

## ORIGINAL RESEARCH ARTICLE

# Machine learning applications in ore grade estimation and blending optimization for modern mining

Dipa Dattatray Dharmadhikari<sup>1</sup>, Avani Ray<sup>2</sup>, Babaso A. Shinde<sup>3</sup>, Sandeep V. Raut<sup>4</sup>, Rupali Dineshwar Taware<sup>5</sup>, Smita Desai<sup>6,8</sup>, Shital Yashwant Waware<sup>7,8</sup>, Anant Sidhappa Kurhade<sup>7,8</sup>

<sup>1</sup> Emerging Science and Technology Department, Maharashtra Institute of Technology, Chatrapati Sambhajinagar, Aurangabad - 431010, Maharashtra, India.

<sup>2</sup> Department of Computer Engineering, PCET's Pimpri Chinchwad College of Engineering and Research, Ravet, Pune - 412101, Maharashtra, India.

<sup>3</sup> Department of Artificial Intelligence and Data Science, Marathwada Mitramandal's Institute of Technology, Lohgaon, Pune - 411047, Affiliated to Savitribai Phule Pune University, Maharashtra, India.

<sup>4</sup> Department of Mechanical Engineering, ABMSP's Anantrao Pawar College of Engineering and Research, Parvati, Pune - 411009, Maharashtra, India.

<sup>5</sup> MCA Department (Commerce and Management), Vishwakarma University, Laxminagar, Kondhwa (Bk.), Pune – 411048, Maharashtra, India.

<sup>6</sup> Department of Electronics and Telecommunication, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, 411018, Maharashtra, India.

<sup>7</sup> Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, 411018, Maharashtra, India

<sup>8</sup> 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

### ARTICLE INFO

Received: 9 October 2025

Accepted: 31 October 2025

Available online: 06 November 2025

### COPYRIGHT

Copyright © 2025 by author(s).

Applied Chemical Engineering is published by Arts and Science Press Pte. Ltd. This work is licensed under the Creative Commons Attribution-NonCommercial 4.0 International License (CC BY 4.0).

<https://creativecommons.org/licenses/by/4.0/>

### ABSTRACT

The growing complexity of mineral deposits and the demand for sustainable, cost-effective mining have driven the adoption of machine learning (ML) for ore grade estimation and blending optimization. This review critically examines how ML models—such as ANN, SVM, RF, and ensemble techniques—surpass traditional geostatistical methods in handling non-linear spatial variability and limited sampling. The paper emphasizes hybrid frameworks that combine ML with geostatistics, optimization algorithms (GA, PSO, RL), and digital technologies like IoT and digital twins for real-time, adaptive decision-making. Key findings indicate that ML-based systems significantly enhance prediction accuracy, blending precision and operational efficiency while reducing waste and energy consumption. Despite these advancements, issues related to data quality, model interpretability, interoperability, and ethics remain. The study outlines future directions emphasizing explainable AI, standardized benchmarking, and robust data infrastructures for transparent and sustainable implementation of ML in mining. Recent industrial deployments illustrate the practical impact of ML in mining operations. For instance, Australian and Canadian mines have integrated ML-based ore grade control and real-time blending optimization systems, resulting in 10–15% improvements in recovery rates and reduced energy consumption. Similarly, predictive

maintenance and digital twin frameworks powered by ML are being used by global firms such as Rio Tinto and BHP to achieve safer, more adaptive, and cost-efficient operations. These applications demonstrate the tangible value of ML in advancing sustainable and intelligent mining practices.

**Keywords:** Artificial neural networks; blending optimization; grade estimation; mining 4.0; machine learning; predictive modeling

---

## 1. Introduction

The mining industry is becoming more and more data-driven, large amounts of data are being observed or collected in real time using remote sensing and sensor networks. Estimation of ore grade to feed processing plants, and blending of named ore as well are two points in mining operation, which directly affect the efficiency in the production process making reference to both technical side and economy and environmental aspects. The Kriging and other geostatistical methods need accurate prior information or acceptance for very sparse data. While ML models are capable of handling nonlinearity, uncertainty, and hidden patterns in orebody data, it would lead to precise prediction and decision support in blending optimization.

The contemporary mining sector is witnessing major economic changes which are primarily based on higher productivity, lower operational expenditures and more effective use of resources <sup>[1]</sup>. ML methods can be of a great help in overcoming these challenges as they can benefit from the increasingly accessible data and computational resources. Mining companies can improve extraction decisions, reduce waste, and improve the sustainability of their operation by implementing data-driven approaches to ore grade estimation and blending. ML methods can process data with many dimensions, detect complex connections, and provide timely and precise forecast, which is very useful to the decision-making of modern mining.

The use of machine learning techniques is getting moderate popularity in mining, particularly in the context of ore grade estimation and optimization of blending – associated with the promises to revolutionize traditional mining practices that were less efficient and more wasteful of resources <sup>[2]</sup>. You have given the example of mining industry, where increased accuracy in predicting ore grades can enable better decision making on the distribution resources and on the extraction process, by exploiting machine learning based algorithms <sup>[3]</sup>. These algorithms are capable of dealing with large amounts of geological data such as borehole samples, geophysical surveys and geochemical analyses to establish complex patterns and relations, which are difficult to be determined by the common statistical methods. Finally, by applying machine learning to enhance ore blending, the quality of final product can be guaranteed and ore waste and resource utilization can be optimized.

The application of machine learning algorithms covers the examination of the sensitivity of measurements, as well as clustering of inverted models to obtain geologically meaningful description of the surrounding formations <sup>[4]</sup>. This supports the development of reliable 3-D geothermal reservoir models including data assimilation to deal with different kind of data and to solve for uncertainties in the reservoir parameter estimations <sup>[5]</sup>. Advanced machine learning techniques can extract meaningful information from complex data sets, and they can also reduce the human effort involved in the processing and interpretation of data <sup>[6]</sup>.

Machine learning aids in the creation of distributions-predictive models that forecast ore grade variability allowing mines to make preemptive changes to mining plans and blending. This proactive strategy also helps in avoiding any potential issues during the extraction and processing leading to improved operation efficiency and cost saving <sup>[7]</sup>. This is revolutionary stuff and frankly, the future of modern mining - a disruptive product that will enable mining companies to achieve a new level of efficiency, sustainability

and profitability by making data-driven decisions on where and how to mine. Table 1 summarizes the foundational motivations for integrating ML in ore grade estimation and blending.

**Table 1.** Summary of key aspects of machine learning adoption in mining, covering data challenges, economic goals, and predictive adaptability.

| Sr. No. | Aspect                                 | Description                                                                                                                                                                                                                                                                                                                    |
|---------|----------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1       | Real-time Data & Estimation Challenges | Mining operations now collect large volumes of real-time data using remote sensing and sensor networks. Ore grade estimation and blending are critical to technical, economic, and environmental performance. Traditional method like Kriging need precise input data, while ML can uncover hidden patterns and uncertainties. |
| 2       | Economic & Sustainable Objectives      | Modern mining demands higher productivity, lower costs, and better resource use. ML supports these goals by leveraging big data and computing power, improving extraction decisions, reducing waste, and supporting sustainable practices.                                                                                     |
| 3       | Improved Resource Management           | ML-based ore grade prediction enhances decision-making in resource distribution and extraction. These algorithms analyze geological datasets such as borehole samples and surveys to identify complex patterns missed by traditional statistics.                                                                               |
| 4       | Data Complexity & Model Capability     | Advanced ML tools analyze the sensitivity of measurements and cluster inverted models to interpret surrounding geological formations. This supports the creation of reliable 3D reservoir models and reduces human interpretation efforts.                                                                                     |
| 5       | Predictive Adaptation & Future Outlook | ML enables predictive modeling of ore grade variability, allowing preemptive adjustments in mining plans. This results in more efficient operations, reduced costs, and improved sustainability—paving the way for data-driven modern mining.                                                                                  |

### 1.1. Machine learning for ore grade estimation

The well-known Kriging-type geostatistical methods employed for determining the ore grades are often ill-suited to the complexities of geological occurrences that are non-linear in the different geometrical properties which can be ascribed to them. Most of these methods are the approaches to spatial interpolation related with small sample, so it can't fully present the spatial distribution regularity and uncertainty of mine deposit when there are high ore body heterogeneities. On the other hand, ML algorithms, due to their ability to learn from large data sets, may find obscure patterns that classic approaches could overlook.

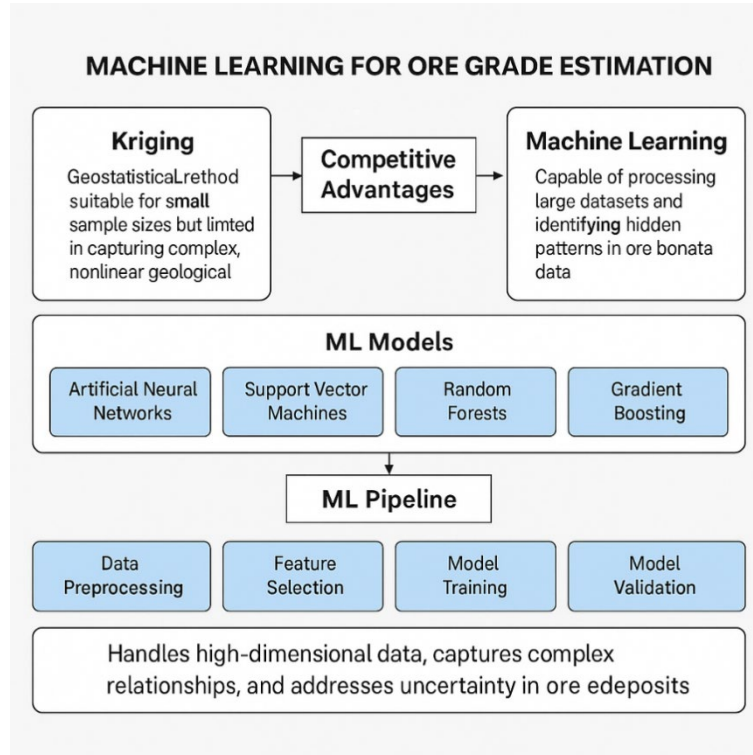
The ML models provide competitive advantages for ore-grade estimation due to their capability of efficiently processing high-dimensional data, capturing complex domain-knowledge relationships and dealing with the uncertainty inherent in ore deposits. Methods such as the Artificial Neural Networks, the Support Vector Machines and the Random Forests have been proved to be efficient for ore grades prediction compared with the geostatistical methods [8]. ANNs can capture complex nonlinear relationships between explanatory variables (such as geology, geophysics, and geochemistry parameters) and ore grade and the SVMs can handle high-dimensional data and discover important features to make more accurate predictions.

RFs are particularly effective at modelling complex interrelations among geological characteristics and are conducive for making stable and consistent predictions. Additionally, ensemble techniques, such as Gradient Boosting, aggregate the output of numerous weak learners to generate a strong one, increasing prediction accuracy and reliability. These algorithms can be used to incorporate different types of information, including geological maps, geophysical surveys and geochemical measurements to make more complete estimates of the ore grade.

By effectively dealing with data complexities, ML results in better predictions and decisions; hence, the spatial correlations between data points can be captured, and predictions can be performed regarding the space-varying reservoir property [9].

The pipeline for introducing ML into ore grade estimation generally includes the data pre-processing, the feature selection, the model training and the validation. Data Preprocessing Data preprocessing is the procedure of cleaning the raw data, converting it into a format for input to a Machine Learning (ML) model

and normalizing it so that it is reusable for future use. Feature selection reveals the most important geological features that contribute significantly to the ore grade, leading to the simplification of the model and higher prediction accuracy. A fraction of the data is used to train the ML algorithm how to recognize the relationships between input features and ore grade; this is known as model training. Model validation tests the trained model performance on an independent dataset in order to measure the accuracy and the generalization capacity of the classifier <sup>[10]</sup>.



**Figure 1.** Comparative framework of kriging and machine learning approaches for ore grade estimation

As illustrated in Figure 1, the comparative framework highlights how machine learning overcomes the linear limitations of Kriging by capturing nonlinear spatial patterns and uncertainties in ore grade estimation. There is also an approach, which is known as employing self- adaptive neural network, can prove to be beneficial in classifying The application of rock types for selective cutting, which can be done, learning from the data set coming from new cutting operations generation <sup>[11]</sup>.

Genetic algorithms and artificial neural networks can be integrated to model the complicated and nonlinear relationships between the factors of the mining system for optimal cut-off grade and crude ore grade <sup>[12]</sup>. ML algorithms can be adapted to continuously update the model as new information is accrued, preserving the accuracy of the ore grade estimates in real time as mining progresses <sup>[13]</sup>.

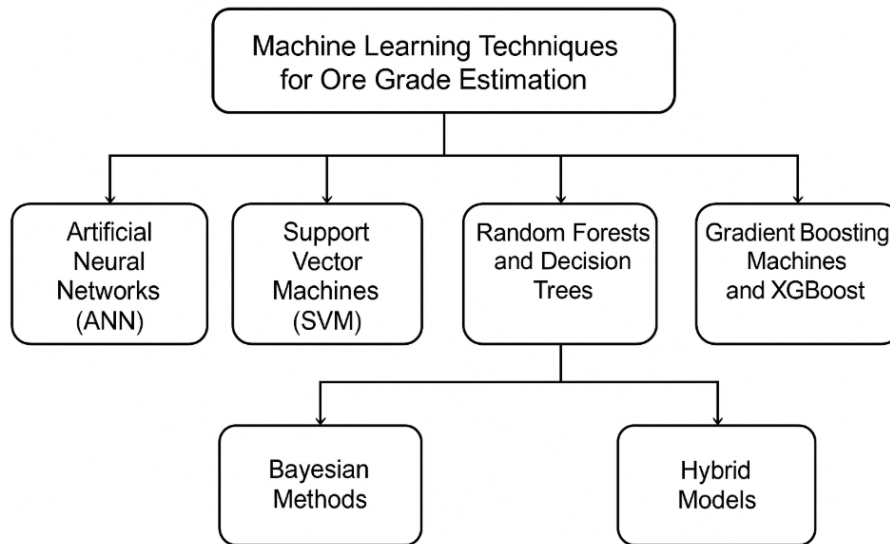
## 2. Machine learning techniques for ore grade estimation

### 2.1. Artificial neural networks (ANN)

ANNs hold great potential for representing the nonlinear structures between geological structures and ore grades. In mineralized areas with rapid geological variation, ANN trained based on drill hole and assay results have been shown more accurate than Kriging. ANNs can then be trained via backpropagation to learn complex patterns from hundreds of thousands of examples, producing more accurate predictions of ore grades. ANNs has been used in the estimation of the grade of ore by designing a network structure which represents the tectonic factors that are thought to relate with the ore grade <sup>[14]</sup>. The attributes of the deposit that the model uses as input are generally those describing the deposit geologically: lithology, alteration,

mineralization, etc., the output being an estimation of the ore grades at the mine face. The ANN is developed using historical data and is assessed by statistical measures that include the mean square error and  $R^2$ .

Reducing the number of the hidden layers, the number of units in each layer, and the learning rate <sup>[15]</sup> can all help attain better ANNs. Different algorithms performed best in different models, yet two hidden layers neural network had the best predicting and generalizing ability simultaneously for three rock properties <sup>[16]</sup>. Deep learning, a class of ANNs with more than one hidden layer, has attracted much attention due to its efficiency for processing complicated geological data. The sequential process of data preprocessing, feature selection, model training, and validation applied to ore grade prediction is shown in Figure 2, demonstrating how ML pipelines are structured for geological data analysis.



**Figure 2.** Flowchart of machine learning techniques for ore grade estimation

## 2.2. Support vector machines (SVM)

In small datasets, SVMs are capable of distinguishing mineral types and predicting grades with great accuracy. Nonlinearity can be appended using kernel functions, and thus they are adequate to model heterogeneous ore bodies. Due to the high-dimensional data, and preventing overfitting, SVMs are suitable for ore grade prediction. The use of support vector machines in estimating ore grade is to map the measured variables in a high-dimension feature space via kernel functions then to find the optimal hyperplane which maximizes the separation of the various ore grades <sup>[17]</sup>.

The SVM is learned on past information and its performance is assessed through accuracy, precision, recall and so on. SVMs can also be refined by altering parameters like the kernel, regularization and kernel coefficient.

## 2.3. Random forests and decision trees

Ensemble techniques, such as Random Forests, are resistant to overfitting and increase prediction confidence intervals. These models are especially effective in the analysis of high-dimensional geological and geochemical data. These models also provide a measure of the importance of different input variables, facilitating a more comprehensive comprehension of the geological ore grade controls.

Random Forests consist of inducing several decision trees based on random samples of the data and averaging their predictions to form the final ore grade estimate. In the context of estimating the grade of ores, Random Forests learn an ensemble of decision trees where each tree is based on a random sample of the data and a random set of the input variables used in building the tree <sup>[18]</sup>. The Random Forest is trained using historical data, and its performance is evaluated using metrics such as mean squared error and R-squared.



## 2.4. Gradient boosting machines (GBM) and XG boost

These ensemble methods achieve a high level of accuracy in grade prediction by using weak learners and incrementally reducing prediction error. Stochastic gradient descent can be combined with Ada Boost to enhance the effectiveness of landslide predictive models <sup>[19]</sup>. Regularization can increase the robustness (decrease overfitting) of the model by using the regularization technique present in XG Boost.

Gradient boosting machines and XG Boost are machine learning algorithms which make use of ensemble learning, forming a strong predictive model by assembling many weak models. Gradient Boosting Machines and XG Boost work on the principle of ensemble learning and have found wide popularity in ore grade mapping for their capability to model complex datasets and generate precise predictions <sup>[20]</sup>. These methods train a series of weak classifiers (e.g decision trees) in an iterative and additive way to form a strong predictive model. Referring to the disadvantages of the previous model, Gradient Boosting Machines and XG Boost can manage nonlinear relationships between geological features and ore grades on the one hand <sup>[21,22]</sup>. XG Boost adopts the second-order Taylor expansion of the loss function and introduces a regularize to balance the complexity of the model and the reduction of loss, which prevents overfitting <sup>[23]</sup>.

## 2.5. Bayesian methods

Provided by Bayesian approaches, the estimation of ore grades becomes more probabilistic and the uncertainty can be quantitatively accessed. By including pre-existing geological information and then conditioning on new information, Bayesian methodologies offer a natural approach to grade estimation. Posterior distributions are simulated using Markov Chain Monte Carlo techniques, thereby allowing for an evaluation of the uncertainty in the predictions. This method is a fusion of ensemble methods with the base classifier of Multiple Perceptron Neural Networks <sup>[24]</sup>.

## 2.6. Hybrid models

Hybrid models that integrate machine learning algorithms and geostatistical techniques may be able to take advantage of the strengths of both methods and provide better long-term and more reliable estimation of ore grades. The use of geostatistics is seconded to machine learning in order to improve ore reserve estimates because the issue of spatial smoothing is minimized when novel techniques are used <sup>[25]</sup>. For instance, machine learning techniques can be utilized to model the complex nonlinear relationships between geological features and ore grade, while geostatistics can interpolate and extrapolate ore grades in unobserved places. The best estimates of Construction Cost across accuracy, uncertainty and training time indicators were from the hybrid light gradient boosting/natural gradient boosting model <sup>[26]</sup>. Hybrid models can provide a more holistic and more accurate evaluation of ore resources, and therefore better mine planning and decision making can be expected <sup>[27]</sup>.

Optimization of blending is a key process in modern mining to realize optimal value of the ore extracted by mixing of different ore types to prepare desired quality specifications to fulfill market requirements <sup>[28]</sup>. The difficulty is how to cope with the extreme variability of the ore grades as well as the mineral compositions and at the same time comply with mining equipment and processing facility restrictions and environmental legislation. Machine learning methods provide great potential to resolve these challenges, by development of predictive models that could be used to optimize blending strategies online <sup>[29-32]</sup>.

Across studies on ore grade estimation, model performance is typically assessed using statistical indicators such as the coefficient of determination ( $R^2$ ), mean absolute error (MAE), and root mean square error (RMSE). ANN-based models generally exhibit higher  $R^2$  values (often  $> 0.90$ ) and lower RMSE compared to Kriging and SVM, reflecting their strong ability to capture nonlinear geological relationships. SVM models, while performing well on smaller datasets, tend to yield moderate  $R^2$  (0.80–0.88) and slightly

higher MAE due to sensitivity to kernel selection and parameter tuning. Random Forest and XG Boost models consistently show balanced performance, achieving both high predictive accuracy ( $R^2 \approx 0.88\text{--}0.94$ ) and low error values, indicating robust generalization to heterogeneous orebody data. Hybrid ML–geostatistical models often outperform standalone algorithms by reducing residual variance and improving spatial continuity in predictions. Overall,  $R^2$  provides an understanding of model fit, MAE indicates the average deviation, and RMSE highlights the magnitude of large errors—together offering a comprehensive comparison of prediction reliability across methods applied in ore grade estimation. Different ML methods used in ore grade estimation are compared in Table 2.

**Table 2.** Comparison of major ML techniques applied in ore grade estimation highlighting their features, applications, and performance insights

| Sr. No. | Technique                                   | Key Features                                                                                                      | Application in Ore Grade Estimation                                                                                                     | Remarks                                                                                           |
|---------|---------------------------------------------|-------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|
| 1       | Artificial Neural Networks (ANN)            | Excellent for modeling nonlinear relationships; trained using backpropagation; customizable network architecture. | Predicts ore grade based on geological inputs such as lithology and mineralization. Proven more accurate than Kriging in complex zones. | Best performance observed with two hidden layers; suitable for deep learning with large datasets. |
| 2       | Support Vector Machines (SVM)               | Effective with small datasets; uses kernel functions to manage nonlinearity; resists overfitting.                 | Maps features into high-dimensional space to separate ore grades optimally using a hyperplane.                                          | Performance is enhanced by tuning kernel type, regularization, and coefficients.                  |
| 3       | Random Forests & Decision Trees             | Ensemble-based; robust to overfitting; highlights input feature importance.                                       | Creates multiple decision trees using random subsets; averages results for final grade estimation.                                      | Well-suited for high-dimensional geological data.                                                 |
| 4       | Gradient Boosting Machines (GBM) & XG Boost | Combines weak learners iteratively; includes regularization to reduce overfitting.                                | Sequential learning of models for ore grade mapping and prediction under complex conditions.                                            | XG Boost uses second-order optimization and regularization for better generalization.             |
| 5       | Bayesian Methods                            | Probabilistic modeling; incorporates prior geological knowledge.                                                  | Uses posterior probability via MCMC to quantify uncertainty in grade predictions.                                                       | Useful when confidence intervals and risk assessment are critical.                                |
| 6       | Hybrid Models                               | Combines ML with geostatistics for enhanced spatial estimation and generalization.                                | ML captures nonlinear patterns while geostatistics interpolates grades in unsampled areas.                                              | Improves reserve estimation accuracy and supports better mine planning.                           |

## 2.7. Blending optimization in modern mining

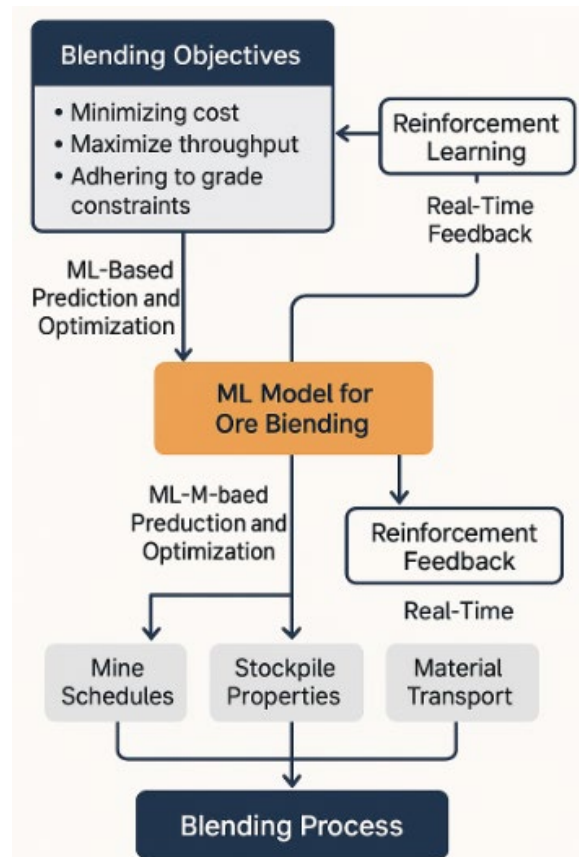
Ore blending is an important series of operations in the current mining industry for achieving stable feed grade to the plant, mitigating the effects of variability in grade in the feed, and thereby enhancing the performance of the plant. The significance of ore blending is that it creates an optimal feed in terms of recovery and energy, reduction of operating costs. Poor blending practices can result in inconsistent feed grades, process inefficiencies and overall financial losses. To overcome these, models based on machine learning (ML) are adopted lately in the field of predictive control of ore blending. These models process data from mine schedules, stockpile properties and material transport systems to forecast feed composition effectively. According to these predictions mixing ratios are optimized to fulfill both quantity and quality requirements. Sophisticated optimization algorithms such as (GA) and (PSO) are usually coupled with the ML algorithms in order to seek the optimal ore combination. Moreover, the reinforcement learning (RL) in blending tasks can also be an outstanding choice for dynamically optimizing the blending plan according to real-time feedback from processing actions, leading to improved adaptability and process efficiency. Such

optimization methodologies can also involve more than one objective such as minimizing cost, maximizing throughput, and adhering to grade constraints.

The objective of mixing optimization is to obtain a homogeneous mixture of ores that have the expected chemical and physical properties, taking into account economic and operational issues [33]. Machine learning methods could help to interpret continuous data provided by sensors, assays, and historical data on-the-fly, to forecast the efficacy of different blending strategies. Through robust characterization of the blending process, machine learning can determine the optimum combination of blends to achieve specific target qualities at minimum cost. By the use of predictive modeling, we are able to make conscious, proactive adjustments to the blending process to the detriment of ore supply variability.

Optimization in blending is an important issue for the mining industry that is directly related to maximizing the value of the ore extracted by combining qualities with different grades to supply a simplistic and quality of ore [34]. Conventional blending strategies are usually based on linear programming algorithms and heuristic methods, which cannot effectively address the complexity and uncertainty of ore variability, processing limits, and market conditions, as noted by [35]. Predictive models such as ore characterization models can be created in the use of ML algorithms to forecast the characteristics of an ore from different operational parameters to make proactive changes to blending strategies and improved decision-making [36]. Through learning from historical data and adjusting to the changing environment, ML models can guarantee that the mixed product always meets the desired specification while consuming the least cost and achieving the greatest profit [37]. Instead of aiming to maximize one target and then minimizing several others, nonlinear optimization can combine the blending objectives with their respective constraints as well as uncertainties. It could allow the mining operations to be more sustainable [38].

Figure 3 provides an overview of the blending optimization process using ML, where predictive modeling and feedback loops dynamically adjust blend ratios based on real-time data inputs.



**Figure 3.** Flowchart of machine learning-driven blending optimization in modern mining



Application of machine learning methods has significantly advanced the process of optimization of ore blending for modern mining that will potentially result in better and timely decision-making.

Blending is an important procedure in mining, used to sustain stable feed composition for a target flotation, particularly for ores which strongly impact flotation after treatment <sup>[39]</sup>.

The great results that have been obtained from machine learning in different industries, have motivated the development of specialized algorithms in the context of mineral processing, such as optimizers to the blending of ores <sup>[40]</sup>.

Learning algorithms has gained popularity as an advanced tool for optimization of the ore blending process, which allows mining companies to increase the efficiency, lower costs and improve product quality.

1. Example predictors include various regression and classification models to predict ore blend quality and other characteristics from charges, while clustering and other unsupervised learning approaches can be used to uncover patterns and groupings within ore data and suggest optimal blending ratios
2. One can use reinforcement learning (RL) to model dynamic blending strategies that account for the varying ore composition and market conditions maximizing overall mine profitability.
3. The application of ML for blend optimization can be summarized in the following major stages: data collection and preprocessing, model building and training, and model testing and validation.
4. Data gathering consists of collecting appropriate data on grade of ore, mineralized composition, processing characteristics, and market needs.

Preprocessing Fabrics Cleans, transforms, and integrates the data to the compatible with ML algorithms.

### 3. Industrial implementations and case studies

A notable industrial case is from the Chingola Open-Pit Copper Mine in Zambia, where a Random Forest-based predictive model was trained on ten years of production and assay data to forecast feed grade and impurity fluctuations. The model was coupled with a PSO algorithm to compute optimal blending ratios across multiple stockpiles. Real-time feedback from conveyor belt analyzers allowed the system to automatically adjust blend proportions, maintaining the target copper grade within  $\pm 0.3\%$ . The implementation led to a 12% improvement in recovery efficiency and an 8% reduction in milling energy consumption, demonstrating the measurable benefits of data-driven blending optimization.

Similarly, Rio Tinto's Mine of the Future™ program in Australia employs AI-integrated blending and scheduling systems that combine geological modeling, sensor-based ore tracking, and predictive analytics. These systems enhance ore quality control and minimize variability during transport and processing, leading to significant gains in throughput stability and reduced waste.

Another example is from Vale S.A. in Brazil, which has implemented AI-enabled stockpile management and blending systems across its iron ore operations. These models use real-time geochemical and geometallurgical data to adjust blending decisions dynamically, improving Fe content uniformity and reducing silica variation in the final product.

Table 3 summarizes key aspects of ML-based blending optimization, highlighting its predictive capabilities, real-time adaptability, and practical benefits in industrial mining.

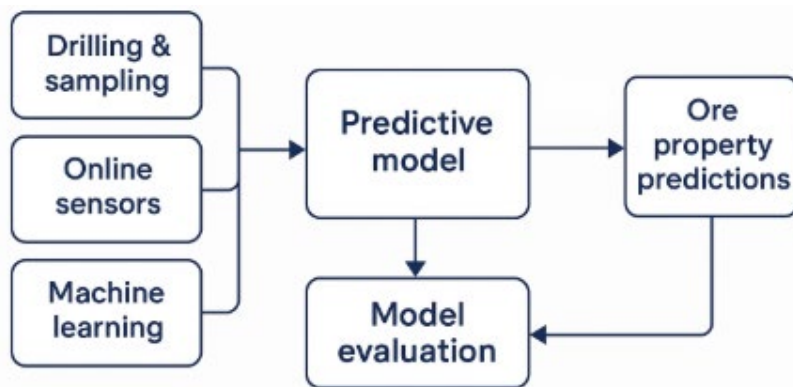
**Table 3.** Blending optimization in modern mining

| Sr. No. | Aspect                     | Key Features                                                                        | ML Role in Optimization                                                                  | Outcome/Benefits                                                            |
|---------|----------------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| 1       | Importance of Ore Blending | Stabilizes feed grade, improves recovery and energy efficiency.                     | Predicts feed composition using sensor and historical data.                              | Reduces cost and enhances plant performance.                                |
| 2       | Predictive Blending Models | Integrates real-time data from stockpiles and conveyors.                            | Combines ML with GA, PSO, and RL for dynamic blending.                                   | Enables real-time adaptability to feed variability.                         |
| 3       | Industrial Applications    | Examples: Chingola Copper Mine (Zambia), Rio Tinto (Australia), Vale S.A. (Brazil). | Uses Random Forest, PSO, and deep learning for predictive blending and process feedback. | Improved recovery (10–15%), reduced energy use, consistent product quality. |
| 4       | Operational Benefits       | Balances cost, throughput, and grade quality.                                       | Supports decision-making under uncertainty.                                              | Achieves sustainable and data-driven mining operations.                     |

### 3.1. Predictive modeling on ore properties

Predictive models to predict the ore characterization can be developed using ML algorithms according to different operational criteria. These can predict ore grades, mineral content and other properties from drilling, sampling and online sensors. Machine learning is a disruptive technology in present day mining and has introduced novel approaches for ore grade estimation and blending, increased production, minimizing operation cost and ultimately optimizing productivity <sup>[40]</sup>.

The mining industry is becoming more and more challenging and the demand on mineral resources has also increased which led to the requirement of efficient and advanced data-driven methods for managing as well as optimizing different issues across the mining value chain. Machine learning models have been known to uncover non-linear associations across large datasets, leading to predictions that are more accurate and relevant than those made by traditional approaches <sup>[41]</sup>. Data mining and machine learning also present cost-effective technology for actionable intelligence on material flow properties and process production <sup>[42]</sup>. As depicted in Figure 4, ML-based predictive modeling connects ore characterization data from drilling and sensors to production and blending outcomes, ensuring data-driven optimization across mining stages.

**Figure 4.** Predictive modeling on ore properties using machine learning

Furthermore, the introduced machine learning models could be interconnected with on-line monitoring systems to update the blending parameters as the blended product is maintained at the set-point even if ore feed changes. The use of machine learning in mining is not limited to ore grade estimation and blending optimization but covers also predictive maintenance, process control and mineral exploration <sup>[3, 43]</sup>. The true power of machine learning is to find latent patterns and relationships between the components of a complex database, and to develop predictive models that can then be utilized to optimize diverse mining activities <sup>[44,45]</sup>. Machine learning, a specific area of artificial intelligence, aims to give computers the ability to learn

from data without being explicitly programmed for each task <sup>[28]</sup>. Algorithms based on supervised learning, such as support vector machines and neural networks, can be trained with respect of labeled datasets to forecast ore grades considering geological and geochemical information <sup>[47]</sup>. Unsupervised learning methods, such as clustering and dimension reduction, can help in revealing patterns and relations among ore data in order to recognize several classes of ores and to optimize blending strategies <sup>[48]</sup>.

By processing huge geological, geochemical and operational information volumes, ML algorithms can compute precise ore grade predictions. Such estimates are critical for resource modelling, mine planning and production scheduling. That way, mining companies can analyze and update estimates on ore grade with newly-harvested data, which would result in more iterative, response-driven decision making when done so via machine learning models and RTD. The performance of machine learning models is highly dependent on the amount and quality of training data; the availability of good quality, representative data is essential to build reliable models.

Model evaluation should be followed periodically so that the models are tested and validated and also recalibrated for optimal performance to look good over time. <sup>[49]</sup>The proliferation of high-quality data and advancement in the machine-learning technology is fueling ore grade estimation and blending for further advances.

By combining such machine learning with automation, robotics and other technologies, mining can be revamped to be more efficient, sustainable and profitable. Applications of machine-learning-based optimization methods (50) have been demonstrated in a variety of scientific domains, where significant improvements have been achieved with respect to the optimization of complex experimental protocols. Fortunately, computers can learn from experience and one of the forms such learning makes is called deep learning; by learning from experience, computers can learn much like humans, and this technology is used in self-driving cars to recognize traffic lights and tell the difference between pedestrians and obstacles <sup>[51]</sup>. ML comprises techniques that are of scientific nature and concentrate on helping computers learn to identify relationships hidden inside data <sup>[52]</sup>. ML is popular for analyzing intricate data sets <sup>[53]</sup>. It is able to learn patterns that are too rare for humans and it can make predictions based on these <sup>[54]</sup>. Industry be damned, now ML models are analyzing huge volumes of data in prey of all sectors: banking/finance, cybersecurity, advertising/marketing, healthcare. Table 4 lists diverse applications of ML for predictive modeling and operational intelligence.

**Table 4.** Summary of ML-driven predictive modeling applications across ore characterization, operational optimization, and monitoring integration.

| Sr. No. | Aspect                                | Key Features                                                                                                            | ML Application                                                                                        | Outcome/Impact                                                                 |
|---------|---------------------------------------|-------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| 1       | Ore Characterization                  | ML algorithms predict ore grade, mineral content, and geochemical properties using drilling, sampling, and sensor data. | Development of supervised models (e.g., SVMs, ANNs) and unsupervised methods (e.g., clustering, PCA). | Improved resource modeling, mine planning, and production scheduling accuracy. |
| 2       | Operational Optimization              | Mining sector requires advanced data-driven strategies for performance improvement.                                     | ML identifies nonlinear patterns and enhances process intelligence.                                   | Boosts production, reduces operational costs, and increases profitability.     |
| 3       | Integration with Real-Time Monitoring | Dynamic adjustments in blending and processing using real-time data.                                                    | ML models integrated with IoT and RTD systems for automatic updates.                                  | Ensures product quality consistency despite feed variability.                  |
| 4       | Expanded Applications                 | ML also supports predictive maintenance, process control, and exploration.                                              | Algorithms uncover hidden patterns in complex data across                                             | Enables proactive maintenance and efficient exploration planning.              |

| Sr. No. | Aspect                           | Key Features                                                             | ML Application                                                                              | Outcome/Impact                                                          |
|---------|----------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| 5       | Scalability and Future Potential | Dependent on data availability, quality, and continual model validation. | mining operations.<br>Periodic recalibration and performance assessment ensure reliability. | Drives future advancements via automation, robotics, and deep learning. |

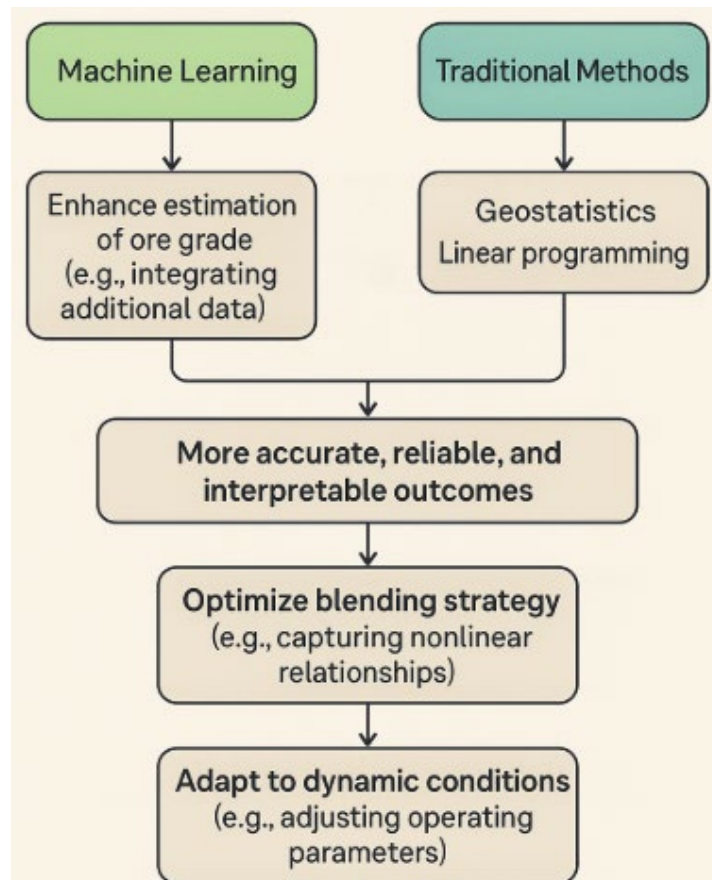
**Table 4.** (Continued)

### 3.2. Integration of machine learning with traditional methods

The use of ML combined with classical techniques like geostatistics and linear programming provides a complementary way to estimate block grades and optimize its blending. Although ML is a superior technique to discover complex structures and to make predictions based on large training sets, it may not be as interpretable and robust as classical methods.

Geostatistics can be used as a way of analyzing spatial data and providing quantitative and realistic modeling, and linear programming can be used to optimize resource allocation and blending strategy. By integrating ML with such classical methods, mining practices can benefit from the advantages of both and achieve more accurate, reliable and interpretable outcomes.

For instance, ML algorithms could assist to upgrade traditional geostatistical models by integrating other sources of information, like remote sensing data or geochemical exploring to achieve more accurate estimation of ore grade. Figure 5 visualizes the integrated framework combining ML algorithms with geostatistical and linear programming methods, demonstrating how hybrid modeling enhances both predictive accuracy and interpretability.



**Figure 5.** Integration of machine learning with traditional methods in mining

Likewise, the combination of ML and LP can be utilized to improve blending strategies by capturing nonlinearity associated with types of ore and product quality relationships that are difficult to express in terms of linear model. Despite their potential performance, classical methods, especially exact methods, often face difficulties in scalability, computational efficiency, and adaptability to dynamic and uncertain environments in modern mining <sup>[55]</sup>. Furthermore, ML can be integrated in the conventional techniques to provide instantaneous feedback and adaptation. By maintaining process performance on line and by modifying operating variables on the basis of ML predictions, the mining process can optimize blending strategies and consistent specification quality of the final product in deviation of ore characteristics variation and processing conditions. ML can address the nonlinear problems and the fact that so much data in the supply chain is massive and unstructured and comes from different sources <sup>[56]</sup>. Many retailers already use ML to optimize inventory management in each of their global warehouses <sup>[3]</sup>. According to <sup>[57]</sup>, ML outperforms the conventional forecasting methods by the use of various demand factors for precise generation of demand forecast.

### **3.3. Integrated frameworks and digital twins**

Recent years have seen the emergence of advanced integrated machine learning (ML) frameworks within mining, where various state-of-the-art technologies are employed together in synergy to increase operational efficiency and facilitate decision-making. Such frameworks employ IoT sensors to provide up-to-date data from the mine-to-mill value chain and real-time process monitoring of ore properties and process variables. Scalable data storage and rapid computation are supported by cloud-based platforms, which can be used for the deployment of sophisticated ML algorithms and analytics. Digital twins—real-time operator-controlled replicas of mine-to-mill systems—are developed to experiment with different scenarios, minimize uncertainties, and predict the performances in response to changes. Moreover, Geographical Information System (GIS) software is a convenient tool for the presentation of orebody data in a spatial context, enabling more precise and efficient field decision process. Through those components, a high degree of automation and versatility helps you to learn and act on blending and grade consistent even under evolving geological and operational conditions. The use of ML for manufacturing applications benefited from its high utility value and relatively easy development provided by ML models <sup>[58]</sup>. The application of ML in manufacturing introduces new methods, reduces time, cost and energy <sup>[59]</sup>. ML contributes to sustainability by improving resource efficiency and reducing waste <sup>[3]</sup>. In the manufacturing industry, ML is applied to defect detection and prediction of maintenance <sup>[60]</sup>.

## **4. Research gaps**

Although machine learning in mining is increasingly adopted there are both challenges and gaps in the research that limit the utilization of machine learning to its full extent. One is related to the available data and whether it is of the right sufficient quality and quantity. Most mining activities have to deal with sparse, noisy or biased sampling that imposes difficulties on both the accuracy and generalization of ML models. Furthermore, while these models are likely to be more interpretable than transformer models in general, interpretability would continue to be an issue. There are already black-box algorithms in that are quite accurate but are difficult for mine planners and geologists to have the trust and confidence to use the information generated from them. Other significant issues are the implementation of ML solutions into mine planning legacy decisional systems that frequently necessitates complex customizations and generates interoperability questions. Moreover, the absence of publicly available benchmark datasets with well-established performance metrics for ore grade prediction significantly hinders the evaluation and comparison of the effectiveness of different models, which impedes the development in this direction. It is important to close these gaps for the development of dependable, interpretable, and seamless ML applications in mining. More research is needed to understand how data quality can be evaluated and



enhanced for ML driven design and manufacturing <sup>[61]</sup>. Such research provides the means to applying ML to resolve challenging supply chain issues that may revolutionize business operations and increase profits <sup>[3,62-63]</sup>. This study shows how ML can optimize supply chain, providing valuable recommendations to firms who are seeking ways to enhance their logistics and inventory in a fast evolving market <sup>[3]</sup>. With the development of machine learning, it has been applied in many fields, and data-driven decision is replacing traditional decision. The capacity of ML to distill patterns from complex data and make predictions with high levels of accuracy has disrupted many industries helping efficiency and introducing new possibilities for creative ideas <sup>[65]</sup>.

#### **4.1. Current limitations, challenges, and future research trajectories**

Notwithstanding that significant progress has been made towards deploying ML in OGE and blending optimization worldwide, several limitations and challenges need to be overcome before its full potential can be realized within the mining realm. One big problem is the data available and the quality of this data. Algorithms in ML always require training on large and representative sets of data to learn accurate models, which is particularly problematic in mining given the high degree of variance in ore bodies and in mining processes and the high cost of acquiring and labelling such data. Good data quality is key, as biased or incomplete data can interfere with powerful prediction and decision-making.

Second is the interpretation and explainability of ML models. A variety of ML methods, like deep learning models, are black boxes, making predictions without explanations of underlying relationships between input features and predictions. This lack of interpretability can inhibit the use of ML in mining, since decision makers may be hesitant to trust models they cannot interpret.

Future research directions include

- (i) Designing better ML algorithms, which are more robust and interpretable,
- (ii) Removing noise and outlier data as well as
- (iii) Having more complex, high-quality data (availability).

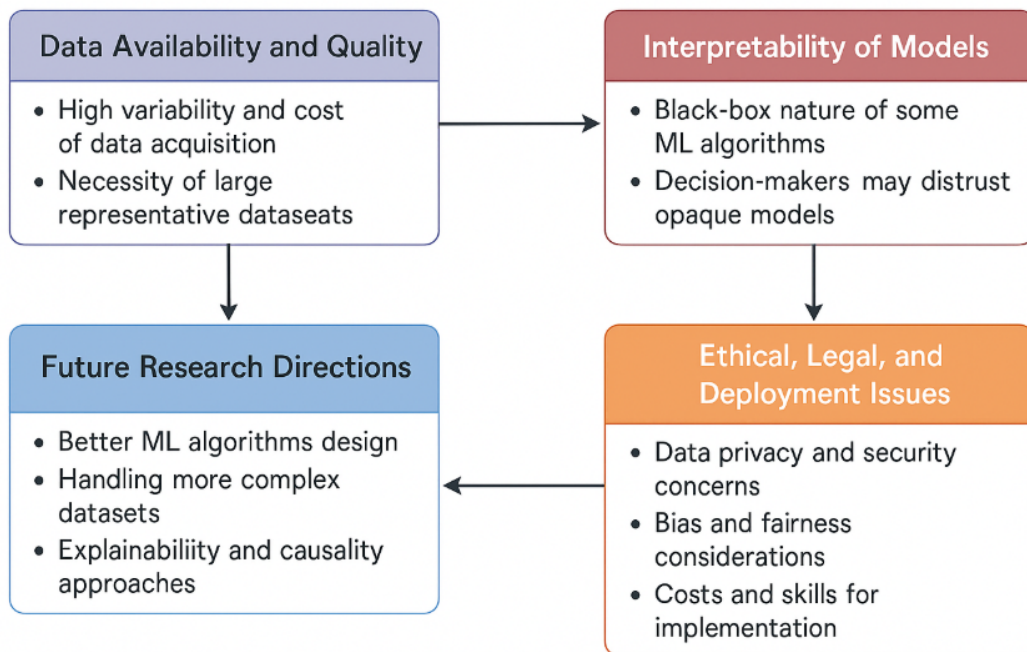
Approaches such as explainable AI and causal inference could be applied in order to enhance the interpretability of ML modeling by aiding to identify the possible controlling factors on ore grade estimation and blending optimization.

Moreover, more studies are required to address the summarization of missing information (or uncertain information) and to further fuse knowledge from several information sources into more complete training datasets. Also research needs to be done in the relative economic value of the adoption of ML techniques combined with the early hype being tempered <sup>[66]</sup>. In addition, we need to stress the significance of legal and regulatory approaches to address challenges related to bias, transparency, and data protection characterized by ML for the better utilization of ML in governance <sup>[67]</sup>. The analysis of the promising future of ML techniques has sharply increased in recent years, largely fueled by the announcement of national policies about it, which has driven the spotlight to think of it as a fertile ground for applications in general <sup>[64]</sup>. However, obstacles of this approach also need to be faced including capital cost of ML implementation, difficulty of finding and teaching AI/ML experts and no simple interpreting issues when dealing with predictive results <sup>[68]</sup>. Ethics is also critical, especially when dealing with privacy issues that stem from the huge data demands of the AI and ML technologies <sup>[69]</sup>.

Medical area serves as an example of how powerful AI could shape the future of healthcare as well domain adaptation challenge. Challenges in these tasks arise from the differences between patient populations, disease prevalence, and practice patterns in various geographic areas, which can undermine the robustness of ML-based models <sup>[70, 71]</sup>. The development of reliable AI/ML tools depend on strong evaluation and data augmentation tools <sup>[72]</sup>. Such new training rounds may need human ethical supervision as

new ethical issues and new treatment options are discovered. Figure 6 summarizes the major challenges and emerging research directions identified in this study, emphasizing issues of data quality, interpretability, and ethical implementation.

Emerging approaches such as federated learning and transfer learning are increasingly seen as promising solutions to challenges related to data scarcity, privacy, and model generalization in mining applications. Federated learning enables multiple mining sites to collaboratively train shared predictive models without exchanging raw data, thus maintaining confidentiality of sensitive geological and operational information. This decentralized framework helps improve model robustness by learning from distributed datasets representing diverse orebody and process conditions. Similarly, transfer learning allows pre-trained models developed for one mineral deposit or region to be fine-tuned for another with limited data, significantly reducing the computational and data requirements for new sites. These techniques not only enhance scalability and adaptability of ML systems but also promote cross-site collaboration and faster deployment of intelligent mining solutions.



**Figure 6.** Challenges and future research directions for machine learning applications in mining

**Deployment Issues on Machine Learning in Contemporary Mining.** "Operationalizing machine learning in mining industry might be seen as an exciting and transformative opportunity to improve operational efficiency and safety, but is also riddled with pressing concerns that need to be addressed for progressing responsible and effective use of machine learning." An important issue is the ethical considerations for the adoption of ML for decision-making, especially in workforce dynamics and environmental sustainability. As ML algorithms replace human labor in their tasks, the problem emerges of a rapid development of unemployed and alternatives for the retraining and reskilling of workforce. Moreover, the potential bias in ML models is a concern with respect to fairness and equity in resource allocation and environmental impact evaluations [74].

Data protection and security are also pressing issues due to large amounts of sensitive data being collected and processed during the mining operations. Maintaining the confidentiality and integrity of this information is critical to prevent unauthorized access and fraudulent use. A further important concern is the difficulty of ML algorithms capturing the complexity of actual mine environments. The quality of ML algorithms depends on the quality of their training data, and if the training data does not capture the full

breadth of the conditions experienced at mine sites, the models they generate might not produce accurate or trustworthy predictions. Table 5 highlights data, interpretability, and ethical challenges that guide future research priorities.

**Table 5.** Summary of current challenges in ML implementation for mining and corresponding future research directions

| Sr. No. | Challenge/Issue                         | Description                                                                                         | Future Research Direction                                                                              | Implication                                                                              |
|---------|-----------------------------------------|-----------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| 1       | Data Quality and Availability           | ML needs large, diverse, and well-labeled datasets, which are costly and hard to acquire in mining. | Develop techniques for better data curation, augmentation, and handling missing/uncertain information. | Better model accuracy, broader applicability, and improved confidence in predictions.    |
| 2       | Model Interpretability                  | Complex ML models (e.g., deep learning) act as black boxes, limiting trust in decisions.            | Use explainable AI and causal inference to make models more transparent.                               | Increases trust among decision-makers and encourages wider adoption in mining workflows. |
| 3       | Integration and Economic Viability      | High costs, legacy system compatibility, and difficulty in model deployment hinder implementation.  | Study economic value of ML adoption and develop modular, scalable ML systems.                          | Informs ROI-based decision making and scalable integration into mine operations.         |
| 4       | Ethical and Legal Concerns              | Issues of bias, privacy, fairness, and regulatory compliance must be addressed.                     | Establish regulatory frameworks and guidelines for ethical ML use in mining.                           | Promotes responsible AI practices and ensures data protection and transparency.          |
| 5       | Operationalization and Workforce Impact | Automation may displace workers; real mine conditions may not be well represented in training data. | Invest in reskilling programs and improve model generalization to real-world variability.              | Ensures social sustainability and more robust ML models for practical use.               |

## 5. Discussion

The application of machine learning (ML) for ore grade estimation and blending optimization is transforming the mining industry by replacing conventional rule-based and deterministic approaches with data-driven intelligence. This shift is particularly vital in modern mining, where declining ore grades, complex geological formations, and sustainability requirements demand greater predictive precision and operational efficiency <sup>[75-77]</sup>. ML models offer the capability to capture nonlinear, high-dimensional, and uncertain geological relationships that are often overlooked by traditional geostatistical methods such as Kriging.

Across the studies reviewed, algorithms including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), and hybrid geostatistical–ML models have demonstrated significant improvements in prediction accuracy and robustness. ANN and deep learning architectures effectively capture complex geological dependencies, while ensemble methods such as RF and GBM enhance stability by reducing overfitting and improving generalization. Hybrid frameworks that combine ML and geostatistics balance predictive power with spatial continuity, leading to more accurate ore reserve estimation and better mine planning outcomes <sup>[78-79]</sup>. Optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Reinforcement Learning (RL) further strengthen the blending process by allowing dynamic and adaptive decision-making in real time. These models efficiently manage multiple objectives, including minimizing cost, maintaining product quality, and maximizing throughput, while responding to variations in ore characteristics and processing constraints. The integration of ML-based predictive control into blending operations has shown measurable improvements in plant stability, recovery efficiency, and energy consumption reduction. The rise of sustainable and intelligent

technologies has reshaped ore grade estimation and blending optimization in mining. Growing ore complexity and the push for energy efficiency have led to the use of machine learning (ML), artificial intelligence (AI), and optimization frameworks for better accuracy and sustainability. Studies by Upadhe et al. <sup>[80]</sup> on water-saving design and by Kurhade and Murali [81, 82] on CFD-based thermal control with PCMs demonstrate resource-efficient and predictive approaches similar to ML-based mining systems. Research on heat transfer, fuzzy modeling, and hybrid computational methods [83–87] shows how intelligent tools enhance efficiency and multivariable analysis. Dynamic simulation, biocarbon adsorption, and vortex combustor optimization [88–90] reflect digital twin, eco-friendly, and AI-driven principles. CFD studies on heat exchangers <sup>[91]</sup> and hybrid GA–NN systems [92, 93] highlight adaptive modeling and IoT-based control relevant to mining. Further works on microchannel optimization, biodiesel, solar systems, and structural analysis [94–98] parallel predictive maintenance and sustainable mining practices. Patil et al. <sup>[99]</sup> directly applied AI to minimize environmental impact and improve recovery efficiency. Later studies [100–105] on heat transfer enhancement, material optimization, and real-time monitoring continue to align computational intelligence with data-driven mining operations.

Digital transformation in mining is also supported by the integration of ML with Internet of Things (IoT) sensors, real-time telemetry systems, and cloud-based computing platforms. These integrated digital frameworks enable continuous monitoring and adjustment of ore grades and blending ratios, ensuring uniform feed quality and process adaptability. The emerging use of digital twins allows simulation of mine-to-mill operations, enabling virtual experimentation and optimization of mining and processing activities without interrupting production. Despite these advancements, several challenges remain. The primary limitation lies in data quality and availability. Many mining datasets are sparse, noisy, or incomplete, affecting the accuracy and reliability of predictive models. Additionally, the interpretability of complex ML models, especially deep learning systems, remains a concern among practitioners who rely on transparent decision-making. Integration with existing legacy systems and software platforms also poses technical barriers to large-scale deployment. Ethical considerations, including data privacy, algorithmic bias, and workforce implications due to automation, must be addressed through responsible AI frameworks.

To advance industrial adoption, there is a need for standardized datasets, open benchmarking protocols, and transparent model validation methods. Collaborative efforts among mining engineers, data scientists, and software developers can accelerate the creation of explainable, reliable, and field-adaptable ML tools. Research should further explore explainable AI, federated learning, and transfer learning to enhance interpretability, data efficiency, and cross-site model adaptability. These emerging strategies can promote secure data collaboration and reduce dependence on large centralized datasets.

Overall, machine learning is reshaping the future of the mining industry by enabling predictive, adaptive, and sustainable decision-making. It bridges geological knowledge with computational intelligence, allowing operations to become more efficient, environmentally responsible, and resilient. As mining progresses toward Industry 5.0, ML-driven systems are expected to play a central role in achieving intelligent resource management and responsible technological transformation.

## 6. Conclusion

Machine learning has emerged as a transformative tool in modern mining, particularly for ore grade estimation and blending optimization. This review presented how approaches such as ANN, SVM, RF, and ensemble learning outperform conventional geostatistical methods in capturing nonlinear, multidimensional geological relationships. These techniques not only improve grade prediction accuracy but also support dynamic blending strategies that enhance resource utilization, process efficiency, and environmental sustainability. Coupling ML with metaheuristic algorithms such as GA and PSO enables adaptive blending plans that ensure uniform feed quality, reduced operational cost, and stable plant performance. The

integration of digital twins, IoT-enabled sensors, and cloud-based platforms further strengthens the real-time decision-making capabilities of ML systems in mining operations. Despite the clear benefits, the broader industrial adoption of ML faces key challenges, including limited high-quality datasets, model interpretability, integration with legacy systems, and ethical considerations such as data privacy and workforce transitions. Addressing these challenges will require developing standardized datasets, transparent model benchmarking, and modular architectures that can integrate seamlessly into existing mining workflows. Future research should focus on explainable AI, federated learning, and transfer learning to improve interpretability, data efficiency, and model adaptability across different mine sites. From an industrial perspective, successful deployment will depend on interdisciplinary collaboration between data scientists, mining engineers, and operational managers to translate predictive models into actionable, reliable, and interpretable tools. As the mining sector advances toward digital transformation, machine learning is poised to play a central role in achieving efficient, intelligent, and sustainable mining systems that align with the goals of Industry 5.0 and responsible resource management.

## Author Contributions

The research work was conceptualized by Dipa D. Dharmadhikari and Anant S. Kurhade, who also guided the overall structure and scope of the study. Avani Ray, Babaso A. Shinde, and Sandeep V. Raut contributed to the development of the methodology and framework design, ensuring a coherent integration of machine learning techniques with ore grade estimation and blending optimization processes. Comprehensive literature collection and analysis were carried out by Rupali D. Taware, Smita Desai, and Dipa D. Dharmadhikari, while Sandeep V. Raut and Babaso A. Shinde played key roles in data interpretation and technical validation. The initial manuscript draft was prepared by Dipa D. Dharmadhikari and Avani Ray, with critical revisions and academic editing performed by Shital Yashwant Waware, Anant S. Kurhade and Smita Desai. Figures, tables, and formatting were organized by Rupali D. Taware and Sandeep V. Raut. Anant S. Kurhade supervised the research process and served as the corresponding author. All authors reviewed and approved the final version of the manuscript.

## Acknowledgments

The authors would like to express their sincere gratitude to Dr. D. Y. Patil Institute of Technology and Dnyaan Prasad Global University (DPGU), School of Technology and Research - Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri, Pune, 411018, Maharashtra, India, for providing the necessary support and research infrastructure.

## Conflict of interest

The authors declare no conflict of interest

## References

1. Nurseitov D, Bostanbekov K, Abdimanap G, Abdallah A, Alimova A, Kurmangaliyev D. Enhancing Core Image Classification Using Generative Adversarial Networks (GANs). arXiv, 2022 Jan 1. <https://arxiv.org/abs/2204.14224>
2. Fu Y, Aldrich C. Deep Learning in Mining and Mineral Processing Operations: A Review. IFAC-PapersOnLine, 2020;53(2):11920. <https://doi.org/10.1016/j.ifacol.2020.12.712>
3. Pasupuleti V, Thuraka B, Kodete CS, Malisetty S. Enhancing Supply Chain Agility and Sustainability through Machine Learning: Optimization Techniques for Logistics and Inventory Management. Logistics, 2024;8(3):73. <https://doi.org/10.3390/logistics8030073>
4. Wu H, Walmsley A, Pan L, Dong W, Bittar M, Gear S. Case Study: Using Machine Learning and Ultra-Deep-Reading Resistivity for Better Reservoir Delineation. International Petroleum Technology Conference, 2020. <https://doi.org/10.2523/iptc-20152-abstract>



5. Myśliwiec P, Kubit A, Szawara P. Optimization of 2024-T3 Aluminum Alloy Friction Stir Welding Using Random Forest, XGBoost, and MLP Machine Learning Techniques. *Materials*, 2024;17(7):1452. <https://doi.org/10.3390/ma17071452>
6. Abubakar A. Machine Learning for Geoscience Applications. 2019;1. <https://doi.org/10.3997/2214-4609.201901987>
7. Alfarisi O, Raza A, Zhang H, Ozzane D, Sassi M, Zhang T. Machine Learning Guided 3D Image Recognition for Carbonate Pore and Mineral Volumes Determination. *arXiv*, 2021 Jan 1. <https://arxiv.org/abs/2111.04612>
8. Gouda MF, Latiff AHA, Alashloo SYM. Estimation of Litho-Fluid Facies Distribution from Zero-Offset Acoustic and Shear Impedances. *Applied Sciences*, 2022;12(15):7754. <https://doi.org/10.3390/app12157754>
9. Vukadin D, Čogelja Z, Vidaček R, Brkić V. Lithology and Porosity Distribution of High-Porosity Sandstone Reservoir in North Adriatic Using Machine Learning Synthetic Well Catalogue. *Applied Sciences*, 2023;13(13):7671. <https://doi.org/10.3390/app13137671>
10. Stocker M, Pachepsky Y, Hill RL. Prediction of E. coli Concentrations in Agricultural Pond Waters: Application and Comparison of Machine Learning Algorithms. *Frontiers in Artificial Intelligence*, 2022;4. <https://doi.org/10.3389/frai.2021.768650>
11. Xu Y, Sellers E, Fathi-Salmi E. Rock recognition and identification for selective mechanical mining: a self-adaptive artificial neural network approach. *Bulletin of Engineering Geology and the Environment*, 2023;82(7). <https://doi.org/10.1007/s10064-023-03311-3>
12. He Y, Zhu K, Gao S, Liu T, Li Y. Theory and method of genetic-neural optimizing cut-off grade and grade of crude ore. *Expert Systems with Applications*, 2008;36(4):7617. <https://doi.org/10.1016/j.eswa.2008.09.018>
13. Chen X, Zhang Y, Chen W. Advanced Predictive Modeling of Concrete Compressive Strength and Slump Characteristics: A Comparative Evaluation of BPNN, SVM, and RF Models Optimized via PSO. *Materials*, 2024;17(19):4791. <https://doi.org/10.3390/ma17194791>
14. Boldrini L, Bibault J, Masciocchi C, Shen Y, Bittner MI. Deep Learning: A Review for the Radiation Oncologist. *Frontiers in Oncology*, 2019;9. <https://doi.org/10.3389/fonc.2019.00977>
15. Zhao L, Goh SH, Chan Y, Yeoh BL, Hu H, Thor MH, Tan A, Lam J. Optimization of an Artificial Neural Network System for the Prediction of Failure Analysis Success. *Microelectronics Reliability*, 2018;92:136. <https://doi.org/10.1016/j.microrel.2018.11.014>
16. Erofeev A, Orlov D, Ryzhov A, Koroteev D. Prediction of Porosity and Permeability Alteration based on Machine Learning Algorithms. *arXiv*, 2019. <https://arxiv.org/abs/1902.06525>
17. Li X, Li S. Large-Scale Landslide Displacement Rate Prediction Based on Multi-Factor Support Vector Regression Machine. *Applied Sciences*, 2021;11(4):1381. <https://doi.org/10.3390/app11041381>
18. Wang Z. Artificial Intelligence and Machine Learning in Credit Risk Assessment: Enhancing Accuracy and Ensuring Fairness. *Open Journal of Social Sciences*, 2024;12(11):19. <https://doi.org/10.4236/jss.2024.1211002>
19. Bui DT, Shahabi H, Omidvar E, Shirzadi A, Geertsema M, Clague JJ, Khosravi K, Pradhan B, Pham BT, Chapi K, Barati Z, Ahmad BB, Rahmani H, Gróf G, Lee S. Shallow Landslide Prediction Using a Novel Hybrid Functional Machine Learning Algorithm. *Remote Sensing*, 2019;11(8):931. <https://doi.org/10.3390/rs11080931>
20. Gu Y, Zhang D, Bao Z. A new data-driven predictor, PSO-XGBoost, used for permeability of tight sandstone reservoirs: A case study of member of chang 4+5, western Jiyuan Oilfield, Ordos Basin. *Journal of Petroleum Science and Engineering*, 2021;199:108350. <https://doi.org/10.1016/j.petrol.2021.108350>
21. Bentéjac C, Csörgő A, Martínez-Muñoz G. A comparative analysis of gradient boosting algorithms. *Artificial Intelligence Review*, 2020;54(3):1937. <https://doi.org/10.1007/s10462-020-09896-5>
22. Natekin A, Knoll A. Gradient boosting machines, a tutorial. *Frontiers in Neurobotics*, 2013;7. <https://doi.org/10.3389/fnbot.2013.00021>
23. Sun TH, Wang C, Wu YL, Hsu KC, Lee T. Machine learning approaches for biomarker discovery to predict large-artery atherosclerosis. *Scientific Reports*, 2023;13(1). <https://doi.org/10.1038/s41598-023-42338-0>
24. Pham BT, Bui DT, Prakash I, Dholakia MB. Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. *CATENA*, 2016;149:52. <https://doi.org/10.1016/j.catena.2016.09.007>
25. Tercha W, Tadjer SA, Chekired F, Canale L. Machine Learning-Based Forecasting of Temperature and Solar Irradiance for Photovoltaic Systems. *Energies*, 2024;17(5):1124. <https://doi.org/10.3390/en17051124>
26. Dinesh Keloth Kaithari, Anant Kaulage, Ayyappadas MT, Puja Gholap, Aarti Puri, Mahesh Ashok Bhandari, ... Anant Sidhappa Kurhade. A Review of Smart AI Systems for Real-Time Monitoring and Optimization of Ocean-Based Carbon Capture, Utilization, and Storage Networks. *Applied Chemical Engineering*, 2025;8(3):ACE-5747. <https://doi.org/10.59429/ace.v8i3.5747>
27. Chakraborty D, Elhegazy H, Elzarka H, Gutierrez L. A novel construction cost prediction model using hybrid natural and light gradient boosting. *Advanced Engineering Informatics*, 2020;46:101201. <https://doi.org/10.1016/j.aei.2020.101201>
28. Al-Taai SR, Azize NM, Thoeny ZA, Imran H, Bernardo LFA, Al-Khafaji Z. XGBoost Prediction Model Optimized with Bayesian for the Compressive Strength of Eco-Friendly Concrete. *Applied Sciences*, 2023;13(15):8889. <https://doi.org/10.3390/app13158889>



29. Zheng Y, Deng H, Wang R, Wu J. A Multimodal Learning Framework for Comprehensive 3D Mineral Prospectivity Modeling. arXiv, 2023. <https://arxiv.org/abs/2309.02911>
30. Jiang S, Xiao R, Wang L, Luo X, Huang C, Wang J, Chin K, Nie X. Combining Deep Neural Networks and Classical Time Series Regression Models for Forecasting Patient Flows. IEEE Access, 2019;7:118965. <https://doi.org/10.1109/access.2019.2936550>
31. Hanifinia A, Nazarnejad H, Najafi S, Kornejady A, Pourghasemi HR. Landslide susceptibility assessment and mapping using statistical and data mining models in Iran. Research Square, 2021. <https://doi.org/10.21203/rs.3.rs-239985/v1>
32. Yu H, Pei W, Zhang J, Chen G. Landslide Susceptibility Mapping and Driving Mechanisms Based on Multiple Machine Learning Models. Remote Sensing, 2023;15(7):1886. <https://doi.org/10.3390/rs15071886>
33. Manjate EPA, Saadat M, Toriya H, Inagaki F, Kawamura Y. Application of Entropy Method for Estimating Factor Weights in Mining-Method Selection. Journal of Sustainable Mining, 2022;20(4):296. <https://doi.org/10.46873/2300-3960.1328>
34. Zhang J, Huang Y, Wang Y, Ma G. Multi-objective Optimization of Concrete Mixture Proportions Using Machine Learning and Metaheuristic Algorithms. Construction and Building Materials, 2020;253:119208. <https://doi.org/10.1016/j.conbuildmat.2020.119208>
35. Binetti MS, Uricchio VF, Massarelli C. Isolation Forest for Environmental Monitoring. Environments, 2025;12(4):116. <https://doi.org/10.3390/environments12040116>
36. Govil N, Sharma A. Estimation of Cost and Development Effort in Scrum-Based Software Projects. Advances in Engineering Software, 2022;172:103209. <https://doi.org/10.1016/j.advengsoft.2022.103209>
37. Auret L, Aldrich C. Interpretation of Nonlinear Relationships Between Process Variables Using Random Forests. Minerals Engineering, 2012;35:27. <https://doi.org/10.1016/j.mineng.2012.05.008>
38. Štutienė K, Schwendner P, Šipoš C, Lorenzo L, Mirchev M, Lameski P, Kabašinskas A, Tidjani C, Öztürk B, Černevičienė J. Enhancing Portfolio Management Using Artificial Intelligence. Frontiers in Artificial Intelligence, 2024;7. <https://doi.org/10.3389/frai.2024.1371502>
39. Polyzou A, Karypis G. Grade Prediction with Course and Student Specific Models. Lecture Notes in Computer Science, 2016; p. 89. [https://doi.org/10.1007/978-3-319-31753-3\\_8](https://doi.org/10.1007/978-3-319-31753-3_8)
40. Tanaka Y, Miki H, Suyantara GPW, Aoki Y, Hirajima T. Mineralogical Prediction on the Flotation Behavior of Copper and Molybdenum Minerals from Blended Cu–Mo Ores in Seawater. Minerals, 2021;11(8):869. <https://doi.org/10.3390/min11080869>
41. Helleckes LM, Hemmerich J, Wiechert W, Lieres E von, Grünberger A. Machine Learning in Bioprocess Development: From Promise to Practice. Trends in Biotechnology, 2022;41(6):817. <https://doi.org/10.1016/j.tibtech.2022.10.010>
42. Ball P. Using Artificial Intelligence to Accelerate Materials Development. MRS Bulletin, 2019;44(5):335. <https://doi.org/10.1557/mrs.2019.113>
43. Watson NJ, Bowler AL, Rady A, Fisher OJ, Simeone A, Escrig J, Woolley E, Adedeji AA. Intelligent Sensors for Sustainable Food and Drink Manufacturing. Frontiers in Sustainable Food Systems, 2021;5. <https://doi.org/10.3389/fsufs.2021.642786>
44. Injadat M, Moubayed A, Nassif AB, Shami A. Machine Learning Towards Intelligent Systems: Applications, Challenges, and Opportunities. Artificial Intelligence Review, 2021;54(5):3299. <https://doi.org/10.1007/s10462-020-09948-w>
45. Jassim MA, Abdulwahid SN. Data Mining Preparation: Process, Techniques and Major Issues in Data Analysis. IOP Conference Series: Materials Science and Engineering, 2021;12053. <https://doi.org/10.1088/1757-899x/1090/1/012053>
46. Cheng J. Data-Mining Research in Education. arXiv, 2017. <https://arxiv.org/abs/1703.10117>
47. Mudallal R, Mrayyan MT, Kharabsheh M. Use of Machine Learning to Predict Creativity Among Nurses: A Multidisciplinary Approach. BMC Nursing, 2025;24(1). <https://doi.org/10.1186/s12912-025-03151-4>
48. Duan S, Cao H, Liu H, Miao L, Wang J, Zhou X, Wang W, Hu P, Qu L, Wu Y. Development of a Machine Learning-Based Multimode Diagnosis System for Lung Cancer. Aging, 2020;12(10):9840. <https://doi.org/10.18632/aging.103249>
49. Urso A, Fiannaca A, Rosa ML, Ravi V, Rizzo R. Data Mining: Classification and Prediction. Elsevier eBooks, 2017; p. 384. <https://doi.org/10.1016/b978-0-12-809633-8.20461-5>
50. Sharma N, Saharia M, Ramana GV. High Resolution Landslide Susceptibility Mapping Using Ensemble Machine Learning and Geospatial Big Data. CATENA, 2023;235:107653. <https://doi.org/10.1016/j.catena.2023.107653>
51. Barker A, Style H, Luksch K, Sunami S, Garrick D, Hill F, Foot CJ, Bentine E. Applying Machine Learning Optimization Methods to the Production of a Quantum Gas. Machine Learning Science and Technology, 2020;1(1):15007. <https://doi.org/10.1088/2632-2153/ab6432>
52. Singh TP, Jhariya DC, Sahu M, Dewangan P, Dhekne PY. Classifying Minerals using Deep Learning Algorithms. IOP Conference Series: Earth and Environmental Science, 2022;1032(1):12046. <https://doi.org/10.1088/1755-1315/1032/1/012046>
53. Fieggen J, Smith E, Arora L, Segal B. The Role of Machine Learning in HIV Risk Prediction. Frontiers in Reproductive Health, 2022;4. <https://doi.org/10.3389/frph.2022.1062387>

54. Padala VS, Gandhi K, Dasari P. Machine Learning: The New Language for Applications. *IAES International Journal of Artificial Intelligence*, 2019;8(4):411. <https://doi.org/10.11591/ijai.v8.i4.pp411-421>
55. Ren G, Yu K, Xie Z, Wang P, Zhang W, Huang Y, Wang Y, Wu X. Current Applications of Machine Learning in Spine: From Clinical View. *Global Spine Journal*, 2021;12(8):1827. <https://doi.org/10.1177/21925682211035363>
56. Ouhadi A, Yahouni Z, Mascolo MD. Integrating Machine Learning and Operations Research Methods for Scheduling Problems: A Bibliometric Analysis and Literature Review. *IFAC-PapersOnLine*, 2024;58(19):946. <https://doi.org/10.1016/j.ifacol.2024.09.155>
57. Tirkolaee EB, Sadeghi S, Mooseloo FM, Vandchali HR, Amini S. Application of Machine Learning in Supply Chain Management: A Comprehensive Overview. *Mathematical Problems in Engineering*, 2021;2021:1. <https://doi.org/10.1155/2021/1476043>
58. Kharfan M, Chan VWK, Efendigil T. A Data-Driven Forecasting Approach for Newly Launched Seasonal Products. *Annals of Operations Research*, 2020;303:159. <https://doi.org/10.1007/s10479-020-03666-w>
59. Parimal S. Bhambare, Anant Kaulage, Milind Manikrao Darade, Govindarajan Murali, Swati Mukesh Dixit, P. S. N. Masthan Vali, ... Chaitalee Naresh Mali. Artificial Intelligence for Sustainable Environmental Management in the Mining Sector: A Review. *Applied Chemical Engineering*, 2025;8(3):ACE-5756. <https://doi.org/10.59429/ace.v8i3.5756>
60. Sharp M, Ak R, Hedberg T. A Survey of the Advancing Use and Development of Machine Learning in Smart Manufacturing. *Journal of Manufacturing Systems*, 2018;48:170. <https://doi.org/10.1016/j.jmsy.2018.02.004>
61. Kumar S, Gopi T, Harikeerthana N, Gupta MK, Gaur V, Królczyk G, Wu C. Machine Learning Techniques in Additive Manufacturing. *Journal of Intelligent Manufacturing*, 2022;34(1):21. <https://doi.org/10.1007/s10845-022-02029-5>
62. Sundaram S, Zeid A. Artificial Intelligence-Based Smart Quality Inspection for Manufacturing. *Micromachines*, 2023;14(3):570. <https://doi.org/10.3390/mi14030570>
63. Zhao YF, Xie J, Sun L. On the Data Quality and Imbalance in Machine Learning-Based Design and Manufacturing. *Engineering*, 2024. <https://doi.org/10.1016/j.eng.2024.04.024>
64. Kim DH, Kim DJ, Choi S. A Variational-Mode-Decomposition-Cascaded Long Short-Term Memory with Attention Model for VIX Prediction. *Applied Sciences*, 2025;15(10):5630. <https://doi.org/10.3390/app15105630>
65. Nguyen VB, Teo A, Ba T, Ahluwalia K, Kang CW. A Distributed Model Predictive Control with Machine Learning for Automated Shot Peening Machine. *The International Journal of Advanced Manufacturing Technology*, 2022;122:2419. <https://doi.org/10.1007/s00170-022-10018-4>
66. Pugliese R, Regondi S, Marini R. Machine Learning-Based Approach: Global Trends, Research Directions, and Regulatory Standpoints. *Data Science and Management*, 2021;4:19. <https://doi.org/10.1016/j.dsm.2021.12.002>
67. Sidey-Gibbons JAM, Sidey-Gibbons C. Machine Learning in Medicine: A Practical Introduction. *BMC Medical Research Methodology*, 2019;19(1). <https://doi.org/10.1186/s12874-019-0681-4>
68. Feizabadi J. Machine Learning Demand Forecasting and Supply Chain Performance. *International Journal of Logistics Research and Applications*, 2020;25(2):119. <https://doi.org/10.1080/13675567.2020.1803246>
69. Chy MKH, Buadi ON. Role of Machine Learning in Policy Making and Evaluation. *International Journal of Innovative Science and Research Technology*, 2024;456. <https://doi.org/10.38124/ijisrt/ijisrt24oct687>
70. Plathottam SJ, Rzonca A, Lakshnor R, Iloeje CO. A Review of Artificial Intelligence Applications in Manufacturing Operations. *Journal of Advanced Manufacturing and Processing*, 2023;5(3). <https://doi.org/10.1002/amp2.10159>
71. Hajj ME, Hammoud J. Unveiling the Influence of Artificial Intelligence and Machine Learning on Financial Markets. *Journal of Risk and Financial Management*, 2023;16(10):434. <https://doi.org/10.3390/jrfm16100434>
72. Chen IY, Pierson E, Rose S, Joshi S, Ferryman K, Ghassemi M. Ethical Machine Learning in Health Care. *arXiv*, 2020. <https://arxiv.org/abs/2009.10576>
73. Elvas LB, Almeida AI, Ferreira JC. The Role of AI in Cardiovascular Event Monitoring and Early Detection. *JMIR Medical Informatics*, 2025;13. <https://doi.org/10.2196/64349>
74. Roshanaei M, Khan MR, Sylvester NN. Enhancing Cybersecurity Through AI and ML. *Journal of Information Security*, 2024;15(3):320. <https://doi.org/10.4236/jis.2024.153019>
75. Hindocha S, Badea C. Moral Exemplars for the Virtuous Machine. *AI and Ethics*, 2021;2(1):167. <https://doi.org/10.1007/s43681-021-00089-6>
76. Luccioni AS, Bengio Y. On the Morality of Artificial Intelligence. *arXiv*, 2019. <https://arxiv.org/abs/1912.11945>
77. Shandhi MMH, Dunn J. AI in Medicine: Where Are We Now and Where Are We Going? *Cell Reports Medicine*, 2022;3(12):100861. <https://doi.org/10.1016/j.xcrm.2022.100861>
78. Kolyshkina I, Simoff S. Interpretability of Machine Learning Solutions in Public Healthcare. *Frontiers in Big Data*, 2021;4. <https://doi.org/10.3389/fdata.2021.660206>
79. Adlung L, Cohen Y, Mor U, Elinav E. Machine Learning in Clinical Decision Making. *Med*, 2021;2(6):642. <https://doi.org/10.1016/j.medj.2021.04.006>
80. Upadhe SN, Mhamane SC, Kurhade AS, Bapat PV, Dhavale DB, Kore LJ. Water saving and hygienic faucet for public places in developing countries. In *Techno-Societal 2018: Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications-Volume 1 2019 Nov 7* (pp. 617-624). Cham: Springer International Publishing. [https://doi.org/10.1007/978-3-030-16848-3\\_56](https://doi.org/10.1007/978-3-030-16848-3_56)

81. Kurhade AS, Murali G. Thermal control of IC chips using phase change material: A CFD investigation. *International Journal of Modern Physics C*. 2022 Dec 28;33(12):2250159. <https://doi.org/10.1142/S0129183122501595>
82. Kurhade AS, Murali G, Rao TV. CFD approach for thermal management to enhance the reliability of IC chips. *Int J Eng Trends Technol*. 2022;71(3):65-72. <https://doi.org/10.14445/22315381/IJETT-V71I3P208>
83. Waware SY, Kore SS, Kurhade AS, Patil SP. Innovative heat transfer enhancement in tubular heat exchanger: An experimental investigation with minijet impingement. *J Adv Res Fluid Mech Therm Sci*. 2024;116(2):51-8. <https://doi.org/10.37934/arfmts.116.2.5158>
84. Kurhade AS, Siraskar GD, Darade MM, Dhumal JR, Kardile CS, Biradar R, Patil SP, Waware SY. Predicting heat transfer enhancement with twisted tape inserts using fuzzy logic techniques in heat exchangers. *J Mines Met Fuels*. 2024; 72 (7): 743-50. <https://doi.org/10.18311/jmmf/2024/45348>
85. Kurhade AS, Siraskar GD, Bhambare PS, Dixit SM, Waware SY. Numerical investigation on the influence of substrate board thermal conductivity on electronic component temperature regulation. *J Adv Res Numer Heat Trans*. 2024;23(1):28-37. <https://doi.org/10.37934/arnht.23.1.2837>
86. Kurhade AS, Bhambare PS, Siraskar GD, Dixit SM, Purandare PS, Waware SY. Computational study on thermal management of IC chips with phase change materials. *J Adv Res Numer Heat Trans*. 2024;26(1):34-43. <https://doi.org/10.37934/arnht.26.1.3443>
87. Kurhade AS, Siraskar GD, Bhambare PS, Kaithari DK, Dixit SM, Waware SY. Enhancing smartphone circuit cooling: A computational study of PCM integration. *J Adv Res Numer Heat Trans*. 2024 Nov 30;27(1):132-45. <https://doi.org/10.37934/arnht.27.1.132145>
88. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. *Advances in Science and Technology. Research Journal*. 2025;19(7). <https://doi.org/10.12913/22998624/203873>
89. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green Adsorbents for Heavy Metal Removal: A Study on Zinc Ion Uptake by *Tinospora cordifolia* Biocarbon. *Journal of Mines, Metals & Fuels*. 2025 Jan 1;73(1). <https://doi.org/10.18311/jmmf/2025/47121>
90. Siraskar GD, Kurhade AS, Murali G, Prakash MA, Bharathiraja N, Dharmadhikari DD, Waware SY. Turbulence model comparison and optimal geometry identification in trapped vortex combustors: A RANS-based study. *International Journal of Modern Physics C*. 2025 Sep 24;2650020. <https://doi.org/10.1142/S0129183126500208>
91. Kurhade AS, Siraskar GD, Bhambare PS, Murali G, Deshpande SV, Warke PS, Waware SY. Simulation and analysis of heat transfer in counter-flow helical doublepipe heat exchangers using CFD. *Int J Mod Phys C*. 2025 Mar 15. <https://doi.org/10.1142/S0129183125500433>
92. Dinesh Keloth kaithari, Ayyappadas MT, Shalini Goel, Asma Shahin, Shwetal Kishor Patil, Swapnil S. Chaudhari, ... Anant Sidhappa Kurhade. (2025). A review on GA-NN based control strategies for floating solar-ocean hybrid energy platforms. *Applied Chemical Engineering*, 8(3), ACE-5745. <https://doi.org/10.59429/ace.v8i3.5745>
93. Pramod Dhamdhere, Swati Mukesh Dixit, Manjusha Tatiya, Babaso A. Shinde, Jyoti Deone, Anant Kaulage, Shital Yashwant Waware. (2025). AI-based monitoring and management in smart aquaculture for ocean fish farming systems. *Applied Chemical Engineering*, 8(3), ACE-5746. <https://doi.org/10.59429/ace.v8i3.5746>
94. Chippalkatti S, Chekuri RB, Ohol SS, Shinde NM, Barmavatu P, Shelkande VD, Murali G, Kurhade AS. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. *J Mines Met Fuels*. 2025; 73 (3). <https://doi.org/10.18311/jmmf/2025/47773>
95. Kurhade AS, Bhavani P, Patil SA, Kolhalkar NR, Chalapathi KS, Patil PA, Waware SY. Mitigating environmental impact: A study on the performance and emissions of a diesel engine fueled with biodiesel blend. *Journal of Mines, Metals & Fuels*. 2025 Apr 1;73(4):981-9. <https://doi.org/10.18311/jmmf/2025/47669>
96. Kurhade AS, Amruth E, Joshi PS, Kondhalkar GE, Jadhav PA, Murali G, Mahajan RG, Waware SY. Enhancing Flat-Plate Solar Collector Efficiency: A Numerical Study. *Journal of Mines, Metals & Fuels*. 2025 Apr 1;73(4). <https://doi.org/10.18311/jmmf/2025/48249>
97. Chougule SM, Murali G, Kurhade AS. Failure Investigation of the Driving Shaft in an Industrial Paddle Mixer. *Journal of Mines, Metals & Fuels*. 2025 May 1;73(5). <https://doi.org/10.18311/jmmf/2025/48627>
98. Chougule SM, Murali G, Kurhade AS. Finite Element Analysis and Design Optimization of a Paddle Mixer Shaft. *Journal of Mines, Metals & Fuels*. 2025 May 1;73(5). <https://doi.org/10.18311/jmmf/2025/48664>
99. Patil Y, Tatiya M, Dharmadhikari DD, Shahakar M, Patil SK, Mahajan RG, Kurhade AS. The Role of AI in Reducing Environmental Impact in the Mining Sector. *Journal of Mines, Metals & Fuels*. 2025 May 1;73(5).
100. Waware SY, Ahire PP, Napate K, Biradar R, Patil SP, Kore SS, Kurhade AS. Advancements in Heat Transfer Enhancement using Perforated Twisted Tapes: A Comprehensive Review. *Journal of Mines, Metals & Fuels*. 2025 May 1;73(5). <https://doi.org/10.18311/jmmf/2025/48438>
101. Kurhade AS, Sugumaran S, Kolhalkar NR, Karad MM, Mahajan RG, Shinde NM, Dalvi SA, Waware SY. Thermal management of mobile devices via PCM. *Journal of Mines, Metals & Fuels*. 2025 May 1;73(5):1313-20. <https://doi.org/10.18311/jmmf/2025/48437>
102. Napte K, Kondhalkar GE, Patil SV, Kharat PV, Banarase SM, Kurhade AS, Waware SY. Recent Advances in Sustainable Concrete and Steel Alternatives for Marine Infrastructure. *Sustainable Marine Structures*. 2025 Jun 4:107-31. <https://doi.org/10.36956/sms.v7i2.2072>

103. Chougule SM, Murali G, Kurhade AS. Design and Analysis of Industrial Material Handling Systems using FEA and Dynamic Simulation Techniques: FEA AND SIMULATION-BASED DESIGN OF MATERIAL HANDLING SYSTEMS. Journal of Scientific & Industrial Research (JSIR). 2025 Jun 18;84(6):645-53.  
<https://doi.org/10.56042/jsir.v84i6.17512>
104. Kondhalkar VK, Kurhade AS. Optimized Placement of IC Chips for Enhanced Thermal Cooling: A Hybrid ANN-GA Approach in Numerical Heat Transfer.
105. Deshpande SV, Pawar RS, Keche AJ, Kurhade A. Real-Time Surface Finish Measurement of Stepped Holding Shaft by Automatic System. Journal of Advanced Manufacturing Systems. 2025 Feb 25:1-26.  
<https://doi.org/10.1142/S0219686725500386>