Coal Grain Analysis

Improving Coal Characterisation Using Machine Learning

Alex Pitt, Paul McPhee, Chad Hargrave

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Introduction

Characterisation of the microscopic structure of coal is fundamental to understanding its chemical and physical behaviour. Analysis of coal samples allows benchmarking of potential yield and ash content during the exploration stage, estimation of washability during processing including fine coal recovery via flotation processes, and estimation of fusible content to improve coal utilisation for coke making or power generation.

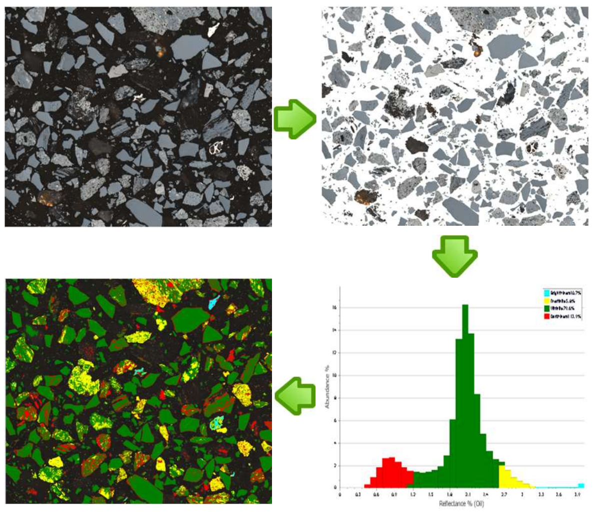

Figure 1: Top Left: microscopy image; Top Right: post-segmentation; Lower Right: reflectance histogram; Lower Left: characterised image

CGA software allows for the automatic analysis of large coal images which provide reliable statistics on the distribution of coal types and impurities. It has been successfully used to analyse hundreds of coal samples. One important feature of this software is the automatic segmentation of coal images into foreground (particle) and background (resin). To date, this feature has been implemented using classical image processing algorithms.

Due to the limitations of hand-engineered image processing and subtle complexities in coal images, the automatic segmentation results then need to be assessed and refined by an expert before proceeding to characterisation. The appeal of reducing this time investment from experts led to investigations into how machine learning could be applied to this feature of CGA software.

Semantic Segmentation

Machine learning has made significant advances in image processing tasks in recent years. One such task is *semantic segmentation*, a supervised learning task wherein a model learns how to map each pixel of an input image to its own output class. Convolutional neural networks (CNNs) are a class of machine learning models that have produced impressive results in the semantic segmentation of natural images, and have been successfully applied to more specialized image domains such as medical microscopy. CNNs are distinguished from other types of neural networks by their use of *convolutional layers* that take advantage of local spatial invariance in images by learning a set of shared weights that are convolved over the entire 2D input much like filter kernels in classical image processing. This avoids the curse of dimensionality and allows CNNs to 'go deep' by incorporating many more layers while remaining efficiently trainable. Very large training sets of input images and corresponding *ground truth* label images are required to learn complex mappings. Many different CNN architectures exist in the literature and they are a topic of on-going research. For our model, we extended the well-known U-Net CNN.

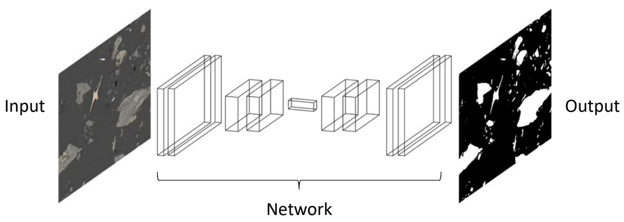

Figure 2: Convolutional layers assembled in a representative CNN architecture.

Learning to Recognise Coal

Compiling a sufficiently large dataset to train our model for the task of semantic segmentation on coal images was made possible due to existing archives of microscopy images and label images generated with CGA software and refined by our experts. Our initial dataset consisted of microscopy lab samples totalling approximately 360 megapixels.

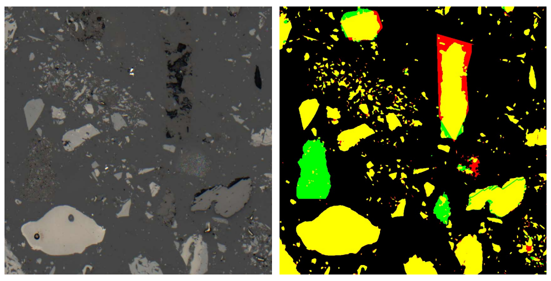

Figure 3: Left: microscopy image; Right: model output vs expert ground truth for label map (green: model, red: export, yellow: both)

Due to the complexity of semantically segmenting coal images, even expert-provided label images will contain some amount of error. However, the literature shows that CNNs are resistant to label noise that is spread across the training set. Our model was able to converge despite this error.

Efficiently training our model required us to divide this dataset into smaller patches to give us a sufficiently large number of individual examples. Additionally, the size of these patches determined the maximum amount of spatial context that could inform the classification of any given pixel, as well as the hyper-parameters and computational requirements of training and prediction. For coal images, experts judged that high-frequency textures and local context around resin-particle interfaces were highly informative to accurate segmentation, whereas longer-range spatial context (e.g. encompassing multiple separate particles) was less informative. A patch size of 256x256 pixels adequately encompassed the typical scales of these superior features and gave us a dataset of 10,000 unique examples. These examples were then shuffled and split into a training set, validation set and test set in an approximate 80%-10%-10% split. During training, randomised image augmentations such as brightness and contrast adjustment, Gaussian blurring and noise, rotation and translation were applied to examples.

Our model contained over 41 million learnable parameters and was trained for 60 epochs over approximately 10 hours on 2x Nvidia Quadro P5000 GPUs. Prediction was then performed on overlapping patches from image data in the unseen test set. Models from our latest training efforts have achieved over 97.8% accuracy, and 96.4% mean intersection-over-union on the test set.

Predictions from our models have already been useful in highlighting instances of human error, and could be used to bootstrap a process of reducing label noise and re-training.

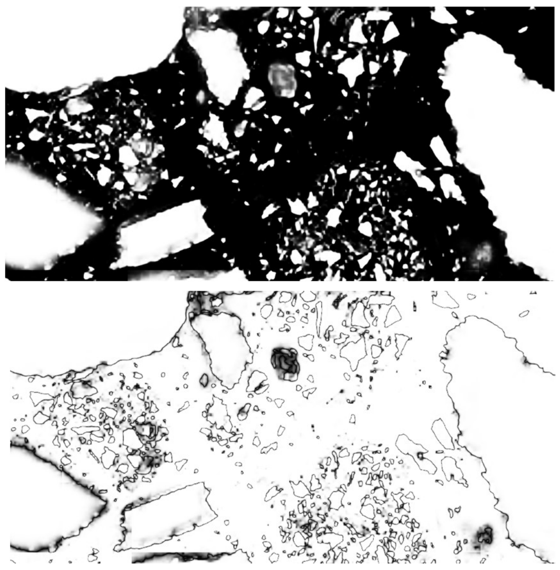

Figure 4: Top: probability map (for particle class); Bottom: certainty map (maximum probability for any class).

Future Work

- Testing more CNN architectures and exploring hyper-parameter spaces.
- Adaptation to segmentation of particles in environmental dust samples.
- Evaluating multi-class segmentation for sub-particle characterisation of material components.
- Exploring machine learning to perform blend partitioning.

FOR FURTHER INFORMATION

Alex Pitt
e Alex.Pitt@csiro.au
ph 07 3327 4705

Paul McPhee
e Paul.McPhee@csiro.au
ph 07 3327 4134

Chad Hargrave
e Chad.Hargrave@csiro.au
ph 07 3727 4523