

Machine Learning in Surface Mining—A Systematic Review

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Abstract

Objective: The objective of this study was to map and critically synthesize empirical evidence on ML/AI applications across surface mining unit operations, and to characterize models, validation practices, and evidence gaps. **Eligibility criteria:** Our eligibility criteria comprised peer-reviewed studies (2020–2025) applying ML/AI to surface mining activities, training/validating models on empirical datasets, and reporting quantitative performance metrics. **Information sources:** Scopus, ScienceDirect, Dimensions, and Web of Science were our information sources, last searched December 2025 and supplemented by website and citation snowballing. **Risk of bias:** Risk of bias was assessed using an adapted domain-based approach based on PROBAST, used to interpret findings without excluding studies. **Synthesis method:** Our research employed a narrative synthesis (no meta-analysis due to heterogeneity in datasets, algorithms, contexts, and metrics), grouped by application domain. **Results:** From 5317 records, 57 studies were included, concentrated in blasting (43), followed by load and haul (6), post-dismantling management (4), extraction (2), and overall exploitation (2). Studies predominantly reported statistical metrics (e.g., R^2 , RMSE, and MAE), with limited operational performance indicators; validation was frequently site-specific. Dataset sizes were not reported consistently across studies. **Limitations:** This study's limitations were database coverage, restricted timeframe, and incomplete reporting (e.g., software/tooling). **Conclusions:** ML/AI shows strong potential, especially in blasting, but scalable deployment is constrained by site specificity, inconsistent reporting, and heterogeneous validation; standardized reporting and operational indicators are priorities. **Registration:** The systematic review protocol was registered in OSF with DOI 10.17605/OSF.IO/5UMKB. **Funding:** EU Erasmus+ STRIM project (1010832727).

Keywords: surface mining; open pit; quarry; machine learning; artificial intelligence; deep learning



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1. Introduction

The extractive industry plays a crucial role in supplying raw materials and is closely linked to geopolitical dynamics [1], influencing supply chains, industrial development, and resource security.

The extraction of raw materials is essential to modern society [2]. These raw materials are used in a wide range of industries, including automotive [3], steel [4], petrochemical [1], energy [5], construction [6], and agriculture [7]. Raw materials extraction is usually classified into surface and underground mining. There is a greater number of surface mining operations than underground mining operations worldwide [2]. For example, currently, underground mining contributes to 12 to 17% of metal ore production, while surface mining accounts for the remaining 83 to 88% [8].

Mining operations can be divided into key stages, such as mine planning and design, drilling and blasting, and haulage and loading [9], all regulated by environmental regulations, occupational safety requirements, and energy consumption, significant challenges for the extractive industry [10].

In underground mining, specific unit operations vary depending on the mining method employed. The most common and general ones are drilling, charging, blasting, loading, bolting, and cleaning [11].

In surface mining, the primary unit operations consist of drilling, blasting, loading, and hauling [2]. Surface mining is also associated with several environmental issues specific to this type of exploitation, including landscape changes, air pollution, water depletion, rock weathering caused by exposed rocks during excavations, soil vibration, and changes in air pressure [12]. These environmental and operational challenges are expected to intensify as global demand for raw materials continues to rise. This will directly influence the number of exploitations (surface or underground) that continue to increase. As demand grows, the availability of shallow deposits has decreased significantly, forcing the extractive industry to exploit ore bodies located at increased depths. This combination of rising extraction needs and increasingly challenging geological conditions makes the extractive sector highly complex. In dynamic workplaces with diverse hazards, there is an increasing need for tools that enhance prediction, monitoring, and decision-making.

In response to the increasing challenges, the sector is gradually relying on digital technologies and advanced technology methods [13].

Within the broad spectrum of digital and advanced technologies being adopted in the extractive industry, including sensor-based monitoring systems [13], automation, and digital twins [14], machine learning (ML) has emerged as an up-and-coming tool. This technological evolution is connected to Mining 4.0, defined as the integration of Cyber-Physical Systems (CPSs) and the Internet of Things (IoT) to create interconnected, autonomous mining operations. The central pillar of this paradigm is the digital twin, which goes beyond static 3D modeling to a dynamic virtual replica that updates in real time in order to mirror the physical status of the exploitation. In this context, ML algorithms act as the analytical engine, enabling these to transition from passive monitoring to predictive decision-making.

It is used to optimize different types of exploitation processes, such as drilling [15], haulage [16], and geotechnical monitoring, to develop predictive models for high precision and to assist in decision-making.

In recent years, there has been a substantial increase in studies focusing on ML prediction of rock fragmentation [17], blast-induced ground vibration [18], blasting air pressure [19], equipment allocation [20], and geotechnical monitoring [21]. To achieve various objectives, different algorithms are employed, including Support Vector Machines (SVMs), Decision Trees (DTs), Random Forests (RFs), Extra Trees, Gradient Boosting (GB), and hybrid approaches that integrate principal component analysis (PCA) or neural networks. These algorithms have demonstrated the ability to reduce uncertainties and improve operational performance [22].

Although ML applications in surface mining have evolved rapidly, important questions remain unanswered regarding the consistency of reported results, the robustness of the applied methodology, and the availability of empirical validation.

Existing reviews of ML in mining often aggregate surface and underground contexts [22], or focus on narrow tasks (e.g., blasting only) [23], limiting the transferability of conclusions across unit operations. A focused synthesis restricted to surface mining unit operations is needed to characterize validation practices, reporting completeness, and evidence gaps relevant to deployment. This characterization is fundamental to understanding

the transition from theoretical models to practical deployment, ensuring that ML tools provide reliable decision support in complex, real-time operational environments

This review aims to map and critically synthesize empirical evidence on ML/AI in surface mining unit operations and to characterize validation practices and evidence gaps.

The guiding research questions addressed by this review are as follows:

- (1) Which ML algorithms demonstrate the highest and most effective performance across unit operations in surface mining?
- (2) How do existing studies evaluate and validate ML models, and how do validation methods affect the reliability of reported results in specific task types?
- (3) What methodological limitations, biases, and evidence gaps create a challenge for the practical use of ML-based decision-making support systems in the mining industry unit operation?

In this review, “surface mining” refers to unit operations conducted from drilling/blasting through loading/hauling and associated on-site operational monitoring/decision support.

2. Methodology

To ensure methodological rigor, transparency, and reproducibility, this study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [24]. This systematic review is registered in OSF with DOI 10.17605/OSF.IO/5UMKB.

2.1. Search Strategy

This research was carried out in December 2025. Four databases were used in this study: Scopus, ScienceDirect, Dimensions, and Web of Science. Keywords related to the subject were identified and grouped into four keyword groups: technological and geospatial modeling terms; artificial intelligence and learning algorithms; mining operations and application context; and sustainability and environmental dimensions.

While the search strategy aimed for consistency across all platforms, queries were adaptively structured to accommodate the specified syntax, Boolean operator limits, and field availability for each database. For instance, ScienceDirect imposes a limit on the number of Boolean connectors, requiring a simplified string that preserves the core conceptual groups without compromising search sensitivity.

For the Scopus database, the search was conducted through the following query, inserted in Title/Abstract/Keywords:

Title/Abstract/Keywords (“LiDAR” OR “laser scanning” OR “point cloud” OR “simulation” OR “model” OR “planning”) AND (“machine learning” OR “artificial intelligence” OR “deep learning”) AND (“fleet optimization” OR “haul road” OR “equipment scheduling” OR “mining” OR “quarry” OR “open pit”) AND (“sustainability” OR “emissions” OR “environmental”).

For the ScienceDirect database, the search was conducted using the following query, entered in the Title, Abstract, or Author-Specified Keywords fields. Due to the platform’s Boolean operator limit, a simplified query was used, ensuring that at least one representative keyword from each group was used:

Title, abstract or author-specified keywords: (“LiDAR” OR “point cloud” OR “simulation”) AND (“machine learning” OR “artificial intelligence”) AND (“mining” OR “open pit”) AND (“sustainability” OR “environmental”).

For the Dimensions database, the search was conducted through the following query, inserted in Title and Abstract:

Title and Abstract (“LiDAR” OR “laser scanning” OR “point cloud” OR “simulation” OR “model” OR “planning”) AND (“machine learning” OR “artificial intelligence” OR “deep learning”) AND (“fleet optimization” OR “haul road” OR “equipment schedul-

ing" OR "mining" OR "quarry" OR "open pit") AND ("sustainability" OR "emissions" OR "environmental").

For the Web of Science database, the search was conducted through the following query, inserted in Topic:

Topic ("LiDAR" OR "laser scanning" OR "point cloud" OR "simulation" OR "model" OR "planning") AND ("machine learning" OR "artificial intelligence" OR "deep learning") AND ("fleet optimization" OR "haul road" OR "equipment scheduling" OR "mining" OR "quarry" OR "open pit") AND ("sustainability" OR "emissions" OR "environmental").

During the preliminary identification phase, automated computational tools were deployed to screen the dataset effectively, excluding ineligible records prior to the subsequent stages of analysis with the following screening stages: (1) date—only articles published between 2020 and 2025 were considered in the first phase; (2) the type of document was limited to research articles (no systematic reviews nor gray literature was considered); (3) only peer-review journals were considered; and (4) only studies written in English were considered.

All the identified reports were exported from the databases to Zotero (7.0.32) and then imported into Rayyan (<https://www.rayyan.ai/> (accessed on 10 December 2025)), facilitating the removal of duplicates and initial screening.

This process was carried out independently by two reviewers, who screened titles/abstracts and full texts; a third reviewer resolved disagreements.

2.2. Eligibility and Exclusion Criteria

To be eligible, each study had to meet strict requirements:

Only peer-reviewed scientific articles that applied ML or AI techniques to surface mining activities published between 2020 and 2025, written in English, were considered.

To be considered eligible, studies were required to develop, train, and validate AI or ML models using empirical datasets.

Studies had to focus directly on exploitation-related activities. Research addressing dust control, land-change dynamics, landscape impacts, or sustainability aspects was included only when these topics were analyzed, action was taken to change the exploitation activities process, and the research contributed evidence on how AI/ML improved operational decision-making or operational outcomes in surface mining.

To ensure comparability across studies, only articles reporting at least one quantitative evaluation metric were included. These metrics are essential for assessing model robustness and validity, as well as the practical impact on mining performance. Where metrics were not directly comparable, results were summarized descriptively, and cross-metric pooling was avoided.

Articles were not excluded from the systematic review if they did not have one of the following types of information: "Software", "Equipment", or "Company/Site".

Studies were excluded if they did not apply ML/AI methods, lacked quantitative performance reporting, focused on underground mining without separate data, relied solely on qualitative descriptions, or provided insufficient methodological detail.

Two reviewers independently screened titles/abstracts and subsequently assessed full texts against the eligibility criteria described above. Discrepancies were resolved by consensus; when unresolved, a third reviewer adjudicated. Screening decisions were recorded in a structured log.

2.3. Data Extraction and Synthesis

Data was extracted using a piloted form. One reviewer extracted data, and a second reviewer verified all extracted fields; disagreements were resolved through discussion.

A Microsoft Excel sheet was used to create detailed tables with the key information from all the articles. The information was divided into four categories:

- (1) General information—author, publication year, and country;
- (2) Site specifications—if it is a quarry or a mine, the type of commodity being exploited, type of unitary operation the study addresses, and company/site;
- (3) Model characteristics—input data, ML model, validation approach, equipment, software, and application scale;
- (4) Methodology and results—implementation protocol, findings, and limitations.

Primary outcomes were defined as R^2 (coefficient of determination) and RMSE (root mean square error), or their task-specific equivalents. Secondary outcomes included MAE (mean absolute error), MAPE (mean absolute percentage error), or similar statistical measures.

In the final stage (December 2025), snowballing techniques were applied, including citation tracking and searching, to identify additional records that could be considered eligible.

A comparative synthesis approach was applied to integrate all the extracted data. The studies were grouped according to their application domain, defined as blasting phase, load and haul, post-dismantling management, extraction, and overall exploitation, and were synthesized within each group. Quantitative performance indicators were compared across studies to identify performance patterns and methodological consistency. To ensure consistency, metric labels were standardized, and the best-reported performance under the primary validation setting was extracted. If any information was missing, it was recorded as “not reported” or “NaN”.

Due to the significant heterogeneity of datasets, algorithms, operational contexts, and reported metrics, no meta-analyses were conducted.

Heterogeneity was studied by data size, validation type (cross-validation vs. hold-out vs. external), and model/machine learning usage.

A narrative synthesis was employed to structure the interpretation of results. Study characteristics and performance metrics were tabulated, and distributions were summarized by domain. To systematize all the information using visual representations, the PRISMA flow, MapChart tools (<https://www.mapchart.net/world.html> (accessed 20 December 2025)), and Microsoft Excel (2602) were used.

The narrative approach allowed the findings to be organized by thematic, methodological trends; application contexts; and comparative performance across different studies, ensuring structured grouping and transparent reporting of the included results.

2.4. Bias Assessment

To ensure methodological integrity, the risk of bias (RoB) was assessed using an adapted version of the Prediction Model Risk of Bias Assessment Tool (PROBAST) [25]. The assessment was performed independently by two reviewers; a third reviewer resolved any disagreements to ensure objectivity and consensus.

Risk of bias was judged per PROBAST domain, using Low Risk (LR), Medium Risk (MR), and High Risk (HR) ratings tailored to the specificities of ML applications in surface mining, evaluating four essential domains: (1) participants (data sources)—representatives of the data, including sample size, data quality, and sampling locations with selection bias; (2) predictors (input variables)—assessed if input variables, such as geomechanical properties, atmospheric conditions, and blasting characteristics, were consistently measured and available at the time; (3) outcome (targets)—verified the definition and measurement of the target variables to ensure they were determined without knowledge of the predictor data; and (4) analysis (algorithmic rigor)—evaluated the transparency of the algorithms, protocols, handling of missing data, and robustness of performance metrics. Additionally,

this domain also assessed the risk of selective reporting by checking consistency between the study objectives and the reported results.

An overall RoB judgement followed predefined rules: a study was classified as HR if at least two domains were rated as high; Low Risk if at least three domains were rated as LR and one as MR; and Medium Risk if at least two domains were rated as MR, even in the absence of a HR domain, or if the study presented a mix of risks not meeting the criteria for Low or High Risk.

Studies assessed as HR were not excluded; instead, they were included to ensure a comprehensive overview of the current state of research. Their findings were weighted with caution and integrated through a narrative synthesis. Studies classified as MR were monitored for consistency and influence, while those classified as LR were treated as robust evidence.

Regarding reporting bias, because quantitative pooling was not performed and protocols were rarely available, a formal assessment was not feasible; instead, selective reporting was qualitatively assessed in the analysis domain during the RoB appraisal.

Finally, the certainty of evidence was assessed qualitatively per domain using a structured framework (considering RoB, inconsistency, indirectness, imprecision, and publication bias), and summarized as high, medium, and low.

3. Results

3.1. Research Results

During the first stage of the PRISMA methodology, 5317 articles were identified and filtered using automated tools from the databases. The reasons for exclusion were as follows: (1) 928 were outside the period of reference, (2) 1199 were excluded due to document type, and (3) 179 were excluded for the publishing language. After reading the article's title and abstract, an additional 2518 articles were excluded because they did not align with the research topic. After this whole process, the articles were uploaded to Rayyan (<https://www.rayyan.ai/> (accessed on 10 December 2025)), where 301 duplicates were identified and removed, and 192 articles were moved to the eligibility assessment stage. Six of the 192 articles could not be retrieved after contacting the authors. After a full-text analysis, 56 were removed because they were about waste management and did not demonstrate a direct influence on the exploitation activities of mineral resources, 21 because they were only dust emission predictions without a direct impact on exploitation, and 20 because they were connected to the processing plant. Others were excluded for not being about the type of exploitation we were looking for: 20 for being underground mining, six for being only related to water management, and six for being a mix of underground mining and surface mining without separation of data. Moreover, five were excluded because they presented solely theoretical discussion without practical application or the use of site data, and three were excluded for being systematic reviews.

A total of 49 articles were incorporated into the qualitative synthesis. Different snowballing techniques were employed, allowing for the addition of eight more articles through website searches (three) and citation searches (five). A total of 57 articles covering different uses of ML in unit operations in surface mining were included in this systematic review. The whole process is summarized in Figure 1.

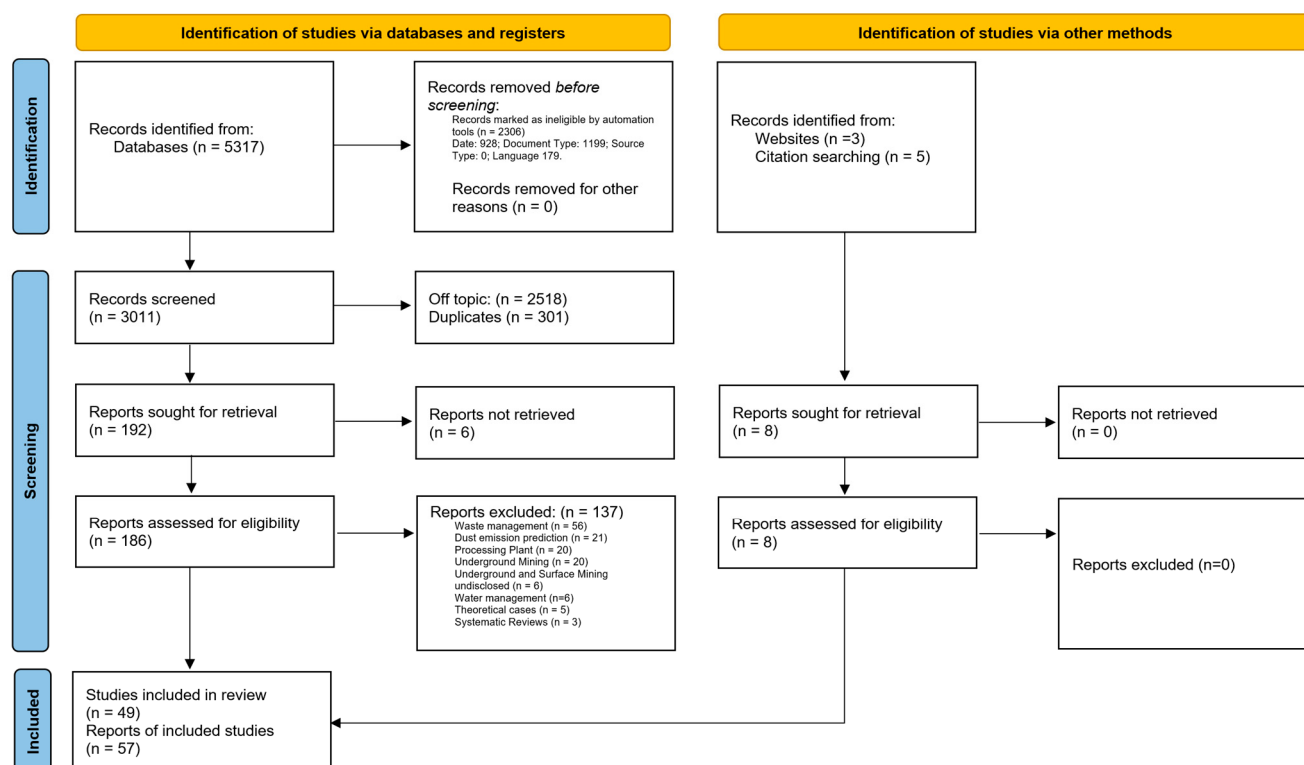


Figure 1. PRISMA flow diagram, adapted from Page et al. [24].

3.2. Studies' Content Analysis

In Figure 2, it is possible to observe the articles' geographical distribution; in addition, there is information in the caption about the number of articles by country. The countries with the highest number of articles are China [26–43], Iran [44–51], and India [52–57]. The other represented nations were as follows: Vietnam [58–60], Japan [61–63], Nigeria [64–66], Turkey [67,68], Ghana [69,70], the United States of America (USA) [71], the Republic of Korea [72], Greece [73], Germany [74], Ethiopia [18], Egypt [75], Spain [76], Canada [77], Botswana [78], and Australia [79].

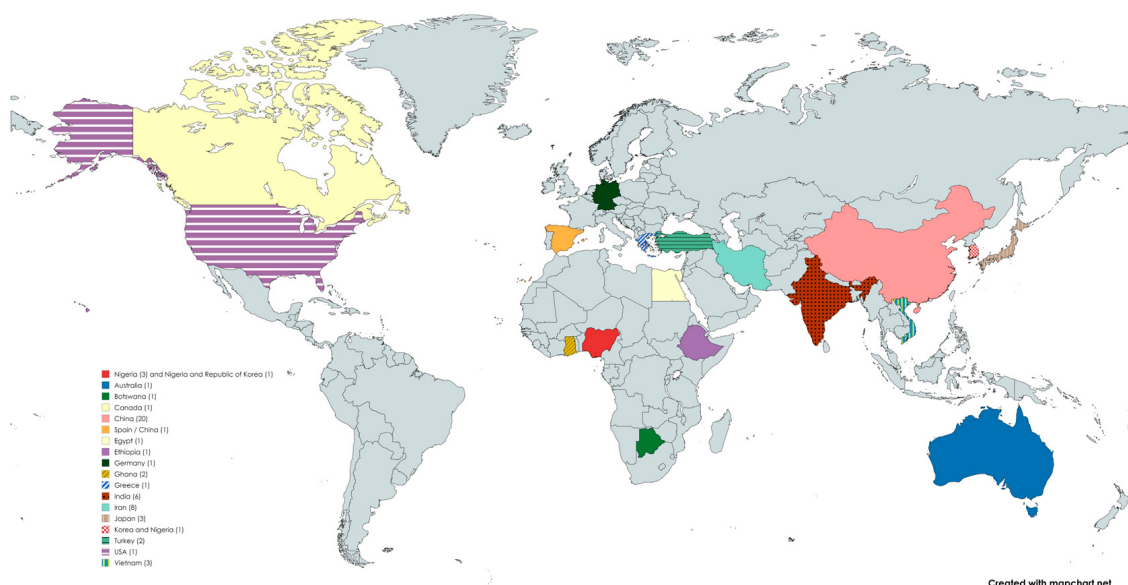


Figure 2. Study distribution by country.

Overall, 19 countries are represented in studies on the application of ML or AI in surface exploitation, underscoring the importance of these technologies in the sector.

In terms of publication dates, the number of articles published over time has increased, with these tools being more widely used in recent years.

Of the 57 articles, 27 were related to mines [27,28,30,37–40,43–46,48,51,53–57,59,60,62,68,69,74,78–80], 23 were related to quarries [18,31–36,42,47,49,50,52,58,61,63,65–67,70,72,73,75,81], seven did not specify whether the site was a mine or a quarry (being described as “Surface Mining”) [26,29,41,64,76,77], and one involved study data from both a mine and a quarry [71].

The 57 articles were categorized into five groups: blasting phase (43 articles), load and haul (six), post-dismantling management (four), extraction (two), and overall exploitation (two). All the main categories are further divided into subcategories, as shown in Figure 3.

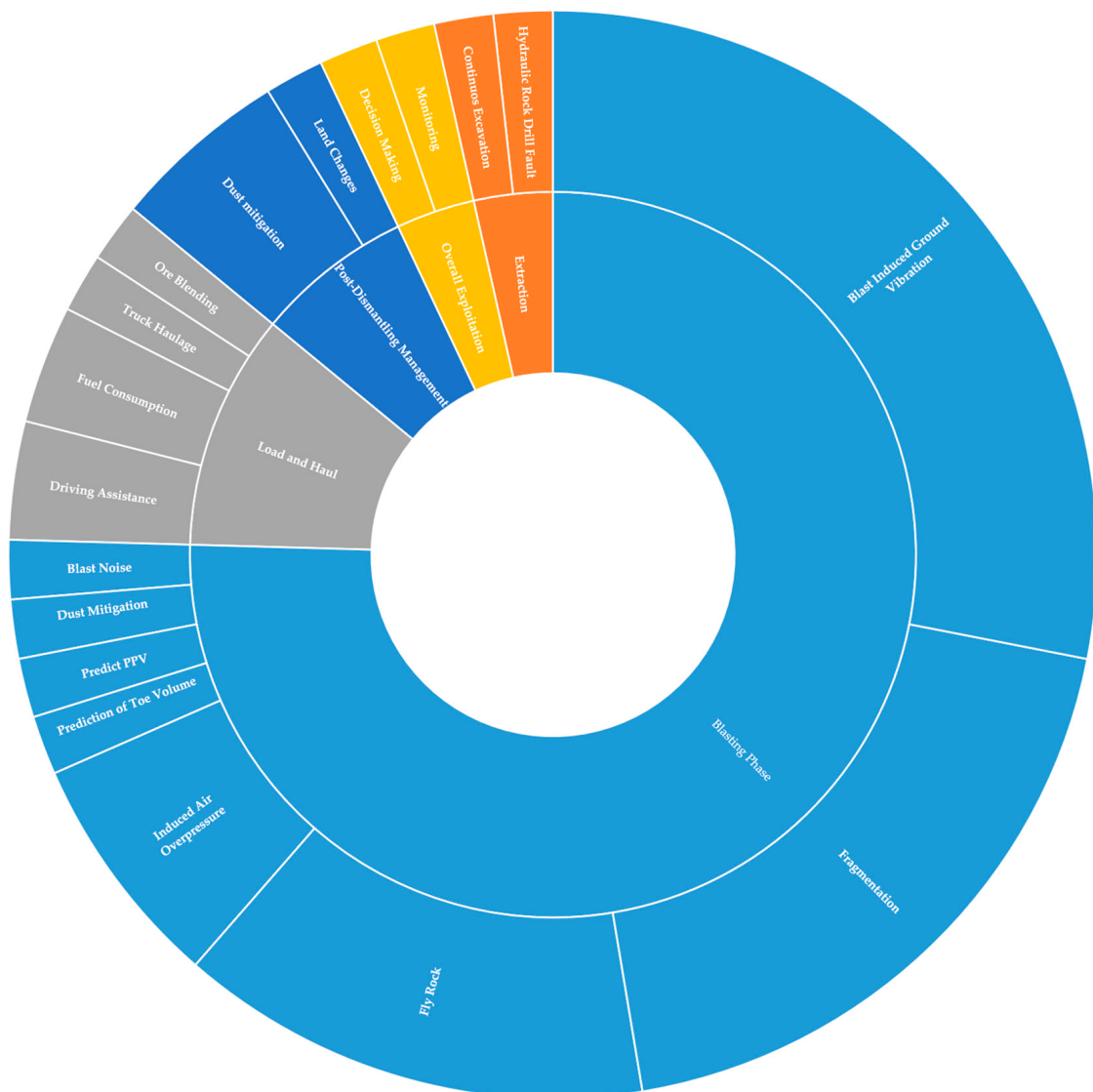


Figure 3. Area of ML/AI application.

By grouping the literature in this way, it is possible to compare validation strategies and dataset scales across equivalent areas, thereby explaining variability and avoiding inconsistencies arising from different mining phases.

To provide a scientometric context, a keyword co-occurrence network analysis was assessed and is illustrated in Figure 4. The high nodal density of “prediction”, “blasting

phase”, “neural network”, and “machine learning” in the central cluster confirms their dominance in the literature. In contrast, the position of “haul” corroborates the lower research volume in this domain compared to blasting and safety monitoring.

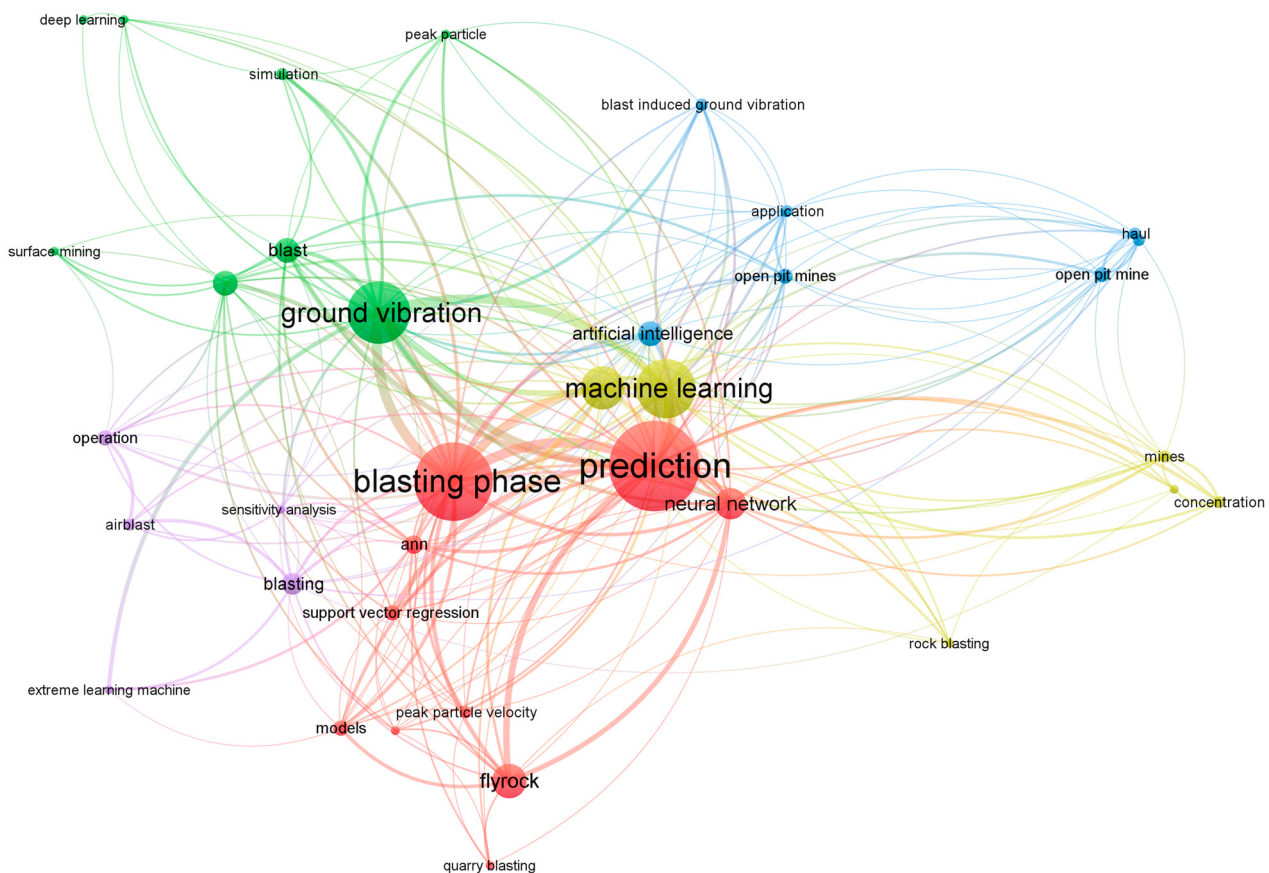


Figure 4. Scientometric analysis of keyword co-occurrence network.

3.2.1. Blasting Phase

The blasting phase had the most articles, totaling 43. They were categorized into ML/AI used in the article and the software used.

In total, 165 individual model mentions were identified across the 43 articles in this category. Of those 165, despite a wide variety of hybrid algorithms, four base models had the highest usage: Support Vector Machine (SVM), with 24; Artificial Neural Network (ANN), with 20; Random Forest (RF), with 19; and Extreme Gradient Boosting (XGBoost), with 10. Together, these four account for 73 model applications, representing 44.2% of all the models used in the blasting phase.

Regarding computational tools, 11 different software/programming languages were identified. In total, the articles mentioned 31 software applications, with one article using one or more of these applications. Of the 43 analyzed articles, 30 (69.8%) specified the software used; in 13 (30.2%), the information was not specified. The most widely used software, MATLAB, appeared in 14 articles, followed by Python, with 12.

All information about the models and software used in each article can be found in Table 1.

Table 1. ML/AI and software used—blasting phase.

Article	ML/AI	Software
[52]	PCA-RF, PCA-XGB, PCA-ANN, PCA-SVM	Split-Desktop (N/S), WipFrag (N/S), FragScan (N/S)
[28]	TPE-ET, TPE-GB, TPE-RF	Python (N/S)
[79]	AW-MKL, KRR, SVR	NaN
[27]	MAIN ONE CB, BAT, BOA, GOA, SSA	Python (N/S), Excel (N/S)
[44]	ICA-ANN, MLP-ANN	MATLAB (N/S)
[69]	NCA-SVM, NCA-BPNN, NCA-GRNN and NCA-RBFNN	MATLAB (N/S)
[61]	BNN, GB, RF, KNN, DT	MATLAB (N/S)
[70]	GPR, ELM, BPNN	MATLAB (N/S)
[31]	SVM, SVM-MFO, SVM-PSO, SVM-GWO, SVM-COA, SVM, WOA	MATLAB (N/S), Python (N/S)
[58]	PSO-ELM, AGPSO-ELM, ELM, GPR, MPMR and LS-SVM	MATLAB (N/S)
[32]	GOA-ELM, HHO-ELM, ELM	MATLAB (N/S)
[33]	FFA-GBM, FFA-SVM, FFA-ANN, FFA-GP	Split-Desktop (N/S)
[34]	FDM-XGBoost-tree, FDM-RF, XGBoost-tree, RF	MATLAB (N/S)
[81]	SCA-ANN, ANFIS, GEP	MATLAB (N/S), Excel (N/S), GEneXpro (tools 5.0)
[35]	RF (Random Forest). CART (Classification and Regression Trees). CHAID (Chi-squared Automatic Interaction Detection). ANN (Artificial Neural Network). SVM (Support Vector Machine)	IBM SPSS Modeler (18.2.1)
[36]	FS-RF, FS-BN	NaN
[67]	Mechanical Simulation Framework (calibrated using (GA)), ANFIS	Python (N/S)
[64]	MARS, CART, SVR	Python (Anaconda3)
[46]	EXGBoosts, ANNs	NaN
[59]	RF, SVM, KNN, CART	NaN
[60]	SVM, RF, k-NN, and GBM	NaN
[65]	ICA-ANN, ANN	MATLAB (N/S)
[62]	RF, DT	NaN
[38]	RF-LSO, RF-POA, RF	NaN
[47]	BRNN, BRCWNN, Z-BRCWNN	MATLAB (N/S), Minitab (N/S)
[48]	AOA-LightGBM, JSO-LightGBM, HHO-LightGBM, GMO-LightGBM, AOA-CatBoost, JSO-CatBoost, HHO-CatBoost and GMO-CatBoost	Python (N/S)
[66]	SVR, ANN, MLP, RF, BRNN, LSTM	MATLAB (Version 2021)
[63]	CapSA-MLP, PSO-ANN	MATLAB (R2024a)

Table 1. *Cont.*

Article	ML/AI	Software
[49]	SAE, WAE, ISM, SSM, BXGBoost	GridSearchCV(N/S), SHAP (N/S), Python (N/S)
[73]	EDML, DF, XGBOOST	NaN
[56]	*INNS, XGBOOST, LSTM, RF, SVM, ANN	Python (N/S)
[68]	XGBoost, AdaBoost, CART, CABoost, RF, DT, ET, GBM, LightGBM, LGBM combination with all	NaN
[75]	Extra Trees Regressor, Random Forest Regressor, Bagging Regressor, Gradient Boosting Regressor, HistGradient Boosting Regressor, XGBRegressor, AdaBoost Regressor	Python (N/S)
[40]	AHA-GPR, GPR, ANN, SVR	NaN
[78]	ANN, SVM, k-NN, RF	NaN
[50]	PDNN, PANN, DNN, ANN MCs	Python (N/S), Matlab (N/S)
[51]	GEP, BRNN, MNLR, MOGWO	Split-Desktop (N/S), GeneXPro Tools (5.0)
[71]	ANN-SVR, ANN	Python (N/S), Keras (N/S)
[77]	DNN with ResNet50, Pixel Classifier,	Split-Desktop (N/S)
[57]	XGBoost, RF, KNN, SVR, ANN	Strayos (N/S), O-PitBlast (N/S)
[18]	RFR, SVR, XGBoost, and ANN	Python (N/S)
[76]	SVR-GWO, SVR-PSO	NaN
[42]	WOA, DNN, RBM	NaN

N/S: Software version not specified in the original study.

3.2.2. Load and Haul

The load and haul class was the second class with the most articles, totaling six articles. Focusing mainly on fuel consumption [45,54], driving assistance [43,55], ore blending [30], and truck assistance [72].

Unlike the blasting phase, which is dominated by regression of physical impacts, the load and haul sector shows a significant interest in reinforcement learning and Computer Vision to address the dynamics of truck movements.

A total of 20 different models were used. The four architectures (RF, ANN/MLP, and SVM) continue to have a significant impact, appearing in nine mentions (45% of the models used in this category). Specifically, neural network variants (ANN, MLP, and RBF) are the most frequent, with five applications, followed by RF, with three applications, and SVM, with two applications.

The articles used nine different software packages [33,49,50,76], with two of the articles not specifying the type of software used [46,67]. The most-used software was Python, being used in three different articles, followed by TensorFlow, used in two articles.

All the models and the software used in each article are presented in Table 2.

Table 2. ML/AI and software used—load and haul.

Article	ML/AI	Software
[30]	MADDPG, DDPG	TensorFlow (N/S), Python (3.6), PyCharm (2019.1.1), MATLAB (N/S)
[45]	MLR, RF, ANN, SVM, K-NN	Python (N/S)
[54]	ANN, RF, ANFIS	WEKA (N/S)
[55]	CISAAC, CNN, SIFT	TensorFlow (N/S), Python (N/S), OpenCV (N/S), KERAS (N/S), PIX4DMpper (N/S), LabelIMG (N/S)
[72]	Random Forest (RF), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Classification and Regression Tree (CART), k-Nearest Neighbors (kNNs) and M5Tree	NaN
[43]	RBF	NaN

N/S: Software version not specified in the original study.

3.2.3. Post-Dismantling Management

Post-dismantling management included four articles that focused on dust mitigation [37,53,80] and land changes [74].

Across these four articles, diverse models were utilized, with RF [37,53,80] and neural networks [74,80] as the primary architectures. Random Forest variants were applied in three of the four articles, showing a high usage for dust prediction.

For software, four different ones were used across two studies, with the other two not specifying which software they used.

All the detailed information is shown in Table 3.

Table 3. ML/AI and software used—post-dismantling management.

Article	ML/AI	Software
[53]	Bagging, RF, DT	NaN
[74]	ChangeFFT, CNN, Transformers, VMamba, A2Net, BIT, ChangeFormer, DMINet, FC-EF, FCNPP, ICIFNet, RDPNet, ResUnet, SiamUnet-Conc, SiamUnet-Diff, and SNUNet	PyTorch (N/S), HuggingFace (N/S), eCognition (N/S)
[80]	LSTM, RFR, SVR, BBN	MATLAB (N/S)
[37]	RF-MC, RF-PSO	NaN

N/S: Software version not specified in the original study.

3.2.4. Extraction

In the “extraction” category, two studies were analyzed, focusing on hydraulic rock-drill fault [26] and continuous excavation [41]. These studies focused on machine monitoring and multi-objective decision-making.

Across these two articles, a total of seven different machine learning models were utilized. While one article used DenseNet, BiLSTM, SVM, and GBDT [26], the other article used DoppelGANger (DG), Contrastive Language-Image Pre-Training (CLIP), and DT [41].

For software, five different software programs were identified and used across the two articles. Python was used in both instances. One of the few Python [26] implementations, E-GCDT, also used Python, in addition to Unity and Visual Studio, for coding within it, and ROS2 Humble Hawksbill [41].

3.2.5. Overall Exploitation

There are two articles classified as overall exploitation that focus on monitoring [29] and decision-making [39].

In the monitoring article, Spatio-Temporal Models (STMs) and Gated Recurrent Unit (GRU) were used. In the decision-making article, the machine learning models used were the Huber Regressor (HR), RF, GBR, SVR, XGBoost Regressor, and CatBoost Regressor (CB-GWO).

As for the software used, the monitoring article used MATLAB, Python, and Unity, while the decision-making software only mentioned Python.

3.3. Training Validation and Results

While the previous section categorized ML applications and software, this section aims to synthesize the validation approaches and training methods used across all reviewed studies.

In the blasting phase, a total of 11 types of training were employed, with one article failing to specify the type of training used. The most-used split for training the ML model was 80% training and 20% testing in 23 articles, and 70% training and 30% testing in 10 articles. These two split types alone account for 76% of the trains.

Dataset sizes in this category vary widely, ranging from small-scale experimental collections of blastings to large-scale operational databases with approximately 3740 observations. As for the validation, the blasting phase used error magnitude metrics as its evaluation metrics, which can be categorized into four groups: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE), used for quantifying the deviation between predicted and observed values. Correlations such as Pearson's Correlation Coefficient (R), Coefficient of Determination (R^2), and Adjusted R^2 were also used. To evaluate the predictive power, Nash–Sutcliffe Efficiency (NSE), Index of Agreement (IoA), and Variance Accounted For (VAF) were used. Finally, accuracy was scrutinized through the Coefficient of Residual Mass (CRM), Bias Factor, and Scatter Index (SI). The most commonly used metrics were R^2 (37 articles), RMSE (33 articles), and MAE (21 articles).

The results obtained reveal a shift toward high-fidelity machine learning architectures that consistently outperform traditional empirical modeling. In Peak Particulate Velocity (PPV) testing, hybrid models such as ELM-HHo and ELM-GOA achieved remarkable statistical reliability, with R^2 values of 0.941 for training and 0.9105 for testing in ELM-GOA [32].

In Flyrock and Air Overpressure, substantial improvements were achieved, with models such as WOA or SVM delivering R^2 values exceeding 0.98, effectively minimizing the MAE to levels that support critical safety decision-making [31,42,78]. In rock fragmentation, methods such as XGBoost and Extra Trees Regression were highly effective, achieving R^2 values over 0.93 [28,57,68].

The complete model's information can be found in Appendix A.

For the load and haul category, three types of training were applied; one article did not specify any training. This category relies on substantial datasets, including records of up to 400,000 observations for fuel-consumption monitoring. Two of the six articles used

an 80% train–20% validation split, while others used reinforcement learning training (RLT), with up to 90,000 iterations, or supervised machine learning (SML).

As for validation, load and haul articles can be categorized into four different groups: statistical reliability, where models such as R^2 , NSE, MSE, MAE, and RMSE were used; signal and image evaluation, using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Visual Information Fidelity (VIF), and the Universal Quality Index (UQI); real-world applicability, where the Convergence Rate and computation time were assessed; and deviation control, where Distance Class Deviation was also used.

The results show a superior predictive capability of neural networks and reinforcement learning frameworks within the load and haul category. As for fuel consumption, models such as ANN achieve R^2 values of 0.989. In ore-blending scheduling, analysis showed that the MADDPG algorithm significantly outperformed DDPG in convergence and precision, minimizing operational deviations. Regarding production and safety, ore production was predicted with high accuracy using SVM, while anticollision systems used RBF networks to provide a precise distance estimation via signal processing. All of this detailed information is in Table 4.

Table 4. Training validation and results—load and haul.

Article	Dataset	Split/Train	Evaluation Method	Best Model
[30]	90.000	Reinforcement learning (RL)	Deviation Control, Convergence Rate, Computation Time	MADDPG
[45]	400.000 registers	80/20 K-fold cross-validation	R^2 , MSE, MAE	ANN
[54]	66 dump trucks: 27 with 190-ton capacity 16 with 120 tons 23 with 100 tons	RF: 20-fold cross-validation ANFIS: split (training) and (testing) ANN: 10 hidden neurons, tanh activation, max 10.000 epochs or 10^{-5} error threshold	R^2 , MAE, RMSE, NSE	ANN: (R^2 : 0.989, RMSE: 0.195, MAE: 0.142)
[55]	7 pieces of equipment with 1550 to 1600 by class Total 11.000 imagens	80/20 K-Fold cross-validation	UQI, SSIM, VIF, PSNR	CISACC for image and architecture SSD–MobileNet for detection
[72]	16,005 datasets were collected, using the downscaling method was applied to downscale the size of the dataset into 3.000 observations	Models were validated using three downscaled. observational datasets, evaluated via standard engineering performance metrics	R^2 , MAE, RMSE	SVM
[43]	NaN	RBF learning: unsupervised clustering for hidden units, followed by supervised output layer training	Average Error, Accuracy, Distance Class Deviations	RBF

In the post-dismantling management category, three different train splits were used across four articles. Data included high-volume datasets featuring 70,000 paired image patches, as well as sensor-based studies with over 265 h. The most-used splits were 70% train and 30% test; 80% train and 20% test; and 60% train, 30% test, and 10% validation.

As for the validation process, two categories were identified: statistical reliability, including MSE, RMSE, MAE, R , R^2 , and MAPE; and model performance, evaluated using F1-score and IoU.

In predicting dust mitigation, models such as the probability-based deep learning algorithm and RF achieved high statistical reliability in managing particulate matter and dust dispersion. As for land-change analysis, deep learning architectures utilizing high-volume paired-image datasets and RF models significantly improved the precision of environmental monitoring and estimation in surface mining. All the detailed information can be consulted in Table 5.

Table 5. Training validation and results—post-dismantling management.

Article	Dataset	Split/Train	Evaluation Method	Best Model
[53]	240	80/20 Recursive Feature Elimination (RFE) prioritized independent variables to optimize model performance	MSE, RNSE, R ²	Bagging with higher precision for PM10 Decision Tree with higher precision for PM2.5
[74]	70,000 paired patches of bi-temporal high-resolution remote-sensing images and pixel-level annotations from 100 mining sites worldwide	60% train, 30% test and 10% validation	F1-Score, IoU	MineNetCD outperformed 12 baselines, with the Swin-T variant achieving optimal performance.
[80]	265 h of valid data was collected	70/30 The LSTM was configured with a 7-feature input layer, a 32-neuron hidden layer, and a single output layer	RMSE, R ² , MAE, MAPE	STM
[37]	41,381 measured datasets	70/30 A 30% test split was implemented, reserving the final 300 data points as a hold-out set for Markov Chain validation	RMSE, R, MAE	RF-MC

In the extraction category, the two articles used two different training models. One of the models utilized cross-validation protocols during training, specifically a “leave-one-operator-out” approach [29], while the other applied offline reinforcement learning, leveraging GAN-enhanced data to augment 18 real trajectories into 155 synthetic samples [41].

Regarding the validation process in these articles, the articles used three different categories: operational efficiency, using indicators such as Full Bucket Rate (FBR); Digging Efficacy (DE); and Digging Time. The stability of the learning process was monitored via Training Loss (MSE) and SD metrics [41].

In the other study, accuracy measures were used, such as Average Accuracy and Average Weighted Accuracy [26].

In predicting hydraulic rock-drill faults, the model based on x-vectors utilizing the Focal Loss function achieved the highest performance across key metrics, such as AA and AWA [26]. In continuous excavation systems, analysis showed that the E-GCDT (DGAN + CLIP + DT) algorithm significantly outperformed both human operators and alternative tested algorithms, demonstrating superior efficiency in autonomous digging tasks [41].

In the overall exploitation, two articles used different types of model learning. Data collection involved high-resolution signals, with 20,000 points per sample for one case, using a 70% train, 15% validation, and 15% test split [32], whereas the other article used an 8-supervised machine learning algorithm [39].

To evaluate predictive accuracy, R^2 , MAE, and RMSE were used. To ensure the measurement precision, the NMSE was used [39]. In the other articles, metrics such as accuracy and measurement precision were applied [29].

In machine monitoring prediction using digital twin integration, the Gated Recurrent Unit (GRU) model achieved the best performance, achieving a test accuracy of 97.42% and correctly identifying vibrational signs with a precision of around 1 mm [29]. In the sustainable gold mining analysis, the CatBoost algorithm, when optimized with GWO, achieved an R^2 of 0.978 and an MAE of 3.361, making it the best-performing model [39].

3.4. Bias Analysis

The PROBAST bias assessment for the blasting phase shows a distribution mainly between “Low Risk” and “Medium Risk”. Most articles in the “Predictors” and “Outcome” domains consistently showed “Low Risk” due to well-defined variables and targets. The most frequent bias was identified in the “Participants” and “Analysis” categories. The “Medium Risk” in “Participants” is often due to the use of single-site datasets. However, recent studies have mitigated this by using data enrichment techniques such as CTGANs and Monte Carlo Simulations. As for “Analysis”, a critical point arises: some studies are categorized as “High Risk”, typically due to limited external validation or a lack of transparency in algorithmic processing. Overall, the category maintains statistical integrity through robust performance metrics despite challenges with site-specific data representativeness. All the details of the blasting phase are shown in Table 6.

Table 6. Bias analysis—blasting phase.

Articles	Participants	Predictors	Outcome	Analysis	General
[52]	MR	LR	LR	MR	MR
[28]	MR	LR	LR	MR	MR
[79]	MR	MR	LR	MR	MR
[27]	LR	LR	LR	LR	LR
[44]	MR	LR	LR	MR	MR
[69]	MR	LR	LR	LR	MR
[61]	MR	MR	LR	HR	MR
[70]	MR	MR	LR	MR	MR
[31]	MR	MR	LR	MR	MR
[58]	MR	LR	LR	MR	MR
[32]	MR	LR	LR	MR	MR
[33]	MR	MR	LR	LR	MR
[34]	MR	LR	LR	MR	MR
[81]	MR	LR	LR	HR	MR
[35]	MR	LR	LR	MR	MR
[36]	MR	LR	LR	MR	MR
[67]	LR	MR	LR	LR	LR
[64]	LR	LR	LR	LR	LR
[46]	MR	LR	LR	MR	MR
[59]	MR	LR	LR	MR	MR
[60]	MR	LR	LR	MR	MR
[65]	HR	LR	LR	MR	MR
[62]	HR	LR	LR	MR	MR
[38]	LR	LR	LR	LR	LR
[47]	MR	LR	LR	MR	MR

Table 6. *Cont.*

Articles	Participants	Predictors	Outcome	Analysis	General
[48]	MR	LR	LR	MR	MR
[66]	LR	LR	LR	MR	LR
[63]	MR	LR	LR	LR	LR
[49]	MR	LR	LR	MR	MR
[73]	MR	LR	LR	MR	MR
[56]	LR	LR	LR	LR	LR
[68]	MR	LR	LR	MR	MR
[75]	MR	MR	LR	MR	MR
[40]	MR	LR	LR	MR	MR
[78]	MR	MR	LR	MR	MR
[50]	MR	LR	LR	MR	MR
[51]	LR	LR	LR	MR	LR
[71]	LR	LR	LR	MR	LR
[77]	MR	LR	LR	LR	LR
[57]	MR	LR	LR	LR	LR
[18]	MR	LR	LR	MR	MR
[76]	MR	LR	LR	MR	MR
[42]	MR	LR	LR	MR	MR

The bias assessment in the load and haul category shows a global MR assessment, with four out of the six articles being considered as such. While the “Outcome” and the “Predictors” domains demonstrate a “Low Risk”, indicating well-defined targets and reliable variables, the overall risk is elevated due to the “Participants” and “Analysis” domains. The reliance on single-site datasets led to a “High Risk” rating in the “Participants” domain for 17% of the articles. At the same time, deficiencies in validation protocols resulted in a “High Risk” rating in the Analysis domain for one study. All the detailed information is shown in Table 7.

Table 7. Bias analysis—load and haul.

Article	Participants	Predictors	Outcome	Analysis	General
[30]	MR	LR	LR	MR	MR
[45]	LR	LR	LR	MR	LR
[54]	HR	LR	LR	MR	MR
[55]	MR	LR	LR	MR	MR
[72]	LR	LR	LR	LR	LR
[43]	MR	MR	LR	HR	MR

As for the post-dismantling category, results indicate that environmental monitoring risks are concentrated in specific domains. Global change detection showcases “Low Risk” due to its robust dataset scale and transparency. However, dust monitoring models exhibit a “Medium Risk” trend, with one study classified as “High Risk” in the “Participants” domain, while “Analysis” showed MR to LR ratings. All the detailed information is shown in Table 8.

Table 8. Bias analysis—post-dismantling management.

Article	Participants	Predictors	Outcome	Analysis	General
[53]	MR	LR	LR	MR	MR
[74]	LR	LR	LR	LR	LR
[80]	HR	LR	LR	MR	MR
[37]	MR	LR	LR	MR	MR

The “extraction” articles present distributions of “Low Risk” [29] and “Medium Risk” [44], reflecting a high level of methodological rigor across both studies. This moderated risk in the latter is primarily linked to the “Participants” and “Analysis” domains, which are common in reinforcement learning applications. Nonetheless, both articles successfully implemented advanced data enrichment (e.g., GAN-enhanced data) and robust validation techniques to address small-sample constraints, providing a reliable foundation for real-world mining operations [26,41].

In the exploitation category, both analyzed articles are classified as “Medium Risk” overall. Despite this, they demonstrate a high level of methodological rigor, particularly in the “Predictors” and “Outcome” domains, which were consistently rated as “Low Risk”. Prioritizing data-driven characteristics and virtual visualization, through digital twin frameworks and multi-objective optimization, these studies establish a foundation for future practical applications in self-sustaining and sustainable mining operations [29,39].

Overall, the “High Risk” studies in specific domains did not alter the study’s conclusions; instead, they necessitated a more cautious interpretation of certain findings. Confidence remains partially constrained, primarily due to the prevalent reliance on single-site data and the scarcity of independent external validation across the analyzed studies.

3.5. Results Synthesis

The synthesis of the 57 studies included in the present review reveals a significant concentration during the “blasting phase”, accounting for approximately 75% of the total sample.

Methodologically, the literature demonstrates a high degree of standardization in data treatment, as 76% of the “blasting phase” studies employed training/testing splits of 80/20 or 70/30. Across all four categories, the primary machine learning architectures identified were SVM, ANN, RF, and XGBoost. These models consistently delivered high-fidelity performance, frequently reporting R^2 values exceeding 0.94 and outperforming traditional empirical formulas.

In contrast, there is heterogeneity in dataset sizes, ranging from small experimental collections of fewer than 100 blasts to industrial databases with over 400,000 records for fuel-consumption monitoring. The RoB assessment indicates that while statistical integrity remains high, the generalizability of findings is limited. Most studies are classified as “Medium Risk” in the “Participants” and “Analysis” domains due to a heavy reliance on site-specific, single-quarry/mine datasets and a lack of independent external validation.

3.6. Reporting Bias

Due to the heterogeneity of the data and metrics, quantitative assessment methods were not feasible. However, a qualitative assessment within the PROBAST “Analysis” domain suggests a risk of reporting bias across the included studies. Several studies focused solely on successful model implementations without reporting negative or null results. Furthermore, the lack of pre-registered protocols in the majority of primary studies prevents a definitive comparison between planned and reported outcomes, suggesting a potential selective reporting bias favoring high-accuracy metrics.

3.7. Certainty of Evidence

According to the qualitative framework defined in the methodology, the certainty of the evidence varies across application domains.

In the “blasting phase”, there is a Moderate Certainty. While the volume of studies is high (43 articles), and statistical metrics are robust, the evidence is downgraded due to the dominance of single-site data and deficiencies in the validation protocol.

In “post-dismantling management”, there is a Low Certainty. Evidence is drawn from only a few studies (four articles). While land change detection benefits from large-

scale datasets and a low risk of bias, the certainty for dust mitigation is reduced by an HR rating in the “Participants” section of one study and the prevalence of MR in the “Analysis” domains.

As for the “load and haul” and “extraction”, there is a Low Certainty. The evidence is limited by a small number of studies (six and two articles, respectively) and by imprecision, with datasets varying significantly in size and consistency, ranging from small experimental setups to large operational databases.

4. Discussion

4.1. Analysis by Category

The geographic concentration of research in China, Iran, and India reflects the massive scale of their extractive industries and specific national strategic priorities. These countries are among the world’s leading producers of raw materials, such as coal and iron ore, necessitating high-volume operational optimization to meet global demand. Driving substantial investment in digital technologies and Industry 4.0 is necessary to maintain competitiveness within global supply chains and geopolitical dynamics. However, this concentration suggests that the specific regulatory frameworks, labor costs, and geological conditions of these regions may heavily influence current findings. Consequently, the generalizability of these results to Western or smaller-scale mining contexts should be approached with caution.

The dominance of the “blasting phase” in current research underscores its critical role in the mining value chain. The direct impact of blasting on operational safety and subsequent downstream costs in the production chain can be understood through this phenomenon. In surface mining, the quality of fragmentation directly determines the efficiency of subsequent loading, hauling, and crushing.

Additionally, the high volume of literature in this category can be attributed to the nature of blasting data, which consists of measurable geological parameters and explosive characteristics, leading to high-quality experimental modeling and regression. Some of the articles used data from other authors to test their own models, thereby facilitating the acquisition of new data. The consistently high predictive performance reported in these studies, where R^2 values frequently exceed 0.94 for PPV, environmental issues, and rock fragmentation [31,32,57,68,78], validates the transition from traditional empirical formulas to ML architecture as the new gold standard.

While base models, such as SVM, ANN, and RF, remain the most common, accounting for 44.2% of all applications in the blasting category, there is a distinct shift toward hybrid model architecture. Hybrid approaches, such as HHO or GOA, integrated with ELM have demonstrated great statistical reliability [32]. Similarly, techniques such as XGBoost and Extra Trees Regression have proven highly effective for predicting rock fragmentation, demonstrating that tree-based methods are remarkably robust against the noise inherent in site-specific blasting data [28,57,68]. This shift toward ensemble and meta-heuristic optimization reflects the industry’s need for models that can better handle the nonlinear complexities of rock–explosive interactions than standalone algorithms.

The contrast between blasting phase (43 articles) and load and haul (6 articles) appears to reflect a combination of operational prioritization and data complexity rather than lack of industrial need. While blasting is the primary lever in “Mine-to-Mill” [82], the scarcity of load and haul studies highlights a significant research gap. In this context, load and haul requires handling dynamic, real-time telemetry, and multi-agent interactions. Consequently, the limited number of studies suggests that while the industry prioritizes the root cause of efficiency, the complexity of modeling dynamic fleet behavior remains an under-addressed challenge.

Unlike blasting, which focuses on physical impact regression, this sector relies on RL and Computer Vision to manage dynamic movements. The success of the MADDPG algorithm over conventional DDPG in ore blending illustrates the necessity for multi-agent frameworks to manage the dynamic operational complexity of surface mining [30]. This focus on RL suggests that while regression is suitable for static physical predictions, the nature of equipment coordination requires algorithms capable of adaptive learning in real-time environments.

In the post-dismantling management category, environmental issues are addressed. In these articles, deep learning [74] and RF models [37,53,80] have provided high statistical reliability in managing particulate matter and environmental estimation, showcasing the role of AI in sustainable reclamation. However, the identified risk of bias in some environmental monitoring studies highlights a critical need for more rigorous data extraction protocols to ensure the long-term reliability of results [80].

As for the extraction category, research focuses on machine monitoring [26] and multi-objective decision-making [41]. Advancement is the use of offline reinforcement learning supported by GAN-enhanced data [41], which allowed algorithms like E-GCDT to outperform human operators in autonomous digging tasks. One of the two articles uses Unity, showcasing the importance of not only planning but also visualizing the tasks [41]. The integration of GAN-enhanced data to augment real trajectories is an example of how the sector is successfully overcoming data scarcity to train robust autonomous systems.

Finally, overall exploitation integrates digital twin technology for self-sustaining machine monitoring [29]. The use of Gated Recurrent Units (GRUs) allowed researchers to achieve high accuracy in identifying vibrational signs while using Unity as a visualization software [32]. At the same time, the CatBoost algorithm proved effective for multi-objective optimization in sustainable low-emission gold mining [39]. These applications of high-resolution signal processing and visualization provide a foundation for real-time decision-making, effectively bridging the gap between digital simulation and physical reality in a smart mine context.

While blasting studies predominantly utilized ML for static regression to optimize single events, the research in overall exploitation and extraction demonstrates the true operational potential of digital twins as dynamic virtual replicas. The integration of GRU with visualization platforms and the use of GAN-enhanced reinforcement learning moves beyond the prediction to autonomous action. Consequently, for ML to fully enable the Mining 4.0 paradigm, research must shift from isolated predictions to integrated systems that can visualize, simulate, and act within a digital twin environment.

These findings directly address Research Question 1 (RQ1), identifying SVM, ANN, and RF as the most effective algorithms across unit operations, while highlighting a transition toward hybrid architectures in blasting and reinforcement learning in dynamic tasks. However, unlike the construction and civil infrastructure sectors, where ML is already widely integrated for predictive maintenance and structural health monitoring [83], surface mining appears to be in a transitional phase. While the blasting domain has reached a maturity level comparable to structural analysis, overall exploitation and digital twin integration remain emerging areas, lagging behind the fully automated process control seen in advanced manufacturing [84].

4.2. Methodological Rigor and Validation Reliability

The adoption of standardized data split ratios of 80/20 and 70/30 suggests a mature methodological framework in ML/AI research in mining, although its application to heterogeneous datasets raises concerns about model reliability. However, the reliability of the reported results is strongly influenced by the extreme heterogeneity in data

sizes, ranging from small collections of 100 blasts [61] to industrial databases containing 400,000 observations for fuel monitoring [45]. This disparity implies that models trained on more databases likely possess significantly greater capabilities [48] than those derived from localized experimental trials, which often require data enrichment techniques such as Monte Carlo Simulation [50,51].

Additionally, the data input during the blasting phase was not entirely homogeneous; in some articles, important information was omitted, which could have affected the results [33,61,70]. Additionally, in most articles, data was used from only one region or piece of equipment, which could affect the model's scalability [30,43,54,55,72,80].

While statistical metrics such as R^2 , RMSE, and MAE are dominant across all categories, the extraction area introduces specific operational efficiency indicators, including Full Bucket Rate and Digging Efficiency [41]. The inclusion of measures such as AWA ensures that the learning process is not only theoretical/mathematical but also operationally stable [26].

This transition from purely statistical to physical performance metrics provides robust validation of the models and demonstrates their utility in a real-world mining environment. By validating specific tasks with human operators and using tools like Unity for visualization, the literature is effectively shifting toward a more pragmatic, evidence-based approach that is essential for Mining 4.0 technologies.

Regarding Research Question 2 (RQ2), this review highlights that validation practices significantly influence the reliability of results. The methodology predominantly relies on random hold-out and k-fold cross-validation (typically 5- or 10-fold), with a notable scarcity of external validation on independent mining sites. Consequently, no meta-analysis was conducted due to significant heterogeneity in datasets, algorithms, and reported metrics. This reliance on internal statistical validation often overshadows operational performance indicators. While statistical metrics like R^2 are ubiquitous, the limited reporting of operational KPIs, such as Full Bucket Rate or Digging Efficiency, constrains the assessment of practical deployability.

4.3. Methodological Limitations and Evidence Gap

The assessment of bias and limitations identifies critical barriers to the practical implementation of ML-based systems. Most investigations are site-specific, relying on empirical datasets from a single mine or quarry, which limits the scalability of the models to different geological/operational contexts [30,33,37,43,54,55,61,70,72,75,80].

Another significant gap is the lack of transparency regarding computational tools. In the blasting category, 13 articles did not specify the software utilized [36,38,40,42,46,59,60,62,68,73,76,78,79], and in load and haul, two did not specify it either [43,72].

The high predictive performance frequently reported in the reviewed literature, with R^2 often exceeding 0.94, demonstrates the strong potential of these technologies but warrants a cautious interpretation regarding generalizability. In studies utilizing complex nonlinear architectures such as ANN or SVM on limited datasets, such metrics likely indicate overfitting. Furthermore, the prevalence of different train-test splits introduces significant data-leakage risks in spatially dependent mining environments, where random splits fail to ensure independence between the training and testing sets.

Addressing these gaps requires more rigorous data extraction protocols and standardized reporting to facilitate the transition to Mining 4.0.

A foundation for digital twin operations and autonomous systems can only be achieved if the industry moves toward open-access datasets and standardized performance metrics that go beyond statistical accuracy. However, widely adopting such frameworks creates substantial barriers. The mining industry's competitive nature fosters a culture of

data secrecy, where high-resolution operational data is treated as proprietary intellectual property to protect strategic advantages regarding production rates and reserve characteristics [85]. Also, the lack of interoperability between the equipment manufacturers' standards creates technical bottlenecks, making the anonymization and standardization required for public sharing both technically challenging and resource intensive.

There is a need to ensure methodological transparency and cross-site validation to enable the extractive sector to successfully integrate ML into its core decision-making process.

Addressing Research Question 3 (RQ3), several barriers persist for practical ML employment. In terms of evidence limitations, across domains, certainty is limited by frequent reliance on site-specific databases, incomplete reporting of feature engineering and software, and a high or medium risk of bias in analysis/validation domains. Regarding the review process itself, this review is limited by the predefined publication window (2020–2025), database coverage, and potential missed non-indexed engineering reports. These constraints may underrepresent emerging applications. Finally, concerning actionable implications, standardized reporting and operational indicators are priorities. For practice, studies should report operational KPIs (e.g., ton/h, cycle time, fuel consumption, and bucket fill), alongside statistical metrics, and provide deployable decision-support validation. For research, minimum reporting checklists for datasets, preprocessing, and validation should be adopted.

5. Conclusions

This systematic review included 57 empirical studies (2020–2025) on machine learning (ML) in applications across surface mining unit operations.

Due to substantial heterogeneity across datasets, algorithms, and metrics, a narrative synthesis was conducted rather than a meta-analysis. Results indicate a significant concentration of research in the blasting phase (43 of the 57 articles), where hybrid architectures such as XGBoost, RF, and SVM consistently achieve high statistical reliability, with R^2 values frequently exceeding 0.94. In contrast, domains such as “load and haul”, “extraction”, and “post-dismantling management” remain less explored but offer promising applications of reinforcement learning and Computer Vision for dynamic tasks, such as digital twin integration. The application of multi-agent frameworks, such as MADDPG algorithms, proves more effective than traditional models for managing complex tasks, such as ore-blending scheduling. However, despite this potential, the robustness of the current evidence is constrained by its reliance on single-site datasets; independent external validation is required before industrial-scale deployment. The start of a digital twin is being achieved by utilizing models such as Gated Recurrent Unit (GRU) and visualization software, such as Unity, which can bridge the gap between digital simulation and physical reality, providing a more robust foundation for real-time decision-making in an exploitation context.

Despite the strong statistical performance observed, the transition to scalable deployment is likely constrained by the context-dependent nature of single-site datasets and the scarcity of external validation. Furthermore, evidence quality is affected by inconsistent reporting of dataset sizes, participant details, and software tools, which limits reproducibility. Across domains, performance is commonly reported using statistical metrics (e.g., R^2 , RMSE, and MAE), but operational efficiency and safety-relevant indicators are inconsistently incorporated, creating a gap between model accuracy and practical utility.

To advance toward robust Mining 4.0 applications, future research must prioritize standardized reporting protocols, specifically regarding data provenance, preprocessing pipelines, and algorithm parameters. Additionally, validation strategies should expand

beyond internal cross-validation to include multi-site testing and operationally meaningful outcomes to ensure these tools provide reliable, deployable decision support.

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Abbreviations

The following abbreviations are used in this manuscript:

ML	Machine learning
CPS	Cyber-Physical System
IoT	Internet of Things
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROBAST	Prediction model Risk of Bias Assessment Tool
XGBoost	Extreme Gradient Boosting
R ²	Coefficient of Determination
AI	Artificial intelligence
SVM	Support Vector Machine
DT	Decision Tree
RF	Random Forest
GB	Gradient Boosting
PCA	Principal Component Analysis
LiDAR	Light Detection and Ranging
RMSE	Root mean square error
MAE	Mean absolute error
MAPE	Mean absolute percentage error
HR	High Risk
MR	Medium Risk
LR	Low Risk
USA	United States of America
ANN	Artificial Neural Network
ETs	Extra Trees
SVR	Support Vector Regression
ANFIS	Adaptive Neuro-Fuzzy Inference System
GEPE	Gene Expression Programming
MARS	Multivariate Adaptive Regression Splines

LSTM	Long Short-Term Memory
LightGBM	Light Gradient Boosting Machine
AHA	Artificial Hummingbird Algorithm
GPR	Gaussian Process Regression
MADDPG	Multi-Agent Deep Deterministic Policy Gradient
DDPG	Deep Deterministic Policy Gradient
MLR	Multiple Linear Regression
CNN	Convolutional Neural Network
SIFT	Scale-Invariant Feature Transform
MLP	Multi-Layer Perceptron
RBF	Radial Basis Function
STM	Spatio-Temporal Models
GRU	Gated Recurrent Unit
MSE	Mean Squared Error
R	Pearson's Correlation Coefficient
NSE	Nash–Sutcliffe Efficiency
IoA	Index of Agreement
VAF	Variance Accounted For
CRM	Coefficient of Residual Mass
SI	Scatter Index
PPV	Peak Particle Velocity
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index
VIF	Visual Information Fidelity
UQI	Universal Quality Index
IoU	Intersection over Union
FBR	Full Bucket Rate
DE	Digging Efficacy
AA	Average Accuracy
AWA	Average Weighted Accuracy
GAN	Generative Adversarial Network
CLIP	Contrastive Language-Image Pre-Training
NMSE	Normalized Mean Squared Error
KPI	Key Performance Indicator

Appendix A

Table A1. Training validation and results—blasting phase.

Article	Dataset	Split/Train	Evaluation Method	Best Model
[52]	125	70/30	R^2 , RMSE, MAE, Adjusted R^2 , Performance Index (PI)	PCA-RF (R^2 : 0.995, RMSE: 0.011)
[28]	3740	80/20	R^2 , MAE, RMSE, Max Error	TPE-ET (R^2 : 0.93, RMSE: 0.04)
[79]	234	85/15, 200 train 34 test	RMSE, MAE, Variance Accounted For (VAF)	AW-MKL (VAF: 99.92, MAE: 0.98, RMSE: 2.05)
[27]	111	80/20 5-fold cross-validation	R, R^2 , IoA, RMSE, MAPE, NSE	CB-BOA (R^2 : 0.989)
[44]	205	80/20	R^2 , RMSE, MAE	ICA-ANN (R^2 : 0.89, RMSE: 5.66 m)
[69]	324	80/20 10-fold cross-validation	RMSE, SI, Coefficient of Residual Mass (CRM)	NCA-BPNN (R: 0.912, RMSE 1.558 dB)
[61]	100	80/20	R, MSE, RMSE	BNN (R: 0.94, RMSE: 0.17)
[70]	101	CV 80/20	R^2 , RMSE	GPR (R^2 : 0.997, MSE: 0.09)

Table A1. Cont.

Article	Dataset	Split/Train	Evaluation Method	Best Model
[31]	76	80/20 10-fold cross-validation	R^2 , RMSE, MAE, VAF	SVM-MFO (R^2 train: 0.9939; test: 0.9941)
[58]	102	70/30	R^2 , RMSE, NSE, CRM, CP	AGPSO3-ELM (R: 0.95, RMSE: 0.08, NSE: 0.9, MAE: 0.07, Cp: 0.94)
[32]	166	80/20 using a trial-and-error approach	R^2 , RMSE, MAPE, MAE, NSE	GOA-ELM (R^2 : 0.9410 (Train) and 0.9105 (Test))
[33]	136	10-fold CV, 80/20	R^2 , RMSE, MAE	FFA-GBM (R: 0.996)
[34]	62	80/20	R, MSE, MAE	XGBTree = 0.929 and MSE = 2.205.
[81]	100	70/30 SCA_ANN used Levenberg–Marquard	R^2 , RMSE	SCA-ANN: 0.9995.
[35]	120	70/30 Feature Selection (FS)	R^2 , RMSE, MAE, VAF	FS-RF (R^2 : 0.83)
[36]	102	70/30 Hyperparameter adjust	R^2	FS-RF
[67]	220	414 data for training and 74 for validation	Absolute Error of PPV, Percentage Error of PPV	GA
[64]	1001	80/20 MARS GCV	R^2 , RMSE	MARS (R^2 : 0.951, RMSE: 0.227)
[46]	162	80/20 Stacked Generalization	R^2 , RMSE, MAE, VAF	EXGBoosts (R^2 : 0.968)
[59]	216	70/30 5-fold cross-validation with 3 repetitions	R^2 , RMSE, MAE	RF Enhanced (R^2 : 0.938)
[60]	183	70/30 10-fold cross-validation	R^2 , RMSE, MAE	Random Forest (RF) (R^2 : 0.874 (train) and 0.826 (validation))
[65]	48	80/10/10 Levenberg–Marquardt (trainlm), Bayesian Regularization (trainbr) Optimization with ICA	R^2 , RMSE, MAPE, ADJUSTED R^2 , PI, VAF	ICA-ANN (R^2 : 0.962, error: 2.7%)
[62]	72	80/20	R^2 , MSE, MAPE	RF (R^2 : 0.924, MSE: 3.40)
[38]	262 + 109	80/20 Optimization: LSO and POA	R^2 , RMSE, MAPE, SI	(LSO-RF e POA-RF) ($R^2 > 0.95$)
[47]	76	70/15/15	R^2 , RMSE, MAE, CP	Z-BRCWNN R^2 of 0.999, 0.988 and 0.983
[48]	252	80/20 Cross-validations	R^2 , RMSE, MAE	JSO-CatBoost has the highest predictive performance
[66]	258	80/20	R^2 , MSE, RMSE, MAE, SI	LSTM (R^2 : 0.999)
[63]	75	80/20 5-fold cross-validation	R^2 , RMSE, SENSITIVITY ANALYSIS	CapSA-MLP (R^2 : 0.904)
[49]	262	80/20 5-fold cross-validation	R^2 , MSE, COEFFICIENT OF VARIATION (COV)	SSM-Bagging (R^2 : 0.974)
[73]	109	70, 20, 10	TAYLOR DIAGRAM, R^2 , RMSE, MAPE	DF-EDML (R^2 : 0.835 (train) and 0.820 (validation))

Table A1. Cont.

Article	Dataset	Split/Train	Evaluation Method	Best Model
[56]	1000+	70/20/10 10-fold cross-validation	R^2 , RMSE, MAE	PINNS + XGBoost (R^2 : 0.92)
[68]	457	75/25 K-Fold cross-validation normalized Min–Max	BIAS FACTOR FOR EVALUATION, R^2 , RMSE, MAE, VAF	The Voting 8 (LightGBM-GBM-DT-ET-RF- CatBoost-CART-AdaBoost-XGBoost) model has the highest R^2 (0.9876, 0.9726)
[75]	1438 Isolation Forest reduced to 992	70/30 GridSearchCV 10-fold cross-validation	R^2 , RMSE	Decision Tree Regressor (DT) optimized (R^2 : 0.997)
[40]	103 + 114	80/20 10-fold cross-validation	TAYLOR DIAGRAM, R^2 , RMSE	AHA-GPR (R^2 : 0.978)
[78]	104	80/10/10	R^2 , RMSE, MAE	ANN model with an architecture of 8-10-1 RMSE (0.273), MAE (0.189), R^2 (0.988)
[50]	118 MCs expanded to 10.000	70/30 trial and error	R^2 , RMSE, VAF	PDNN's
[51]	1032 MCs 10,000	70/30 range of 2–11 for the number of hidden nodes in BRNN	ACCURACY, R^2 , RMSE, MAE, VAF	GEP (R^2 : 0.97)
[71]	102	90 Train, 12 test, 20% train set aside for validation hyper-parameter tuning via the grid search using the 5-fold cross-validation	R^2 , RMSE	ANN (R^2 : 0.87, MSE: 0.0031)
[77]	63,116 sample images were produced. Sample images contain a total of 23,125,486	61,853 samples for training, 631 for validation, and 632 for testing	PERCENTAGE ERROR OF PPV, RESIDUAL ERROR, MSE	ResNet50
[57]	102	80% training and 20% testing 10-fold cross-validation	R^2 , MAPE, RMSE	XGBoost (R^2 : 0.952). Fragmentation Prediction (R^2 : 0.94, RMSE: 1.82, MAE: 1.4518) PPV (R^2 : 0.92, RMSE: 1.15, MAE: 0.8819)
[18]	219	199 data points were considered for training the network, 9 data points for cross-validation, 11 data points for testing the model	R^2 , MSE, RMSE, MAPE, MAE	ANN (architecture 5-64-32-16-1)
[76]	76	80/20 5-fold cross-validation	R^2 , MSE, VAF	SVR-GWO (R^2 : 0.8353)
[42]	240	80/20 Greedy layer-wise with RBM WOA for optimization	R^2 , RMSE	DNN

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