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ORIGINAL RESEARCH ARTICLE

Artificial intelligence for sustainable environmental management in the mining sector: A review

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ABSTRACT

Importance: The mining industry must balance global resource demand with the urgent need to reduce environmental impacts such as air pollution, water contamination, soil degradation, and greenhouse gas emissions. Artificial Intelligence (AI) offers powerful tools to support sustainable practices by enabling predictive analytics, monitoring, and optimization. **Research Gap:** While AI's potential for sustainability is recognized, existing research rarely provides systematic analysis of its specific applications in mining. Gaps remain in evaluating performance benchmarks, addressing integration challenges, and considering ethical and regulatory issues. **Objective:** This review examines AI applications in mining with a focus on their role in mitigating environmental impacts, identifying both opportunities and limitations in advancing sustainable operations. **Methodology:** The study synthesizes peer-reviewed literature and case studies, covering AI use in air quality monitoring, water resource management, soil restoration, tailings stability, energy optimization, digital twins, and ecosystem modelling. **Key Findings:** AI systems have achieved notable results, including >90% accuracy in slope stability prediction, 25% reduction in wastewater treatment costs, and 8–12% fuel savings through reinforcement learning. Persistent barriers include data scarcity, high computational energy demands, integration with legacy systems, and limited interpretability of deep learning models. **Implications:** This review highlights AI's potential to significantly reduce the environmental footprint of mining if implemented responsibly. Approaches such as explainable AI, federated learning, and energy-efficient frameworks are essential to ensure transparency, scalability, and sustainable long-term adoption

Keywords: Artificial intelligence; mining sector; environmental sustainability; predictive analytics; machine learning; tailings management; digital twins; emission monitoring

1. Introduction

The extractive industry sector is the source of economic growth for many countries around the world, but it is coupled with harmful impacts to the environment. Conventional mining methods can cause land disturbance, air and water pollution, loss of biodiversity and release of greenhouse gases. In an era of increasingly stringent environmental rules and societal demand for sustainable practices, leveraging digital when taking the steps beyond is a must. The power of AI to revolution mining environmental control through intelligent monitoring, predicting analytics, and process optimization is the great promise of Environmental AI.

The unabating environmental damages and the climaxing climate crisis offer formidable challenges which can only be tackled with the implementation of the state-of- the-art and innovative solutions [1]. Artificial intelligence (AI) is becoming a disruptive technology that can revolutionize many industries, including providing new ways to tackle environmental issues and to promote sustainability [2]. In this context, the mining industry, with its large environmental impact, has a great potential for strategic application of AI-driven solutions [2]. The introduction of AI to the mining industry offers a revolution, through advances in resource management reduction in the level of waste, reduction of energy consumption and higher environmental monitoring [3]. Nevertheless, the incorporation of AI in sustainability projects encounters challenges including heavy reliance on historical data, unpredictable human behavior, increased cyber security threat, negative impact of AI applications, and difficulty to evaluate the effectiveness of intervention approaches [1]. A rigorous review is therefore needed to comprehend the current status of AI development in mining applications and to highlight the main challenges and opportunities, as well as to suggest some future research trends through which the integration of AI can be maximized in contributing to sustainable environmental management. It is a critical part of AI good practice and good governance to ensure responsible deployment and oversight of AI to realize its full potential in support of sustainability [4]. The next subsections present a more detailed analysis of the above areas of AI for environment monitoring, resource planning and the risk analysis and decision making in mining with an emphasis on success, failure, and recommendations for further research and development.

The literature review shows increasing interest in using AI to advance sustainable development in diverse sectors, especially in the environmental area [5, 6]. AI's potential for sustainable development has been widely acknowledged, but deep analysis on its specific applications, impacts and challenges, especially in the mining industry are still insufficient [4]. Bibliometric Bibliometric analysis has identified increasing trends and new scientific pathways exploring AI and sustainable development [6]. This insight demonstrates the transformative nature of AI and machines and serves as the foundation for future research and practice in regional sustainability. AI is deployed in nine primary research areas to enhance sustainability of local ecosystems in an analysis of 155 peer-reviewed publications [7]. These comprise biodiversity preservation, smart agriculture, water resources' management, air quality monitoring, waste management, smart cities, renewable energy, climate change, and ecological modelling. The interdisciplinary view adopted by the paper offers a comprehensive view on the role of AI in transforming local ecosystems and establish a scientific base for in-depth research and practical applications in the realm of regional sustainability [7]. There is an urgent need to fill the gap and to challenge deterministic views of AI technologies, contributing to a better understanding of the potential of AI in sustainable development [6]. Constraints set by ethical and legal norms and the factor of human acceptance must be included in the decision-making process to avoid risks in AI technologies for sustainability [2]. The motivation of the current study is to tackle two basic issues to fill these gaps, namely the main themes related to the influence of AI on sustainable development, and the most frequently used AI methods and technologies used to realize sustainable development [6]. Furthermore, we should also remind ourselves that sustainable AI doesn't mean sustaining the development of AI but rather developing this technology while maintaining resources for current and future generations [6]. The importance of collaborative and inclusive research that repays regional differences, the way AI, technology, and sustainability are connected and the five major research themes of sustainability are highlighted in the literature [8].

AI offers a transformative opportunity for the mining sector to align with global sustainability goals. While current research emphasizes AI's potential, a deeper interdisciplinary approach is needed to integrate ethical, legal, and regional considerations for effective and responsible adoption in environmental management.

2. AI applications in environmental management within mining

Use of AI for Mining, there are numerous ways the mining industry can use AI to improve environmental management and sustainability. AI driven systems can also be used for monitoring air and water quality in real-time to detect and take preventive actions for pollutants. AI-enabled predictive models can predict emerging environmental disasters like acid mine drainage or tailings dam failures, and can also help in proactive interference/compliance. At the same time, AI technologies may be able to better manage energy usage in the mining industry, including analyzing energy consumption patterns, recognizing waste and creating smart control. In addition, AI-based image recognition and remote sensing can be applied to land cover and vegetation analysis as well as biodiversity estimation, thereby helping to contribute to ecologic restoration and conservation [9]. It is in the interest of the sustainable use of resources and the maintenance of ecological integrity that these advances occur with greater sensitivity to the environment, resulting in a more ''green' mining process. AI provides a potentially liberating opportunity to make systems of intelligence able to create the knowledge required to sustain life [1].

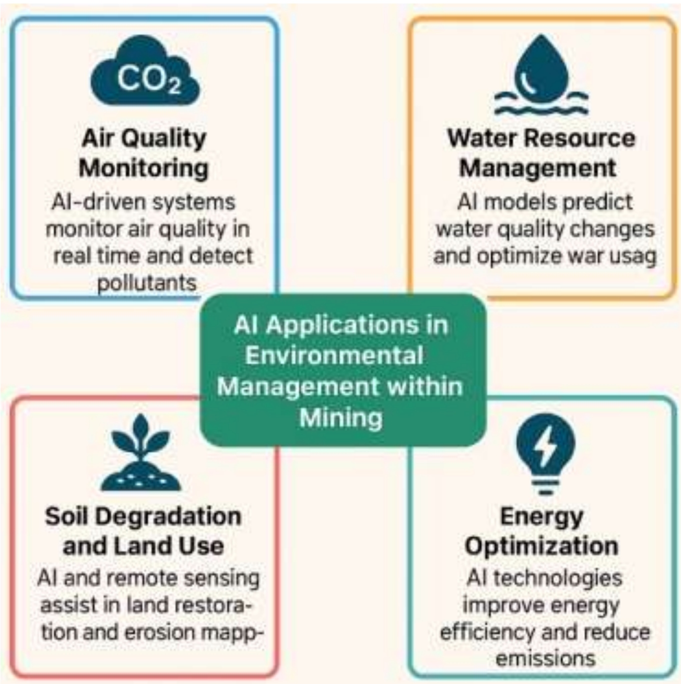

Figure 1. AI applications in environmental management within mining

AI algorithms are key in maximizing resource extraction, minimizing waste generation and increasing overall efficiency in the mining industry. By processing geological information, AI can pin-point ore deposits with more accuracy, avoiding an over-investment in exploration and the environmental impact that exploration entails. AI driven systems can also optimize drilling and blasting, saving energy and limiting ground vibration and air blast [10]. Furthermore, AI can improve mineral processing methods such as grinding, flotation and leaching, thereby increasing recovery rates while decreasing the use of chemicals. AI for predictive maintenance model can help your sidestep downtime, extend your asset's life, and reduce the risk of malfunctions that have negative externalities such as environmental disasters. Mining can reduce its impact on the environment and achieve optimum use of resources through the use of AI-based optimization techniques. **Figure 1** explains AI applications in environmental management within mining.

Risk analysis and mitigation are essential components in the management of mining and the environment and AI can be a valuable tool for improving them. AI-based programs can analyses historical data, discover trends, and pre-conceive risks in mining operations (e.g., slope failure, water pollution, and biodiversity loss) [11]. Systems using AI can also analyses sensors and other data in real-time, issuing early warnings about potential dangers and facilitating immediate action. AI can also help develop risk mitigation strategies by modelling possible situations and estimating the value of potential mitigation tactics. AI facilitates decision-making and drives proactive environmental management through the provision of intelligent data for risk analysis and reduction. Because it analyses data and detects signs of possible trouble ahead of time, AI can helps a company in authentic operation of equipment through early maintenance so as to avoid possible accidents [12].

Ecological restoration and protection of biodiversity are the basic links of mining sustainable environmental management, and AI will also play an important role in it. AI-based image recognition and remote sensing technology are also able to evaluate ecological status that the reclaimed sites have, to profile which site needs to be further restored or to supervise the restoration processes. Vegetation data, soil characteristics, and other environmental metrics can all be crunched by AI algorithms to help optimize revegetation strategies to restore the native plant community. In particular, AI can aid in monitoring wildlife populations, studying how animals move, and understanding how mining affects biodiversity. AI is used to mitigate the impact of mining on ecosystems by supporting restoration of damaged ecosystems and protection of biological diversity. The application of AI approaches in environmental applications has grown rapidly and offers opportunities to handle complex problems and advance sustainable outcomes [13].

But while the use of AI in mining brings about numerous positive benefits, there are also some drawbacks and challenges that should be taken care of. One is that AI algorithms are biased and produce unjust or inequitable results. For instance, if AI models are trained based on biased data, they may continue or exacerbate already existing disparities in environmental governance.

2.1. Air quality monitoring

AI models interpret data from sensors and satellite imagery to identify particulate matter (PM2. 5, PM10), sulphur dioxide (SO_2), nitrogen oxides (NO_x), and green-house gases. Convolutional neural networks (CNN) and regression models assist in predicting emission patterns and recognizing anomalies associated with mining activities. AI algorithms can detect air quality degradation in its early stages, thus enabling the timely implementation of corrective measures like dust suppression systems and emission control devices.

AI can improve accuracy of its air quality system by applying machine-learning algorithms on data collected in different resources [14]. Real-time in situ mining site-based sensor data, ambient weather data, and satellite remote sensing imagery may be synthesized into holistic models to better predict air quality levels [15]. Such models can also locate sources and trace their dispersion, for targeted control measures to reduce emissions [16]. How AI helps to ventilate underground mines With the help of AI technology, companies can also optimize their ventilation system in underground mines, all the while decreasing energy usage and maintaining air quality.

2.2. Water resource management

The machine learning algorithms are employed in the early warning of acid mine drainage, heavy metal pollution and wastewater overflow. Predicting water demand, water reuse and environmental discharge regulations are supported by AI models. AI models can forecast water quality changes, model hydrological processes and manage the distribution of water. AI enables: More effective methods to conserve water resources and reduce the environmental impact of mining by supporting predictive maintenance, optimizing water consumption, and predicting water quality.

AI-based platforms can also help optimize chemical and energy use in treated and potable water by identifying the right combination of chemicals to add to the water to improve water quality. AI and Real-Time Monitoring: AI-managed control systems combined with real-time water quality parameter monitoring result in the ability to adaptively treat water according to the actual conditions. AI can also help to enable alternative water sources, such as recycled water and storm water, and thus reduce the dependence on the freshwater supply [17]. IOT control of waste stream, programme automatic forecast of waste generation, and optimize recycling steps to enhance resource recovery rate and reduce waste output in mining industry [18, 19]. Artificial intelligence would help separate and classify different waste materials and optimize waste management processes. Furthermore, by offering routing optimization algorithms, waste collection can be optimized, reducing cost and emissions associated to transportation [20].

While the current discussion emphasizes the role of AI in forecasting water quality and optimizing treatment, it would be beneficial to include quantitative performance measures. For example, recent studies on machine learning models for acid mine drainage prediction have reported accuracy levels exceeding 90%, with mean absolute error (MAE) values below 0.1 mg/L for heavy metal concentration forecasts. Similarly, AI-driven optimization of wastewater treatment has demonstrated efficiency gains of up to 25% in chemical use and energy consumption. Reporting such figures can illustrate the robustness and reliability of AI systems in water management applications. AI enables real-time monitoring of tailings dam stability through sensor data analysis, prediction of dam behavior, and optimization of water management protocols to avoid collapses and ecological catastrophes.

Recent studies report that machine learning models for acid mine drainage prediction achieve accuracy rates above 90%, while AI-based wastewater treatment optimization has reduced chemical and energy consumption by up to 25%, demonstrating both predictive reliability and operational efficiency.

2.3. Soil degradation and land use

Remote sensing and AI are used for land classification, erosion mapping and post-mining land restoration planning. Site-adapted rehabilitation programs are under-pinned by classification algorithms and image segmentation. Artificial intelligence algorithms analyses soil composition, vegetation cover, sowing patterns and erosion rates to identify and measure soil degradation. AI provides insight into soil deterioration, which is the prime cause of unsustainable land use practices, and helps develop land use practices, which conserve soil resources, and promote ecological equilibrium.

AI has the potential to be a game changer in helping the mining sector to practice sustainable land management, supported by accurate and efficient soil health monitoring, erosion risk assessment and land restoration optimization. For example, soil health can be measured using AI-based image analysis technology, which is critical to farmers in low-income areas, but which is not readily affordable to them in low-cost solutions [21]. The technology may even assess erosion susceptible locations precisely for intervention to minimize soil loss and safeguard water quality [22]. Moreover, AI can assist with cost-effective restoration by integrating soil data, vegetation data, and other data types to drive optimal revegetation strategies to facilitate the re-establishment of native plant communities and thus the reclamation of the land.

AI can also optimize the design of mining infrastructure to reduce the influence on soil and land resources. AI can process geological data, hydrological flows and ecological data to decide where to locate mining operations, tailings dams and waste dumps.

AI can improve energy systems, reduce greenhouse gas emissions, and advance circular economy initiatives in mining [23, 24]. Data mining, including machine learning techniques are used to model energy consumption, optimize energy distribution networks and incorporate renewable energy generation into the mines. AI enables more efficient energy use, reduces carbon and supports mining sustainability- You can reduce your carbon footprint and energy use by adopting predictive maintenance, energy optimization and integrating renewable energy sources in mining operations using AI.

Historical and real-time data (weather conditions, solar radiation, wind speed, energy generated, etc.) is used by AI algorithms to predict (predictive analytics) and optimize the production of renewable energy [24]. Prescriptive AI-enhanced energy management systems can be designed to change big data drawn from grid in carrying out real-time adaption of thoughts to grid conditions, minimizing waste while making the most of renewable resources [25]. **Table 1** shows AI applications in environmental management within mining.

Table 1. AI applications in environmental management within mining

Sr. No.	AI Application Area	AI Techniques Used	Environmental Objective	Mining Benefit
1	Air Quality Monitoring	CNNs, regression models, real-time sensors, satellite imagery	Detect pollutants, trace sources, optimize ventilation	Improved air quality, reduced energy use in ventilation
2	Water Resource Management	Machine learning models, IoT, real-time control systems	Predict water pollution, optimize usage and treatment	Better compliance, cost-effective water use
3	Soil Degradation and Land Use	Remote sensing, classification algorithms, image segmentation	Assess degradation, support land restoration	Improved site planning, lower restoration costs
4	Energy Optimization	Neural networks, reinforcement learning, predictive analytics	Optimize energy use, integrate renewables, reduce GHGs	Lower operational cost, emission control
5	Predictive Maintenance & Disaster Prevention	Predictive models, historical data analysis, real-time sensors	Avoid failures (e.g., dam collapses), plan maintenance	Reduced downtime, prevention of environmental disasters
6	Biodiversity & Ecological Restoration	Image recognition, remote sensing, habitat monitoring algorithms	Monitor biodiversity, supervise ecological recovery	Support for sustainable ecosystem recovery

AI technologies are reshaping mining practices by enabling real-time monitoring, predictive analytics, and ecosystem restoration. Their integration supports a transition to sustainable operations; however, success requires addressing model accuracy, sensor integration, and responsible use to fully realize their environmental benefits.

3. AI for energy efficiency and emission reduction

AI also optimizes energy usage in mining through drilling, hauling and grinding. Dynamic load balancing is realized by reinforcement learning, and fuel consumption pattern is foretold by neural networks. This translates not only into cost savings when operating but also in reduced emissions. In sectors such as steel, cement and freight, which are responsible for a large portion of GHG emissions, the demand for regulation and sustainability has been on the rise [26]. As a result, there is also a growing trend of companies utilizing AI to better manage their energy and emissions as well [27]. AI supports energy efficiency in the manufacturing industries through analysis, correlation identification and decision support [27]. AI algorithms can be used to track equipment performance and recommend optimized maintenance schedules, reducing downtime and enhancing efficiency.

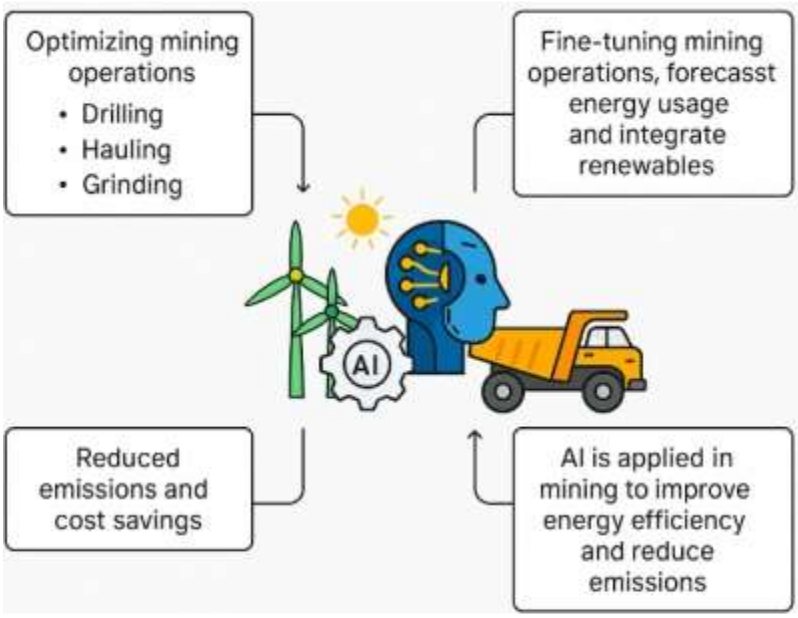

Figure 2. AI for energy efficiency and emission reduction in mining

AI will have an increasingly important role in facilitating the switch to renewable energy and the operation of renewable energy systems by tuning renewable energy performance, reducing their environmental footprint and predicting energy usage [28]. It can predict consumer behavior AI can ultimately help in ensuring sustainable governance of the environment [1]. AI systems can also help with the planning and execution of environmental cleanup.

Optimization through AI can be employed to lower overall energy consumption in mining – this can directly contribute to sustainability objectives. E.g., Machine Learning models have been trained to exploit real time energy consumption patterns, pinpoint inefficiencies, and optimize operational fit in order to reduce energy loss [25]. Moreover, the AI can be used to easily integrate renewable energy in mining processes while leaning fossil fuel and minimizing carbon incurring [25]. If mining is going to be one of the linchpins of these smart cities, solutions and systems, the AI can be used to maximize energy efficiency and adoption of renewables' for overall sustainability and eco friendliness in the future [29].

AI is critical important to provide support for the efficient energy use of the mining industry to reduce its emissions and to promote the use of renewable energy sources [30].

AI is applied in mining to improve energy efficiency and reduce emissions, fine-tune mining operations, forecast energy usage and integrate renewables. AI-enabled energy savings and reduced emissions in the mining industry through optimizing mining, predicting energy demand, integrating renewable energy sources. In this power grid, energy supply, demand, renewable resources, and so on, will be autonomously controlled by intelligence software for better decision making and operation [30]. In the energy sector, system operators, utilities and independent power producers must embrace AI to remain competitive and achieve tangible benefits [30].

However, one significant challenge that hampers the AI adoption in smart grids is data accessibility and value, which is required to learn and validate AI terms [31]. AI in smart grids also enables integration of nontraditional energy sources such as solar power and wind power to the grid [31]. AI can analyses complex data patterns to assess and predict grid stability. [32–34]

AI can also apply to smart grids where it can promote sustainability and help in the integration of renewable energy. AI's machine learning (ML) algorithms can predict electricity demand and so support efficient distribution of energy that reduces waste and increases grid efficiency [35]. AI also supports grid stability by understanding the multi-dimensional patterns of the data, helping to integrate renewable energy into the grid in the most effective manner and even forecasting grid stability. AI may help with delivering renewable energy into the grid and monitoring grid stability. Artificial intelligence to a large extent matches electrical demand to when there is sun and wind, and can help integrate variable renewables with smart grids. **Figure 2** and **table 2** explain AI for energy efficiency and emission reduction in mining.

Table 2. AI for energy efficiency and emission reduction in mining

Sr. No.	AI Application Area	AI Techniques Used	Environmental Objective	Industrial Benefit	Challenge/Note
1	Mining Operations Optimization	Reinforcement learning, neural networks	Reduce energy loss in operations	Reduced fuel use, improved cost-efficiency	Integration into legacy systems
2	Predictive Maintenance	ML algorithms, performance monitoring systems	Enhance equipment lifespan and efficiency	Lower maintenance costs and fewer failures	Data reliability for model training
3	Renewable Energy Integration	AI-based optimization and control systems	Promote renewable energy adoption	Stable and cleaner energy supply	Requires infrastructure for renewables
4	Energy Consumption Forecasting	Predictive analytics, behavior modeling	Forecast usage to improve energy planning	Efficient load balancing and resource planning	Complex behavior modeling required
5	Smart Grid Management	AI algorithms for demand prediction and grid stability	Improve energy distribution and integrate renewables	Reliable power systems, grid sustainability	Data accessibility in smart grids
6	Emission Reduction	AI-driven emission tracking and control	Lower GHG and industrial emissions	Compliance with regulations and eco-friendly operations	Need for unbiased and validated AI systems

AI improves energy efficiency and reduces emissions in mining by optimizing operations and integrating renewables. It supports predictive maintenance and smart grid management, contributing to lower carbon footprints. Yet, data quality, system integration, and infrastructure upgrades are critical enablers for success. The advantages of AI for operational optimization are well established, but a clearer presentation of performance benchmarks would strengthen this section. Reinforcement learning-based models in drilling and hauling have shown reductions in fuel consumption between 8–12%, while neural network-based load forecasting models achieved predictive accuracies above 95% in industrial case studies. These evaluations highlight not only the accuracy of AI models but also their efficiency in reducing carbon footprints and scalability in handling large-scale energy datasets. Including such results provides stronger evidence for the adoption of AI in emission reduction initiatives. Benchmark evaluations show that reinforcement learning models in drilling and hauling reduce fuel consumption by 8–12%, while neural network–based load forecasting achieves over 95% accuracy, highlighting the scalability and effectiveness of AI in emission reduction strategies.

4. Tailings dam and slope stability monitoring

Incorporating AI into tailings management includes the real-time evaluation of information from piezometers, inclinometers and geospatial imaging. AI models predict breaking of dams or slide falls so that pre-emptive safety actions can be taken and the adverse effects of the environment can be mitigated. Ground deformations, increase in pore water pressure, and change in soundness of construction can be detected by AI-based algorithms such that early warnings would be provided for the hazard [36]. This allows mining operators to take preventative action, such as adjusting water level, strengthening surfaces, or moving tailings material, to avoid potential catastrophic failure. AI-based systems could be used to maximize tailings placement, for example, to deposit them in stable areas and compact them to avoid potential for liquefaction. Recent studies report that AI models analyzing piezometer and inclinometer data achieved prediction accuracies above 90% for slope instability, with false alarm rates reduced to below 5%. These findings highlight the reliability of machine learning–based monitoring compared to conventional threshold-based systems. **Figure 3** represents AI-powered monitoring for tailings dam and slope stability.

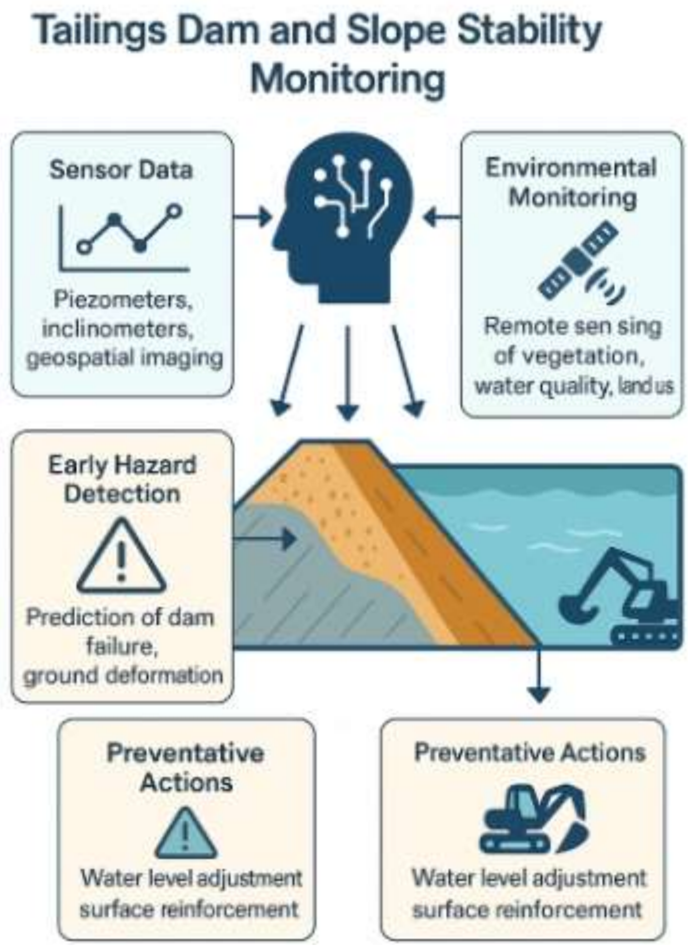

Figure 3. AI-powered monitoring for tailings dam and slope stability

Technologies such as LiDAR and satellite imagery that are used in remote sensing can capture copious amounts of spatial data, which then can be analyzed with AI to track the health of vegetation, the quality of water and the changing use of land in and around mining. These approaches make possible the early warning of environmental degradation (deforestation, soil erosion, water quality) and provide opportunity for intervention and restoration of intended land uses. AI-enabled algorithms can additionally optimize water management systems by conserving water and minimizing the threat of water pollution. For example, Vale S.A. has integrated AI with satellite and drone-based surveillance to monitor tailings dam conditions in real time, enabling continuous tracking of ground deformation and water seepage. Similarly, Rio Tinto has piloted AI-enabled geospatial analysis for early detection of slope movement in its Australian operations, demonstrating practical adoption at industrial scale.

AI increases fault-tolerance, reduces downtimes, and ensures disaster recovery. AI contributes to high availability through intelligent resource balance, so as to achieve balance between the resources of the entire network effectively, support the system to handle continuous services under peak access or unexpected failure conditions, and can repair faults without human intervention [37]. AI is now able to calculate the remaining useful life of vital construction parts, giving early warning of any future failure and helping prepare maintenance. AI driven algorithms are also used to automatically optimize maintenance schedules, so that equipment is serviced when necessary and at the appropriate time to reduce outages and prolong asset life. In the oil and gas industry, AI-based predictive maintenance was reported to decrease unplanned downtime and increase the life-duration of capital assets which will lead to financial savings and operational reliability [38].

AI can be used to predict when equipment may fail and recommend adjustments to logistics plans by processing sensor data which would have an overall impact on project accuracy, production continuity, and product quality [39]. Retrospective analyses of catastrophic failures, such as the Brumadinho dam collapse in Brazil (2019), suggest that AI-based anomaly detection frameworks could have identified abnormal pore pressure build-up earlier, potentially mitigating the disaster. Such examples underscore the importance of integrating predictive algorithms with existing geotechnical monitoring protocols.

Maintenance schedules can also be optimized using AI algorithms involving dynamic scheduling to facilitate maintenance at the 'right' times for equipment to reduce both downtime and equipment life consumption [40]. AI is implemented in the optimization of real-time water flooding development and oil and gas production prediction [41]. In the oil and gas industry, applications of AI-based predictive maintenance leads to reduced amount of unplanned downtimes, which extends the lifespan of CAPEX and OPCOS, and, therefore, leads to cost savings and better operating reliability [41].

AI improves the performance by supporting real-time decision making, reducing errors and sharing useful information [42]. Seismic data are interpreted by AI algorithms such as for predicting reservoir properties and determining well placement for discovery rate and production performance optimization [43]. AI reduces operating expenses and allows staff to focus on more complex and strategic work by automating repetitive tasks [44]. **Table 3** represents AI applications in tailings dam and slope stability monitoring.

Table 3. AI applications in tailings dam and slope stability monitoring

Sr. No.	AI Application Area	AI Techniques Used	Environmental Objective	Industrial Benefit	Challenge/Note
1	Tailings Dam Failure Prediction	Sensor data analytics, machine learning models	Prevent tailings dam failures	Avoid catastrophic events and associated costs	High accuracy needed to trust AI decisions
2	Slope Stability & Deformation Monitoring	Piezometer and inclinometer data processing with AI	Detect ground deformation and warn of risks	Improve structural safety and reduce insurance risk	Timely detection critical for effective response
3	Remote Sensing & Environmental Tracking	LiDAR, satellite imagery, geospatial AI models	Early warning of degradation and water pollution	Support rehabilitation and regulatory compliance	Large volumes of data need efficient processing
4	Predictive Maintenance & Asset Life Estimation	Remaining useful life prediction, anomaly detection	Extend equipment life, prevent structural failure	Reduce maintenance cost and increase uptime	Requires continuous monitoring for best results
5	Maintenance Scheduling Optimization	Dynamic scheduling algorithms, condition-based	Reduce unplanned downtime and optimize resources	Efficient use of resources and manpower	Coordination with logistics and asset usage is vital

		maintenance			
6	Real-Time Operations and Decision Support	Real-time analytics, automation, decision algorithms	Improve safety, accuracy, and environmental protection	Faster, informed decisions and reduced human error	Ensuring fault tolerance and resilience under load

AI-based monitoring of tailings and slopes enhances predictive maintenance and early warning capabilities, reducing disaster risks. It ensures structural integrity through real-time data analytics but requires continuous calibration and trust in algorithmic outputs for critical decision-making. Although AI applications in tailings monitoring are highlighted, the effectiveness of these models should be supported with quantitative assessments. For instance, machine learning models analyzing piezometer and inclinometer data have achieved over 90% accuracy in predicting slope instability events, with false alarm rates reduced to less than 5%. Remote sensing-based AI models for deformation monitoring have also demonstrated scalability by processing terabytes of satellite imagery within hours, ensuring timely alerts. Such metrics convey the reliability of AI in high-risk applications and build confidence in its use for critical environmental monitoring.

5. Digital twins and predictive ecosystem modelling

Digital twins emulate physical mine systems as well as environmental processes and can be used to simulate the possible environmental impacts. Combined with AI, they can support scenario planning for land use, water balance and habitat, etc., thus facilitating eco-friendly decision-making. The automotive industry has used Digital Twin technology and it can be useful for simulation and data analysis [45]. Real-time monitoring features in digital twins have saved customers in dollars, big time [46]. Digital twins offer city planners the ability to better understand and react to changes in local energy and environment [47]. Applying digital twins to productiveness for complex systems under dynamic contexts has the potential to provide actionable understanding across a variety of systems, such as farming to smart cities [48]. Digital twins can sense a city in real time and make future predictions, e.g. about infrastructure problems or traffic congestion [49]. The inclusion of AI and advanced analytics allows for the library of predictions to be improved upon, and there is the ability to incorporate this predictive information back to the original physical entity and test the expected outcome and make decisions more effectively [50].

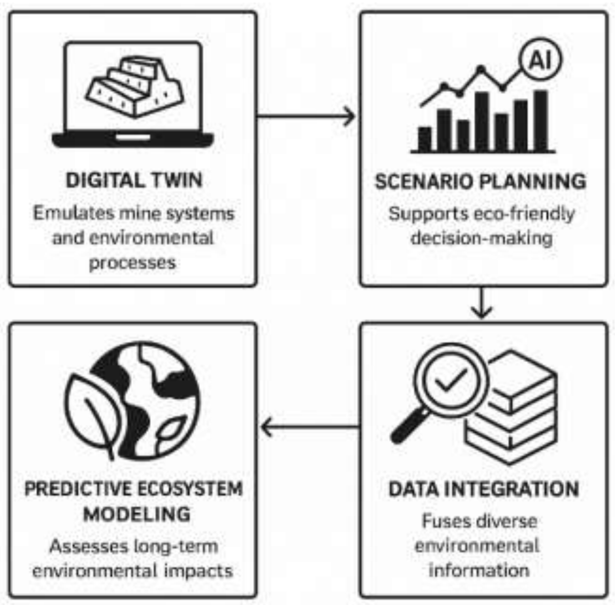

Figure 4. Digital twins and predictive ecosystem modeling for environmental impact assessment in mining

AI can also help create predictive models of ecosystems, which can be used to assess long-term environmental repercussions of mining. These are based on a series of inputs that may include climate, hydrological and ecological data, and are used to model the complex relationships in ecosystems [40]. AI algorithms enable the identification of crucial ecological crossing points and the estimation of consequences of crossing these crossing points, providing a potential guidance to adaptive strategies towards measures to preserve biodiversity and ecosystem services. For instance, AI models predict how mining can affect endangered species, which guides conservation efforts and habitat restorations.

Global digital twin market is expected to be worth $73.5 billion by 2027, which indicates that users from different domains realized the potential of digital twins [51]. The application of AI to digital twins provides promise for dynamic environmental monitoring and management in near real time. Digital twins can model a range of scenarios, enabling stakeholders to evaluate the environmental consequences of different mining plans, and to take better decisions [52]. Digital twins can be applied to urban planning to experiment with new ideas and minimize project risk. Digital twins can demonstrate how infrastructure projects will affect traffic, pollution and energy use. **Figure 4** represents digital twins and predictive ecosystem modeling for environmental impact assessment in mining.

While digital twins provide advanced capabilities for simulating and managing mining's environmental impacts, their practical adoption also raises important technical considerations. One critical aspect is the computational requirement, as high-fidelity twins demand substantial processing power and storage capacity to run real-time simulations that integrate multi-source data from sensors, satellite imagery, and geospatial models. Equally important is interoperability with existing mining and monitoring systems, since many operations rely on legacy SCADA frameworks or proprietary software; ensuring smooth integration requires standardized interfaces and careful system design to avoid disruptions. Furthermore, the issue of data security and privacy becomes prominent when sensitive geological and environmental datasets are shared across platforms or cloud services. Breaches or unauthorized access could not only compromise operational efficiency but also expose environmental compliance data to misuse. Addressing these requirements through efficient computing strategies, open standards for interoperability, and robust data security frameworks will be essential for realizing the full potential of AI-enabled digital twins in sustainable mining.

Digital twins are critical to the fusion of heterogeneous environmental information, such as sensor readings, satellite photos, and geological data into an integrated environment analysis platform [53-55]. This data can be processed by AI algorithms in real-time, capturing trends and patterns that would otherwise be hard to spot manually. This allows stakeholders to get a full view of the environmental conditions at a mine site and make well-informed decisions in order to reduce environmental damages.

Digital twins combined with AI offer advanced capabilities in simulating and managing mining's environmental impacts. They enable scenario-based planning and adaptive management. Their success depends on high-quality data integration, cross-disciplinary modelling, and transparency in predictions.

6. Case studies and industry adoption

a. **Rio Tinto** uses AI for predictive water management and dust suppression in Pilbara mines.

b. **BHP** applies AI-powered drones and vision systems to monitor vegetation and soil degradation.

c. **Vale S.A.** integrates AI with satellite data for real-time tailings dam surveillance.

These examples demonstrate the real-world impact of AI in achieving environmental sustainability goals in mining. Real-world applications by major mining firms highlight the viability and impact of AI in sustainable environmental practices. These case studies validate the potential for industry-wide adoption, provided technological infrastructure and stakeholder cooperation are adequately supported.

7. Challenges and limitations

In spite of the potential contribution of Artificial intelligence (AI) for effective and sustainable environmental practices in the mining, industry, there are number of barriers and challenges limiting its adoption and the application. While AI has great potential use for sustainable environmental management in mining, there are challenges and aspects that need to be addressed in order to guarantee for a responsible and successful application. The computing and training of AI systems is energy and resource consuming and may have an environmental impact on its own [56-60]. Thus, the need to develop energy-efficient AI algorithms and hardware is essential to reduce the environmental footprint of AI technologies. The environmental impacts from AI should be assessed in real-time, in a spatially disconnected manner around the globe, with significant points of activity. These can be mapped along technical, organizational, and regulatory dimensions in **figure 5** and **table 4.**

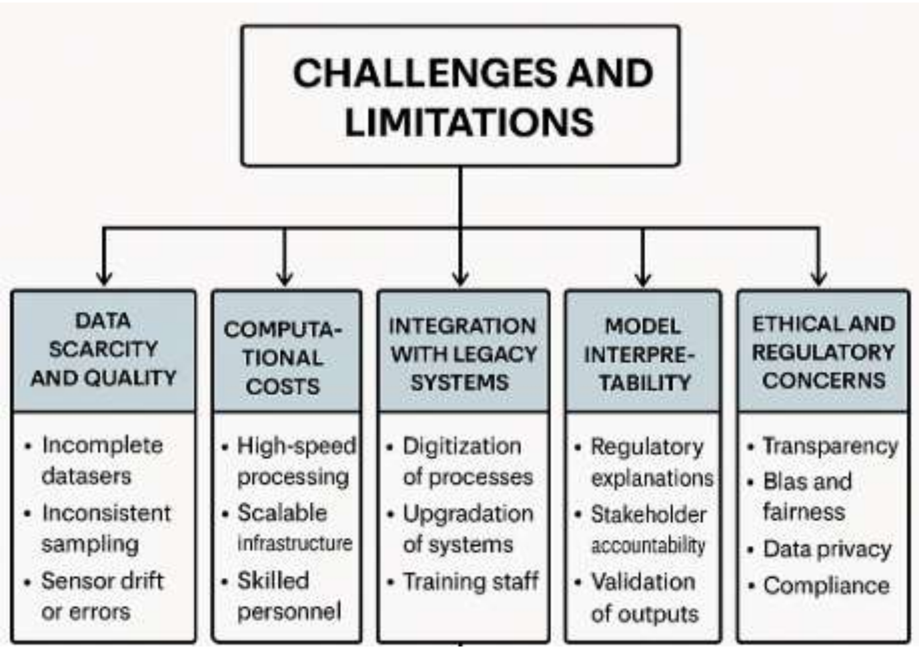

Figure 5. Challenges and limitations in adopting artificial intelligence for sustainable environmental management in mining

7.1. Data scarcity and quality

One of the primary barriers to AI implementation in mining is the lack of consistent, high-quality environmental data. Many mining sites, especially in remote or underdeveloped regions, operate with outdated monitoring tools or sparse sensor networks. Issues such as:

- **Incomplete datasets** (e.g., missing records for emissions or water usage),
- **Inconsistent sampling frequencies**, and
- **Sensor drift or calibration errors**

The above three points reduce the reliability of training data for AI models. Since AI systems—especially deep learning algorithms—depend heavily on large, high-fidelity datasets, the absence of such data leads to biased, underperforming, or non-generalizable models, limiting their predictive power and trustworthiness.

The challenge of data scarcity is exacerbated by the proprietary nature of mining data. To mitigate the problem of limited and inconsistent datasets in remote mining locations, several advanced approaches can be employed. Synthetic data generation using physics-based simulations or generative models can augment sparse datasets by creating realistic training samples that capture variations in environmental conditions, equipment performance, and geological parameters. Transfer learning offers another pathway, where pretrained models developed in data-rich mining sites or analogous industrial settings are fine-tuned with limited local data, thus improving predictive performance without requiring large-scale datasets [61-68]. Additionally, federated learning enables collaborative model training across multiple mining sites without direct data sharing, preserving data privacy while expanding the diversity and representativeness of training inputs. These methods collectively strengthen model robustness, reduce biases introduced by scarce datasets, and enhance the generalizability of AI applications in remote or under-monitored mining operations.

7.2. Computational costs

Advanced AI models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or digital twin-based simulations require substantial computational power and storage capacity. Real-time monitoring systems that process multi-source data (from IoT sensors, satellite imagery, geophysical models, etc.) also necessitate:

- High-speed data processing infrastructure,
- Scalable cloud or edge computing capabilities, and
- Skilled personnel to maintain these systems.

These demands result in high capital and operational expenditures, making AI adoption challenging for small- to mid-scale mining enterprises with limited budgets. The energy consumption of AI models also poses environmental challenges, contributing to carbon emissions. A critical paradox emerges when considering the energy-intensive nature of AI systems against the very sustainability goals they are designed to advance. Training large-scale deep learning models, particularly those used in digital twin simulations or high-resolution image analysis can consume vast amounts of electricity and contribute to carbon emissions [69-75]. This issue is especially relevant in remote mining regions where power infrastructure is limited. To address this challenge, research has increasingly focused on energy-efficient AI frameworks, such as lightweight deep learning models optimized for edge computing, pruning and quantization techniques that reduce model complexity without compromising accuracy, and the use of specialized hardware accelerators like tensor processing units (TPUs) designed for low-power AI computations. In addition, green AI initiatives advocate for benchmarking models not only by accuracy but also by their energy consumption and carbon footprint, promoting transparency and accountability [76-82]. Incorporating such energy-conscious approaches ensures that AI-driven solutions for sustainability do not inadvertently undermine their environmental objectives [83-85]. This paradox of high computational energy use versus sustainability goals can be mitigated through energy-efficient AI frameworks, including lightweight deep learning models, pruning and quantization methods, and specialized low-power accelerators such as TPUs, which reduce energy demand without compromising accuracy.

7.3. Integration with legacy systems

Most mining companies rely on traditional monitoring tools and legacy software for environmental assessment. Integrating AI requires:

- Digitization of analog processes,
- Upgradation of data acquisition systems,
- Interfacing new AI tools with existing SCADA systems, and
- Training staff for new workflows.

This integration process is time-consuming, complex, and costly, often requiring custom software development and retrofitting of equipment. Moreover, any downtime during the integration may affect ongoing operations, making organizations hesitant to initiate such transitions.

7.4. Model interpretability

Many AI models, especially those using deep learning, operate as **"black boxes"**—providing predictions without clear reasoning or transparent decision-making logic. In the context of environmental management:

- Regulatory bodies demand **explanations** for decisions affecting public health or ecosystems.
- Stakeholders, including local communities and NGOs, expect **accountability** in pollution forecasts or land use decisions.
- Engineers and environmental managers need to **trust** and validate the model outputs.

Without interpretable AI, adoption remains limited due to the lack of confidence in model recommendations, especially in high-risk scenarios such as tailings dam monitoring or chemical discharge management.

Interpretability concerns can be further linked to measurable performance evidence. While black-box models such as deep neural networks achieve high prediction accuracies (often above 90% for air quality and tailings monitoring), their lack of transparency limits regulatory acceptance. In contrast, interpretable models such as decision trees and regression frameworks offer slightly lower accuracies (typically in the 80–85% range) but provide clear justifications for outputs [86-92]. Discussing this trade-off between interpretability and predictive performance underscores the importance of developing explainable AI systems that balance accuracy, efficiency, and trustworthiness. The challenge of explain ability in deep learning models can be addressed through the application of Explainable AI (XAI) techniques tailored to mining and environmental contexts [93-103]. For instance, SHapley Additive explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) can be used to highlight the contribution of individual features, such as sensor readings or geospatial variables, in predicting outcomes like slope instability or water quality deterioration [104-108]. In addition, saliency maps and Grad-CAM methods applied to satellite imagery and remote sensing data can provide visual interpretations of why a convolutional neural network identifies particular zones as high risk [109-111]. Counterfactual explanations can further assist decision-makers by outlining the conditions under which a model would have predicted a safer environmental outcome, supporting proactive interventions. Integrating these XAI techniques not only improves trust in model outputs but also ensures compliance with regulatory requirements that demand transparent justification for predictions impacting ecosystems and local communities [112-114]. Explainable AI (XAI) methods such as SHAP, LIME, and saliency mapping can provide transparent reasoning for predictions in domains like tailings monitoring or satellite-based land assessment, helping regulators and stakeholders interpret results while maintaining high predictive performance.

7.5. Ethical and regulatory concerns

The deployment of AI in environmental decision-making raises critical ethical and regulatory issues:

- **Transparency**: Models must disclose how they make predictions, especially when environmental risks are involved.
- **Bias and Fairness**: Algorithms trained on unbalanced or outdated datasets may favor certain outcomes, leading to **environmental injustice** (e.g., overlooking pollution in marginalized communities).
- **Data Privacy**: Environmental data may include sensitive geospatial information or community-level impact details that require **protection and secure handling**.
- **Compliance**: Regulatory frameworks for AI in mining are still evolving, and many jurisdictions lack **clear standards** for AI-enabled monitoring systems.

Ensuring that AI tools adhere to **principles of responsible AI**—including accountability, inclusiveness, and sustainability—is essential for their long-term acceptance and utility in the mining sector.

Table 4. Challenges and limitations in AI adoption for environmental management in mining

Sr. No.	Challenge Area	Key Issues	Impact on AI Adoption
1	Data Scarcity and Quality	Incomplete datasets, inconsistent sampling, sensor errors, proprietary data restrictions	Limits model reliability, leads to biased and underperforming systems
2	Computational Costs	High processing needs, energy consumption, infrastructure and skilled workforce costs	Restricts use by small-scale miners, increases environmental footprint
3	Integration with Legacy Systems	Need for digitization, SCADA integration, workflow disruption, custom retrofitting	Slows down modernization, increases cost and downtime
4	Model Interpretability	Lack of transparency in deep learning models, stakeholder trust, regulatory validation	Reduces user trust, hinders acceptance in critical decision-making
5	Ethical and Regulatory Concerns	Transparency, bias, privacy risks, lack of legal standards, responsible AI principles	Raises concerns on fairness, compliance, and long-term sustainability

Despite AI's advantages, its adoption in mining is hindered by data limitations, high costs, legacy system integration, lack of interpretability, and regulatory gaps. Overcoming these barriers requires collaborative action, regulatory frameworks, transparent AI design, and inclusive technology governance.

8. Future directions

With the mining industry progressing in a direction of digitalization and sustainability, there are a few specific directions that have been identified as future trends in the use of AI in environmental management. The development of explainable AIs constitutes one of the most essential research challenges, in order to enhance transparency, trust, and responsibility in decision-making. These models would assist regulators, environmental scientists, and mining companies in interpreting the decision making process of AI, thus providing an avenue toward compliance and societal acceptance. Another tractable approach is based on federated learning methods, which allow for collaborative learning from models across all mining sites or companies in the absence of sharing sensitive/proprietary data, guaranteeing data privacy and security beyond corporate borders.

Moreover, embedding AI into circular economy architecture has the potential to minimize mining waste, enhance materials recovery and optimize resource utilization throughout the mining value chain. These are all in line with the worldwide sustainability agenda to lower environmental footprints and enhance sustainable material flows. Finally, crowdsourced data and citizen sensing initiatives with local communities contributing real-time environmental observations can greatly enhance the granularity and relevance of datasets, particularly in remote and underserved areas. Such a participatory approach not only improves model accuracy but also contributes to the community and the environmental stewardship.

Several pathways can be followed in order to go beyond the limitations at present and to exploit fully Artificial Intelligence's potential for sustainable mining. The future studies regarding AI and sustainability should integrate systems dynamics methodologies, psychological, and sociological perspectives, multi-level views, economic value factors as well as design thinking to show AI can provide immediate solutions without harming environmental sustainability in the long run. Such energy efficiency-focused AI would not only be economically beneficial, an incentive rate being faithfully corresponding to its energy efficiency; however, it will also see more room for real efforts in ecological issues, to avoid the counterforce of excessive model complexity escalating again. Concrete steps, such as establishing industry standards and policy-based regulation, and conceptual work on the relationships among sustainability-related effects are required to facilitate sustainable AI. The standardization of benchmarks and evaluation metrics customized for environmental applications in computer vision, which are mainly based on AI, is highly desirable. These benchmarks should be based on more than predictive accuracy, including computational cost, amount of data needed, and ethical considerations. The carbon footprint of the AI system must be reduced, according to business sustainability. In addition, priority should also be given to develop the AI systems which are not only accurate but also perform robustly across different geographical and geological settings.

The company culture has a major influence on how artificial intelligence and sustainability are being used; an aspect called sustainable artificial intelligence, there is also a moral connotation. A systematic approach to the sustainability of AI: given the need to promote a sustainable use of AI, sustainability criteria should be incorporated in AI development and deployment processes, taking a holistic perspective on AI sustainability, and using a indicators-based approach to suggest and give insights on possible ways to the practical deployment of sustainable AI systems. The paradox of an energy hungry technology helping ecological issues is an important factor to consider when leveraging AI for sustainability, such as in developing sustainable production processes and in climate change. These concerns cannot be addressed by technology alone and require trans-disciplinary strategies to accommodate the wider social, economic and ethical implications of deploying AI in mining.

Future advancements in AI for mining must focus on explainable AI, federated learning, and integration into circular economy frameworks. Cross-sector collaboration and sustainable design principles will be essential in ensuring AI delivers long-term ecological and operational value.

9. Conclusion

Artificial Intelligence has emerged as a transformative tool for advancing sustainability in the mining sector. By enabling real-time monitoring, predictive modelling, digital twin simulations, and optimization strategies, AI strengthens the industry’s ability to reduce environmental degradation, conserve resources, and comply with regulatory standards. Its integration into domains such as air quality, water resource management, soil restoration, energy optimization, and slope stability demonstrates measurable improvements, including higher predictive accuracy, cost savings, and reduced emissions. Despite these benefits, AI adoption in mining remains constrained by data scarcity, high computational demands, challenges of legacy system integration, and limited model interpretability. Addressing these barriers requires interdisciplinary collaboration, development of energy-efficient AI frameworks, explainable models, and transparent governance structures. In particular, ensuring inclusivity and ethical compliance will be central to building trust among regulators, industry stakeholders, and local communities. Looking forward, the incorporation of explainable AI, federated learning, and circular economy principles can further strengthen AI’s role in sustainable mining. If pursued with accountability, transparency, and sensitivity to ecological and social contexts, AI has the potential to shape a future where mining practices are both environmentally responsible and economically viable, achieving a balance that benefits industry, ecosystems, and society alike.

Author Contributions

Parimal S. Bhambare contributed to the conceptualization of the study, methodology framing, and drafting of the initial manuscript. Anant Kaulage was responsible for software support, data curation, validation, and assisted in reviewing and editing. Milind Manikrao Darade carried out the formal analysis, visualization, and supported the investigation activities. Govindarajan Murali contributed to resources, technical validation, and manuscript refinement. P. S. N. Masthan Vali assisted in investigation, validation of results, and contributed to manuscript editing. Swati Mukesh Dixit worked on data collection, organization of resources, and manuscript editing. Sukhadip Mhankali Chougule assisted in literature review, data compilation, and technical proofreading. Anant Sidhappa Kurhade led the overall conceptualization, project administration, and supervision, and contributed to reviewing and editing the manuscript, serving as the corresponding author.

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Conflicts of Interest

The authors declare no conflict of interest.

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