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Review

Advancements in Machine Learning for Optimal Performance in Flotation Processes: A Review

Alicja Szmigiel [1], Derek B. Apel [1,*], Krzysztof Skrzypkowski [2,*], Lukasz Wojtecki [3] and Yuanyuan Pu [4]

[1] School of Mining and Petroleum Engineering, University of Alberta, Edmonton, AB T6G 2R3, Canada; szmigiel@ualberta.ca
[2] Faculty of Civil Engineering and Resource Management, AGH University of Krakow, 30-059 Krakow, Poland
[3] GIG Central Mining Institute, 40-166 Katowice, Poland; lwojtecki@gig.eu
[4] State Key Laboratory of Coal Mine Disaster Dynamics and Control, Chongqing University, Chongqing 400044, China; haoxueyue@cqu.edu.cn
* Correspondence: dapel@ualberta.ca (D.B.A.); skrzypko@agh.edu.pl (K.S.)

Abstract: Flotation stands out as a successful and extensively employed method for separating valuable mineral particles from waste rock. The efficiency of this process is subjected to the distinct physicochemical attributes exhibited by various minerals. However, the complex combination of multiple sub-processes within flotation presents challenges in controlling this mechanism and achieving optimal efficiency. Consequently, there is a growing dependence on machine learning methods in mineral processing research. This paper provides a comprehensive overview of machine learning and artificial intelligence techniques, presenting their potential applications in flotation processes. The review demonstrates advancements discussed in scholarly research over the past decade and highlights a growing interest in utilizing machine learning methods for monitoring and optimizing flotation processes, as demonstrated by the increasing number of studies in this field. Recent trends also suggest that the course of flotation process monitoring, and control will increasingly focus on the refinement and deployment of deep learning networks developed specifically for froth image extraction and analysis.

Keywords: flotation; machine learning

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1. Introduction

Flotation is a widely employed method in mineral processing and beneficiation for effectively separating mineral particles. The investigation for consistent monitoring and precise control of the flotation process has been a persistent pursuit among engineers, reflecting the importance of maintaining optimal conditions for efficient mineral separation. However, implementing such a complex control system requires substantial financial investments in equipment, leading to considerable costs. Furthermore, the ongoing maintenance required to sustain the high standards of a monitoring system adds additional expenses. In response to these challenges, estimation models appear to constitute efficient and economically reasonable solutions for managing the complexity of the flotation process.

Machine learning (ML) involves the development of algorithms and models that enable computers to learn from and make predictions or decisions based on data provided, without being explicitly programmed. The construction of ML models involves several key steps, including data collection, preprocessing, feature engineering, model selection, training, validation, and testing. Preprocessing of the data is particularly important as it involves cleaning, transforming, and organizing the raw data to make it suitable for model training. This step may include handling missing values, normalization, feature scaling, and encoding categorical variables. Effective preprocessing ensures that the data are of high quality and that the model can learn meaningful patterns and relationships from it. Choosing an appropriate machine learning model is crucial as it directly impacts the accuracy, interpretability, and generalization ability of the predictions. Different machine learning algorithms have varying strengths and weaknesses, and selecting the right model ensures that the data are effectively captured and utilized to make informed decisions. Validation and testing are essential steps that allow the assessment of the performance and generalizability of models beyond the training data.

The influence of machine learning and artificial intelligence is transforming diverse fields, ranging from daily life to advanced scientific applications. Witnessing rapid integration across various disciplines, including voice and facial recognition, self-driving cars, spam filtering, and social media platforms, the influence of these technologies is evident on a global scale. Over the past decade, researchers have brought to light various challenges within the mineral beneficiation process, presenting the potential solutions that exist in machine learning and artificial intelligence techniques. This trend closely aligns with the rapid progress in computing sciences, a substantial expansion of available data, and an expanded understanding of machine learning and artificial intelligence methods. The accumulation of these advancements has yielded ML techniques that are more accessible, extending their applicability across many fields. These models can effectively address various challenges associated with the flotation process, including predictions of grade and recovery, optimization of reagent dosages, and other critical parameters essential for enhancing process efficiency and productivity.

In this review, our objective was to explore recent advances in machine learning applications within froth flotation processes, focusing on developments from the past decade to provide a comprehensive understanding of the field's current state. To achieve this, we conducted an extensive search of scholarly publications, and categorized them into distinct groups such as predictive models for grade and recovery, evaluation of flotation parameters, and froth image analysis. Additionally, we conducted a detailed analysis to visualize trends in ML applications over time and within specific research areas, identifying popular ML models and their impact on predictive modeling and performance monitoring strategies. Our review underscores the increasing interest in ML for optimizing flotation processes, especially in the development of deep learning networks for froth image analysis and extraction.

2. Background and Methodology: Flotation Processes and Review Composition

Flotation, a highly popular method in mineral processing, has a significant influence in the segregation of valuable mineral particles from accompanying waste material. Its efficacy comes from the diverse physicochemical surface properties displayed by various minerals, distinguishing them as either hydrophobic or hydrophilic. The effectiveness of the flotation mechanism lies in exploiting these differences, allowing for a selective and efficient separation process based on the tendency of minerals to adhere to either water or air bubbles.

2.1. Description of the Floatation Process

The flotation process occurs in the aquatic environment within dedicated flotation cells that are aerated to generate air bubbles. A motor is employed to agitate and stir the slurry, ensuring the particles remain suspended uniformly throughout the duration of the process. The rotational speed of the motor depends on factors such as the size of the cell, the motor type, and the properties of the materials, ranging from dozens to hundreds of rotations per minute. Hydrophobic particles tend to adhere to the air bubbles and are then carried by them to the surface and create a froth that is continuously removed from the cell. Hydrophilic particles, however, do not float into the froth and are depressed to the bottom of the cell. The perfect flotation process appears when each valuable particle collides and adheres to the air bubble and does not detach from it until removed with the froth. Throughout the flotation process, various reagents including collectors, depressants, frothers, and activators are utilized to enhance the efficiency of mineral separation [1].

The effectiveness of flotation relies on the interaction of multiple factors, including particle characteristics, hydrodynamic conditions, and gas dispersion [2]. An example of a froth flotation cell is shown in Figure 1, and a real photo from the flotation plant is shown in Figure 2.

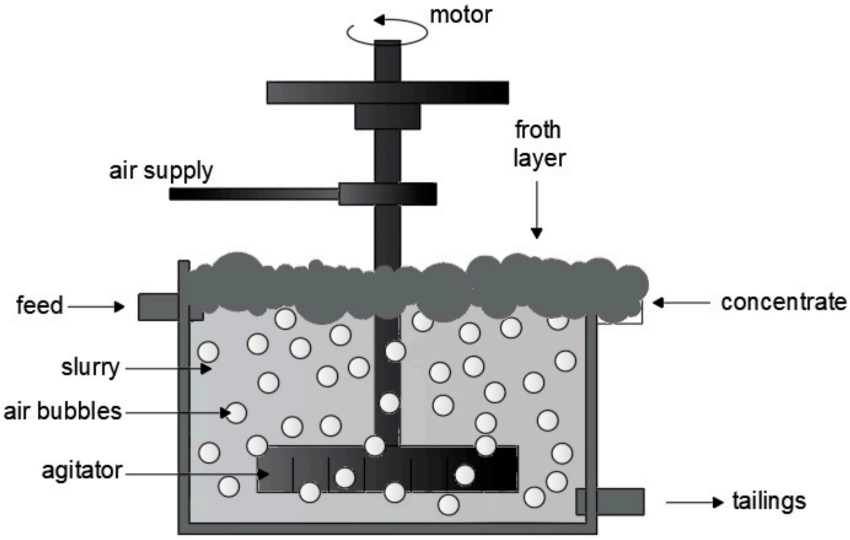

Figure 1. Flotation cell.

Figure 2. Photo of real flotation cells from the processing plant (photo taken by the authors).

2.2. *Difficulties and Challenges in Flotation Processes*

Flotation is a separation mechanism engaging numerous interconnected sub-processes, the collective operation of which determines its overall success. The complexity and interrelationship of various factors involved directly impact the development of a successful prediction model [3]. A satisfying system of controlling flotation is challenging to obtain because of the dynamic and non-linear nature of the mechanism [4].

To develop a machine learning model, it is crucial to collect data with an extensive number of variables. Such variables include characteristics of the pulp that is being fed into the flotation cell (flow rate, amount of material, distribution of particles size, grade, etc.), physicochemical information (the quality of water, types and amounts of reagents used in the process, temperature of the flotation environment, pH value, bubble distribution, aeration rate, etc.) [5]. The size, structure, and strength of air bubbles significantly impact the success of the flotation process. If the bubbles are too large, they are prone to bursting, potentially causing valuable minerals attached to them to sink to the bottom of the cell and be treated as tailings [6].

The optimal performance of the flotation process relies on achieving a suitable balance between the grade and recovery of the concentrate. In many cases, when the grade of concentrate is raised using controlling methods, a higher amount of important minerals might be wasted in tailings. However, if it is decided to increase the recovery of the product, more unwanted gangue minerals could float with the bubbles, reducing the quality of the concentrate. Given the substantial volume of material processed in the plant, even minor unfavorable alterations can lead to considerable economic losses [7]. The complexity of the flotation mechanism is further compounded by the sequential nature of the process. Typically, multiple flotation cells operate simultaneously within processing plants. The output from one cell is transferred to another cell for further processing. Moreover, tailings often undergo additional cleaning flotation in subsequent cells to ensure comprehensive recovery of valuable minerals.

The primary indicators of process efficiency are the concentration of valuable particles in the final product and the recovery. Hence, it is essential to monitor and regulate both the feed grade entering the flotation circuit and the grade of the final concentrate. This information can be obtained through online measurements from various monitoring devices and laboratory analyses. Using these data, the recovery can be determined through straightforward calculations. However, a significant drawback of this approach is the high cost associated with the equipment and the challenges in maintaining optimal conditions. Consequently, machine learning and artificial intelligence models offer a potential solution to replace traditional measurement techniques [8].

2.3. Methodology and Composition of the Review

In this review, our objective was to explore the latest advancements in machine learning applications within the area of froth flotation processes. Our focus on advancements from the past decade ensures a comprehensive understanding of the most recent developments and trends in utilizing ML methodologies in this field.

For data collection, we conducted an extensive search of scholarly publications focusing on machine learning applications in flotation processes. The search encompassed reputable online resources such as academic databases, scientific journals, and conference publications. By employing comprehensive search strategies using relevant keywords and filters, we aimed to ensure the inclusion of high-quality and impactful research contributions in the field. Moreover, to enhance the reliability and validity of our findings, we prioritized peer-reviewed publications and selected studies with a demonstrated scholarly impact, including citations and journal impact factors. This detailed approach to data collection enabled us to compile an efficient dataset comprising recent and influential research papers that significantly contributed to the advancement of machine learning methodologies in froth flotation processes.

To effectively navigate the extensive literature available, we organized our review into distinct categories to provide a structured analysis. These categories included 'Predictive Models for Grade and Recovery', 'Models Developed to Evaluate the Importance of Flotation Parameters', and 'Flotation Froth Images Analysis with Machine Learning'. The latter category was further subdivided into 'Froth Image Extraction', 'Bubble Size and Distribution Analysis', 'Predictions of Flotation Performance and Feature Importance Analysis Based on Froth Images', and 'Froth Images Analysis and Predictions for Ash Content in Coal Flotation Process'. By categorizing publications in this manner, we aimed to provide a clear overview of the diverse applications of ML in flotation processes.

In addition to categorizing publications, we conducted a thorough analysis by creating plots to visualize the trends and patterns in machine learning applications within the context of flotation processes. One such plot presents the number of publications released each year, providing insights into the evolving interest and research activity in this field over the past decade. This temporal analysis allowed us to identify periods of heightened interest and potential shifts in research focus. Furthermore, we divided the publication counts for each year into the previously mentioned categories to discern trends in specific research areas. Additionally, we created plots illustrating the distribution of ML models utilized within each category to assess their popularity and effectiveness in addressing particular challenges. This analysis enabled us to identify the most commonly employed ML models and their influence on the development of predictive models, feature extraction techniques, and performance monitoring strategies within the flotation domain.

3. Machine Learning Applications

Over the past 10 years, a significant advancement in machine learning applications in flotation processes has become evident. Research has approached different challenges in this mechanism by employing various models that have been specifically developed and adjusted for a particular flotation problem.

3.1. Predictive Models for Grade and Recovery

The main objective of the flotation process is to obtain a final concentrate with a grade of valuable minerals suitable to be transported to following processes like smelting and refining, or to be filtered and dewatered and presented as a final product. Whatever the purposes of the material, the certain quality of the final product is always required to be achieved in flotation. It is also important to maintain a balance between the recovery and grade to have an optimal and economically profitable process. The possibility to predict the final concentrate properties has always been an objective for engineers and researchers. The results presented in the last decade show that machine learning methods are very successful in determining those parameters for various minerals and flotation scenarios.

The study presented by Nakhaei and Irannajad [9] employs two models, the radial basis function neural network (RBFNN) and layer recurrent neural network (RNN), to predict the grades and recoveries of copper and molybdenum after the flotation process. The study considered the parameters in the flotation circuit such as the chemical reagent dosage, froth height, air and water flow rates, gas holdup, Cu and Mo grades in the feed, flotation column feed, column tail and final concentrate streams. A total of 90 data pairs had been selected to be used in the modeling process. The results revealed that both models have almost similar predictive capabilities achieving almost identical accuracies; however, it was discovered that the RBFNN model has a shorter computing time in this case. Some limitations of the RBFNN model were discovered showcasing that it is more sensitive to dimensionality and has more difficulties if the number of units is large. Later in 2015, the same researchers approached the same problem, adding a multivariate nonlinear regression (MNLR) model to their comparison [10]. This time, the study focused only on the Cu grade and recovery after the process and resulted in the RNN model obtaining the best results. In 2015, Allahkarami et al. [11] have also addressed the copper and molybdenum grade and recovery predictions with a multilayer perceptron neural network. In this study, the pH, collector, frother and F-Oil concentration, size percentage of feed passing 75 microns, moisture content in feed, solid percentage, grade of copper, and molybdenum and iron in feed were considered as inputs to the network. The optimum structure of the ANN model was determined using the trial-and-error procedure; satisfactory results were obtained showing that the feed-forward ANN with a 10-10-10-4 structure can be applied to determine the relationships between inputs.

Comparative studies serve as a powerful tool for evaluating, optimizing, and advancing machine learning applications in flotation processes. They offer a systematic and evidence-based approach to understanding the strengths and weaknesses of different methodologies, contributing to the development of more effective and reliable models for enhancing the effectiveness of flotation operations. Such a comparison was performed by several researchers to find the model that works best for a specific investigated database. Cook et al.'s [12] study focuses on predicting the flotation of metal sulfides efficiency by employing specifically developed hybrid models and comparing it with various classic machine learning models. The created model was a hybrid of a Random Forest and firefly algorithm (RF-FFA) followed by comparison with the ANN, SVM, the M5Prime model tree algorithm, RF and firefly. The hybrid RF-FFA model consisted of three stages of data processing. The RF model was used in stage I, with properly adjusted hyperparameters such as the number of decision trees and depth of each tree, followed by the use of the firefly algorithm in stage II, and final predictions in stage III. The flotation feed contained high amounts of metal sulfides such as galena, sphalerite, pyrite, and chalcopyrite. The database consisted of 66 unique data records, and the goal of the algorithms was to predict the grades and recoveries of Cu and Pb in final concentrate. The results showed that the multilayer perceptron ANN and SVM models were unable to capture the correlations between the input variables and outputs of the database. The prediction performance of the M5Prime model tree was the worst among all ML models that were employed, and RF has superior prediction performance compared to the remaining models. The predictive ability of the RF model was strengthened when joined with the firefly algorithm to form the RF-FFA hybrid model; the highest accuracy of predictions achieved by this model shows that it has potential as a tool for the optimization of froth flotation processes at the plant scale.

Another study focused on the prediction of purities was presented by Pu et al. [13], where the focus was on employing a long short-term memory (LSTM) model derived from a recurrent neural network (RNN) but equipped with higher memory power and capable of remembering the outputs of each node for a more extended period of time. The objective of this study was to develop a model to successfully predict the grade and recovery of iron as well as assess the separation of iron from the undesired gangue mineral, which is silica. To compare the model predictive performance, it was compared with the RF model that was fitted to same database. The LSTM model significantly outperformed the RF model and was able to make highly accurate predictions, where the RF model failed to extract meaningful characteristics from the training data. This study showed that even though the RF model might have been successful in different studies and different databases, it may not always be suitable for every case. The same researchers, Pu et al. [14], approached the same database with a newly developed deep learning algorithm—FloatationNet. This created network was specifically developed to accommodate the complexity of the database; it has two branches receiving data, where the first branch receives the main inputs, which are the concatenation of two input material purities and two processed product purities. Those parameters are passed to a stacked LSTM architecture and are converted into main outputs. The second branch, with only one layer, receives inputs that are all process operating parameters. The input purities and process operating parameters were treated differently in FlotationNet since they have different roles in the froth flotation system. Considering that silica is an undesired waste product, the loss function was specifically developed to give priority to the iron prediction results. FlotationNet was compared with the classic LSTM and the FNN models, demonstrating a considerably improved prediction accuracy for iron purities; however, the silica prediction accuracy shown by FlotationNet was the least accurate of the three proposed models.

The grade and recovery estimations were introduced by several more research studies including that of Pural [15], who presented a data-driven soft sensor developed to predict the silicate impurity where ridge regression, multilayer perceptron and random forest were employed. The study aimed to accurately estimate the residual content of silica in the final concentrate, where the RF model achieved the best performance. Ren et al. [16] approached the copper concentrate prediction with a least-squares support vector regression, where they investigated the relationship between the color features of minerals extracted from the microscopic images and concentrate grade. The results showed that there was a strong correlation between the concentrate grade and color features, and that the LS-SVR model can capture this relationship and produce accurate predictions.

3.2. Models Developed to Evaluate the Importance of Flotation Parameters

In the flotation process, evaluating the importance of parameters and implementing effective control strategies is crucial for optimizing performance and achieving accurate outcomes. By understanding the significance of variables such as reagent dosages, froth depth, and airflow rates, operators can tune the process to maximize recovery, minimize operating costs, and ensure consistency in product quality. Controlling key parameters prevents process drawbacks, adapts to ore variability, and enhances the overall process understanding. Additionally, these efforts contribute to meeting particular concentrate specifications, addressing environmental considerations, and advancing sustainability in flotation operations. Recent years have contributed especially to the research focused on machine learning applications developed to evaluate and adjust the parameters in flotation processes.

One of the common challenges in the flotation of coal is the slime coating that most likely occurs when fine grinding is applied to liberate coal particles. It is caused by the admixture of clay and other impurities that are distributed into fine fractions, and it has been recognized as a challenging problem since the slime coating prevents the bubble-particle attachment and increases the reagent consumption [17]. In flotation processes, polymers have been utilized as binders to improve the flotation performance by agglomerating the clay particles, reducing their surface area, reagent adsorption, and hydraulic entrainment. Presented by Khodakarami et al. [18], the study employed ANN architectures to test a novel synthesized polymer as a potential ash depressant in fine coal flotation. Not only was the polymer dosage evaluated in this study but also its conditioning time, effect of impeller speed, dispersant dosage, and pH value of the pulp. The results of ANN model were compared with experimental results and revealed that the pH had a considerable effect on the flotation process. The coal recovery was better in the pH range of 5.5 to 7.8; outside these values, the recovery of coal significantly dropped. The impeller speed influences the gas holdup rate and the bubble size distribution within the flotation cell. The results showed an optimal impeller speed between 1700 and 1900 rpm for the highest coal recovery in the final product. In the case of the polymer dosage, it was discovered that the coal recovery and ash rejection were best at lower polymer dosages and increasing the conditioning time up to 6 min, but not more than that, had a positive impact on the results. The optimal value of dispersant dosage was also revealed, where coal recovery was maximal. The proposed ANN model could accurately predict the behavior and outcomes of the flotation processes without many experiments.

Shahbazi et al. [3] employed a Random Forest model with associated variable importance measurements (VIM) to evaluate the effect of various flotation variables such as particle characteristics (size and circularity) and hydrodynamic conditions (bubble Reynolds number, energy dissipation, and bubble surface area flux) on the flotation rate constant and recovery. The flotation processes were conducted on quartz particles under various parameters, and then the responses and outcomes were recorded and analyzed with VIM and RF. The results indicated that the bubble surface area flux and particle size had the highest importance for flotation rate and recovery predictions and that energy dissipation had the lowest influence on the predictions. The results suggest that RF models can be employed to estimate other complex parameters in froth flotation as well as other mineral processing methods.

A similar study conducted by Chelgani et al. [19] applied a variable importance measurement and mutual information (MI) tool followed by a support vector regression model to evaluate the responses of coal flotation. Parameters such as the particle size, circularity, particle Reynolds number, bubble Reynolds number, energy dissipation, microscale turbulence and bubble surface area flux and their representative metallurgical response recovery and kinetic constant rate were determined and calculated based on standard procedures. The results obtained from VIMs by MI indicate that the particle Reynolds number and energy dispersion have the highest influence on the recovery prediction among all parameters, and the particle size and bubble Reynolds number exhibit the highest influence on the prediction of kinetic constant rate. These results showed that MI for variable selection and SVR for modelling are efficient tools that can be employed for variable selection and modelling of froth flotation processes.

Monitoring and controlling the flotation of fine ash coal is a common challenge in industry, and several other research studies have approached it. A study by Ali et al. [20] employed several machine learning models to predict the flotation behavior of coal in the presence of a specifically developed "hybrid" ash depressant. The investigated models were random forest, artificial neural networks, the adaptive neuro-fuzzy inference system (ANFIS), Mamdani fuzzy logic (MFL) and a hybrid neural fuzzy inference system (HyFIS), where the MFL model obtained the best results. The results also showed that the novel hybrid polymer positively impacted the final product's quality.

Presented by Gomez-Flores et al. [21], the research considered a wide range of variables that impact the flotation process, nine physicochemical and nine operational ones, with an analysis of the importance of each variable. Models such as Multiple Linear Regression, K-Nearest Neighbors, Decision Tree, and Random Forest were employed, with RF selected as the most successful model. Following those results, recursive feature elimination with cross-validation was implemented to use the feature importance attribute to represent the output rank in the RF model. The observation was made that the type of mineral had the highest influence on the final predictions, and pH and ionic strength had the lowest effect.

In the study by Alsafasfeh et al. [22], the artificial neural network model was applied to predict and optimize phosphate flotation performance. The process parameters used as data inputs for the model included the type and dosage of the silicate's depressant, the flotation time, and the pH of the pulp. Results from the developed ANN model were used to optimize the flotation performance. Two polymers where selected and compared to promote the depression of silicates and improve the flotation of phosphates: chitosan and Hy-PAM. Results showed that the optimum flotation performance in the presence of Hy-PAM could be obtained at a higher dosage, low pH, and shorter flotation time. With chitosan's presence, the optimum flotation efficiency could be obtained at a higher dosage, medium pH, and longer flotation time. Monyake et al. [23] also investigated chitosan polymers for the selective separation of metal sulfides in the flotation process, where ANN and RF models were employed to predict the efficiency of this reagent. Based on statistical parameters determined from the model's outputs, it was revealed that the RF model was superior to the ANN model in terms of prediction accuracy.

3.3. Flotation Froth Images Analysis with Machine Learning

Froth images analysis with various machine learning and deep learning methods has been the area with the most significant number of advancements in recent years. The integration of computer vision for monitoring flotation processes has been strongly established in the mineral industry. According to a recent survey focused primarily on plants in Southern Africa [24], approximately 67% of the surveyed plants were equipped with froth imaging techniques. These commercially available systems are predominantly designed to oversee parameters such as bubble size distributions, froth color, movement, and stability. This monitoring capability serves as crucial decision support for operators and facilitates mass pull control between flotation cells. Notably, ongoing advancements highlight the potential of froth image analysis, extending its applications to soft and operational state sensors. These innovations contribute to the development of tools for monitoring and controlling the performance of flotation systems.

3.3.1. Froth Image Extraction

Extracting information from froth images and analysis has been approached with machine learning methods by many researchers within the mineral processing area. Horn et al. [25] analyzed images obtained from a platinum flotation circuit, with a pre-trained convolutional neural network model (CNN) showing promising effectiveness. CNN has been one of the most popular networks employed for image extractions; Fu and Aldrich [26] investigated AlexNet implementation for platinum flotation for image analysis. The study showed that supervised feature extraction can yield significantly better results than what could be achieved with features not directly extracted to achieve the same goal. Additionally, it was shown that this could be achieved by using CNNs that have been pretrained on image data from a different domain. Later, the same researchers [27] investigated AlexNet, VGG16 and ResNet34 implementations for platinum flotation froth image analysis. The results of the proposed models showed considerable improvement over the use of networks previously proposed in the literature. The main challenge of these methods is that the classification accuracy is dependent on the design of the feature extraction algorithm. Fu and Aldrich have also presented a study where the CNN models AlexNet and VGG16 were employed to develop froth image sensors [28], showing that these networks can generate highly accurate predictions despite being trained on image data from a different domain.

Zarie et al. [29] conducted a study where a CNN was developed to classify images taken from an industrial coal flotation column under diverse process conditions and compared it with the ANN classifier. For the ANN model, the visual features of froth were initially measured and then provided into the network, whereas, in the CNN classifier, the image is directly fed into the network. The results showed that CNN significantly outperformed the ANN regarding classification accuracy and computation time. Galas and Litwin [30] approached the application of machine learning (ML) techniques for recognizing flotation froth images in both stable and unstable flotation processes. The study found that while ML algorithms can effectively classify images and predict the froth content, their efficiency is influenced by the stability of the flotation process. In stable flotation processes, where the variation in froth content is lower, ML algorithms demonstrate higher effectiveness in image classification compared to unstable processes. ML algorithms based on Linear Discriminant Analysis (LDA) are utilized to construct image recognition algorithms, with results showing classification with higher accuracy for stable than for unstable processes. The study also highlights challenges in stabilizing the flotation process parameters and suggests that improving the stability of these parameters could enhance the performance of ML algorithms in froth image recognition.

Unsupervised machine learning could be advantageous for extracting information from flotation images due to its ability to uncover complex patterns without the need for labelled data, adapt to varying system configurations, and provide interpretable results, making it well-suited for analyzing large volumes of data and facilitating deeper insights into froth behavior. This approach was investigated by Wang et al. [31], who introduced an unsupervised method for extracting semantic features from flotation froth images using a combination of generative adversarial networks (GANs) and autoencoders. Human-understandable semantic features are automatically extracted by mapping froth images to a latent semantic space and decomposing the resulting matrix. These features demonstrate interpretability and effectiveness in tasks like flotation condition recognition and concentrate grade prediction. Experimental results confirm the superiority of the proposed method over existing hand-crafted feature extraction approaches.

These study examples prove the capabilities of convolutional neural network models as successful tools in extracting the information from the froth images as well as accurate classifications.

3.3.2. Bubble Size and Distribution Analysis

Bubble size and distribution are important in the flotation process, directly influencing efficiency. The size of bubbles impacts the surface area available for particle attachment. Properly adjusted bubbles increase the likelihood of successful collision and adhesion between air bubbles and valuable mineral particles. Optimal control of bubble characteristics, including size and distribution, is essential for maximizing process efficiency, reducing energy consumption, and ensuring the economic expectations of mineral processing operations. Typically, the assessment of bubble size in flotation operations relies on froth image analysis. Evaluating bubble size and distribution within froth images often involves segmenting the images along bubble boundaries. However, this task creates challenges since the boundaries may not be clearly defined, and the sizes of bubbles can significantly fluctuate within a single image.

Jahedsaravani et al. [32] conducted a research study introducing a watershed algorithm integrated with a neural network classifier that combines whole and sub-image classification techniques. An unsupervised neural network classifier was selected to classify the entire froth image consisting of closely packed large and small bubbles. The sub-images were composed of bubbles with more consistent and narrower size distributions. Hence, a trained, supervised neural network was employed to classify the froth images based on their white spot features. The effectiveness of this algorithm was validated through successful testing with various laboratory and industrial froth images captured under diverse process conditions. The outcomes suggest that the devised algorithms, particularly the segmentation algorithm based on sub-image classification, exhibit accurate and reliable identification of both small and large bubbles within real froth images. Recently, Jahedsaravani et al. presented a study that focused on measuring the bubble size and froth velocity with a CNN network [33]. They proposed a pre-trained residual network (ResNet-18) as a classifier for bubble size and GoogLeNet as a feature extractor to measure froth velocity from flotation images. The computational times for bubble size measurement between classical methods and the ResNet-18 algorithm were compared, and it was established that the ResNet-18 method significantly reduced that time. The study revealed that pre-trained neural networks outperform classical image processing algorithms in terms of accuracy and computational efficiency.

In their study, Liu et al. [34] proposed an online bubble size distribution monitoring scheme by incorporating a multiscale-deblurring full convolutional network and a multistage jumping feature-fused full convolutional network. The models employed aimed to deblur the images of froth from the flotation process with a multiscale-deblurring network, followed by segmentation of each image, where several model configurations of networks were investigated. Comparative experiments conducted on a natural copper-mine flotation process demonstrated that the proposed method performs better when compared to current froth image segmentation methods.

3.3.3. Predictions of Flotation Performance and Feature Importance Analysis Based on Froth Images

Predicting the performance of the flotation process through froth image analysis and machine learning holds significant importance for the mineral processing industry. Real-time insights from froth images contribute to proactive decision-making, enabling operators to optimize conditions efficiently. Presented by Hosseini et al. [35], the study explores the relationship between process conditions, surface bubble size, and performance in batch flotation of a copper sulfide ore, utilizing neural networks for modelling. Flotation experiments under varied conditions were conducted, and an adaptive marker-based watershed algorithm successfully segmented froth images, enabling the measurement of bubble size. Strong correlations were found between process conditions and bubble size, essential for control purposes. The analysis identified the gas flow rate as the most influential variable, followed by the slurry solids %, frother dosage, pH, and collector dosage. While the bubble size increased with the gas flow rate, it decreased with the frother dosage, slurry solids %, and pH due to viscosity effects and changes in ionic strength. Neural network models accurately predicted the froth bubble size and metallurgical parameters, indicating the potential for machine vision-based control systems.

A similar investigation into the copper sulfide flotation process was examined by Jahedsaravani et al. [4], where the relationship between process conditions, froth characteristics, and metallurgical performance in batch flotation was investigated, aiming to predict performance using image analysis and neural networks. Through laboratory experiments with varying operating conditions, froth properties such as the bubble size distribution, froth velocity, froth color, and bubble collapse rate were quantified using image processing algorithms. Neural networks were then employed to model the complex relationship between these froth features and metallurgical parameters like copper recovery and concentrate grade. The results demonstrate significant correlations between process variables, froth characteristics, and metallurgical performance, with froth features like bubble size and froth velocity showing strong predictive capabilities. Nakhaei et al. [36] studied the prediction of sulfur removal from iron concentrate in column flotation using froth features extracted through image analysis. Various machine learning models, including multiple linear regression (MLR), k-means clustering, backpropagation neural network (BPNN), and convolutional neural network (CNN), were compared for their predictive accuracy. Froth features such as color, bubble shape and size, texture, stability, and velocity were extracted and used as inputs for the models. Results show that the BPNN and CNN models outperform MLR and k-means, suggesting the potential of employing these models to predict sulfur recovery accurately and possibly other metallurgical parameters of flotation processes.

The research studies published in flotation processes and image analysis highlight the significant benefits of CNN models in extracting valuable insights from froth images. Jahedsaravani et al. [37] presented another study that aimed to predict the performance of the flotation process with CNN model. Various CNN architectures were utilized and compared with traditional image processing methods, including AlexNet, GoogLeNet, VGGNet, ResNet, and SqueezeNet. Two case studies were conducted: one on a laboratory batch copper flotation system and another on an industrial coal flotation column. In both cases, pre-trained CNNs were employed to extract features from froth images, which were then used to predict metallurgical parameters. The results indicate that GoogLeNet outperforms other CNN architectures in accurately predicting flotation behavior and performance. Additionally, the study highlights challenges such as the disparity between froth sampling and image capturing rates and suggests potential solutions like transfer learning to fine-tune pre-trained networks for specific industrial datasets.

By combining supervised and unsupervised feature extraction methods, including CNN, proposed by Bendaouia et al. [38], the Hybrid Features Extraction (HFE) approach achieved a high accuracy in predicting elemental composition (Pb, Fe, Cu, Zn) of minerals in real time. Comparative analysis demonstrates HFE's superiority over other feature extraction methods, particularly regarding average prediction error. While the system shows promising capability, challenges such as continuous model retraining, precision compared to traditional methods, and computational resource constraints are acknowledged. Some other studies that employed a CNN model to predict and monitor the flotation process include Park et al. [39], which presented the classification of froth mobility in the flotation process. The study proposes a novel method for monitoring froth mobility using a CNN trained with images. This method offers several advantages over traditional algorithms, including extracting froth mobility from a single image and monitoring large surface areas across the flotation cell. However, it may struggle to quantify the mobility of slow-moving froth without adjusting camera settings, depending on its frequency in normal operations. The CNN model achieves high accuracy in classifying froth images into three mobility classes. The method shows good agreement with commercial software, suggesting its potential as a simple and low-cost tool for froth mobility monitoring and indicating flotation performance. However, limitations include the need for a froth image dataset to train the CNN model and challenges in accurately classifying slow-moving froth mobility.

Bendaouia et al. [40] also investigated the Convolutional Long Short-Term Memory model for real-time monitoring of chemical composition grades in flotation froth. The model's deployment architecture enables real-time monitoring of elemental concentrate grades, facilitating adjustments to flotation parameters for enhanced process efficiency. The evaluation results demonstrated the model's accuracy, particularly in predicting zinc concentrate grades, with implications for improving operational performance and efficiency in mineral flotation circuits. Zhang et al. [41] have also investigated the applicability of a long short-term memory-based grade monitoring system using a video sequence from the zinc flotation process. Unlike traditional machine vision systems, which rely on froth images or videos, this model utilizes temporal information within froth video sequences, enhancing monitoring accuracy. The LSTM network effectively addresses the challenge of varying sample rates in industrial data and utilizes unlabeled froth videos. The integration of rougher feed grades further improves accuracy. Experimental results demonstrate the effectiveness of the proposed model, showing satisfying results compared to traditional neural networks.

3.3.4. Froth Images Analysis and Predictions for Ash Content in the Coal Flotation Process

The analysis of coal ash in the flotation process is important for several reasons. Firstly, it helps understand the efficiency of coal separation and recovery during flotation, as the ash content affects the quality and purity of the coal concentrate. Secondly, accurate analysis of coal ash assists in optimizing flotation conditions and reagent dosages to enhance the removal of ash-bearing minerals from coal. Additionally, monitoring the coal ash content enables the assessment of flotation performance over time, facilitating process control and optimization efforts to improve coal quality and maximize economic returns.

Wen et al. [42] approached ash content prediction of coal concentrate from froth images with several CNN networks (AlexNet, VGG_16, VGG_19, ResNet_18, ResNet_34, ResNet_50 and ResNet_101). Industrial validation confirms the potential of CNNs in this application, highlighting the need for more efficient algorithms and larger datasets to address the challenge of concentrate ash content prediction. In a similar study, Wen et al. [43] explored the application of feature engineering in predicting the ash content of coal flotation concentrate. Various image processing techniques were employed to extract relevant information from froth images, including morphoscopic, statistical, and color space features. The correlation analysis reveals strong relationships between morphoscopic features and ash content.

Additionally, statistical features such as the gray level histogram and gray level co-occurrence matrix exhibit varying degrees of correlation with ash content. The study employs Support Vector Regression (SVR) models for prediction and demonstrates that Principal Component Analysis (PCA) can enhance model accuracy by reducing feature dimensionality. The findings suggest that feature engineering significantly improves prediction accuracy, enabling precise estimation of coal flotation concentrate ash content.

The study by Tang et al. [44] presents a real-time prediction system for monitoring the ash content of flotation concentrate, employing image processing techniques and a back-propagation neural network model. The system collects froth images using an industrial camera, processes them to enhance contrast, remove noise, and segment effectively, and extracts parameters such as gray value, bubble number, and average bubble diameter. The study establishes significant correlations between these parameters and concentrate ash content, achieving high prediction accuracy. Yang et al. [45] introduce a novel hybrid model for ash determination of coal concentrate. This proposed model, called the Convolution-Attention Parallel Network (CAPNet), was developed to rapidly and accurately determine the ash content by analyzing froth images. CAPNet integrates the classic ResNet model with attention mechanisms, allowing them to run in parallel to improve model performance. The proposed CAPNet was compared extensively with baseline models, including

ResNet variations, other CNN models, and traditional machine learning methods. The results show that CAPNet outperforms other accuracy, stability, and speed methods. The study demonstrates that CAPNet can reduce the ash determination time from hours to milliseconds, making it suitable for industrial applications. Additionally, CAPNet achieves high accuracy with fewer parameters than other deep learning models, highlighting its efficiency and effectiveness.

Lu et al. [46] achieved high accuracy in detecting the clean coal ash content in the coal froth flotation process by integrating deep learning with the likelihood function. The study established a novel data processing and prediction framework by combining a deep learning Keras neural network with the likelihood function from probability statistics. The study utilizes the SIFT algorithm to extract key feature points and descriptors from images, along with keypoint matching and mean-shift clustering algorithms to accurately obtain information on froth motion trajectories and velocities. By incorporating optimized likelihood function parameters into the deep neural network, an efficient prediction model is constructed for the dosage of flotation reagents, froth velocity, and clean coal ash content.

4. Summaries and Future Work

In this review, we focused on the advancements in machine learning (ML) applications in flotation processes over the past decade, highlighting various models developed to address specific challenges within these processes. Different ML models, such as Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), Layer Recurrent Neural Network (RNN), Multilayer Perceptron Neural Network, Hybrid Models like Hybrid Random Forest and firefly algorithm (RF-FFA), Convolutional Neural Networks (CNN), long Short-Term Memory (LSTM) models and so on, have been employed to predict parameters such as grades and recoveries of valuable minerals. Comparative studies have been conducted to assess the performance of these models, with findings indicating the effectiveness of certain models over others depending on the specific database and problem investigated. Additionally, ML models have been used to evaluate the importance of flotation parameters, such as particle characteristics and hydrodynamic conditions, in optimizing flotation performance. In froth image extraction, researchers have investigated machine learning methods, particularly Convolutional Neural Networks (CNNs), to capture insights from froth images. Various CNN architectures, including AlexNet, VGG16, and ResNet, have demonstrated enhanced feature extraction and classification efficacy compared to traditional approaches. These studies demonstrate the potential of ML in enhancing process control, optimizing performance, and advancing our understanding of flotation processes, thereby contributing to improved efficiency and productivity in mineral processing operations.

A summary of all reviewed publications is shown in Figure 3. The growing interest in monitoring and controlling the flotation process with machine learning models is evident. The year 2024 has already started with some insightful research studies presented by Bendaouia et al. [38,40] in the area of froth image extraction and analysis, and it is expected that more research in this field will be presented.

Figure 4 summarizes all reviewed publications, separated into the categories introduced in this paper. The growing interest in froth image analysis is apparent. Recent years show that the future of monitoring and controlling the flotation process will be primarily based on advancing froth image extraction by employing and developing more complex and tailored deep learning networks.

Figure 5 shows all the machine learning models that were employed in the reviewed publications, separated into categories. The regression models include models such as multiple non-linear regression (MNLR) [10], M5Prime [12], ridge regression (RR) [15], support vector regression (SVR) [19,43], and least-squares SVR (LS-SVR) [16]. The hybrid model presented by Cook et al. [12] combined a random forest with a firefly algorithm, and the novel models were FlotationNet [14] and CAPNet [45].

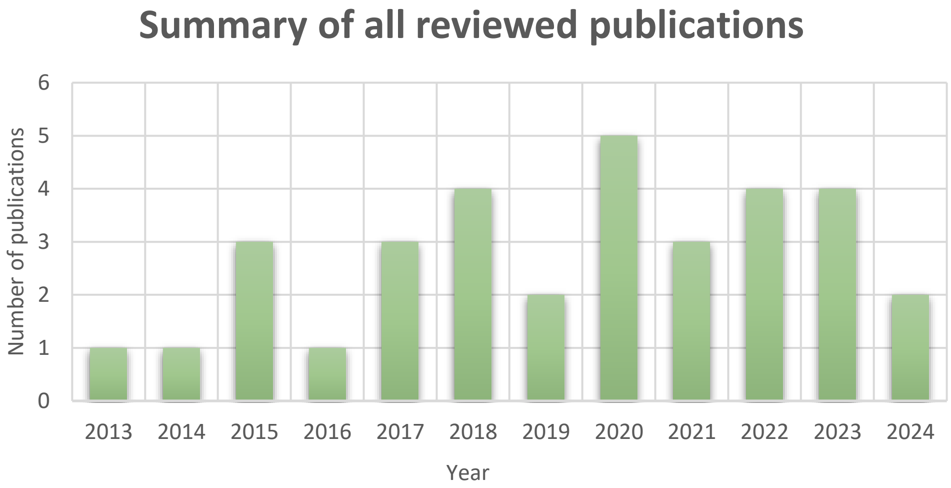

Figure 3. Histograms of all reviewed publications vs. year of publication.

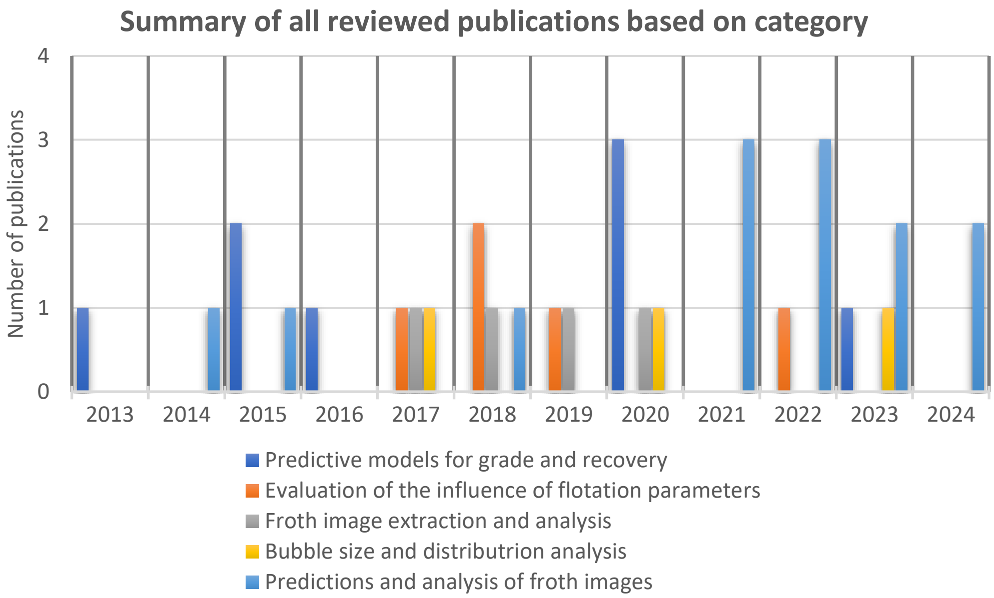

Figure 4. Histograms of all reviewed publications within each discussed category vs. year of publication.

It is noticeable that ANN and CNN models are the most popular among others to be employed to analyze, monitor and control the flotation process. This preference for ANN and CNN models can be attributed to their adaptability, robustness, and efficiency in handling complex datasets from flotation processes. ANNs and CNNs are flexible frameworks, well suited for modeling nonlinear relationships and capturing challenging patterns. CNNs, specifically designed for processing visual data, excel in extracting features from froth images, thus facilitating accurate classification and prediction tasks. The increasing utilization of CNN networks for froth image analysis has become evident in recent years, and it is anticipated that the importance and further development of these models will continue to expand in the coming years.

Future work in machine learning applications in flotation processes could focus on several aspects for further advancement. Firstly, there is a need to explore the integration of advanced deep learning architectures, such as graph neural networks, recurrent neural networks, and attention mechanisms, to capture more complex relationships within froth images and process variables. Additionally, research efforts could target the development of hybrid models that combine machine learning with physics-based models to enhance predictive accuracy and interpretability. Moreover, there is growing interest in incorporating reinforcement learning techniques to automate the optimization of flotation parameters and control the process in real time. The generalizability of machine learning models needs to be addressed to ensure their applicability across different flotation systems and mineral types. Lastly, efforts to deploy machine learning solutions in industrial settings should address data acquisition, preprocessing, and model deployment challenges to facilitate smooth integration into existing operations. Overall, future research work should aim to push the boundaries of machine learning applications in flotation processes to achieve greater efficiency, sustainability, and profitability in mineral processing operations.

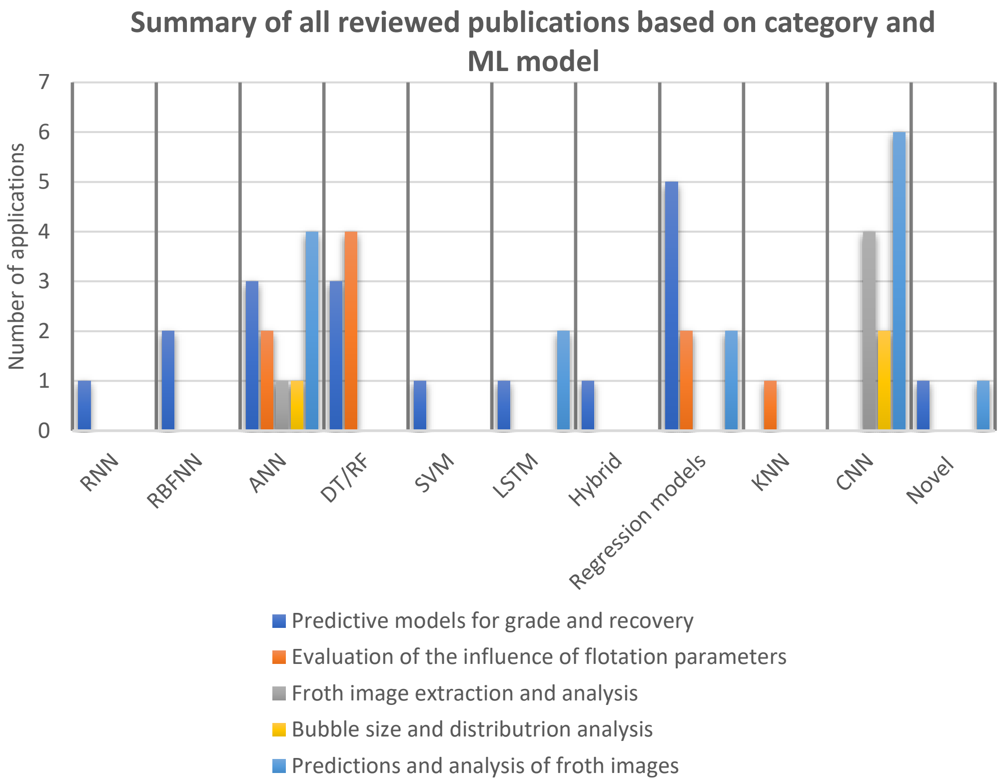

Figure 5. Histograms of all reviewed publication based on the ML models employed.

5. Conclusions

Machine learning presents substantial opportunities and impacts on mineral processing, particularly in flotation and mining engineering. ML techniques offer the potential to reform traditional methods by enabling more accurate predictions of mineral grades, recoveries, and process effectiveness. By applying ML algorithms, engineers can optimize flotation processes, leading to increased productivity, reduced energy consumption, and improved cost-effectiveness. Additionally, ML facilitates proactive decision-making through real-time monitoring and control, thereby enhancing overall operational performance and sustainability in the mining industry.

This paper extensively reviews machine learning and artificial intelligence techniques applied to froth flotation in the mineral processing industry. It highlights the challenges inherent in flotation processes, including the complexity of the mechanism, the need for extensive data collection, and the importance of balance between concentrate grade and recovery. The review presents the importance of controlling pulp characteristics, physicochemical factors, and bubble properties to optimize flotation effectiveness. We focused on advancements in machine learning applications in flotation processes over the past decade, showcasing various models developed to address specific challenges within these processes. Different ML models, including artificial neural networks (ANNs), recurrent neural networks (RNNs), radial basis function neural networks (RBFNNs), convolutional neural networks (CNNs), and Long Short-Term Memory (LSTM) and so on, have been employed to predict distinct parameters and optimize performance. Comparative studies have highlighted the effectiveness of certain models over others, depending on the specific database and problem investigated. In froth image extraction, CNN architectures like AlexNet, VGG16, and ResNet have demonstrated superior feature extraction and classification efficacy. The review demonstrates the potential of ML in enhancing process control, optimizing performance, and advancing our understanding of flotation processes. Future work could explore advanced deep learning architectures, hybrid models, and reinforcement learning techniques and could address data acquisition and preprocessing challenges to further advance ML applications in flotation processes.

By examining advancements over the past decade, this study demonstrated the evolving role of ML in mineral processing, emphasizing their potential impact on froth flotation process optimization and understanding.

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