EXIMIOUS
Mapping Exposure-Induced Immune Effects
MEMBER OF THE
European Human Exposome NETWORK

Hyperspectral Imaging as an exposure assessment tool

Carolina Blanch-Perez-del-Notario [1], **P. Bertier** [2] , **M. Jayapala** [1] & **A. Lambrechts** [1]

1 Imec, Kapeldreef 75, 3001 Leuven, Belgium

2 Belgian Center for Occupational Hygiene, BeCOH, Brusselsesteenweg 46, 3000 Leuven, Belgium

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SPIE. PHOTONICS WEST

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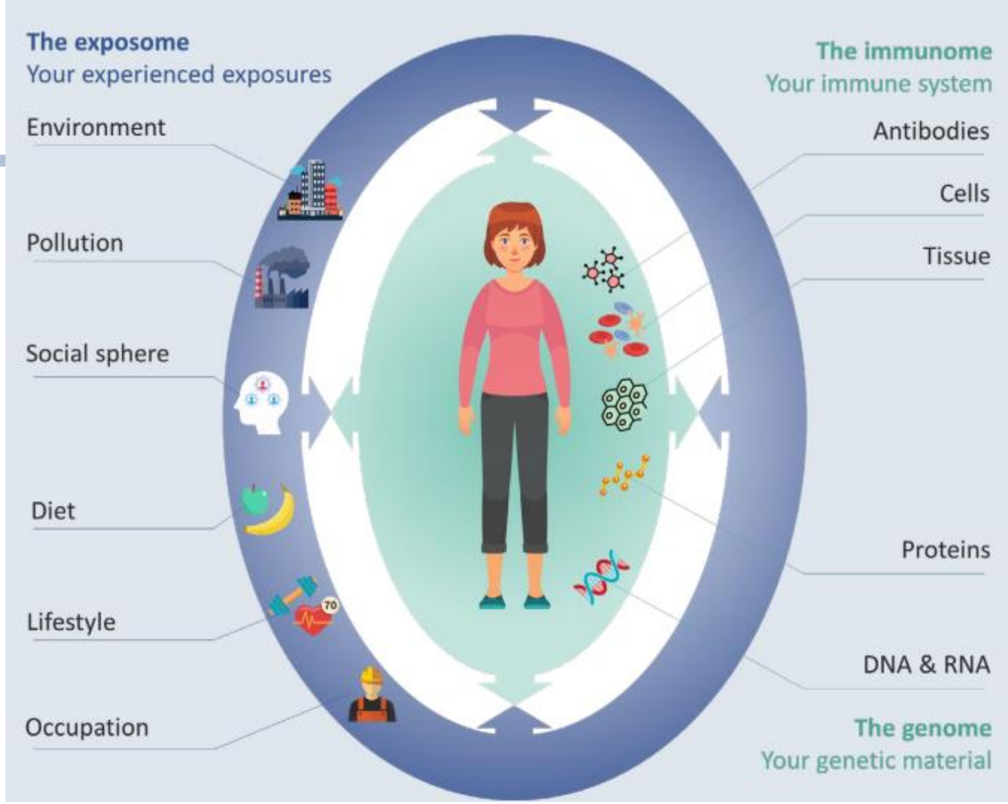
Context of EXIMIOUS

Mapping exposure-induced immune diseases

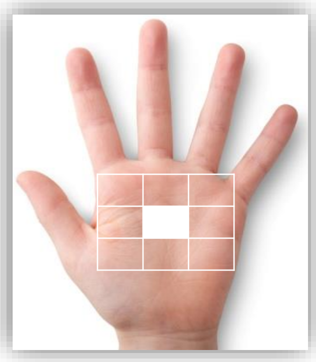


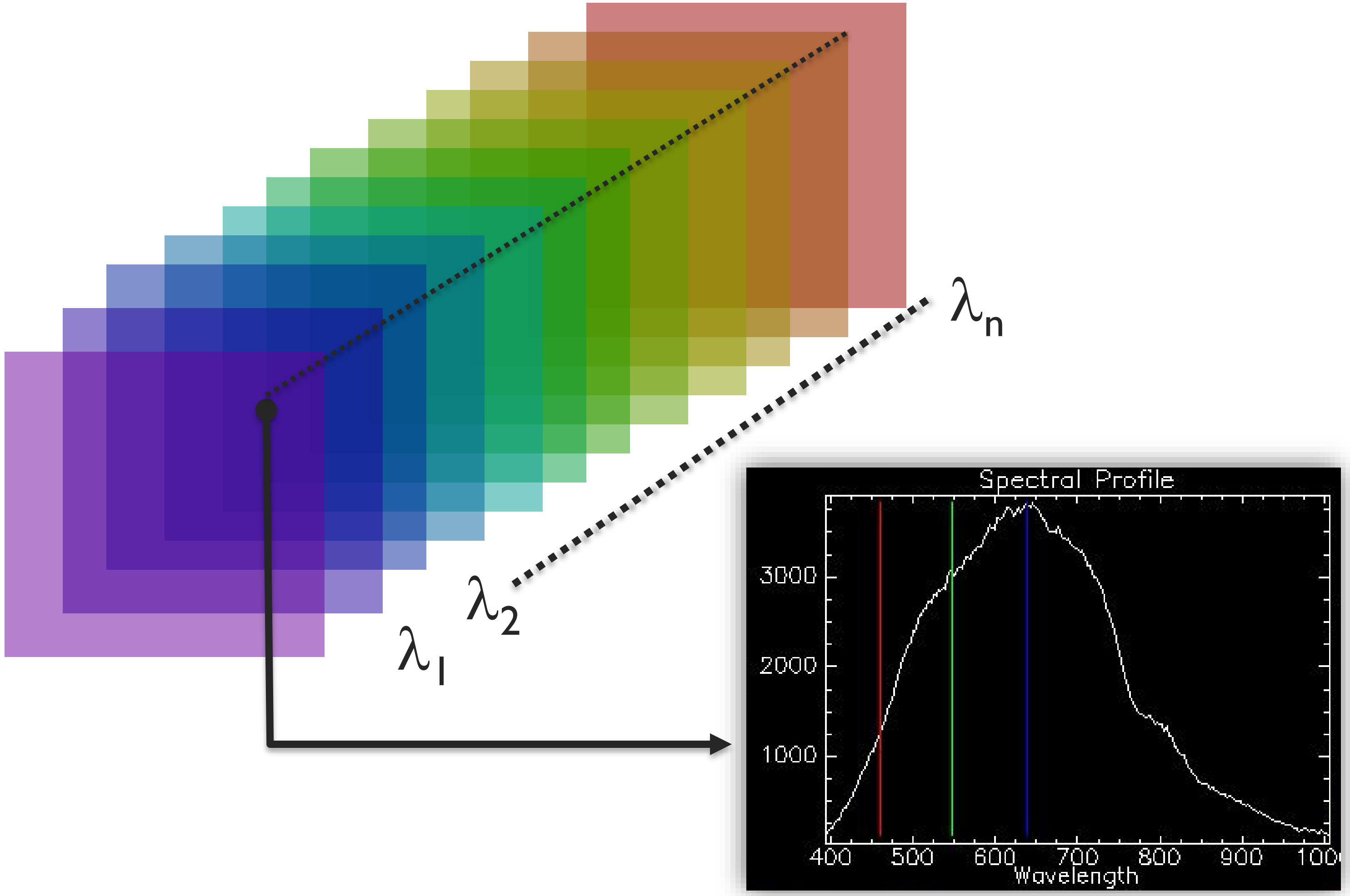
- Exposure samples
  - **Silica** (skin & inhalation) + toxicity of silica
  - Volatile organic substances (skin & inhalation)
  - General particulate matter (skin & inhalation)
  - **Metals and metalloids** (skin & inhalation)
  - Organic compounds
  - Organic dusts - microplastics and natural polymers
- Current techniques for exposure assessment:
  - Sampling: active sampling (e.g. filters), diffusive sampling ...
  - Analysis: Scanning Electron Microscopy (SEM), X-Ray Diffraction Analysis (XRD), Fourier Transform Infrared (FTIR)....

  Lab methods → both time and cost demanding

Hyper Spectral Imaging: a combination of spectroscopy and imaging

Improves machine vision by using spectral information of surface material being imaged

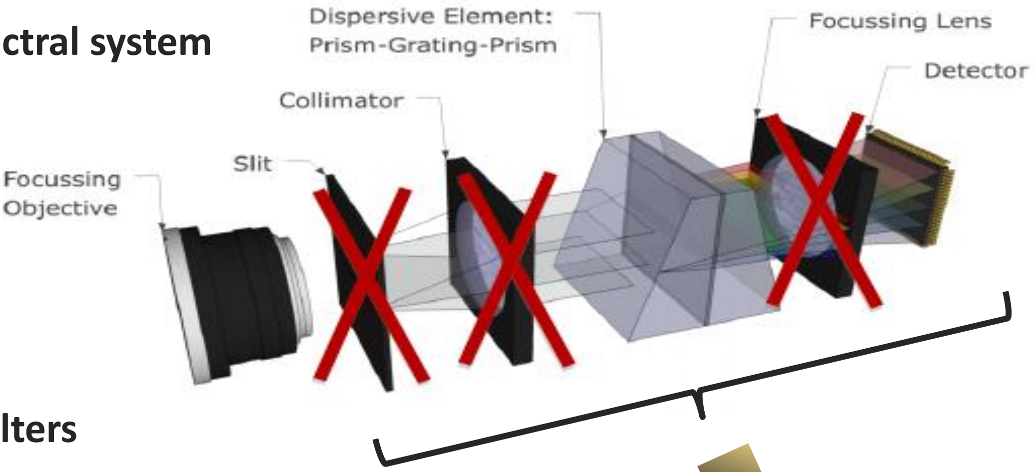




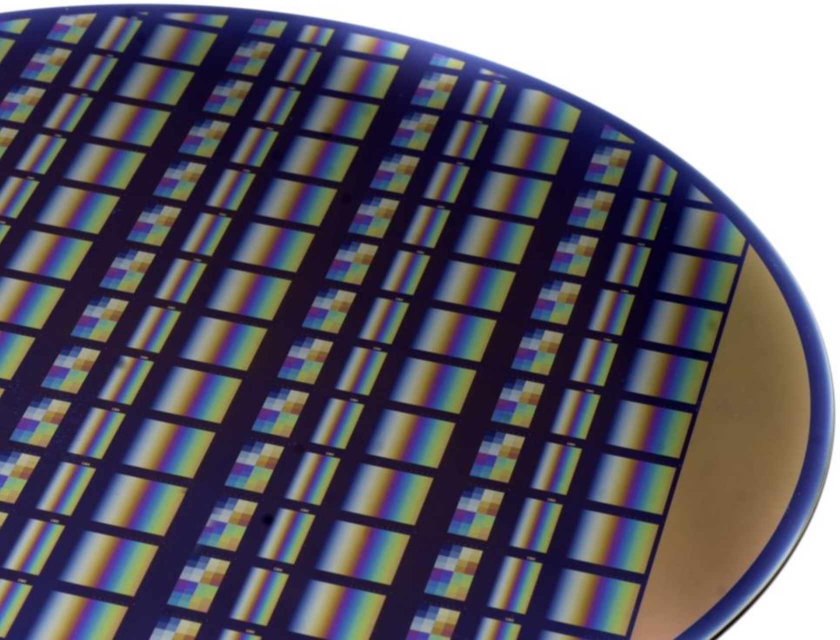
Imec integrated approach

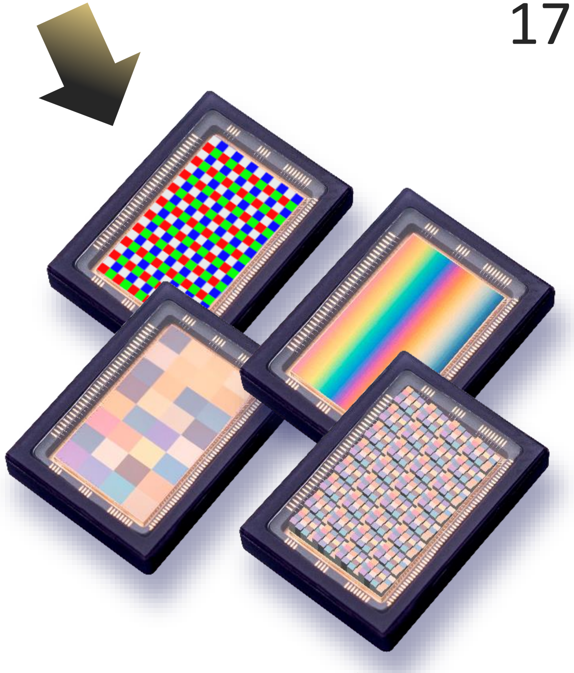
ON-CHIP SPECTRAL IMAGING

Traditional spectral system



imec on-chip filters





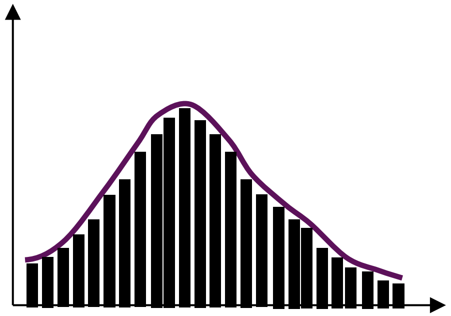
On-chip spectral filters

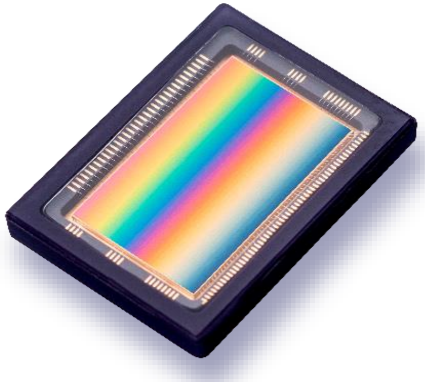
- Scalable CMOS process → lower cost
- Miniaturized and robust
- Scanning at higher resolution
- Snapshot/video at lower resolution
- VNIR (400-1000nm) and SWIR (1100-1700 nm)

Snapscan versus Snapshot Imaging systems

Snapscan systems

Hyperspectral



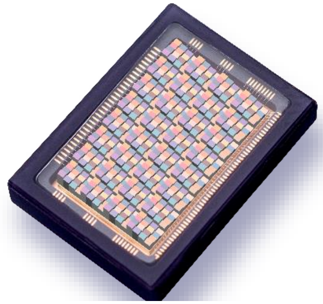


Snapscan High Resolution

100 / 150+ bands

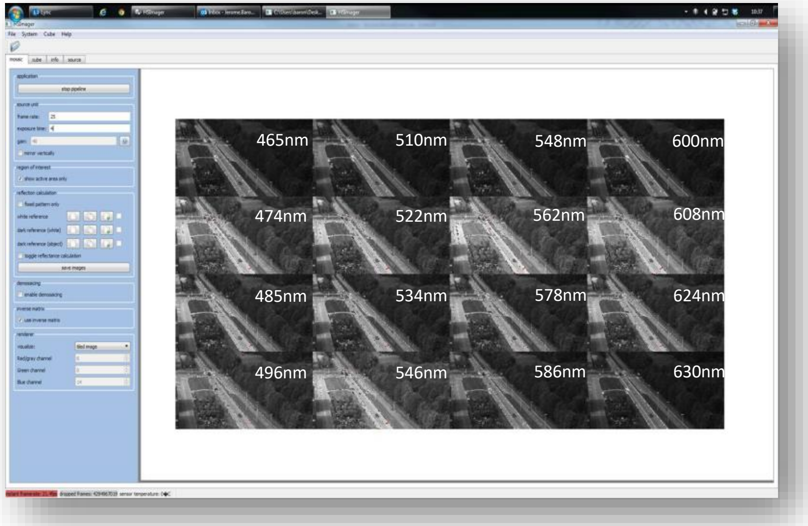
VNIR (7Mpx) or SWIR (0.8Mpx)

Snapshot systems



Lower resolution Snapshot

9/16/25 bands	~180 fps
VIS/NIR/SWIR	512*256px



Unique spectral signatures of materials.

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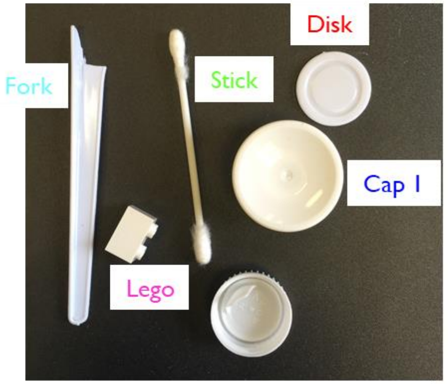
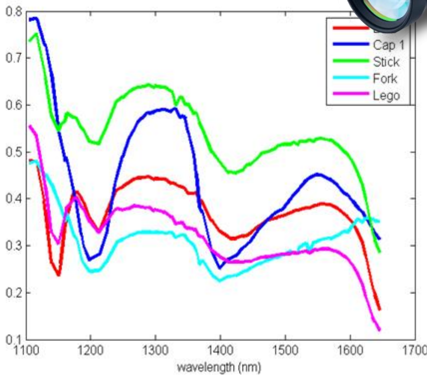
Mapping Exposure-Induced Immune Effects

...ENABLES POTENTIAL USE OF HYPERSPECTRAL IMAGING

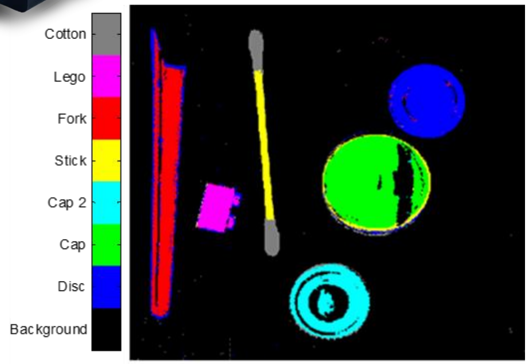
Material sorting/recycling

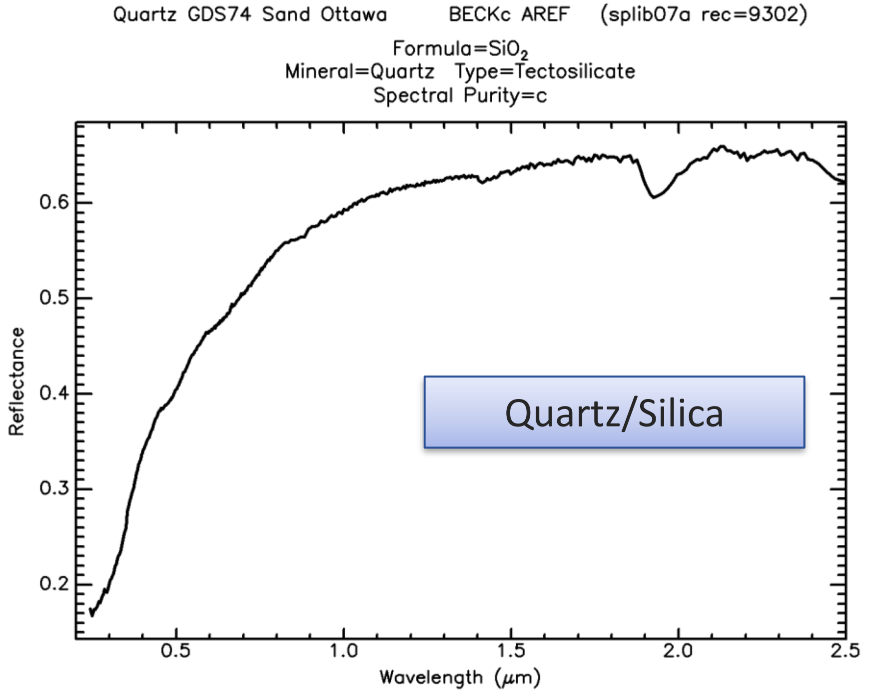


Mean reflectance spectra



Classified (QDC classifier)



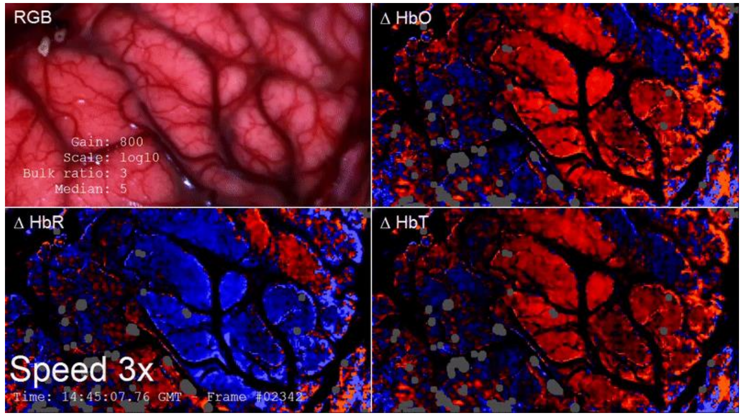


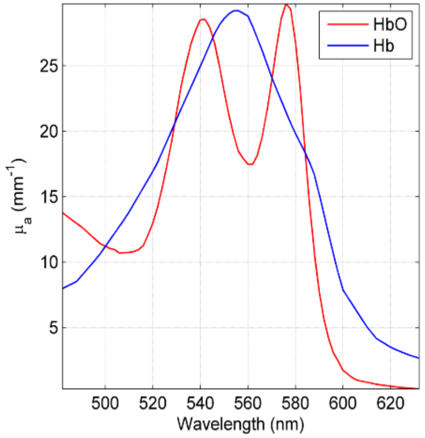
Citation: Kokaly, R.F., Clark, R.N., Swayze, G.A., Livo, K.E., Hoefen, T.M., Pearson, N.C., Wise, R.A., Benzel, W.M., Lowers, H.A., Driscoll, R.L., and Klein, A.J., 2017, USGS Spectral Library Version 7: U.S. Geological Survey Data Series 1035, 61 p., https://doi.org/10.3133/ds1035

ASCII data=splib07a_Quartz_GDS74_Sand_Ottawa_BECKc_AREF.txt HTML metadata=Quartz_GDS74_Sand_Ottawa_BECKc_AREF.html

[ref]splib07a_Quartz_GDS74_Sand_Ottawa_BECKc_AREF_range2_vis_to_swir.gif (1610×1260) (usgs.gov)

Medical (oxygenation measurement)





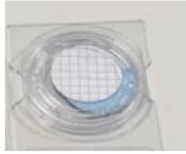
POLYTECHNIQUE MONTRÉAL
LE GÉNIE EN PREMIÈRE CLASSE

Note, properties can be different depending on their states:
Bulk → Particles → Aerosols

Potential for on-site particle inspection

Potential for quick on-site assessment of contaminant exposure

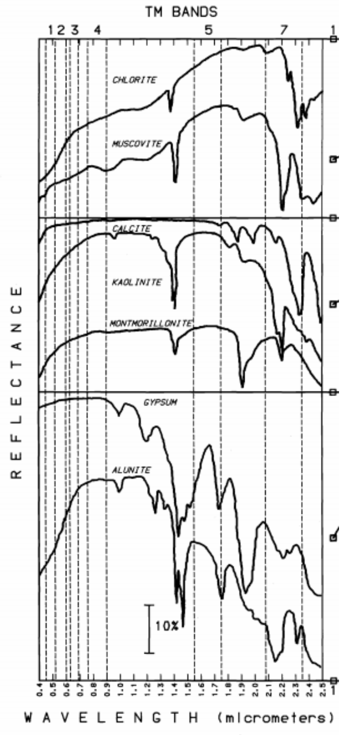
Evaluation of optimal substrate/sampling for dust deposits



Traditional sampling methods versus practical approach

Potential spectral discrimination

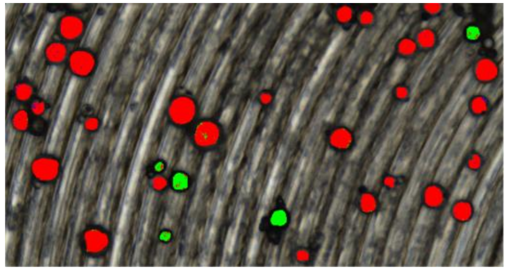
Spectral library of materials



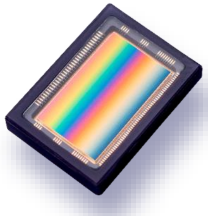
Classification Method

(Machine learning)

Classified image of particles



Potential for miniaturization/ integration of HSI sensor with portable microscope for on-site use



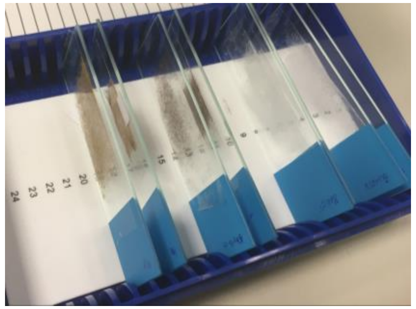
System on chip without bulky optical components

Ocus-40 www.grundium.com

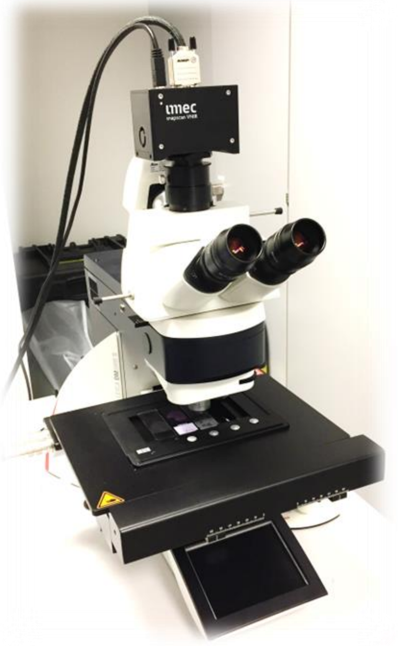
Sampling method for exposure assessment

Practical sampling approach to sample particles at worksite

Glass slide + tape pressed onto surface (e.g shelf)

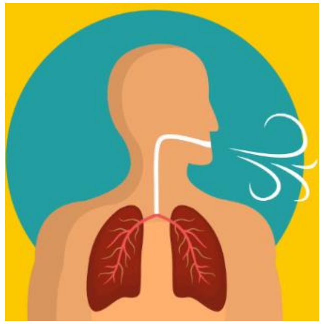


Snapscan VNIR on Transmission microscope



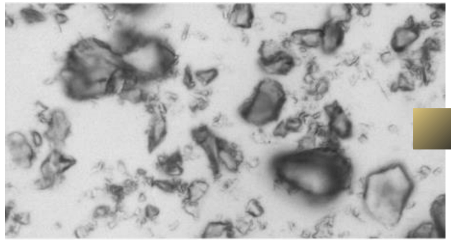
Mimic 15 sample materials (type and size distribution) from worksite

Parameter	Calcite	Carbon	Dolomite	Gibbsite	Gypsum	Hematite	Kaolinite	Barite
Mean (μm)	4.80	6.36	3.44	6.72	3.80	3.99	4.82	6.49
StandardDev	4.34	5.18	2.66	4.83	2.25	2.93	3.34	5.99
Parameter	Feldspar	Muscovite	Phlogopite	Quartz	Rutile	Smectite	K-spar	
Mean (μm)	5.03	0.42	3.39	3.78	0.31	1.59	5.01	
StandardDev	3.53	0.30	2.32	2.12	0.54	1.06	3.19	

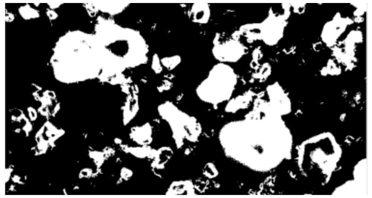


Respirable particles (< 15μm)

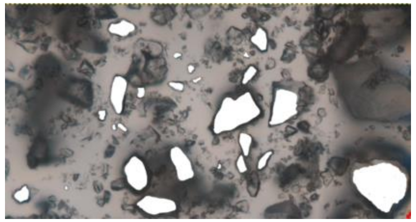
Processing pipeline



High contrast image (band 67)



Background-foreground segmentation by thresholding



Manual particle segmentation

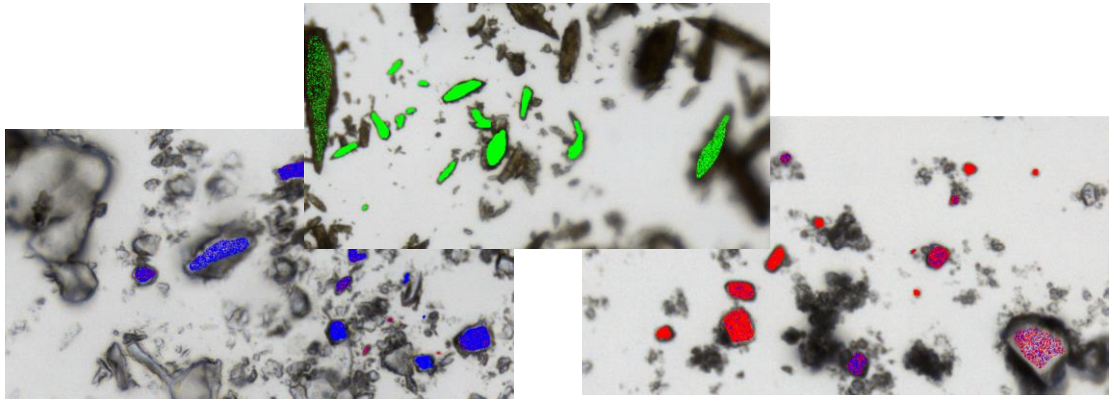
Automatic particle segmentation/clustering

Means of 100 pixels within each particle

Classifier based on spectral data means

Barite (76%)
Goethite (100%)
Quartz (88%)

Classified images



🟥 Barite

🟩 Goethite

🟦 Quartz

Accurate discrimination of all 15 materials

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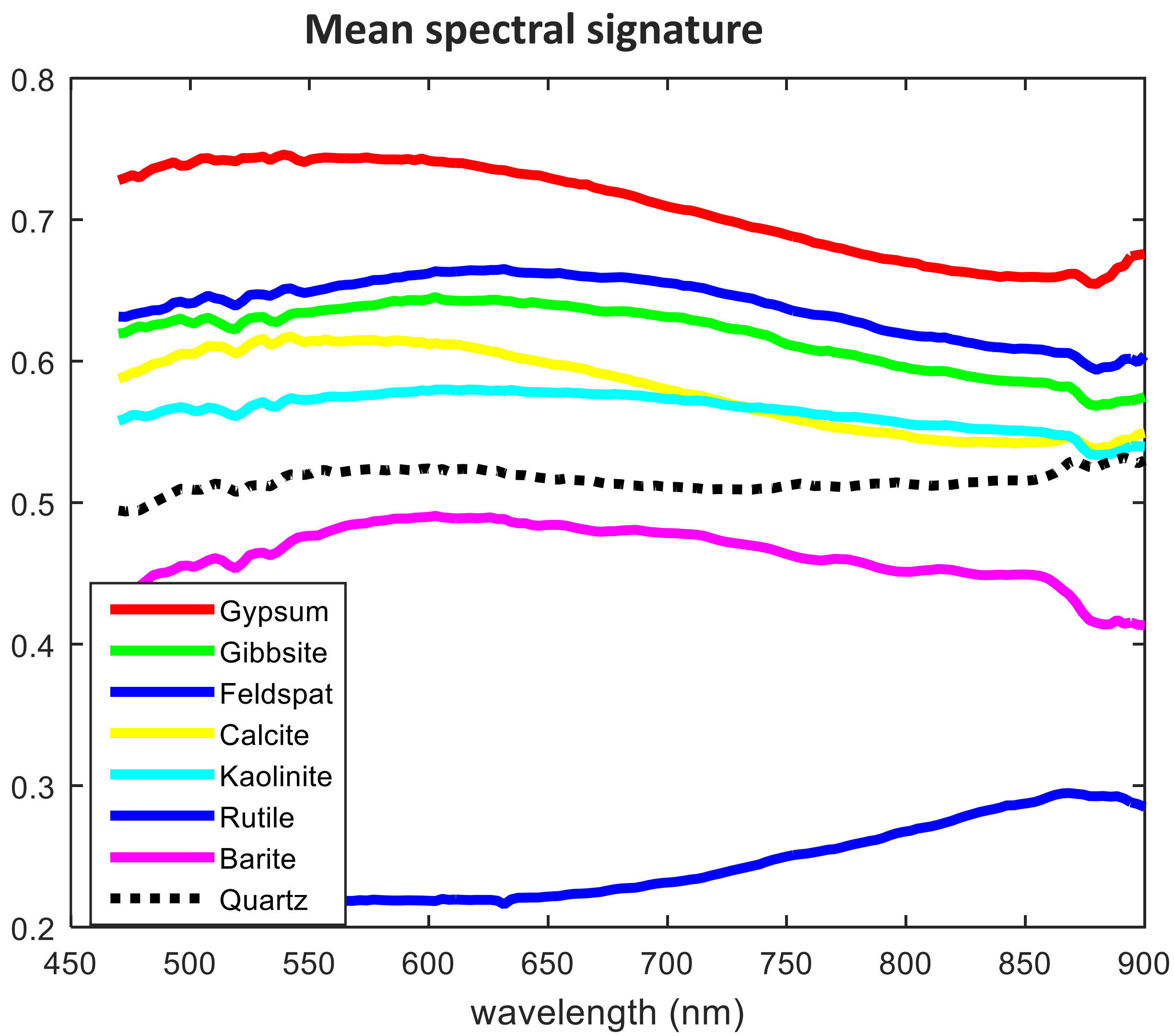
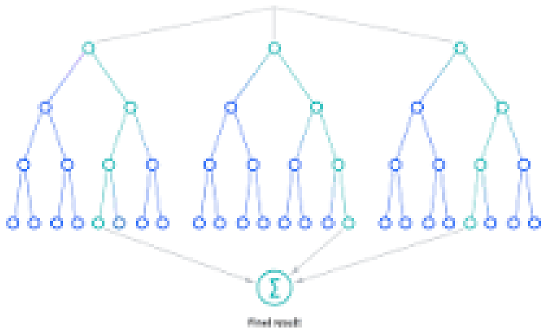
Confusion Matrix for Random Forest classifier model

	True labels	Decisions															
		1:1	2:2	3:3	4:4	5:5	6:6	7:7	8:8	9:9	10:10	11:11	12:12	13:13	14:14	15:15	16:16	sum
Background	1:1	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00
Hematite	2:2	0	0.97	0	0	0	0	0	0.02	0	0	0	0	0	0.02	0	0	1.00
Muscovite	3:3	0	0	0.94	0.01	0.01	0.00	0.01	0	0.00	0.00	0.01	0.00	0.01	0	0	0.01	1.00
Dolomite	4:4	0	0	0.01	0.83	0.01	0.01	0.03	0	0.01	0.01	0.03	0.02	0.02	0	0	0.02	1.00
Phlogopite	5:5	0	0	0.03	0.03	0.83	0.00	0.06	0	0.00	0.00	0.01	0.01	0.01	0	0	0.00	1.00
Smectite	6:6	0	0	0.00	0.00	0.00	0.99	0.00	0	0.00	0	0.00	0.00	0.00	0	0	0	1.00
K-spar	7:7	0	0	0.03	0.02	0.03	0.00	0.84	0	0.02	0.01	0.02	0.01	0.01	0	0.00	0.01	1.00
Coal	8:8	0	0.00	0	0	0	0	0	1.00	0	0	0	0	0	0.00	0	0.00	1.00
Gypsum	9:9	0.00	0	0.00	0.01	0.01	0.00	0.02	0	0.94	0.00	0.00	0.00	0.00	0	0	0.00	1.00
Gibbsite	10:10	0.00	0	0.01	0.01	0.00	0	0.01	0	0.01	0.93	0.01	0.01	0.02	0	0.00	0.00	1.00
Feldspar	11:11	0	0	0.01	0.01	0.01	0.00	0.02	0	0.01	0.01	0.93	0.01	0.01	0	0.00	0.00	1.00
Calcite	12:12	0	0	0.01	0.01	0.00	0.00	0.02	0	0.01	0.00	0.02	0.91	0.01	0	0.00	0.01	1.00
Kaolinite	13:13	0	0	0.01	0.02	0.00	0.00	0.01	0	0.01	0.02	0.01	0.01	0.89	0	0.01	0.01	1.00
Rutile	14:14	0	0.00	0	0	0	0.00	0	0.00	0	0	0	0	0	1.00	0.00	0.00	1.00
Barite	15:15	0	0	0.00	0.00	0	0.00	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	1.00
Quartz	16:16	0	0	0.01	0.02	0.00	0.01	0.00	0	0.01	0.01	0.01	0.01	0.03	0	0.01	0.89	1.00

Accurate classification based on particle spectra


Mean spectral signature



Classifier	Mean Acc	Max Acc	Min Acc
LDA + QDC	69.38%	97%	12% (5<50%)
Random Forest (RF)	**93%**	**100%**	**83%**
LDA + RF	90.5%	99%	78%

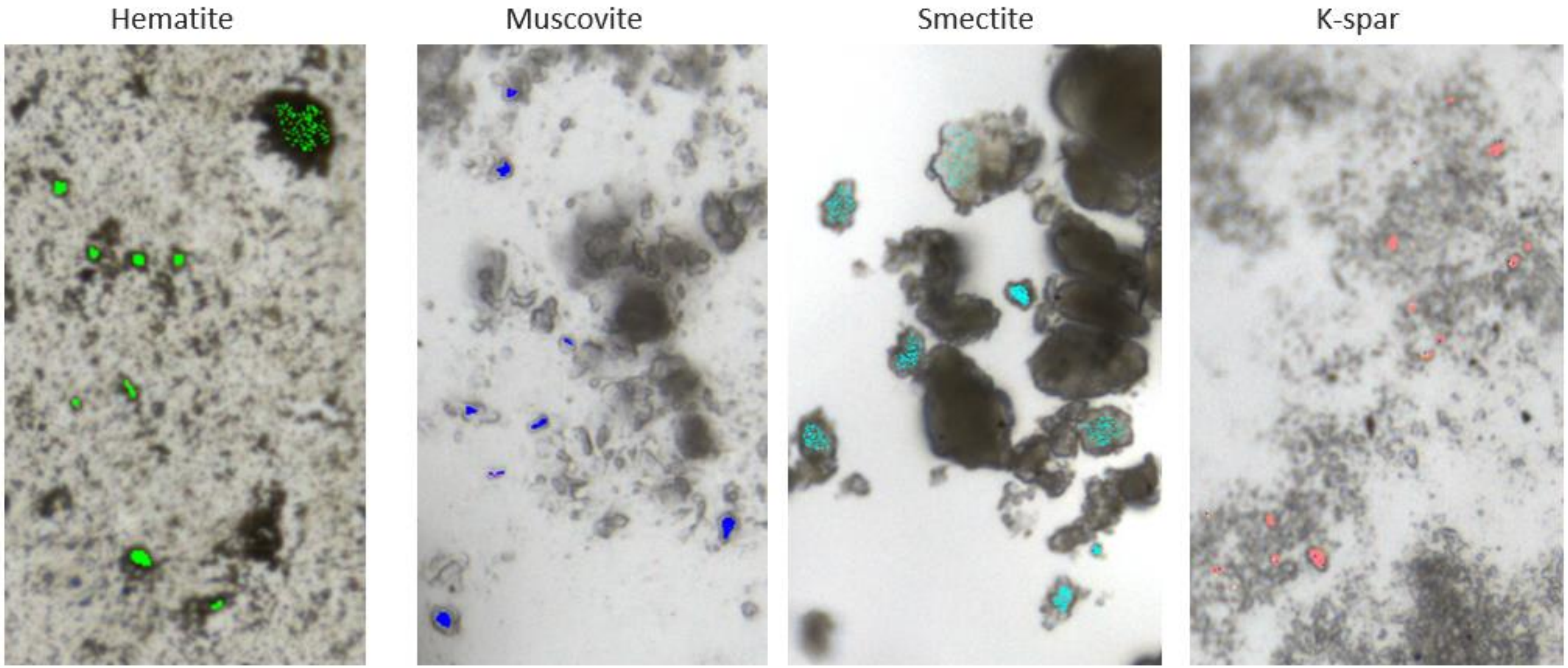
Pixel Accuracy for material set

Higher accuracy at particle level when obtaining ‘majority vote’

Classified Images

- 🟩 Hematite
- 🟦 Muscovite
- 🟪 Dolomite
- 🟨 Phlogopite
- 🟦 Smectite
- 🟧 K-Spar
- ⬜ Coal

- ⬜ Gypsum
- ⬛ Gibbsite
- 🟪 Feldspar
- 🟩 Calcite
- ⬜ Kaolinite
- ⬛ Rutile
- 🟩 Barite
- 🟥 Quartz



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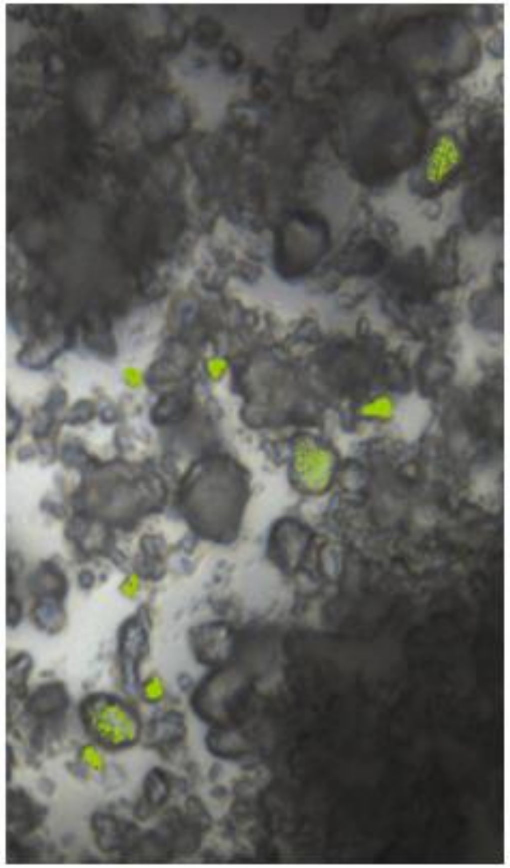
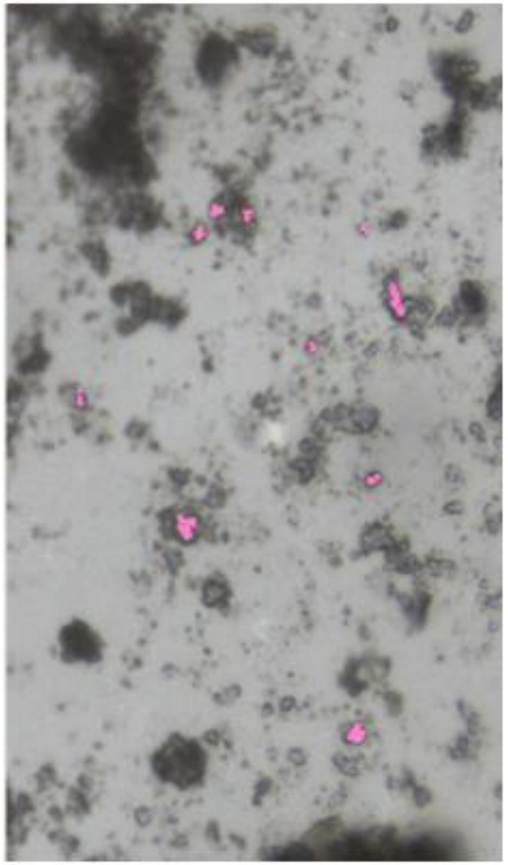
- 🟩 Calcite
- ⬜ Kaolinite
- ⬛ Rutile
- 🟩 Barite
- 🟥 Quartz

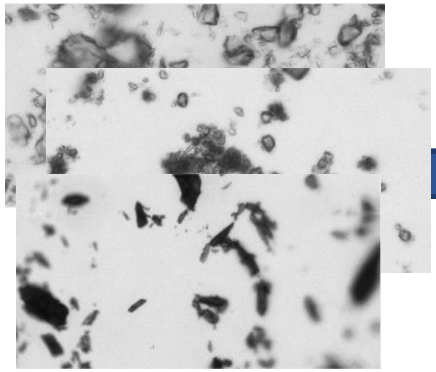
Barite



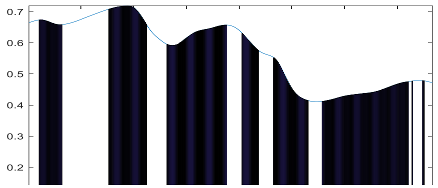
Kaolinite



Analysis of relevant bands



Genetic Algorithm



Band selection

Machine learning classifier

Band selection reduces processing and memory requirements. In addition, we may use a low resolution/high speed camera

Snapscan
(High resolution)
150 bands

Snapshot
(High-speed, Lower resolution)
16-25 bands

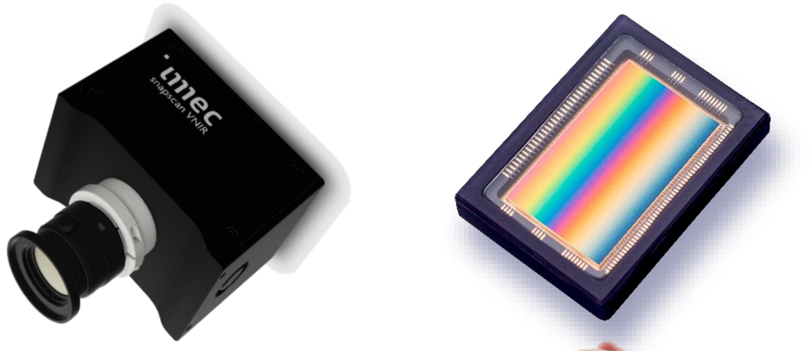
Band relevance analysis

Range	Mean	Max	Min
Snapscan VNIR 150 bands 460-900 nm	92.9%	99%	83%
Best 9 bands (470-472.8-513-726.8 -816.3-850.9-874-879.8)	90.7%	99%	77%
Best 5 bands (484.4-562.2-640.2-850.9-885.5)	90.5%	99%	75%
Best 3 bands (643.1-718.1-871.1)	90.3%	99%	71%
Snapshot NIR 25 bands (675-950 nm)	90.2%	99%	76%
Snapshot NIR 16 bands (600-850 nm)	90.1%	99%	81% (quartz)

Mean Pixel Classification accuracy (%) for different particle materials

Conclusions

- Hyperspectral Imaging enables material discrimination while offering:
    - High resolution imaging
    - Higher acquisition speed
    - Higher portability for on-site measurement
    - Lower cost
- Multiple applications are feasible
- Potential for further miniaturization and real-time discrimination



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Thanks for your attention!

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