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COMPARISON OF METHODS FOR CALCULATING FRAGMENTATION OF BLAST MUCK PILES IN QUARRIES

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Abstract: The size distribution and fragmentation level of the blasted rock mass are crucial factors in enhancing the efficiency of loading, transportation, crushing, and milling processes. This article provides a comparative analysis of grain size distribution curves derived from image analysis using various methods. The first method compares representative fragments of the muck pile through manual analysis, commercial software, and an Open-Source Algorithm. The second method evaluates the grain size distribution curves of the entire muck pile, utilizing both commercial software and an open-source algorithm.

Keywords: *fragmentation; fragment size distribution, fracture; blasting; quarries*

1. INTRODUCTION

The design of blasting operations represents a critical phase in the overall process of aggregate rock extraction, as it significantly impacts both safety and cost-efficiency in the subsequent stages of production (McKee and Il 2013; Zeggeren and Chung 1975). Therefore, research efforts have increasingly focused on optimizing

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blasting techniques by examining the factors that influence the fragmentation outcomes.

Quarry managers recognize the substantial role that high-quality drilling and blasting play in optimizing production processes and achieving associated economic gains (Dumakor-Dupey et al. 2021). To maintain high standards at the mineral extraction stage, these tasks are frequently outsourced to specialized external contractors (Pal 2021; Isheyskiy and Sanchidrián 2020). The effectiveness of these operations is typically assessed by analyzing the resulting muck pile, with particular attention given to quantifying the proportion of oversized fragments.

The extraction of rock materials is a complex process that requires meticulous planning and the coordination of multiple operational stages over time. The effects of suboptimal drilling and blasting practices are particularly significant in the context of rock extraction using explosives. Overcharging can result in excessive fragmentation, which reduces the economic value of the extracted material (Nikkhah et al. 2022). In mining operations, excessive fragmentation can reduce profitability by lowering the quality of the extracted raw materials. When drilling and blasting activities are carried out by external contractors, financial penalties may be imposed if the material produced fails to meet the specified grain size requirements. Additionally, excessive fragmentation can have significant economic and environmental consequences, such as increased risks of damage to areas adjacent to the quarry due to fly rock (Bhatawdekar et al. 2023; Ding et al. 2023). The requirement for comprehensive planning is largely driven by regulatory standards governing the use of explosives in mining operations. However, the extent of such planning frequently exceeds the minimum requirements established by national regulations. Conversely, if the amount of explosive deployed is inadequate and the rock face is insufficiently fragmented, the transport of larger rock fragments may be significantly hindered or even rendered infeasible (Dotto and Pourrahimian 2024). Even if oversized fragments can be transported to the crusher, they present
a significant risk of blockages, which could potentially disrupt or completely halt mining operations. To mitigate such operational risks, large boulders must be further comminuted to reduce their size.

Over the past several decades, various empirical models have been developed to predict fragment size distribution based on the parameters of blast design (Amoako et al. 2022; Mulenga 2020; Esen and Bilgin 2000; Ouchterlony 2005; Ouchterlony and Sanchidrián 2019). Among these models, the Kuz-Ram model remains the most widely applied. These empirical models continue to undergo refinement and are incorporated into software tools to aid the operational activities of drilling and blasting companies. However, it should be noted that the Kuz-Ram model often yields idealized predictions, which can result in significant deviations from actual blasting outcomes (Figueiredo et al. 2023). Consequently, an accurate assessment of the grain size distribution of the muck pile formed after blasting is necessary.

2. FRAGMENTATION MEASUREMENT METHODS AFTER BLASTING WORK USED IN QUARRIES

Among the current methods for analyzing rock fragmentation, two primary categories can be distinguished: direct and indirect techniques (Kawalec et al. 2019). The direct method of screening (sieving) is considered the most accurate and precise. In this technique, a representative sample of a specified mass is collected from the muck pile and passed through a series of sieves with progressively smaller mesh sizes. The material retained on each sieve is weighed, and the percentage contribution of each fraction to the total mass of the muck pile is calculated accordingly. Although this method provides highly accurate results, it is also time-consuming and costly (Stojanovic et al. 2023). Furthermore, its application often leads to disruptions or interruptions in the production process. Due to these limitations, indirect methods have been developed, such as the oversize boulder count method, the shovel loading rate method, the photogrammetry method, and the most widely used technique: image analysis (Nanda and Naik 2023).

The oldest method, which is now being replaced by more modern, accurate, and faster solutions, is the manual analysis of the grain size of the muck pile. Manual methods also include those that do not require direct sampling. One such example involves identifying a representative area of the muck pile in a photograph and using a CAD program to outline the grain boundaries. The data regarding the surface area of these outlined fragments are then exported to an external program where the necessary calculations are performed. However, selecting a sample that perfectly represents the entire pile mass is virtually impossible, making it relatively easy to question the validity of the results obtained. A critical step in this method is determining the equivalent diameter of each identified grain to account for the irregular shapes of the crushed rock. Based on this, each rock fragment is classified and assigned to a specific size fraction. The primary disadvantage of this method is its significant time requirement. Furthermore, advancements in image analysis technology have rendered it largely obsolete in quarrying applications.

The most commonly used method for assessing rock fragment size distribution is now the image processing technique. This approach does not interrupt or hinder the production process in quarries. Its primary advantage is the ease of use, facilitated by a wide range of software tools (such as WipFrag, Orica BlastIQ, K-Mine, Fragalyst, Split-Desktop, and others), which enable intuitive analysis and rapid results (Nanda and Pal 2020; Nanda and Naik 2023; Stojanovic et al. 2023). The quality of captured images and advancements in image analysis are enabling a shift from the commonly used method of analyzing a representative fragment to analyzing the entire of the muck pile obtained after blasting. Scientific studies have demonstrated that analyzing the entire formed muck pile provides a much more accurate representation of reality, thereby resulting in greater precision of the analysis (Engin et al. 2020). An image taken with a drone or digital camera is uploaded to the software, which then employs built-in algorithms to analyze the photograph, identify, and delineate the edges of the detected grains. The user is responsible for verifying the accuracy of this process, with the option to manually correct the boundaries of each detected rock fragment. Once the identification is confirmed, the software generates a report that includes, among other data, a size distribution curve and a histogram of the fragmented muck pile. A notable limitation of these programs is their reliance on proprietary algorithms for edge detection, which are not accessible to the user. These algorithms are typically branded by the manufacturer, without the possibility of reviewing the specific methods or procedures used for edge detection and grain size estimation.

Currently, the most rapidly developing trend, also in the mining industry, is the shift from commercial software tools and applications to more advanced, custom algorithms that are better suited for tasks related to data acquisition and analysis. This transition is part of the broader Mining 4.0 framework, where the integration of digital systems, machine learning, and custom algorithms plays a crucial role in optimizing operations and enhancing productivity (Zhironkin and Ezdina 2023). Therefore, an increasing number of professionals involved in this field are developing algorithms specifically tailored to the data acquisition methods used in analysis, whether 2D or 3D (Li et al. 2023). This direction is currently the most actively developed; however, it requires users to have specialized knowledge not only of mining operations but also of programming skills. The use of such algorithms allows for a more comprehensive understanding of the entire muck pile, providing more accurate and reliable results while requiring a combination of mining expertise and advanced computational skills. Additionally, users can obtain supplementary information regarding the analysis being conducted. This allows for the inclusion of additional checkpoints in the procedure, enabling verification and control of the reliability of the obtained results. The results from the deep learning models were compared with traditional manual measurements, conventional image analysis techniques data obtained from 3D photogrammetry, and results derived from empirical models such as the Kuz-Ram model (Yoshino et al. 2022; Ikeda et al. 2023; Vu et al. 2021).

This article presents a comparison of grain size distribution curves obtained through image analysis using different methods. The first approach involves comparing representative fragments of the muck pile using a manual method, commercial software (WipFrag), and oper-source algorithm. The second approach compares the grain size distribution curves of the entire muck pile using commercial software and open-source algorithm.

3. MATERIALS AND METHODS

The muck pile fragmentation assessment was conducted at the Kujawy quarry, located in central Poland, where limestone is extracted to meet the needs of the cement plant. Limestone extraction is performed using the long-hole blasting method. The entirety of the crushed rock material is designated for use by the cement plant. A general view of the muck pile for which a grain size distribution analysis was conducted is presented in Fig. 1.

Fig. 1. General view of the muck pile for which a grain size distribution analysis was conducted

3.1. METHOD I: MANUAL IMAGE PROCESSING

After the blasting operations, a drone survey was conducted to obtain photographic material. To ensure proper calibration of the images, the coordinates of reference points were measured using a GNSS receiver before commencing the drone flights. Additionally, an object with known dimensions was placed within the muck pile area to serve as a reference point.

Fig. 2. Selected representative fragment for analysis with dygitize boundaries of grains

The main part of the analysis was carried out in AutoCAD, where the image of the muck pile was imported, and data were prepared to enable proper calibration. Subsequently, a representative fragment of 10 m × 10 m was selected for analysis. In the next step, the edges of individual grains within the selected area were delineated (Fig. 2) and their volumes were calculated.

The data obtained were exported to an Excel spreadsheet, where the necessary transformations and calculations were performed: the equivalent diameter of each identified rock was calculated, volumes were assigned to respective size fractions, and a grain size distribution curve was plotted based on this information (Fig. 3).

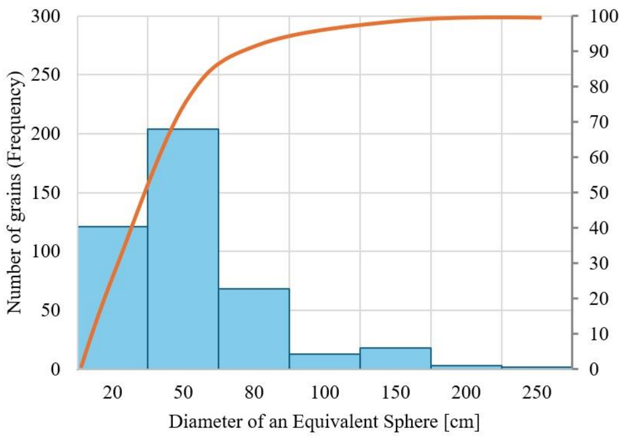

Fig. 3. Grain size distribution curve prepared using the manual method

3.2. METHOD II: IMAGE PROCESSING USING COMMERCIAL SOFTWARE

For the analysis using commercial software, Wipfrag4 was selected, developed by the Canadian company WipWare, which specializes in photoanalysis devices and software used in mines worldwide. The work in the program begins with uploading the captured image and setting the scale by marking reference points. For the purposes of this article, two images were analyzed: an image of the representative fragment selected for analysis using Method I and an image of the entire muck pile.

The analysis procedure was conducted in accordance with the guidelines provided in the software manufacturer's manual (Fig. 4). Among the available options for edge detection analysis, the Deep Learning method was selected. To enable comparison, the data obtained from Wipfrag (percentage of size fractions, statistical parameters of the analyzed sample) were exported to Excel. The results of the analysis are presented in Fig. 5.

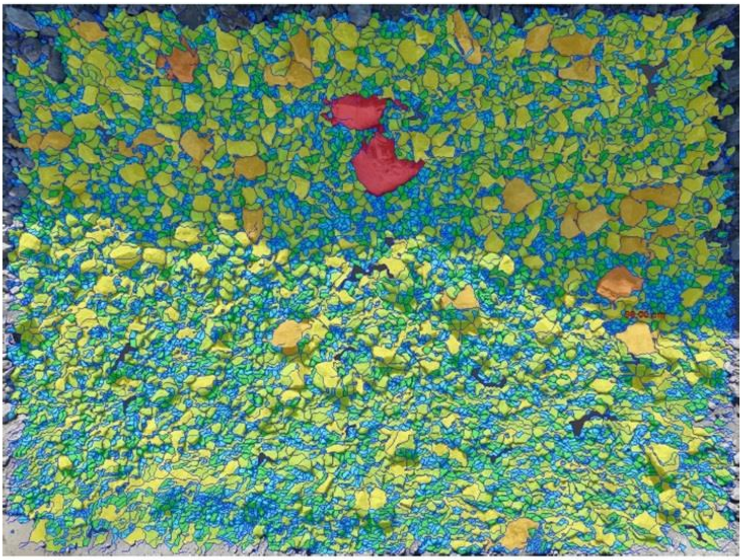

Fig. 4. Color classification of the size of detected grains in the WipFrag program

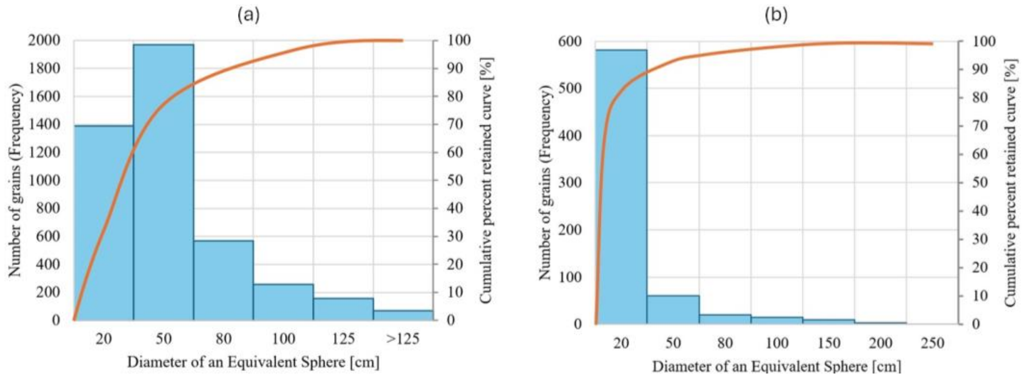

Fig. 5. Grain size distribution of the entire muck pile (a) and a representative fragment of the muck pile (b) generated in Wipfrag Deep Learning mode

3.3. METHOD III: IMAGE PROCESSING USING DEEP LEARNING ALGORITHM

The application of Open-Source Algorithm in grain size distribution analysis involves using advanced neural networks, particularly convolutional neural networks (CNNs), to automatically detect and classify the sizes of particles or grains in images of a muck pile or rock fragments. This approach leverages deep learning models' ability to recognize patterns and features in complex datasets, making them particularly effective in analyzing images for particle size distribution.

To achieve the most accurate results, the image for entire muck pile was divided into two areas before the main analysis (Fig. 6). This division was carried out in such a way as to separate the shaded area from the well-lit area as much as possible. This step was necessary because, during the conversion to a binary image, it was impossible to establish a threshold point that would allow edge detection across the entire image simultaneously.

Fig. 6. Division of the muck pile into sectors

For this reason, the processing procedure in Matlab was conducted separately for Sector 1 and Sector 2. The algorithm for grain size distribution analysis consists of several image processing steps that enable edge detection of the grains, image segmentation, and identification and analysis of individual grains. The results obtained from these procedures (Fig. 7) were exported to Excel, where they were combined and a comprehensive analysis of the grain size distribution was performed (Fig. 8a).

Subsequently, the analysis procedure employing the open-source algorithm was applied to a representative fragment of the muck pile (Fig. 2). The results of this analysis are displayed in Fig. 8b.

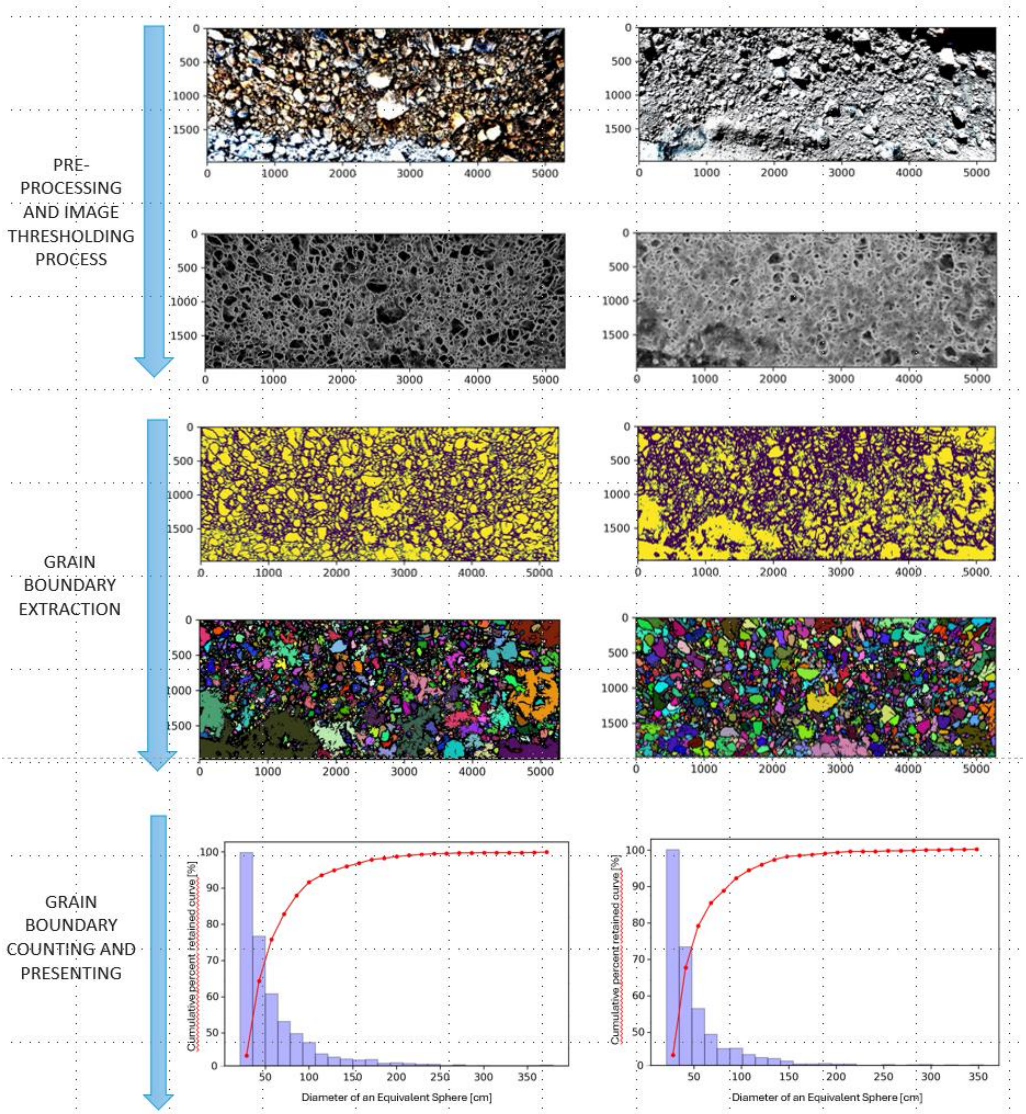

Fig. 7. Individual outputs of the grain size distribution curve generation procedure using open-source algorithm in Matlab

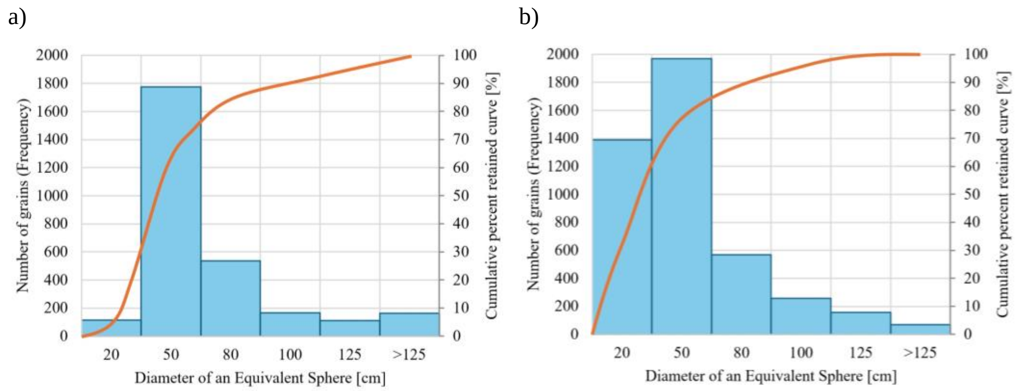

Fig. 8. The result of the grain size distribution of the entire muck pile (a) and a representative fragment of the muck pile (b) obtained using open-source algorithm in Matlab

4. RESULTS

The grain size distribution curves of the representative fragment of the muck pile obtained by Methods I, II and III are presented in the Fig. 9, while the table (Table 1) summarizes the basic statistical parameters of the analysis results.

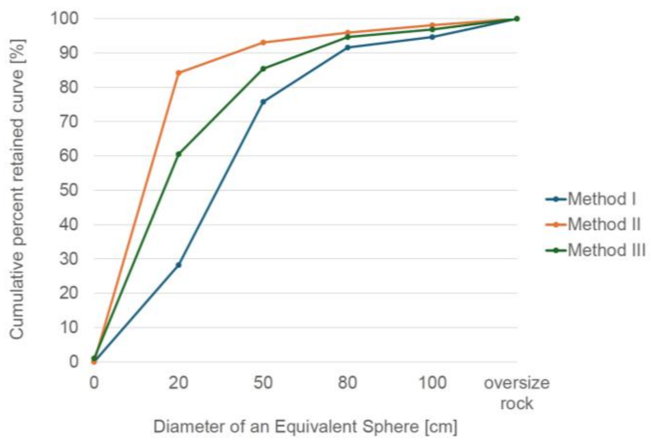

Fig. 9. Grain size distribution curves of the representative fragment of the muck pile obtained using Method I, Method II and Method III

The main difference in the obtained results lies in the number of detected grains across the various size fractions. The WipFrag software identified over 200 additional particles, with a noticeable predominance in the <20 cm fraction. In the case of the manual method, this fraction constituted approximately 30% of the total particle count, whereas the commercial software estimated the share of this fraction to be as high as 80% of all particles. The discrepancies for the larger fractions are less pronounced, with differences gradually decreasing until reaching a maximum value. Several factors may account for these variations in the results. Firstly, the commercial software employs a proprietary algorithm for estimating non-visible fractions, which represents a notable advantage, as these estimation methods are continuously refined through machine learning based on user analyses. Secondly, during the analysis, there was noticeable over-segmentation of certain particles, particularly at the edges of the analyzed area and in regions with varying illumination. Both methods, however, indicated a relatively low content of oversized particles (fractions above 100 cm) within the analyzed area, amounting to 2% according to the manual analysis and 5% according to the WipFrag analysis.

Table 1. Basic statistical parameters of analysis results for the muck pile fragment

Parameter	Unit	Manual method	Wipfrag 4	Open-Source Algorithm
Total number of grains	[–]	429	690	542
<20	[cm]	121	581	328
20.01–50.00	[cm]	204	61	135
50.01–80.00	[cm]	68	20	50
80.01–100.00	[cm]	13	15	12
>100.00	[cm]	23	13	17
Min.	[cm]	5.53	no data*	2.20
D25	[cm]	19.01	89,43	5.33
D50	[cm]	28.54	124,81	12.86
D75	[cm]	49.6	176,2	34.54
Max.	[cm]	204.1	231	190.28
Average	[cm]	39.35	no data*	24.88
Median	[cm]	28.54	124,81	12.86
Standard deviation	[cm]	30.43	no data*	28.69

* The program does not generate values.

The grain size distribution curves of the entire muck pile are presented in Fig. 10. The table (Table 2) summarizes the basic statistical parameters obtained from analyses.

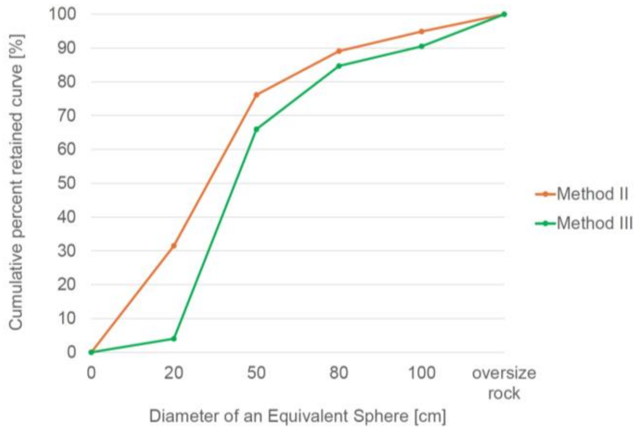

Fig. 10. Grain size distribution curves of the representative fragment of the muck pile obtained using Method II and Method III

Table 2. Basic statistical parameters of analysis results for the muck pile fragment

Parameter	Unit	WipFrag 4	Open-Source Algorithm
Total number of grains	[–]	4408	2863
<20	[cm]	1388	114
20.01–50.00	[cm]	1969	1775
50.01–80.00	[cm]	569	536
80.01–100.00	[cm]	257	166
>100.00	[cm]	225	272
Min.	[cm]	no data*	17,2
D25	[cm]	81,82	28,6
D50	[cm]	120,73	40,29
D75	[cm]	189,83	62,07
Max.	[cm]	442,99	379,32
Average	[cm]	no data*	53,51
Median	[cm]	124,81	40,29
Standard deviation	[cm]	no data*	39,92

* The program does not generate values.

As in the analysis of the muck pile fragment, the grain size distribution curve also demonstrates discrepancies, particularly in the smallest fraction range. The algorithm used in Method II was the only one that did not detect the presence of the <20 cm fraction. To address this issue, an estimation algorithm for this fraction could be incorporated, similar to that employed in commercial software.

The statistical data for both methods are presented in Table 2. The commercial software identified nearly twice the number of grains compared to the open-source algorithm. In both methods, the highest proportion of grains was observed in the 20–50 cm size fraction. The oversized fractions constituted 15.93% according to the open-source algorithm and 10.93% as per the WipFrag software. Although the number of detected grains across most fractions is relatively comparable, the percentage distribution differs due to the disparity in the total grain count. This variation is primarily attributed to differences in sample size.

5. DISCUSSION

Following the analysis, several differences were identified that could have a significant impact on the results obtained and the method's potential applicability within the industry. These observed differences have been systematically summarized in Table 3.

Table 3. Comparison of image analysis methods for grain size distribution

Function	Manual image analysis method	Method using commercial software	Open-source algoritm
Analysis time	Very time-consuming; manual digitization of edges limits the analysis to a representative fragment of the muck pile image.	Generally faster due to optimized and compiled algorithms, but in specific settings, the analysis may take up to 40 minutes.	Variable; may be slower due to the use of neural networks.
Input requirements	Minimal input data	Minimal input data; highly automated	Many parameters need to be manually set.
Flexibility	High; allows customization at every stage	Lower; limited to the set of functions available in the software	High; allows customization at every stage.
Accuracy	High; requires full user oversight and decision-making regarding edge detection.	High, due to proprietary algorithms and calibration tools	Potentially high with the appropriate model and parameters, capable of processing high-resolution images without the need for size compression.
Hardware requirements	Minimal; the only requirements may relate to the graphics card; in practice, the analysis can be performed on any computer.	Requires a high-performance system but is optimized for speed.	Requires a good CPU/GPU for efficient processing
Customization of results	High; the user can modify the edges, result sets, and visualization.	Moderate; limited to predefined templates and outputs	High; the user can modify processing steps and visualization.
Ease of use	Low; requires proficiency in CAD software and Excel	High; designed for users without programming knowledge	Low; requires programming knowledge and parameter tuning.

Cost	Free (if using CAD software in open-source mode)	Commercial software; requires a license	Free (open-source)

The complete analysis of the representative fragment of the muck pile using Method I (manual) in AutoCAD, followed by processing in Excel, required approximately 8 hours. The most time-intensive phase (about 7 hours) involved accurately delineating the grain contours. In contrast, conducting the contouring and analysis for the same area in WipFrag 4 was considerably faster. The observed differences depended on the mode utilized in WipFrag:

- *Simple Mode*. This mode allows for selecting the grid density via a slider. The program was most efficient at detecting the boundaries of larger fragments. However, its accuracy diminished significantly for smaller grains, particularly at the image's periphery, where the algorithm often failed to close the contours of fragments. Due to the limited control over grid density, there were frequent instances of over-segmentation of larger rocks in some areas, while in others, the detected edges did not align with those visible in the image.
- *Advanced Mode.* This mode provides two analysis options: manual adjustment of values within specific ranges and the Best Fit function, which includes three algorithms (Quick: ~3 minutes, Regular: 8–10 minutes, and Thorough: 45–50 minutes). The automatically generated contours in this mode showed a higher degree of accuracy in matching the visible edges in the image, with the accuracy improving as the grid settings were refined. However, the software also exhibited difficulties in edge detection at the image boundaries, necessitating manual intervention to correct the grain contours in those regions.
- *Deep Learning Mode*. This mode employs a machine learning algorithm to generate the grid, completing the process in less than 30 seconds. Although requiring fewer user-defined settings, the algorithm demonstrated superior accuracy in detecting grain edges compared to the other modes. Nonetheless, some manual adjustments were still necessary, and upon closer examination, this mode yielded the most accurate results among the tested methods. However, similar to the Simple Mode, it did not detect fragments located at the edges of the image.

An important aspect to consider when evaluating these methods is their accuracy. The manual method, due to its inherent nature, is highly accurate and seldom results in excessive or insufficient segmentation of fragments. In contrast, the algorithm using the Deep Learning setting exhibited some instances of these segmentation errors, although they were less frequent than in the Simple and Advanced settings. It is also noteworthy that during manual corrections, the intersection of existing lines with newly drawn ones often created small areas or single pixels that were misinterpreted by the program as grains, subsequently categorized into the finest fraction. The reduction in the resolution of the imported image may also have influenced the accuracy of the analysis; for example, an image of the entire muck pile initially had a resolution of 5280 × 3956 pixels, which was reduced to 1440 × 1079 pixels upon import into the software. This reduction likely aims to expedite algorithm performance by decreasing the number of pixels to be processed, but it also leads to a significant loss in image quality and clarity.

The duration of the analysis using the open-source algorithm is variable and influenced by several factors, including image size and resolution, hardware specifications (CPU, RAM), and algorithmic complexity. The algorithm encompasses multiple processing steps, such as Gaussian blurring, thresholding, and connected component analysis, each contributing to the overall computation time. It is estimated that loading the model and image takes minimal time, measured in milliseconds, while preprocessing steps (blobbing and cropping) require moderate time, depending on image dimensions. The most computationally intensive step is edge detection using the Holistically-Nested Edge Detection (HED) network, which involves neural network inference and can take several seconds per image, depending on available hardware resources (CPU or GPU). Other steps, such as thresholding and connected component analysis, typically require a few seconds, while post-processing tasks, including coloring, filtering, and centroid marking, are less time-consuming and generally take less than a second.

The open-source algorithm based on Holistically-Nested Edge Detection also necessitates the manual configuration of several parameters, unlike WipFrag, which is more automated and user-friendly. These parameters include paths to model files, the path to the input image, mean pixel values for image normalization, the thresholding method, and connectivity settings for connected component analysis.

Compared to WipFrag, the open-source algorithm offers several advantages and disadvantages. One of the primary advantages is its adaptability; users have full control over each step of the image processing workflow, allowing them to customize the algorithm to specific needs and image types. Another benefit is the absence of licensing costs, as the algorithm is open-source and therefore free to use. Its high flexibility enables modifications for various applications. However, the disadvantages include the time-consuming nature of the analysis, particularly during the neural network inference stage, and the required expertise of the user, who must possess programming skills, knowledge of image processing, and the ability to fine-tune parameters. Additionally, the lack of official technical support and regular updates can be a drawback compared to commercial solutions.

In contrast, WipFrag offers several benefits, such as ease of use—it is designed for engineering users who do not need specialized programming knowledge. The software also provides optimized processing speed due to its compiled and optimized algorithms, as well as regular updates and technical support from the provider. It includes built-in calibration tools that aid in verifying and calibrating the accuracy of the analysis. However, the disadvantages of WipFrag include its cost, as it requires a commercial license, which may be a barrier for some users, and its limited flexibility, as users have fewer options to customize the analysis for non-standard cases.

Another factor affecting the effectiveness of the analysis is the number of possible metrics that can be computed, such as the mean, median, or quartiles. In the manual method, the use of Excel allows for the calculation of any desired metric. In contrast, WipFrag only provides results for predefined metrics, which do not include basic statistics like the minimum value, mean, or standard deviation, even though these metrics were available in the previous version of the software (WipFrag 3) when exporting results to a .csv file.

6. CONCLUSION

Both commercial and open-source tools can provide accurate grain size distribution results. However, open-source algorithms offer greater flexibility to adjust the analysis parameters, which can lead to better performance in specific or complex conditions. Commercial tools are generally optimized for speed and ease of use but may lack flexibility in adapting to unique or non-standard conditions. Open-source algorithms have a clear advantage in terms of cost and accessibility. They are free to use and modify, which makes them appealing for academic researchers and small-scale operations.

Commercial software tends to be more user-friendly, with intuitive interfaces and streamlined workflows that require less technical knowledge. Open-source tools may require more expertise in programming and data analysis, which could limit their use to more technically skilled users.

The choice between commercial software and open-source algorithms for grain size distribution analysis depends on the specific needs of the mining operation, available resources, and the desired balance between cost, flexibility, and ease of use. While commercial software provides a fast and user-friendly option for routine applications, open-source algorithms offer a more customizable and cost-effective solution for users with the necessary technical skills to modify and adapt the tools to their specific requirements.

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