Rapid Mineralogy Analysis Validations for Conventional and Coarse Particle Flotation Slurries

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Introduction

Understanding the mineralogy of ore in the feed of a separation unit during mineral processing is critical for achieving optimum recovery and separation efficiency. The operational setpoints of separation modules and the chemical-physical properties of the slurry are typically adjusted based on the ore's mineralogy. However, traditional mineralogical analyses are time-consuming and costly, with results often becoming available only after the ore has already been processed in the plant. The MinDet laboratory device was developed to reduce the turnaround time by performing rapid mineralogical analyses, making the process more affordable and providing plant operators with actionable insights to optimize at operation level. MinDet utilizes machine vision and a trained AI-Algorithm to estimate the modal mineralogy of a slurry stream sample in real time. The algorithm continuously analyses samples from the slurry stream, reporting mineralogy by size, particle size distribution, mineral liberation, and associations within the slurry particles.

The methodology was initially validated for a conventional flotation process feed's sample and products at 80% passing particle size of 150 µm. In this study, the methodology was extended to Coarse Particle Flotation (CPF) feed sample where the particles are coarser (100% passing 600 µm) and valuable mineral bearing particles are floated at very low liberation degrees, as low as 5%.

Methodology

The MinDet device performs mineralogical analysis on freshly collected slurry samples from separation processes, pilot plants, or laboratory flotation tests. The system uses a robotized digital microscope to capture high-resolution images of thousands of particles per minute. These images are then analysed by a machine vision AI algorithm trained to identify and quantify mineral phases within each particle.

The AI algorithm was trained using extensive datasets generated from Scanning Electron Microscope Energy Dispersive Spectroscopy (SEM–EDS) analyses of ore particles and minerals. The EDS spectra and morphological features from these reference datasets were used to train the model to recognize individual mineral grains and particle textures under reflected light imaging. Prior to release, each version of the algorithm undergoes a rigorous quality assurance and quality control (QA/QC) process, during which its mineral recognition accuracy is verified across multiple samples. The system's confidence levels in mineral identification and grain delineation are continuously monitored and refined.

This methodology was developed and validated using sulfide polymetallic ore samples from four Australian operations. Samples were collected from major flotation streams, including feed, concentrate, and tailings, from both conventional and coarse particle flotation (CPF) circuits. Microscopic images of the particles were classified according to mineralogy and used to train and test the AI model. The workflow for generating tagged particles for algorithm training is shown schematically in Figure 1.

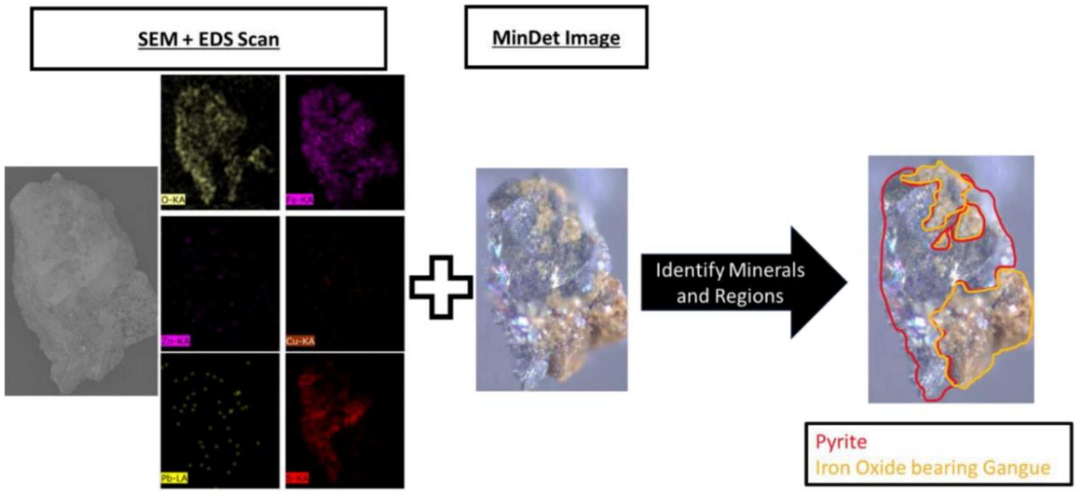

Figure 1- The workflow for generating tagged particles for AI algorithm training.

After algorithm development and testing, fresh slurry samples were collected from the target process streams for validation. The sample preparation procedure for MinDet analysis is straightforward and fast. Approximately 10 grams of a representative slurry sample is sub-sampled and wet-screened at around 20 µm to separate ultrafine particles from the coarser fraction. Each fraction is then loaded into a transparent cuvette for scanning. This simple preparation allows for rapid analysis—typically delivering full mineralogical results within a few hours—thus dramatically reducing turnaround time and cost compared to traditional methods.

The device can process up to six cuvettes simultaneously, enabling batch analysis of multiple samples (Figure 2). The system reports results in real time through its integrated software interface. Key parameters generated by MinDet include:

- Particle size distribution
- Bulk mineral grade
- Elemental grade (calculated from mineral grades and stoichiometric composition)
- Mineral liberation by size fraction
- Mineral associations

Scanning enough particles ensures statistical robustness, and the device can generate size-by-size mineralogical data in under a minute for most conventional flotation samples.

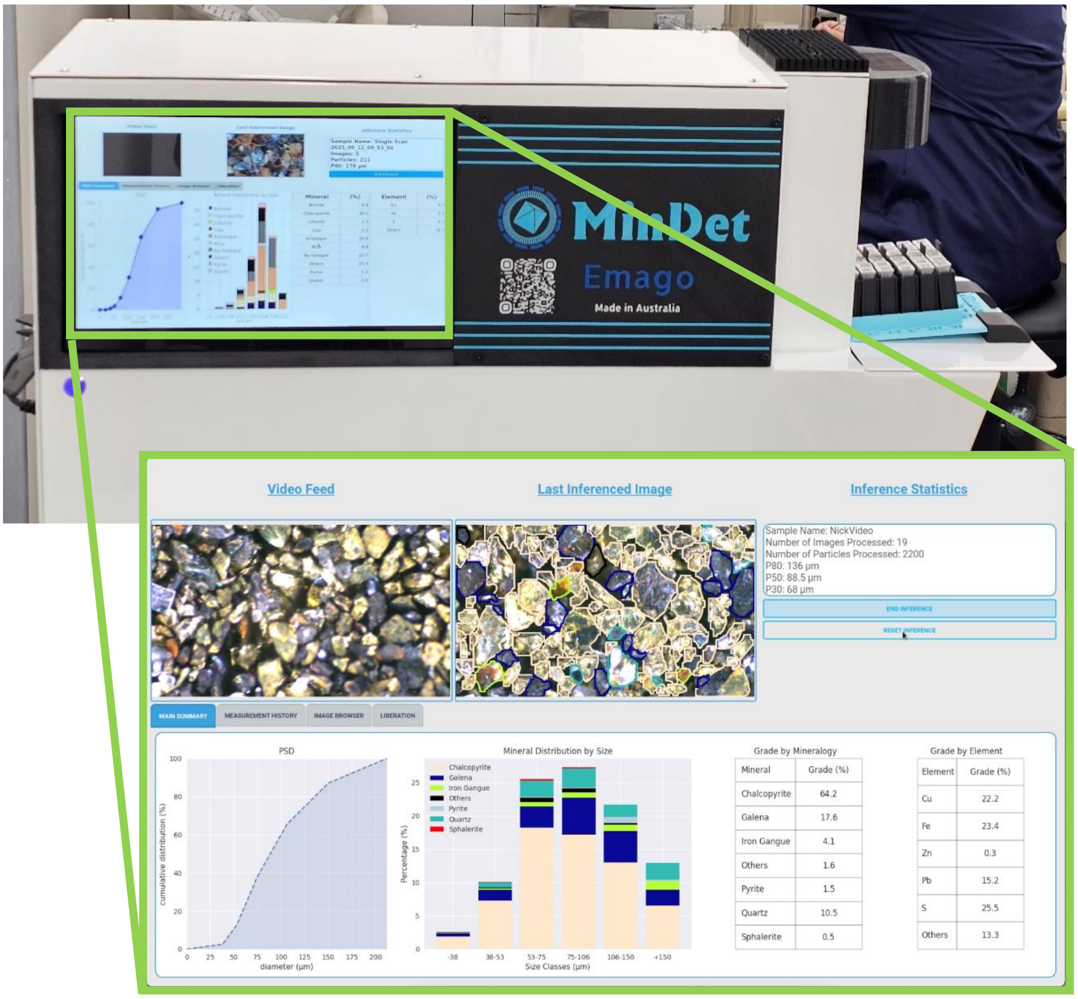

Figure 2 – Emago, the laboratory mineral identification device and the MinDet software User Interface (UI).

The methodology was validated on four copper flotation samples—three from conventional flotation and one from a CPF feed stream. The results obtained by MinDet were compared against conventional SEM–EDS measurements and conventional elemental assays (ICP and XRF). Since MinDet derives elemental grades from mineralogy data, these comparisons were crucial for validating the conversion accuracy between mineral composition and elemental assay.

The modal mineralogy data generated by MinDet also enabled the calculation of liberation degree by size fraction, a key metric for optimizing grinding and flotation processes. Liberation curves are essential for determining the optimal grind size that maximizes metal recovery while minimizing energy consumption. This capability is especially valuable for CPF systems, where coarse and poorly liberated particles can still be recovered. By identifying the liberation threshold that ensures sufficient surface exposure for flotation, operators can reduce grinding costs and improve process efficiency. The MinDet software includes a liberation calculator toolkit that performs these calculations in real time during sample scanning.

Results and Discussion

High- and low-grade flotation samples, along with a CPF feed sample, were analysed using SEM–EDS and XRD. The same samples were subsequently imaged using the MinDet device for comparison and validation. Minerals were identified and classified by a professional mineralogist, and the digital microscope images were used to cross-check SEM–EDS classifications. This process enabled machine vision specialists to annotate mineral grains and textures, thereby refining the algorithm's recognition accuracy. Figure 3 illustrates an example of this classification, where major minerals were categorized by colour, texture, and reflectance.

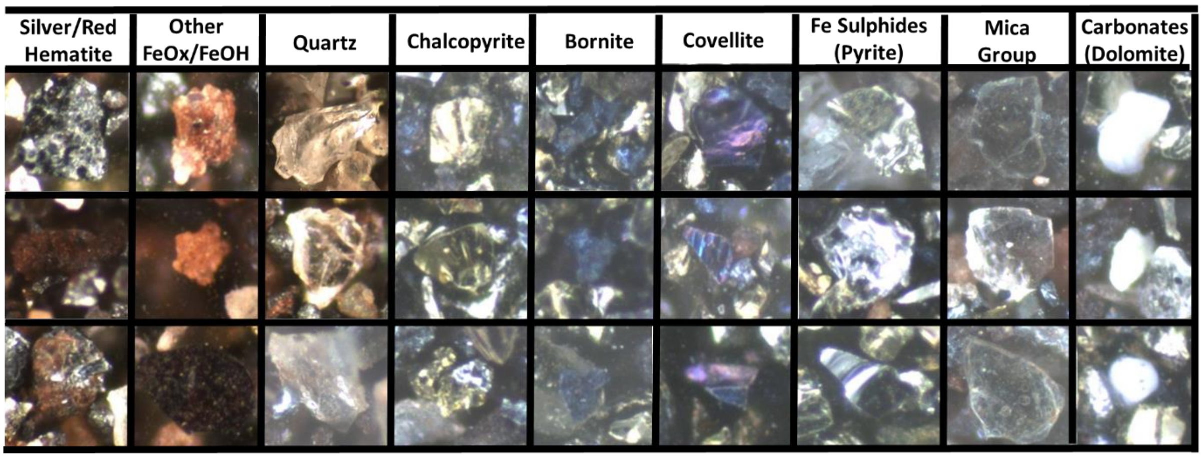

Figure 3 – Categorised mineral grains based on SEM-EDS, XRD and optical microscopic images.

Once trained with data from all four operations, the updated MinDet algorithm was used to analyze the collected slurry samples. The major elemental assays calculated from the MinDet results were compared with laboratory conventional assays (ICP or XRF) for the three conventional flotation samples. As shown in Figure 4, strong correlations were observed for most elements, particularly for copper, zinc, and lead. The average absolute error for copper was below 0.6% across all samples. The largest discrepancy was observed for iron, where MinDet underestimated Fe by approximately 7% in samples from Operation B. This was attributed to the presence of Fe-bearing gangue minerals that had not been included in the training dataset. Incorporating hematite and related Fe oxides in the subsequent version of the algorithm (Operation C) reduced this error to 1.4%, confirming that expanded mineral training libraries enhance accuracy (details demonstrated in Table 1).

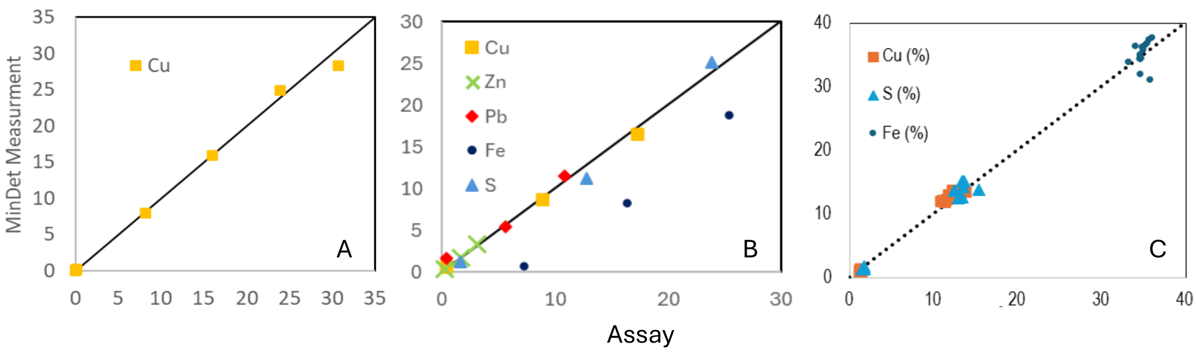

Figure 4 – parity chart MinDet elemental data vs laboratory assay operations for three Australia, 7.6 Mt (A), 4 Mt (B), 5 Mt (C).

These results indicate that multiple analytical steps within MinDet—such as particle segmentation, mineral grain delineation, mineral identification, and mineral-to-element conversion—are functioning correctly. The consistency between laboratory assays and

MinDet's predicted values confirms the statistical reliability of the dataset and the robustness of the algorithm.

Table 1 – Absolute error between MinDet elemental assay and laboratory assays.

Element	Operation A	Operation B	Operation C
Copper (Cu)	0.47	0.41	0.6
Zinc (Zn)	N/A	0.66	N/A
Lead (Pb)	N/A	0.15	N/A
Sulfur (S)	N/A	1.03	0.7
Iron (Fe)	N/A	6.84	1.4

Figure 5 demonstrates mineral grain detection and mineral association mapping for the CPF feed sample. Section A shows a 206 µm particle with a chalcopyrite surface exposure of 36%, while Section B shows a coarser 243 µm particle with less than 6% chalcopyrite exposure. Section C of the figure highlights the differentiation of pyrite grains, recognizable by their cubic morphology and high reflectance compared to the darker and softer chalcopyrite grains. These examples illustrate the algorithm's capability to quantify surface exposure, which directly influences flotation kinetics and recovery in CPF circuits.

Each scanned particle receives a comprehensive profile, including particle size, mineral grain composition, and calculated mineral and elemental assays. After a sufficient number of particles are scanned, MinDet compiles a complete modal mineralogy and elemental profile by size fraction. The results are displayed in the user interface (UI) for further statistical and metallurgical interpretation.

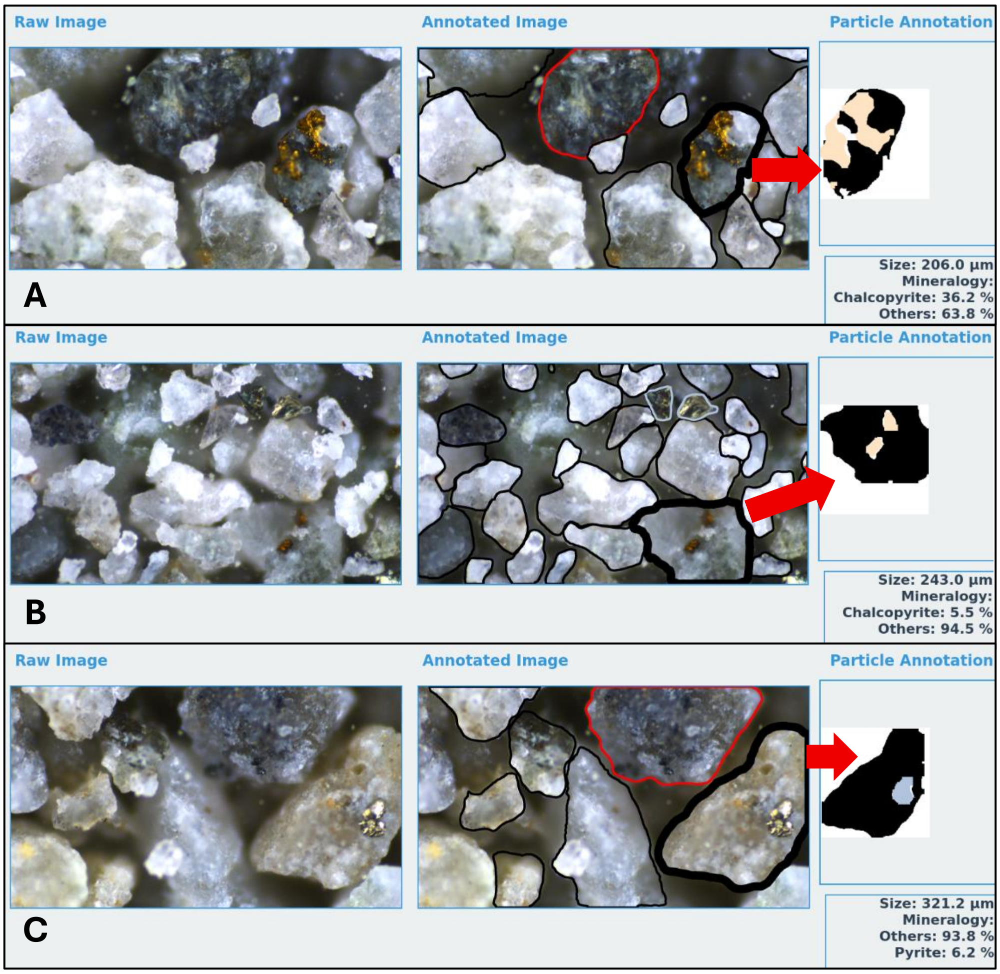

Figure 5 - CPF feed mineral grains and mineral association (MinDet software UI).

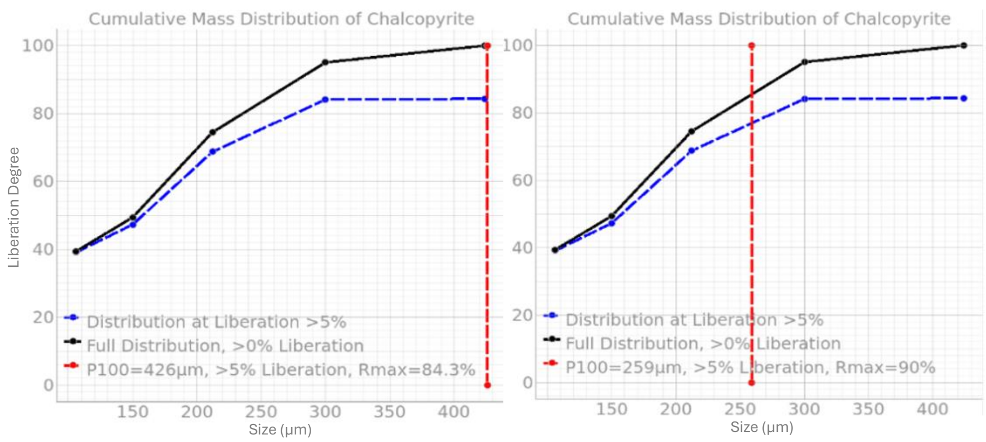

Figure 6 – Liberation degree by size for chalcopyrite in CPF feed.

A key application of MinDet is generating liberation degree profiles as a function of particle size, which provide valuable insights into the recovery potential under different grinding conditions. In Coarse Particle Flotation (CPF) systems, copper-bearing particles exhibiting at least 5% surface exposure of chalcopyrite are typically considered floatable. The MinDet liberation analysis tool enables users to define such surface exposure thresholds and model the corresponding theoretical recovery across a range of grind sizes. This capability facilitates rapid scenario testing to identify the most cost-effective grind size that balances metallurgical recovery with plant throughput. For example, as illustrated in Figure 6, the predicted recovery of chalcopyrite particles with ≥5% surface exposure increased from 84.3% to 90% when the grind size (100% passing size) was reduced from 426 μm to 259 μm. Because operational revenue is ultimately driven by the rate of metal production, such analyses provide direct, data-driven guidance for optimizing process performance and eventually metal production rate.

Furthermore, laboratory test planners and technicians can use MinDet results to proactively optimize bench-scale or pilot plant tests. By rapidly identifying suboptimal liberation or mineral associations, they can adjust parameters such as reagent dosage, grind size, or air flow before running subsequent tests. Extending this capability to full-scale plants would allow continuous feedback-driven optimization, where process operators adjust real-time setpoints based on updated mineralogical information—maximizing recovery and minimizing energy consumption.

Conclusions

This study demonstrates the successful application of robotic microscopy assisted by an AI-driven machine vision algorithm (MinDet) for rapid mineralogical characterization of flotation slurry samples, including coarse particle flotation (CPF) feeds. The comparison between conventional laboratory assay data and MinDet-derived elemental assays—calculated from mineralogical composition and distribution—showed strong correlations across three Australian base metal operations.

The detailed modal mineralogy data provided by MinDet—including mineral and elemental grades, particle size distribution, and mineral liberation by size—are essential for designing and optimizing grinding and separation circuits. The ability to obtain such data rapidly and at a lower cost enables operators to fine-tune key process parameters such as grind size and reagent dosage, thereby maximizing metal recovery and reducing operational expenditure.

MinDet's capacity to analyze coarse particle flotation feeds in real time allows for rapid assessment of grind size targets and recovery potential. This makes it a valuable tool not only for laboratory and pilot-scale test work but also for full-scale operations aiming to transition toward energy-efficient coarse particle recovery. Moreover, by identifying whether metal losses to tailings arise from mass-related issues or inadequate liberation, MinDet supports root-cause diagnostics and targeted optimization.

Overall, MinDet represents a transformative advancement in digital mineralogy, bridging the gap between laboratory-scale mineralogical analysis and real-time plant control. Its integration into process optimization workflows offers substantial potential for improving recovery, reducing costs, and advancing the development of next-generation mineral processing operations.