Advancing Flotation Process Optimization Through Real-Time Machine Vision Monitoring: A Convolutional Neural Network Approach

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Abstract: The mining industry's continuous pursuit of sustainable practices and enhanced operational efficiency has led to an increasing interest in leveraging innovative technologies for process monitoring and optimization. This study focuses on the implementation of Convolutional Neural Networks (CNN) for real-time monitoring of differential flotation circuits in the mining sector. Froth flotation, a widely used technique for mineral separation, necessitates precise control and monitoring to achieve maximum recovery of valuable minerals and separate them from gangue. The research delves into the significance of froth surface visual properties and their correlation with flotation froth quality. By capitalizing on CNN's ability to identify valid, hidden, novel, potentially useful and meaningful information from image data, this study showcases how it surpasses traditional techniques for the flotation monitoring. The paper provides an in-depth exploration of the dataset collected from various stages of the Zinc flotation banks, labeled with elemental grade values of Zinc (Zn), Iron (Fe), Copper (Cu), and Lead (Pb). CNNs' implementation in a regression problematic allows for real-time monitoring of mineral concentrate grades, enabling precise assessments of flotation performance. The successful application of CNNs in the Zinc flotation circuit opens up new possibilities for improved process control and optimization in mineral processing. By continuously monitoring froth characteristics, engineers and operators can make informed decisions, leading to enhanced mineral recovery and reduced waste.

1 INTRODUCTION

The mining industry is undergoing a transformative phase driven by the advent of the 4th industrial revolution, which is becoming a pivotal factor in ensuring sustainability, success, and competitiveness. The depletion of mineral resources over the past decade has spurred the minerals engineering community to explore innovative exploitation techniques. Consequently, there has been a paradigm shift in the mining sector, with an increasing focus on industrial innovation in mining, exploration, process optimization, logistics, and marketing, aimed at addressing challenges such as depleting mineral reserves, rising energy costs, and unpredictable fluctuations in raw material availability.

Among various strategies employed to separate valuable minerals from ore, flotation stands out as the most common and widely utilized technique in the mining industry. However, the advanced modeling of flotation processes has long been constrained by classical mathematics and modeling techniques. Recognizing the need for transformative solutions, the mineral engineering community has recently embraced the application of emerging technologies in flotation processes. These disruptive mining technologies, driven by innovative Information Technologies (IT), have paved the way for enhanced energy efficiency and sustainable practices in the mining industry.

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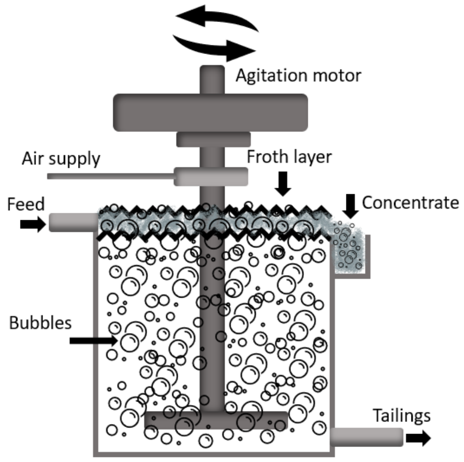

Figure 1: Froth flotation separation technique.

The need for optimizing and controlling the flotation process is further intensified by the complexity of diverse minerals' separation based on their varying hydrophobicity levels (Rajapakse et al., 2022). As a result, real-time monitoring and precise control of the flotation circuit have become increasingly challenging. To address this crucial issue, this paper explores the application of Convolutional Neural Networks (CNN) for real-time monitoring of the zinc flotation circuit in the mining industry. By harnessing the power of CNN, this study aims to provide an innovative and efficient solution for enhancing, in real time, the flotation process's effectiveness and sustainability in the mining sector.

The paper is structured as follows: Section 1 provides an introduction to the context and problem statement; Section 2 presents a literature review encompassing similar applications in mineral processing and flotation froth analysis; Section 3 describes the methodology for data collection and preparation; Section 4 provides the results and evaluation of our proposed method, followed by a discussion; and finally, Section 5 concludes the paper and offers perspectives for future research.

2 STATE OF THE ART

2.1 Machine Vision for Flotation Monitoring

The mineral engineering community has been increasingly captivated by the potential of utilizing Machine Vision (MV) techniques to monitor flotation processes (Aldrich et al., 2022)(Jovanović et al., 2015). These methods have shown promising applications in optimizing various stages of the flotation circuit, enabling more efficient mineral separation and recovery.

Machine Vision techniques offer an innovative and non-invasive means to capture and analyze froth properties in real-time. By continuously monitoring bubble size, texture, and color changes during the flotation process, engineers and operators can make informed decisions and adjustments to enhance overall process efficiency. The integration of MV with advanced control systems can lead to a more sophisticated and adaptive flotation process, one that can adapt to varying ore conditions and achieve optimal mineral recovery under different operating scenarios. To inspect and assess flotation froth, conventional approaches have often relied on RGB-based methods, which offer valuable insights into bubble size and texture. Bubble size and shape hold significant importance, as they significantly impact the efficiency and effectiveness of the process. Various factors influence these characteristics, including the rate of the gas stream, dosage of reagents, particle granularity, hydrophobicity of minerals, and the pH of the pulp. Understanding the interplay of these factors is essential for achieving optimal flotation performance, as it directly affects the recovery of valuable minerals and the rejection of gangue.

Since the flotation froth is heavily influenced by froth concentrate grade, and bubble deformation is positively correlated to the flotation froth quality, many froth image inspection systems were developed (Ai et al., 2018)(Liu et al., 2020)(Zhang and Xu, 2020)(Massinaei et al., 2019)(Tang et al., 2021). Bubble size detection, which is the main technique to obtain information of flotation cells has taken the biggest portion of the flotation froth inspection(Ai et al., 2018)(Zhang and Xu, 2020)(Kaartinen et al., 2006).

2.2 Deep Learning for Flotation Froth Features Extraction

Traditional texture and bubble size extraction methods consider limited feature types. The developed froth image inspection systems has responded to the real time challenge but stills on the way to be more accurate. Deep learning methods are an alternative which does not suffer these disadvantages. The quality of convolutional neural networks (CNN) features was compared to those from traditional texture feature extraction methods(Horn et al., 2017)(Bendaouia et al., 2022). Performance of CNN as feature extractors was found to be competitive, showing similar performance to the other texture feature extractors. A classification CNN algorithm was compared to a conventional artificial neural network (ANN). The results show that the flotation froth classification model CNN-based significantly outperforms the ANN classifier in terms of accuracy and computation time(Zarie et al., 2020).

The predominant applications in this domain primarily revolve around froth classification using Convolutional Neural Networks (CNN). This preference stems from the CNN's inherent ability to learn intricate hierarchical features from image data. Additionally, CNN's computational power in deep learning facilitates effective feature extraction from froth images, enhancing the classification process (Zhang and Gao, 2021), (Zarie et al., 2020), (Cao et al., 2022), and (Wen et al., 2021).

In the context of supervised learning for regression tasks, previous studies has explored the use of ConvLSTM on video data(Bendaouia. et al., 2023a) and Fast Fourier based features extraction along with Machine Learning(Bendaouia. et al., 2023b). This study aims to capitalize on the capabilities of CNNs, aiming to revolutionize real-time monitoring of the Zinc flotation circuit. We present a CNN-based image analysis soft sensor designed for online monitoring of industrial flotation. Our proposed analyzer not only classifies froth images accurately, but predicts the grades of four minerals: Zn, Cu, Fe, and Pb in the cleaners of the Zinc circuit. The objective is to achieve more precise and efficient assessments of mineral concentrate grades and overall flotation performance. By leveraging the potential of CNNs in this regression-based problem, this research opens up new avenues for enhancing mining industry practices through improved process monitoring and optimization.

3 METHODOLOGY

3.1 The Differential Flotation Circuit at CMG Morocco

The flotation circuits employed at CMG (Compagnie Minière de Guemassa) in Morocco for processing a complex ore from two extraction sites, "Daraa Lasfar" and "Kodiat Aicha," located around the city of Marrakech, are known as a complex differential flotation circuit. At the CMG flotation site, three minerals are valuated: $CuFeS_2$ Copper sulphide (Chalcopyrite), ZnS Zinc sulphide (Sphalerite) and PbS Lead sulphide (Galena). Each of these minerals follows a specific flotation circuit consisting of three stages: roughing, scavenging, and cleaning. The primary objective of these consecutive cells is to maximize the concentrate grade and recovery of valuable minerals while effectively separating them from the gangue. This study focuses specifically on the Zinc flotation circuit, as presented in Figure 2. The Zinc flotation circuit comprises three roughers, two scavengers, and six cleaners. For each type of flotation bank, specific reagents, such as frothers, collectors, and depressors, are added. The roughing stage initiates the flotation process, with the primary aim of separating as much valuable mineral as possible from the initial ore feed. The scavenging stage is intended to recover any remaining valuable mineral that might not have been separated during the roughing stage. Lastly, the cleaning stage produces the concentrate with the highest achievable grade of the valuable mineral. These three stages play a pivotal role in optimizing the grade and recovery of valuable minerals while efficiently isolating them from the gangue.

3.2 CNN for Knowledge Discovery and Features Extraction

Convolutional Neural Networks (CNN) can play a crucial role in extracting Knowledge Discovery (KD) from froth flotation data. By leveraging their powerful capabilities in image processing and pattern recognition, CNNs can uncover valid, hidden, novel, potentially useful, and meaningful information from the froth images obtained during the flotation process. CNNs can be applied to extract KD from froth flotation data in by different aspects:

- Froth Image Analysis: CNNs can process and analyze the froth images captured during the flotation process. By learning hierarchical features from these images, CNNs can identify important patterns and structures within the froth, including bubble sizes, textures, and color variations.
- Froth Segmentation: CNNs excel at froth segmentation, accurately distinguishing between valuable minerals and gangue particles present in the froth. This segmentation provides valuable insights into the distribution of minerals within the froth, aiding in the evaluation of flotation performance and mineral recovery.
- Feature Extraction: CNNs are adept at feature extraction, allowing them to identify relevant characteristics in the froth images that might not be apparent through traditional algorithms. This extraction process helps uncover hidden patterns and correlations, contributing to a deeper understanding of the flotation process.
- Predicting Mineral Grades: With the knowledge gained from froth image analysis and feature ex-

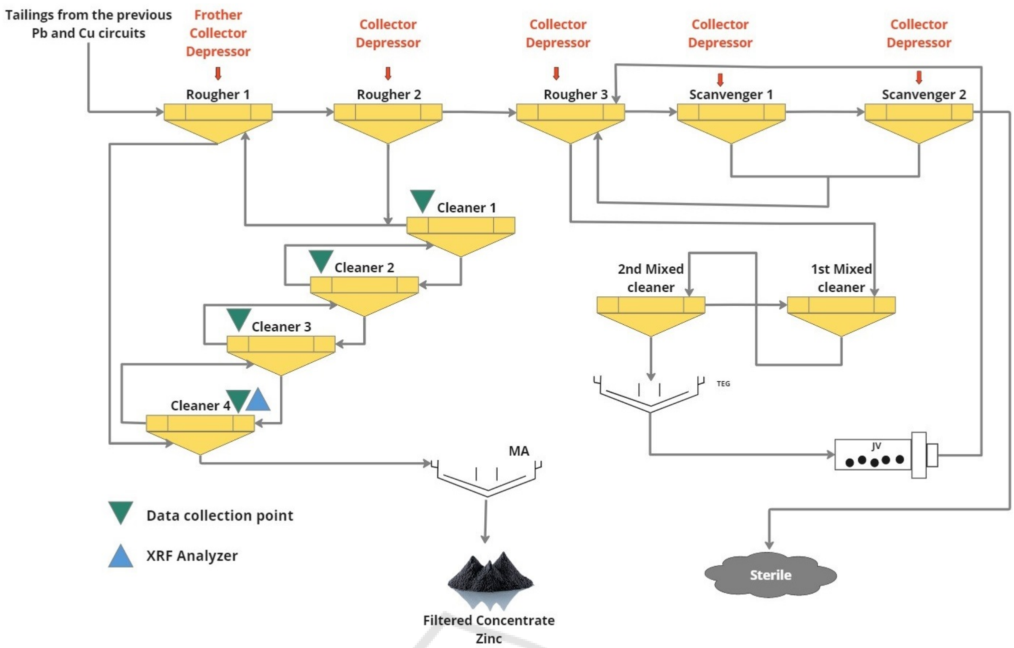

Figure 2: Flowchart of the Zinc flotation circuit in the differential flotation plant at CMG Morocco.

traction, CNNs can predict mineral grades more accurately than traditional methods. This predictive capability is vital in optimizing the flotation process and maximizing the recovery of valuable minerals.

- Process Optimization: By providing insights into froth behavior and mineral distribution, CNNs assist in process optimization. They can recommend adjustments in gas flow rates, reagent dosages, and other process parameters to enhance flotation efficiency and overall performance.
- Identifying Anomalies: CNNs can detect anomalous froth behavior, indicating potential issues or deviations from expected flotation patterns. Early detection of anomalies allows for timely corrective actions, preventing potential process inefficiencies or disruptions.
- Real-time Monitoring: CNNs can facilitate real-time monitoring of the flotation process, enabling continuous data analysis and feedback. This real-time monitoring ensures prompt decision-making and adaptive control, enhancing process stability and productivity.

CNNs contribute significantly to Knowledge Discovery in froth flotation data by effectively processing and analyzing froth images, identifying valuable patterns, predicting mineral grades, optimizing process parameters, and enabling real-time monitoring. Their ability to extract meaningful information from froth images revolutionizes the way the mining industry approaches flotation monitoring and process optimization, leading to increased efficiency, improved mineral recovery, and sustainable mining practices.

3.3 Data Collection and Image Capturing

To effectively apply Convolutional Neural Networks (CNN) for real-time monitoring of the Zinc flotation circuit, comprehensive data collection and image capturing procedures were conducted. The dataset used in this study was collected from different cleaner cells of the Zinc flotation circuit in an actual industrial flotation setting.

Table 1: Statistical analysis of the different mineral grades of the collected samples.

	Mean	Std	Min	Max	Variance
Cu %	0.98	0.36	0.41	1.86	0.13
Fe %	15.00	3.60	8.77	21.24	12.93
Pb %	1.34	0.46	0.60	2.70	0.22
Zn %	42.17	5.18	30.59	51.95	26.81

The data is collected from the cleaners of the Zinc flotation banks within a real-industrial mining environment Figure 3. It comprised a total of 6462 froth flotation images utilized for the training phase, along with an additional 1738 images for testing purposes. Each image was meticulously labeled with four elemental grade values: Zinc (Zn), Lead (Pb), Iron (Fe), and Copper (Cu) (See Figure 1). To ensure uniformity

Figure 3: The data acquisition system of the flotation froth image data from the Zinc circuit.

Parameter	Value
Resolution	1200x1200
File Format	AVI compressed
Compression Bit Rate	35 Mbits/s
Camera Height	30 cm
Exposure Time	20000 um
Acquisition Frame Rate	49 Hz

Figure 4: The image capturing characteristics during data collection.

in the visual aspect parameters, the images were captured using an RGB camera under stable luminosity conditions as described in the Figure 4.

The data collection process was from different shifts, encompassing different operational settings. This extended duration allowed for a comprehensive examination of the froth surface characteristics under varying conditions, contributing to a more thorough understanding of the flotation process. The Figure 5 presents the mineral grades distribution of the collected samples from the cleaner of Zinc circuit.

4 FLOTATION FROTH MONITORING CNN-BASED

4.1 CNN Architecture Description

The used CNN architecture has an input of 400x400x3 as height, weight and depth of the images with RGB color channels Figure 6. The model uses a rectified linear unit (ReLU) activation function, which allows for non-linearity in the model. The Adam optimizer is used for training, with a learning rate of 0.001, which helps the model converge faster. The loss function used is 'mean absolute percentage error' which measures the mean absolute percentage error between the predicted and actual values. The batch size used is 32, which means that the model updates its parameters after processing 32 images. The model is trained for 100 epochs using a GPU. The model has a total of 47,538,628 trainable parameters, which represents the number of weights and biases that are updated during the training.

4.2 Experimental Evaluation

To assess the performance of the CNN-based model designed for predicting mineral grades in flotation froth, we conducted an experimental process using a new deployment dataset. The model's evaluation was conducted using a separate test dataset, consisting of froth images, with each image labeled with corresponding mineral grades.

Various metrics were employed to measure the accuracy of the model, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the average error on real deployment data. The Mean Squared Error metric was used to evaluate the disparity between the predicted and actual values, while the average error on real deployment data gauges the model's ability to generalize and predict outcomes in real-world industrial flotation scenarios. Additionally, we visually represented the prediction results of the trained models for a new sample of image data (see Figure 7).

Table 2: The evaluation metrics of the CNN model on deployment data of the Zn Cleaners of CMG flotation circuit.

Elements	**Evaluation metrics**			
	MSE	**RMSE**	**MAPE**	**Average Error**
Cu	0.18	0.43	79.47	0.42
Fe	29.33	5.42	28.75	4.75
Pb	0.89	0.94	144.79	0.88
Zn	82.90	9.11	19.07	7.52

4.3 Discussion of the Results

Through rigorous evaluations and analyses, the table 2 displays the MSE, RMSE, MAPE and average error values for each elemental composition. Concerning the Zn mineral, and the RMSE value is 9.11, while the variance of the Zn collected samples is 26.81. This outcome is considered as accurate considering the variation in Zn mineral grades observed within

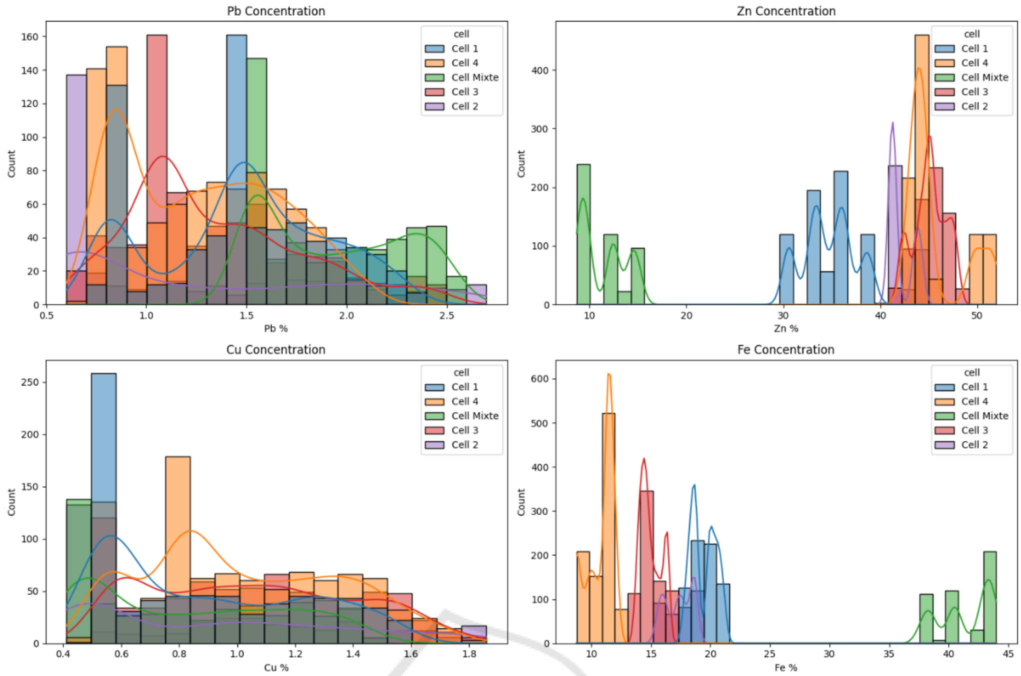

Figure 5: Mineral grades distribution of the collected samples from the cleaner of the Zinc circuit at CMG.

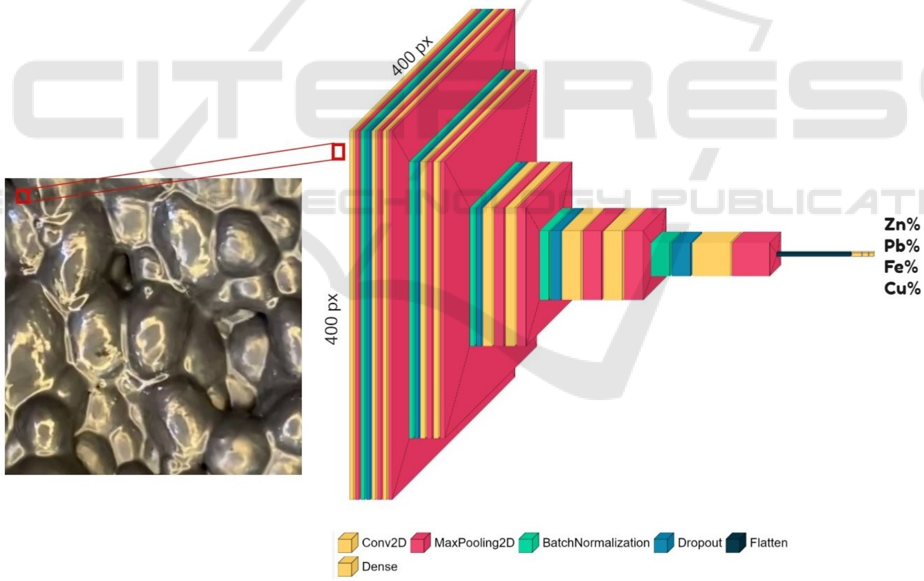

Figure 6: The used CNN architecture for features extraction from the froth images.

the Zn flotation circuit. The low values of these metrics suggest that the model provides more precise predictions, taking into account the high standard deviation of the Zn mineral grades. Furthermore, the table underscores that the model's performance varies depending on the mineral, owing to the diverse distributions of concentrate grades. Notably, when compared to other minerals, Copper exhibits lower MSE, and MAPE values, indicating the model's heightened accuracy in predicting this particular low grade mineral. This study demonstrates the reliability and accuracy of the developed CNN-based models in predicting the elemental composition of flotation froth. These results validate the effectiveness of the model and its potential for enhancing process monitoring and optimization in the mining industry.

In previous studies, we explored more intricate methods for identifying mineral grades, including

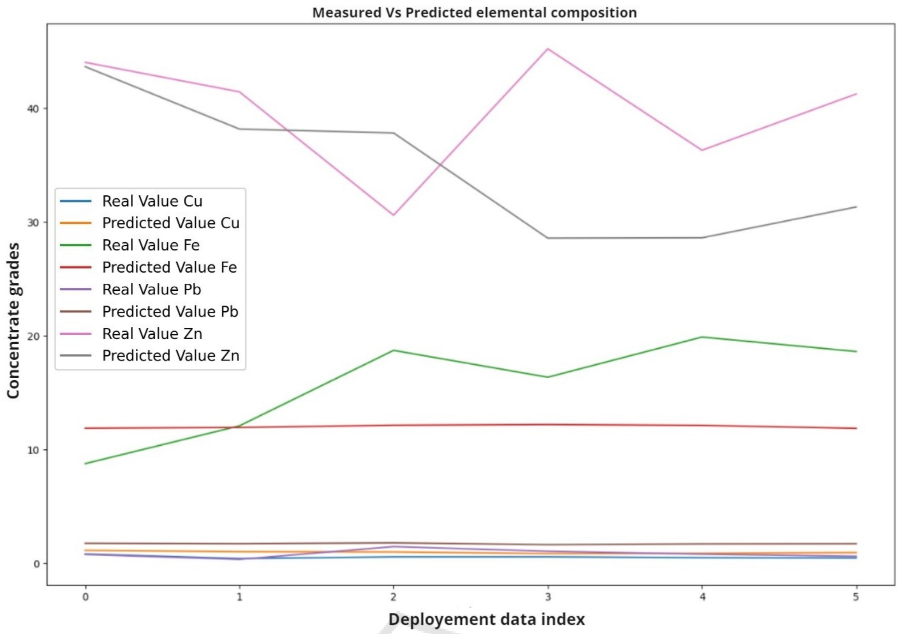

Figure 7: The measured values of zinc, iron, copper and lead with the predicted values provided by the CNN-based architecture on deployment data from the Zn cleaners.

feature extraction based on image processing (Bendaouia et al., 2022), ConvLSTM (Bendaouia. et al., 2023a) and Fourier Transform with baseline Machine Learning methods (Bendaouia. et al., 2023b). The CNN-based approach is considered less complex and easier to implement in IoT systems, given its reduced complexity and lower time consumption. While the CNN-based solution shows promise, it is essential to acknowledge that its accuracy may not match the precision of traditional techniques, such as laboratory analysis or XRF fluorescence. These established methods may currently yield more accurate results; however, the CNN-based approach presents a vision for the future of flotation monitoring. With further advancements and accumulation of more comprehensive datasets, the model's accuracy is expected to improve over time.

5 CONCLUSIONS

In this paper, we have explored the potential of Convolutional Neural Networks (CNN) for real-time monitoring of the Zinc flotation circuit in the mining industry. Our research has demonstrated the significance of froth surface visual properties in relation to flotation froth quality, highlighting CNN's superiority in froth monitoring compared to traditional techniques. By harnessing the power of CNNs, we have successfully extracted valuable Knowledge Discovery (KD) from froth flotation data, enabling precise assessments of mineral concentrate grades and overall flotation performance. The application of CNNs in the Zinc flotation circuit has paved the way for enhanced process control and optimization in the mining industry. The CNN model's ability to continuously analyze froth images, predict mineral grades, and monitor froth behavior has led to more efficient mineral separation and improved recovery rates. Moreover, the simplicity and computational efficiency of CNNs have made them an attractive feature extraction method compared to conventional supervised techniques.

By extending CNNs to other circuits, integrating the flotation Digital Twin (Hasidi et al., 2022), designing a deployment architecture, and deploying real-time process adjustment, future research holds promising prospects for enhancing mining operations' sustainability, productivity, and competitiveness.

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