Particle Size Analysis using Deep Learning Techniques

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Abstract

Recent times have seen immense progress in deep learning techniques and its ability to solve image-based problems to the point of exceeding human performance. Particle sizing of ore and coal from images has been used in the minerals processing industry for many years and provides an important measurement for crushing and milling operations. This paper shows how modern deep learning models have been utilized to provide a step-change in measurement accuracy. The new technique is shown to be more human-like and much more robust to deterioration in image quality caused by sunlight, shadows and dust. The paper also shows the increase in performance in an industrial application where image analysis is used to detect large boulders on haul trucks in order to avoid crusher damage and consequential downtime.

1. Introduction

Online Particle Size Analysis (PSA) has become a vital measurement in the Mining and Minerals Processing Industry. Continuous measurement of particle size distributions can address pain points experienced by plant operators in the mining, crushing and grinding sections of the plant.

Sub-optimal blasting profiles, crusher and screen damage due to oversize material, suboptimal crusher gap settings, poor fines-to-coarse ratio and plant downtime due to manual sampling are only some of the problematic operating conditions that can be addressed by online particle size analysis (Hulthén, 2010; Leighton, 2009).

Traditional image processing techniques used in particle segmentation include water shedding and edge detection (De Jager, Mkwelo and Nicolls, 2003). These techniques are beneficial in their measurements to address operator pain points, however, non-ideal imaging conditions have been shown to affect the accuracy of the PSA. Deep learning techniques have been developed to address the shortcomings of using traditional PSA methods, increasing the accuracy of the online measurements significantly.

2. Watershed Based PSA Approach

In order to detect particles of different sizes and both dark and light coloured particles using traditional water shedding methods, multiple processing lines are used as shown in Figure 1. Bilateral filter banks allow for various degrees of smoothing in order to detect both finer particles as well as larger particles. After these multiple levels of intensity, thresholding allows for both light and dark coloured particles to be detected as markers. These markers are used during a water shedding process to detect the boundaries of the candidate particles. The candidate particles are then classified to obtain the true particles.

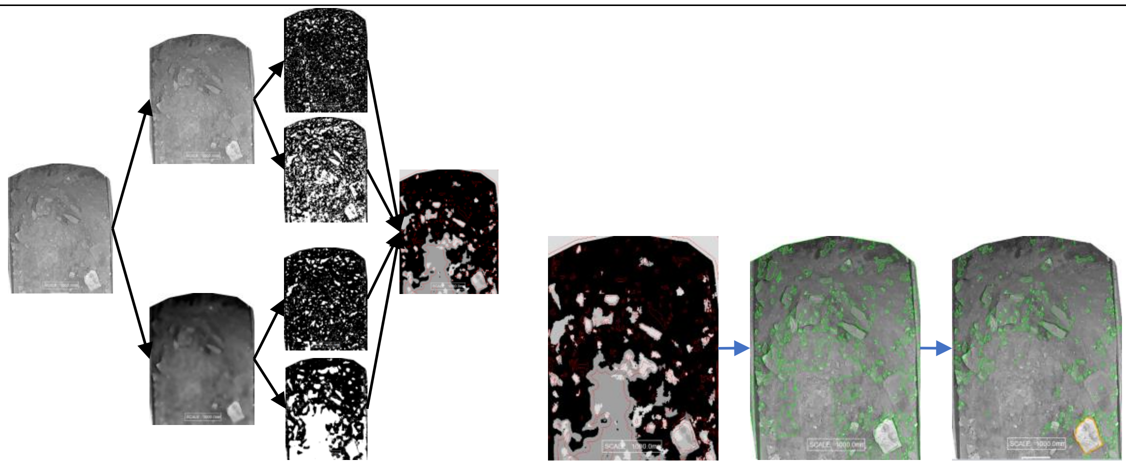

Figure 1

This image depicts the multiple processing lines required in traditional PSA technology. Bilateral filtering allows the detection of finer and larger particles, after which intensity thresholding is used to detect light and dark coloured particles as markers. By means of water shedding techniques, the markers are used to establish the boundaries of the particles.

Due to the large number of image processing parameters, it remains notoriously difficult to configure the water-shedding system for a wide range of imaging conditions, as depicted in Figure 2. Examples of applications where water shedding might not be accurate include the detection of rocks displaying both light and dark regions, the detection of half-covered rocks as well as detecting particle size in situations where shadows are cast over the material.

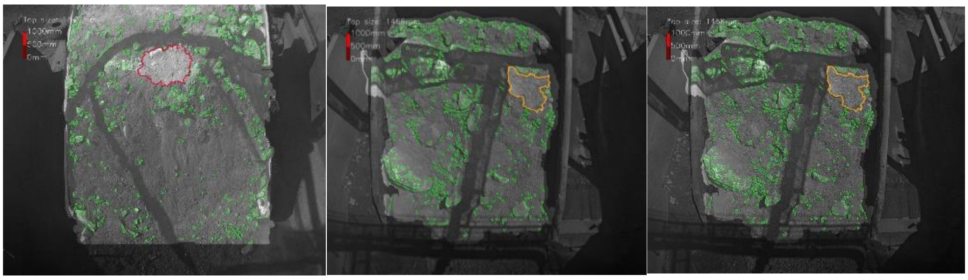

Figure 2

Images obtained by means of particle size analysis on a truck bed using water shedding techniques. This image depicts the inability of the water-shedding system to detect large particles due to shadows and specs of dark colours on the rocks.

3. Deep Learning PSA Approach

Accurate particle size analysis requires instance segmentation of individual particles. Each rock in an image needs to be identified rather than identifying that rocks are present, which is known as classification or that a certain region contains rocks known as semantic segmentation.

The U-Net architecture, as depicted in Figure 3, has been used for both detections of the ore region and segmentation of individual particles. The name of the U-Net architecture comes from the distinctive shape of the model (Ronneberger, Fischer and Brox, 2015).

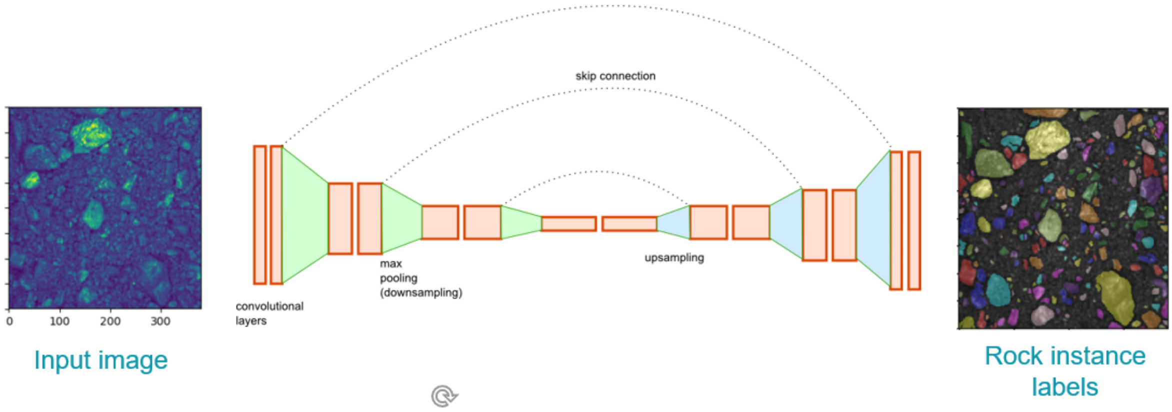

Figure 3

Successive layers in the U-Net architecture are smaller than the ones before expanding back up to the full resolution of the input image. The U-Net architecture is able to capture contextual information well due to its hourglass shape. To this are added skip connections at multiple resolutions, that improve localisation performance.

The output of the rock particle segmentation algorithm is a full-size image that can be used for visual confirmation of the position and borders of the particles identified, as shown in Figure 4. This approach allows the user to recognize whether the system has correctly identified the larger particles in the image. The system is fully convolutional; inference can be performed for any input image resolution.

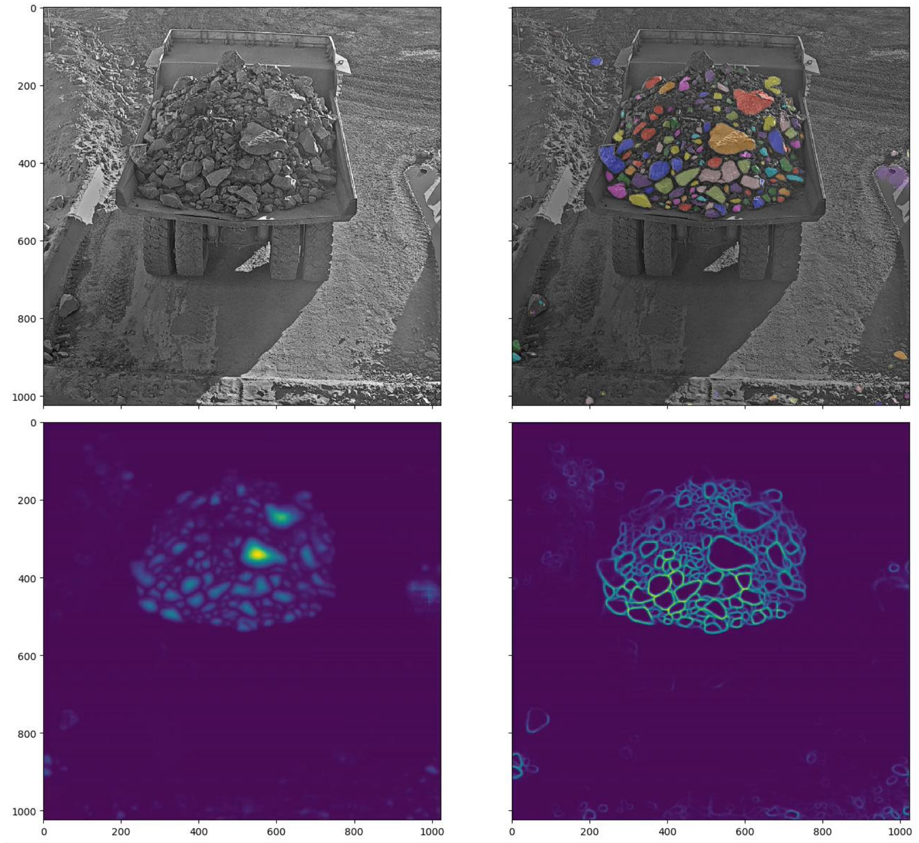

Figure 4

To train the neural model, hundreds of thousands of rocks were labelled by humans before being fed into the model. The network was trained to predict the centre and edges of each rock based on the hand-labelled images, resulting in human-like segmentation performance.

Deep learning algorithms have been found to be more robust in their detection of different size particles compared to traditional techniques. Combining the results of the ore region detection and rock particle segmentation allows the ratio of fine particles to be calculated. Segmentation of rock particles has been found to be possible even in cases where rock is partially hidden by fine material. Figure 5 depicts the improved accuracy in particle detection using deep learning techniques in applications where shadows are cast over the ore material.

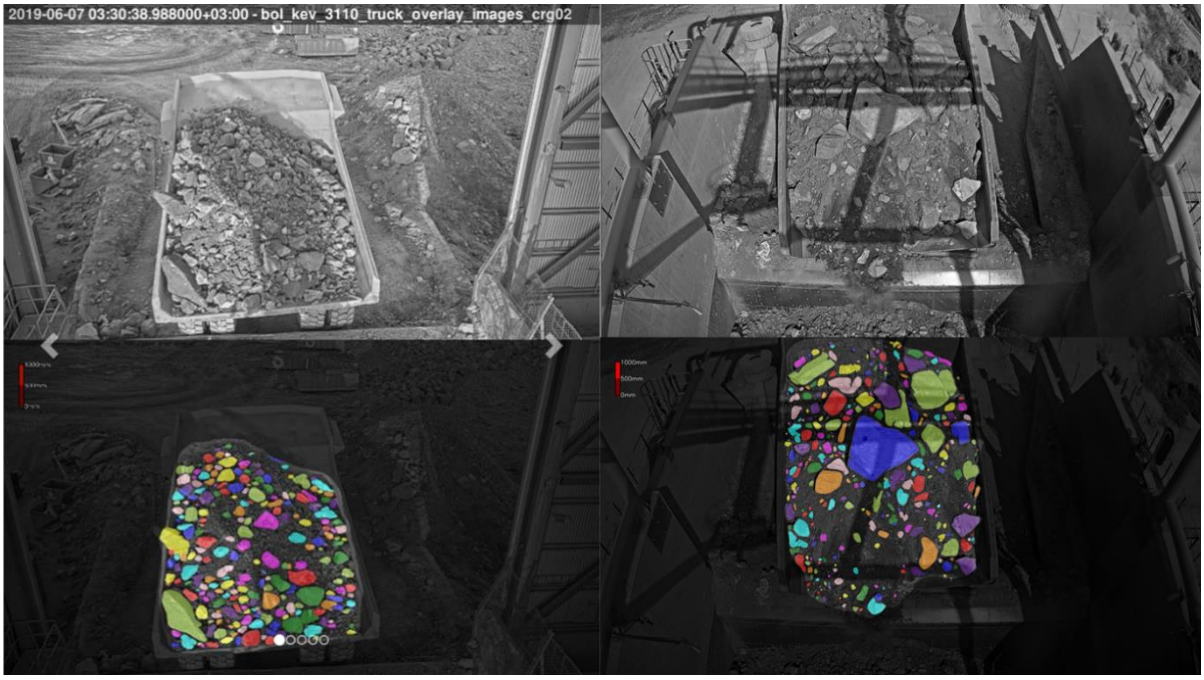

Figure 5

Particle size analysis based on deep learning techniques is human-like in the detection of large particles or partially exposed particles. This results in the accurate segmentation of ore material in the presence of shadows and different lighting conditions.

The use of GPU hardware results in images being processed in less than a second, whereas the water-shedding algorithm has an analysis time of between 4 seconds and 15 seconds per frame.

4. Comparative Case Studies

A study conducted by Stone Three at a mine in Zambia entailed a Particle Size Analysis (PSA) sensor on a truck payload to detect oversize material which can cause damage and downtime to the primary crusher circuit. Initially, the technology used to detect the oversize material were based on water shedding techniques which were later upgraded to deep learning software. Since the upgrade, the mine reported a threefold decrease in the initial false positive rate due to shadows during the daytime. The true positive rate experienced by the mine since the upgrade has increased to ten times the initial true positive rate which is a complete step-change in the accuracy of the predictions.

Another study conducted by Stone Three utilised a particle size analyser on a conveyor belt. Three sets of data were compared with each other; the ground truth (GT) images which are images marked up by humans, the images obtained by means of water shedding techniques and the images processed by deep learning technology. Snapshots of the data used in the comparison are depicted in Figure 6. Assuming that the ground truth data are 100% accurate, the study concluded that the deep learning software proved to be 90% accurate compared to the water shedding software with a 50% accuracy.

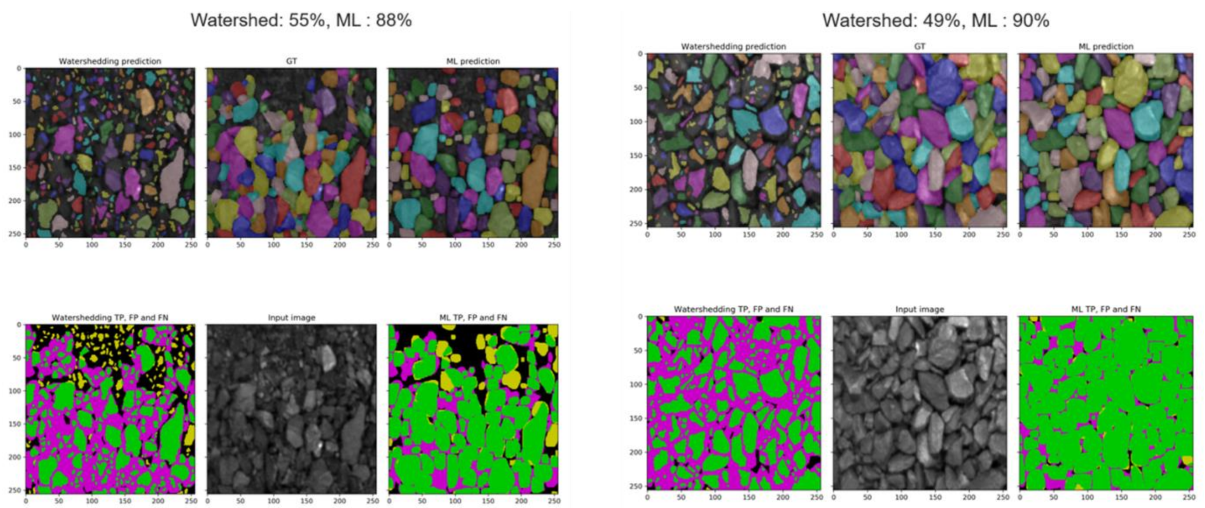

Figure 6

Images of material on a conveyor belt are segmented into particles using human labelling (GT), deep learning techniques as well as water-shedding techniques. Based on the ground truth images, an accuracy of 50% and 90% were obtained for the water-shedding technology and deep learning technology respectively.

5. Future Developments

Based on the success of the deep learning technology in particle size analysis, a requirement for material-specific detection was identified. Further deep learning model development is in progress to allow identification of foreign objects on truck payloads and conveyor belts, for example, tramp metal, wood and rubber.

This technology can then be interlocked with the plant to redirect trucks with unwanted material and stop downstream equipment that could be damaged by the foreign material.

6. Conclusion

Traditional image processing techniques used in particle size detection applications are beneficial in predicting the particle size distribution of material and detecting certain outliers, but certain conditions such as shadows over the ore material, partially covered particles or dark speckles on the material can affect the accuracy of the prediction.

Deep learning technology allows for human-like detection of particles that overcomes traditional image processing limitations. This results in a step-change in particle detection accuracy. Developing this technology can broaden the scope of material detection to any visible unwanted objects such as tramp metal.

7. References

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