PORTABLE MICROSCOPY AS A NEW CONCEPT FOR REAL-TIME COAL MINE DUST MONITORING

NESTOR SANTA

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VIRGINIA TECH

Acknowledgements

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ALPHA FOUNDATION

01

BACKGROUND AND MOTIVATION

Background and Motivation

- Inhaling dust particles can cause debilitating lung illnesses and ultimately result in death.
- 252 deaths (2018-2019)
- Federal Coal Mine Health & Safety Act passed in 1969.
- Declining incidence of lung disease until the mid 1990s.
- Resurgence in the last 2 decades.

How to explain the increasing number of cases of occupational lung disease in US miners over the last 20 years?

5-year moving average percentage of progressive massive fibrosis in miners with 25 years of underground tenure, Virginia, Kentucky, and West Virginia. Taken from Hall et al., 2019.

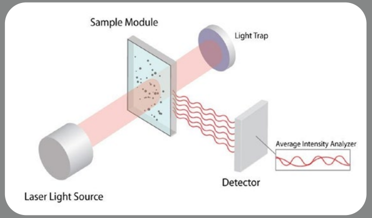
Current Monitoring Technologies

Gravimetric

- Personal dust monitor.
- Helmet-CAM.
- Microfluidics.

Light Scattering

Measures Intensity of light scattered.



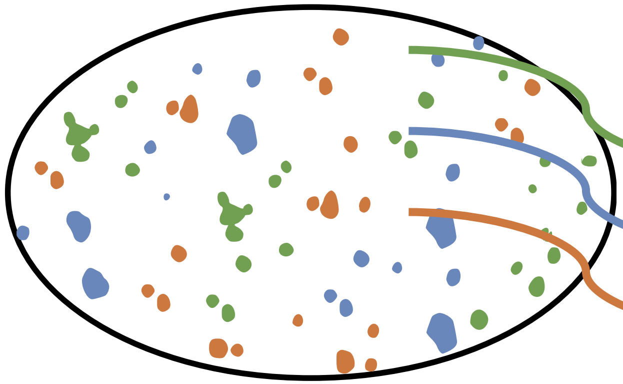
NIOSH FTIR

End-of-shift to quantify quartz (prototype).

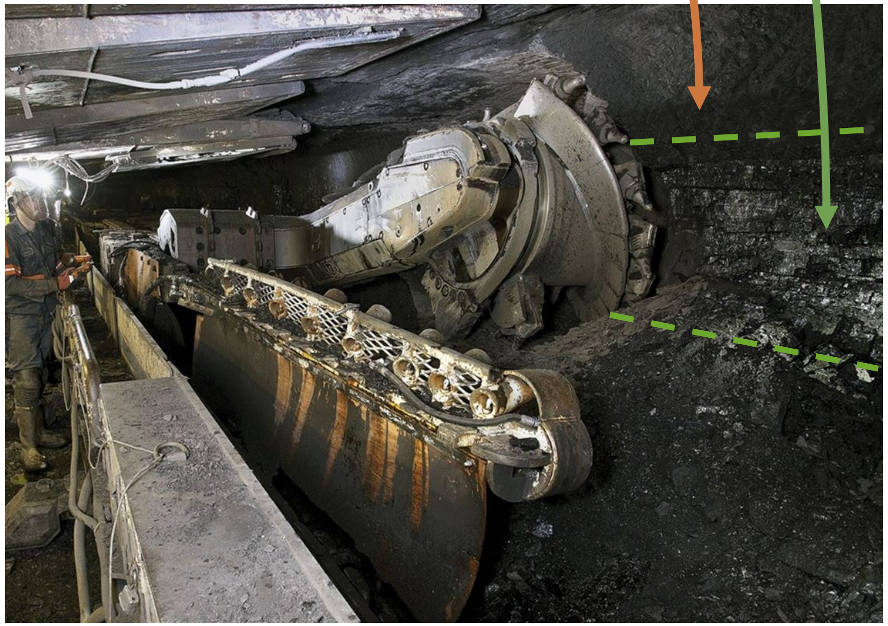
Chemiluminescence

Silica particles are bound to light-emitting molecule (prototype).

Dust Sources



Particle class	Likely source
Coal	Coal strata cutting
Carbonate	Rock dust application
Silicate, silica	Rock strata cutting

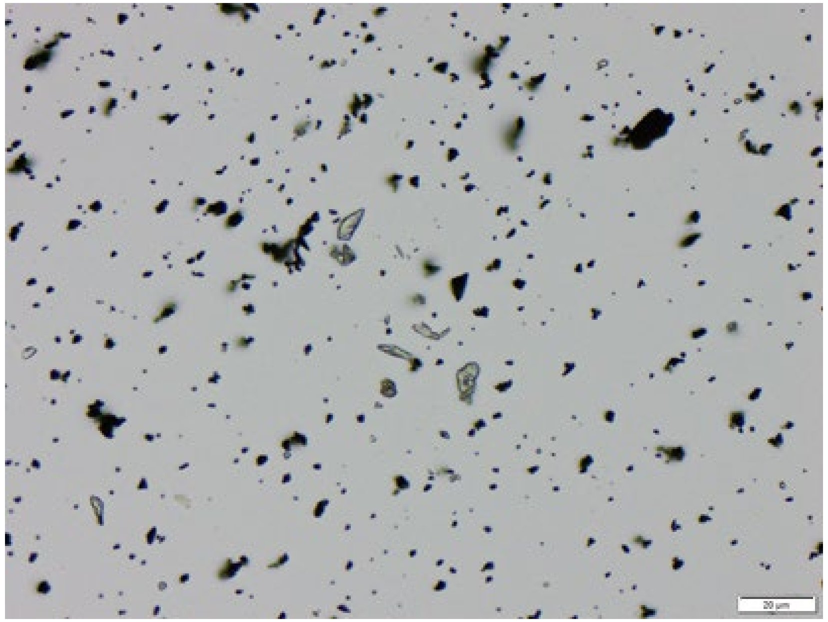


Dust particle types:

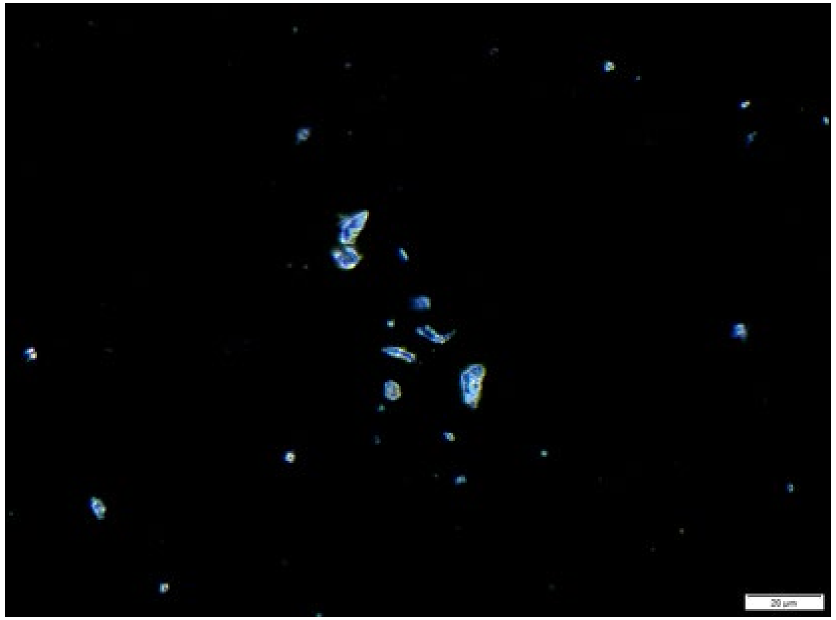
- Coal
- Silica
- Kaolinite
- Calcite

Optical Microscopy

Has been widely used to characterize mineral particles in several applications.



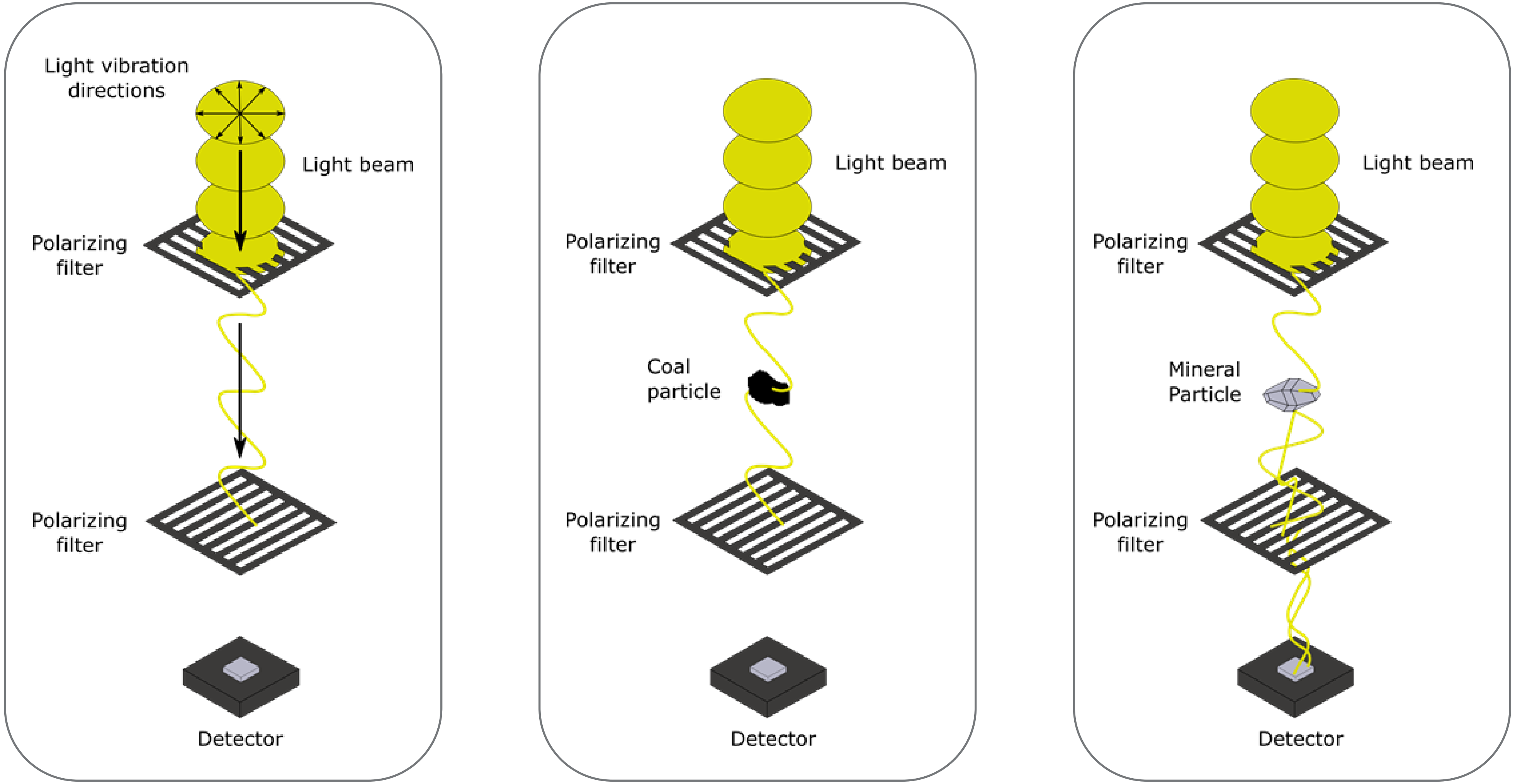
Plane-polarized light



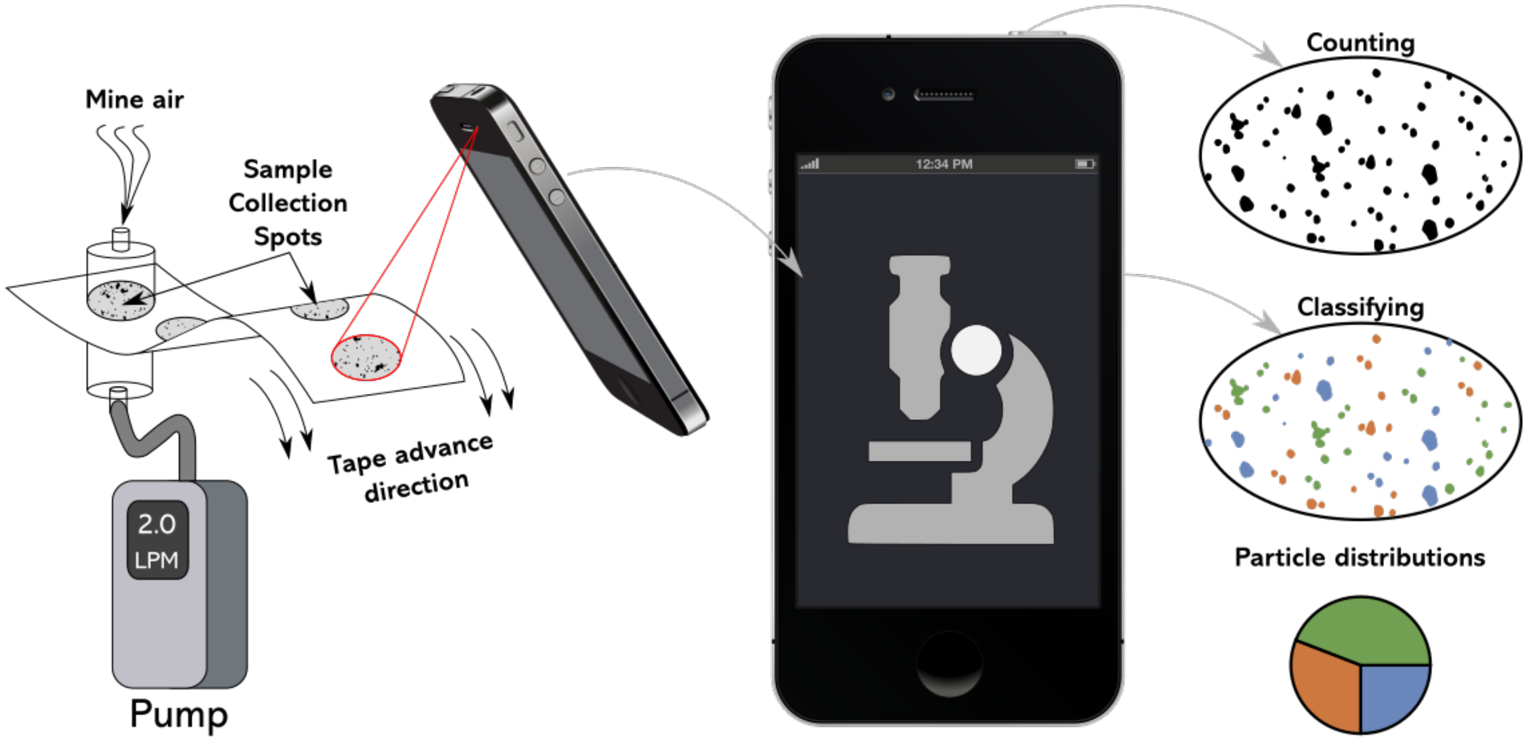
Cross-polarized light

- Identification of minerals.
- Particle size and shape.
- Health-based monitoring.

Birefringence



Novel Monitoring Concept



Envisioned dust monitor:

- Portable microscopy.
- Automated image analysis.

Advantages:

- Field deployable.
- Semi-continuous.
- Fast analysis.

Limitation:

- Particle size

Objectives

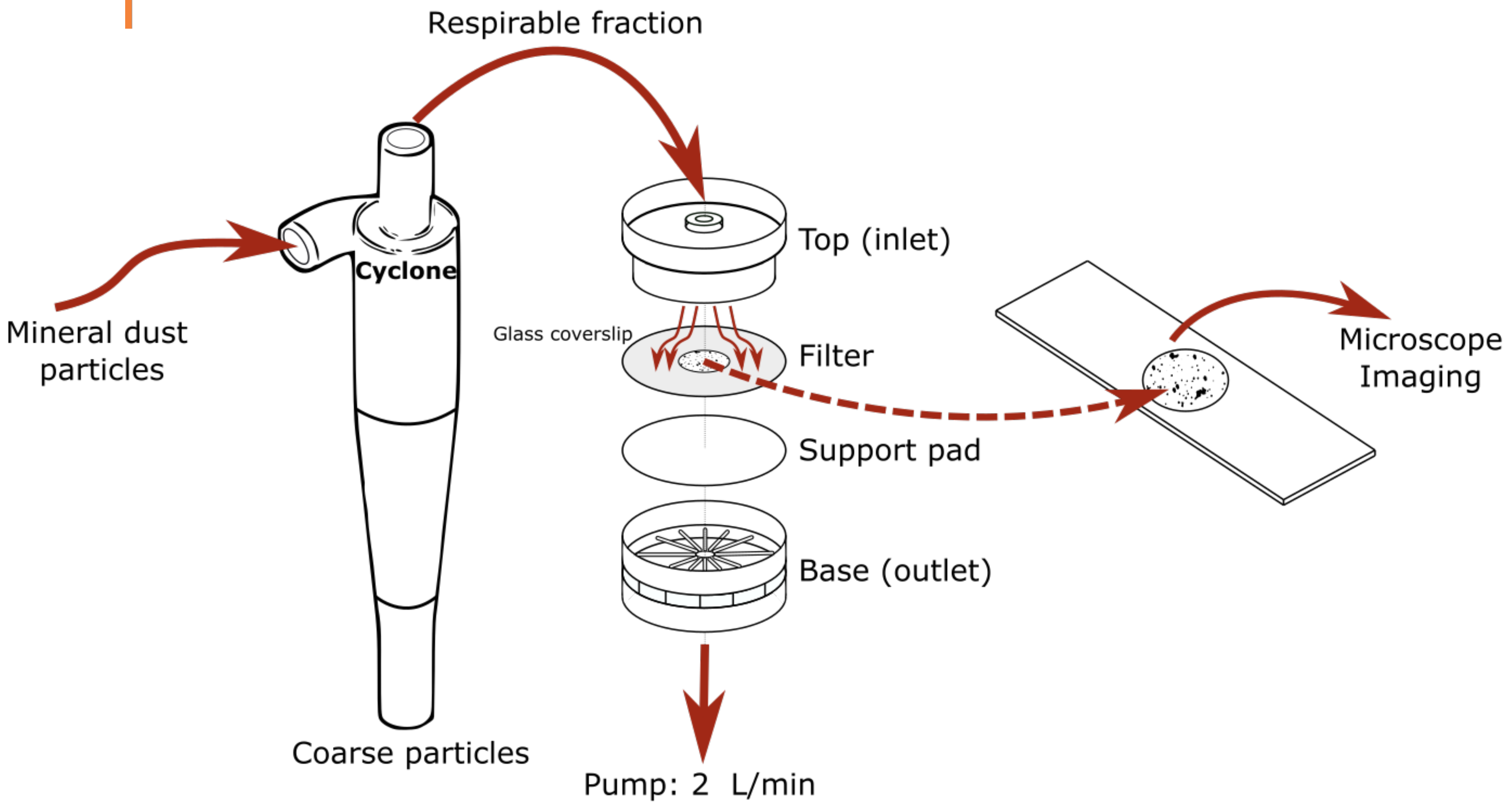
- Demonstrate that OM and automated image analysis can be used to separate coal and mineral fractions in respirable coal mine dust.

- Develop a classification model for distinguishing between major types of mineral dust particles.

02

MATERIALS AND METHODS

Materials and Methods
Sample preparation

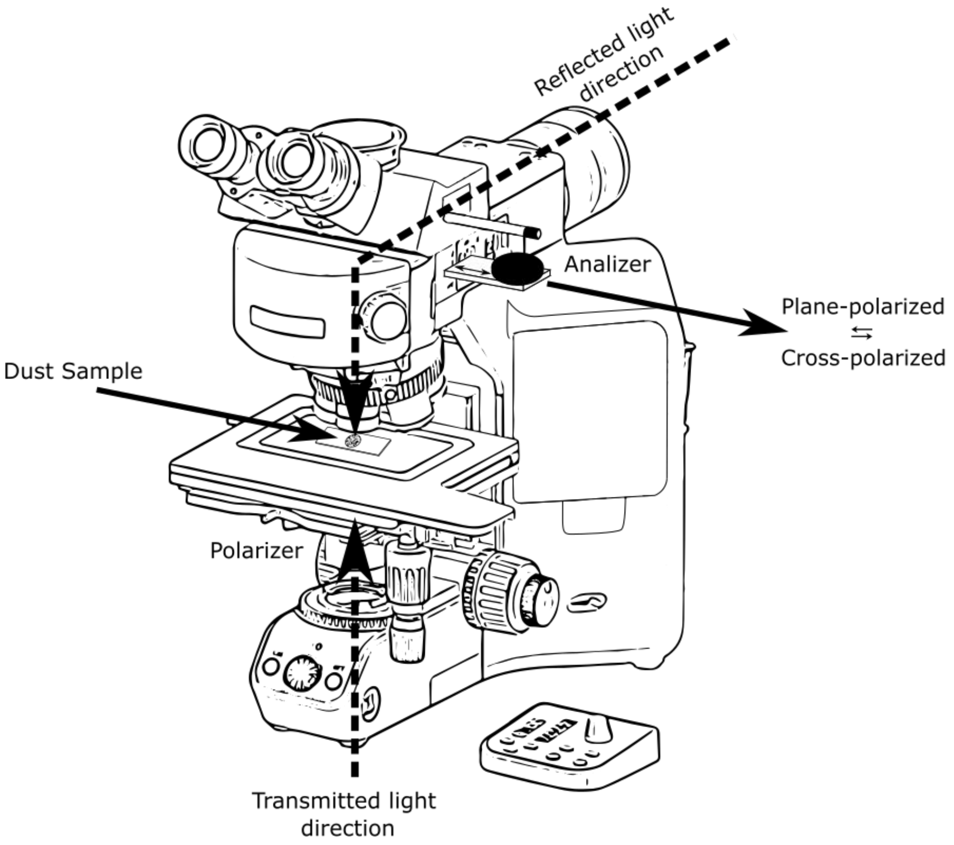


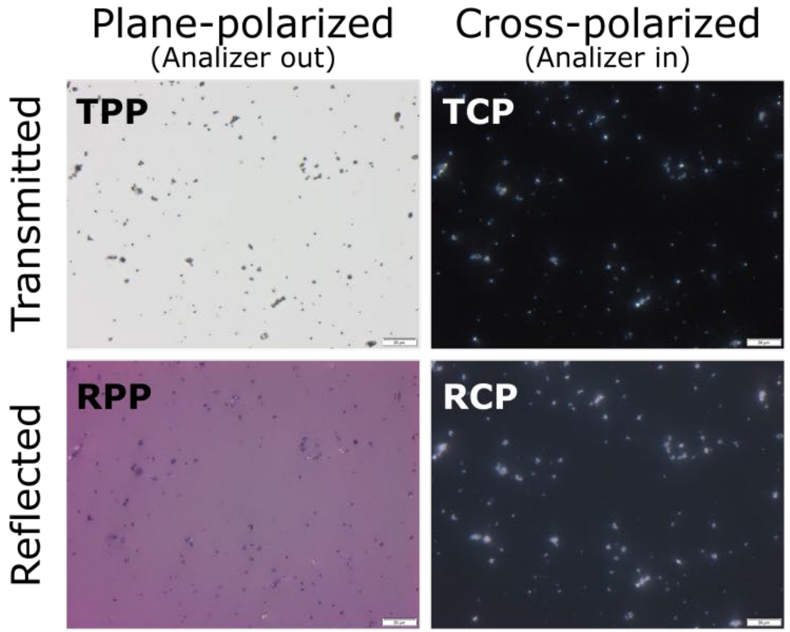
- Pump working at 2 L/min
- 10-mm nylon cyclon
- Respirable dust deposited on filter and coverslip
- Filters used for SEM analysis

Materials and Methods

Imaging

Olympus BX53M polarizing microscope



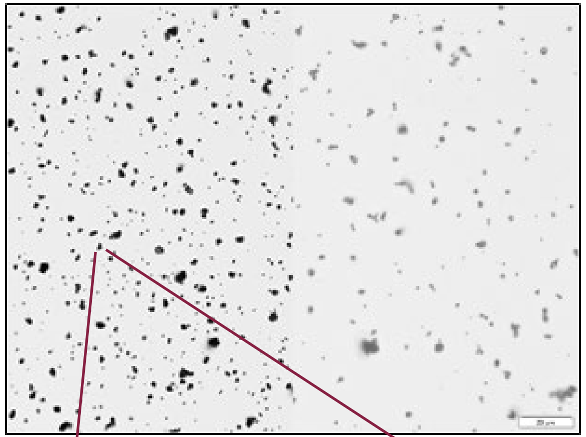


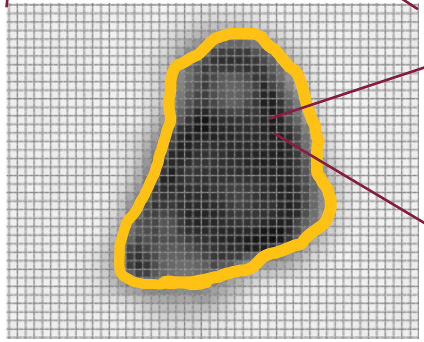
- **Image frame**
  - TPP
  - TCP
  - RPP
  - RCP
- **Standard lighting conditions:**
  - Exposure time.
  - Color balance
  - Light intensity

Materials and Methods

Particle Identificaiton-Feature Extraction

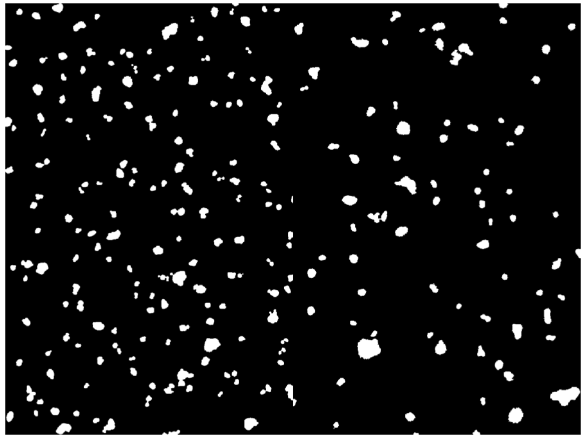
1. Transmitted plane-polarized





3175	3206	3242	3193	3162
3211	3213	3227	3203	3189
3189	3164	3180	3217	3207
3178	3169	3179	3199	3209

2. Adaptive thresholding algorithm



3. Binary mask

Labeling and location of all particle pixels.

4. Dataset of particles

- Particle intensity
- Particle size & shape

03

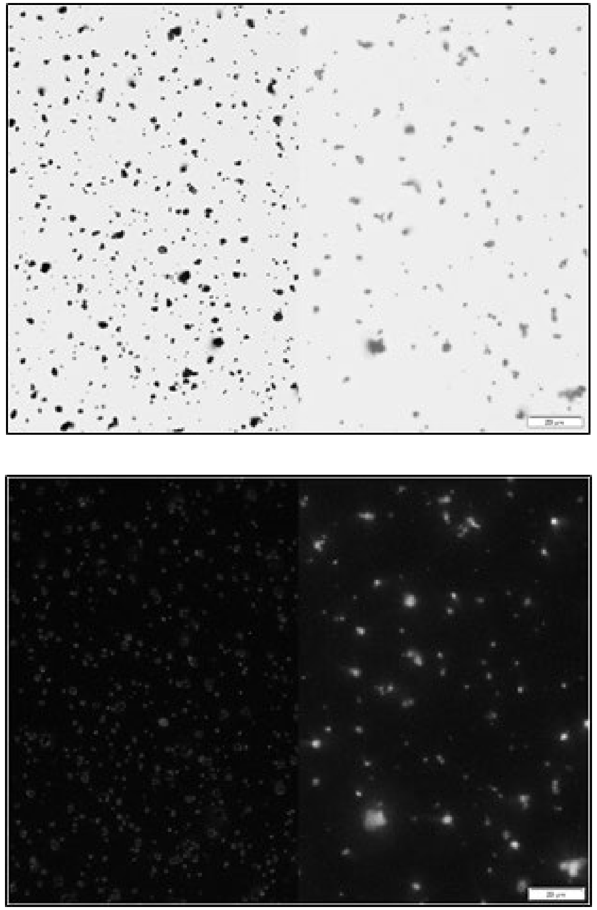
COAL VS. MINERAL CLASSIFICATION

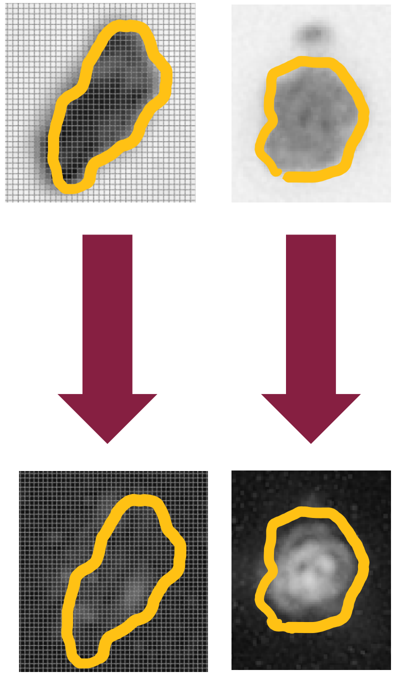
Coal vs. Mineral Classification
Dataset

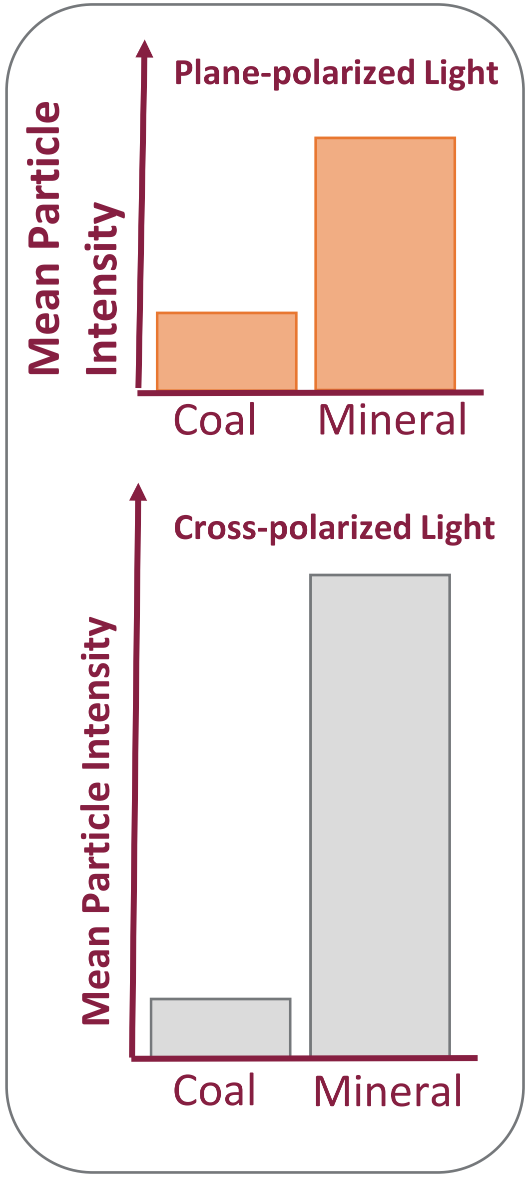
Dust samples		Number of samples	Frames imaged/sample	Number of frames	Total number of Images	Total particles identified (≥ 27 pixels)
Single material	Coal	3	50	150	600	24573
	Kaolinite	3	50	150	600	20125
	Rock dust	3	50	150	600	20512
	Silica	3	50	150	600	8835
Composite	Coal + Kaolinite	1	20	20	80	329
	Coal + Rock dust	1	20	20	80	303
	Coal + Silica	1	20	20	80	3167

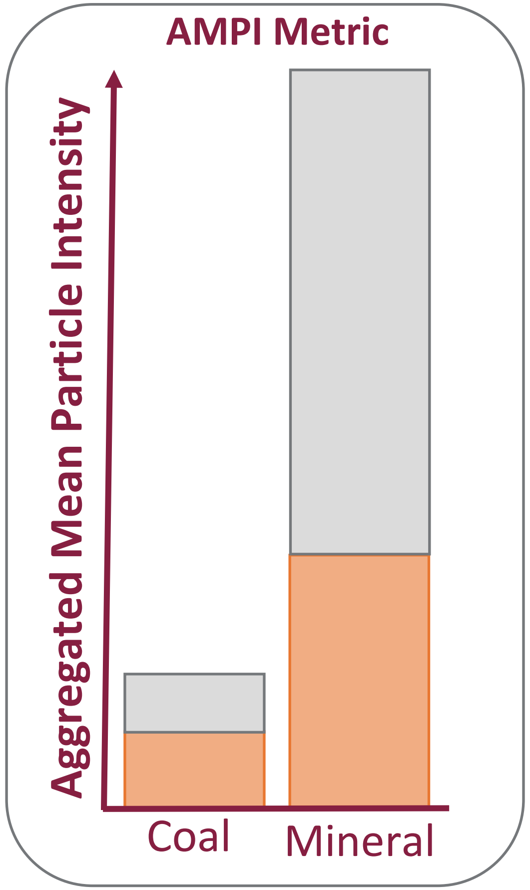
Coal vs. Mineral Classification

Agregated Mean Particle Intensity

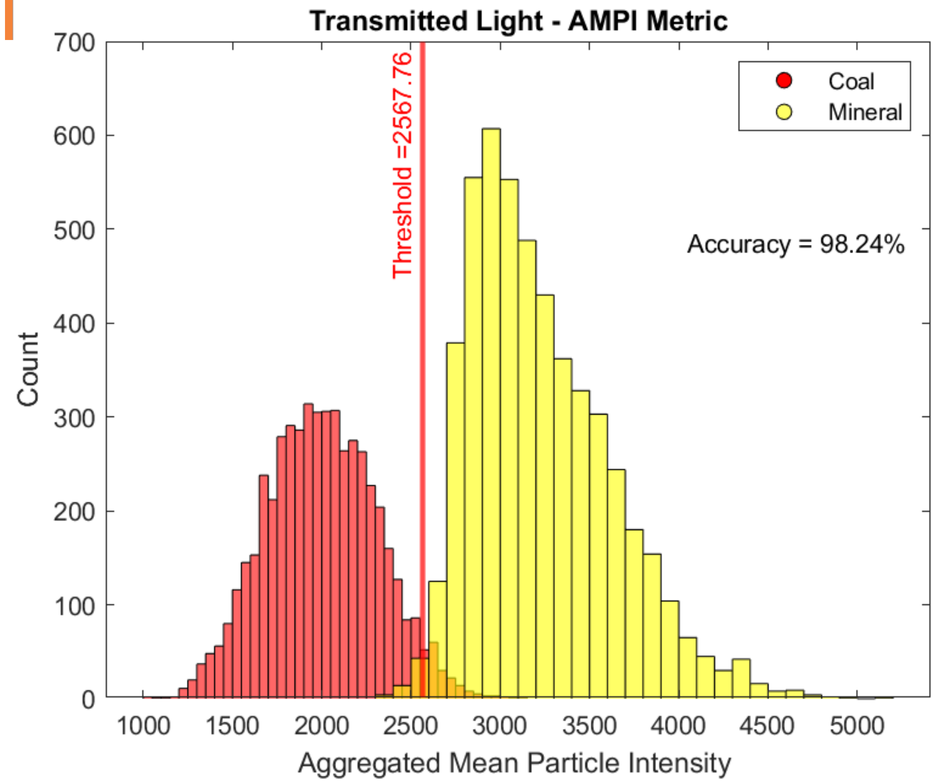








Coal vs. Mineral Classification Modelling

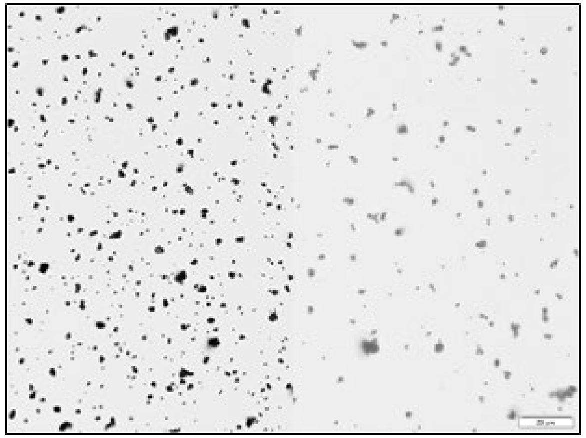


		Coal	Kaolinite	Rock dust	Silica
Training set (98.24%)	True	19472	17831	18310	8235
	Predicted	18616 (96%)	17596 (99%)	18285 (99.9%)	8225 (99.9%)
	Misclassified	856 (4%)	235 (1%)	25 (0.1%)	10 (0.1%)
Test set (97.7%)	True	5101	2294	2202	600
	Predicted	4909 (96%)	2253 (98%)	2202 (100%)	599 (99.8%)
	Misclassified	192 (4%)	41 (2%)	0 (0%)	1 (0.2%)

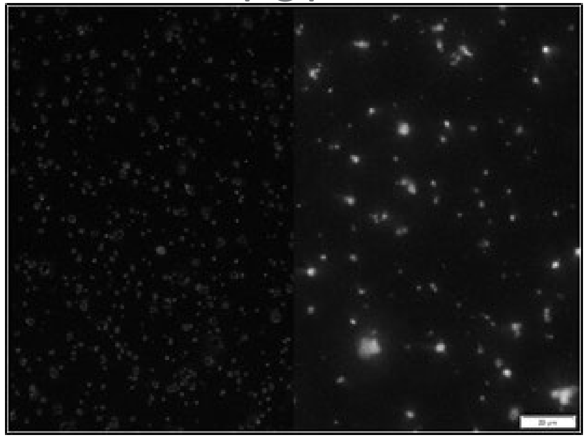
- Coal particles are misclassified more often than minerals.
- Impurities.
- Orientation of particles.

Coal vs. Mineral Classification Testing

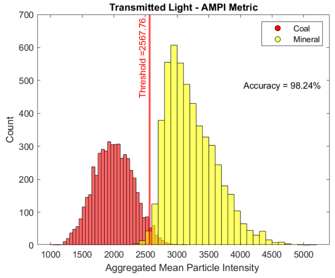
TPP

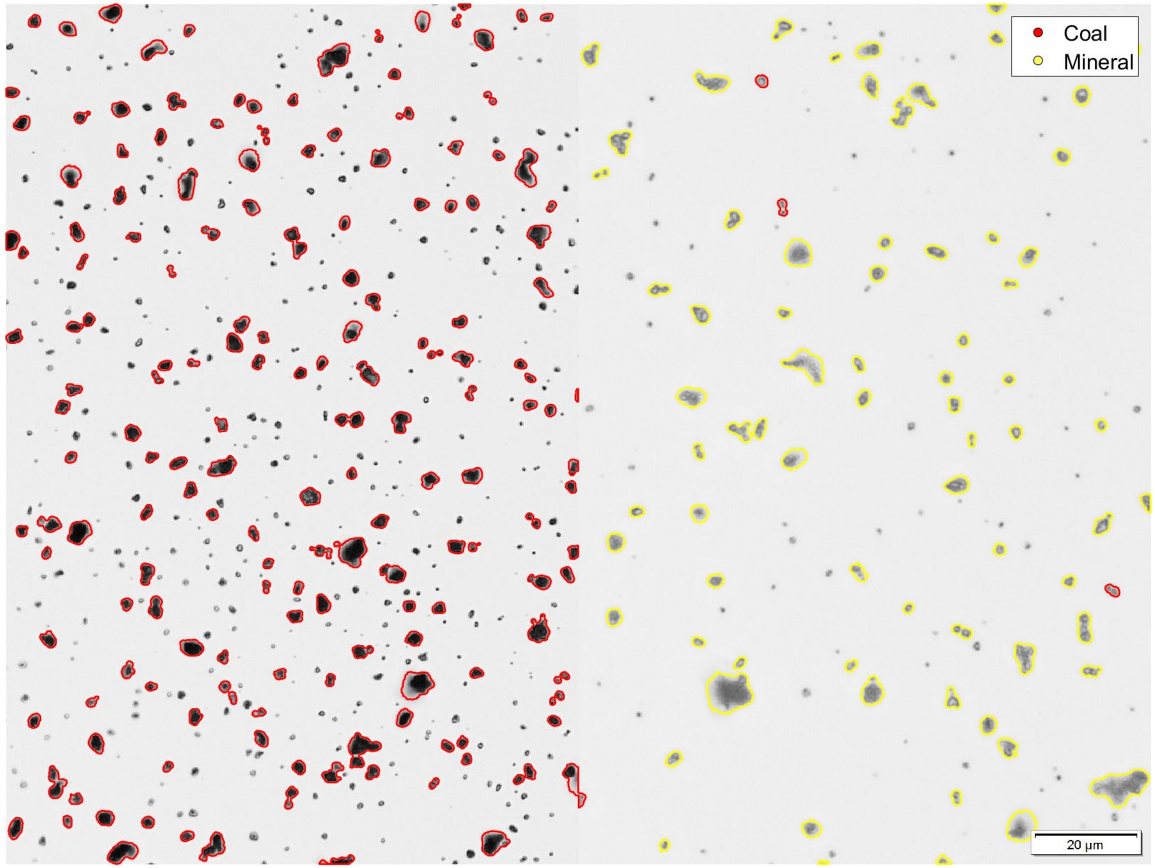


TCP

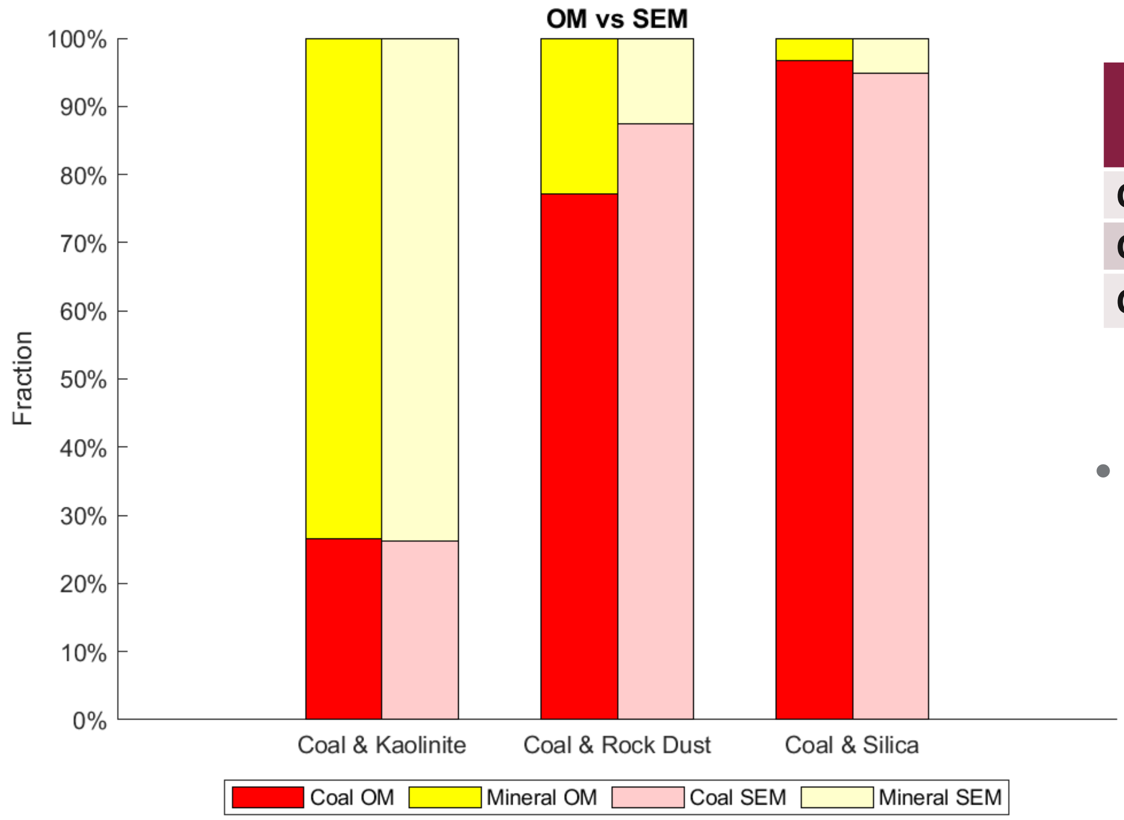


Classification Model





Coal vs. Mineral Classification
Results on Composite Samples



Sample	OM		SEM-EDX	
	Coal %	Mineral %	Coal %	Mineral %
Coal & Kaolinite	27	73	26	74
Coal & Rock dust	77	23	87	13
Coal & Silica	97	3	95	5

- Results in very good agreement with those indicated by scanning electron microscopy (SEM)

04

MINERAL SUBCLASSIFICATION

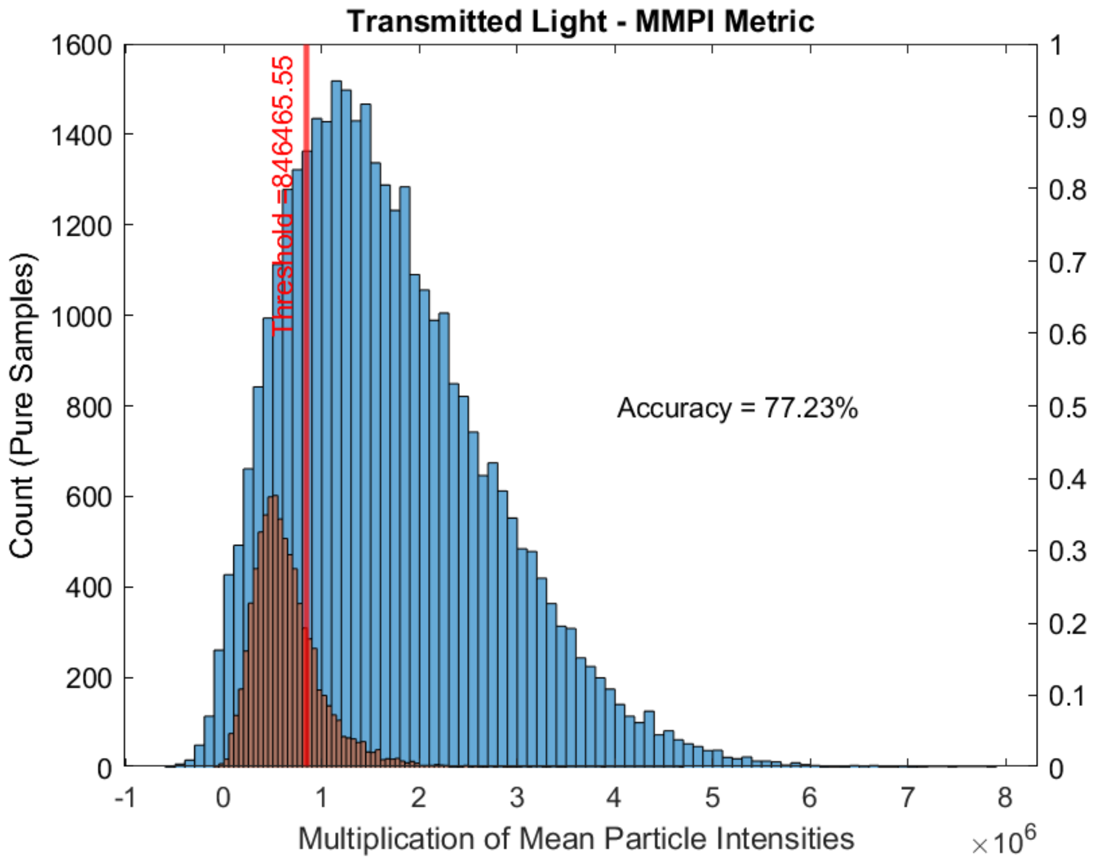
Mineral Subclassification Dataset

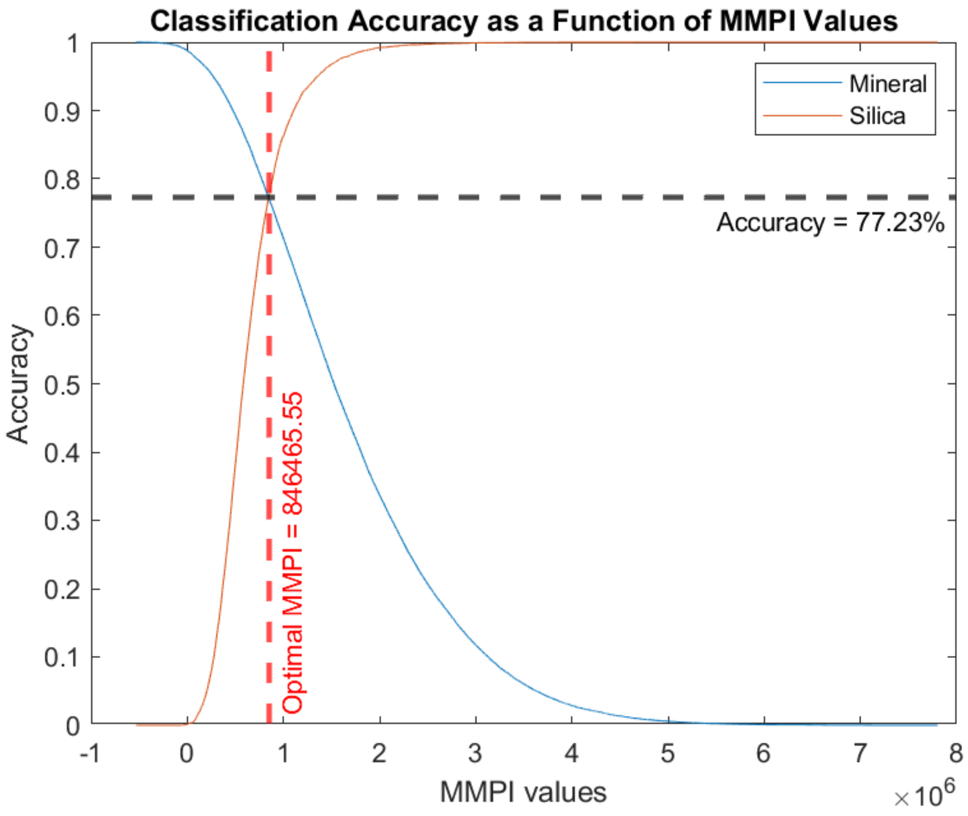
Sample Type	Material	Number of samples	Frames imaged/sample	Total particles identified (≥ 27 pixels)
Single material	K	3	50	20125
	RD	3	50	20512
	S	3	50	8835
Composite (coal + one mineral)	C+K	1	20	329
	C+RD	1	20	303
	C+S	1	20	3167
Composite (3 minerals)	K+RD+S_1	1	20	5298
	K+RD+S_2	1	20	6296
	K+RD+S_3	1	20	5315
Composite (3 minerals + coal)	K+RD+S+C_1	1	30	2702
	K+RD+S+C_2	1	30	3432

All sample preparation and dust imaging methods were the same as described earlier

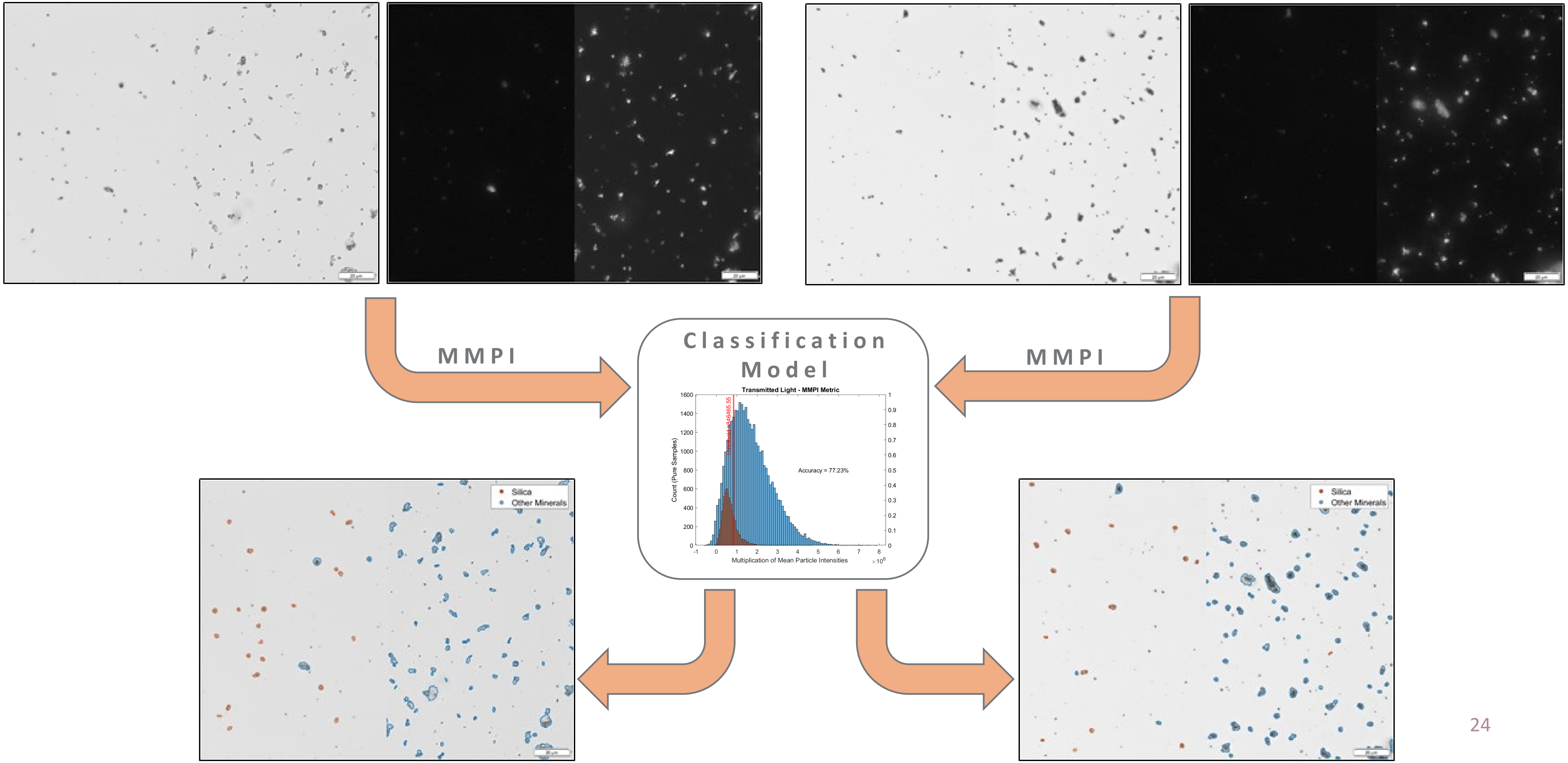
Mineral Subclassification
Feature Selection

- Exploration of a combination of more than 80 particle features
- Stepwise method to separate coal, then silica (binary classification)





Mineral Subclassification



Mineral Subclassification

		Silica	Other minerals Kaolinite	 Rock dust
Training set (77%)	True	8235	17831	18310
	Predicted	6361 (77%)	12875 (72%)	15038 (82%)
	Misclassified	1874 (23%)	4956 (28%)	3272 (18%)
Test set (81%)	True	600	2294	2202
	Predicted	463 (77%)	1808 (79%)	1868 (85%)
	Misclassified	137 (23%)	486 (21%)	334 (15%)

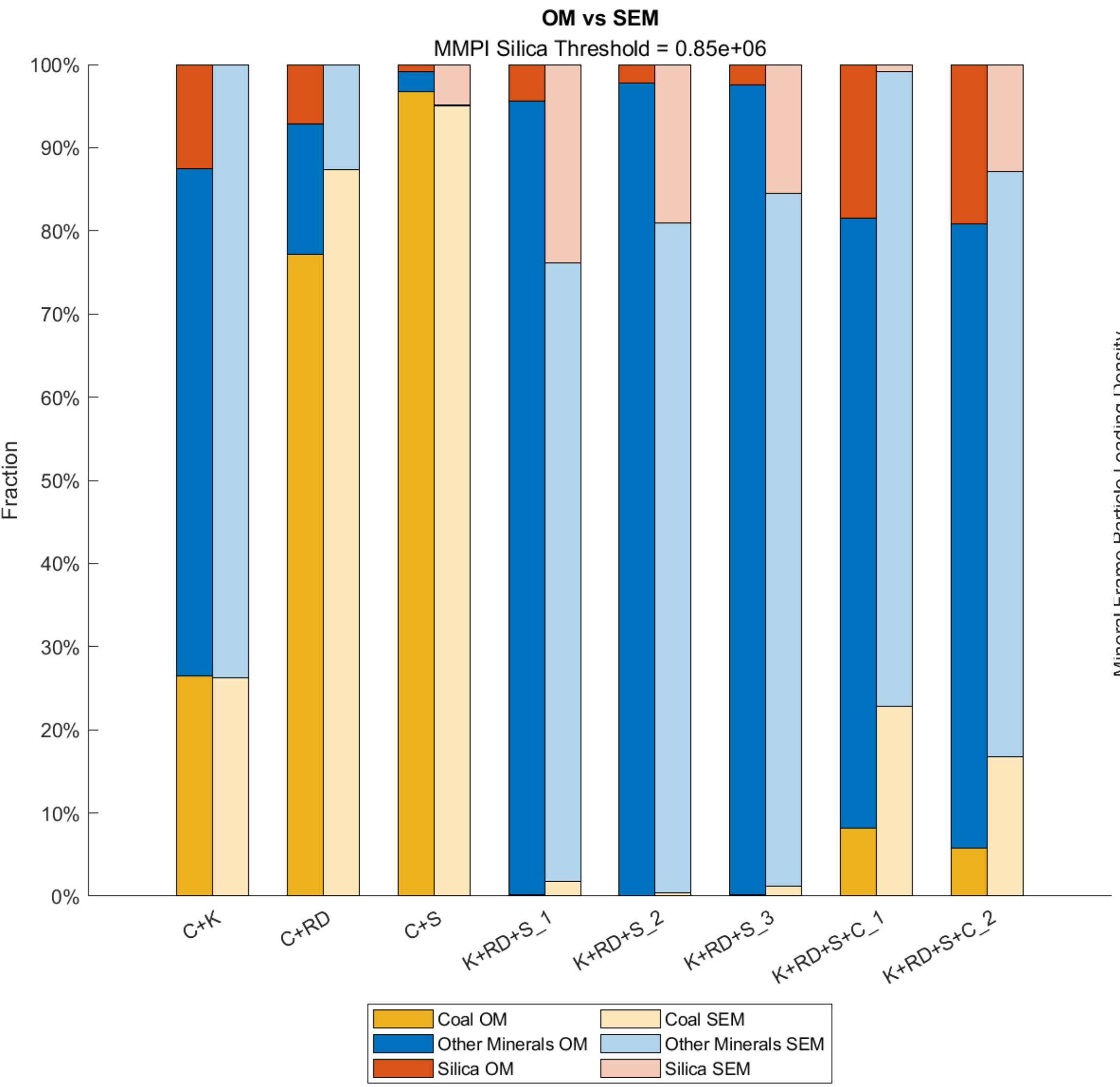
Training set

- The model tends to misclassify mineral particles as silica

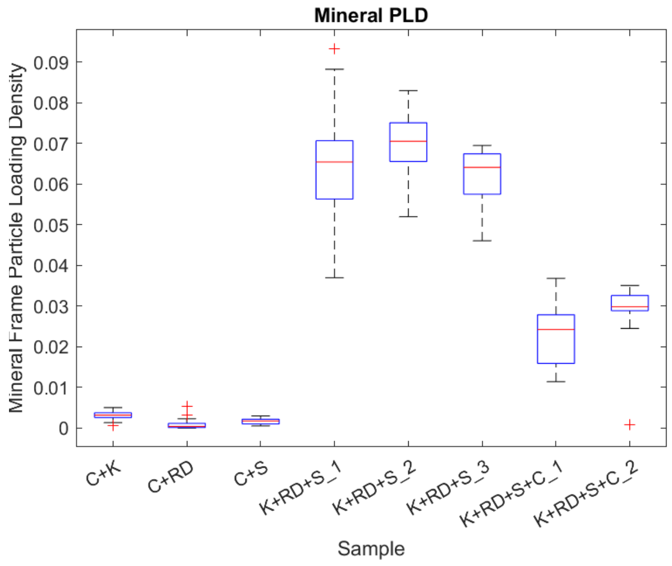
Test set

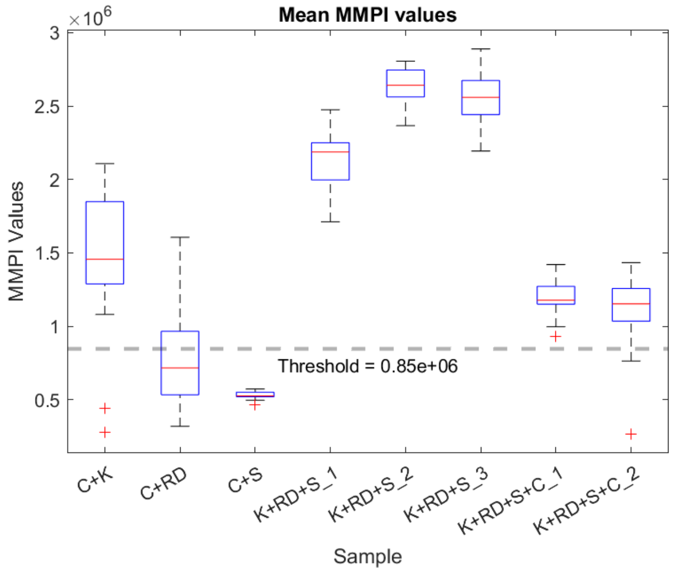
- The model tends to misclassify silica particles as other minerals in

Mineral Subclassification
Results on Composite Samples

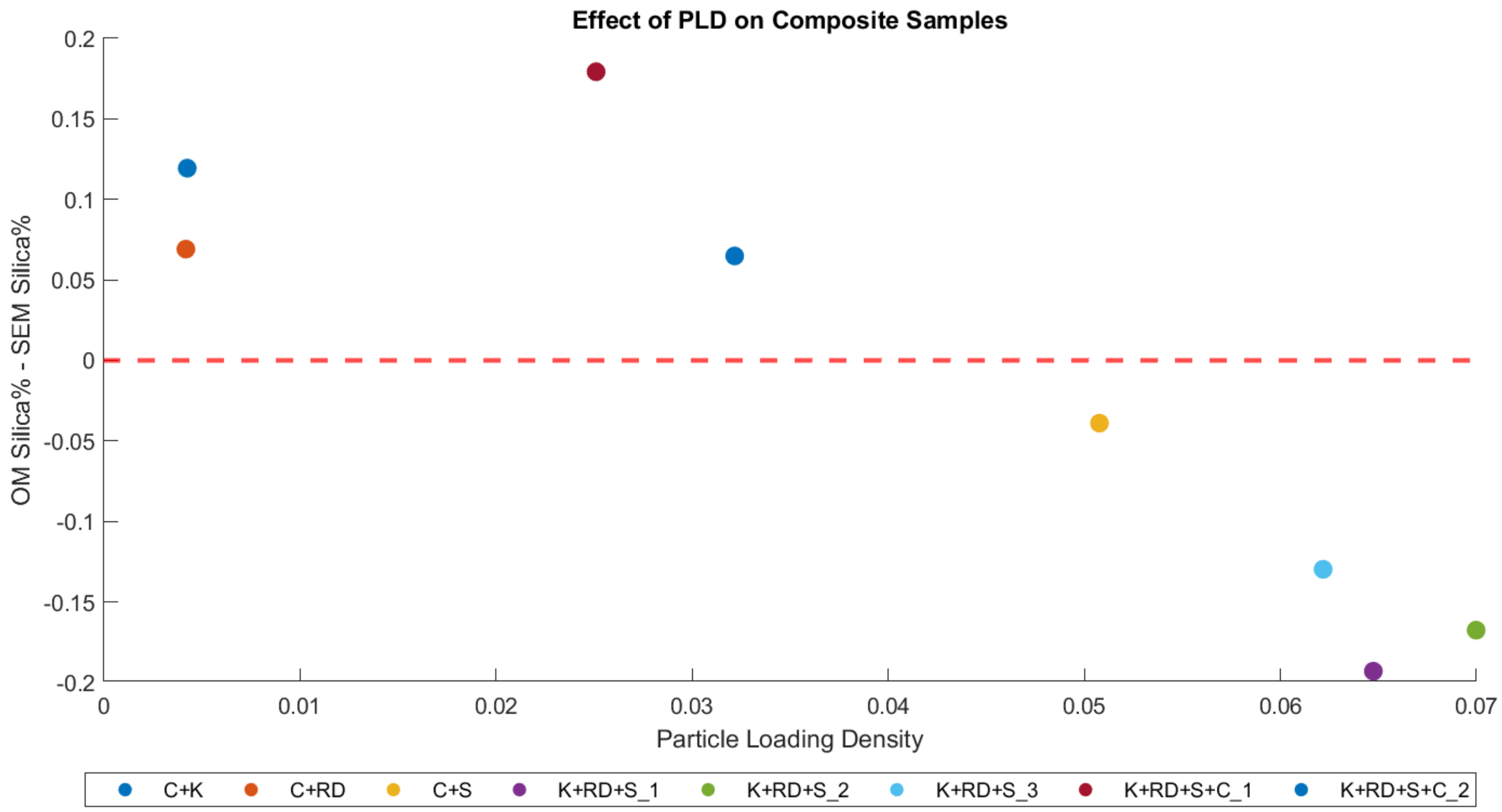


Effects of particle loading density in classification accuracy





Mineral Subclassification



Positive values

- OM is overestimatig silica relative to SEM

Values near 0

- OM and SEM results match well

Negative values

- OM is understimating silica relative to SEM

05

Conclusions and Recommendations

Conclusions

- More information about specific dust constituents and enhanced monitoring is critically needed.
- Portable optical microscopy and image processing techniques are potentially good candidates for near real-time monitoring.
- Coal and mineral fractions can be effectively separated using TCP and TPP image pairs with outstanding classification accuracy (>97%) and good agreement with SEM results.
- The model for classifying silica showed relatively good results. However, composite samples revealed that particle loading density was a key factor in terms of model performance.

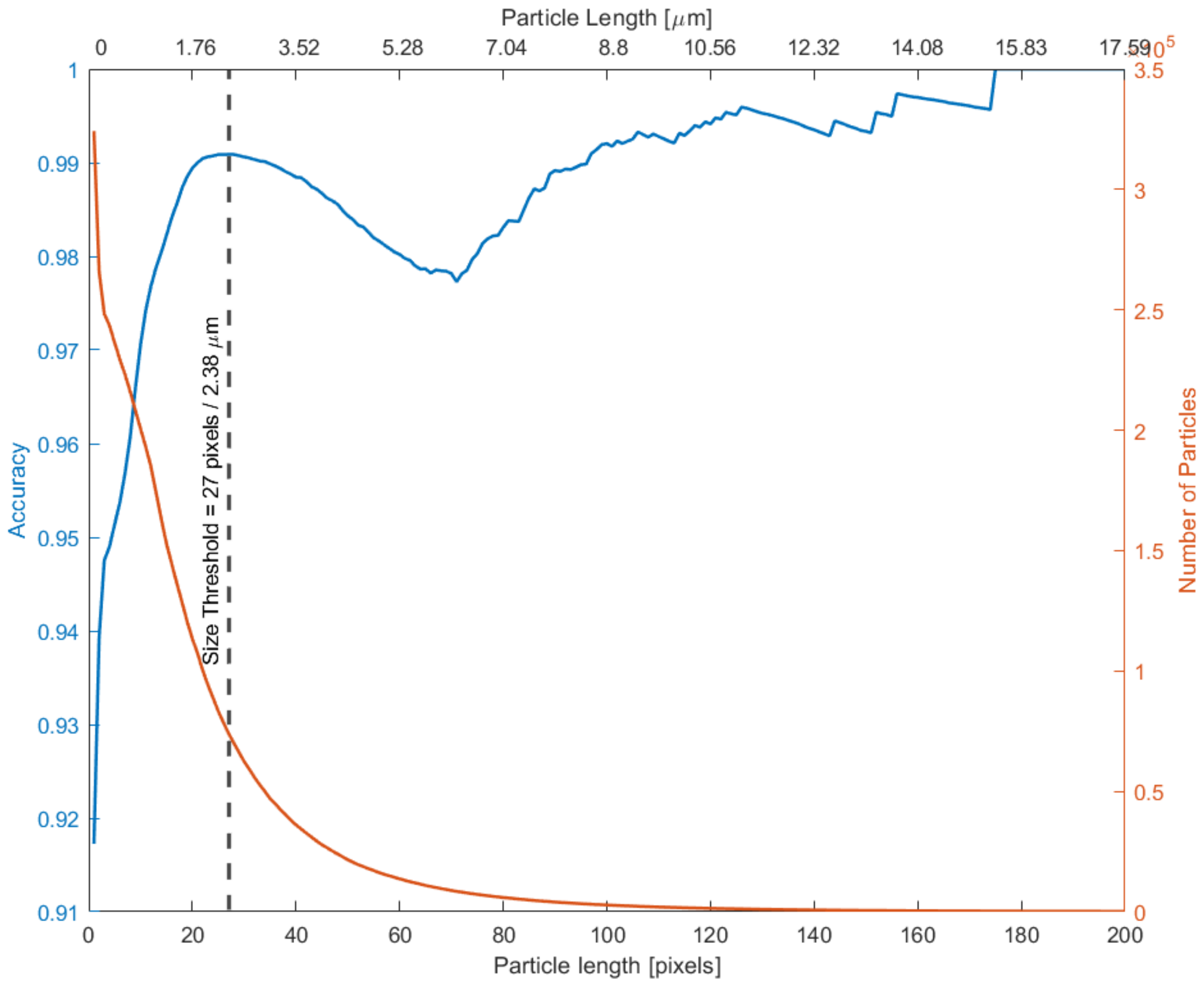
Future Work

- Find optimal particle loading density (PLD)
  1. Determine best method to control particle deposition.
  2. Prepare samples that capture the variability of PLD for each type of material.
  3. Find PLD value that maximizes particle classification accuracy.
- Balance the datasets to have similar number of observations in all particle types.
- Develop a criterion to transform the 2-dimensional particle data into a more practical mass-based fashion

THANK YOU!

APPENDIX

Effect of Particle Size



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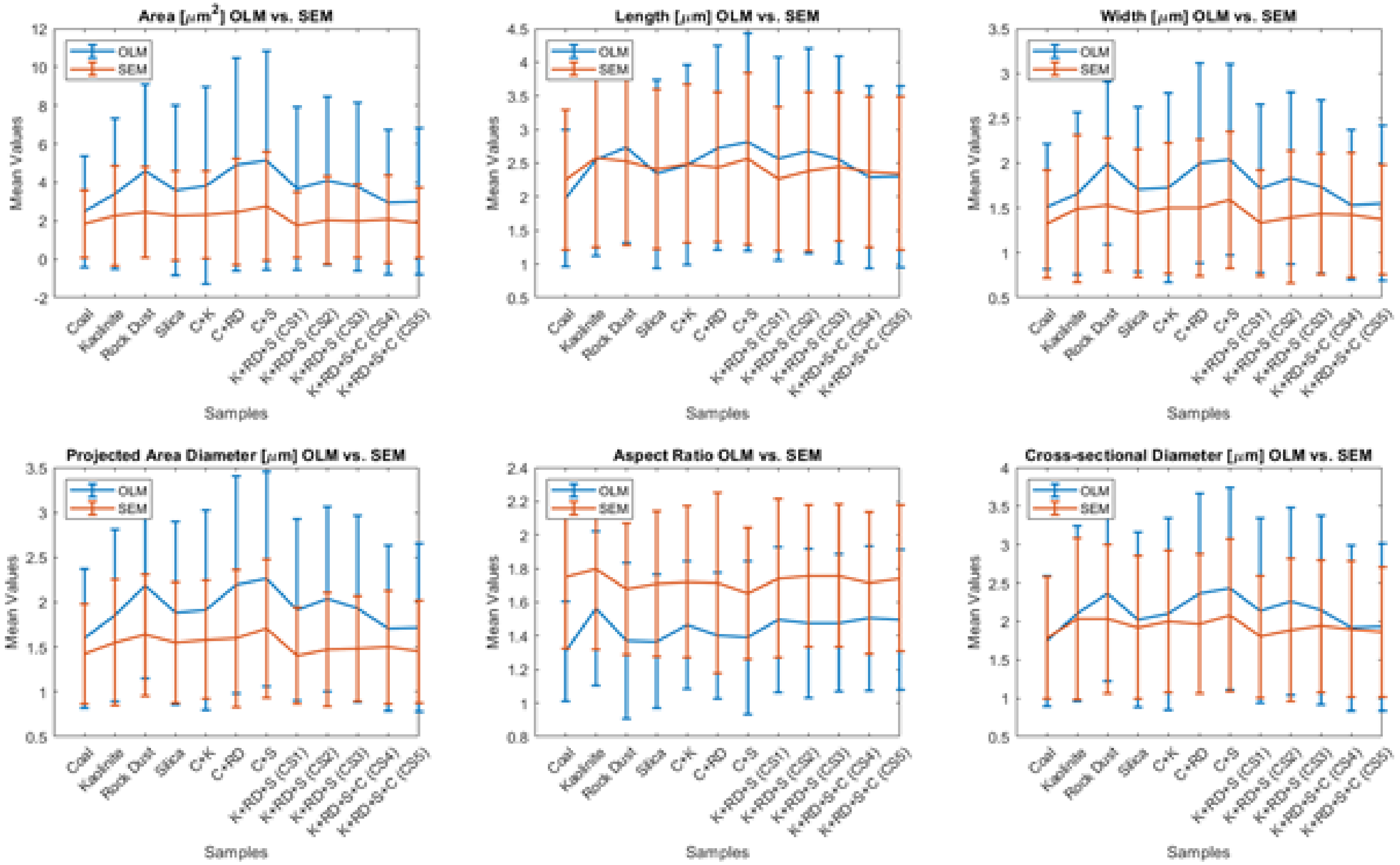
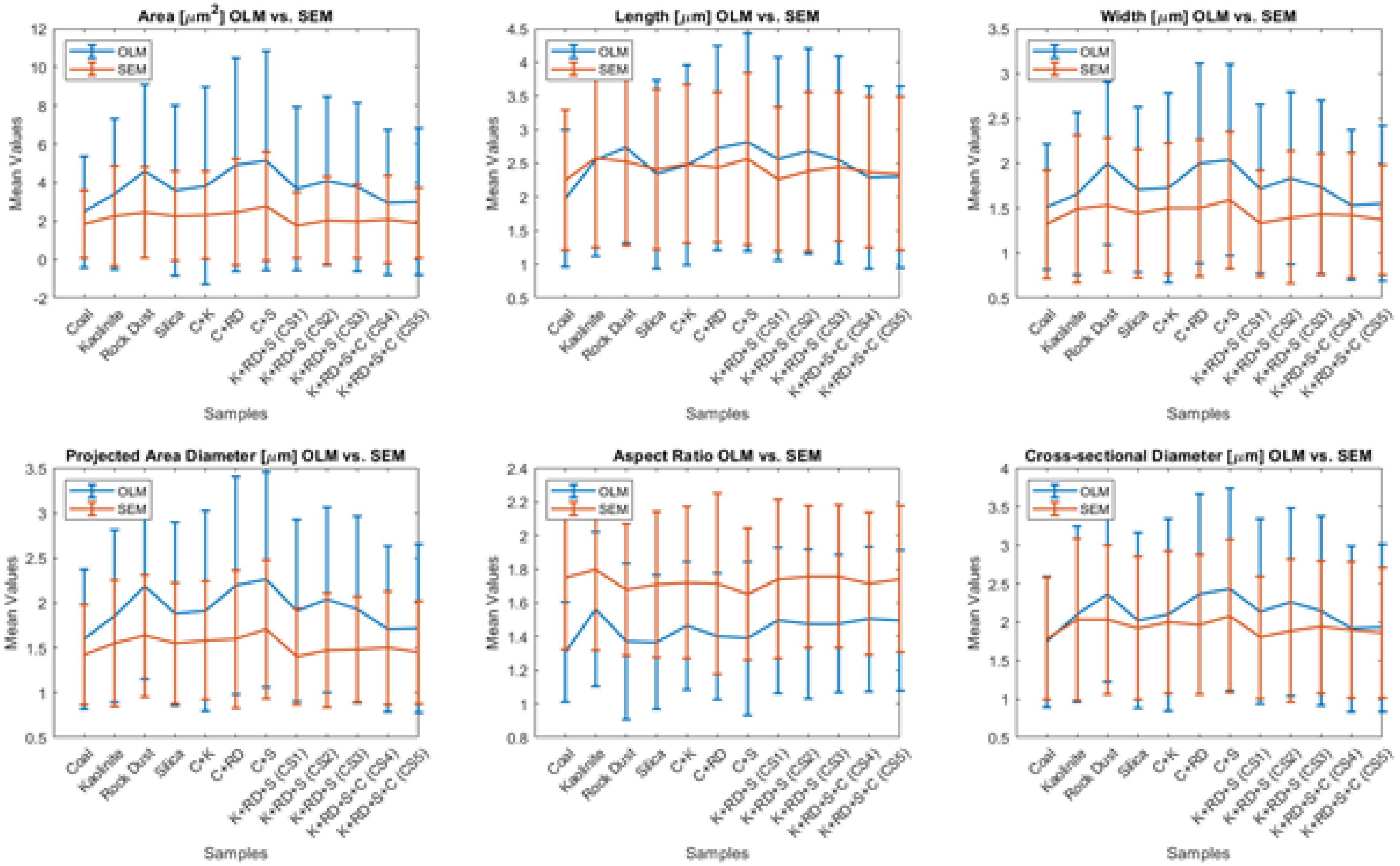
Effect of Particle Size



Effect of Particle Size



Mineral Subclassification

Feature Selection

Feature	Kaolinite vs. Rock dust	Kaolinite vs. Silica	Rock dust vs. Silica	Kaolinite vs. other minerals	Rock dust vs. other minerals	Silica vs. other minerals	Mean f.o.m
Transmitted AMPI	0.382	1.24	0.805	0.538	0.096	0.981	0.67
Transmitted MMPI	0.285	1.22	0.946	0.453	0.015	1.056	0.66
TPP GSD	0.012	0.828	0.969	0.186	0.174	0.888	0.51
Homogeneity	0.583	0.537	0.065	0.568	0.437	0.273	0.41
Reflected DMPI	0.384	0.209	0.594	0.211	0.442	0.397	0.37