies, and the immature nature of certain AI/ML technologies, which may not justify the return of investment [36]. Unintended security vulnerabilities and a rise in energy consumption resulting from computer-intensive AI/ML models may be other concerns. Efficiently adopting AI requires heavy investment on hardware and software infrastructure, including hiring professionals specialized in AI and ML techniques [37]. AI technologies have great potential for the innovation of product and production process domains [38]. The human-in-the-loop work has been exploited to solve a variety of manufacturing problems for its advantages, i.e., the exploitation of the interaction between the use and design of AI system as resources to learn to solve a given task. With an exposure to human-centric AI that underlines the cooperation between human and AI systems, we must consider using a variety of AI technologies to realize sustainable manufacturing. Businesses need to adopt these game-changing AI technologies to serve as competitive hinges in the fast-paced world they operate in. The Value of AI is to insert advanced information technologies to manufacturing process to bring benefits such as improving in productivity quality and cost reduction [39]. AI will further improve users' energy consumption for building a sustainable, scalable, and intelligent energy system [28]. Manufacturers can become competitive through automation [40].

AI in the manufacturing sector AI has been widely applied in the manufacturing sector [36]. The manufacturing industry has been greatly affected by the quickly evolving computational power and data analytics. AI promises close to 50% savings in maintenance costs and overall machine downtime [41] through good health management. The advanced manufacturing paradigm is being empowered by the capabilities of machine learning, pattern recognition, and deep learning [42]. Various AI features like ML, deep learning and computer vision can offer sizeable strides in resource management, waste reduction and enhancing energy usage [43]. The effects of AI-based automations are not just increased efficiency. It also encourages a deeper appreciation of its influence.

The current momentum toward Smart Manufacturing and Industry 4.0 has sparked unmatched interest in ML for manufacturing [44]. ML in the manufacturing operation to tap the potential special skills, a technology for smart manufacturing, where the technology automatically corrects potential errors in real-time to avoid any wastages, can be provided [45]. Machine Learning for Manufacturing Coming together of machine learning and manufacturing will create a virtuous union and massively accelerate improvements. When the Industry 4.0 comes, the artificial intelligence and machine learning are perceived as the wholesale revolution of a smart factory [46]. Application of AI in manufacturing and production is anticipated to revolutionize industries. AI,2017 Zwilling et al., 2017 AI could bring in a revolution in the field of manufacturing by enhancing the OEE, Process optimization, and Product quality improvement [3]. AI and ML in manufacturing Machine is now able to do cognitive tasks like problem solving, decision making and learning.

AI has the potential to revolutionize industries due to its broad reaching applications [47]. AI is a force multiplier that can be used repeatedly at little to no additional marginal cost. AI can be used to tackle a wide range of business problems, and is frequently more scalable than traditional approaches. The industry that is predicted to be the biggest gainer from AI application is manufacturers [47]. The introduction of AI makes planning and scheduling more effective, minimizes wastes, and values value adding activities [48]. Some of the advantages of incorporating AI are increased productivity, real-time optimization, predictive maintenance, as well as better quality control. In addition, AI techniques of machine learning, deep learning, and computer vision have had a significant impact on the development of the manufacturing assembly robots where these robots have been able to operate more efficiently, safely, and intelligently [49]. The application of AI in the manufacturing pipeline might see hesitation because of its unavailability and unsolved issues [50]. This requires initiatives to raise awareness on potential AI applications in the manufacturing industry, and to alleviate the barriers that hinder its adoption [50]. Table 1 compares AI applications across different industrial sectors—mineral processing, oil & gas, manufacturing, and smart energy. It outlines the AI techniques used, their specific purposes, benefits achieved, and major challenges faced in each domain.

Table 1. Summary of Artificial Intelligence Applications in Mineral Processing and Related Industrial Domains

Application Domain	AI Technique/Tool	Purpose	Benefits	Challenges
Mineral Processing	ML, DL, Neural Networks	Ore characterization, sorting, grinding/flotation optimization	Enhanced recovery, reduced reagent use, faster mineral identification	Data quality, algorithm selection, legacy systems
Oil & Gas Industry	ML Forecasting Models	Production prediction, optimization, maintenance	Improved oil recovery, reduced risk and maintenance costs	Complexity of processes, data integration
Manufacturing	Smart Automation, Computer Vision	Process optimization, quality control, supply chain resilience	Real-time adjustments, higher OEE, waste reduction, energy efficiency	High investment, skill shortage, tech immaturity
Smart Energy & Sustainability	Predictive Models, Big Data	Renewable energy integration, energy use prediction	Cost-effective operations, sustainability, emissions control	Privacy, model interpretability, cybersecurity
Industry 4.0 / Smart Factories	ML, Digital Twins, Robotics	Smart factories, error correction, cognitive automation	Productivity, predictive maintenance, real-time optimization, safety	Lack of awareness, adoption hesitation, retraining needs

Recent research shows a clear trend toward the use of machine learning for real-time ore characterization. Techniques such as support vector machines and convolutional neural networks have enabled rapid grade prediction and automated mineral classification. These models, when combined with hyperspectral imaging, provide high spatial resolution and reduce dependency on manual assays. Collectively, such advances demonstrate a shift from laboratory-based analysis to intelligent, data-driven systems suitable for in situ decision-making during mineral processing.

3. AI in ore characterization

Ore characterization Ore is an important constituent in mineral processing and its characterization is very essential to understand the physical, chemical and mineralogical properties in ore sample [41]. Conventional ore characterization techniques (e.g., microscopy, X-ray diffraction, chemical assays) are time-consuming and labor-intensive, and provide only limited information [42]. With the availability of large datasets throughout various ore characterization methods, AI methods, in particular machine learning algorithms, provide a powerful and effective method of analyzing the data. Fault detection or prediction of Faults is accomplished by AI algorithms, replacing periodic maintenance with predictive one [41]. The figure 3 categorizes AI-enabled ore characterization into three key domains: mineralogical mapping, grade prediction, and digital twin simulation. It visually demonstrates how AI techniques such as CNNs, machine vision, and supervised learning algorithms enhance mineral detection, ore grade estimation, and dynamic modelling of orebody behavior.

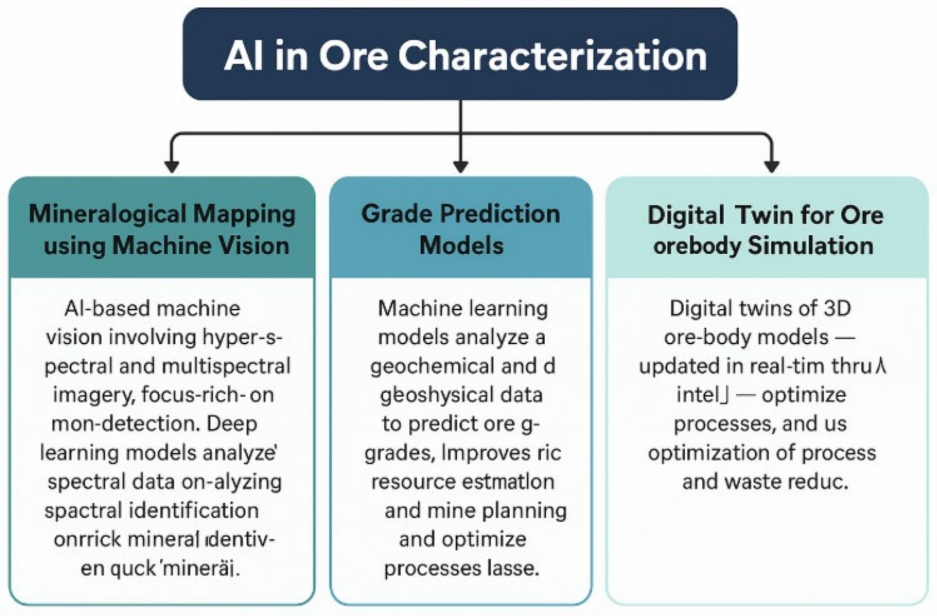

Figure 3. Key Applications of AI in Ore Characterization—Mapping, Grade Prediction, and Digital Twin Simulation

3.1. Mineralogical mapping using machine vision

AI-based machine vision systems, notably those using hyperspectral and multispectral imagery, have revolutionized mineralogical mapping with a non-destructive, high-throughput means of mineral detection. These instruments record data in intervals through a wide range of wavelengths (far past the visible) that can be used to identify subtle differences in mineralogy. Deep learning, specifically Convolutional Neural Networks (CNNs), learns from the large spectral libraries to identify and categorize certain minerals fairly based on their characteristic spectral signatures. Once trained, these CNNs are capable to analyses image data nearly instantaneously allowing for rapid and precise phase maps throughout the entire ore body. This method diminishes the reliance on time consuming and destructive laboratory analyses, and offers spatially high resolution details that are important for the exploration and ore processing industry. These approaches free themselves from manual labor of inspection and expertise [51]. AI is very good at automating away labor intensive work. The utilization of AI in this field makes mineral identification faster and more accurate, yielding a more efficient control in subsequent processes. An AI can access information at the same time from many different sources. -There are opportunities to use AIM tools in conjunction with automated mineralogy methods to contribute to a timely and accurate ore characterization.

AI-empowered mineralogy enables in-situ decision making for process optimization. Streamline of mineralogical data into instantaneous information and informed real-time decisions transforming mineral processing [52]. The use of AI and automated mineralogy can also be expanded to ore behavior forecast during processing. An understanding of the extent of mineral liberation is difficult, but once obtained, advanced analysis prediction models, should, with future developments, be able to predict the floatability of a mineral with an accuracy of ± 2% Floatability being a rougher floatation recovery of a grinding product. AI for mineral liberation analysis benefits mineral separation in order to achieve better recovery rates and less waste.

3.2. Grade prediction models

Models based on machine learning technology are also increasingly being applied for the accurate and flexible prediction of the ore grade in comparison to conventional geostatistical methods. Supervised techniques such as Random Forests, Support Vector Machines (SVM) and XG Boost are exposed to historical geochemical and geophysical measurements. These models are trained to find complex, non-linear patterns within the data that enables them to capture variations in ore grade even in geologically complex deposits. The result is enhanced resource estimation, more accurate mine planning, and more focused extraction methods, leading to greater overall economic feasibility of mining projects. They are able to integrate various sources of information to estimate mineral potential and define areas where exploration should be undertaken [53]. By enhancing the accuracy in grade prediction, AI can be used to optimize mine planning and enhance the economic potential of mining investments. Kassian's team also uses AI to forecast the behavior of various ore types during processing, enabling the process to be tuned in real time. The combination of AI methods into grade prediction models provides more advantages such as less use of resources and environmental impact. AI efficiencies unlock better prediction, smarter decision-making and refined mining processes AI algorithms are key in the following areas: 1. AI can be integrated to forecast stock market return by using the past price and firm financial statements [54].

3.3. Digital twin for orebody simulation

In mining, digital twins are digital counterparts of the physical ore body modelled in 3D with information updated in real time through the use of data generated by sensors and data analyzed in real time through AI algorithms. These virtual ore body models represent the ore body behavior in the extraction and processing stages and ensure ore variability, mass movement and grade variation. AI-enabled digital twins enable dynamic decision-making and scenario analysis by incorporating real-time input from drilling, blasting, hauling, and processing equipment. This results in optimal process flows, less energy- and reagents consumption as well as waste reduction through exact adjustment of the extraction process. Therefore, digital twins effectively minimize over-processing and improve overall yield and operational efficiency across the mining value chain. Simulating products and systems using real-time digital twins is enabled. The figure 4 compares three concepts: a Digital Model uses manual one-way data flow from the physical object; a Digital Shadow has automatic one-way data flow; and a Digital Twin features continuous two-way automatic data exchange between the physical and digital objects [55].

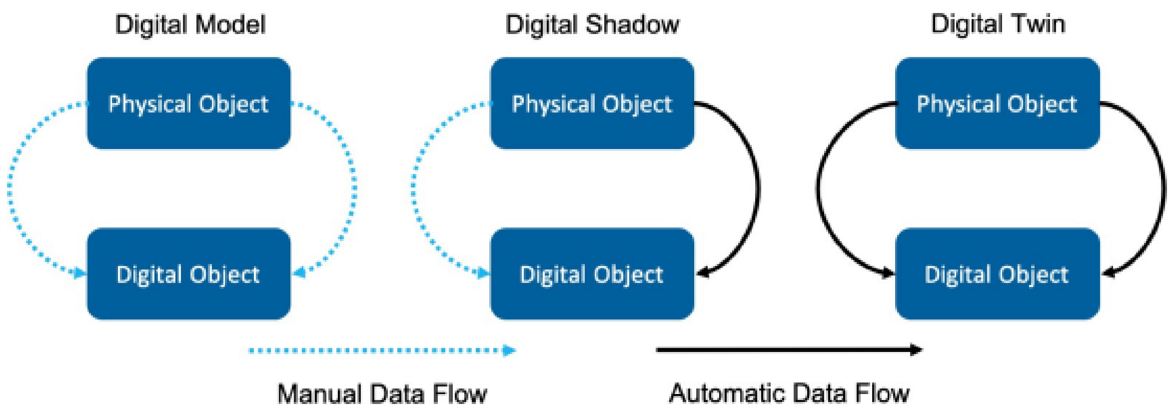

Figure 4. Digital model, shadow and twin

This enables the ability to forecast future actions, to maximize operations, and to fine tune the control system [56]. AI-supported digital twins are employed to run through the different operation conditions, to analyses the process parameters, and to anticipate the effects of process alterations. In this range of simulation, adjustments could even be made before a divergence to improve the carcass operation and avoid breaks. Process parameters and disturbance may be broken down by means of digital twins. Digital twins can be employed to enhance performance and efficiency through integrative sensory data, past experience, and human know-how [57]. Digitization of the mineral resource, and the mineral reserve, geotechnologies and control allows for the production, and to be a snapshot of the marketing [58, 59]. The search, mining, dressing and utilizing of the coal are also improved [59]. With digital twin technology, one can realize real-time prediction, optimization, monitoring and control through the integration of data and simulators [60, 61]. A DT can test products and systems with real-time data, and to predict the future behaviors, optimize the operations and fine-tune the control strategies [61-64]. NASA Apollo employed digital twins to produce 2 duplicates of a spaceship [65]. AI for characterization accelerates ore measurements and the pace of planning and process control. The table 2 provides a detailed breakdown of how different AI models (like CNN, Random Forest, SVM, etc.) are applied to various aspects of ore characterization. It summarizes their applications, advantages, expected outcomes, and associated limitations or challenges.

Table 2. AI Techniques and Applications in Ore Characterization for Smart Mineral Processing

Ore Characterization Aspect	AI Technique/Model	Application	Advantages	Outcomes	Limitations/Considerations
Mineralogical Mapping	Machine Vision, CNN, Hyperspectral Imaging	Non-destructive mineral identification and mapping	High-throughput analysis, reduced lab time, spatial precision	Faster mineral ID, real-time mapping, better process control	Requires spectral libraries and training data
Grade Prediction	Random Forest, SVM, XGBoost	Ore grade estimation using geochemical/geophysical data	Captures complex patterns, works in heterogeneous zones	Improved resource estimation, optimized extraction strategy	Model accuracy depends on historical data quality
Ore Behaviour Prediction	AI Integration with Mineralogy	Forecast mineral liberation and floatability	Real-time adjustment of processing parameters	Increased recovery, reduced waste	Accurate modelling of mineral floatability is challenging
Orebody Simulation	Digital Twins + AI	Real-time simulation of ore body and process behaviour	Scenario testing, proactive decision-making	Optimal yield, reduced reagent use, minimized over-processing	High setup cost, integration of real-time sensors needed
Control Optimization	AI-driven Simulation	Parameter control and disturbance analysis	Forecasting, fault detection, fine-tuned control	Enhanced performance and minimized breaks	Depends on accurate sensory inputs and calibration
Resource Digitization	AI with Geotechnologies	3D modelling of mineral reserves and resource planning	Live updates, performance evaluation	Efficient marketing, mining, and dressing plans	Digital infrastructure and standardization required

A comparative evaluation of AI algorithms used in mineralogical mapping and ore sorting reveals notable differences in performance and adaptability. Convolutional Neural Networks (CNNs), for example, have demonstrated high accuracy (often exceeding 95%) in image-based mineral classification due to their ability to automatically extract spatial and spectral features from hyperspectral and multispectral datasets. In contrast, Support Vector Machines (SVMs) tend to perform well with smaller datasets and in cases where feature spaces are well-defined, but their accuracy typically decreases when handling heterogeneous or high-dimensional data. Random Forest (RF) models offer a balance between interpretability and predictive capability, especially in grade prediction tasks involving geochemical data, though they generally underperform CNNs in tasks requiring spatial feature learning. This comparison suggests that algorithm selection in mineral processing should be guided by data type, dimensionality, and real-time performance requirements—CNNs being more suitable for high-resolution image analysis, while SVMs and RF are preferred for structured tabular datasets.

4. AI for intelligent ore sorting

AI is turning and powering ore sorting into a smart and more efficient process where sensor-based technologies, computer vision and robotic control systems play a fundamental role in reaching an improved mineral recovery and a high waste rejection process. Smart ore-sorting systems use sensors and machine learning to make split-second decisions to separate ore from waste. The above techniques streamline the sorting process making it faster and more accurate, particularly in high-throughput mining operations. The figure 5 illustrates an integrated AI framework for smart ore sorting, combining sensor technologies (e.g., XRT, LIBS), computer vision, and robotic control systems. It shows how AI facilitates real-time mineral detection, image-based feature extraction, and robotic actuation for precise and efficient separation of ore from waste.

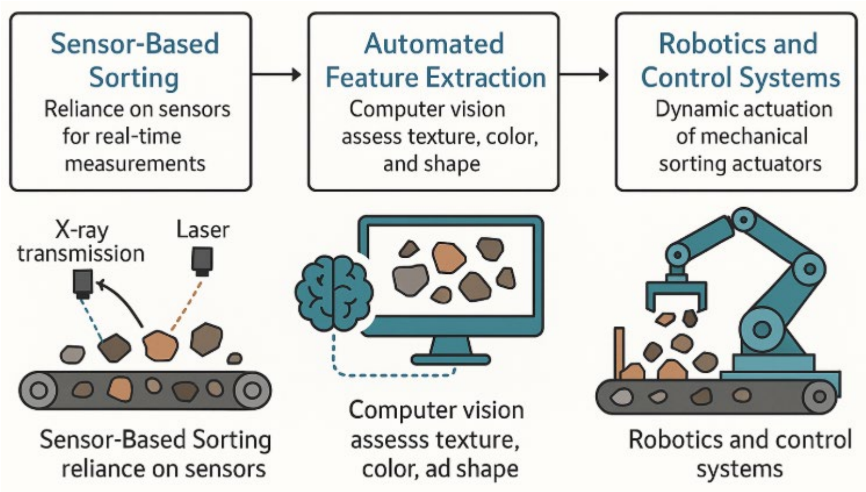

Figure 5. AI-Driven Framework for Intelligent Ore Sorting Using Sensors, Computer Vision, and Robotics

4.1. Sensor-based sorting

Sensor-based ore sorting systems rely on the real-time quality measurements from a set of sensors (e.g. X-ray Transmission, X-ray Fluorescence, Laser-Induced Breakdown Spectroscopy, Near Infrared) to estimate the internal or surface composition of the ore particles on the belt. This information is essential for the aids, as it gains insights into varying divisional fragment of mineral, density, or elemental makeup of the fragment. A supervised machine learning model is used to classify this sensor package data to automatically discern ore from waste. This process lessens the reliance on manual involvement, and increases the amount of recovery by allowing the recovery of low grade, but valuable, ore and expeditiously discarding actual waste. The dule-energy X-ray sorting technologies have been undertook increasing attention. The system shown in figure 6 uses an X-ray source and detector to scan raw ore on a conveyor; an industrial computer analyses the data and activates a valve powered by an air bottle to separate valuable ore from waste [66].

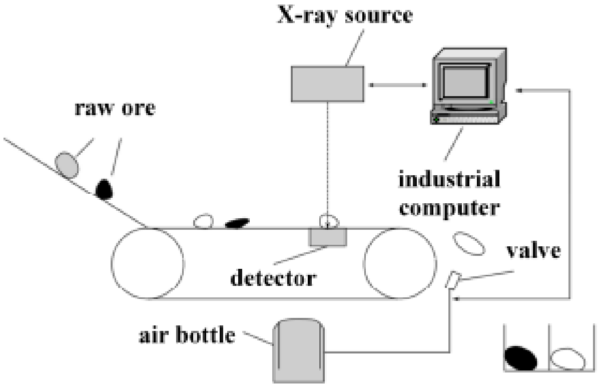

Figure 6. Antimony ore sorting device

It is based on the different attenuation of high and low energy X-rays when they pass through the material [67]. Such systems tend to include some form of robotics for physically segregating the ore and waste materials to a high degree of accuracy and at high speed [68]. The data streams from the robotic sorters can also inform about composition and efficiency, which helps verify the quality and progress of the AI algorithms, as well as subsequent processes [69]. It can also improve the efficiency and quality of classification of municipal solid waste through the application of robots [70]. Combining robotics with AI based decision-making improves the accuracy and throughput of sorting, and reduces the need for manual labor [68].

4.2. Automated feature extraction

AI-driven computer vision systems can also improve sorting accuracy by assessing visual parameters, for example, texture, colour, size, and shape features of the ore particles. Images of the material flow are recorded by high-resolution cameras and meaningful patterns and visual markers – those associated with valuable minerals – recognized by algorithms. These features extracted are fed into classification models (e.g. CNN) to identify the type of ore. The models are trained to recognize fine visual features that can be virtually impossible to be seen by a human, leading to highly precise and consistent sorting decisions even when lighting and presentation of the ore are not clean and fixed. Among them, the visual sensor is most commonly used due to its excellent non-destructive and fast detection [71]. Computer vision is the process of acquiring, processing, analyzing, and understanding images and then extracting information from it that can be processed or interpreted by a computer. Machine vision can achieve image recognition by acquiring hyperreal images by devices and features extraction [72].

4.3. Robotics and control systems

Physical sorting infrastructure is combined with robots and smart controls, to add an AI-driven aspect to the sorting and thus complement AI-based identification. These AI-powered systems dynamically actuate mechanical actuators, such as air jets, flaps, or pushers, to physically divide the material stream in accordance with the AI classification. Furthermore, by using feedback from AI models, conveyor belt speeds, flow rates of feeders, and reject gates can be controlled in real time. Sort parameters are dynamically adjusted such that the throughput is maximized while maintaining a high degree of sorting accuracy. This combination of AI, sensor, and robot is enabling mines to handle more extensive range of material with more accuracy and less cost of operation. AI algorithms can forecast systems breakdowns, optimize maintenance timing and tweak system performance to reduce downtime. Yet systems can be very costly to damage during an abnormal event involving a sensor failure etc. [73]. The application of computer vision, natural language processing, process control, and sensor systems have increased the attention being given to robot-based automatic sorting fields. The system in figure 7 integrates speech and 3D visual perception to match user commands with scene rules, generating a semantic map that guides automatic robot programming and real-time task execution. [74].

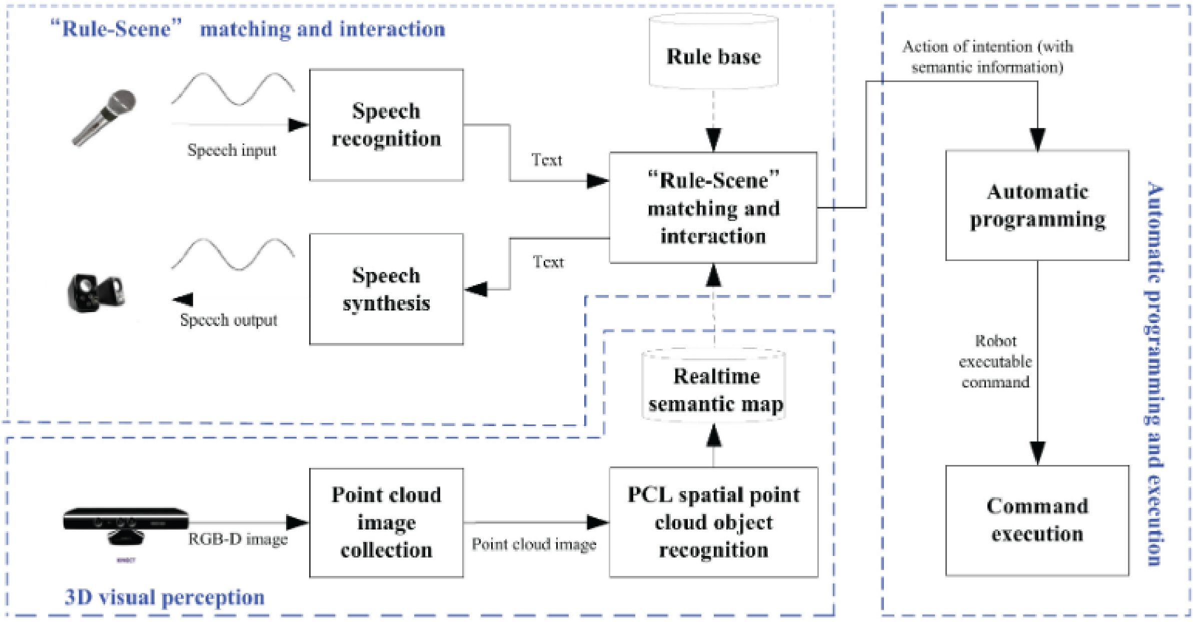

Figure 7. Automatic operating system for robots

Sorting systems of waste materials by automatic systems typically employ image recognition artificial intelligence (AI) and robots to sort mixed types and properties of objects into categories as recyclable materials [75]. The tendency to handle multiple shapes and sizes of robots makes this act more flexible and faster [76]. The table 3 summarizes the technological components and AI techniques used in intelligent ore sorting systems. It includes sensor-based sorting, automated feature extraction, robotics, control systems, and integrated systems. The table outlines each component's function, benefits, expected results, and practical limitations.

Table 3. AI for Intelligent Ore Sorting

Ore Sorting Component	AI Technique/Technology	Application	Advantages	Outcomes	Challenges/Limitations
Sensor-Based Sorting	Supervised ML, XRT, LIBS, NIR	Real-time mineral identification via multi-sensor data	Reduces manual sorting, handles low-grade ore	Improved recovery and waste rejection rates	Requires calibrated sensors and robust ML training
Automated Feature Extraction	Computer Vision, CNNs	Detection of texture, colour, shape from high-res images	Non-destructive, fast detection, precision sorting	Consistent classification even under variable conditions	Lighting and ore presentation variations may affect accuracy
Robotics in Sorting	AI-Controlled Actuators, Real-Time Feedback	Automated physical segregation via actuators like air jets	Increased speed and sorting precision	Reduced labour, scalable high-throughput sorting	System failures or sensor faults can cause costly disruptions
Smart Control Systems	Feedback-Driven AI Algorithms	Dynamic adjustment of belts, feeders, gates	Process optimization, real-time control	Maximum throughput with minimal manual input	Complexity in control logic integration
Quality Monitoring	Data Analytics from Robotic Streams	Evaluation of sorting	Feedback for continuous AI	Higher classification	Requires high-frequency data

Ore Sorting Component	AI Technique/Technology	Application	Advantages	Outcomes	Challenges/Limitations
		composition and system efficiency	algorithm improvement	reliability and downstream efficiency	processing capability
Integrated Systems	AI + Robotics + Sensor Fusion	Full intelligent sorting loop from sensing to actuation	Comprehensive automation, cost and labour efficiency	Enhanced adaptability in variable ore environments	High capital cost and maintenance requirements

Table 3. (*Continued*)

5. AI for operational efficiency and optimization

Being deployed in all areas of mining, AI is revolutionizing the way production processes can be conducted, provides greater control over the maintenance of production infrastructure, predicts equipment's failure, etc. It also saves on the use of energy and mineral resource, by allowing for them to be used more efficiently. By combining AI models with live sensor and control data, mining companies can make intelligent, data-guided decisions that help to maintain productivity, cut downtime and promote sustainability. One of the touted benefits of the technology is that AI can handle mundane tasks that are often monotonous and unfulfilling for humans, such as compiling data from meetings and appraising the quality of fruit [77]. The figure 8 summarizes various AI applications used for operational efficiency, including process parameter optimization, predictive maintenance, and energy/resource optimization. It outlines how AI leverages real-time sensor data and analytics to drive sustainable and cost-effective mining operations.

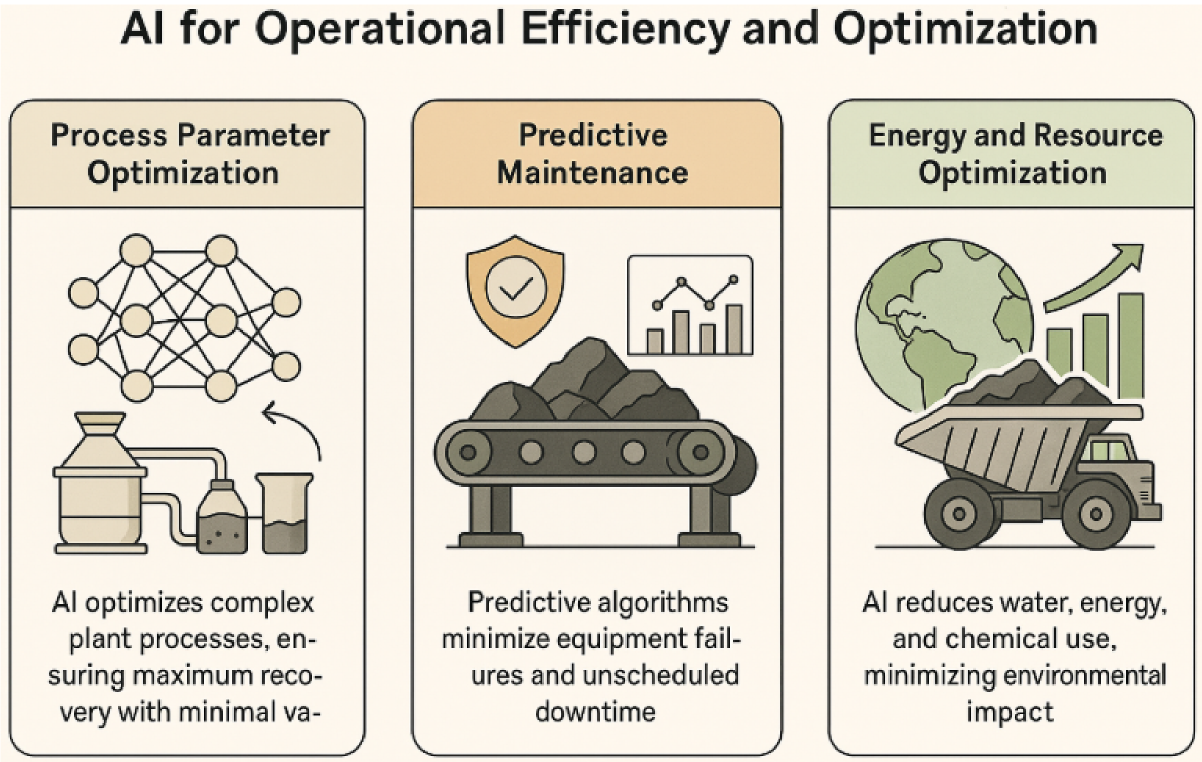

Figure 8. AI Applications for Enhancing Operational Efficiency and Optimization in Mining

5.1. Process parameter optimization

Reinforcement learning and artificial neural networks (ANNs) etc. are used to model and optimize complicated non-linear relations between process and output performance. In a mineral processing plant (e.g. grinding mills, flotation cells, leaching tanks), parameters such as grinding speed, reagent dosages, pH, and air flow can have a major influence on recovery rate and product quality. Some AI models are trained on both historical and real-time process data to predict the impact of parameter changes and provide real-time tuning recommendations. In the case of reinforcement learning, systems can continuously optimize, adapting dynamically based on a trial and error approach that is continually refining the process for the highest yields, minimized variability, and maximized energy efficiency. AI, as well, is taught the application to enhance wastewater process control or to forecast hardly determinable parameters [78]. By AI one can also apply the optimization technology of the processes, leading to rapid decision and enhancing the efficiency, stability and safety of the production of the chemical products [79].

5.2. Predictive maintenance

AI-based predictive maintenance solutions are used to avoid unscheduled equipment breakages and minimize unplanned downtime in assets like crushers, conveyors and grinding mills. These systems process monitoring information such as vibration signatures, thermal readings, acoustic emissions, power consumption, etc., in real-time to alert operators of the early stages of mechanical degradation or component failure. Machine learning algorithms detect patterns and outliers that precede failures, so an early warning is available to prevent potential incidents Authors All TBI You see TBI Anomaly Detection is the most advanced Predictive Maintenance API in the world! So that maintenance intervals can be maximized, stockholding minimized, machine life optimized – to enable operational reliability and control of costs. According to them "The use of AI has delivered increased efficiency on inspection and detection of anomalies such as unusual turbine vibration in its early stage, and recommendation of measures for maintenance proactively, resulting in avoidance of a break down" [80]. Leveraging AI in maintenance practices indicates a decrease in unexpected downtime and extending life of capital assets [81]. Predictive maintenance uses machine learning models to identify possible failures in advance to allow preventive act, thus avoiding unexpected downtimes [82]. AI for predictive maintenance is strategically used by organizations, enabling them to achieve a competitive advantage of efficiency, cost-effectiveness, and sustainability [52]. Explainable AI methods are essential because they explain why predictive maintenance alerts are given (providing explanations), improving the system's starts modern and assumed into expected decision-making in user confidence [83]. AI for predictive maintenance represents an evolution toward enhancing maintenance with advanced analytics [84].

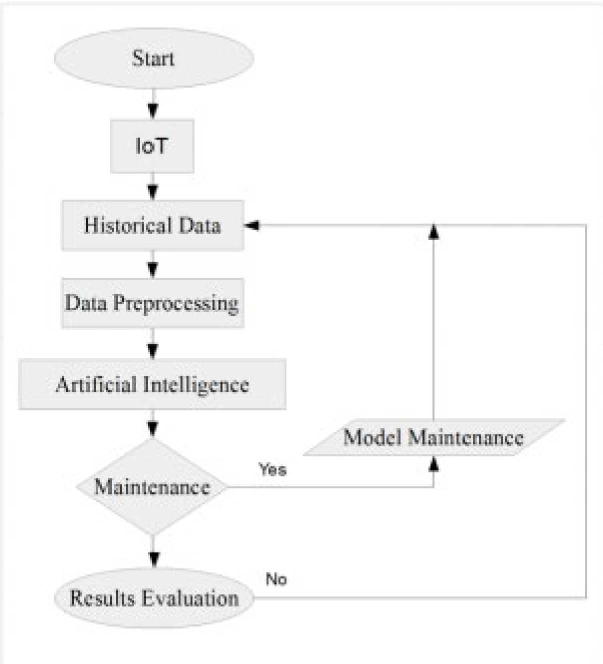

Figure 9. PdM using AI Flowchart

This figure 9 illustrates the working of an AI-driven predictive maintenance system. It outlines the stages from real-time sensor data acquisition to anomaly detection, predictive modeling, and maintenance action. The diagram shows how AI can prevent equipment failures and optimize maintenance schedules. This is corroborated with the incorporation of component, machine and systems level parameter measurements to supply condition prediction trend reference models [85]. For example, predictive maintenance not only provides the benefits of higher machine performance, condition prediction, and fault detection through data analytics, but also allows for an early operator warning of an erroneous operation [86]. By shifting or supplementing maintenance cycles with prediction maintenance, it guarantees that machines work correctly and on time and reduces unnecessary maintenance costs [87]. The further usage of predictive maintenance reduces the amount of unused maintenance and failure of critical nature, improving the efficiency of the system and reducing production down time [88].

5.3. Energy and resource optimization

Mining is extremely resource-intensive, as it requires significant quantities of water, fuel, power, and chemicals. AI enables multi-objective optimization algorithms that trade-off between these conflicting objectives, like maximizing production and minimizing environmental damage. State-of-the-art simulation models and artificial intelligence (AI) based decision-support systems are used to compare different operational scenarios to identify the most sustainable and economical processing layouts. For example, AI algorithms can improve ventilation in underground mines, and improve energy efficient whilst minimizing wastage in and optimum water use in flotations circuits, thereby reducing energy inefficient water waste. With such AI-driven tactics, mining companies are also pursuing improved environmental compliance and lower carbon emissions and ecological footprint, without significantly reducing operational output. In addition, the deployment of AI in predicting malfunctions of equipment dial accounts for improved preventive maintenance thereby reduces the cost of production and environmental cost of maintenance. Artificial intelligence's capability to analyze data and interpret patterns contributes to more informed decisions and predictions, ultimately resulting in fewer mistakes and less wastage and more well-ordered resource utilization. The integration of AI into the maintenance planning is also a way that could outperform common procedures, with the possibility of contributing to an enhancement, both economically and ecologically, the results achieved by applying the latter, based on certain characteristics of the evaluation [89]. With the help of AI, the transition to renewable energy and the use of alternative fuels, reducing the fuel use and maximum efficiency [90]. Analyzing usage patterns and identifying inefficiencies, machine learning methods are essential for the optimal operation of energy systems with considerable reduction of CO 2 emissions [91]. This optimization goes beyond specific processes to enhance overall environmental management aspects, such as water and waste management, which helps maintain mining activities in a sustainable manner [92].

Ethics is important to make sure that AI contributes positively to sustainability, in particular when also combining environmental and social data in multi-objective optimization [93]. Simulated PCM-cooling enhanced thermal management of the smart phone [94], and numerical calculation of the flat plate solar collectors improved the performance [95]. PCM cooling based on CFD decreased IC chip temperature [96], while optimized CFD flow paths enhanced thermal reliability [97]. Minijet impingement improved heat exchanger performance experimentally [98], and ANN-GA models optimized the IC chip placement for improved cooling [99]. They improved the heat exchanger performances with Nano fluids [100], and also developed a hygiene water-saving public faucet [101]. Holed twisted tapes increased the convective heat transfer [102] and cooling techniques for severe electronics were reviewed critically [103]. Diesel engines [104], and aluminum of MCW Ref. [105] were subjected to diesel engine, solar collector, and bio-diesel for drying hence demonstrated the feasibility in eco-C (a) (b) drying. Substrate conductivity was critical for component cooling [106] and CFD-optimized aero foils by enhanced aerodynamic efficiency [107]. Fuzzy logic facilitated the prediction of heat transfer for helical tapes [108] and PCM assisted IC chip layouts were found to lead to improved thermal performances [109]. Nano fluids enhanced MQL grinding performance [110], particularly Al2O3-based Nano fluids [111]. Improved double pipe heat exchangers using corrugated twisted tapes [112–114]. The substrate had a significant effect on electronics cooling [115], and twisted tape holes enhanced convection [116]. Systematically review of Ruggedized Electronics cooling methods [117].

Sensor of wind turbine parts were mapped temperature changes with them [118] and circuits of smart phone showed the cooling effect via applying PCM [119]. The strength of welded plates depended on the overlap angle [120] and the spring types were compared mechanically [121]. An automated surface finish measurement system was also developed [122] and helical double-pipe exchanger analysis was performed using CFD [123]. HVACR duct design was automatized through coding [124], and once more Nano fluids enhanced exchanger efficiency [125]. New bumper enhanced vehicle safety through energy absorption [126] and tinospora based adsorbents were used to clean heavy metals [127]. The strength of laser welded TRIP steels was thickness dependent [128], as was the response of curved plate [129].

PCM cooling of IC chips was modelled and verified to be efficient [130], while fuzzy models were utilized for heat transfer of wavy tape inserts [131]. Oxygenated additives reduced emissions in gasoline engines [132], and coil-type exchangers were compared in terms of performance [133]. PCM lowering cooled EV batteries [134], and plastic waste was studied for fuel generation [135]. IC cooling by PCM presented heat-regulation advantages [136] and rock damage was detected by deep learning sorting [137]. Heat sink design was implemented based on microchannel optimization [138], and use of biodiesel blends resulted in enhanced engine performance [139–140].

Enhancements in heat transfer with trapezoidal ducts with vortex generators were also observed [141–142] and paddle mixer shaft failures were investigated [143]. Temperature: PCM was applied in controlling the heat of smartphones [144], and FEA increased the durability of the mixer shaft [145]. The twisted tape augmentation was reviewed [146] and AI for sustainable mining was described [147]. Vibratory feeder dynamics were modeled [148] and cut sections enhanced helical insert performance [149]. Neither did EGR using mohua oil for emission reduction [150], AI-metallurgical efficiency [151] nor minijet nozzles for improved heat transfer [152-156]. The table 4 outlines the main AI-enabled functions related to operational efficiency, including process optimization, predictive maintenance, energy/resource optimization, and sustainability enhancement. For each application, it lists the corresponding AI methods, primary functions, resulting benefits, and strategic implications.

Table 4. AI for Operational Efficiency and Optimization in Mining

Application Area	AI Technique/Model	Purpose/Function	Benefits/Outcomes
Process Parameter Optimization	Reinforcement Learning, ANN	Modelling and optimizing complex non-linear relationships between input parameters and output performance	Higher yield, real-time process tuning, improved energy efficiency, stability, and safety
Predictive Maintenance	Machine Learning, Anomaly Detection	Early identification of mechanical faults using sensor data (vibration, temperature, etc.)	Reduced downtime, optimized maintenance schedules, longer equipment life, cost savings
Energy and Resource Optimization	AI Decision-Support Systems, Multi-Objective Optimization	Balancing production targets with resource efficiency and sustainability	Reduced carbon footprint, minimized waste, improved ventilation and water use, enhanced compliance
Sustainability Enhancement	AI + Simulation & Forecasting	Improving renewable energy integration and environmental management in mining	Optimized fuel usage, CO_2 reduction, better water and waste management, circular economy support

Despite the growing body of research on Artificial Intelligence (AI) applications in mineral processing, several notable gaps persist. Current studies primarily focus on demonstrating individual AI applications such as ore characterization, sensor-based sorting, and process optimization. However, there is a lack of integrative frameworks that unify these AI tools into a cohesive, real-time operational ecosystem. Additionally, limited research addresses the challenges of AI implementation in legacy mining infrastructures, especially with regard to data quality, model interpretability, and workforce readiness. There is also insufficient exploration of explainable AI (XAI) techniques tailored specifically for safety-critical and environmentally sensitive mining operations. Furthermore, while digital twin and AIoT concepts are emerging, empirical studies validating their long-term impact on sustainability and economic efficiency in real mining settings are scarce. These deficiencies present a clear opportunity for research that bridges these gaps by offering scalable, explainable, and integrated AI-driven solutions tailored for the complex and resource-intensive mining sector.

6. Challenges and limitations

While AI offers significant benefits in mineral processing, its practical implementation is hindered by several challenges. Addressing these issues through targeted strategies is essential for enabling wider industry adoption.

6.1. Data scarcity and quality

A lack of comprehensive, high-resolution datasets remains a major obstacle, especially in legacy operations with limited sensor coverage.

Mitigation: Deploying low-cost IoT sensors and adopting data augmentation techniques can progressively build richer datasets. Synthetic data generation and transfer learning methods may also help reduce the dependence on fully labeled training data.

6.2. Legacy infrastructure

Many mining sites operate on aging mechanical and control systems that are incompatible with AI and IoT technologies.

Mitigation: Implementing modular and cloud-compatible middleware platforms (e.g., edge gateways) allows AI tools to integrate with existing Supervisory Control and Data Acquisition (SCADA) systems without complete infrastructure overhaul.

6.3. Model interpretability

The “black-box” nature of deep learning models creates trust and compliance challenges, particularly in safety-critical operations.

Mitigation: Use of Explainable AI (XAI) frameworks—such as SHAP or LIME—can provide transparent decision rationale and support regulatory requirements. Hybrid models combining physical process knowledge with data-driven predictions may also improve interpretability.

6.4. Skilled workforce shortage

The mining sector faces a shortage of professionals with combined expertise in AI and domain-specific mining knowledge.

Mitigation: Upskilling programs, interdisciplinary training, and industry–academia partnerships can help bridge the talent gap. AI-assisted dashboards and user-friendly interfaces may also reduce dependency on specialized personnel.

These strategies provide a roadmap for overcoming existing limitations, thereby accelerating the transition to intelligent, AI-driven mineral processing systems.

Several recent case studies demonstrate the operational benefits of AI in active mining environments. At the Yandi Iron Ore Mine in Western Australia, BHP deployed a machine learning system to optimize haul-truck maintenance scheduling, resulting in estimated annual savings of USD 5.5 million and an increase in planned-job accuracy from 10% to 85%. In Shandong Province, China, the implementation of IIoT-enabled predictive maintenance in conveyor and processing equipment reduced failure rates by nearly 70% and cut total maintenance costs by 30%. Similarly, at the Renison Bell Tin Mine in Tasmania, Australia, AI-powered ore sorting improved recovery rates by approximately 30% while reduces waste dilution. These examples from geographically diverse mines demonstrate that AI technology delivers consistent performance gains when applied to real-world mineral processing challenges.

7. Future directions

As the mining sector continues to evolve with the digital transformation, AI's future is one that is set to become more transparent, decentralized, and environmentally-friendly. New technologies and techniques will not just improve what we do today, but will bring those operations in line with world expectations around sustainability, productivity, and smart automation. The following are the new trends that will define the next chapter in the integration of AI into mining.

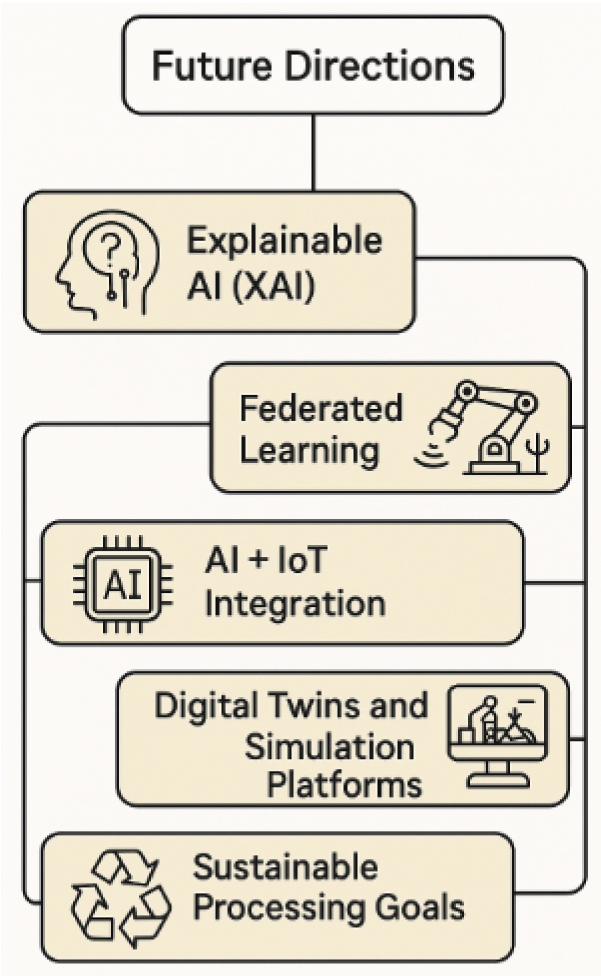

Figure 10. Future Trends in AI Integration for Sustainable and Intelligent Mining

7.1. Explainable AI (XAI)

A key issue for modern AI is that these systems are not interpretable, and this can present important problems in high-stakes industries such as mining. Explainable AI (XAI) is a field that tries to fill this gap by creating models that are understandable (transparent) as well as powerful. They serve as human-interpretable explanations on binaries of how and why decisions are taken—for example, why a given ore fragment is considered waste/to be processed, or why such and such product received predictive maintenance alerts. Such transparency is important to ensure regulatory compliance and operator confidence, as well as ethical accountability, particularly in domains such as safety, environmental surveillance, and process control.

7.2. Federated learning

Classic AI model training, on the other hand, needs data to be centralized, which at a time of concerns about data privacy and ownership is an issue – particularly in a globally distributed and competitive industry like mining. Federated learning solves this by allowing multiple mining sites / companies to collectively train an AI model without sharing raw data. Rather, algorithms are trained in the local domain and only models updates are exchanged without exposing sensitive geospatial, operational, or proprietary information. This method improves data security and also facilitates the development of generalized and robust AI models that can be transferred to various mining environments.

7.3. AI + IoT Integration

At the nexus of AI and IoT, AIoT is reinventing mining decision-making in real-time. Embedded across mine equipment and infrastructure, smart sensors collect endless streams of data—from vibrations and pressure to mineral content and environmental temperatures. This data can then be combined with edge computing and AI models to enable instantaneous decision making at the source, minimizing lag and lowering our reliance on centralized data centers. This enables adaptive control of both blasting, drilling and ore sorting improving safety, production and process stability.

7.4. Digital twins and simulation platforms

Over time, digital twins will be a cornerstone of operations. These are living, virtual copies of physical mining assets—think plants or haul roads—that are constantly refreshed with real-time data and artificial intelligence. Type your paragraph here. "If I can run different scenarios using simulations, I could optimize the plant operations." "Using simulations, I can simulate how much cooling energy the plant equipment would require to operate efficiently, how much energy it should consume, and how much water it should use for irrigating without risk," he says. Learning from new data, they become a self-optimizing system – they themselves can suggest production adjustments, identify faults and reduce inefficiencies, plant-wide. This deployment shifts decision-making from reactive to predictive and to prescriptive.

7.5. Sustainable processing goals

Future mining will have to reconcile production with responsibilities toward the environment. Circle of (Sustainable) Life AI will be instrumental in realizing sustainable processing targets through circular economy applications, like resource recovery maximization, tailings minimization, and reduction of energy and water consumption. AI-based analytics can be used to locate resources of value as secondary resources within waste streams or to optimize recycling and reprocessing strategies. Additionally, AI has the power to support life cycle assessments, predict environmental impacts and track emissions – enabling mining companies to achieve tighter ESG (Environmental, Social and Governance) targets while remaining profitable.

Several recent pilot projects demonstrate the growing industrial interest in next-generation AI applications for mining. For example, Rio Tinto has begun testing explainable machine learning models at its

Iron Ore Operations Centre in Perth, enabling real-time drill and blast optimization with transparent decision logic for field operators. Similarly, Newmont Corporation has partnered with Microsoft to develop a federated learning platform for gold mines across Nevada that allows predictive models to be trained collectively without sharing sensitive site-specific data. In another case, Sandvik's AutoMine system has integrated a digital twin of Finnish underground mine to simulate haulage operations, achieving up to 18% improvement in equipment utilization during trial runs. These pilot initiatives highlight how emerging AI tools are moving beyond theory toward scalable deployment, advancing the vision of Mining 4.0 through safer, smarter, and more autonomous mineral extraction.

8. Conclusion

Artificial Intelligence is becoming an enabler of change in mineral processing which is enhanced by data driven solutions to the challenges of the industry and the desire to reach new goals on sustainability. AI supports holistic ore characterizations, precise sorting and optimization of the entire process chain – thanks to intelligent sensors and advanced modelling, real time analytics. For ore characterization, AI-powered image processing, machine vision and grade prediction models add a lot of value with detailed mineralogical understanding and real-time prediction. Likewise, smart AI-powered sorting systems combine sensor data and computer vision with robotic automation to improve throughput and resource return. In MIIoT, AI-digital twins make it possible process variable optimization and predictive maintenance in plants, which results in plant savings and longer equipment life. But the path to widespread AI adoption is not without its challenges. The barriers include, among other issues, data quality challenges, difficulty integrating with legacy systems, the black box nature of AI models, and the shortage of domain experts to bridge the gap between the mining engineer and the data scientist. Addressing these challenges will require a concerted, multistakeholder effort and continued investment in digital infrastructure, workforce development, and ethical AI.

Considerations Beyond digital transformation, the integration of AI with IoT, edge computing, and digital twin technologies will advance predictive and autonomous as well as sustainable mining. Explainable AI and federated learning will build trust and secure data, and AI-powered sustainability models will further circular economy efforts. These developments represent a transition: From reactive, human-centric operations to intelligent, self-optimizing systems that are more secure, efficient, and trustworthy. This review addresses these gaps by presenting a comprehensive, system-level analysis of AI tools in mineral processing. It explores not only technical applications but also proposes solutions for integration, scalability, model interpretability (via XAI), and sustainable deployment using digital twins and AIoT. Thus, this work serves as a timely and necessary roadmap for AI-enabled intelligent and sustainable mineral processing under the Mining 4.0 paradigm. In summary, AI is not simply a technological advance, but the cornerstone of the future of sustainable mineral processing. Sustained research, regulatory encouragement and industry-academia partnership are required for AI to thrive and develop a future-prepared, smart mining ecosystem. Artificial intelligence is reshaping mineral processing by enhancing ore characterization, automating sorting, and improving operational efficiency through predictive analytics and real-time optimization. These capabilities have been validated in industrial settings, where AI has enabled measurable gains in recovery, cost reduction, and system reliability. Despite the progress, challenges such as data quality, integration with legacy systems, and model interpretability still limit widespread adoption. Future work should prioritize explainable AI, scalable digital twin architectures, and workforce upskilling to support responsible deployment. With continued innovation and collaboration across industry and academia, AI has the potential to deliver smarter, more sustainable mining systems aligned with the goals of Mining 4.0.

Author Contributions

All authors contributed significantly to this work. **Ramdas Biradar** led the conceptualization of the study, supervised the research activities, and provided critical revisions to the manuscript. **Babaso A. Shinde** developed the methodology, managed the data collection, and drafted the initial manuscript sections. **Milind Manikrao Darade** carried out the detailed literature review, generated visual elements, and refined the manuscript. **Tushar Gaikwad** supported the validation and investigation processes, including preparation of technical figures. **Seeram Srinivasa Rao** contributed through formal analysis, interpretation of results, and proofreading. **Aarti Puri** assisted in manuscript editing, resource management, and data analysis. **Ashwini G. Thokal** provided software support, validated computational models, and participated in the editing process. **Anant Sidhappa Kurhade** coordinated the project, wrote the original draft, and managed communication among authors, ensuring final approval of the manuscript. **Govindrajan Murali** offered supervisory guidance, review oversight.

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Conflict of interest

The authors declare no conflict of interest

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