Conv-LSTM for Real Time Monitoring of the Mineral Grades in the Flotation Froth

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Abstract: Accurate monitoring of the mineral grades in the flotation froth is crucial for efficient minerals separation in the mining industry. In this study, we propose the use of ConvLSTM, a type of neural network that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, to create a model that can extract spatial and temporal patterns from flotation froth video data. Our model enables the analysis of both spatial and temporal patterns, making it useful for understanding the dynamic behavior of the froth surface in the flotation processes. Using ConvLSTM, we developed a more accurate and reliable model for monitoring and controlling the flotation froth quality. Our results demonstrate the effectiveness of our approach, with mean absolute error (MAE) of 2.59 in a lead, copper and zinc differential flotation site. Our findings suggest that artificial intelligence can be an effective tool for improving the flotation monitoring and control, with potential applications in other areas of the mining industry.

1 INTRODUCTION

In recent years, research has demonstrated a significant decline in mineral resources. This decline can be attributed to both the depletion of existing mineral reserves and the unpredictable reductions in raw materials. In response to these challenges, the mining industry has been compelled to innovate in various aspects of its operations, including mining, exploration, processing, logistics, and marketing. This industry-wide push towards innovation has been further supported by the emergence of the fourth industrial revolution, also known as Industry 4.0. This revolution is characterized by the integration of digital technologies and physical systems, resulting in the development of smart factories that are highly productive and efficient. Industry 4.0 is reliant on a range of disruptive technologies, including the Internet of Things (IoT), cloud computing, big data, and Cyber-Physical Systems (CPS) (Qassimi and Abdelwahed, 2022). Within this context of digital transformation, our study aims to investigate how disruptive technologies and innovations can be utilized to optimize mineral processing productivity and efficiency in the mining industry.

Given the challenges facing the mining industry regarding the declining mineral resources and the need for innovation, one technique that has gained significant attention is the flotation separation. The flotation has emerged as a promising technique in the last century. It is a mineral processing method that leverages the differences in surface properties of minerals to separate them (see figure 1). This approach is widely employed in the mining industry to extract valuable minerals from ores. Recent developments in technology and research have led to the creation of new flotation separation methods, including the use of innovative reagents and equipment. Against the backdrop of the digital transformation of the mining indus-

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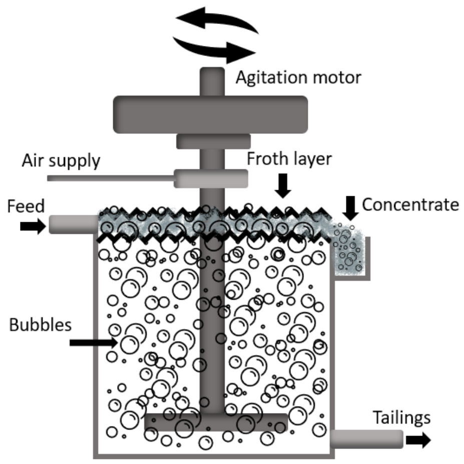

Figure 1: Froth flotation separation technique.

try and the need for enhanced efficiency and productivity, this research aims to propose a new flotation monitoring technique based on artificial intelligence that can be utilized to optimize the flotation monitoring.

This paper focuses on the monitoring of the flotation froth and proposes a cost-effective and low-maintenance solution that enables real-time measurement of mineral grades. To achieve this goal, we employ artificial intelligence and deep learning techniques in the mineral processing flotation-based. This paper is organized into five sections. The first section provides an introduction and outlines the general context of the research, while the second section presents the state of the art in flotation froth monitoring and the use of deep learning techniques. The third section details the methodology employed, including the data types and preprocessing steps, model architecture, and experimental process. The fourth section reports the application and results of the proposed solution, including mineral grade identification, performance evaluation, and discussion. Finally, the fifth section offers a conclusion and perspective on the research findings.

2 STATE OF THE ART

2.1 Flotation Froth Monitoring

To achieve the optimization and control of the flotation process, accurate monitoring of the flotation concentrate grades is crucial. While several existing monitoring techniques are available, they can be expensive to implement and may have high maintenance requirements in addition to their latency. Currently, the most used monitoring techniques are XRF-fluorescence-based or laboratory analysis basically the Atomic Absorption (AA). The laboratory analysis method is considered the most accurate but has limitations due to manual sampling and preparation, leading to latency issues. The online mineral control method using X-ray fluorescence (XRF) detection, specifically the XRF-based Courier 6G, is used at the Compagnie Minière de Guemassa (CMG) flotation factory where this study was conducted. This method can measure up to six individual process streams, making it suitable for monitoring complex polymineral-lic flotation circuits that contain lead, copper, iron and zinc. However, XRF analysers require continuous and high-cost maintenance and suffer from insufficient detection of lightweight materials (Uusitalo et al., 2020).

2.2 Deep Learning for Flotation Monitoring

In recent years, both literature and practical experience acknowledge that the visual characteristics of the froth surface are significant and strongly correlated with the quality of the flotation froth (Liu et al., 2020) (Farrokhpay, 2011) (Kaartinen et al., 2006) (Aldrich et al., 2022). This alternative solution for the flotation monitoring based on Machine Vision is not only cost-effective but also requires minimal maintenance. Furthermore, the visual inspection of the flotation froth offers the added benefit of enabling real-time measurement of mineral grades, providing a significant improvement over current monitoring techniques such ad XRF-fluorescence and laboratory analysis. The biggest portion of these applications are froth classification based on Convolutional Neural Networks (CNN). Basically because of the capacity of CNN to learn rich hierarchical sets of features from images. Furthermore, CNN enables the computational power of the deep learning to extract the features from froth images for classification (Zhang and Gao, 2021) (Zarie et al., 2020) (Cao et al., 2022) (Wen et al., 2021). CNNs have proved their capability of determining the mineral grades more accurately than the classical Machine Learning along with the supervised features extraction of the flotation froth (Bendaouia et al., 2022). In addition to the CNNs, Long Short-term-memory based (LSTM) networks was used for mineral grades monitoring using flotation froth video sequences (Zhang et al., 2021). LSTM architecture is also used for damage detection in pipelines (Huang et al., 2022), anomaly detection for technical systems (Lindemann et al., 2021) and predicting the electric power consumption (Cascone et al., 2023). Researchers and engineers are benefiting from the LSTM capability of extracting temporal patterns in time series data.

The froth flotation video sequence can be considered as temporal information that can improve the monitoring accuracy. Therefore, in our study, we propose the use of ConvLSTM to create a model that can extract spatial and temporal patterns from flotation froth. ConvLSTM is a type of neural network that combines the properties of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This allows the model to analyze both spatial and temporal patterns in data, making it useful for understanding the dynamic behavior of the froth surface in flotation processes. By using ConvLSTM, we created a more accurate and reliable model for monitoring and controlling the flotation froth quality.

3 METHODOLOGY

The flotation process is a physio-chemical process that is influenced by numerous parameters. The minerallurgist operators acquire the expertise of visually monitoring the flotation froth based on the froth characteristics. An important factor is the color and texture of the froth surface, which contains valuable information about the mineral composition (Farrokhpay, 2011). By identifying the mineral types based on the color and texture of the froth surface, the flotation performance can be assessed, and operation instructions can be adjusted accordingly.
In this study, we propose a digital approach that seeks to replicate the expertise of human operators in visually monitoring the flotation froth. Specifically, we propose the use of Conv-LSTM, which combines the strengths of Convolutional Neural Networks (CNNs) in image classification with Recurrent Neural Networks (RNNs) for processing sequential data, such as video frames figure 2. By using Conv-LSTM, we can extract sequential characteristics from the video frames of the flotation froth, enabling a more accurate assessment of the mineral composition and thus better optimization of the flotation process.

3.1 Experimental Process

The experimental process employed in our study to predict the percentages of minerals in flotation cells using a Convolutional Long Short-Term Memory (ConvLSTM) network consisted of the following steps:

- Data Collection: A large dataset of labeled video frames of the flotation froth of the Zn circuit was collected, where each video frame was labeled with the corresponding percentages of the four minerals (Zn, Cu, Fe, and Pb) in the flotation froth.
- Data Preprocessing: The collected video frames were preprocessed by resizing them to a consistent size and format and splitting them into sequences of frames that could be used as input to the ConvLSTM network.
- Model Architecture: The model architecture was defined using the Sequential class. The hyperparameters were selected after many training and evaluation operations.
- Model Training: The model was trained using the labeled video sequences as input and the corresponding percentages of the minerals as output. The model was trained for several epochs using the Adam optimizer and the mean squared error (MSE) as the loss function.
- Model Evaluation: The trained model was evaluated using a separate test dataset of video sequences and corresponding mineral percentages. The model's performance was measured using metrics such as accuracy and mean squared error.
- Model Deployment: The trained model was deployed for use in the flotation froth cells, where it was used to predict the percentages of the minerals in real-time. The predictions were utilized for monitoring the flotation process and improve the efficiency of the separation of the minerals.

3.2 Data Collection

We collected a real world dataset from the differential flotation site of CMG Managem group in Morocco figure 3. This dataset includes visual aspect parameters and the elemental composition of Pb, Cu, Zn and Fe. During the data collection phase, we collected a sample from the flotation froth and analyzed it in the laboratory using atomic absorption. Additionally, we recorded a video of the flotation froth using an RGB camera under stable luminosity to capture the visual aspect parameters as described in the figure 4.

3.3 Data Augmentation

To further explain the approach used in the study, the following paragraph describes the dataset and model used for training and testing. The study utilized 340 videos from the flotation site of CMG Managem-Group in Morocco, which were processed into seven-frame sequences with each frame having a shape of

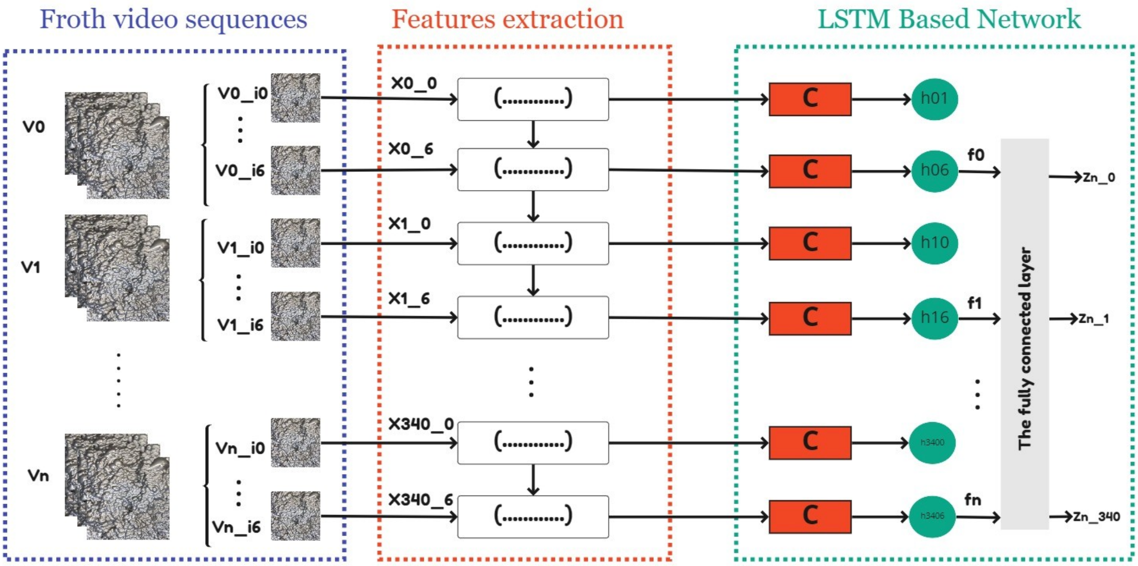

Figure 2: Framework of the LSTM-based mineral grade monitoring system using the froth flotation video data.

Figure 3: The data acquisition system of the flotation froth videos.

224x224x3. The sequences were then used as input for a recurrent neural network (RNN) designed to predict the percentages of copper (Cu), iron (Fe), lead (Pb), and zinc (Zn) in the videos. The dataset was split into 313 training videos and 27 testing videos, with each target value containing the concentrations of Cu, Fe, Pb, and Zn. The seven-frame sequences and target mineral grades were combined to enable the model to accurately predict mineral concentrations by capturing the patterns and dependencies in the data. Additionally, the data was augmented by adding noise between 0 and 0.25 to artificially increase the dataset size and improve the model's performance. The controlled addition of noise was an effective way to introduce variability and diversity into the labels while preserving their overall structure and meaning.

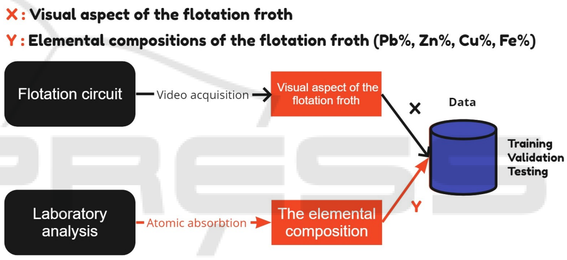

Figure 4: The data sources and types.

3.4 ConvLSTM-Based Network

We are using ConvLSTM to build a model that can extract simultaneously both spatial and temporal patterns from the flotation froth. ConvLSTM is a type of recurrent neural network that combines the strengths of CNNs and LSTMs, allowing it to process both spatial and sequential data effectively. In a ConvLSTM, convolutional operations are applied to the input, forget, and output gates of an LSTM cell, enabling the network to learn spatial and temporal patterns simultaneously. This makes ConvLSTM a powerful tool for tasks such as video prediction and time-series forecasting. The equations for a ConvLSTM cell are shown below:

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} \odot c_{t-1} + b_i)$$
$$f_t = \sigma(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} \odot c_{t-1} + b_f)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c)$$
$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{co} \odot c_t + b_o)$$
$$h_t = o_t \odot \tanh(c_t)$$

- x_t is the input at time step t
- h_{t-1} is the hidden state at time step $t-1$
- c_{t-1} is the cell state at time step $t-1$
- i_t, f_t, o_t are the input, forget, and output gates, respectively, at time step t
- σ is the sigmoid activation function
- $*$ denotes convolution operation
- $\odot$ denotes element-wise multiplication
- W and b are the weight matrices and bias vectors, respectively, for the input, hidden state, and cell state

4 Conv-LSTM FOR MINERAL GRADES DETERMINATION

4.1 Model Architecture

The ConvLSTM network architecture was used in our study to predict the percentages of four different minerals in flotation cells from video data figure 5. The architecture was effective in processing both the spatial and temporal information present in the video frames and sequences, which was crucial for our task. In addition to the ConvLSTM layer, the model also included a BatchNormalization layer, a MaxPooling3D layer, a Dropout layer, a Flatten layer, and a Dense layer. The Adam optimizer with a low learning rate of 0.0001 was chosen for its effectiveness in adapting the learning rate for each parameter and avoiding overshooting the optimal solution.

4.2 Performance Evaluation

To evaluate the performance of our model in predicting the percentages of the mineral grades from the froth video, we utilized a separate test dataset that was not used during the training process. Evaluation was conducted using several metrics, including accuracy, mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Evaluation is particularly crucial for this study aiming to predict mineral percentages from froth videos for several reasons. Evaluation allows us to determine how close the model's predictions are to the true values and how much error is present in the predictions. This information can be leveraged to choose the best model for deployment or identify the key factors that influence the model's performance. As the model is deployed and new data is collected, it is essential to assess its performance to ensure that it continues to make accurate predictions. The figure 6 shows a comparison between the measured and the predicted mineral grades using our proposed model. The table 1 evaluate the model according to the MSE, MAE, MAPE evaluation metrics. The Standard deviation (STD) was also calculated for the different elements in the data test.

Table 1: The evaluation metrics of the ConvLSTM model on datatest.

Elements	**Evaluation metrics**			
	MSE	**MAE**	**MAPE**	**STD**
Zn	11.43	2.59	6.22	16.10
Cu	0.66	0.68	77.70	0.31
Fe	5.81	1.98	15.037	10.54
Pb	0.168	0.313	65.51	0.78

4.3 Discussion of the Results

The table 1 displays the MSE, MAE, and MAPE values for each elemental composition. Each metric value corresponds to a specific target mineral. For the Zn mineral, the MAE value is 2.59, and the MAPE value is 6.22 while the standard deviation is 16.10, which is an accurate result according to the variation of the Zn mineral grade in the Zn flotation circuit. The low values for these metrics indicate that the model is making more precise predictions according to high standard deviation of the Zn mineral grades. Additionally, the table emphasizes that the model's performance varies depending on the mineral, which is due to the variety of the concentrate grades distributions. Compared to other minerals, the Copper has lower MSE, MAE, and MAPE values, indicating that the model is making more accurate predictions for this particular mineral.

The model's performance varies among the different minerals. Overall, the predictions are more accurate for the low grade elements copper (Cu) and lead (Pb).

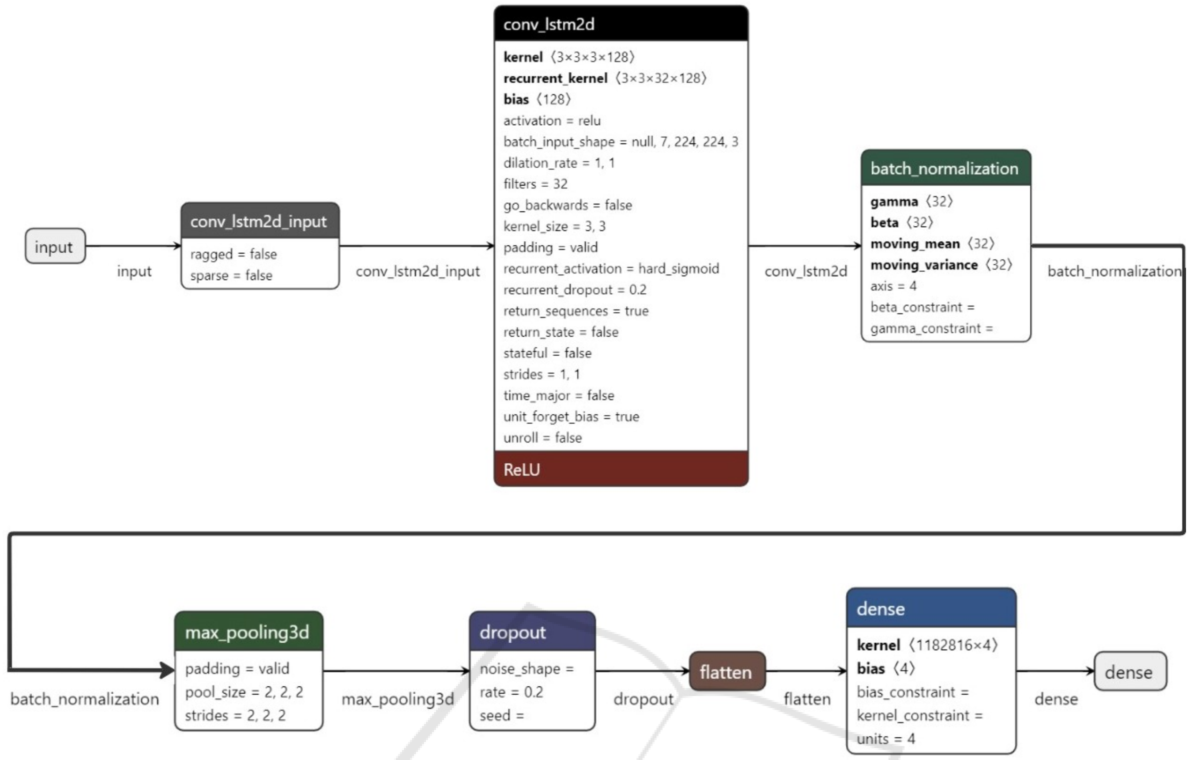

Figure 5: The used architecture for the Zn, Fe, Cu and Pb mineral grades prediction.

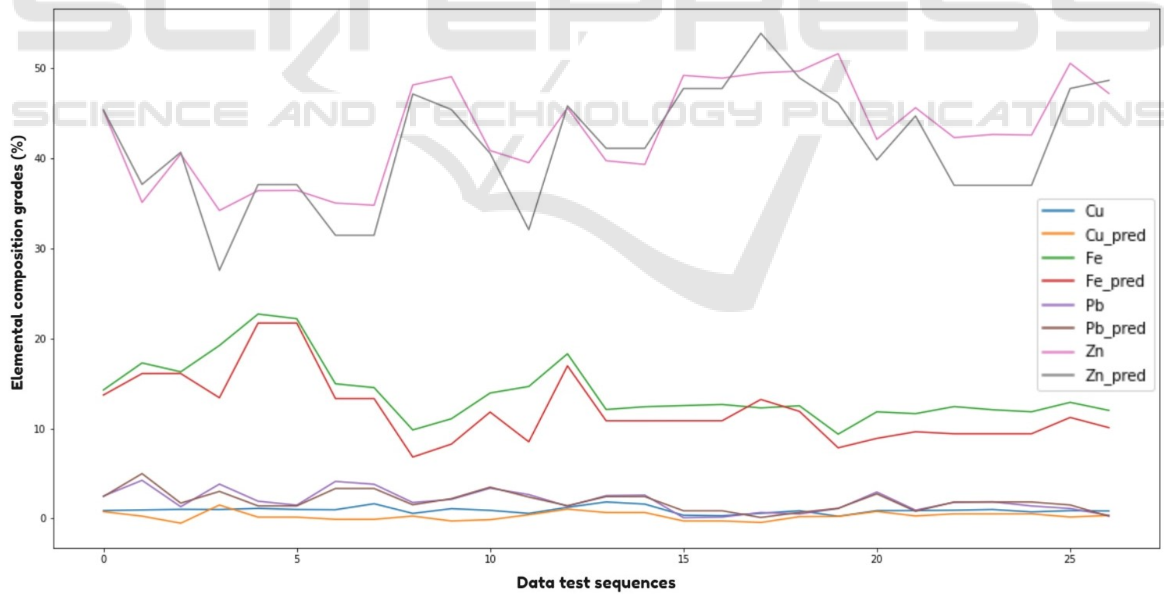

Figure 6: The measured values of copper, zinc, lead, and iron with the predicted values provided by the ConvLSTM-based network on deployment data.

5 CONCLUSIONS

Our study demonstrated the added value an industrial application of artificial intelligence in mining industry. We used a Convolutional Long Short-Term Memory (ConvLSTM) network to accurately predict the percentages of minerals in real time in flotation froth. By utilizing video data as input, the model was

able to effectively process both spatial and temporal information, resulting in precise predictions of mineral percentages. Our proposed approach has a direct added value on the monitoring of flotation processes. The model demonstrated a good level of accuracy and precision, indicating its ability to be generalized on the whole differential flotation. The use of the ConvLSTM network in flotation froth monitoring, showcases its potential for similar industrial applications that require processing of spatial and temporal information.
The real time monitoring the flotation froth is a crucial aspect of optimizing and controlling the flotation process. Our proposed approach offers significant advantages over existing monitoring techniques, as it is not only less expensive and low-maintenance but also provides real-time information on mineral grades. This makes it a valuable addition to the flotation monitoring process. Once implemented on the zinc circuit, our proposed soft sensor will be tested for its ability to accurately monitor the mineral grades of the CMG differential flotation circuit's three base minerals: lead, copper, and zinc. By combining froth features, physio-chemical sensors, and intelligent control techniques, this innovative approach has the potential to become a reliable and effective flotation monitoring system. Our proposed approach of using ConvLSTM neural networks for real-time monitoring of mineral grades in flotation froth has significant potential for future industrial applications beyond lead, copper, and zinc differential flotation sites. Specifically, we will be testing the generalization of our approach to other mineral compositions using froth video data, an aspect that will be addressed in future work. We acknowledge the limited experimental data used in this study and are committed to conducting further research to validate the effectiveness of our proposed solution in a wider range of industrial settings.

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