



وقائع مؤتمرات جامعة سبها  
Sebha University Conference Proceedings

Conference Proceeding homepage: <http://www.sebhau.edu.ly/journal/CAS>



## Real-time Rock Cutting Characterization using Validated Image-based Dual Shape Measurements

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### Keywords:

Automation  
Drill Cuttings  
Image Analysis  
Shape Distribution  
Size Distribution

### ABSTRACT

Real-time characterization of drill cuttings is increasingly recognized as a valuable tool for drilling optimization, providing insights into lithology, bit wear, and rock breakage mechanisms beyond conventional sieve and laser diffraction methods, which are limited to offline analysis and lack shape data. Recent advances in image-based techniques address these limitations by enabling automated monitoring of particle size and morphology during drilling operations. This study aims to develop and validate an image-based methodology that integrates dual size and shape analysis of drill cuttings for improved real-time performance evaluation. Over 160 cutting samples from large-diameter disc cutter field trials were analyzed using both ASTM-standard sieve analysis and dynamic image analysis (DIA). A custom imaging system with controlled lighting and automated camera motion captured high-resolution images, which were processed using watershed segmentation and shape descriptors (circularity and roundness). Results showed that image-based shortest dimension measurements closely matched sieve distributions for particles  $>0.075$  mm, while the dual shape-size classification provided actionable insights into drilling efficiency. Error analyses confirmed minimal discrepancies, except at very fine sizes. The validated approach demonstrates strong potential for integration into drilling automation, enabling optimized parameter control, reduced mechanical specific energy, and enhanced decision-making for field-scale operations.

### التوصيف الفوري لقطع الصخور باستخدام قياسات الشكل المزدوج المعتمدة على الصور الموثقة

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### الكلمات المفتاحية

الآتوميشن  
تحليل الصور  
توزيع الحجم  
توزيع الشكل  
فتات الحفر

### الملخص

يُعدّ التوصيف الفوري لفتات الحفر أداة متزايدة الأهمية لتحسين أداء الحفر، حيث يوفر رؤى حول الليثولوجيا وتآكل فأس الحفر وآليات تكسير الصخور، بما يتجاوز حدود طرق الغربلة أو حيود الليزر التقليدية التي تقتصر على التحليل غير الفوري وتفقر لبيانات الشكل. وقد عالجت التطورات الحديثة في تقنيات التحليل بالصور هذه القيود من خلال تمكين المراقبة الآلية لتوزيعات الحجم والشكل أثناء عمليات الحفر. تهدف هذه الدراسة إلى تطوير منهجية قائمة على الصور ومُعتمدة تجمع بين تحليل مزدوج للحجم والشكل لفتات الحفر بغرض تحسين التقييم الفوري للأداء. تم تحليل أكثر من 160 عينة مأخوذة من تجارب ميدانية باستخدام فؤوس حفر بالأقراص ذات الأقطار الكبيرة بواسطة كل من الغربلة القياسية ASTM والتحليل الديناميكي للصور. استُخدم نظام تصوير مخصص بإضاءة محكمة وحركة تلقائية للكاميرا لالتقاط صور عالية الدقة، تمت معالجتها بخوارزميات فصل الجسيمات (Watershed) ومعاملات شكل مثل الاستدارة والدائرية. أظهرت النتائج أن قياسات البُعد الأقصر بالتحليل الصوري تتطابق بشكل وثيق مع نتائج الغربلة للجسيمات الأكبر من 0.075 مم، بينما وُقر التصنيف المزدوج للحجم والشكل رؤى عملية حول كفاءة الحفر. أكدت تحليلات الأخطاء وجود فروق طفيفة فقط عند

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Article History : Received 20 February 2025 - Received in revised form 01 September 2025 - Accepted 07 October 2025

## 1. Introduction

Drill cuttings are the fragmented rock particles generated during drilling operations of oil and gas wells or during the excavation of mineral deposits in mining applications. While often considered as waste by-products, these materials offer significant untapped value as diagnostic indicators of subsurface conditions [1]. The characterization of drill cuttings provides essential insights into downhole phenomena such as lithology, bit wear, rock breakage mechanisms, and overall drilling efficiency [2]. As such, systematic analysis of drill cuttings is increasingly recognized as a valuable, cost-effective approach for real-time drilling optimization and performance monitoring.

Traditionally, cuttings analysis has been conducted in laboratory settings using techniques such as sieve analysis and laser diffraction [3], [4]. Although reliable for determining particle size distributions, these methods possess the following limitations: they are not suitable for real-time feedback due to their offline processing nature, and they fail to provide information on particle shape which is an important factor related to fragmentation behaviour, bit-rock interaction, and energy transfer efficiency.

To overcome these limitations, image-based analytical methods have emerged as promising alternatives. These approaches enable not only particle size characterization but also detailed shape analysis, and they are well-suited for automation and real-time deployment. According to ISO standards, image analysis is classified into static and dynamic categories [5], [6]. In static image analysis, particles are captured while stationary, whereas in dynamic image analysis, images are taken of particles in motion, allowing integration into continuous drilling workflows for real-time diagnostics. Nevertheless, image analysis techniques are not without challenges. Issues such as low resolution, overlapping particles, and poor segmentation due to thresholding inconsistencies can reduce the accuracy and reliability of the results [7]–[9]. While particle size distribution is relatively standardized, there remains a lack of universally accepted methodologies for assessing and interpreting particle shape distributions in the context of drilling performance. This study aims to address these gaps by developing a validated, real-time image-based methodology for dual shape and size analysis of drill cuttings. The proposed approach integrates high-resolution imaging, dual shape descriptors (e.g., circularity and roundness), and advanced segmentation algorithms to improve measurement fidelity. By linking particle morphology to drilling performance metrics, this research supports more responsive, data-driven decision-making in drilling operations

## 2. Materials and Methods

In this study, there are several fundamental steps carried out before generating the shape and size distributions of the cuttings. This section therefore discusses and validates the different methods used in this paper.

This study introduces a new methodology for presenting the shape of the cuttings and adds on existing particle size distributions, it is

important to ensure that extensive quality checks and validations are performed. As such over 160 bags of about five kilograms each, were analyzed with both the sieve analysis method and the image analysis method. The drill cuttings used were collected from field trials performed in 2021 using large diameter disc cutters. Upon collection the cuttings were dried in a microwave at 100 degrees celsius for 8 hours then left inside overnight to ensure that all moisture content had been eliminated. Sieve analysis was then carried out following the procedures of the ASTM [10],[11] standards. Sieve analysis was taken as the reference for comparisons with image analysis on the developed set up. Image analysis was then performed where cuttings images were captured on the developed experimental setup.

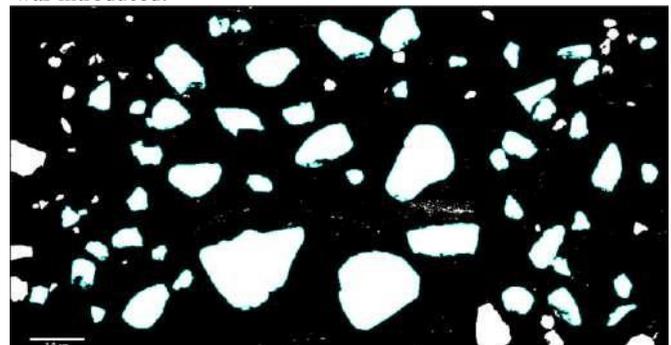


**Fig. 1:** Automated Image Capture setup showing camera mounted on the slider

The developed experimental setup was designed based on the standards where there are lighting sources used and a camera slider that allows the camera to automatically move from one to another as shown in fig.1. A Nikon D5300 digital SLR camera with a 24.2-megapixel APS-C CMOS sensor (6000 x 4000-pixel resolution) was used. The criteria used to select the camera was its compatibility with the camera slider and high resolution. Most of the study was spent developing this setup because it had to be designed such that it is robust for various drilling conditions. This is why this experiment was performed on wet cuttings, dry cuttings and different background materials. As displayed in fig.1, during the experiments, the lighting sources used are the only sources of light, this is done as a method to monitor the lighting conditions and introduce uniform illumination.



**Fig. 2:** Actual image of cutting's sample before image processing  
After the images are automatically captured, they are then analyzed on ImageJ software using customized scripts which allow for automated batch processing. Images were enhanced by adjusting the brightness and contrast and further segmentation and edge detection was performed. Fig.2 shows some of the samples used before processing. Fig.3 shows how the cuttings look like after processing, which involves thresholding and filling holes and other enhancement techniques. After the analysis is performed, imaging size distributions are generated and then compared to the distributions from sieve analysis. Initially the sieve analysis size distribution was compared to the image analysis distribution graph that is based on the longest dimension of the cuttings. However, after running multiple experiments and the need for thorough quality check, another measurement dimension was introduced.



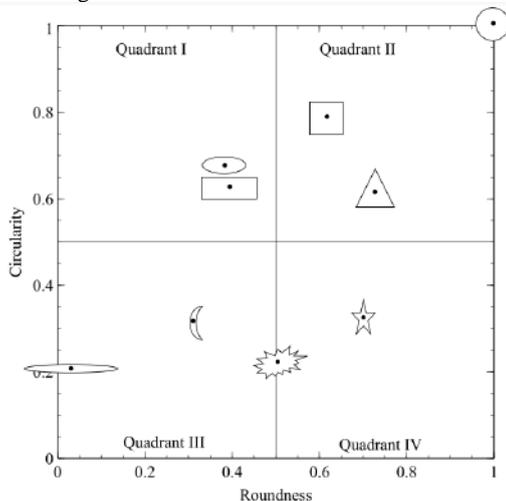
**Fig. 3:** Cuttings image after processing has been completed

This was the shortest dimension of the cutting, this is because sieve analysis is based on the shortest dimension of the cuttings that can pass through the sieves. Therefore, it seemed reasonable to then compare that to the shortest dimension of the cuttings as well rather than just focusing on the longer dimension. Having the three graphs (sieve analysis, imaging-longest dimension and imaging-shortest dimension) on the same plot is essential for thorough comparisons and analysis. As the particle size distributions are performed, the error analysis was then performed between all three methods, this is to check the discrepancies between them, to ensure the reliability and validity of the image analysis method.

In error analysis, the standard method for calculating is as shown by Equation 1 where the estimated value is subtracted from the true value. However, to tailor the equation to this study, the percentage error is calculated by subtracting the percentage passing at particle size  $x$  from imaging method from the percentage passing at particle size  $x$  from the sieving method.

$$\text{Error} = \text{Estimated value} - \text{true value} \quad (1)$$

For cuttings shape and analysis, a new method was developed where a graph divided into quadrants was used. In shape analysis, there are normally shape parameters such as aspect ratio, solidity, circularity, roundness and many more. However, the issue arises as there seems to be a need for shape distribution method. This study focuses on two shape parameters, circularity and roundness, this is because roundness is the inverse of aspect ratio therefore will give perception on the elongation and the circularity gives information on the angularity of the cuttings. These two shape parameters are then presented on a graph with roundness on the x-axis and the circularity on the y-axis. On both the axis, the graph is constrained to the interval  $[0,1]$  to ensure boundedness, because if one of the shape parameters would have been substituted for aspect ratio, the graph may extend indefinitely. The shape distribution graph was then divided into four quadrants, which are then used to classify these cuttings' shape and further relate the quadrant to the drilling parameters, allowing for the drilling operators/ engineers to adjust the drilling parameters according.

**Fig. 4:** Illustrative particle shape distribution using standard shapes

The observations of the particle size and shapes enables the drilling operators to adjust the drilling parameters accordingly. For instance, the drilling operators may be able to adjust the WOB, the rotary speed, the fluid properties and check for the bit wear, all these actions are efficient in optimizing the drilling performance, which when optimized, productivity can be increased, and operational costs may be reduced. To enhance interpretability, standard reference shapes were plotted on the graph, serving as visual benchmarks to guide and validate when actual cuttings are implemented. Fig.4 shows the previously mentioned graph divided into four quadrants. With Quadrant I illustrating the region for low roundness and high circularity, Quadrant II as the region for high roundness and high circularity, Quadrant III showing low roundness and high low circularity. Lastly, the Quadrant IV shows the region of low circularity but high roundness. A clustering of cuttings within a specific quadrant indicates a predominance of cuttings that exhibit the corresponding shape characteristics

associated with that region.

Like other analytical methods, image analysis is subject to limitations, particularly in cases of overlapping particles. When particles are introduced for the image capture process, particles may overlap, which can affect the precise identification and measurement of individual particles. In this study however, watershed algorithms are then used to detect individual particles from touching ones.

**Fig. 5:** Overlapping cuttings before image processing

Fig. 5 shows unprocessed drill cuttings with overlapping particles, highlighting a key challenge in image-based analysis. The close contact between fragments can hinder accurate segmentation and shape detection, emphasizing the need for preprocessing techniques to isolate individual particles for reliable measurement. Where fig.6 presents the processed version of the overlapping drill cuttings shown previously in fig. 5. Image segmentation techniques have been applied to isolate individual particles by enhancing contrast and defining boundaries. The processed binary image clearly separates the cuttings (white) from the background (black), facilitating accurate shape and size analysis. This transformation is critical for mitigating errors caused by particle overlap and improving the reliability of automated image-based measurements in drilling performance monitoring. Lastly, fig.7 shows the software now being able to detect each individual particle with the help of the separation technique. When cuttings are introduced to the image capture system, they are likely to touch, regardless of the physical separation technique implemented.

**Fig. 6:** Overlapping cuttings after image processing

Fig.7 shows the result of applying the watershed segmentation technique to overlapping drill cuttings. The algorithm effectively separates adjacent particles by identifying boundaries based on gradient variations and morphological features. This method resolves the segmentation challenges observed in fig. 5 and fig.6, allowing for the accurate isolation of individual particles despite contact or overlap, and enabling more precise computation of shape and size parameters.

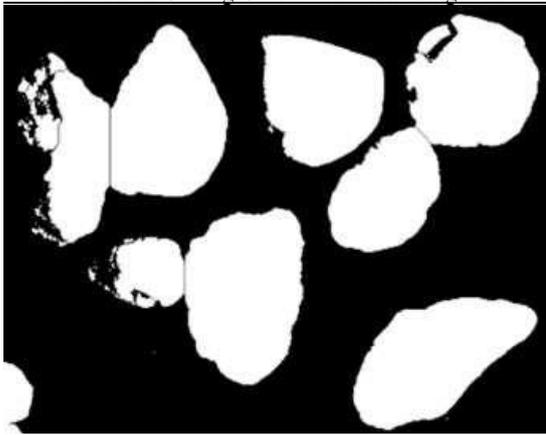


Fig. 7: Watershed technique applied to the overlapping particles

3. Discussion and Results

This section presents the results from the experiments and what they potentially mean in monitoring drill performance. In fig.8 below, all the three techniques have been implemented to generate the particle size distributions of the samples. Since the IA-shortest dimension is based on shortest width of the cuttings, it is expected to have the highest percentage passing.

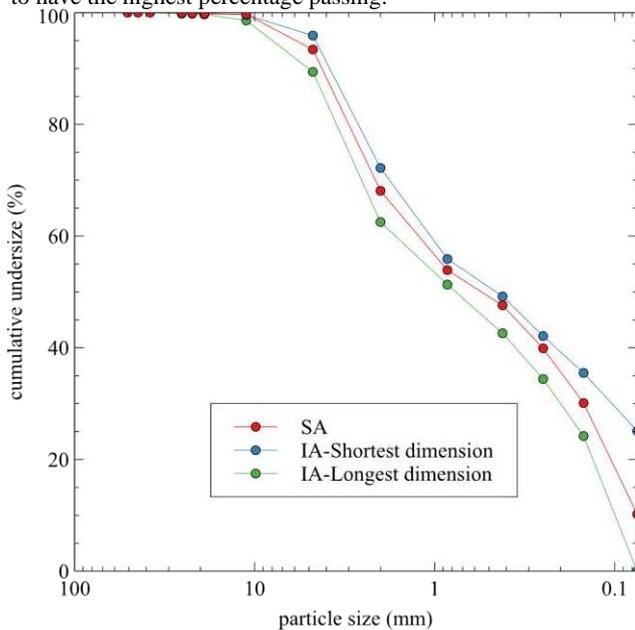


Fig. 8: PSDs of sieve analysis, IA-shortest dimension and IA-longest dimension

This trend is observed in fig.8 where the IA-shortest dimension is to the left of both the sieve analysis and IA-longest dimension. The IA- longest dimension being to the right of both the IA-shortest dimension and Sieve analysis indicates that the IA-LD suggests that the cuttings a larger than what the other two methods portray.

042	47.6	42.6	5.0
0.25	39.9	34.4	5.5
0.149	30.1	24.2	5.9
0.075	10.2	0	10.2

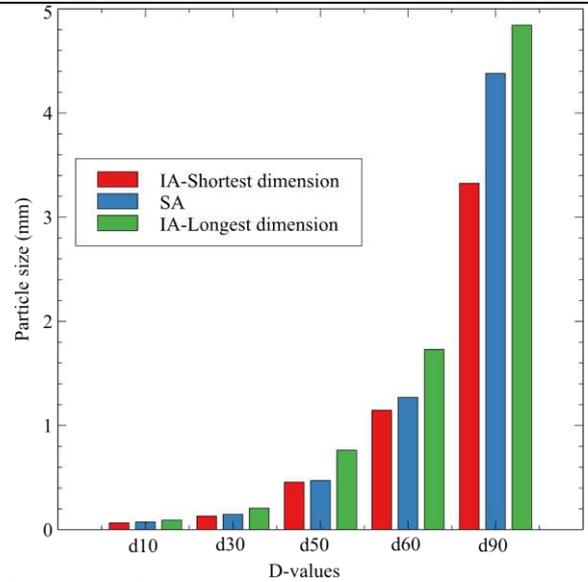


Fig. 9 d-values of sieve analysis, IA-longest dimension and IA-shortest dimension

D-values are important in the classification of the soil particles, as they are essential in evaluating particle size distribution. Based on the dvalues such as d10, d30 and d60 shown in fig.9, gradation coefficients can be calculated then essentially used to determine whether the cuttings are gravel, silt or sand.

According to the “d” values in fig. 9, the Cu across all three techniques indicates that the particles are well graded; however, the cuttings are not well distributed across these size ranges. For example, the coefficients of curvature recorded were 0.233, 0.269 and 0.230 for the sieve analysis, IA-longest dimension and IA-shortest dimension, respectively. This shows that the cuttings are not well distributed across the sizes because based on the standards those Cc values should be between 1 and 3.

Table 1: Error analysis between the sieve analysis and IA-longest dimension

Bins (mm)	Sieve analysis (%)	IA-longest dimension (%)	Percentage Error (%)
50.8	100	100	0.0
44.45	100	100	0.0
38.1	100	100	0.0
25.4	100	99.8	0.2
22.225	99.9	99.8	0.1
19.05	99.8	99.7	0.1
11.1252	99.7	98.6	1.1
4.75	93.4	89.4	4.0
2	68.1	62.5	5.6
0.85	53.9	51.3	2.6

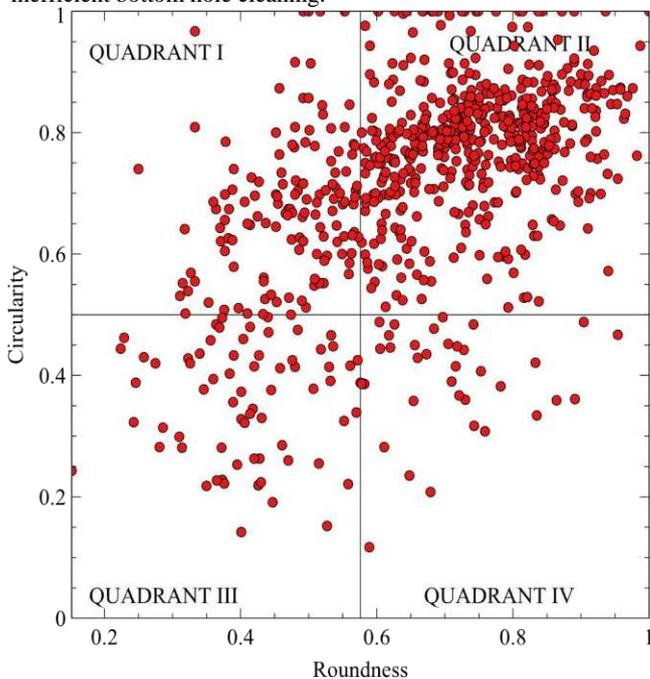
Error analysis was then performed as indicated in Table 1. This was performed to check the accuracy of the image analysis methods.

Table 2: Error analysis between sieve analysis and IA-Shortest dimension

Bins (mm)	Sieve analysis (%)	IA- Shortest dimension (%)	Percentage Error (%)
50.8	100	100	0.0
44.45	100	100	0.0
38.1	100	100	0.0
25.4	100	100	0.0
22.225	99.9	99.9	0.0
19.05	99.8	99.9	0.1
11.1252	99.7	99.6	0.1

4.75	93.4	95.9	2.5
2	68.1	72.2	4.1
0.85	53.9	55.9	2.0
0.42	47.6	49.2	1.6
0.25	39.9	42.1	2.2
0.149	30.1	35.5	5.4
0.075	10.2	25.1	14.9

From both Tables 1 and 2 it can be concluded that the image analysis methods are relatively comparable to the sieve analysis method, with the only substantial discrepancy being at the 0.075 mm particle size. Table 2 proves the assumption that was made that sieve analysis and image analysis based on the shortest dimension are expected to show a closer correlation. An error analysis was performed between the sieve analysis method and the IA-shortest dimension method, this was done as a quality assurance to ensure the reputability of using the shortest dimension. As observed in table 2, there is no significant discrepancy between the two techniques for the larger size from 11.1252 mm to 50.8 mm. A notable difference is observed at the 0.075 mm with a 14.9% error. The discrepancy at 0.075mm arises because image analysis measures individual particles, while sieve analysis is mass-based. Consequently, sieve analysis may underestimate fine particles. Overall, the error analysis proves that the shortest dimension can also be used for analyzing the particle size. Fig. 10 shows the shape distribution of the drill cuttings. To draw conclusions on the shape of the cuttings, it is important to study the clustering pattern. Even though cuttings are present in all the quadrant, from the fig.10, most of the cuttings are clustered at quadrant II. Based on this observation, drilling engineers can have a clear picture of the downhole conditions. Quadrant II is a region of high circularity and high roundness, therefore showing that there is inefficient drilling. This is because rounded cuttings are associated with low ROPs, high MSE and inefficient bottom hole cleaning.



**Fig. 10:** Particle shape distribution shown through quadrants  
Having drawn this conclusion, drilling engineers are able to optimize the drilling operations by adjusting the drilling parameters. For instance, they can increase the WOB, adjust drilling fluid properties, change the rotary speed and even check the bit for any form of wear. Optimizing the drilling performance is important because it can increase productivity, hence reducing the operational time which overall can reduce the operational costs.

#### 4. Conclusion

This study presents a robust, validated image-based method for real-time characterization of drill cuttings, with dual focus on particle size and shape. Through extensive experimentation and comparison against conventional sieve analysis, the methodology demonstrated high reliability, particularly when the shortest dimension was used for size distribution. The developed shape classification system using circularity and roundness further enhanced the analysis by offering practical perception into drilling efficiency.

By integrating high-resolution imaging, automated batch processing, and watershed segmentation techniques, this method provides accurate and real-time feedback on downhole conditions. This enables dynamic adjustment of drilling parameters, leading to improved rate of penetration, reduced mechanical specific energy, and better bit management. While challenges remain, particularly with cuttings in moisture-rich environments, the results strongly support the method's applicability for field-scale deployment. Ultimately, this approach contributes to the growing toolkit of drilling automation technologies, enabling smarter, faster, and more cost-effective operations through informed data-driven decision-making.

#### 5. Abbreviations and Acronyms

ASTM- American Society for Testing and Materials  
Cc- Coefficient of Curvature  
Cu- Coefficient of University  
DIA- Dynamic Image Analysis  
IA-LD- Image Analysis- Longest dimension  
IA-SD- Image Analysis- Shortest dimension  
ISO- International Organization for Standardization  
MSE- Mechanical Specific Energy  
PSD- Particle Size Distribution  
ROP- Rate of Penetration  
SIA- Static Image Analysis

#### 6. Acknowledgement

This work was conducted in the Drilling Technology Laboratory (DTL) at Memorial University of Newfoundland, St. John's, Canada, established by the Government of Canada Atlantic Innovation Fund, Cenovus Energy and Suncor Energy. This work was funded by Novamera Inc. and the National Scientific and Engineering Research Council of Canada through collaborative research for the Development and Optimization of Surgical Mining Technologies. Additional funding to Unabatsho Modise was provided by the School of Graduate Studies at Memorial University of Newfoundland.

#### 7. References

- [1] Costa, C. L., Carvalho, F. C., Soares, F. A., (2023), Physical and Chemical Characterization of Drill Cuttings: A review., *Marine Pollution Bulletin.*, 194, 115342. DOI: <https://doi.org/10.1016/j.marpolbul.2023.115342>
- [2] Ismailova, L., Dochkina, V., Ibrahim, Al. M., et al., (2022), Automated Drill Cuttings Size Estimation., *Journal of Petroleum Science and Engineering.*, 209, 109873
- [3] Karimi, M., (2013), Drill Cuttings Analysis for Real-Time Problem Diagnosis and Drilling Performance Optimization., Paper Presented at the SPE Asia Pacific Oil and Gas Conference and Exhibition. DOI: <https://doi.org/10.2118/165919-MS>
- [4] Blott, J. S., Croft, J. D., Pye, K., et al., (2004), Particle Size Analysis by Laser Diffraction., Geological Society Publications., 232. DOI: <https://doi.org/10.1144/GSL.SP.2004.232.01.08>
- [5] ISO 13322-1:2014, Particle size analysis, Image analysis methods. Part 1: Static image analysis methods and ISO 13322-2:2021, Particle size analysis, Image analysis methods, Part 2: Dynamic image analysis methods, International Organization for Standardization, Geneva.

- [6] Zhang, Z., Lan, X., Wen, G., et al., (2021), An Experimental Study on the Particle Size and Shape Distribution of Coal Drill Cuttings by Dynamic Image Analysis., *Geofluids.*, 4488248.DOI: <https://doi.org/10.1155/2021/5588248>
- [7] Huo, F., Li, A., Zhao, X., et al., (2021), Novel Lithology Identification Method for Drill Cuttings under PDC Bit Condition., *Journal of Petroleum Science and Engineering.*, 205, 108898. DOI: <https://doi.org/10.1016/j.petrol.2021.108898>
- [8] Yamada, T., Santo, D. S., Bondabou, K., et al., (2024), LiOBIA: Object- Based Cuttings Image Analysis for Automated Lithology Evaluation., *Petrophysics.*,624-648. DOI: <https://doi.org/10.30632/PJV65N4-2024a14>
- [9] Grossi, D. C., Hummels, H. Y., Meleiros, A. L., et al., (2023), CuttingsReturn Analysis by Visual Imaging: Novel Technology to Support Drilling Automation., *SPE/IADC International Drilling Conference and Exhibition.* DOI: <https://doi.org/10.2118/212441-MS>
- [10] ASTM D6913/D6913M-17 Standard Test Methods for Particle- Size Distribution (Gradation) of Soils Using Sieve Analysis
- [11] ASTM D422 Standard Test Method for Particle Size Analysis of Soils