minerals

Review

Systematic Review of Machine Learning Applications in Mining: Exploration, Exploitation, and Reclamation

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Abstract: Recent developments in smart mining technology have enabled the production, collection, and sharing of a large amount of data in real time. Therefore, research employing machine learning (ML) that utilizes these data is being actively conducted in the mining industry. In this study, we reviewed 109 research papers, published over the past decade, that discuss ML techniques for mineral exploration, exploitation, and mine reclamation. Research trends, ML models, and evaluation methods primarily discussed in the 109 papers were systematically analyzed. The results demonstrated that ML studies have been actively conducted in the mining industry since 2018, mostly for mineral exploration. Among the ML models, support vector machine was utilized the most, followed by deep learning models. The ML models were evaluated mostly in terms of their root mean square error and coefficient of determination.

Keywords: mining; machine learning; artificial intelligence; mineral exploration; mineral exploration; mine reclamation

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1. Introduction

Humans learn from their day-to-day lives owing to their ability to think; for example, they can learn from an education or from their thoughts and memories. However, computers learn through algorithms, unlike humans. This is called machine learning (ML). ML uses computer algorithms to simulate human learning and allows computers to identify and acquire knowledge from the real world, thereby improving the performance of certain tasks based on the newly acquired knowledge. Precisely, ML is defined as follows: "A computer program is said to learn from experience E corresponding to certain class of tasks T and performance measure P, if its performance at tasks T, as measured by P, improves with experience E" [1]. Although initial concepts of ML originated in the 1950s, ML was considered as an independent field in the 1990s [1]. ML algorithms are used in the fields of computer [2,3], health [4], environment [5], medicine [6,7], energy [8], and services [9].

Smart mining is being considered in the mining industry. Smart mining technology is the introduction of cutting-edge information and communication technologies, such as Internet of Things (IoT), big data, mobile, artificial intelligence (AI), augmented reality, and virtual reality, in the field of mineral resource development [10]. Because of the development of smart mining technologies, a large amount of data is being produced, collected, and shared in real time. The availability of various data—such as drilling data, data received from sensors, and measurement data—development of AI techniques, advancement of computation skills of computers, and ML have gathered attention to data science in the mining field.

Various projects are being implemented to apply ML at mining sites. To obtain additional gold deposits from the Red Lake mine in Canada, geologists at Goldcorp used IBM's Watson Artificial Intelligence Supercomputer to interpret the exploration data and then discover new minerals [11,12]. Manufacturers of heavy equipment for construction and mining, such as Komatsu and NVIDIA, implemented joint projects to help identify workers and equipment at mining sites. The technologies developed can identify inefficient equipment and keep workers safe [13]. Newtrax, a company that provides safety and operational management system services in underground mines, and IVADO, a Canadian artificial intelligence research institute, are collaborating on pilot projects to collect big data from sensors installed in mining equipment, analyze data via ML to predict when mining equipment has failed and requires maintenance [14,15].

In [16–19], ML applications have been reviewed for mineral processing as well as soft computing technology in exploration, digitalization trends in the mining industry, and automation in the mining sector. However, the study lacks a systematic review of ML applications in mining, which includes mineral exploration, exploitation, and mine reclamation.

Therefore, this study systematically reviews the methods used by ML research projects and their implementations in the mining field. The ML research trends, ML models and ML model evaluation metrics used in research projects are mainly examined. It should be noted that the ML research projects for mineral processing were not considered in this study because their reviews were already reported in the literature [16].

2. Methods for Systematic Review

A systematic literature review (often referred to as systematic review) facilitates the identification, evaluation, and interpretation of all the available research related to a particular research question, subject, or a phenomenon [20]. The review intends to provide solutions to research related questions.

In this study, research questions were initially organized to define the scope and overall objectives of the analysis. Subsequently, a search method was designed to efficiently find research papers related to the research questions, which was followed by the establishment of standards to select suitable studies from the search results. Later, the abstract and results of the papers were examined to find their relevance in the research field. The process was followed by the data extraction from the paper to distinguish and structure the related information as follows:

- RQ 1: What are the ML research trends in the mining industry (yearly, publication sources, detailed application fields)?
- RQ 2: Which ML models were used in your research (data type, large data, model usage frequency, detailed application in the field)?
- RQ 3: How did you evaluate the ML models (model evaluation data, evaluation metrics, quantification of the evaluation results by models)?

The primary purpose of this review was to report the current status of ML usage in the mining sector. Research questions were selected according to the purpose. RQ 1 aimed at describing the trends in ML research in the mining field. Comprehensively, it referred to the current status of the yearly thesis publication and their detailed applications in the field. RQ 2 classified the ML model used in the study. Specifically, it referred to the learning data type, utilization of a large amount of data, and usage frequency of the model and its detailed application in the field. RQ 3 analyzed the evaluation of ML models. In detail, it referred to ML model evaluation data, evaluation metrics, and evaluation results by the model.

2.1. Search Method

We used Google and Scopus as search engines. We derived search keywords related to the subject of this review: mine, mineral, machine learning, deep learning, open-pit, underground mine. The keywords, machine learning and deep learning, were used to find papers that use ML and deep learning methods among various research methods. The rest of the keywords defined the field. To analyze research trends of the past decade, only the research projects that were conducted between January 2011 and September 2020 were considered. We secured 264 candidate papers using the described method.

2.2. Selection Criteria

Published papers can be considered to have met the criteria of originality, high influence, and high standards. This is because such manuscripts are reviewed by experts and then revised accordingly before publication. Therefore, we have chosen published papers. The selection criteria were as follows: (1) research papers; (2) full-text; (3) mineral processing exclusion. These criteria were chosen because of the following reasons: only research papers were used to analyze current status of ML, and full-text enabled an accurate analysis of the content of the paper. The mineral processing was excluded because a few recent studies had reviewed and published on the subject of ML applications in mineral processing [16].

The search results database included 263 papers. Because of the first criterion, the number of related papers decreased to 251. The second criterion decreased the number to 249. After three steps, 109 papers were selected, as shown in Figure 1.

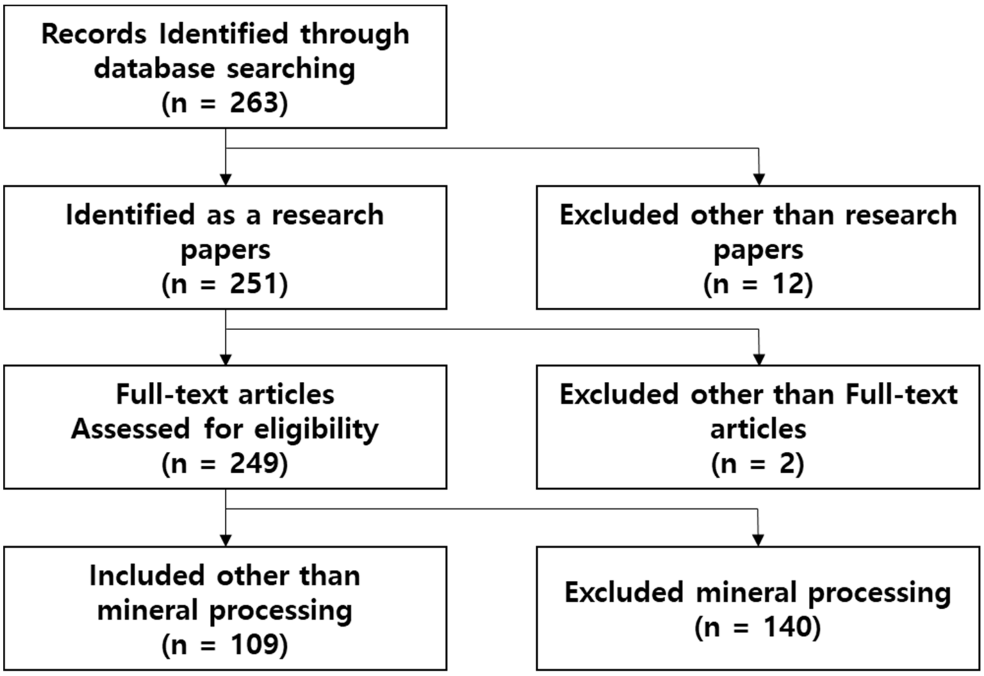

Figure 1. Flow chart of the selection process.

3. Results

3.1. RQ 1: ML Research Trends in the Mining Industry

3.1.1. Publication Year

To examine the research trends, we decided to inspect the publication year of the research papers as an initial step. Figure 2 shows the distribution of research from January 2011 to September 2020. It exhibits an intense upward trend for the last three years. It can be observed that 51 out of 109 papers were studied before 2018. The number of studies conducted in 2018, 2019, and September 2020 were 18, 28, and 12, respectively. In 2018, the number of articles published were three times higher than the previous year. Research conducted in the last three years accounted for approximately 53% of the total research conducted in the last ten years.

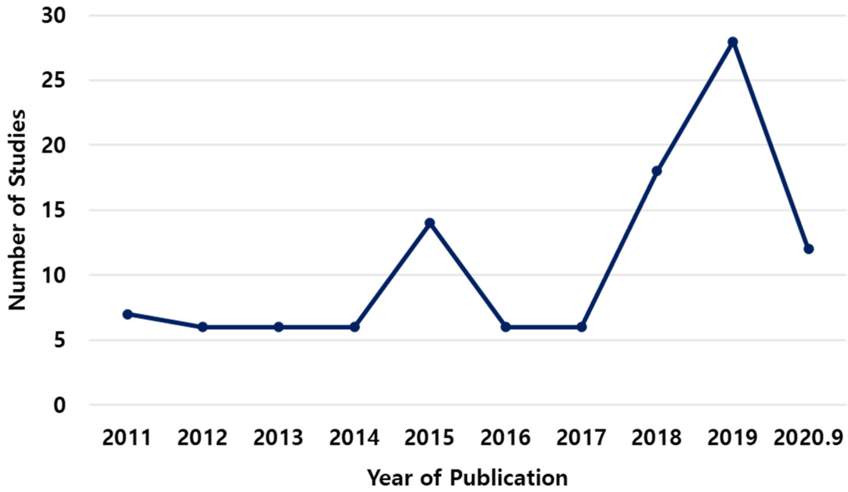

Figure 2. Publications per year (January 2011–September 2020).

3.1.2. Publication Source

Several research papers have been published in various journals. Table 1 summarizes the details of the publications in top journals along with the number of papers published. The highest number of papers were found in *Natural Resources Research*, *Ore Geology Reviews*, *Applied Sciences*, followed by others.

Table 1. Summary of top publications.

Publication Name	Number of Research Papers
Natural Resources Research	7
Ore Geology Reviews	6
Applied Sciences	3
Acta Geophysica	2
Computers & Geosciences	2
Engineering with Computers	2
Environmental Earth Sciences	2
IEEE Access	2
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	2
International Journal of Remote Sensing	2
Journal of Geochemical Exploration	2
Journal of Mining Science	2
Journal of Vibration and Control	2
Resources Policy	2
Rock Mechanics and Rock Engineering	2
Sensors	2

3.1.3. Detailed Fields of Application

We analyzed the fields involving active research. For the classification of work, a technical map of the mining sector was created. The first stage included three stages of the mining process, which were exploration, exploitation, and reclamation. Each item was classified in detail. The second stage consisted of mineral exploration and targeting, and mine planning and evaluation under the exploration phase. The exploitation phase was classified as drilling and blasting, equipment management, geotechnical management, and mine safety. The reclamation phase was divided into land cover (monitoring) and mine hazard (assessment). In the third stage, we added related fields under the second stage item. Using 109 papers, we divided the mining field into 34 fields, as shown in Figure 3.

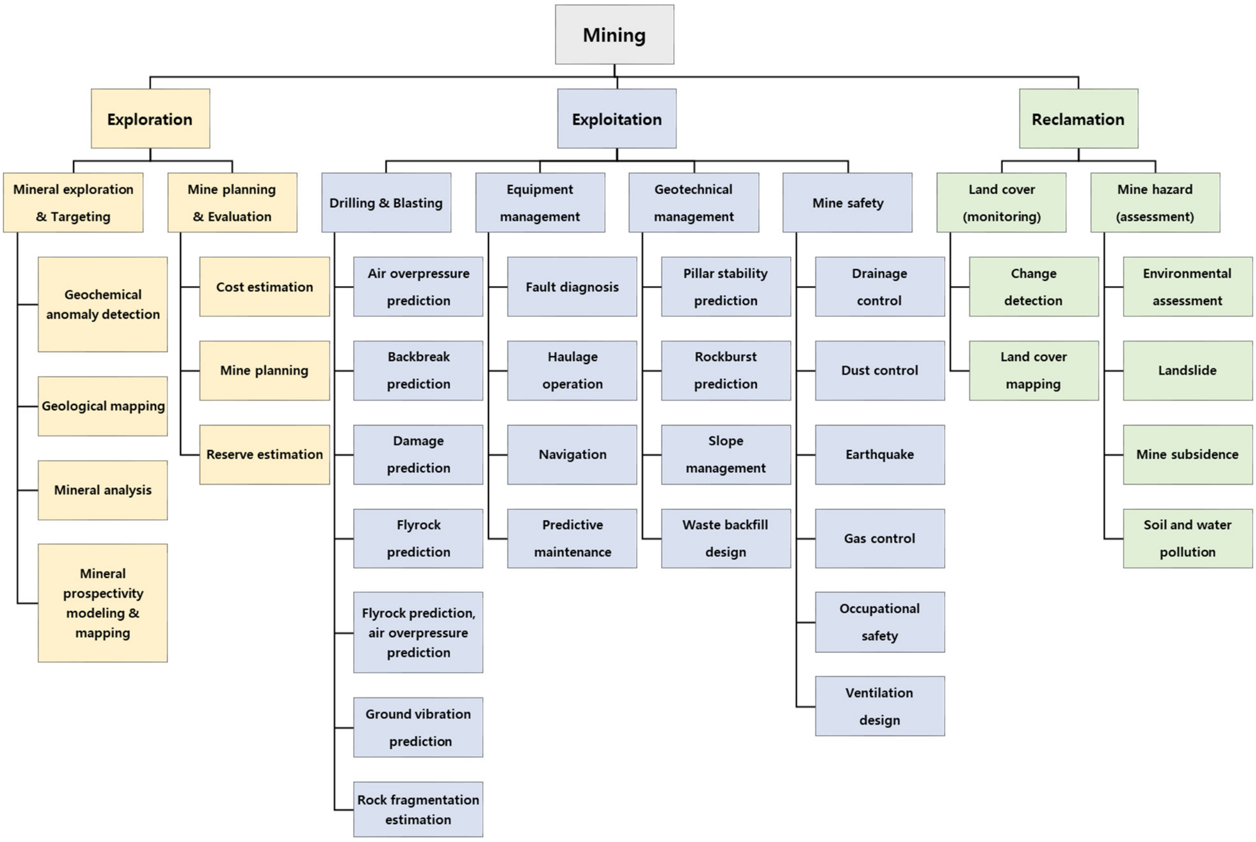

Figure 3. Research application fields.

In the first stage of classification of the mining process, 59 studies were conducted in the exploitation stage (shown in Figure 4). Figure 5 shows the research status of the items in the third stage of classification. A total of eleven studies related to mineral prospectivity modeling and mapping in the field of exploration, ten studies related to ground vibration prediction in the field of exploitation, and six studies related to soil and water pollution in the stage of reclamation were conducted.

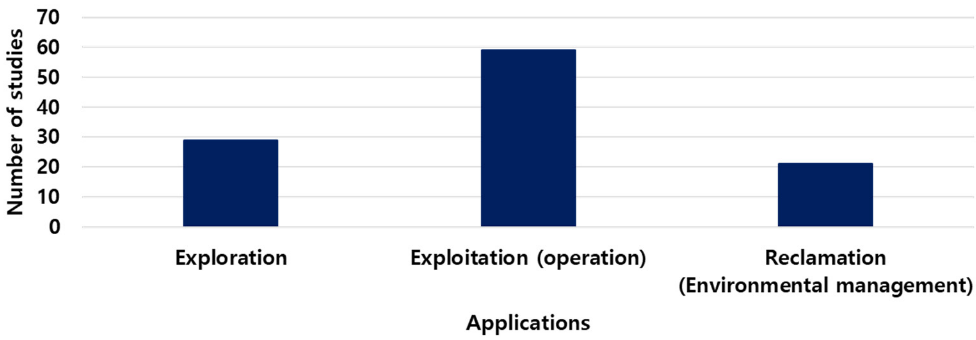

Figure 4. Number of studies based on the study of application fields.

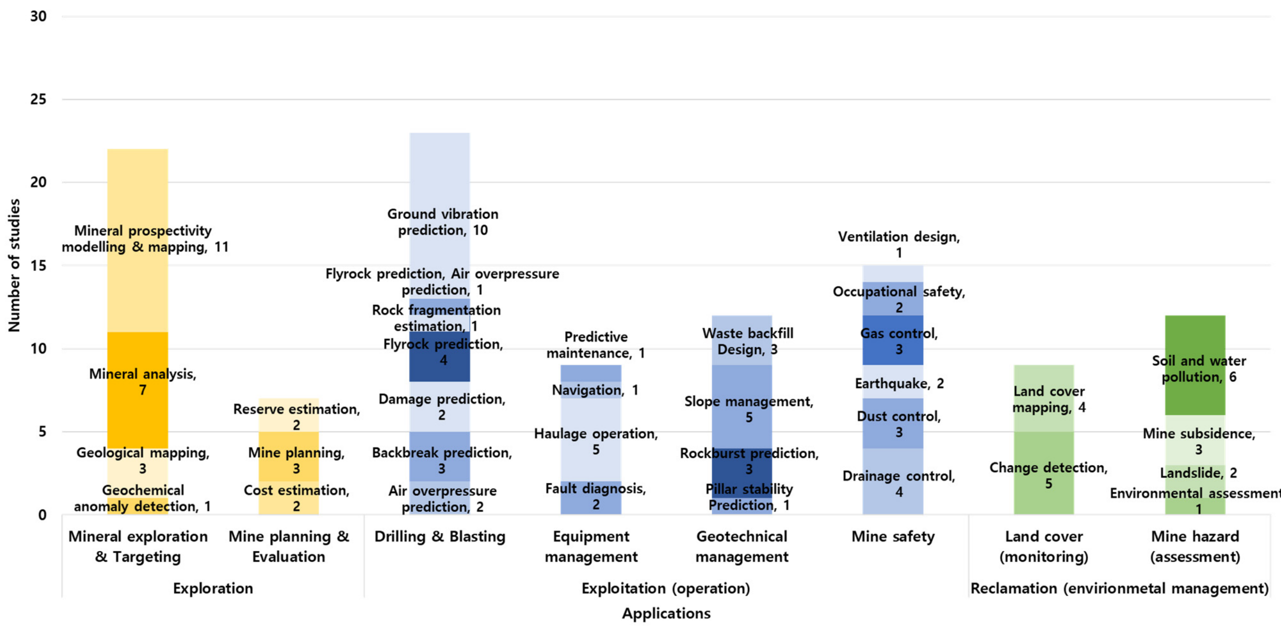

Figure 5. Detailed graph presenting the number of publications.

The research status of each field was examined as the elements of second stage. In the field of mineral exploration and targeting, a geochemical anomaly detection [21] study that uses the exploration data to detect geochemical abnormalities was conducted. Geological mapping [22–24] studies were conducted using the characteristics of rocks. A mineral analysis [25–31] was conducted using drilling data or samples. A mineral prospectivity modeling and mapping [32–42] study was performed to evaluate the potential of minerals using the exploration data.

In the areas of mine planning and evaluation, research on cost estimation was performed [43,44] to predict mine operation expenses and mine planning [45–47] to optimize the mine design. Reserve estimation [48,49] research was conducted that considered the reserves and economic values required for mine operations.

In the drilling and blasting items, air overpressure prediction [50,51], backbreak prediction [52–54], flyrock prediction [55–58], flyrock prediction and air overpressure prediction [59], ground vibration prediction [60–69], and rock fragmentation estimation [70] were performed to investigate the changes in the barometric pressure, vibration, monument, and earthquake created while drilling and blasting. A damage prediction [71,72] study was conducted, wherein the damage caused to the surrounding residential areas by a blasting from an open-pit mine was predicted [71].

In the equipment management category, a fault diagnosis [73,74] study that diagnosed equipment defects was performed. Haulage operations [75–79] and navigation [80] studies were conducted to optimize the transportation means, such as trucks and loaders, and to indicate the travelling mode of equipment, respectively. Predictive maintenance [81] study was performed to enhance the mine operation efficiency by predicting the equipment failure.

In the ground management category, a pillar stability prediction [82] technique predicted the stability of underground mine columns. Rockburst prediction [83–85] was performed to classify and predict the explosion of rocks by using the characteristics and time data of the exploded rocks. Slope management [86–90] studies were conducted to predict the slope deformation of the mine and to evaluate its stability. The waste backfill design [91–93] predicted the design and strength of the backfill.

In the mine safety item, a study on the drainage control [94–97] was conducted to predict the groundwater level or the inflow of mines. Dust control studies evaluated and predicted the air quality of mines [98–100]. A study predicted the occurrence of an earthquake [101,102] by considering the time data of the increasing seismic activity in coal mines. A gas control [103–105] study was conducted to predict the generation of hazardous gases in mines. There were studies on occupational safety [106,107] that detected the equipment and predicted accident probabilities, thereby preventing accidents and facilitating the designing of suitable ventilations [108].

In the area of land surface detection, change detection [109–113] and land cover mapping [114–117] studies were performed to detect the land surface that changed during mine operation, and to classify the surface composition, respectively.

In the mine risk assessment section, an environmental assessment [118] study assessed and classified the geographical environmental quality. Several studies were conducted to assess and map the risk of landslides [119,120] and mine subsidence [121–123]. A study was conducted to predict and evaluate soil and water pollution [124–129] caused by the mine operation.

3.2. RQ 2: ML Models

3.2.1. Data set type

Several data sets have been used in ML studies. The data were acquired either from publicly available open-sources or individually in the case of private data. Therefore, the data were classified into the data that can be acquired directly used in the field, the data that must be acquired in the field, followed by a laboratory processing, and can later be used publicly. Open-source data sets used are publicly available or are private in nature (such as RapidEye, NASA, and Minto) [2]. In a study, research was conducted using various data. Therefore, the total number of data utilization was 121. The highest number of used data was 57, which were acquired from an open source (Figure 6).

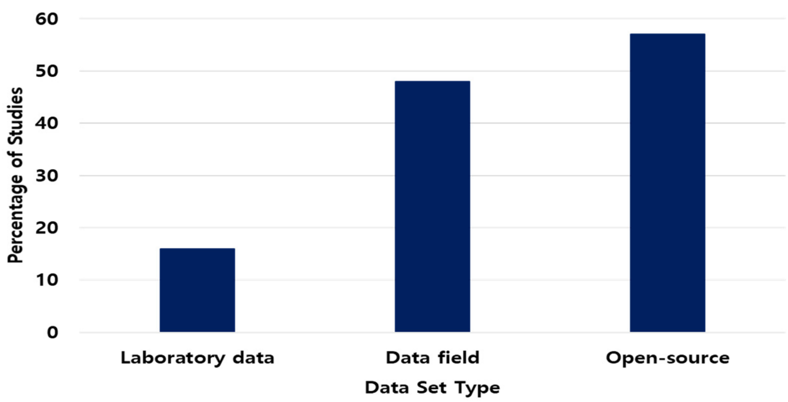

Figure 6. Data set type.

3.2.2. Big Data

Big data is typically from 1 terabyte to 1 petabyte of data and comprises structured data (e.g., tables of numbers) and unstructured data (e.g., photos and documents) [130]. In other words, it is a technology that utilizes a lot of data. ML algorithms, by definition, improve their performances with access to additional data [8]. Therefore, data influences the research involving ML. A large amount of data is beneficial and can be applied to varying sites and laboratories. Therefore, we considered studies that had discussions or comments on big data. Table 2 presents the number of studies that include or mention big data in their manuscripts.

Table 2. Big data technologies.

Big Data Technologies	Number of Studies	Studies
Yes	9	[32,36,38,45,49,76,77,87,92]
No	100	Other studies

3.2.3. ML Models

Based on the selected paper, the ML model was classified. In a particular study, studies used various models to compare models. As a result of analyzing the studies, the total number of models used was found to be 255. The models were categorized into a total of 12 types: deep learning, ensemble, clustering, dimensionality reduction, genetic algorithms, neural network, bayesian, decision tree, instance based, regression, support vector machine (SVM), and gaussian process. Figure 7 represents the classification details of ML technique. Figure 8 indicates the usage frequency of ML models in the study. The most frequently used models were SVM (n = 58), deep leaning (n = 56) and ensemble (n = 56) (Figure 8). Figure 9 shows the distribution of the ML technologies; a minimum of three model categories are based on each of the technologies.

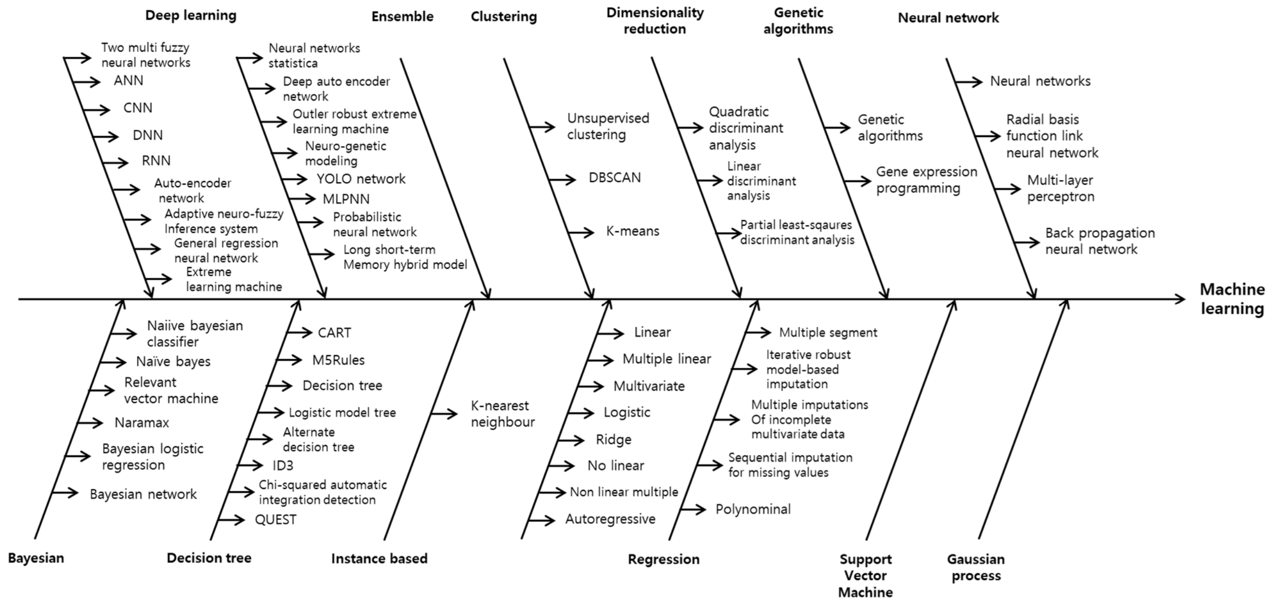

Figure 7. Classification of ML techniques. ANN: artificial neural network, CNN: convolutional neural network, DNN: deep neural network, RNN: recurrent neural network, DBSCAN: density-based spatial clustering of applications with noise, YOLO: you only look once, MLPNN: multiple-layer perceptron neural network, CART: classification and regression tree, ID3: iterative dichotomiser 3, QUEST: quick unbiased efficient statistical tree algorithms.

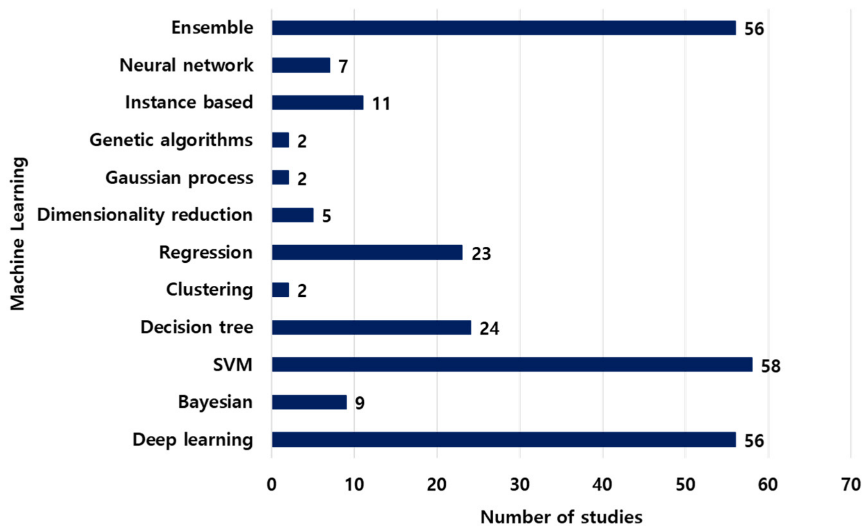

Figure 8. Usage frequencies of ML models.

Figure 9. Distribution of the detailed ML model usage.

3.2.4. ML Model Used for Specific Purposes in Mining

We compared stage two items in mining with 12 ML models and examined the usage frequencies of models in each field. In mineral exploration and targeting, ensemble and decision tree methods were extensively used in mine planning and evaluation. Deep learning was primarily used in drilling and blasting, equipment management, ensemble in geotechnical management, and mine safety. In several cases, SVMs were used in land cover monitoring and mine hazard assessment. In the third stage of mining process, ensemble, deep learning, and SVM methods were used in the exploration stage, exploitation stage, and reclamation stage, respectively (Figure 10).

3.3. RQ 3: ML Model Evaluation

3.3.1. Model Evaluation Data

Data were required to evaluate the performance of ML models. After training an ML model, data were provided to evaluate the accuracy of the model; these data include training data for realizing ML, validation data, and test data. Validation data are used for verification purposes to select the most suitable model among all ML models. Test data are used to determine how well the selected ML model works [131]. The data used to evaluate the model were used in 75 studies (Figure 11). Finally, to measure the performance of the model, evaluation metrics were utilized.

3.3.2. Model Evaluation Metrics

Evaluation metrics are used to compare and evaluate the developed ML model and various statistical techniques. The evaluation indices depend on the purpose of the ML model. ML models used for classification (e.g., prediction of ore production and crusher utilization [76] and prediction of flyrock in open-pit blasting operations [57]) are generally evaluated in terms of the receiver operating characteristic/area under the curve (AUC) or confusion matrix. Models associated with regression (e.g., to estimate the cost of a mine, the cost is estimated using various variables such as the capacity of the mine and the distance from the railroad [43,44]) are generally evaluated in terms of the mean squared error (MSE), mean absolute error (MAE), or coefficient of determination (R) [2]. However, several studies have used similar evaluation metrics without considering the purpose of the ML model, as shown in Figure 12. A total of 30 evaluation matrices were used: coverage, negative predict value, positive predict value, specificity, sensitivity, support, Pearson correlation, relative absolute error, MSE, mean absolute difference, least mean square, fractional error, error, corresponding to relative errors, rank probability skill score, root mean square error (RMSE), MAE, F-measure, recall, precision, F1-score, AUC, kappa, accuracy, R, multivariate adaptive regression spline, variant allelic frequencies, median absolute error, mean absolute percentage error, and root relative squared error.

	Exploration		Exploitation (operation)				eclamation (Envirionmetal Management		
	Mineral Exploration & Targeting	Mine Planning & Evaluation	Drilling & Blasting	Equipment management	Geotechnical management	Mine safety	Land cover (Monitoring)	Mine hazard (Assessment)	Total
Deep learning	6	3	17	4	8	11	2	5	56
Bayesian					3	3	1	2	9
Ensemble	12	1	12	5	15	6	5		56
Decision tree	2	4	3		4	5		5	23
Instance based	1		3		2	3	1	1	11
Clustering	2								2
Regression	4		11	1	2	1		4	23
mensionality reduction	1				4				5
Genetic algorithms				1	1				2
Support vector machine	10	1	12	3	11	6	8	8	59
Neural network	2	1				4			7
Gaussian process	1				1				2
Total	41	10	58	14	51	39	17	25	

Figure 10. Mining applications underpinned by ML models.

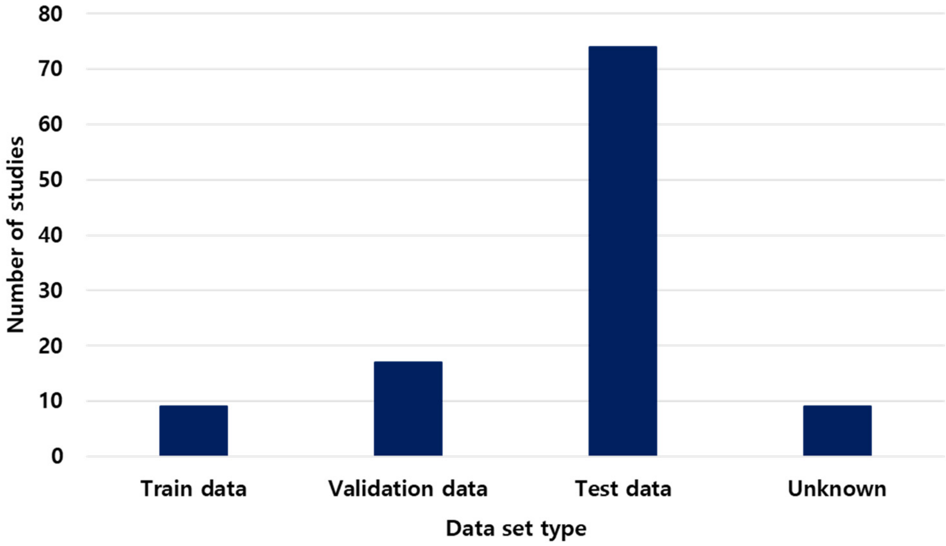

Figure 11. Model evaluation based on the data set type.

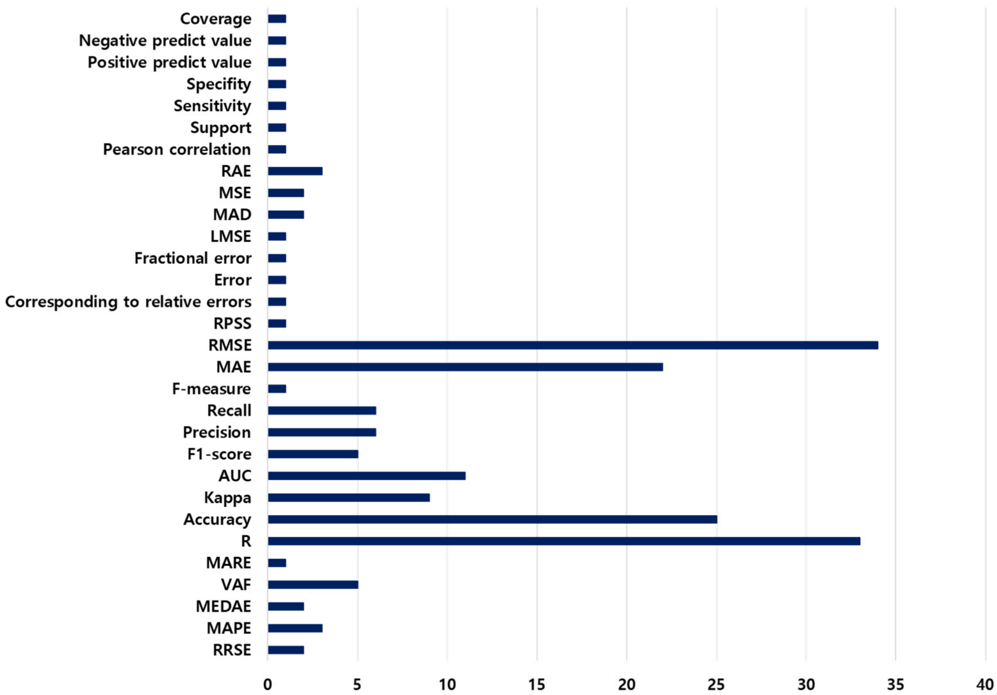

Figure 12. Studies employing different performance measurements(RAE: relative absolute error; MSE: mean squared error, MAD: mean absolute difference, LMSE: least mean square, RPSS: rank probability skill score, RMSE: root mean square error, MAE: mean absolute error, AUC: area under the curve, R: coefficient of determination, MARE: multivariate adaptive regression spline, VAF: variant allelic frequencies, MEDAE: median absolute error, MAPE: mean absolute percentage error, RRSE: root relative squared error).

A total of 34 studies used RMSE, making it the method with the highest number of applications, followed by the R, accuracy, MAE, and AUC. An ideal prediction is represented by R = 1.0, RMSE and MAE = 0, and AUC = 1.0 [132]. The evaluation metrics results of each ML model of five evaluation indicators used in several studies were summarized using Boxplot (shown in Figures 13–17). This enabled us to analyze the overall evaluation metrics of ML techniques. In terms of RMSE, deep learning performed best with an average of 0.000608 calculated based on 34 studies, followed by the SVM and ensemble models. However, the model that exhibited the worst performance was deep learning. Based on the 35 papers using R, SVM performed best with an average of 0.996, followed by ensemble and deep learning. Based on the 25 studies wherein the evaluation index was accuracy, SVM performed best with an average of 1.0, followed by ensemble and deep learning. Based on the 22 papers considering MAE, deep learning exhibited the best performance with an average of 0.009, followed by SVM and regression. In the 11 papers considering AUC, the best-performing model was ensemble with an average of 0.96, followed by Bayesian and decision tree.

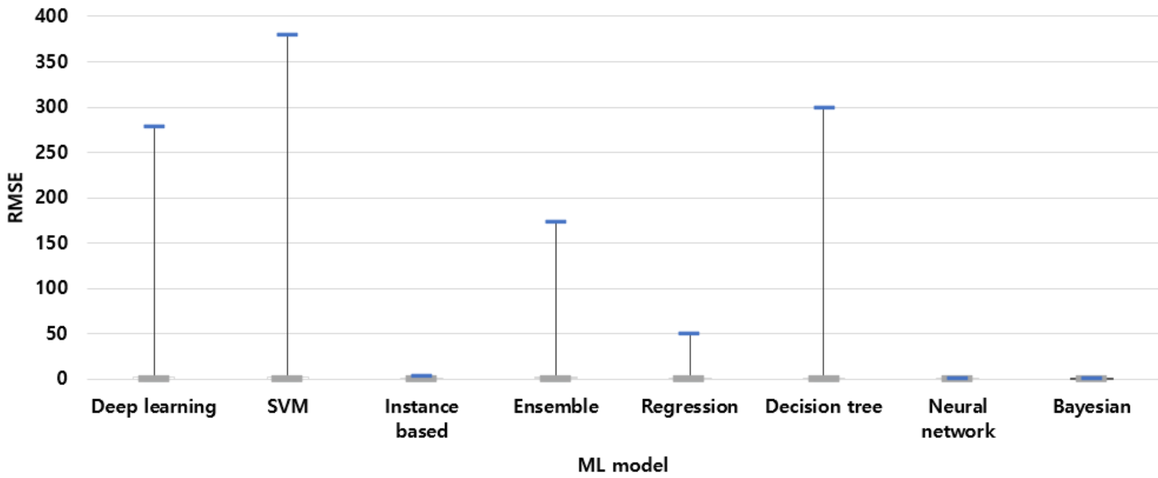

Figure 13. Box plots for RMSE.

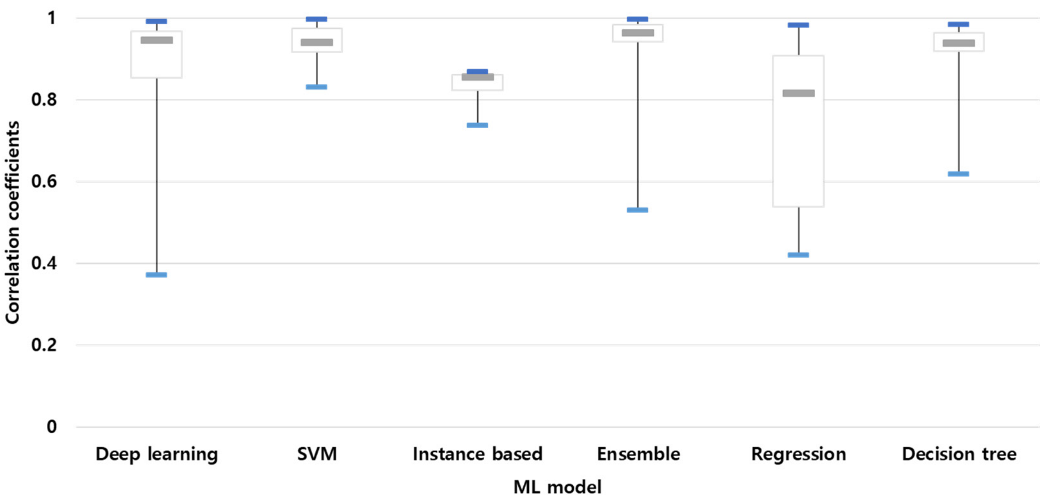

Figure 14. Box plots for R.

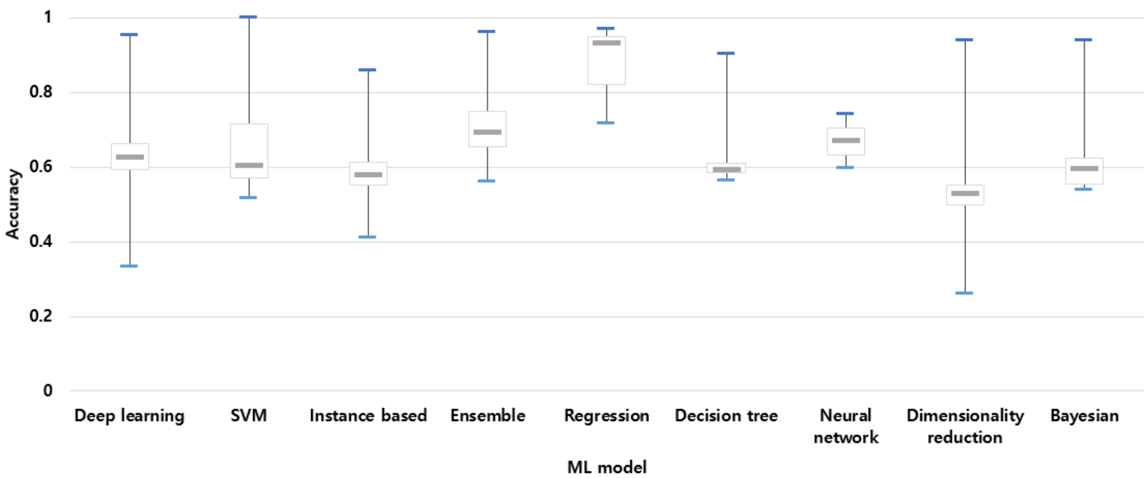

Figure 15. Box plots for accuracy.

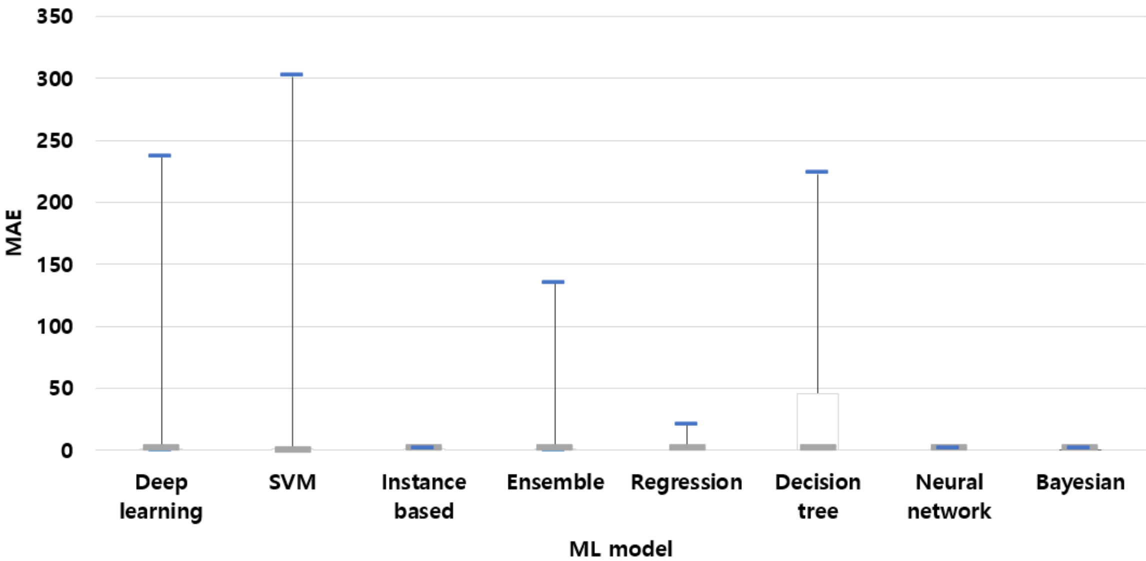

Figure 16. Box plots for MAE.

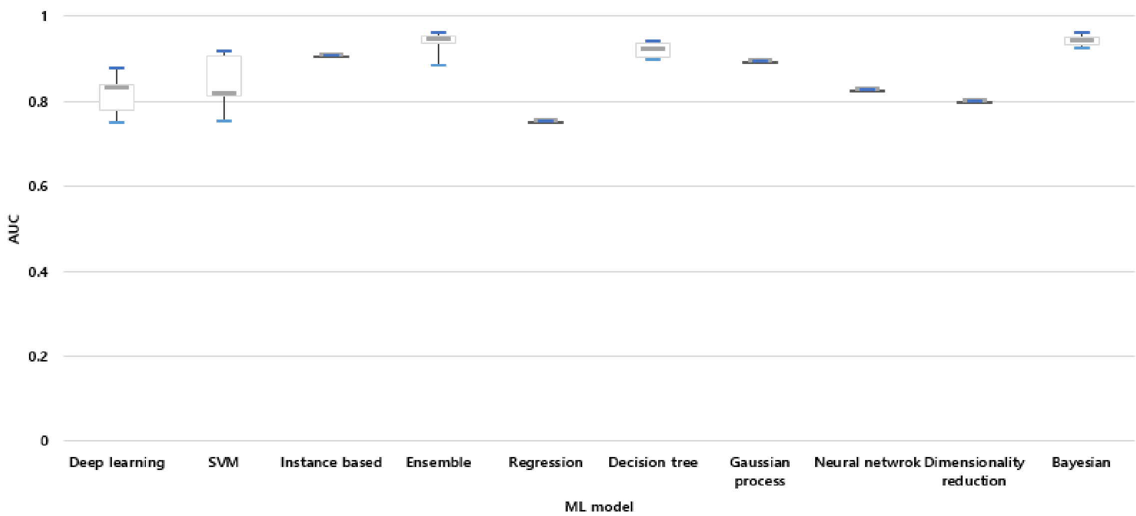

Figure 17. Box plots for AUC.

4. Conclusions

Systematic reviews were conducted to examine the current trends in ML research related to the mining industry and analyze previous studies in the specific subject areas. The review provides an overview of the research conducted so far and assistance for future research.

The answers for research questions are summarized as follows:

- Several studies have been conducted since 2018, and the highest number of studies have been conducted in the drilling and blasting items in the exploitation stage.
- The research was conducted using the open-source data predominantly. Ensemble, deep learning, and SVM were extensively used in the fields of exploration, exploitation, and reclamation, respectively.
- The ML model was evaluated using test data, and the evaluation metrics used were RMSE, R, accuracy, MAE and AUC.

Since 2018, several studies have been conducted on ML techniques in the mining industry, demonstrating the increased attention ML-related research has been receiving. In addition, the fact that research is being actively conducted in the fields of drilling and blasting shows that a large amount of corresponding data is now available. We employed open-source data that are relatively easy to obtain. Open-source data based on ML techniques can be easily accessed by researchers. An ML model can be effectively selected by considering the research purpose to improve the performance of the model. Ensemble, deep learning, and SVM are commonly used because these models can be configured in various manners according to their purpose. To evaluate the performance of the ML model, an evaluation index can be selected according to the objective of the study. If the aim is to reduce error, you can choose RMSE and MAE; to evaluate accuracy, accuracy and AUC; to compare model performances, R.

Author Contributions: Conceptualization, Y.C.; Methodology, Y.C.; Software, D.J.; Validation, D.J.; Formal Analysis, D.J.; Investigation, Y.C.; Resources, Y.C.; Data Curation, D.J.; Writing—Original Draft Preparation, D.J.; Writing—Review & Editing, Y.C.; Visualization, D.J.; Supervision, Y.C.; Project Administration, Y.C.; Funding Acquisition, Y.C. All authors have read and agreed to the published version of the manuscript.

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