computer vision
& data science

Computer Vision

Hyperspectral Imaging

(Cameras and applications)

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Klaas Dijkstra

k.dijkstra@nhl.nl

Hyperspectral Imaging

<this chapter is under construction>

Overview:

- Introduction
- Camera technologies
- Applications

Hyperspectral Imaging

Introduction:

- **Electromagnetic spectrum**
- **Multispectral and hyperspectral**

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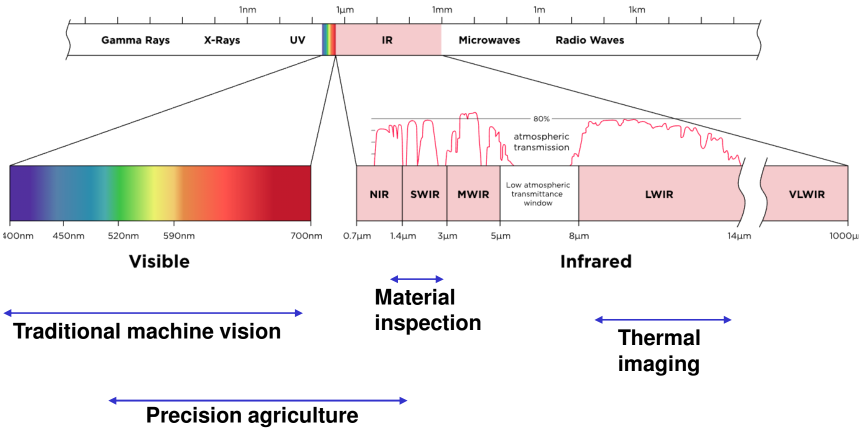
The electromagnetic spectrum



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Multi-spectral and hyper-spectral

Multispectral imaging:

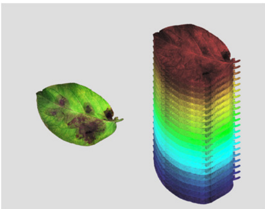
"Operating in or involving several regions of the electromagnetic spectrum."
– Source: Google Dictionary

Hyperspectral imaging:

"Hyperspectral imaging, like other spectral imaging, collects and processes information from across the electromagnetic spectrum."
– Source: Wikipedia

Multispectral and hyperspectral

Multispectral imaging:
- **Less spectral bands (between 2 and 10 bands?)**
- **Broad bands (100nm for VIS)**



Hyperspectral imaging:
- **More spectral bands (more than a 100 bands?)**
- **Narrow bands (10nm for VIS)**

Both techniques aim to record more than the traditional three RGB slices of any spectrum.

Hyperspectral Imaging

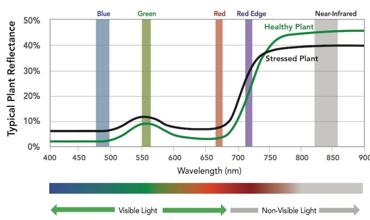
Camera technologies:
- **Multi-camera-one-shot**
- **Single-camera-multi-shot**
- **Single-camera-one-shot**
- **Other**

Multi-camera-one-shot

- **Using optical filters**
- **Satellites**
- **VIS/NIR**

MICASense RedEdge-M

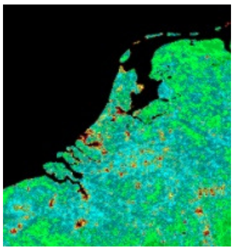
- **Pros**
  - **Excellent spatial resolution**
  - **Narrow bands**
  - **Flexible**
- **Cons**
  - **Parallax error**
  - **Low spectral resolution**



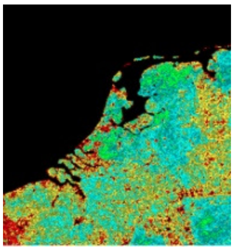
Multi-camera-one-shot application: Vegetation Index

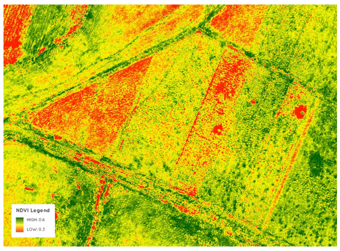
NDVI = (NIR – Red) / (NIR + Red)

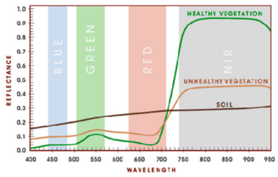
NDVI in June

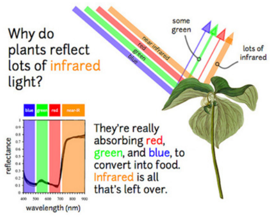


NDVI in October









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Single-camera-multi-shot

- **Filter wheel**
- **Electrically tuneable optical filter**
- **Push-broom scanner**

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Single-camera-multi-shot
Filter wheel

https://www.indiamart.com/comtekscientific-instruments/spectral-cameras.html

https://lot-qd.de/en/products/optics/filter-accessories/product/motorized-filter-wheel/

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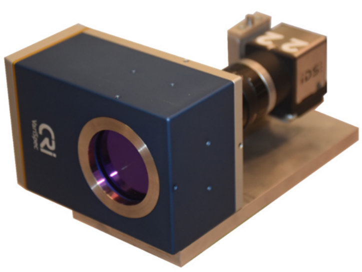
Single-camera-multi-shot
Electrically tuneable optical filter

VariSpec (400 - 720 nm, 32 bands)



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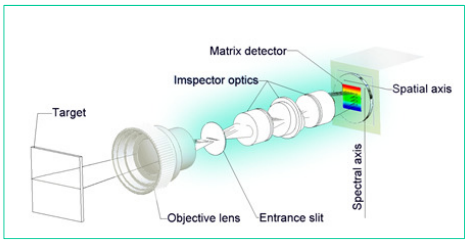
Single-camera-multi-shot Push-broom scanner



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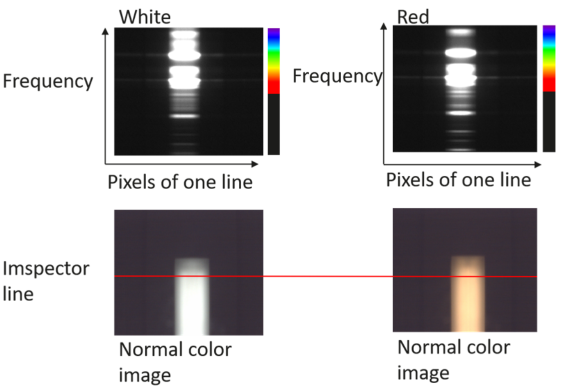
Single-camera-multi-shot Push broom scanner



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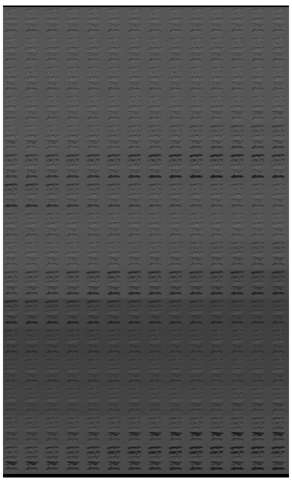
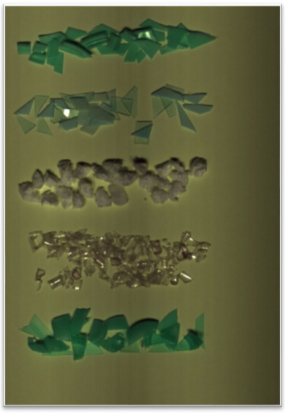
Single-camera-multi-shot
Push-broom scanner

Specim FX10 VIS/NIR, 400 - 1000 nm, 224 bands
Specim FX17 NIR/SWIR, 900 - 1700 nm, 224 bands

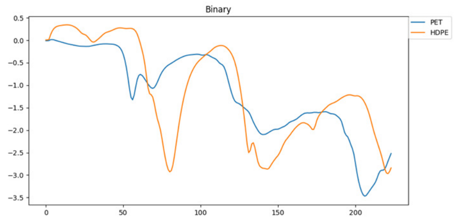
Single-camera-multi-shot
Application plastic sorting (chemical finger printing)

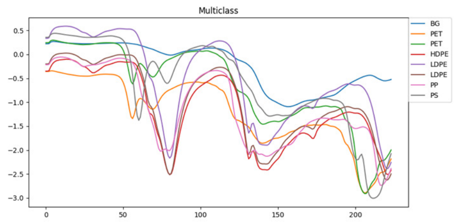




Single-camera-multi-shot
Application plastic sorting

The SWIR absorbance depends on the type of polymer





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Single-camera-multi-shot

- **Pros**
  - **Good spatial resolution**
  - **Excellent spectral resolution**
  - **No parallax error**
  - **Narrow bands**
- **Cons**
  - **High temporal error**
  - **Object movement needed for push-broom scanner**

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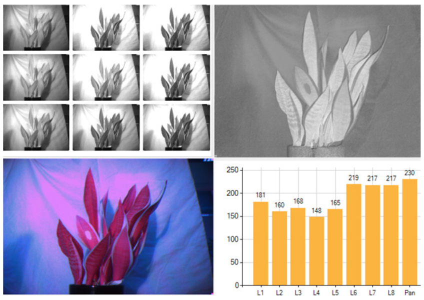
Single-camera-one-shot

- Regular RGB cameras
- MCFA cameras
  - VIS: XIMEA 4x4, 470 - 630 nm, 16 bands
  - NIR: XIMEA 5x5, 600 – 950 nm, 25 bands
  - VIS/NIR: Silios CMS-V, 550 – 850 nm, 9 bands



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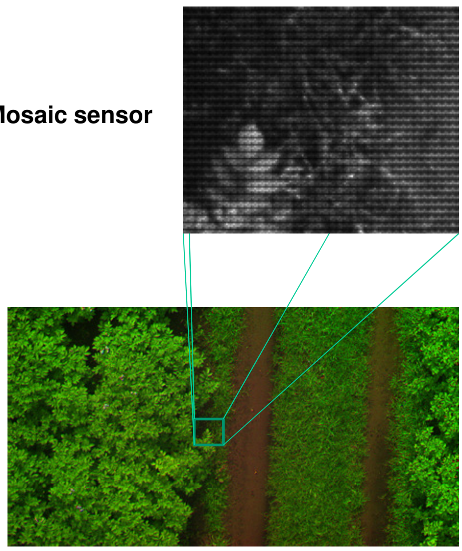
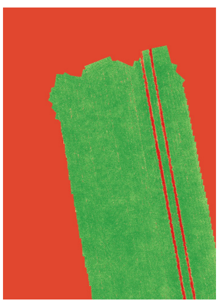
Single-camera-one-shot

Mosaic sensor





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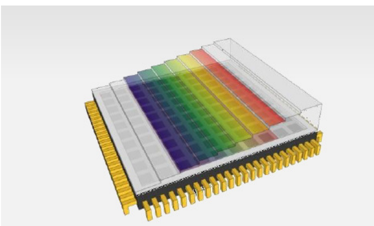
Single-camera-multi-shot

- Pros
  - Reasonable spectral resolution
  - No temporal error
  - No parallax error
- Cons
  - Crosstalk
  - Low spatial resolution
  - Broad band

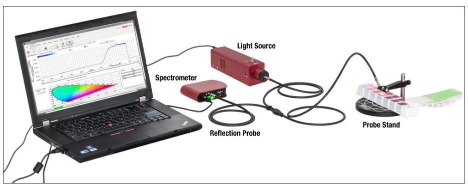
Other approaches

Hybrid one-camera-single-shot and one-camera-multi-shot



Source: Imec

Point spectrometer



Hyperspectral Imaging

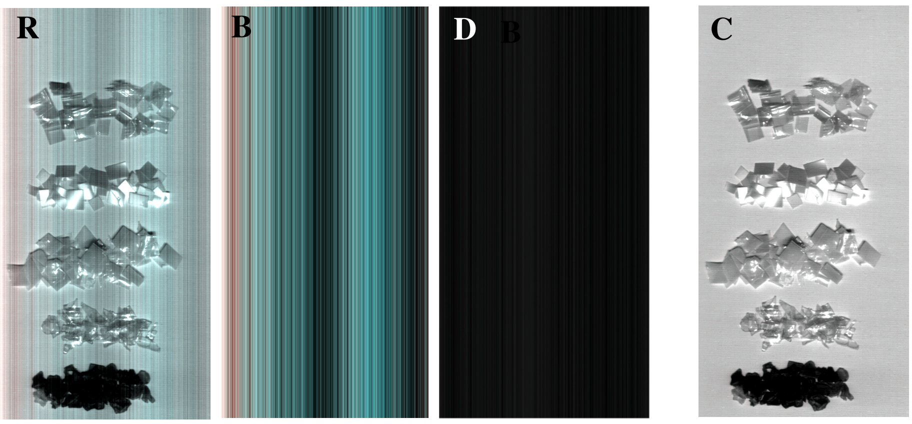
Calibration:

- **Bayer interpolation**
- **Flat field correction**
- **Crosstalk correction**
- **Hyperspectral derivative**

Flat field correction

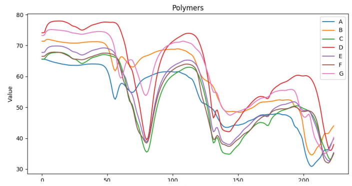
$$C = \frac{R - D}{B - D}$$

R = Raw
C = Corrected
B = Brightfield
D = Darkfield

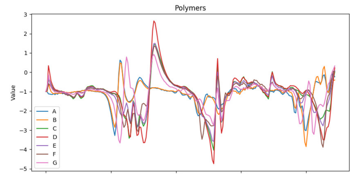


Hyperspectral derivative

Pixel values



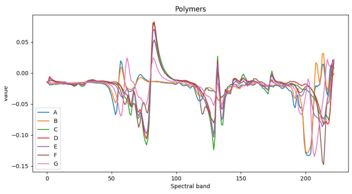
Derivative:
$\mathbf{f' = b[i+1] - b[i]}$



Logarithmic derivative:

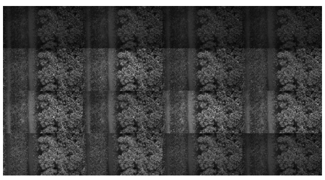
$$\mathbf{lf' = \frac{b[i+1] - b[i]}{b[i]}}$$

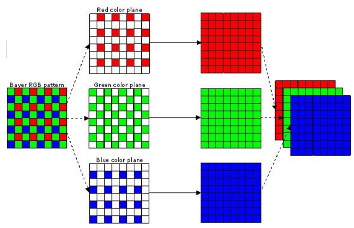
$$\mathbf{= \frac{b[i+1]}{b[i]} - 1}$$

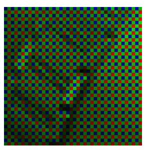


Bayer interpolation

Hyper-spectral "Bayer" interpolation

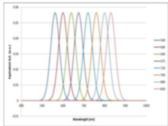






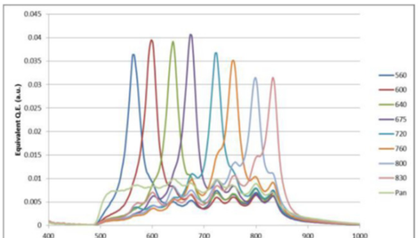
Crosstalk correction

1. Calibrated by illuminating a white reference with 1 nm increments
2. Determine ideal response
3. Calibrate using a linear model

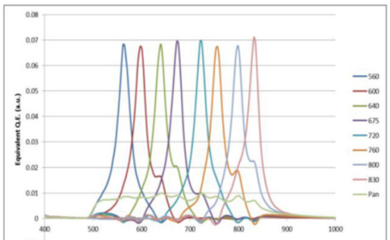


$$f(\mathbf{X}) = \mathbf{X}_{\mathrm{n\times m}} \times \mathbf{C}_{\mathrm{m\times m}} = \mathbf{Y}_{\mathrm{n\times m}}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are the input and output matrices,
$\mathbf{C}$ is the correction matrix,
n and m are the number of pixels and number of bands



X = input



Y = output

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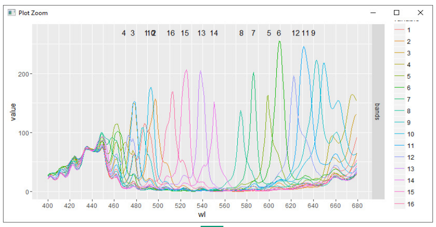
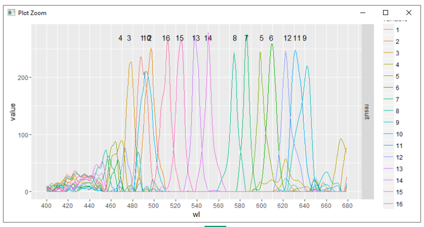
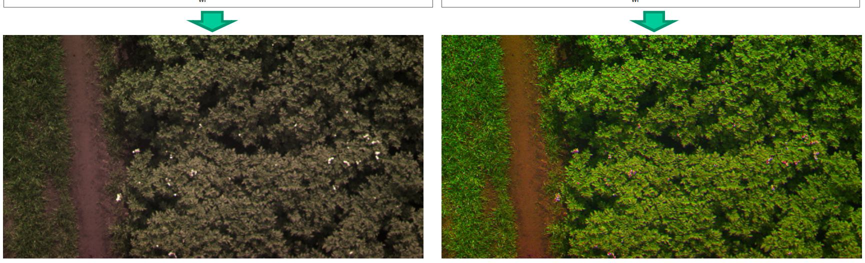
Crosstalk correction







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Hyperspectral Imaging

Applications:
- **Potato disease classification**
- **Polymer classification**

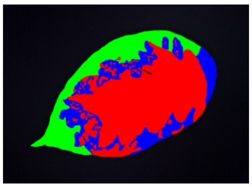
Hyperspectral frequency selection for the classification of vegetation diseases

Objectives
- **Reducing the use of pesticides by visual detection of potato-plant diseases**
- **Narrow-band hyper-spectral imaging is required because of color similarities**
- **Payload constraints on unmanned aerial vehicles require reduction of spectral bands**
- **Hyperspectral frequency selection and per-pixel classification of individual leaves**

Materials

5 Leaves with Alteraria
5 Leaves with Ozon
Reference image (Ground Truth)



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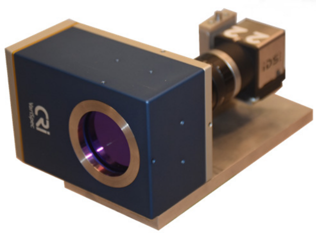
Materials

Perkin Elmer Varispec
- Liquid crystal tunable filter
- 28 spectral bands 400-720 nm

IDS UI-3370 Mono
- CMOSIS 1" sensor
- 80.0 fps, 12 bit, 2048 x 2048



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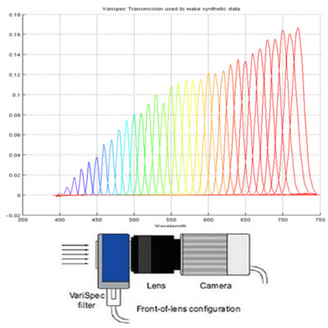
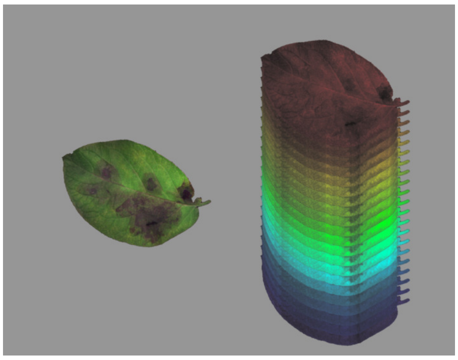
Materials

Hyperspectral image cubes of 2048 x 2048 x 28





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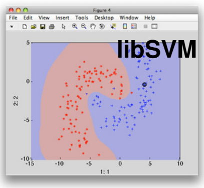
Materials

VisionLab	**(Computer Vision)**
DDSL / C++	**(Gauss/Naïve Bayes)**
Caffé	**(Multilayer Perceptron)**
libSVM	**(Support Vector Machine)**
ArrayFire	**(PCA, LDA)**
R	**(kNN)**

Caffe

ArrayFire



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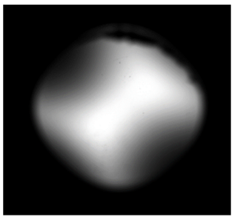
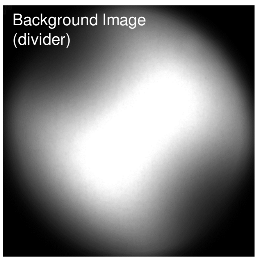
Methods

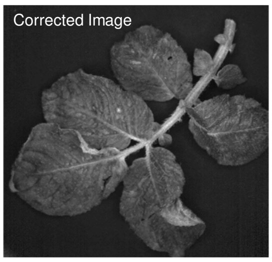
1. **Normalization**
2. **Feature extraction / Feature selection**
3. **Classification**

Normalization

Inhomogeneous transmission of Varispec filter







Feature Extraction / Feature Selection

- Each pixel lives in a 28 dimensional feature space
- In wich dimensionality do potato diseases live?

Feature extraction:

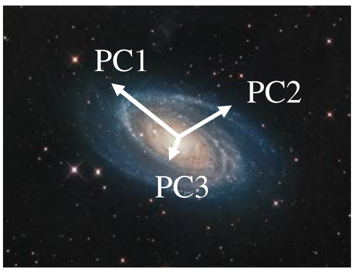
Use a new projection of the existing set of spectral bands

Feature selection:

Use only a subset of spectral bands

Feature Extraction / Feature Selection

Principle Component Analysis

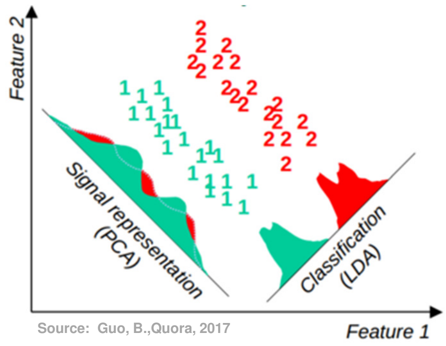


Reproject

Feature Extraction / Feature Selection

Linear Discriminant Analysis

- **"PCA which respects original classes"**
- **Usable when inner class variance is greater than between class variance**



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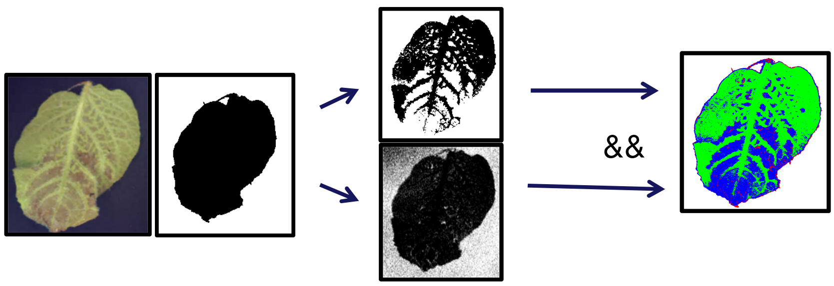
Classification

Cascaded classifier



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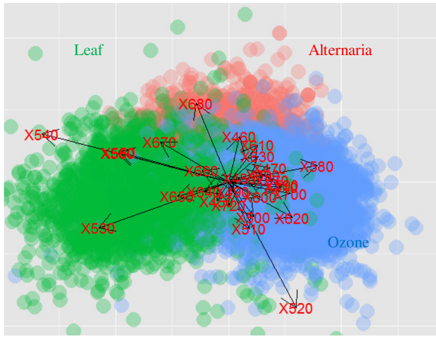
Results

Linear Discriminant Analysis



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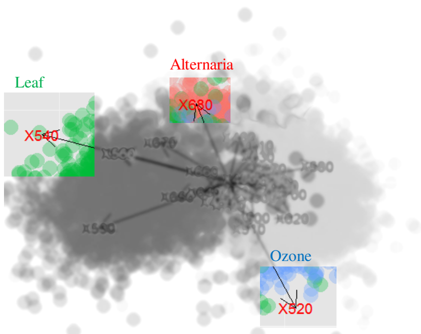
Results

Select only 3 spectral bands



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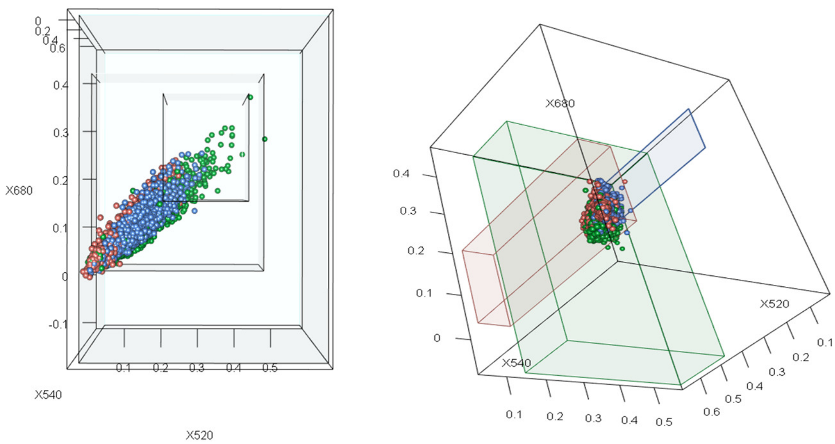
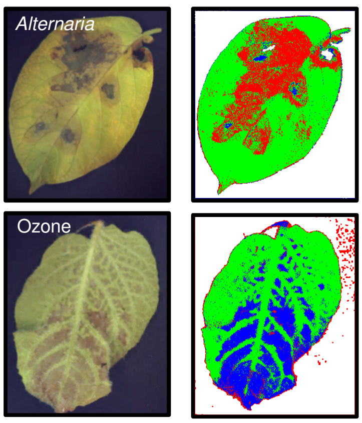
Results



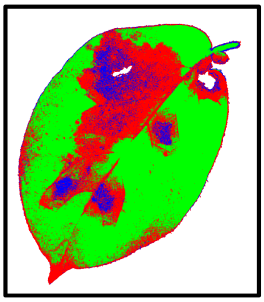
Results

28 spectral bands



Results

28 bands



Results

All 28 wavelengths	Error Damage	Error Disease
MLP ReLU	13.6 %	**1.5 %**
MLP TanH	16.0 %	1.7 %
SVM	**13.4 %**	1.9 %
kNN	18.9 %	8.3 %
Gauss.	49.7 %	27.4 %

Three Wavelengths	Error Damage	Error Disease
MLP ReLU	23.8 %	9.2 %
MLP TanH	24.7 %	16.1 %
SVM	23.0 %	14.0 %
kNN	**22.5 %**	**7.3 %**
Gauss.	29.9 %	29.9 %

LDA projection	Error Damage	Error Disease
MLP ReLU	16.3 %	3.9 %
MLP TanH	16.8 %	4.0 %
SVM	14.5 %	2.9 %
kNN	25.9 %	11.8 %
Gauss.	**14.2 %**	**2.6 %**

PCA projection	Error Damage	Error Disease
MLP ReLU	28.9 %	16.3 %
MLP TanH	28.8 %	19.7 %
SVM	**28.2 %**	42.6 %
kNN	32.6 %	19.3 %
Gauss.	30.6 %	**16.0 %**

Conclusions

- **A Multilayer perceptron with a ReLU activation function obtains the best results (1.5% error)**
- **Detecting damage on leaves is more difficult than distinguishing diseases (13.4% vs. 1.5%)**
- **Reducing dimensionality to 2, using LDA, slightly increases error rates (1.5% to 2.6%)**
- **When selecting the 680nm, 520nm and 540nm wavelengths, error rates increase to 7.3%.**

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- **Paper/poster**

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Polymer classification

- Plastics are used in many applications
- Disposed plastics can negatively impact the environment
- Proper recycling is required

- Plastics can be distinguished using the SWIR spectrum
- A hyperspectral SWIR camera is used to measure that spectrum
- Deep learning is used to segment the plastics

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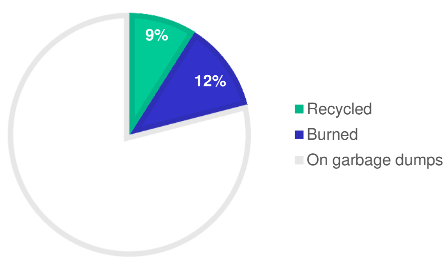
Plastic disposables

- In 2015 the University of California did research on the waste of plastics in the last century
- 75% of plastics made between 2004 and 2017 are already discarded



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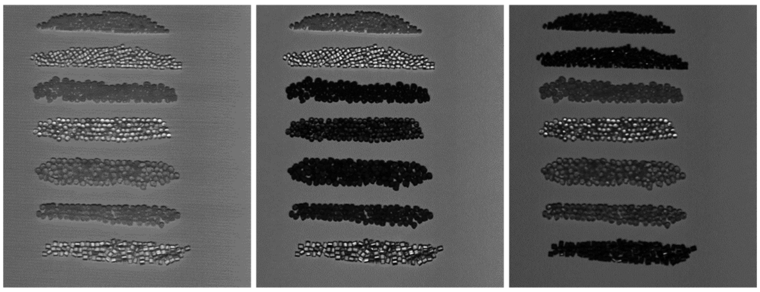
Hyper-spectral imaging

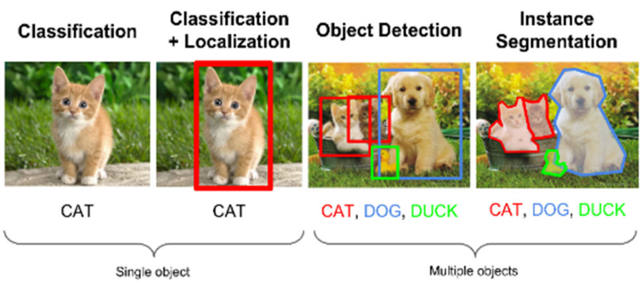
Image taken with the Specim FX17 (900-1700nm, 224 bands)



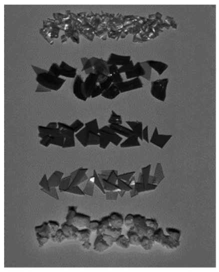
Band 1 Band 80 Band 208

Deep learning

- **Deep learning is part of a broader family of machine learning methods based on learning data representation**
- **Deep learning an alternative to task-specific algorithms**



Dataset



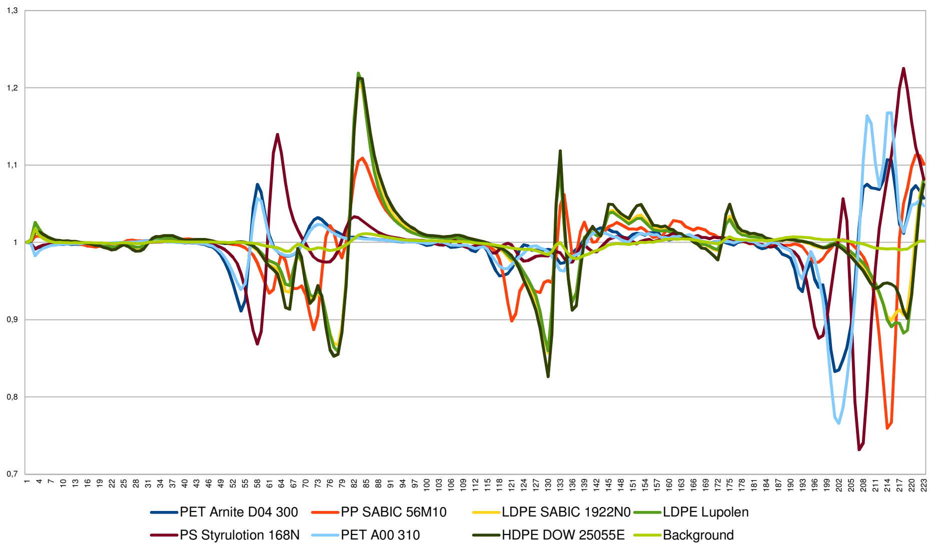
The dataset contains:

- **55 photos for training (pellets)**
- **5 evaluation photos (pellets)**
- **15 testing photos (flakes)**

There are 8 classes

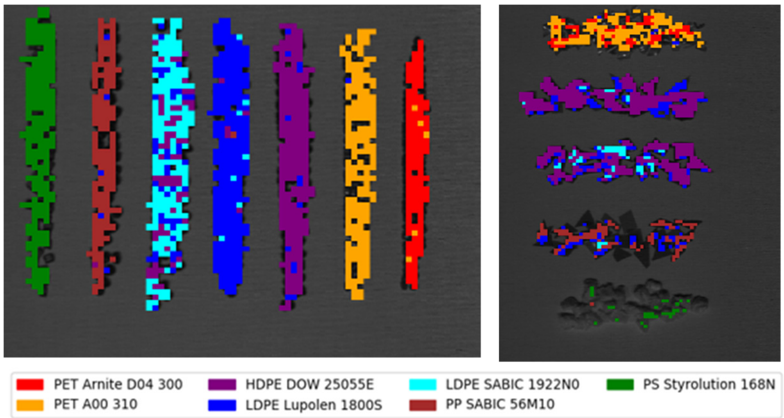
- **Background**
- **PET Arnite, PET A00, HDPE DOW, LDPE Lupolen, LDPE SABIC922N0, PP SABIC, PS Styrulotion**

Spectra



Results of classification network

First result with a classification per patch



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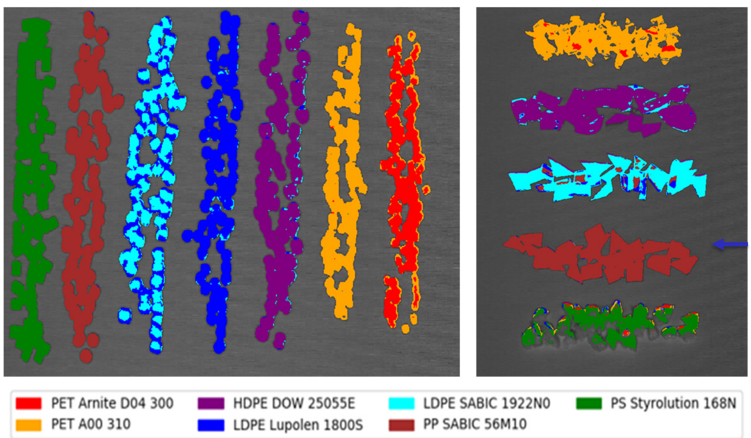
Results of segmentation network

Result with a classification per pixel (segmentation)



Unexpected separation between HDPE and LDPE

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Logarithmic derivative of samples

- The network is be able to distinguish similar polymers (HDPE an LDPE)
- Maybe as a result of batch specific features like brightness?
- Experiment with the logarithmic derivative

Derivative:

$$\mathbf{f'} = \mathbf{b}[i+1] - \mathbf{b}[i]$$

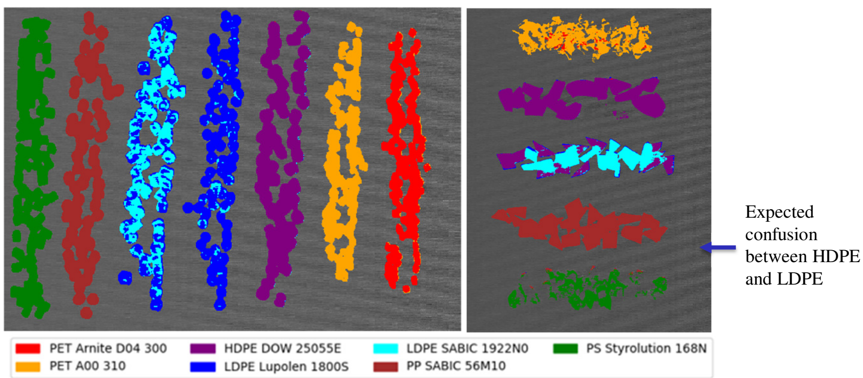
Logarithmic derivative:

$$\mathbf{lf'} = \frac{\mathbf{b}[i+1] - \mathbf{b}[i]}{\mathbf{b}[i]}$$

$$= \frac{\mathbf{b}[i+1]}{\mathbf{b}[i]} - 1$$

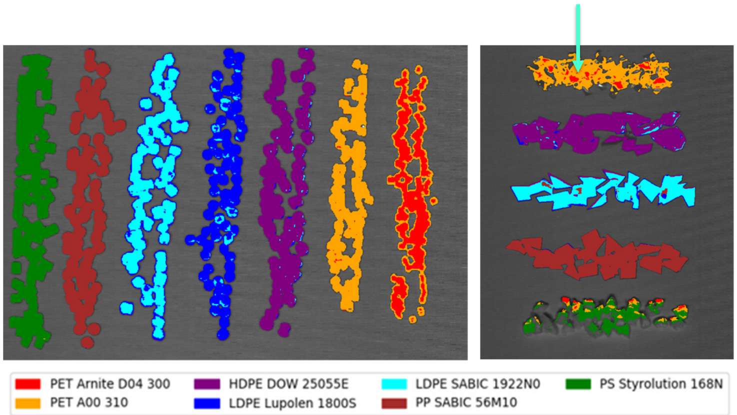
Segmentation with log. derivative

- Less noise
- More confusion between LDPE and HDPE in flakes



Adversarial neural networks

- **Overall accuracy lower**
- **Less small noise (classifier tries to reconstruct pellets)**



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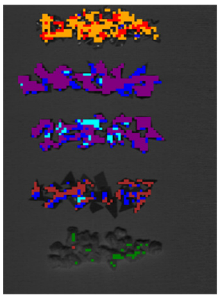
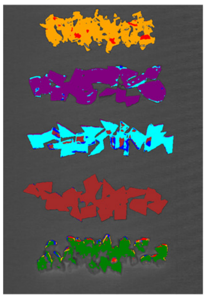
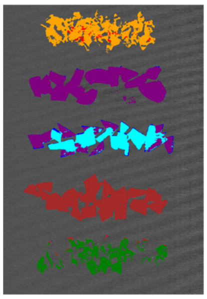
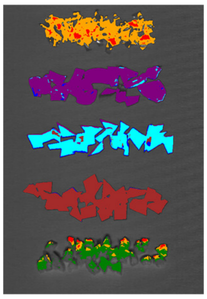
Comparison on testing set


Classification


Segmentation


Log. derivative


Adversarial

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Accuracy of networks

Accuracies are measured on validation and testing sets

Network	Accuracy (validation)	Accuracy (Testing)
Classification network	93%	54%
Segmentation network	97%	87%
Segmentation network (log. derivative samples)	95%	82%
Segmentation with Adversarial	95%	87%