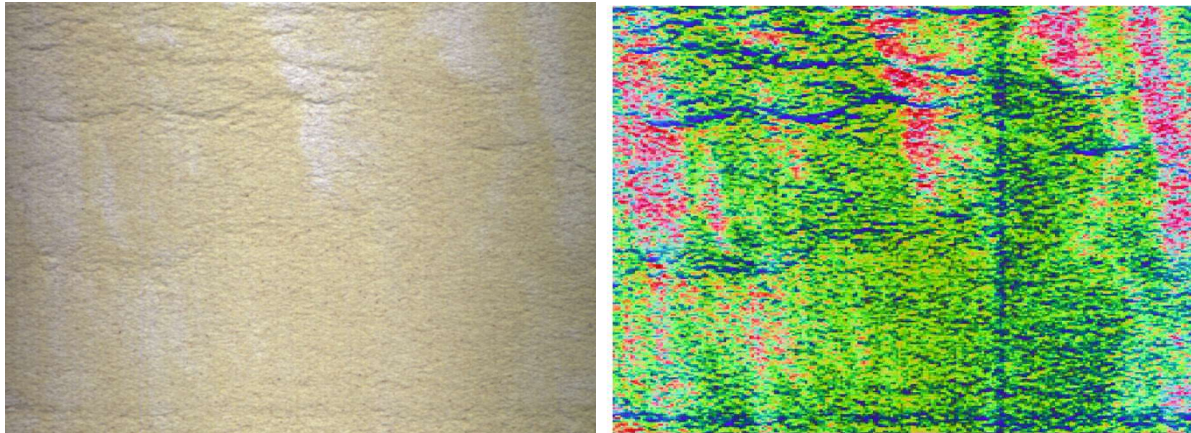


Capturing Spatial Information of Hyperspectral Imaging Using Pretrained Embeddings Models

Antoine Deryck^{1,2}, Juan Antonio Fernández Pierna¹, José Ramón Quevedo Pérez³, Elena Montanés Rocés³, Toon Goedemé²



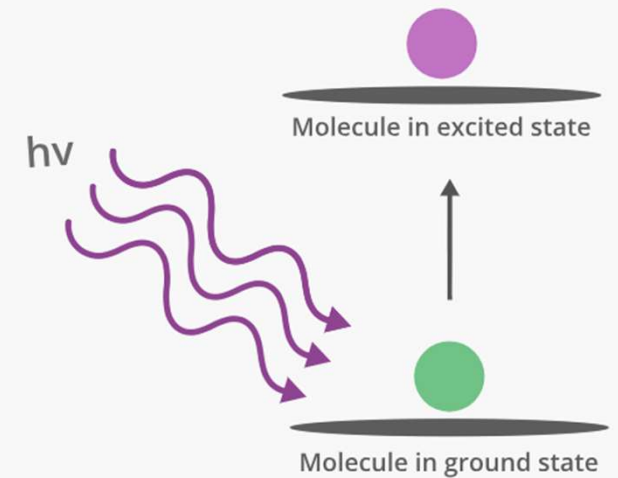
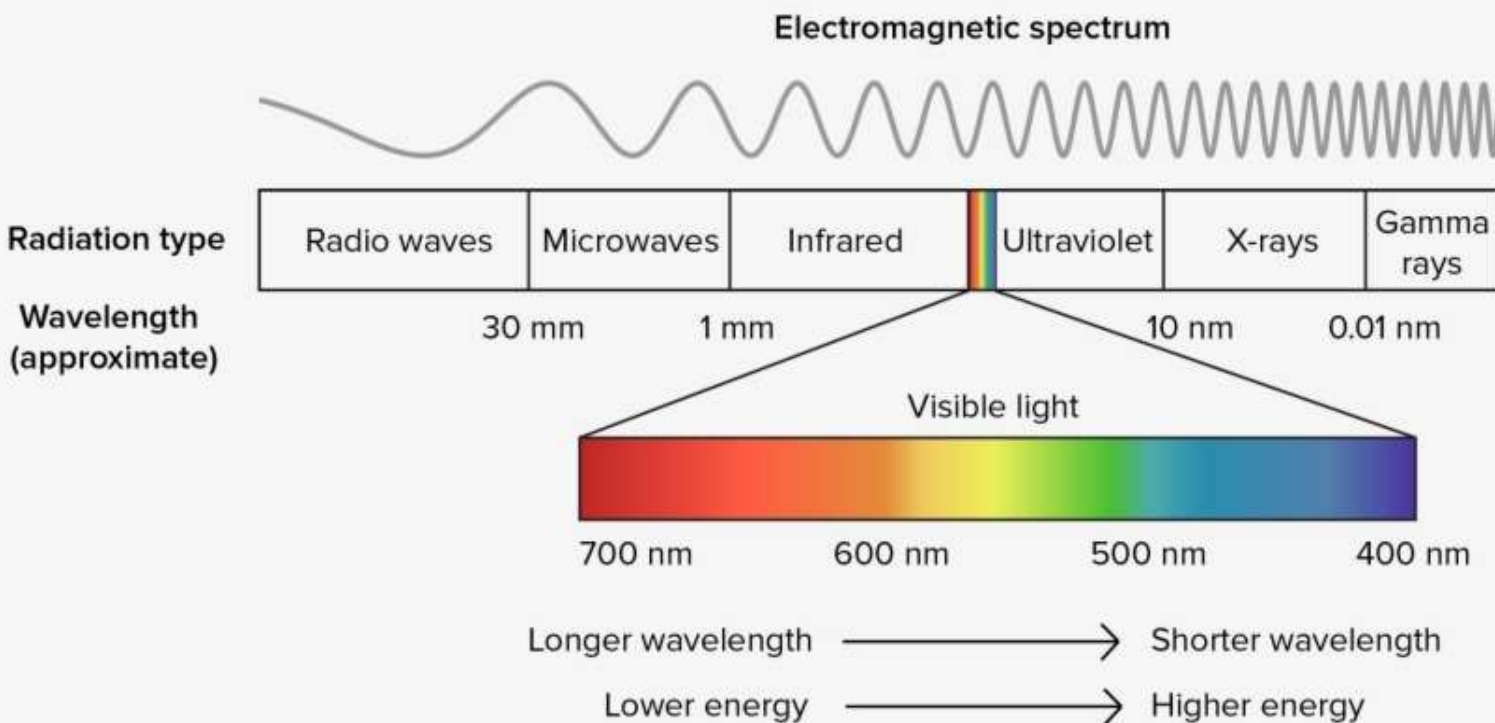
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² KU Leuven, Embedded and Artificially intelligent VISION Engineering (EAVISE) research group, toon.goedeme@kuleuven.be

³ University of Oviedo, Artificial Intelligence Center, quevedo@uniovi.es - montaneselena@uniovi.es

1. Context - Spectroscopy

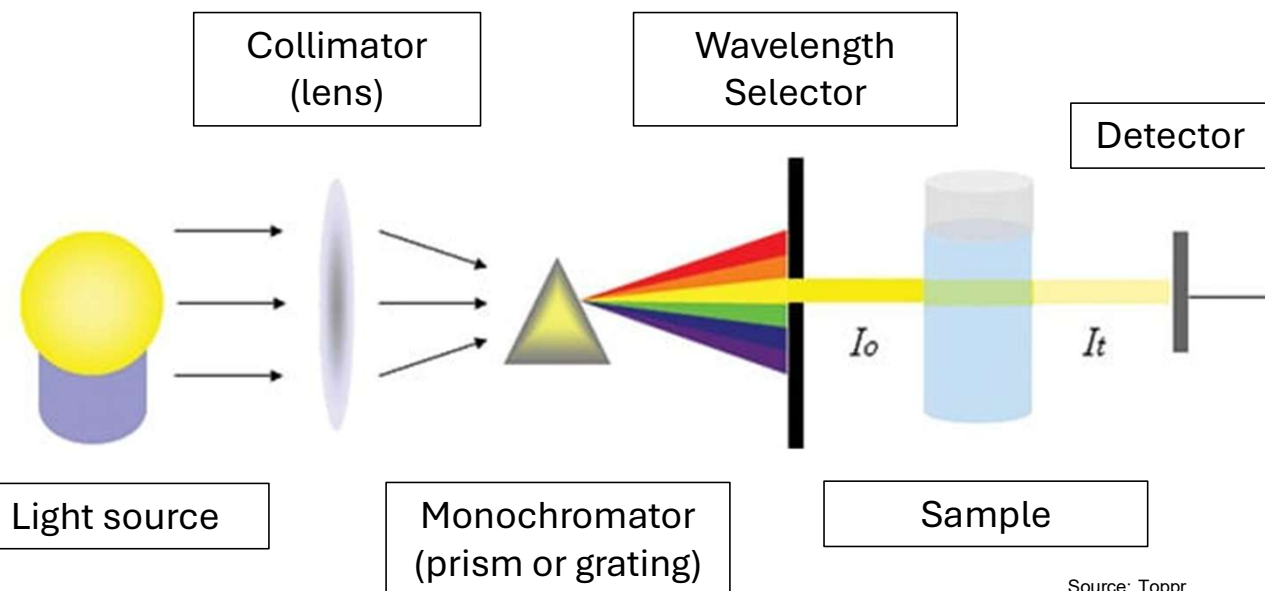
Spectroscopy = Study of the interaction between electromagnetic radiations and matter



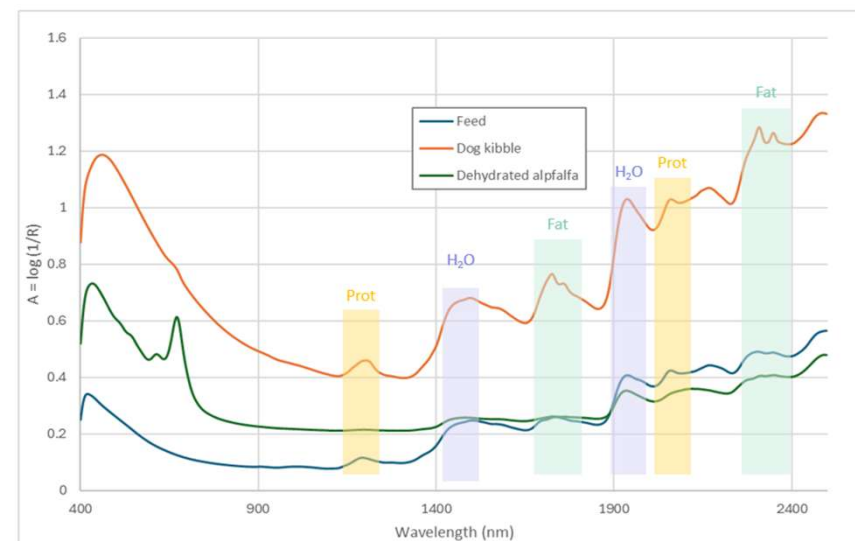
Source: Quizlet

Source: Psiberg

1. Context - Spectroscopy



Source: Toppr



Source: L. Paternostre



Fast

Green

Non-invasive

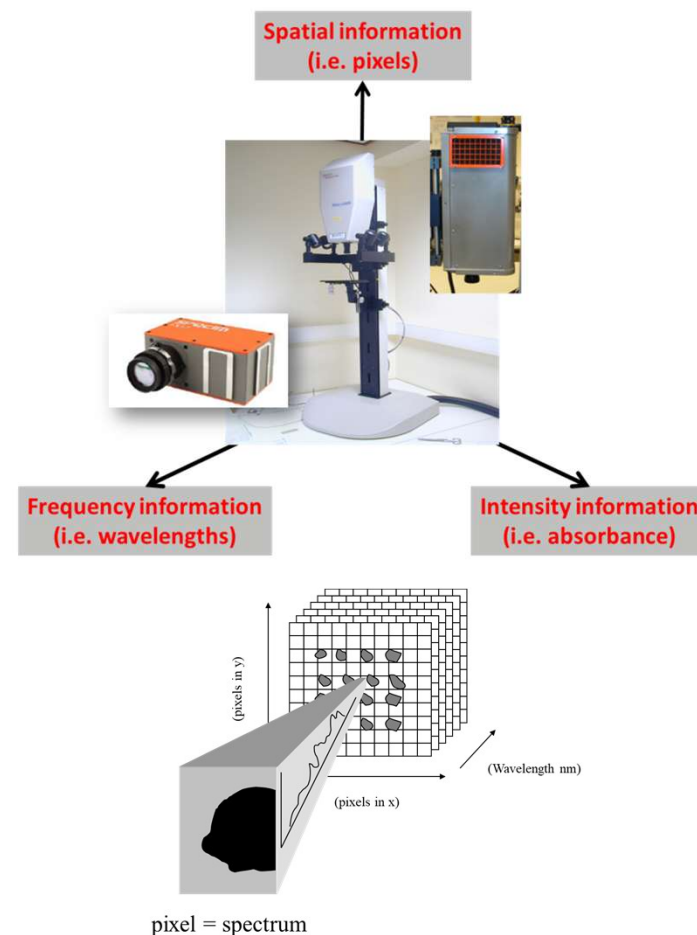
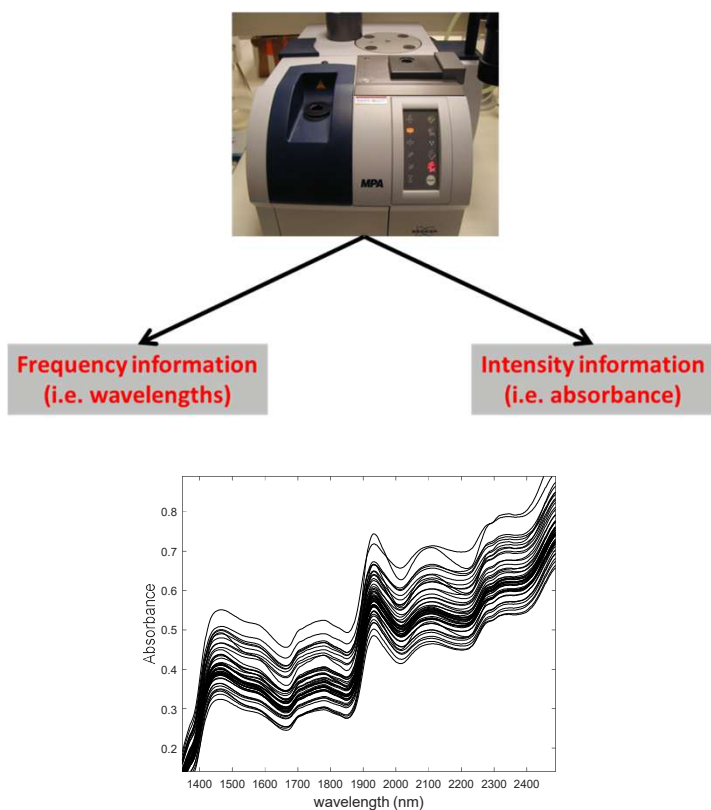
Cost-efficient

No or limited sample prep

Multi-constituents

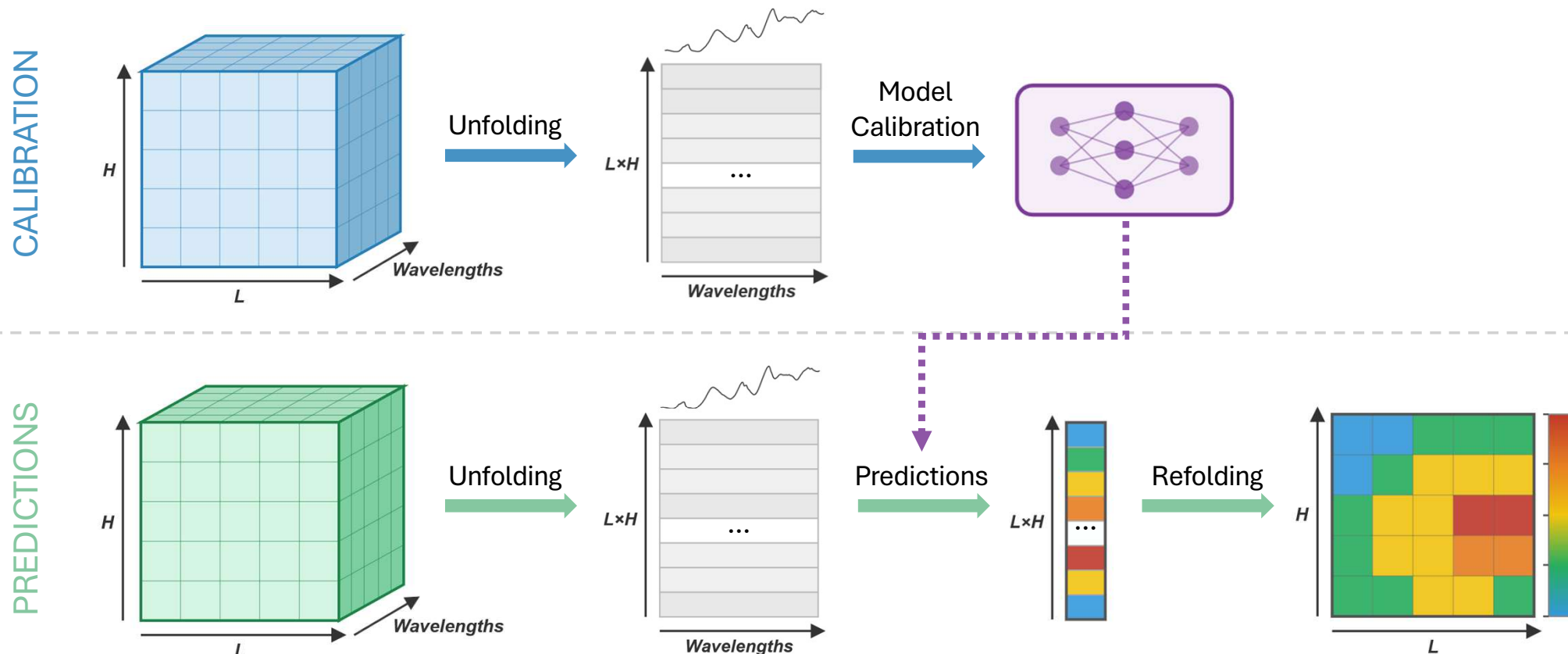
1. Context – Hyperspectral imaging

From 1 spectrum/sample to 10^n spectra/sample with $n \gg 3$



1. Context – HSI x Deep Learning

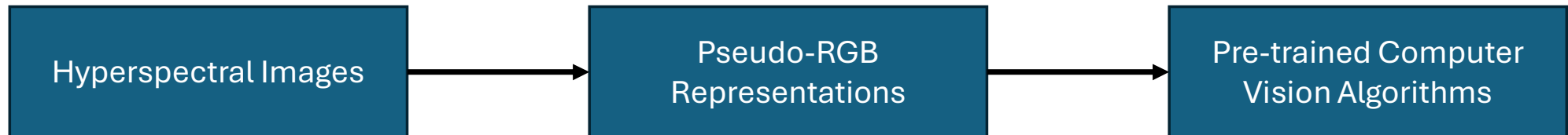
The unexploited spatial information in HSI analysis



2. Pseudo-RGB images for DL applications

Goals:

- Propose solutions to solve loss of spatial information in hyperspectral imaging
- Deep Learning as a solution
- Adapting the data instead of the algorithms
- Leverage pre-trained computer vision models



- Apply this methodology to use cases

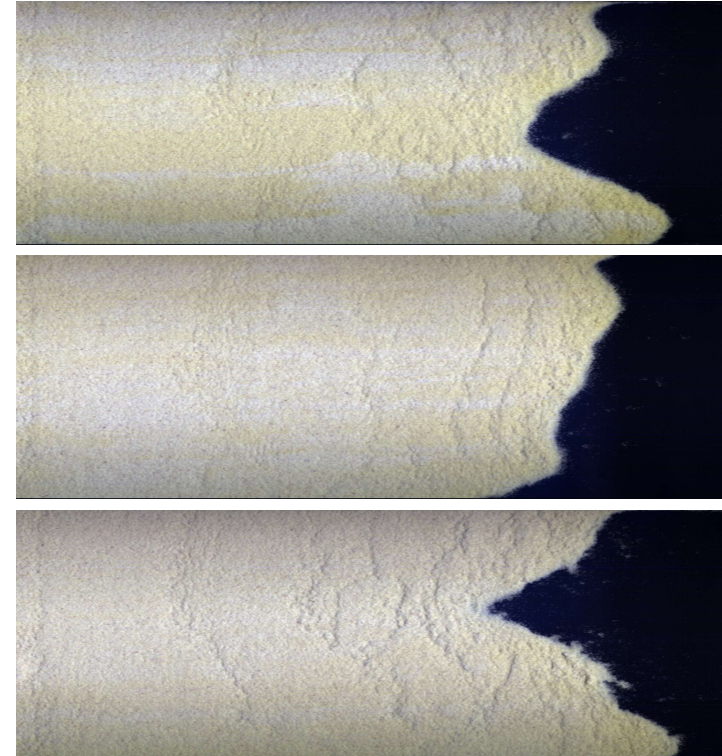
2. Pseudo-RGB images for DL applications

Use Case: Importance of Homogeneity in Powder Mixtures

- Critical to ensure uniform distribution of mixture properties
- Challenge for food and pharmaceutical industries
- Current monitoring methods are destructive, time-consuming and sensitive to sampling bias
- Semolinas: Valorisation of high value cereals requires traceability and authentication



Potential of hyperspectral imaging for continuous and non-destructive monitoring



Blending time

How much blending to reach desired homogeneity?
Is my sample homogeneous?

2. Pseudo-RGB images for DL applications

Dataset - Semolinas

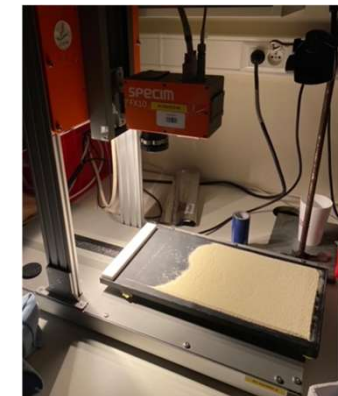
- Mixtures of bread wheat and durum wheat semolinas
- Measured with Specim FX10 (400-1000 nm)
- Hypercube of dimensions 400x200x224
- 274 images (1 image per sample)
- 5 replicas (different varieties) x 11 proportions x 5 blending times

Mixture	Bread wheat (%)	Durum wheat (%)	Number of samples
MIX 1	100	0	25
MIX 2	90	10	25
MIX 3	80	20	25
MIX 4	70	30	25
MIX 5	60	40	24
MIX 6	50	50	25
MIX 7	40	60	25
MIX 8	30	70	25
MIX 9	20	80	25
MIX 10	10	90	25
MIX 11	0	100	25

Blending time (s)	Number of samples
0	55
15	55
30	54
60	55
120	55



Blender: Heidolph Reax 20 mixer 3 rpm



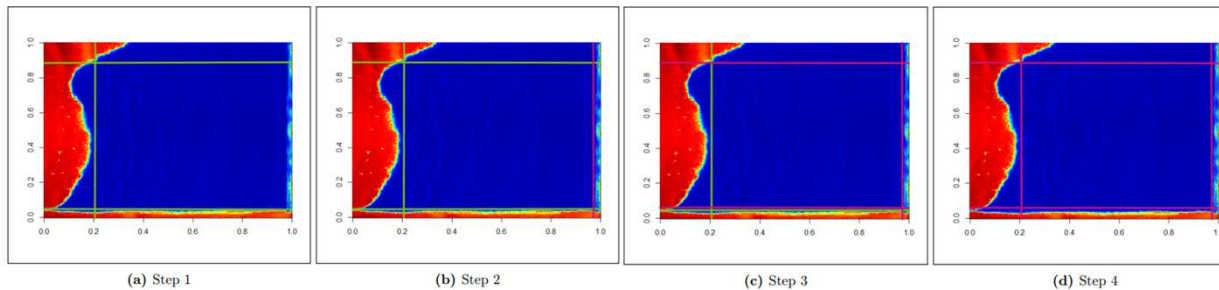
Camera: specim FX10 (Specim, FI)

2. Pseudo-RGB images for DL applications

Data Preparation

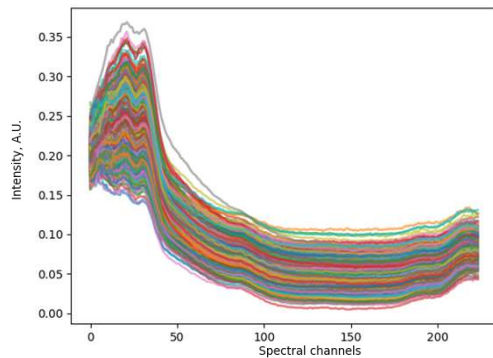
1) Reflectance to Absorbance

2) Background Removal (Frame selection Algorithm)

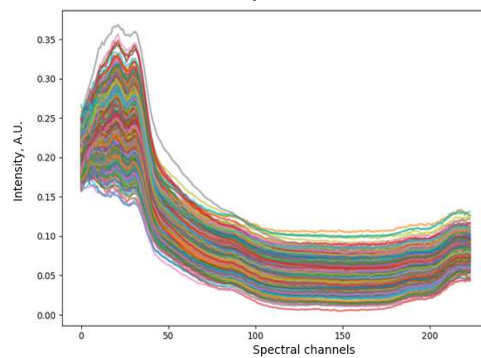


3) Preprocessing (4 pipelines):

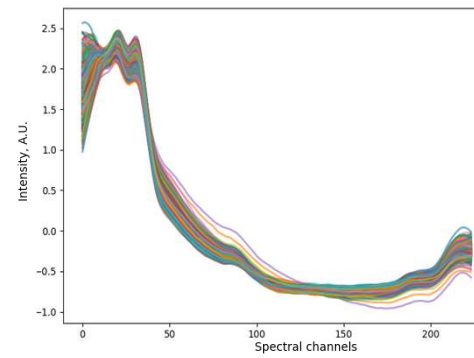
Raw data



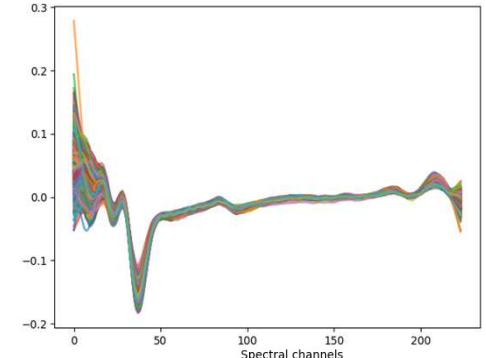
No spikes



No spikes + SNV + SG (smoothing)



No spikes + SNV + SG (1st derivative)



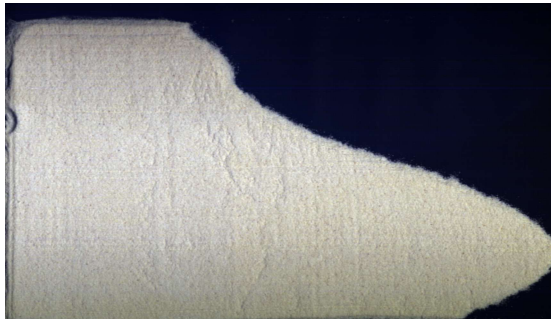
2. Pseudo-RGB images for DL applications

Data Preparation

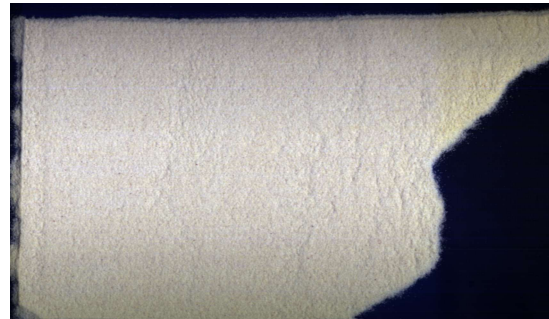
4) Image Resizing

➡ Irregular spreading of semolinas led to frames of different sizes – Reshaping to 152x170x224

DA-4-015-3



DA-9-120-4



5) Data Split

- Test set: Biological replicate 4 (20%)
- Training set: Biological replicate 1-2-3-5 (80 %)

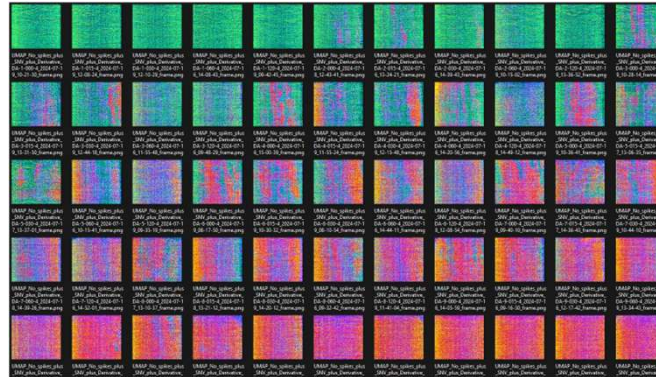
2. Pseudo-RGB images for DL applications

Pseudo-RGB images

- PCA and UMAP calibrated on 10% of images from training + LV scores and Wavelengths selection (VIP scores) based on PLS calibrated on images from training and applied to test (from 224 wavelengths to 3 comp)
- Normalization by percentiles to obtain values between 0 and 1

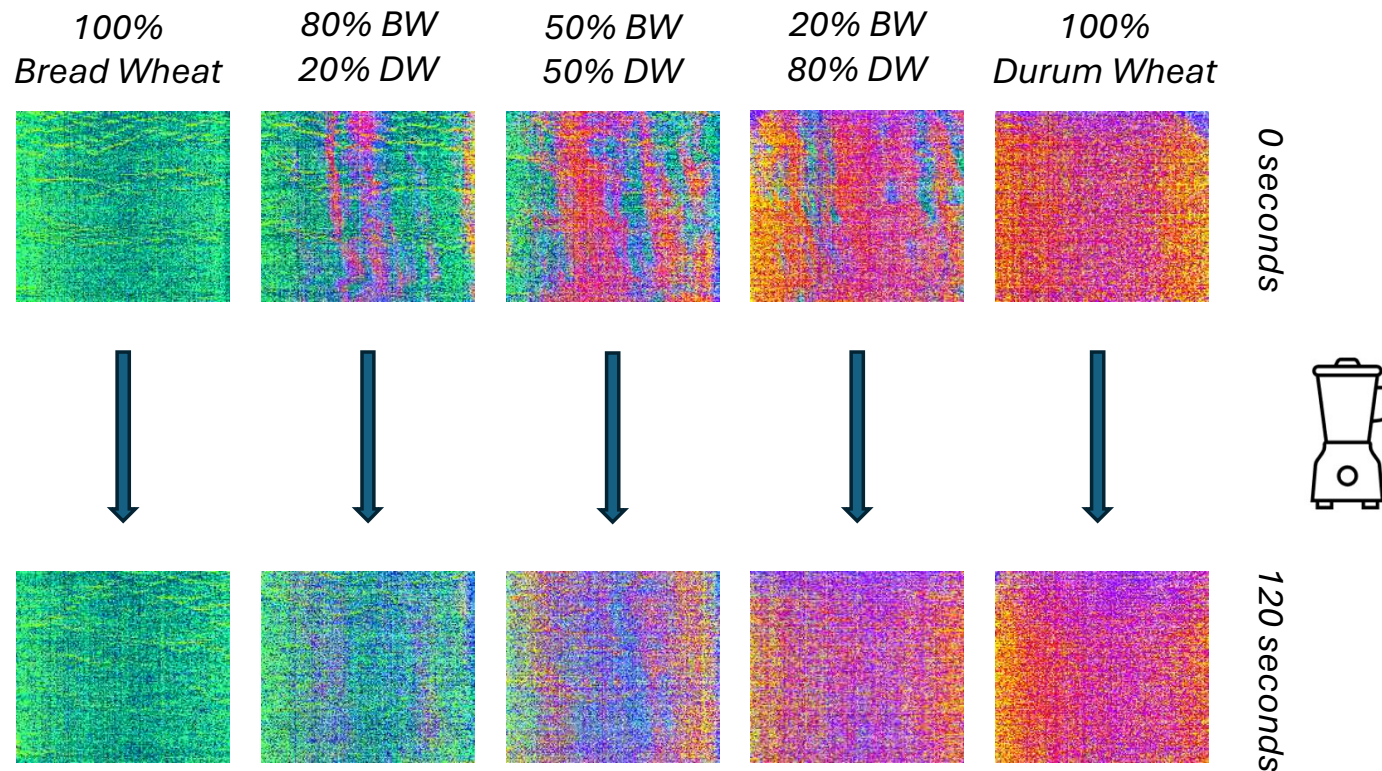
$$x' = \frac{x - P_5}{P_{95} - P_5}$$

- Obtention of the pseudo-RGB images
- Best preprocessing + dimensionality reduction method visually selected (*UMAP + No spikes_SNV_Derivative*)



2. Pseudo-RGB images for DL applications

Pseudo-RGB images



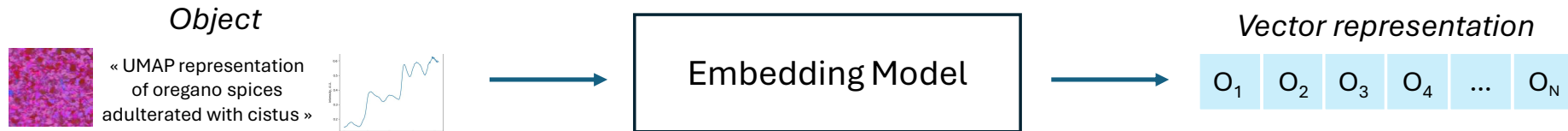
Opens the way to the use of pre-trained computer vision algorithms:

- Classification
- Segmentation
- Object detection
- Embeddings

...

3. Embeddings on Pseudo-RGB images

Embeddings



- Megahed, F. M. e al. (2025). *Adapting OpenAI's CLIP Model for Few-Shot Image Inspection in Manufacturing Quality Control: An Expository Case Study with Multiple Application Examples*. <https://doi.org/10.48550/arXiv.2501.12596>

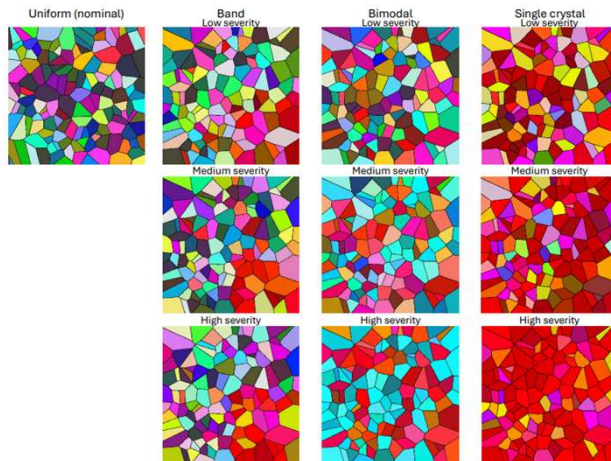


Figure 10: Examples of simulated microstructures with different crystal orientation distributions

Table 9: Few-shot classification performance metric for the microstructure classification case study.

Test mode	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
Two-class	0.898	0.987	0.809	0.838	0.906	0.952

Use of pretrained embedding models on our data

OpenAI CLIP = clip-vit-large-patch14

Google SigLIP = siglip-large-patch16-256

Facebook Dinov3 = dinov3-vitlarge16

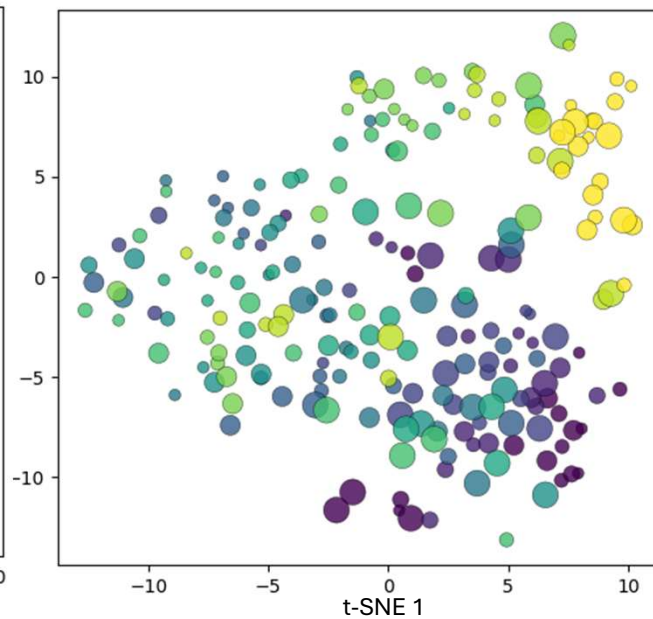
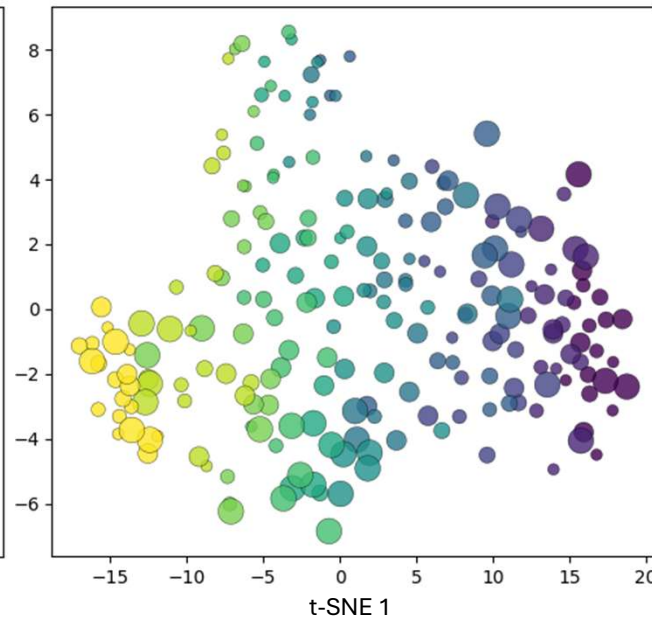
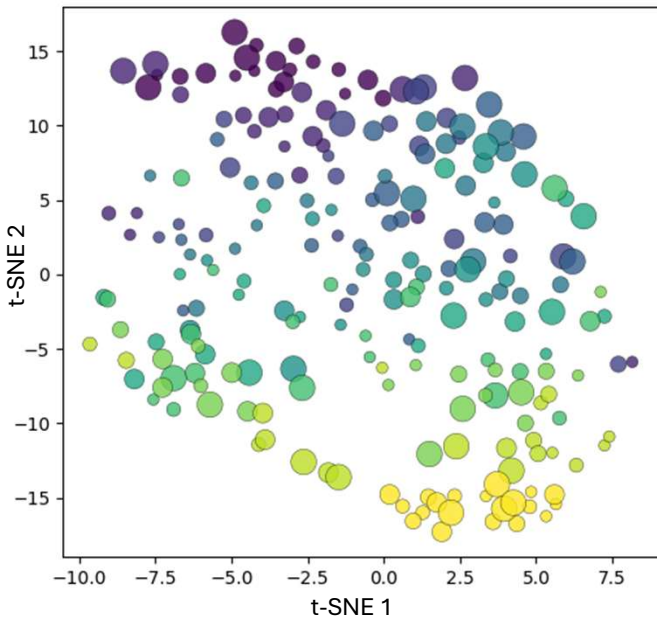
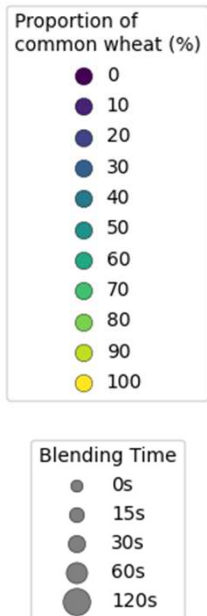
3. Embeddings on Pseudo-RGB images

Embeddings T-SNE Visualization

clip-large-patch14

siglip-large-patch16-256

facebook/dinov3-vitlarge16



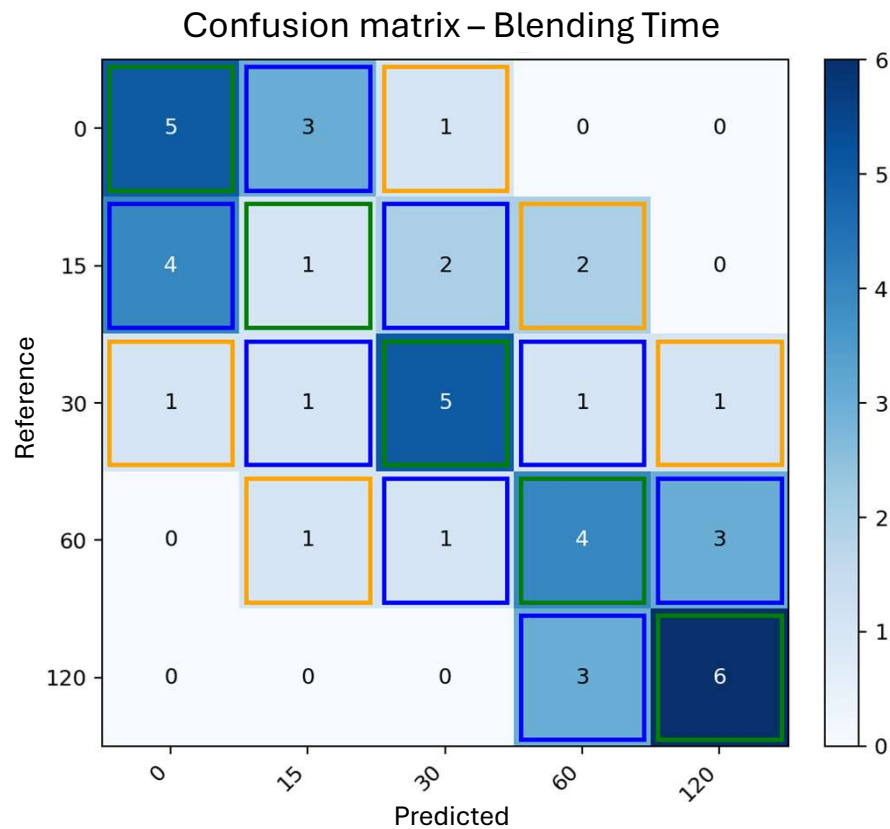
3. Embeddings on Pseudo-RGB images

Predictions of proportions and blending time from the embeddings

- Calibration set = Library of references embedding
- Prediction of new sample by KNN approach (5 NN-cosine similarity). Label = majority class
- Problem: Embeddings of 768 (CLIP), 1024 (SIGLIP), and 1024 (DINO) dimensions.
- Extracting the dimensions associated to a specific feature requires variable selection methods
- Trial with a simple approach: KNN based on the n dimensions with the highest covariance with the feature of interest. Choice of the dimensions based on CV on calibration set.

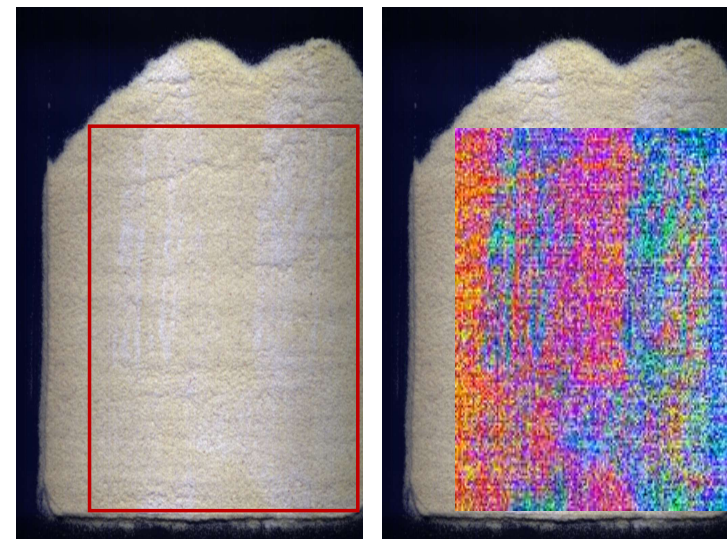
3. Embeddings on Pseudo-RGB images

Blending time prediction results – 90 dimensions CLIP



Accuracy of 0,47... Bad performances?

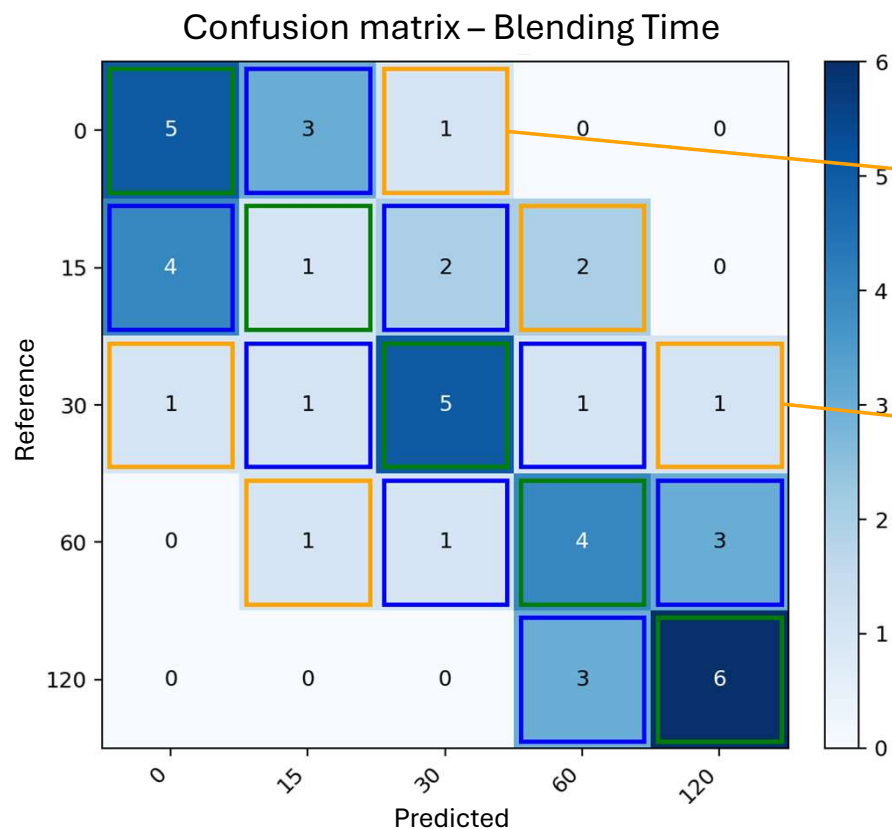
Not full images. Example with 8-000-4



3. Embeddings on Pseudo-RGB images

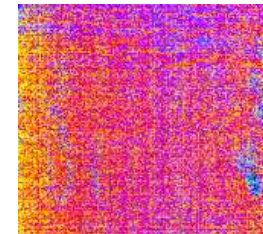
Blending time prediction results – 90 dimensions CLIP

Accuracy of 0,47... Bad performances?

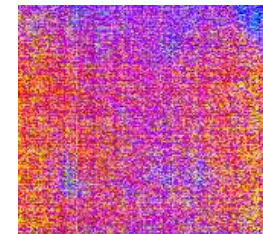


- Impact of blending lesser at high proportions

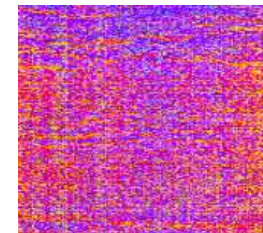
10-000-4



10-030-4



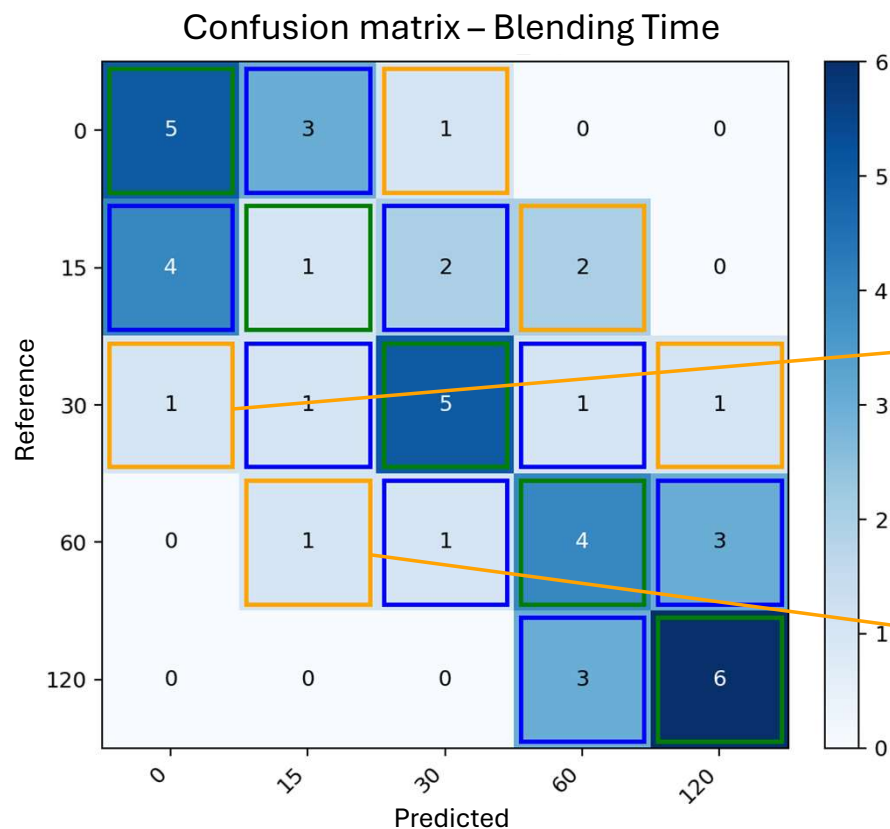
10-120-4



3. Embeddings on Pseudo-RGB images

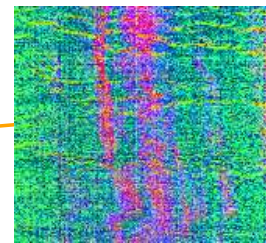
Blending time prediction results – 90 dimensions CLIP

Accuracy of 0,47... Bad performances?

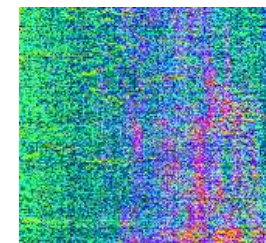


- Impact of blending lesser at high proportions
- Spatial distribution not always exactly related to blending time

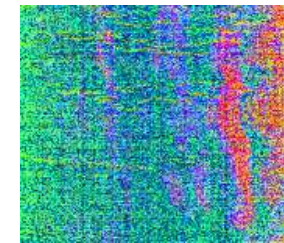
3-000-4



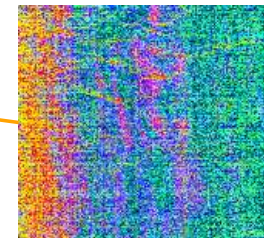
3-015-4



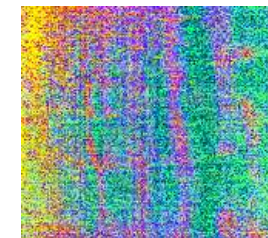
3-030-4



4-015-4



4-060-4



3. Embeddings on Pseudo-RGB images

Conclusion and perspectives

- Goal was to investigate whether such pretrained models could be applied to pseudo-RGB representation of HSI.

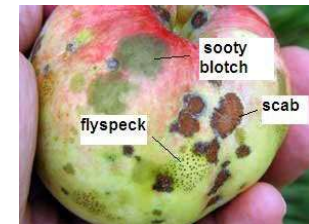
➡ Yes but feature extraction/selection technique is critical.

- Potential for applications where spatial information matters.

For example: Plant diseases, fruit defects, ... (similar spectral response but different spatial patterns)



Credits: 10.3390/plants12244162



Credits: Michigan State University

- Potential for anomaly detection based on a distance threshold
- Future work: Use of pretrained embedding models to improve cocoa bean genotype discrimination performance

Thank you for your attention

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