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Estimating Particle Size Distribution of Mine Dump Materials using CenterMask Neural Network

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***Abstract* -** Particle size distribution potentially affects the shear strength of mine overburden dump materials. Estimating particle sizes at the dump site is crucial to determine the shear strength of dump materials. Delineation of particle sizes from dump images possesses challenges due to the variations in size, shape, color, texture and granularity. Increasing computational capabilities and advancements in Artificial Intelligence-based algorithms facilitate to apply the neural networks to solve industry problems. In the present study, a novel application of a deep neural network is proposed to generate segmentation masks over the dump particles. CenterMask network is trained on a manually labelled and annotated dump dataset. The model's performance is evaluated by comparing the predicted segmentation masks with the ground truth data. The trained model predicts the fine particles as less than as five millimetres to the maximum present in the dump image. The accuracy of CenterMask is compared with Mask R CNN, a popular instance segmentation algorithm on the dump dataset. The coordinates of predicted segmentation masks are used to determine the particle size distribution curves. A web application is developed to generate particle size distribution curves. The model's accuracy and inference time make it suitable as a quick and reliable source of estimating the sizes of particles.

Keywords: particle size, dump constituents, neural networks, instance segmentation, dump dataset

1. Introduction

Surface mining is a method of extracting the ore bodies near the earth's surface and dumping the excavated materials into a limited land area referred to as overburden dumps. The overlying earth materials consist of soil-rock mixtures [1], [2]. With an increase in open pit mine's production capacity, millions of cubic meters of overburden are removed every year. Maintaining the stability of such massive structures is of prime concern for mine management to ensure the proper functioning of mining operations [3]. The shear strength of dump materials is determined to design the benches of dump slope as per the ability of the constituents to respond to load and stress. Particle size, shape and distribution, and other parameters are the fundamental considerations for the shear strength of soil-rock mixture [4]. Traditionally, sieve analysis is performed to determine the particle size distribution curves. However, with the rising developments in image analysis methods, studies have been conducted to evaluate the particle sizes from images [5].

Most research has been conducted where the soil or rock particles are segregated and spread on a flat surface. Apart from this, the particles segmented from the images are laboratory-scale. The industrialists opt for the software used for analyzing the blast fragments, such as Split-Desktop, FRAGALYST, WipFrag etc., to characterize the dump materials. These color contrast-based software uses digital image processing techniques such as filtering, thresholding, binary image processing, and edge detection algorithms. Thurley [6] applied morphological operations to assess the measurement of limestone particles.

Nowadays, deep learning-based algorithms have gained popularity in performing computer vision tasks such as image classification, object detection and segmentation. Instance segmentation algorithms predict the bounding boxes with a segmentation mask on the objects of interest. It performs per pixel projections and assigns an instance identity to the pixels. The most popular and representative architecture, Mask R CNN [7], is a two-stage method that implies the principle of first detect then segment. Being dependent on the bounding box detections, the accuracy of mask predictions is subjected to the performance of detection heads. The recently proposed CenterMask [8] algorithm beats the Mask R CNN in accuracy and speed of inference. It is a single-stage object detector that predicts the segmentation masks without the proposal step. An anchor-free method, backed by an efficient backbone network, may solve the challenging task of delineating dump particles from images.

Several studies reported using neural networks to analyze the characteristics of geomaterials. Liang, Zhengyu et al. used a lightweight U-net to extract particle shapes from images [9]. Padarian, Minasny and McBrateny determined soil properties by training a CNN in regional spectral data [10]. To study digital rock physics, Karimpouli and Tahmasebi designed an auto encoder-decoder network [11]. In the present context, the CenterMask algorithm is implemented to learn the features of dump particles by training it on a prepared dump dataset. The dataset contains manually annotated and labelled dump particles collected from a dump site. The trained model attempts to fulfil the research gap by its capability to segment the heterogenous geomaterials that vary widely in size, shape and color in real-time. Moreover, the intact dump materials are occluded, highly overlapping and sometimes lie in shadowy regions. The technique can be suggested to be incorporated in monitoring the particles transported through industrial belts, estimating amount of geomaterials carried by dump trucks, assessment of blast fragmentation etc.

The study is organized into sections: Section 2 and 3 describes the custom dataset and CenterMask architecture in detail, followed by the results of designed experiments in Section 4. Lastly, Section 5 discusses the conclusions and future works.

2. Dump dataset

To prepare a dump dataset, images were collected from an active overburden dump of an iron ore mine. The dump constituents were colored shale particles. The primary dump slope was formed with five benches of a height of 15~20 meters with an overall slope angle of 48°. Images were captured at different locations of all the benches from several distances perpendicular to the slope to accommodate the variability of dump particles. The particles appear larger in images shot at a closer distance and smaller when the distance between the particles and the camera increases. A sequence of images was captured with some particles overlapping that can be used to merge the particle sizes for a larger area of dump slopes in various scales. For converting the particle sizes in pixels into real-world coordinates, a white-colored scale was put on the dump slope. The images were taken at different daytimes using a Canon EOS 200D digital SLR camera with a tripod. The images taken by the camera were of resolution 6000×4000.

Approximately 45000 particles were annotated and labelled after removing the distorted images from the dump dataset. A large dataset is required to train an AI model to make the model learn the variations in finer details of the objects. VGG Image Annotator (VIA) version 2.0.8 was used to mark the distinct boundaries of the particles and attach a class label, namely, "particle" and "scale" to them. The data were stored in a JSON format that is input to the AI model and images. Ground rules were designed and followed to make the procedure of dataset preparation uniform. Some of the annotated images are shown in Fig. 1.

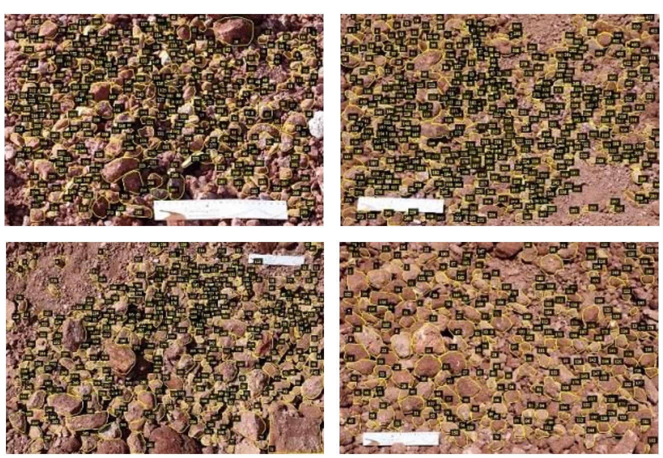

Fig. 1. Samples of annotated and labelled images from training dataset.

3. CenterMask Architecture

CenterMask network designed by Lee et al. is based on an anchor-free Fully Convolutional One Stage (FCOS) object detector. The neural network assigns each pixel to a pre-defined label to detect an object on an image. The features are extracted using the pyramid network of the VoVNetV2 backbone network. The novel spatial attention-guided SAG-Mask branch puts on the masks over the detected objects. The model highlights several key features that make it state-of-the-art in instance segmentation tasks. It offers a well-balanced backbone network that performs better in speed and accuracy. On the same backbone network, CenterMask surpasses the popular Mask R CNN, a two-stage instance segmentation method used broadly for predicting masks. The architecture of the CenterMask, as shown in Fig. 2, is briefly explained below.

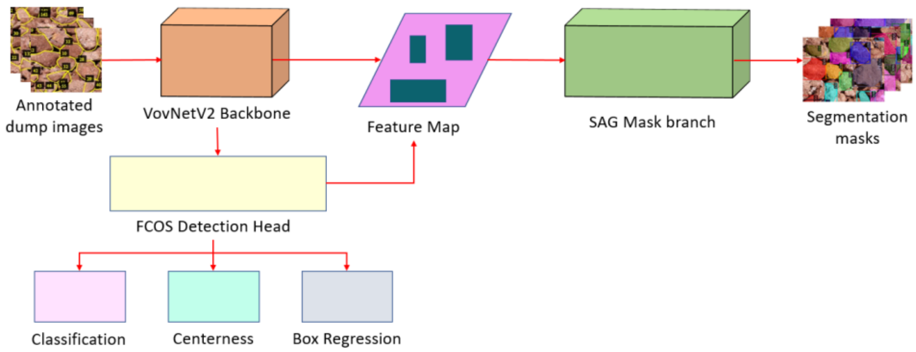

Fig. 2. Schematic diagram of Centermask architecture showing the input images, detection head, backbone network, SAG-mask branch and output segmented image.

3.1. Prediction of potential ROIs

The first step to detecting the target objects is to generate the Region of Interests (ROIs). The ROIs contain the bounding boxes that may contain a potential object. In this study, dump particles are the target classes that are required to be identified and delineated from the images. The traditional object detectors such as Faster R CNN [12], YOLACT [13], and RetinaNet [14] use anchor boxes that require extensive hyperparameter tuning. CenterMask is designed to use FCOS as a detection head which predicts a 4D vector representing the four sides of the bounding box with a class label. Apart from that, a score of centerness is introduced to predict the pixel's deviation from the bounding box's centre.

3.2. Extraction of features

CenterMask proposes a backbone network, VoVNetV2, that extracts the diversified feature representations at a multi-scale level. The backbone network adopts the One-shot aggregation (OSA) module that concatenates all the features only once in the last feature map, which allows for enlarging the new output channels. This module is efficient in GPU computations as it consists of fewer layers. The residual connections introduced with the CenterMask optimize the OSA module to prevent the degradation of accuracy of deeper models. In the present study, the extracted features need to be highly scalable to detect the dump particles from smallest to maximum size present in the image.

3.3. ROI Align operation and generation of masks

The ROIs from the detection head and features extracted from the VoVNetV2 are warped by scale-adaptive ROI Align operation. After generating warped features to predict the segmentation masks over the detected boxes, a branch is appended. In CenterMask, a spatial attention-guided mask (SAG-Mask) helps to focus on essential pixels and reduce the noise. The average and max pooling operations are performed to exploit the spatial attention map. The masks are predicted for individual bounding boxes through a 1×1 convolutional layer.

4. Experiments and Results

4.1. Training strategy

The neural network CenterMask is trained using an anchor-free, one-stage object detector: FCOS with backbone network of VovNetV2 network. The FCOS object detector employs Feature Pyramid Network (FPN) to extract multiple features at different scales. The model uses pre-trained weights trained on ImageNet that contains 1000 classes. The model weights were downloaded from the repository maintained by the developers of CenterMask. The concept of using the model's pre-trained weights on a large dataset avoids the relearning of initial layers. This adopted strategy is a Transfer Learning approach where the model learns the representations of the target datasets without being trained from scratch. The transferred layers of the pre-trained models are frozen while the Fully Connected layers attached at last are trained. This method saves ample time and computational resources using the preserved features from the ImageNet dataset.

The images in the dump dataset were augmented in several steps by randomly cropping, translating, rotating, flipping, scaling and adding Gaussian noise. The size of the dataset increases, and the model is better generalized after training on additional variabilities. From the dataset, the data for training the model comprises the images that contain a total of 80% of the particles of the entire dataset. Each 10% of the particles from the dataset were kept for validation and testing purposes. The validation dataset accompanies the ground truth data, which were manually annotated, and the model's predictions. The model is tested on the validation dataset for optimizing the hyperparameters. The validated model tests new unseen dump images to obtain the segmented dump particles. The same multi-task loss function given by the CenterMask authors was implemented as a sum of losses for centerness L_{center}, classification L_{cls}, box regression L_{box} and mask L_{mask} given by (1).

$$L = L_{center} + L_{cls} + L_{bbox} + L_{mask} \tag{1}$$

4.2. Implementation details

The AI experiments are conducted on a virtual computing cloud platform: Colab pro, offered by Google. The machine provides 25GB RAM of Tesla P100 GPU resource along with a storage of 165GB. The model is built on Detectron2 framework, a popular deep learning library written in PyTorch. The CenterMask model is trained several times to optimize the hyperparameters associated with it. Six images are processed per batch, with two sub-processes loading simultaneously into the RAM. The dump dataset does not require any pre-processing before being input to the model. All the images are resized into 480×480, 512×512 and 640×640 square pixels. A learning rate of 0.025 is chosen with values of decay and momentum mentioned in Table I. As the CenterMask is trained with FCOS, the hyperparameters related to anchor boxes are avoided, saving the computational calculations during training. The model is trained up to 10000 iterations which takes almost 8~9 hours. The model configurations that yielded the best training

Table 1. Configuration of CenterMask model after optimizing hyperparameters.

Configuration	**Values**
Images per batch	6
Initial learning rate	0.025
Warmup iterations	500
Momentum of Stochastic Gradient Descent (SGD)	0.9
Weight decay	0.0001
Number of workers	2
Inference threshold in training	0.01
NMS threshold used on FCOS	0.3
Reduction of learning rate by Gamma	0.05
Number of steps to evaluate during training	500

accuracy and lower training loss were saved and presented in Table I. The best model is then evaluated against the test dataset.

4.3. Segmentation results

Learning of finer details of dump particles requires a high training accuracy with a lower value of the total loss. Fig. 3 shows the CenterMask training accuracy and the decreasing trend of losses calculated during training. At the end of the

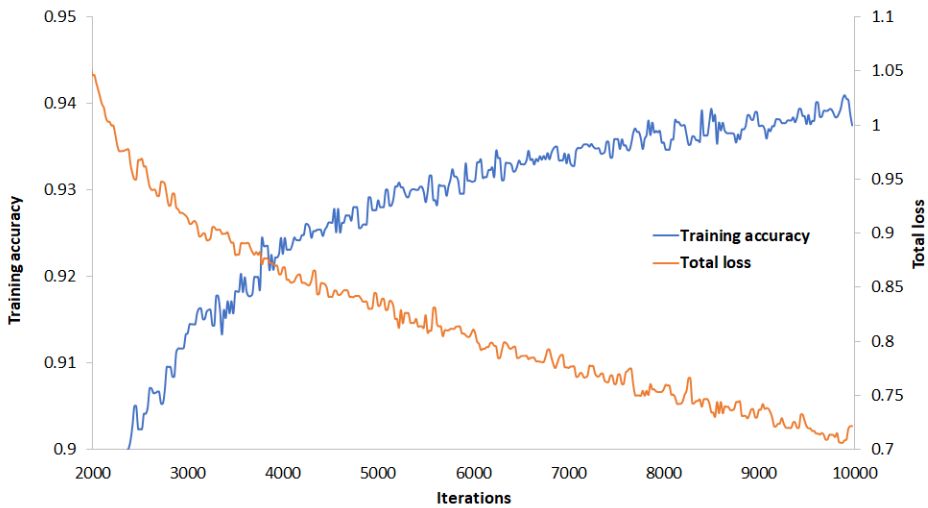

Fig. 3. A plot depicting training accuracy and the total loss incurred during training of the model.

10000th iteration, the model attains 94.12% training accuracy, and the total loss incurred is 1.01.

The model was evaluated against the validation dataset. The research objective behind the presented study is to segment the dump particles to predict the size distribution curves. For an accurate estimate, the model's predicted segmentation masks must be closely aligned with particle boundaries to obtain the surface area. To ensure this, two metrics are adopted. The first metric, Average Precision (AP), assesses how well the model generalizes to unseen test images. The AP is commonly used to evaluate the models trained on MSCOCO [15] dataset. AP depends on the IoU threshold, a ratio between Intersection over Union of the detection and ground truth value. In MSCOCO, AP is computed as an average over IoU thresholds 0.5:0.95, 0.5 and 0.75 referred to as AP, AP50 and AP75, respectively. Table 2 shows that AP is calculated for bounding boxes and segmentation masks. The AP values are determined during training for every 500 iterations, and the training is stopped when AP saturates. The model achieves an AP value of 57.08 for segmentation masks and 51.85 for bounding boxes.

Table 2. Comparision of CenterMask metrics with Mask R CNN metrics (Data taken from [28])

Metric	**CenterMask**	**Mask R CNN**
AP_{seg}	57.08	35.69
AP_{bbox}	51.85	34.31
AR_{seg}	60.8	38.7
AR_{bbox}	56.4	37.3
Percentage error in mm	1.01	1.27
Standard deviation in mm	0.73	0.44
Percentage of particles detected in validation dataset	92.46	87.37

The second metric in this context can be an absolute comparison of the model's predictions with manually annotated ground truth data. As mentioned earlier, the validation dataset contains both the data, which can be used to verify the results statistically. Fig. 4 demonstrates the bar chart, highlighting the variations in percentage error calculated to compare the predictions and ground truth data over the common number of particles in annotated and predicted images. A percentage error of 1.01 mm was found with a standard deviation of 0.73 mm for the entire validation dataset. Some of the predicted outputs are shown in Fig. 5.

Fig. 4. Image input to the model and the predicted image containing segmentation masks.

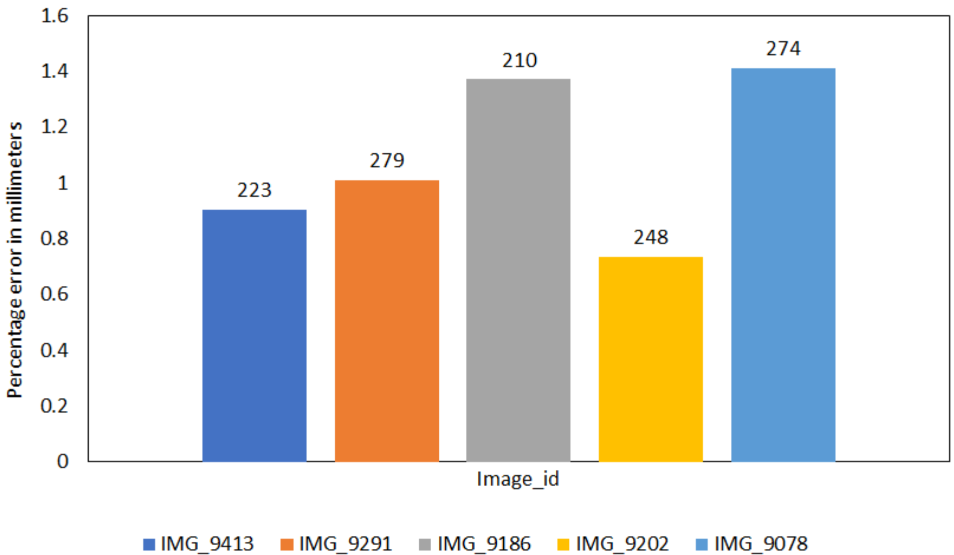

Fig. 5. Bar chart showing percentage error determined by comparing model's predictions with ground truth data in validation dataset for five randomly selected images. Numbers mentioned in the chart area denotes the particles common to model's prediction and ground truth data.

4.4. Comparison with Mask R CNN

The dump dataset was trained on Mask R CNN architecture, and the results were published [16]. Mask R CNN uses Region Proposal Network (RPN)to propose potential ROIs. The model is backed by ResNet50 with a Feature Pyramid Network (FPN) to extract multi-scale features. Fully Convolutional Networks (FCN) and Fully Connected (FC) layers predict segmentation masks and bounding boxes. Compared with the CenterMask network, the capability of ResNet50 and VovNetV2-39/57 is similar to a backbone network. Therefore, the accuracy of these two models can be compared.

As shown in Table III, the metrics show that the CenterMask network performed better than Mask R CNN. The number of particles predicted by the models is counted and compared with the total particles in the validation dataset. Mask R CNN detected 87.37% of particles while CenterMask outperforms it by detecting 92.46% of the total particles. The AP values between the CenterMask and Mask R CNN model differ by a more considerable margin, clearly portraying the better generalization capability of the CenterMask algorithm. The training time to complete 10000 iterations was almost similar.

Table 3. AP values calculated during evaluation.

Metric	Bbox Regression	Segmentation
AP	51.85	57.08
AP50	70.66	71.57
AP75	67.91	69.56
AR	56.4	60.8

4.5. Web Application

From the dimensions of the white-colored scale, pixels of the predicted segmentation masks are converted into real-world coordinates. Particle size distribution curves are generated from these dimensions following the procedure mentioned in [16]. A standalone web-based application was developed that asks the users to input dump images and outputs the segmented image along with particle size distribution curve. Equipped with a user-friendly frontend, the application can be accessed through any device having internet facility. A server processes the requests in the backend part and submits the job after running the model's prediction code block. The backend part is built on Flask, a microweb framework based on Python. Fig. 6 shows the user interface, segmented output, and size distribution curve.

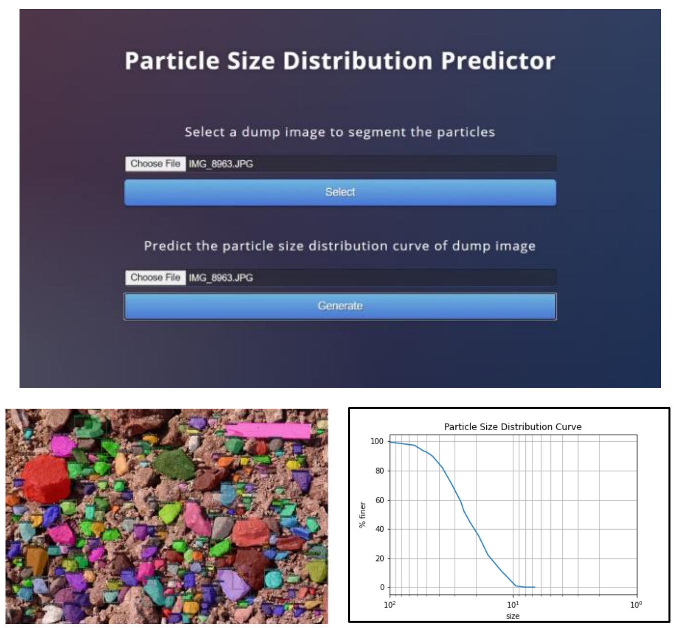

Fig. 6. A web-based application developed to predict particle size distribution. A user-friendly interface, output segmented image and size distribution curve is shown.

5. Conclusion

The presented study in this article proposes a novel application of Artificial Intelligence to delineate particles from dump images. The extracted coordinates of segmentation masks are used for determining the particle size distribution curves. The real-time predictions of shear strength along different sections of overburden dump may assist the industrialists in better designing dump benches. The model can predict particles ranging from five millimeters to the maximum size present in an image. In this study, a CNN architecture, CenterMask, is implemented to segment dump particles. The model is trained to achieve an accuracy of 94.12%. The AP of 57.08 and its capability to predict 92.43% of particles in the validation dataset suggests the model's performance on new images. The percentage error of 1.01 mm with a standard deviation of 0.73 mm demonstrates that the segmentation masks were laid upon the particles accurately. CenterMask network based on FCOS as detection head that uses VovNetV2 network efficiently handles the complexity involved in detecting geomaterials. The finer details such as color, texture, granularity etc., and the wide variations in size and shape are learnt during the training. The model projected 250 to 300 particles from a single unseen image, sufficient to predict the size distribution curves. In the future, the CenterMask model may be improved by fine tuning the network heads. The dataset may be appended to accommodate images from coal or other ore deposit dumps.

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