

A Low-Complexity Algorithm for Estimation of The P80 Rock Granulometry Indicator Based on Digital Image Processing

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ABSTRACT

This work presents an algorithm that automatically measures rock size distribution during primary crushing in mining, continuously monitoring without interrupting production or causing issues in subsequent crushing stages due to oversized rocks. Existing commercial solutions demand significant investment and infrastructure, making them unfeasible for small mining operations. As a result, these companies typically halt production and send samples to a laboratory to determine the P80 granulometric factor. Most current research focuses on edge detection and rock segmentation, often overlooking the estimation of granulometric parameters. The proposed algorithm uses low-complexity image processing techniques that can run on a small-board computer. Images are captured by a camera positioned above a conveyor belt within an image acquisition enclosure and processed using watershed segmentation and morphological operations like erosion and dilation. The P80 value is estimated through the Rosin-Rammler linearization model. Results show 89% accuracy compared to laboratory measurements and a 91.3% success rate.

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1. INTRODUCTION

In the mining sector, the granulometry is important for the comminution stage of a concentrator or leaching plant. The design of plant equipment is based on the sizes of the ore rock introduced and produced for each comminution substage: primary, secondary, tertiary crushing, and, in some cases, quaternary crushing. The final product will enter stages where the mineral of interest will be recovered, so the particle size distribution or granulometry must be appropriate in every stage to achieve the best recovery percentage results. In the primary crushing stage, suitable material must be delivered, since as the crushing process continues, the power consumption increases to further reduce the rock size as can be seen in Table 1 [1]. For these reasons, it is important to keep a continuous track of the ore size.

Furthermore, it is difficult to estimate rock size in real time during primary crushing in concentrator plants, thus not ensuring a suitable material for the following process stages. Nowadays, in some processes, granulometry control is carried out through visual inspection by an operator. Then, the close size setting (CSS) of the primary crusher is adjusted and two possible actions are taken: grading the product size or coordinating with the mine department to improve the selection of the ROM (run of mine) ore sent to the plant. This type of monitoring is often inefficient, since it relies on the specialist's experience and is often subjective. Furthermore, field operators have other functions that require time facing hazard warning and poor visibility due to weather conditions (fog, darkness during the night shift, rain). Although there is a metallurgical procedure for sampling and finding the granulometry of the material ensuring reliable data, it requires shutting down the belt where the mineral size is measured, which causes production losses. Thus, current methods use visual inspection done by field operators, online systems and image processing techniques to get the granulometry. Table 2 shows the commercial solutions used in the leading companies.

Table 1. Power consumption in the crushing stages

Stage	Substage	Size range	Power consumption (KWh/t)
Crushing	Primary	100 to 10 cm	0.3 to 0.4
	Secondary	10 to 1 cm	0.3 to 2
	Tertiary	1 to 0.5 cm	0.4 to 3
Grinding	Primary	10 to 1 mm	3 to 6
	Secondary	1 to 0.1 mm	4 to 10

Note. Adapted from [1].

Additionally, Table 3 shows state-of-the-art proposals which perform rock segmentation and calculate the area of each rock.

A limitation of the state-of-the-art proposals is the lack of estimation of the P80 particle size distribution factor, since they only manage to do the segmentation of the samples and determine the area of rocks. Additionally, most commercial solutions need a cable to send images from the belt to a control room, to be processed in remote computers. Furthermore, the state-of-the-art does not consider the visualization of the results on the mineral transport belt, thus the operator is not able to monitor and take immediate actions when an event or problem takes place. While, in some studies, image processing requires high computational load; thus, this procedure is done on PCs. Considering the aforementioned limitations, the principal contributions of this research can be summarized as follows:

Table 2. Similar commercial solutions

Reference	Description	Strengths	Weaknesses
[2]	Quantifies rock particles size in conveyor belts.	A widely tested system with good results. Software offers OPC communication to pair with every control system.	Calibration requires belt detection and specialized metallurgical analysis execution. The system requires a client-server architecture for its operation. A cable is needed, for the camera, from the belt to the server room.
[3]	Quantifies rock particles size in conveyor belts.	Shows material granulometry data, volume control and belt load profile. Calibration is not required.	A cable is needed, for the camera, from the facility to the server room. Does not have an alarm in the field to alert the operator.
[4]	Quantifies rock particles size in conveyor belts.	Algorithms are developed according to the plant. Normal operation requires minimal maintenance.	A cable is needed, for the camera, from the facility to the server room. Does not have an alarm in the field to alert the operator.

1. A lightweight, low-computation algorithm capable of segmenting rocks in digital images captured from the ore conveyor system after primary crushing, specifically designed for execution on small-board computing devices.
2. An algorithm for estimating the P80 particle size indicator based on image processing and the Rosin-Rammler distribution model.

The following sections will provide a detailed description of the proposed algorithm, the results, the discussion, and the corresponding conclusions.

Table 3. State-of-the-art

Reference	Description	Strengths	Weaknesses
[5]	Rock images classification by using deep convolution neural network.	Propose the use of convolutional neural networks to recognize rocks. The obtained results of different color spaces are shown.	Training and testing data are not shown. It is assumed they have high contrast and a distributed histogram, making detection accessible.
[6]	Image process of rock size distribution using DexiNed-based neural network.	Developed an application of the DexiNed architecture to generate a rock edges map located over a conveyor belt. The area is calculated for each identified rock.	Granulometry distribution of the samples is not calculated.

Reference	Description	Strengths	Weaknesses
[7]	Dense extreme inception network: towards a robust CNN model for edge detection.	Use a convolutional neural network based on edge detection called DexiNed, which does not require prior training to be used, producing optimal results.	Granulometry distribution of the samples is not calculated.
[8]	Segmentation techniques in digital image processing.	Present three different image segmentation techniques. They show the main features of each technique. DINOv2's features effectively capture and distinguish subtle geological patterns, enabling accurate classification and segmentation tasks.	Algorithms are used for high contrast images between the background and the object to be segmented.
[9]	Analysis of CT-scanned rock samples using fine-tuning DINOv2 and kNN.		Experiments were conducted using resource-intensive GPUs since oversampling and denoising techniques are applied.

2. MATERIALS AND METHODS

This section describes the materials and methods used in the present work. The aim is to achieve a low computational load algorithm in both software and hardware, with a successful performance for estimating the P80 indicator from rock images acquired over a mineral conveyor belt.

2.1. Granulometric Analysis and the P80 Factor

Granulometric analysis is every manual or mechanical procedure used to divide the rock particles based on their size to calculate the quantities of each one, in mass units. Several methods are used; however, the most widely is rock sieving [10].

2.1.1.1. Sieve Particle Size Analysis

The aim of this analysis is to estimate the weight percentage of the samples whose size is between two different rocks. For the segmentation process, the samples are sieved through different types of sieves; hence, the samples sizes will be determined according to the sieve where they get trapped [11]. As an example, in Figure 1, material sifted and unsifted after sieving are shown.

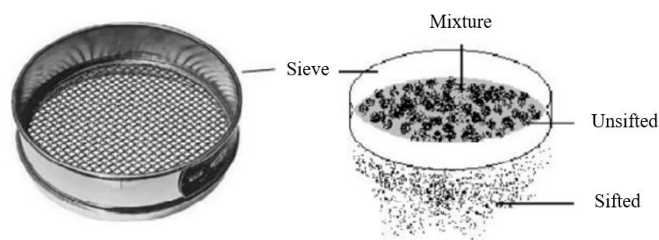


Figure 1. Sieving Process [11]

In this process, sieves with several layers of different sizes are shown in Figure 2. These sieves are assembled in a tower and are shaken; thus, the sample can pass through all possible ones.

The results of a granulometric analysis are shown in Figure 3 considering the accumulated pass-through percentage and particle size using a Logarithmic-Cartesian scale instead of the Cartesian scale, since it tends to become congested for the fine regions (smaller sizes) [11].



Figure 2. Types of Sieves [12]

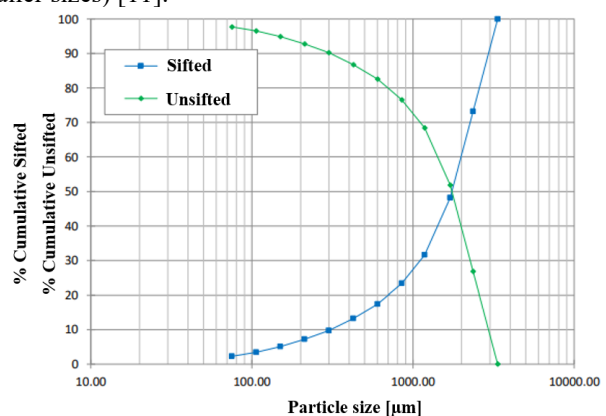


Figure 3. Granulometric analysis result [11]

According to Figure 3, the evolution percentage of the passing and retained material are shown. However, both percentages always add up a 100% at each particle size, since the sample quantity neither decreases nor increases during the process. Likewise, it should also be understood that a part of the first stage pass through percentage will be retained in the second stage and will increase the amount of retained material (decreasing the passing material). Hence, the P80 factor can be defined as the particle size where 80% of the processed sample is smaller than this factor.

2.1.2. Image Acquisition and Dataset Building

A prototype enclosure with a camera a white lighting is built to capture rock images. The enclosure is installed over a prototype conveyor belt to emulate the output belt of a mining company's primary crushing production line. For image acquisition, an 8Mpx Camera Module V2 (3280 x 2464 pixels) with mechanical focus adjustment is used, which connects to a Raspberry Pi via a CSI port with a flat cable [13]. A single-board computer Raspberry Pi 4B with 8GB RAM and 64-bit Quad-Core Cortex A72 (ARM v3) CPU@1.5 GHz is chosen for image processing, due to its size, low cost and the required computational capacity to execute image processing algorithms. Also, it has dedicated ports for connecting devices such as the camera, display, router, and discrete electronics (GPIO). The camera is positioned at a height of 255 mm, measured from the lens to the surface of the conveyor belt where the rocks pass. This height is calculated considering the camera's viewing angle and the area of interest which is where the samples are placed. On the other hand, since the images of stones are acquired during the movement of the conveyor belt, it is required to adjust the camera shutter speed to 10001 μ s to avoid motion distortion.

The resolution of the acquired images is 1280 (columns) x 720 (rows) in true color format Red-Green-Blue (RGB, 24 bits per pixel). The three primary components are $I_R(x,y)$, $I_G(x,y)$ and $I_B(x,y)$, where (x,y) represent the spatial coordinates of the image. In this case $x = 0,1, \dots, 719$ and $y = 0,1, \dots, 1279$. Figure 4 shows three captured images.

To compile the image database, 100 rock samples are passed through the conveyor belt. The rocks are no larger than 30mm in diameter. Five images are acquired for each sample, gathering a total of 500 images. For 100 rock samples, 85 are used for algorithm calibration and 15 for the validation process. Table 4 summarizes the image distribution.



Figure 4. Captured images for processing.

Table 4. Use and distribution of database images

Use	Image quantity
Calibration	425
Validation	75
Total	500

The 15 validation samples are sent to a geotechnical laboratory for analysis and processing (Gold Standard test) to get the reference P80 factor for each sample to be used in the validation process. As can be seen in Table 5, the P80 range for the 15 samples analyzed in laboratory is between 15 and 28mm. With these reference values, it is possible to measure the performance of the proposed algorithm and get the results that are presented and discussed in section 3.

Using white light inside of the enclosure reduces external interference and image quality, since the captured image must not have shadows or blobs in order to minimize the quantity of undesired objects which can affect the segmentation process [14]. Furthermore, the camera's manual focus adjustment has a strong influence in achieving a clear image as shown in Figure 5.

2.2. Description of the Proposed Algorithm

In this section, the methods used for image processing and for determining the P80 factor from the rock particle size distribution (80% cumulative throughput) are selected, considering the P80 estimation performance, computational load and efficiency. Figure 6 shows the block diagram of the proposed algorithm.

The input RGB image is acquired using controlled lighting. The pre-processing block uses binary filters and thresholds to reduce noise. For rock segmentation, edge detection techniques and morphological transformations are used. The result of this stage provides the individual size of each rock and the P80 is determined using a particle size distribution model. Each part of the proposed algorithm is described in the following sections.

Table 5. P80 factor of the validation samples

Sample	Laboratory P80 (mm)
M1	22.34
M2	23.80
M3	22.14
M4	15.93
M5	24.11
M6	25.90
M7	21.20
M8	23.01
M9	23.61
M10	24.87
M11	25.54
M12	27.64
M13	22.76
M14	17.58
M15	24.65



Figure 5. Image before doing the manual adjustment (left side) and after the manual focus adjustment (right side)

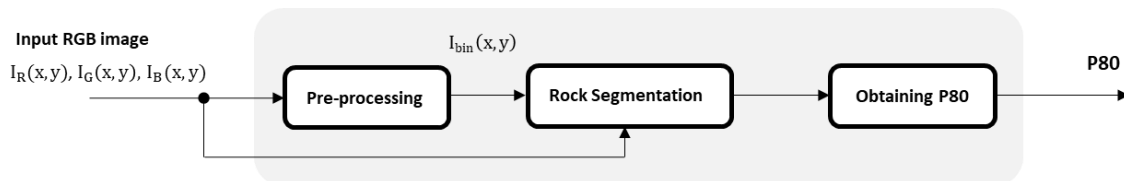


Figure 6. Block diagram of the proposed algorithm

2.2.1. Pre-Processing

The pre-processing stage is shown in Figure 7, where the input RGB image is converted to grayscale, enhanced and binarized. P80 is estimated through a geometric measure of the detected objects (rocks) in the image; hence, photometric features lost after binarization are not relevant.

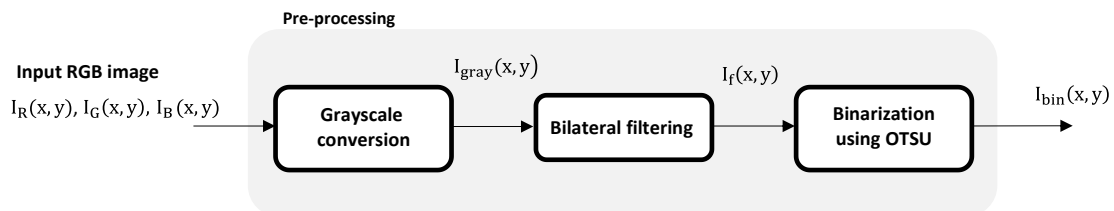


Figure 7. Image preprocessing block diagram

Since P80 estimation could be hindered if binarization drastically alters objects' geometry, the image is first filtered bilaterally and then binarized.

RGB to grayscale conversion is done through the equation NTSC (National Television Standards Committee) [15]:

$$I_{\text{gray}}(x, y) = 0.299I_R(x, y) + 0.587I_G(x, y) + 0.114I_B(x, y) \quad (1)$$

Then, a bilateral filter with 5x5 kernel, intensity sigma $\sigma_r = 25$ and spatial sigma $\sigma_s = 50$ is used to remove noise from the rocks' rough surface while preserving the edges. These values were chosen after performing several tests with different rock sizes and analyzing the final segmentation results.

The bilateral filter applied to $I_{\text{gray}}(x, y)$ can be expressed through bidimensional convolution [16]:

$$I_f(x, y) = \frac{1}{W_p(x, y)} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_{\text{gray}}(x, y) G_{\sigma_s}(x - m, y - n) G_{\sigma_r}(I_{\text{gray}}(m, n) - I_{\text{gray}}(x, y)) \quad (2)$$

for $x=0, 1, \dots, M+5-2$ and $y=0, 1, \dots, N+5-2$, $M=720$, $N=1280$

Where $G_{\sigma_s}(m, n)$, $G_{\sigma_r}(k)$, $W_p(x, y)$ correspond to the spatial Gaussian filter, intensity Gaussian filter and normalization factor, respectively [16]. They are defined as:

$$G_{\sigma_s}(m, n) = \frac{1}{2\pi\sigma_s^2} e^{-\frac{1}{2}\left(\frac{m^2+n^2}{\sigma_s^2}\right)} = \frac{1}{2\pi 50^2} e^{-\frac{1}{2}\left(\frac{m^2+n^2}{50^2}\right)} \quad (3)$$

For $m = 0, 1, \dots, 4$, $n = 0, 1, \dots, 4$, $\sigma_s = 50$

$$G_{\sigma_r}(k) = \frac{1}{\sqrt{2\pi}\sigma_r^2} e^{-\frac{1}{2}\left(\frac{k^2}{\sigma_r^2}\right)} = \frac{1}{\sqrt{2\pi} 25^2} e^{-\frac{1}{2}\left(\frac{k^2}{25^2}\right)} \quad (4)$$

For $k = 0, 1, \dots, 255$, $\sigma_r = 25$

$$W_p(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} G_{\sigma_s}(x - m, y - n) G_{\sigma_r}(f(m, n) - f(x, y)) \quad (5)$$

For $M = 720$, $N = 1280$

As a result of the bilateral filtering process, the image $I_f(x, y)$ is shown in Figure 8.

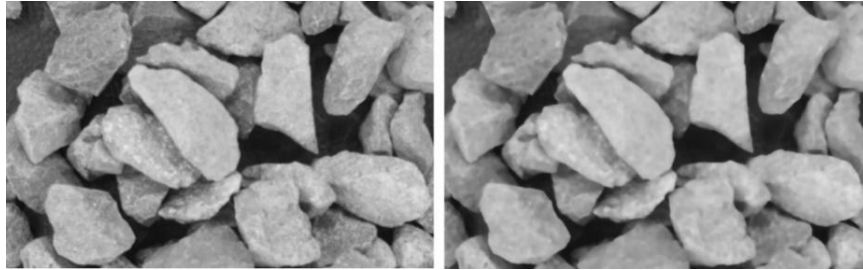


Figure 8. Grayscale Image $I_{\text{gray}}(x, y)$ (left) and bilateral filtered image $I_f(x, y)$ (right).

Finally, the image binarization is done to complete the preprocessing stage. Several methods were analyzed through testing, such as a fixed threshold based on image histogram or Sauvola's pixel bias thresholding [17]. However, Otsu [18] has better results due to its adaptability in finding the optimal threshold μ_0 for each image. In this context, since the input image is between 0 and 255 (256 gray levels), Otsu's outcome is the threshold value within the range of values.

Once the Otsu threshold is found, the binary image $I_{\text{bin}}(x, y)$ is acquired from $I_f(x, y)$:

$$I_{\text{bin}}(x, y) = \begin{cases} 255, & I_f(x, y) \geq \mu_0 \\ 0, & I_f(x, y) < \mu_0 \end{cases} \quad (6)$$

Figure 9 shows the result of applying the thresholding to an image after bilateral filtering.

2.2.2. Rock Segmentation

A Low-Complexity Algorithm for Estimation of The P80 Rock Granulometry Indicator... (José Aybar et al)

Rock segmentation has a direct impact on the objects' geometry and, therefore, on the estimation of the P80 indicator. Thus, the Watershed algorithm is recommended for homogeneous textures and weak gradient intensity which are characteristics in images of rocks that have undergone a crushing process. In Figure 10, the block diagram of rock segmentation is presented where the assignment of markers from the binary mask obtained in the preprocessing and the Watershed algorithm, which performs the segmentation, are the main processes.

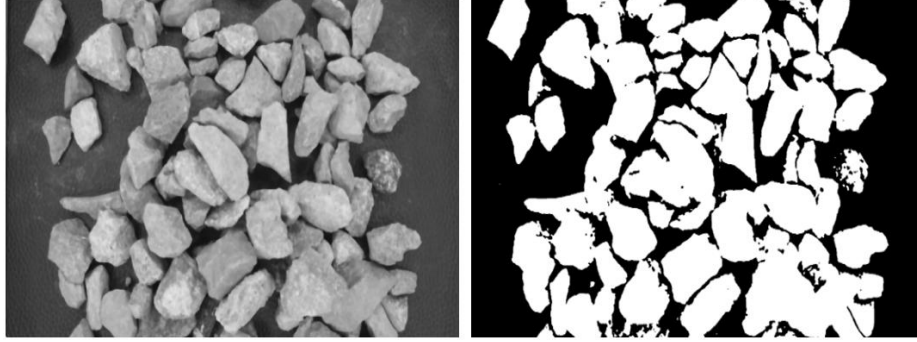


Figure 9. Grayscale image obtained by bilateral filtering $I_f(x, y)$ (left) and the image resulting from binarization $I_{bin}(x, y)$ (right).

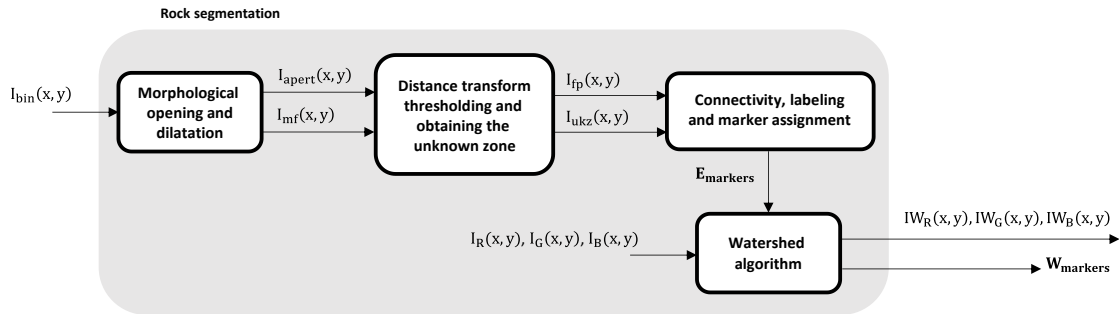


Figure 10. Block diagram of the rock segmentation process

2.2.2.1. Marker Assignment and Application of the Watershed Algorithm

Marker assignments are used with the Watershed algorithm, allowing the identification of regions of interest which need to be segmented and avoiding over-segmentation of objects in the resulting image. The assignment process is described below:

Step 1: Using the binary image $I_{bin}(x, y)$ resulting from the pre-processing, any noise that may be present in the background of the objects is removed using morphological closing with a 3x3 square kernel or structuring element ES_1 :

$$ES_1 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (7)$$

$$I_{apert} = (I_{bin} \ominus ES_1) \oplus ES_1 \quad (8)$$

Where:

ES_1 : Structuring element.

I_{bin} : Is the binary image $I_{bin}(x, y)$ represented as matrix.

I_{apert} : I_{bin} opening outcome with structuring element ES_1 .

Step 2: Applying dilation to I_{apert} with ES_1 , results in an image I_{mf} from the background as seen in Figure 11:

$$I_{mf} = I_{apert} \oplus ES_1 \quad (9)$$

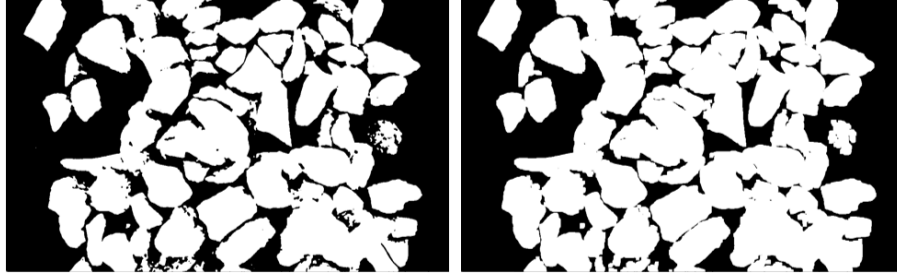


Figure 11. Binary Image I_{bin} (left) and dilation result I_{mf} (right)

Step 3: As can be seen in Figure 12, the I_{mf} image shows overlapped and conjoined rocks, which influence the segmentation results. To solve this problem, the distance transform DT [19] is applied considering a 3x3 window size together with a threshold to get the foreground of the rock's segmentation.

The distance transform is expressed as:

$$I_{DT}(x, y) = DT(I_{apert}(x, y)) = \min \{ D_{0n}(x, y) \}, \quad 1 \leq n \leq N_0 \quad (10)$$

Where:

$DT(x, y)$: Distance transform.

x_{0n}, y_{0n} : nth coordinates where $I_{bin}(x, y) = 0$.

N_0 : Number of pixels with zero value of the image $I_{bin}(x, y)$.

$D_{0n}(x, y)$ is the Euclidean distance between coordinates (x, y) and (x_{0n}, y_{0n}) of the image defined as:

$$D_{0n}(x, y) = \sqrt{(x - x_{0n})^2 + (y - y_{0n})^2}, \quad 1 \leq n \leq N_0 \quad (11)$$

After determining the distance transform, $I_{DT}(x, y)$ is binarized considering a threshold of 15% of the maximum value of $I_{DT}(x, y)$. The threshold results from the experimental tests that yield the best rock segmentation results. The binarization applied to $I_{DT}(x, y)$ can be expressed as:

$$I_{fp}(x, y) = \begin{cases} 255, & I_{DT}(x, y) \geq 0.15 \times I_{DTmax} \\ 0, & I_{DT}(x, y) < 0.15 \times I_{DTmax} \end{cases} \quad (12)$$

Where:

$I_{DT}(x, y)$: Distance Transform resulting image.

$I_{fp}(x, y)$: Image foreground.

I_{DTmax} is the maximum value of $I_{DT}(x, y)$ expressed as:

$$I_{DT}(x, y) < I_{DTmax} \quad \forall \quad (x, y) \quad (13)$$

Figure 12 shows the results of step 3 (Distance Transform and binarization).

Step 4: The rocks outside the foreground region (unknown region) are found by comparing the difference between the background image $I_{mf}(x, y)$ with the foreground $I_{fp}(x, y)$. This can be expressed as:

$$I_{ukz}(x, y) = I_{mf}(x, y) - I_{fp}(x, y) \quad (14)$$

Where:

$I_{ukz}(x, y)$: Unknown region's image

The outcome $I_{ukz}(x, y)$ is shown in Figure 13.

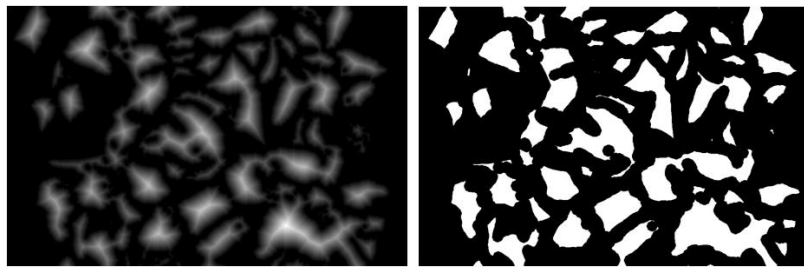


Figure 12. Distance Transform result $I_{DT}(x, y)$ (left) and foreground result with separated objects $I_{fp}(x, y)$ (right).

Step 5: The segmented rocks of $I_{fp}(x,y)$ are labeled by using 8-connectivity and then labelled, resulting in the E_{markers} matrix. Additionally, the positions where the unknown zone $I_{ukz}(x,y)$ has a value of 255 are replaced with a value of zero in the E_{markers} array. This completes the marker generation procedure, and the Watershed algorithm [20] is applied, where the input parameters are the RGB image components $I_R(x,y)$, $I_G(x,y)$, $I_B(x,y)$ and the markers. The result of watershed is a W_{markers} matrix of the same size as the input image where each object is labeled with an integer greater than 1, the object outlines have the value of -1 and the background is labeled with 1. Then, only in order to visualize the object segmentation, the resulting label matrix W_{markers} is used to label the initial color image ($I_R(x,y)$, $I_G(x,y)$ y $I_B(x,y)$) with different colors, giving as a result, the color image shown in Figure 14 which can be expressed by its primary components defined as $IW_R(x,y)$, $IW_G(x,y)$ y $IW_B(x,y)$.

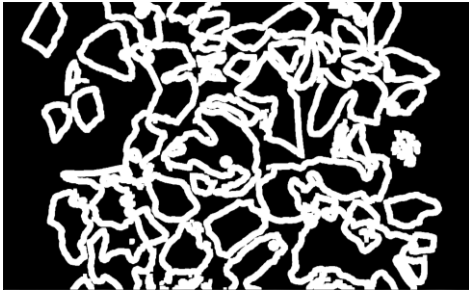


Figure 13. Image $I_{ukz}(x,y)$ corresponding to the unknown region

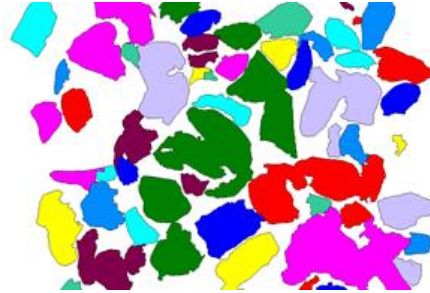


Figure 14. Color image with primary components $IW_R(x,y)$, $IW_G(x,y)$, $IW_B(x,y)$, acquired through W_{markers} .

2.2.2.2. Removal Of Objects Located at the Image Edges

Incomplete rocks might appear and must be removed to avoid errors in the estimation of the P80 factor. Likewise, part of the strip structure of the belt which is sometimes visible on the sides of the acquired image must be removed. The developed algorithm runs through the entire contour of the W_{markers} matrix, looking for values different from 1 (background marker) and -1 (object contour marker). All markers that fulfill this condition, will be stored in a list which will be the result of the algorithm. The objects in the algorithm's resulting list are removed from the image and will not be processed to determine the P80 factor. As an example, in Figure 15 an image where the objects in a removal list have been highlighted in yellow is shown.

2.2.2.3. Rock Separation Algorithm

Despite applying the watershed algorithm, it is found that some segmented rocks remain joined looking like a single object which permanently modifies their original geometry. Thus, a rock splitting algorithm is applied, which is based on consecutive erosion iterations:



Figure 15. Objects (in yellow) which will be removed.

Step 1: The image of a segmented rock is defined as input to the algorithm and an iteration counter $N_{\text{iter}} = 0$ is initialized. The maximum number of iterations to be executed is defined as:

$$N_{\text{max_iter}} = 0.5 \times p_{\text{ma}} \times L_{\text{ma}} \quad (15)$$

Where:

$N_{\max_{\text{iter}}}$: Maximum number of iterations.

L_{ma} : Object's minor axis length (in pixels)

p_{ma} : Minor axis percentage factor ($0 < p_{\text{ma}} \leq 1$)

In this case, $p_{\text{ma}} = 0.8$. This value is used because it represents a balance between achieving good rock segmentation and not distorting the shape and size of the rocks.

Step 2: The image is eroded, then segmented using the watershed algorithm, and the number of objects obtained is counted. In this case, this is named N_0 .

Step 3: If the major axis of one of the objects acquired is less than 20, then the following step will be the number 4. Otherwise, $N_{\text{iter}} = N_{\text{iter}} + 1$ and return to step 2 as long as $N_{\text{iter}} < N_{\max_{\text{iter}}}$.

Step 4: If $N_0 = 1$, then the final result is the input image to the algorithm with a final number of rocks equal to N_0 . If $N_0 > 1$, each segmented rock is placed in a single image and dilated N_{iter} times. The result is the N_0 images corresponding to the N_0 segmented rocks. Figure 16 shows the iterative erosion process of two rocks which are joined together.

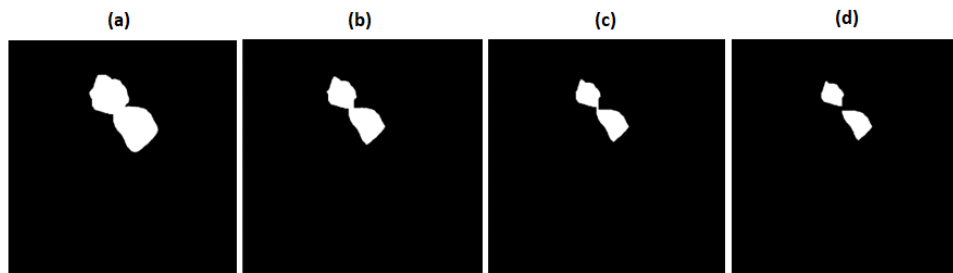


Figure 16. (a) Initial image, (b) Image after 3 erosion iterations, (c) Image after 5 erosion iterations, (d) Image after 7 erosion iterations.

Both rocks that are successfully divided by the algorithm and those that did not enter the separation algorithm are passed through another algorithm to acquire their area and minor axis. These values are stored in a vector **vtam** (minor axis) and **varea** (rock area), respectively. These values are used to find the required P80 factor. Rocks which could not be divided, are not considered for the P80 factor estimation.

As can be seen in the state-of-the-art, convolutional neural networks are the most common used since these achieve outstanding results; however, they are designed to run on computers larger than single-board alternatives. Furthermore, the evaluations are generally conducted using backgrounds and objects with high color contrast. In the proposed approach, it is considered that the developed software will be executed on a single-board computer, which introduces challenges such as optimizing the algorithm's computational load while ensuring portability and low energy consumption.

2.2.3. Obtaining the P80 Factor

To acquire the P80 factor, the measurements of each rock storage in **vtam** and **varea** must be expressed in length units rather than pixel count, which requires knowing the images spatial resolution. This is done by using a rectangular object of known dimensions. In this case, it is an 87 mm x 43 mm object (see Figure 17). With the object positioned in the acquisition area, an image is taken (see Figure 17) and the object is segmented (see Figure 18) to determine the total number of pixels (area expressed in number of pixels).

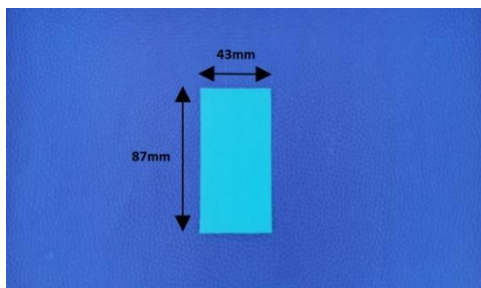


Figure 17. Image acquired from the object of known dimensions.

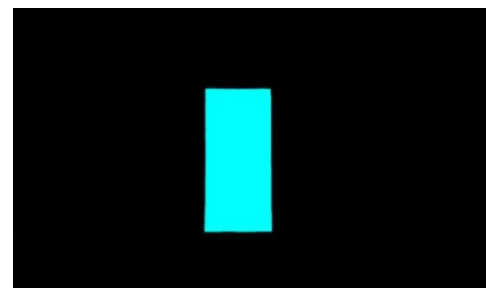


Figure 18. Image of the segmented object.

After the segmentation process, the object area, which is 62092 pixels, is placed in Equation 16, where the spatial resolution value is acquired assuming a square pixel format image:

$$M_{px} = \sqrt{\frac{87 \times 73}{62092}} = 0.2454573435 \text{ mm/pixel} \quad (16)$$

Where:

M_{px} : Image spatial resolution (mm per pixel)

To validate the result, rocks are placed on the belt and in each case the measurement of its major axis is determined by image processing and by manual measurement using a vernier caliper (see Figure 19).

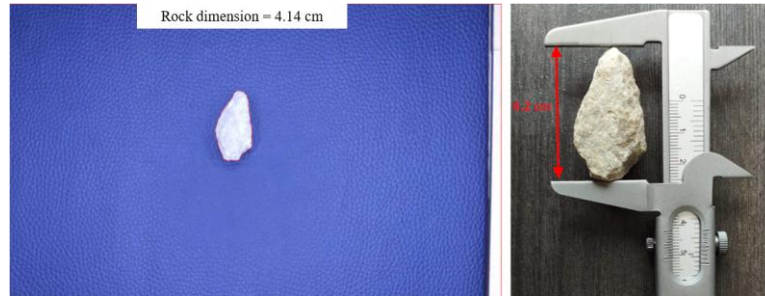


Figure 19. Measuring the major axis of a rock (a) Measurement by image processing. (b) Manual measurement using a vernier caliper.

In the spatial resolution validation process, 50 measurements are taken, yielding an average error of 3.9%, which is considered satisfactory, as the average value falls within the expected range defined as the scope of the present study. Once the rock dimensions are expressed in length units, these values are stored in the vector **vtamreal**, and the sieve sizes to be used are defined. The sizes are chosen based on the P80 design of the crushing equipment. For this case, the Tyler series sieves, which is an international standard, is used as shown in Table 6.

After defining the sieve sizes, the list of size values for each segmented rock stored in **vtamreal** (values in mm) is filtered. This is used to find the accumulated pass-through area where each rock that passes through a mesh, will have its area added iteratively until all the rocks have been evaluated. Once this process is completed, the percentage of pass-through area for each mesh is calculated, hence the area accumulations are divided between the total area of the rocks. Table 7 shows a laboratory example with Tyler series mesh sizes, mesh opening in mm and the cumulative percentage of rocks passing through.

Table 6. Table of the Tyler meshes used

Nº	Mesh Number	Aperture (mm)
1	2"	50.8
2	1 1/2"	38.1
3	1"	25.4
4	3/4"	19.1
5	1/2"	12.5
6	3/8"	9.52
7	1/4"	6.3
8	N 4	4.76

Table 7. Tyler meshes and cumulative percentage [21]

Mesh Number	Opening (mm)	Sifted cumulative percentage
3"	76.20	100.0
2 1/2"	62.50	100.0
2"	50.80	100.0
1 1/2"	38.10	100.0
1"	25.40	91.4
3/4"	19.10	48.0
1/2"	12.50	10.2
3/8"	9.520	1.9
1/4"	6.300	0.1
Nº 4	4.760	0.1
Nº 10	2.000	0.1
Nº 20	0.840	0.1
Nº 40	0.425	0.1
Nº 60	0.250	0.1
Nº 140	0.106	0.0
Nº 200	0.075	0.0

To estimate the P80 value, approximation models are applied based on the relationship between cumulative percentage and sieve size. In this case, we evaluated the performance of two approximation models: Rosin–Rammler and Gaudin–Schuhmann.

Rosin Rammler Model:

For the application of the Rosin-Rammler model [22], sieve size values with a cumulative percentage of 100 or zero are first excluded, as the algorithm does not take extreme values into account. The model is then solved using a simplification procedure that aims to reduce it to a linear equation. The procedure is as follows:

Step 1: The model equation is specified.

$$\ln \left(\ln \left(\frac{100}{100 - F(d)} \right) \right) = m \times \ln(d) - m \times \ln(d') \quad (17)$$

Step 2: The linear approximation is performed using the following equations:

$$S_y = m \times S_x + b \quad (18)$$

$$S_y = \ln \left(\ln \left(\frac{100}{100 - F(d)} \right) \right) \quad (19)$$

Where:

$$S_x = \ln(d) \quad (20)$$

$$b = -m \times \ln(d') \quad (21)$$

Where:

$F(d)$: Sifted cumulative percentage for a size d .

d : Particle size.

d' : Rosin-Rammler size module where $P(x)$ equals to 63.2%.

m : Rosin-Rammler distribution module.

Based on the laboratory sample in Table 7, Table 8 is generated, containing the mesh opening size d , the cumulative passing percentage $F(d)$ obtained using the algorithm, the independent variable of the linear equation (S_x), and the dependent variable (S_y).

Step 3: Using the values from columns S_x and S_y in Table 8, the data are plotted and a linear regression is performed, as shown in Figure 20.

Step 4: Once the slope of the line ($m = 3.9834$) and the y-intercept ($b = -12.107$) are determined, the value of d' is calculated using Equation 21:

$$d' = e^{b/m} = e^{-12.107/3.9834} = 20.89 \quad (22)$$

Table 8. Estimation table for linearization.

d	%F(d)	S_x	S_y
Abertura (mm)	% Acumulado	$\ln(d)$	$\ln(\ln(100/(100 - F(d))))$
76.200	100.0	4.33336146	-
50.800	100.0	3.92789635	-
38.100	100.0	3.64021428	-
25.400	88.3	3.23474917	0.763410539
19.100	54.0	2.94968834	-0.252921561
9.520	3.6	2.25339485	-3.305960358
4.760	0.3	1.56024767	-5.807641112
2.000	0.2	0.69314718	-6.213607264
0.840	0.2	-0.17435339	-6.213607264

Step 5: Finally, using the values of m and d' , the value of d can be expressed as a function of $F(d)$ using Equations 18, 19 and 20.

$$d = d' \left(\ln \left(\frac{100}{100 - F(d)} \right) \right)^{\frac{1}{m}} \quad (23)$$

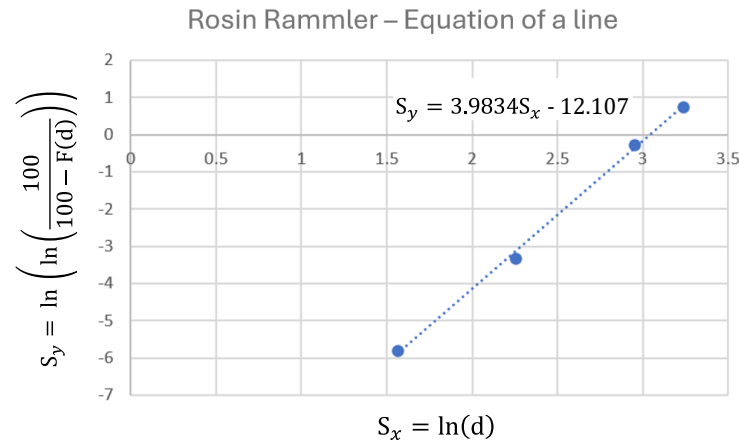


Figure 20. Line graph with sample data processed by the algorithm

With this expression, it is possible to determine the particle size (in units of length) for any desired passing percentage. In this case, the target value is the 80% passing size (i.e., the P80 indicator), for which $F(d) = 80$ is considered. Substituting into Equation 23 yields the following result:

$$d = 20.89 \left(\ln \left(\frac{100}{100 - 80} \right) \right)^{\frac{1}{3.9834}} \quad (24)$$

$$d = 23.54 \text{ mm}, \text{ (P80 obtained from the data in Tables 7 and 8)} \quad (25)$$

Gaudin-Schuhmann Model:

The Gaudin-Schuhmann [22] model represents the size distributions acquired from the sieving process. The mathematical model is shown in Equation 26.

$$P(q) = 100 \times \left(\frac{q}{k} \right)^a \quad (26)$$

$P(q)$: Cumulative throughput (%) for a size q .

q : Particle size, units

k : Gaudin-Schuhmann size module where $P(q)$ equals 100%.

a : Gaudin-Schuhmann distribution module.

After simplifying Equation 26, Equation 27 is estimated.

$$\log P(S_x) = a \times \log(S_x) - \log \left(\frac{100}{k^a} \right) \quad (27)$$

As it can be seen in Equation 27, it resembles a straight line (Equation 28), hence, making the equivalence, the value of m and b could be directly estimated as the slope of the line and the independent term when performing a linear regression. Finally, k is acquired by clearing Equation 29 as shown in Equation 30 [23].

$$S_y = m \times S_x + b \quad (28)$$

$$m = a$$

$$b = \log \left(\frac{100}{k^m} \right) \quad (29)$$

$$k = (10)^{\frac{2-b}{m}} \quad (30)$$

One of the samples, M1, is analyzed both by a laboratory and the proposed models. The overall results show an average error of 5.39% using the Rosin-Rammler method, while the Gaudin-Schumann method shows an error of 11.49%. The results of the 10 analyses performed are shown in Table 9.

Table 9. Sample M1 analysis results.

Sample M1	Lab P80	Rosin Rammler			Gaudin Schumann		
		P80	Error	Error (%)	P80	Error	Error (%)
Analysis 1	22.34	23.02	0.68	3.05	20.10	2.24	10.02
Analysis 2	22.34	25.56	3.22	14.42	19.62	2.72	12.17
Analysis 3	22.34	23.48	1.14	5.11	24.95	2.61	11.69
Analysis 4	22.34	24.26	1.92	8.60	20.05	2.29	10.24
Analysis 5	22.34	20.20	2.14	9.57	25.12	2.78	12.45
Analysis 6	22.34	22.09	0.25	1.11	26.34	4.00	17.91
Analysis 7	22.34	22.94	0.60	2.69	20.10	2.24	10.02
Analysis 8	22.34	22.20	0.14	0.62	20.77	1.57	7.02
Analysis 9	22.34	21.47	0.87	3.89	19.85	2.49	11.14
Analysis 10	22.34	21.26	1.08	4.83	25.07	2.73	12.23
		Mean Error (%)		5.39	Mean Error (%)		11.49

Thus, the Rosin Rammler method is chosen, since it results in a lower error for 9 of the 10 analyses.

2.2.4. Performance Evaluation Metrics

The relative error percentage is used to validate the proposed algorithm. In this case, the computed error compares the P80 factor acquired by the proposed algorithm and the one from the laboratory analysis. The relative percentage error is defined as:

$$\%Error = \frac{|P80_{lab} - P80_{prototype}|}{P80_{lab}} \times 100 \quad (31)$$

Where:

%Error : Relative error percentage.

$P80_{lab}$: Estimated P80 factor with laboratory data.

$P80_{prototype}$: Estimated P80 factor by prototype

Table 10 shows a proposed performance scale, which depends on relative error ranges. These values were defined by three leading specialists with extensive experience in various mining companies operating in Peru: A metallurgical engineer serving as operations manager of the concentrator plant, a senior metallurgical engineer supervising concentrator plant operations, and a chemical engineer supervising metallurgy at the concentrator plant. All of them are duly registered with the College of Engineers of Peru.

Table 10. Performance Levels

Performance	Error Range
Good	%Error < 15%
Regular	15% ≤ %Error < 25%
Bad	%Error ≥ 25%

3. RESULTS AND DISCUSSION

The validation procedure used 15 samples. Each sample was processed 10 times to obtain the P80 value and then the error was computed. Each sample was inserted into the prototype 10 times to ensure continuity in the readings, since rocks distribution upon placement in the conveyor belt is never the same.

Tables 11 and 12 show the outcome of the sample analysis. The column “Sample” shows the name of each sample, “P80 Laboratory” points out the P80 value obtained with laboratory reports. Finally, the last 10 columns of “Analysis” have two sub columns: “P80” which is the P80 value obtained by the developed algorithm and “Error (%)” which is the percentage of the relative error applied in equation 31.

Table 13 shows the 15 processed tests and estimated error summary for the 10 estimations from the algorithm (A1 through A10). Additionally, the table summarizes the average error percentage, the outcomes which have an error above 25% are in color red.

The average error for each sample is less than 11%. The maximum error is 10.73% for the sample M4 and the minimum is 5.39% for M1. According to Table 10, an 11% error corresponds to a “Good performance”. Accordingly, the accuracy of the proposed algorithm is determined as follows:

$$Accuracy = 100\% - \text{maximum error} = 100\% - 11\% = 89\% \quad (32)$$

Likewise, the success rate can be estimated based on the following expression [15]:

$$Success Rate = \frac{\text{Number of hits}}{\text{Number of tests}} \times 100 \quad (33)$$

From Table 13 and equation 32, the success rate result is acquired:

$$\text{Success Rate} = \frac{137}{150} \times 100 = 91.3\% \quad (34)$$

The outcome is acceptable and reflects the performance of the system.

Table 11. Sample Analysis from 1 to 5.

Sample	Lab P80	Analysis 1		Analysis 2		Analysis 3		Analysis 4		Analysis 5	
		P80	Error (%)	P80	Error (%)	P80	Error (%)	P80	Error (%)	P80	Error (%)
M1	22.34	23.02	3.05	25.56	14.42	23.48	5.11	24.26	8.60	20.20	9.57
M2	23.80	21.92	7.91	21.80	8.41	23.60	0.85	21.18	11.02	27.36	14.94
M3	22.14	20.54	7.24	19.35	12.61	19.41	12.34	22.00	0.65	18.24	17.63
M4	15.93	11.82	25.82	13.76	13.64	18.15	13.91	15.12	5.10	17.50	9.83
M5	24.11	22.63	6.13	22.22	7.83	22.49	6.71	21.37	11.36	20.27	15.92
M6	25.90	27.36	5.65	22.35	13.69	22.41	13.46	22.55	12.92	25.81	0.33
M7	21.20	18.26	13.85	21.80	2.85	20.69	2.39	22.05	4.03	22.92	8.13
M8	23.01	21.75	5.48	26.37	14.60	21.11	8.26	20.29	11.82	21.36	7.17
M9	23.61	24.41	3.41	22.42	5.02	22.92	2.91	26.34	11.58	19.75	16.33
M10	24.87	29.58	18.95	22.66	8.88	26.49	6.52	27.60	10.99	23.85	4.09
M11	25.54	25.88	1.34	22.94	10.17	27.18	6.43	26.93	5.45	26.98	5.65
M12	27.64	24.92	9.85	22.05	20.23	28.97	4.80	23.98	13.25	24.94	9.78
M13	22.76	24.08	5.80	20.02	12.04	23.02	1.14	24.65	8.30	18.98	16.61
M14	17.58	16.50	6.13	20.70	17.76	18.43	4.85	15.30	12.96	19.22	9.34
M15	24.65	25.38	2.96	26.33	6.81	23.43	4.95	21.56	12.54	23.37	5.19

Although each sample was analyzed 10 times, the algorithm in each scenario yielded a different result, since, through the images, only the rocks found in the upper part of the belt are accessible and, in each test, the order of rocks in the conveyor belt was different. Typically, high errors occurred due to the arrangement of the rocks in the conveyor belt since rocks overlapped, which generated error in the segmentation.

Table 12. Sample Analysis from 6 to 10.

Sample	Lab P80	Analysis 6		Analysis 7		Analysis 8		Analysis 9		Analysis 10	
		P80	Error (%)	P80	Error (%)	P80	Error (%)	P80	Error (%)	P80	Error (%)
M1	22.34	22.09	1.11	22.94	2.69	22.20	0.62	21.47	3.89	21.26	4.83
M2	23.80	21.91	7.95	21.79	8.46	25.01	5.07	22.53	5.35	23.07	3.08
M3	22.14	20.72	6.43	20.34	8.14	22.25	0.48	18.00	18.71	20.15	9.00
M4	15.93	15.50	2.72	17.71	11.15	18.46	15.86	17.30	8.58	15.83	0.65
M5	24.11	22.20	7.92	23.83	1.15	26.34	9.26	22.10	8.33	22.69	5.88
M6	25.90	27.44	5.96	22.03	14.93	23.78	8.17	22.58	12.81	25.35	2.11
M7	21.20	21.85	3.09	16.86	20.46	18.09	14.65	21.05	0.69	22.47	6.01
M8	23.01	22.33	2.96	19.93	13.39	24.53	6.60	20.00	13.08	25.93	12.69
M9	23.61	23.02	2.48	24.72	4.72	20.41	13.54	20.38	13.67	24.78	4.97
M10	24.87	25.73	3.47	23.76	4.45	21.85	12.14	26.41	6.20	28.13	13.12
M11	25.54	24.09	5.67	24.09	5.67	21.97	13.97	25.59	0.20	25.54	0.01
M12	27.64	26.74	3.27	26.59	3.81	26.90	2.69	29.13	5.38	25.24	8.69
M13	22.76	24.76	8.78	22.88	0.52	23.43	2.94	22.42	1.50	23.26	2.19
M14	17.58	16.03	8.81	14.37	18.25	16.18	7.95	17.20	2.15	17.46	0.67
M15	24.65	22.88	7.18	23.90	3.04	19.86	19.43	22.71	7.87	24.50	0.61

4. CONCLUSIONS

This study has proposed an algorithm capable of measuring the granulometry (P80) of rocks in conveyor belts. It is important to highlight that simple image processing techniques were applied to achieve a continuous delivery of results using low computational load. Regarding the P80 factor, both Gaudin-Schumann and Rosin-Rammler models were evaluated and compared, with the latter showing the best performance.

The rock's movement on the belt introduced errors into the captured images; thus, the enclosure was placed as far from the load transfer area. Although rocks should not be detected when the belt is empty, the dust causes alterations in algorithm detection process, giving inconsistent outcomes. Hence, to reduce this impact, a minimum number of detected rocks is set to estimate the P80 factor. For the segmentation issue, due to the rock overlap, it was necessary to create a function to separate the rocks and reconstruct them through erosion and dilation.

On the other hand, an accuracy of 89% was obtained in comparison with the outcome issued by a geotechnical laboratory. The system achieved a success rate of 91.3% according to the performance classified

as “Good” in Table 10. This result is relevant because, unlike standard GPU-based laboratory setups, this system runs entirely on a Raspberry Pi 4, proving its viability for on-site industrial deployment.

Future research could assess the use of Artificial Intelligence to improve the results; however, this would increase the computational burden of the algorithm. Thus, it would be necessary to evaluate whether the improvement justifies the effort and resources involved.

Finally, the proposed algorithm can be implemented in single-board computers inside the equipment, allowing it to operate directly on conveyor belts in the field. This would enable operators to take immediate action, avoiding the need to install computers and servers for remote monitoring of the crushing process.

Table 13. Acquired data from each sample.

Sample	Lab P80	P80 % Error										Avg. % Error	Count %Error < 15
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10		
M1	22.34	3.05	14.42	5.11	8.60	9.57	1.11	2.69	0.62	3.89	4.83	5.39	10
M2	23.80	7.91	8.41	0.85	11.02	14.94	7.95	8.46	5.07	5.35	3.08	7.30	10
M3	22.14	7.24	12.61	12.34	0.65	17.63	6.43	8.14	0.48	18.71	9.00	9.32	8
M4	15.93	25.82	13.64	13.91	5.10	9.83	2.72	11.15	15.86	8.58	0.65	10.73	8
M5	24.11	6.13	7.83	6.71	11.36	15.92	7.92	1.15	9.26	8.33	5.88	8.05	9
M6	25.90	5.65	13.69	13.46	12.92	0.33	5.96	14.93	8.17	12.81	2.11	9.00	10
M7	21.20	13.85	2.85	2.39	4.03	8.13	3.09	20.46	14.65	0.69	6.01	7.61	9
M8	23.01	5.48	14.60	8.26	11.82	7.17	2.96	13.39	6.60	13.08	12.69	9.60	10
M9	23.61	3.41	5.02	2.91	11.58	16.33	2.48	4.72	13.54	13.67	4.97	7.86	9
M10	24.87	18.95	8.88	6.52	10.99	4.09	3.47	4.45	12.14	6.20	13.12	8.88	9
M11	25.54	1.34	10.17	6.43	5.45	5.65	5.67	5.67	13.97	0.20	0.01	5.46	10
M12	27.64	9.85	20.23	4.80	13.25	9.78	3.27	3.81	2.69	5.38	8.89	8.18	9
M13	22.76	5.80	12.04	1.14	8.30	16.61	8.78	0.52	2.94	1.50	2.19	5.98	9
M14	17.58	6.13	17.76	4.85	12.96	9.34	8.81	18.25	7.95	2.15	0.67	8.89	8
M15	24.65	2.96	6.81	4.95	12.54	5.19	7.18	3.04	19.43	7.87	0.61	7.06	9

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Pool Tasayco: Conceptualization, Formal analysis, Research, Methodology, Software, Writing – original draft. **José Aybar:** Conceptualization, Formal analysis, Research, Methodology, Software, Writing – original draft. **Guillermo Kemper:** Conceptualization, Funding acquisition, Research, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

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