# Short-wave Infrared Hyperspectral Imaging for Predicting Closed Sandwiches’ Toppings

Esther Kok, Michele Tufano, Aneesh Chauhan, Edith Feskens, Guido Camps

## Background

A poor diet is known to be an important risk factor for the onset of many non-communicable diseases, such as cardiovascular disease, obesity, and type 2 diabetes. Nutritional epidemiology uses dietary assessment as the tool to study the origin and prevention of these diseases. Innovations have been made using RGB images for automatic detection of dietary intake, but traditional RGB contain no information about the chemical composition of the food. When both spatial characteristics and chemical composition need to be considered, hyperspectral imaging is an excellent candidate for data acquisition. Machine learning may aid in the generation of objective observations for dietary assessment.

## Objective

We aimed to use hyperspectral images (HSI) to determine the spreads on closed sandwiches, which is the most common type of sandwich in the Netherlands, by automatic detection of food identification in hyperspectral images (HSI).

## Data Acquisition

The dataset used in this study consists of hyperspectral images captured from prepa red closed sandwiches. The captured hypercubes were measured by the IMEC SWIR Snapscan, a spectral range from 1116.141162 nm to 1670.623839 nm. The final dimensions were 512 by 640 pixels, and 108 bands. Sandwiches (n=24) were constructed out of two types of bread, butter, and six different toppings. A region of interest (ROI) of dimensions 100 by 200 pixels was selected for each sandwich.

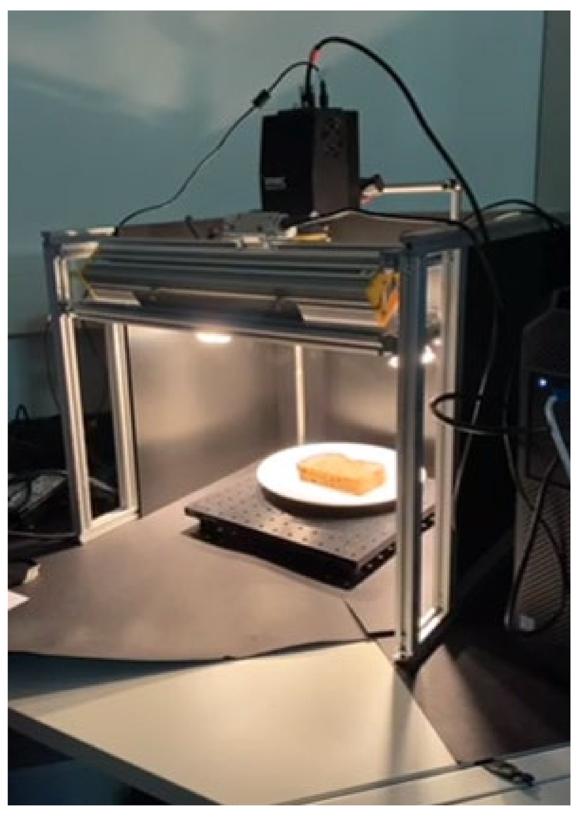

**Figure 1.** Hyperspectral camera lab setup

## Pre-processing

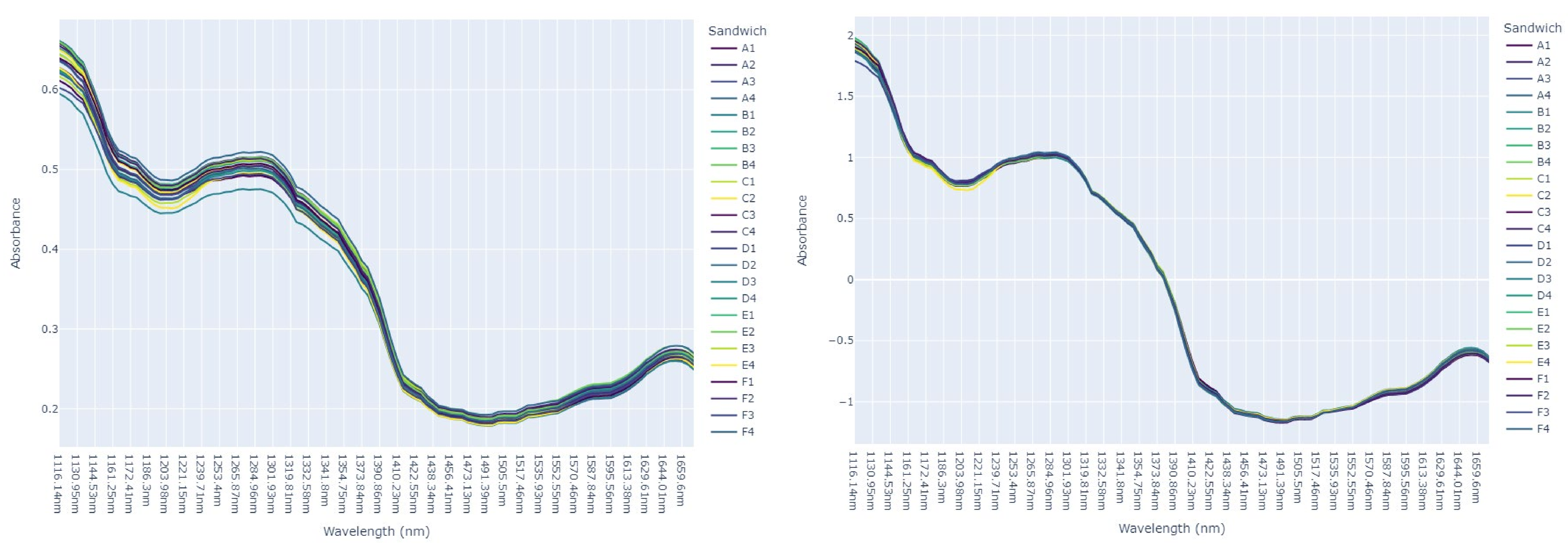

**Figure 2.** A) Average spectrum absorbance per sandwich before pre-processing, B) Average spectrum per sandwich after pre-processing, reducing scattering effects, and mean centering the data.

To prepare the data of the 24 sandwiches, the spectra of the ROI, e.g. the sandwich area, was pre-processed using Standard Normal Variate (SNV) filtering:

$$X_i^{snv} = (X_i - \bar{X}_i)/\sigma_i$$

## Feature Generation

Additional features were generated from first, second, and third order derivatives.

$$X_i^{first} = \frac{dA_{X_i}}{dX_i} \qquad X_i^{second} = \frac{d^2A_{X_i}}{d\lambda^2_{X_i}} \qquad X_i^{third} = \frac{d^3A_{X_i}}{d\lambda^3_{X_i}}$$

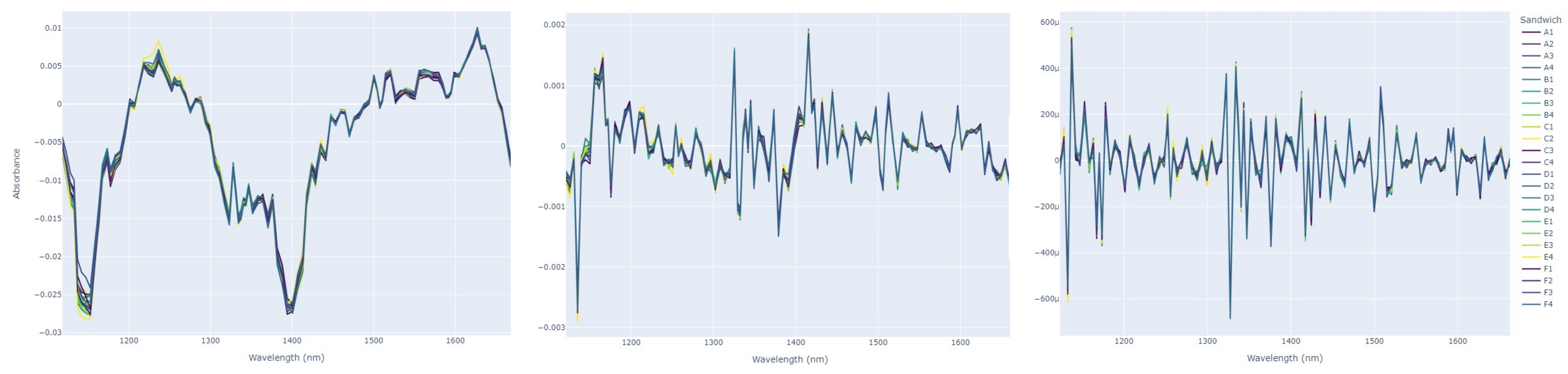

**Figure 3.** Average spectrum absorbance per sandwich for A) first order derivatives, B) second order derivatives, C) third order derivatives.

## Sampling Strategy

To reduce data interdependency, spectrum samples were taken from the ROI to split into training and testing data. This was achieved by splitting the ROI into six areas, assigning each area to either train or test set, cutting each area into 5 by 5 pixels and taking the center pixel as the final sample.

## Model Training and Evaluation

The train set (n=13440) was used to train a multilayer perceptron. Evaluation of the model on the test set (n=5760) resulted in table 1.

| | | | Predicted | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Bread | | Butter | | Topping | | | | | |
| | | | White | Whole wheat | Yes | No | Mature cheese | Low fat mature cheese | Jelly | Low sugar jelly | Peanut butter | Chocolate sprinkles |
| Groundtruth | Bread | White | 0.84 | 0.16 | | | | | | | | |
| | | Whole wheat | 0.17 | 0.83 | | | | | | | | |
| | Butter | Yes | | | 0.63 | 0.37 | | | | | | |
| | | No | | | 0.44 | 0.56 | | | | | | |
| | Topping | Mature cheese | | | | | 0.26 | 0.16 | 0.18 | 0.06 | 0.21 | 0.14 |
| | | Low fat mature cheese | | | | | 0.15 | 0.22 | 0.17 | 0.07 | 0.23 | 0.17 |
| | | Jelly | | | | | 0.12 | 0.13 | 0.28 | 0.1 | 0.17 | 0.19 |
| | | Low sugar jelly | | | | | 0.11 | 0.13 | 0.21 | 0.15 | 0.2 | 0.21 |
| | | Peanut butter | | | | | 0.14 | 0.16 | 0.14 | 0.07 | 0.34 | 0.16 |
| | | Chocolate sprinkles | | | | | 0.09 | 0.11 | 0.17 | 0.09 | 0.19 | 0.35 |

**Table 1.** Confusion matrix that captures the model performance as accuracy in terms of percentage correct predictions. We can see from the results that the model performs successfully on predicting the type of bread and butter, and above random assignment for the toppings, which leaves room for improvement.

## Conclusions

- We can use hyperspectral imaging and machine learning to look at food composition beyond surface level, and predict its content.
- Future research should cover less homogeneous foods, such as wraps or lasagne, and improved sampling.

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Wageningen University & Research
P.O. Box 123, 6700 AB Wageningen, the Netherlands
Contact: esther.kok@wur.nl
T + 31 (0)317 480 080
https://www.wur.nl/nl/project/Hungry-Robots-Lab.htm

Hungry Robot Lab
Contact: guido.camps@wur.nl
T + 31 (0)317 480 080
https://hungryrobots.guidocamps.com/