

# KRAK

OP ZOEK NAAR DE PERFECTE  
CRUNCH

JAN 2025–  
DEC 2026

## TETRA PROJECT

BEPALING VAN DE PRODUCTKWALITEIT VAN VOEDING  
AAN DE HAND VAN GEAVANCEERDE GELUIDSANALYSE



MET DE STEUN VAN

AGENTSCHAP  
INNOVEREN &  
ONDERNEMEN



Vlaanderen  
is ondernemen



FLANDERS'  
FOOD

EEN SAMENWERKING TUSSEN

KU LEUVEN

hogeschool  
**VIVES**

HBC.2024.0136

[www.project-krak.be](http://www.project-krak.be)

KRAK – Steering Group– 14 November 2025

# **A G E N D A**

**14<sup>th</sup> November 2025**

12:00 – 12:30 Lunch

12:30 – 12:40 Introduction & Agenda Review

12:40 – 14:15 KRAK Work Presentation & Discussion

14:15 – 14:30 Preparation for Plant tour

14:30 – 15:15 Plant tour

15:15 – 15:30 Break

15:30 – 15:45 Kellanova Presentation

15:45 – 16:00 Wrap-up

16:00 – 16:30 Closing & Networking

# CONSORTIUM OVERVIEW

## STEERING COMMITTEE



## PARTNERS



## FEDERATIONS & RESEARCH



# The KRAK Team



## **Food Processing**

Michaël Verlinden

Kevin Vynckier

Thomas Sprangers

Lore Benthein

## **Mechatronics**

Catherine Middag

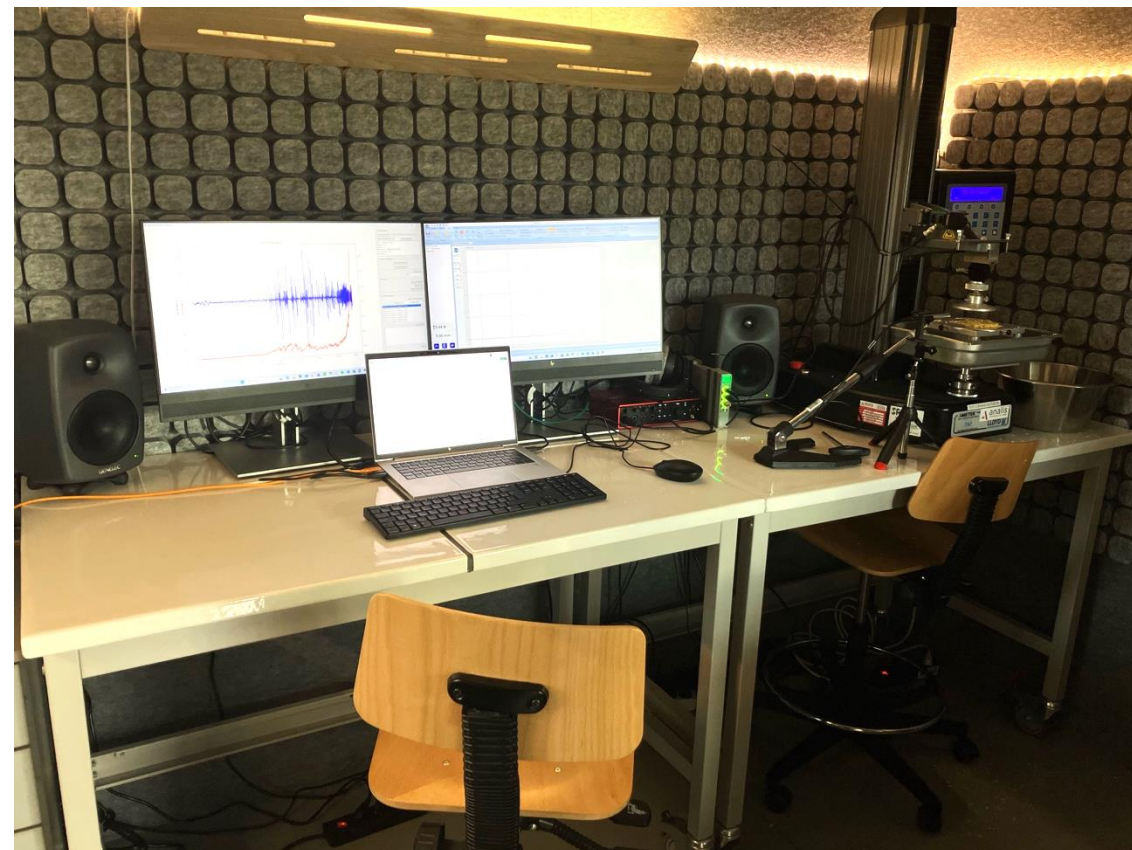
Tom Vangaever

## **MeBios**

Mohammed Saif Ismael Hammeed

# 1. The audiolab

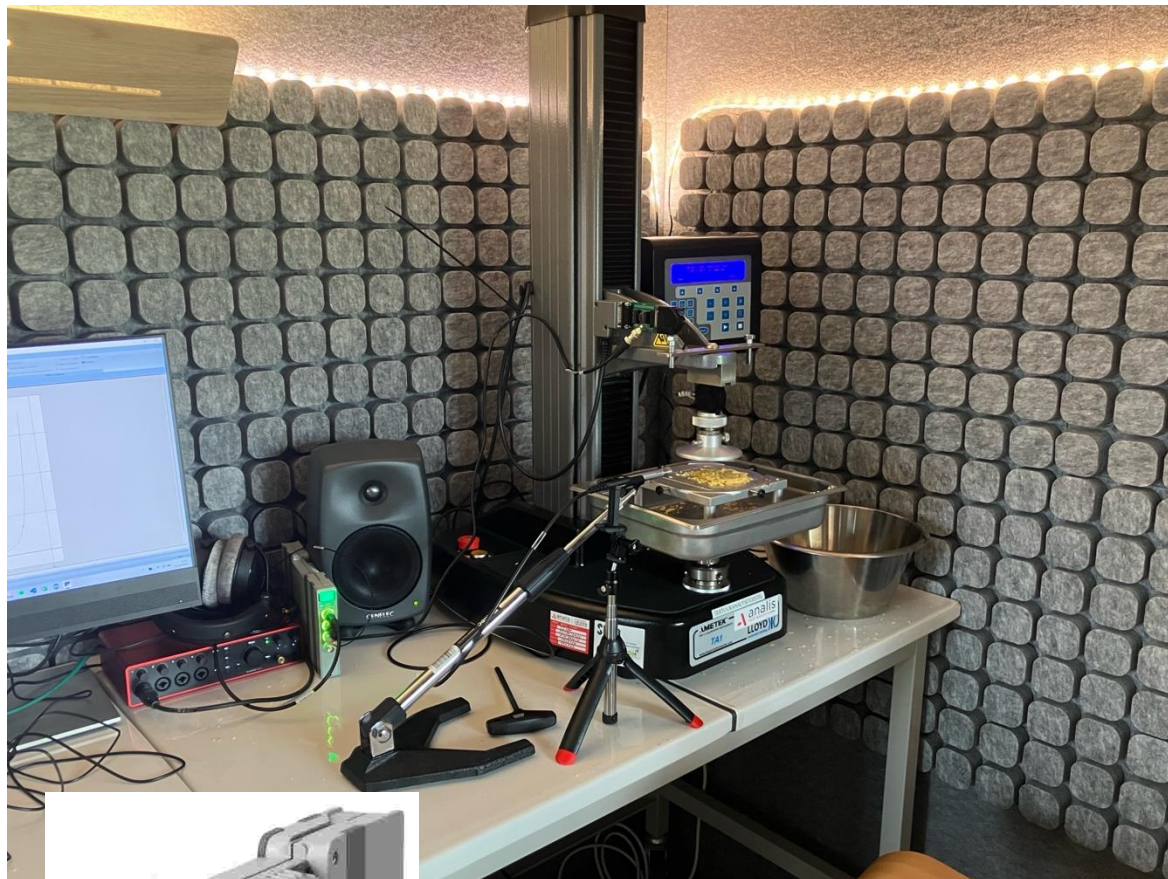
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**Audiobooth**

Isolation index: 45dB – ISO 717-01

Double Wall



- 1/2' Free-field Microphone, Bruël & Kjær, 6.3 Hz to 20 kHz
- High Temperature Preamplifier 1706



Accelerometer, CCLD, 100m/g



4-Channel Input DAQ Module  
LAN-XI, Type 3676

# 2. Methods

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-1-  
Chips



-2-  
French  
Fries



-3-  
Cookies



-4-  
Bread  
(Baguette)



-5-  
Chocolate



-6-  
Breaded &  
Battered  
products



-1-  
Chips



-2-  
French  
Fries



-3-  
Cookies



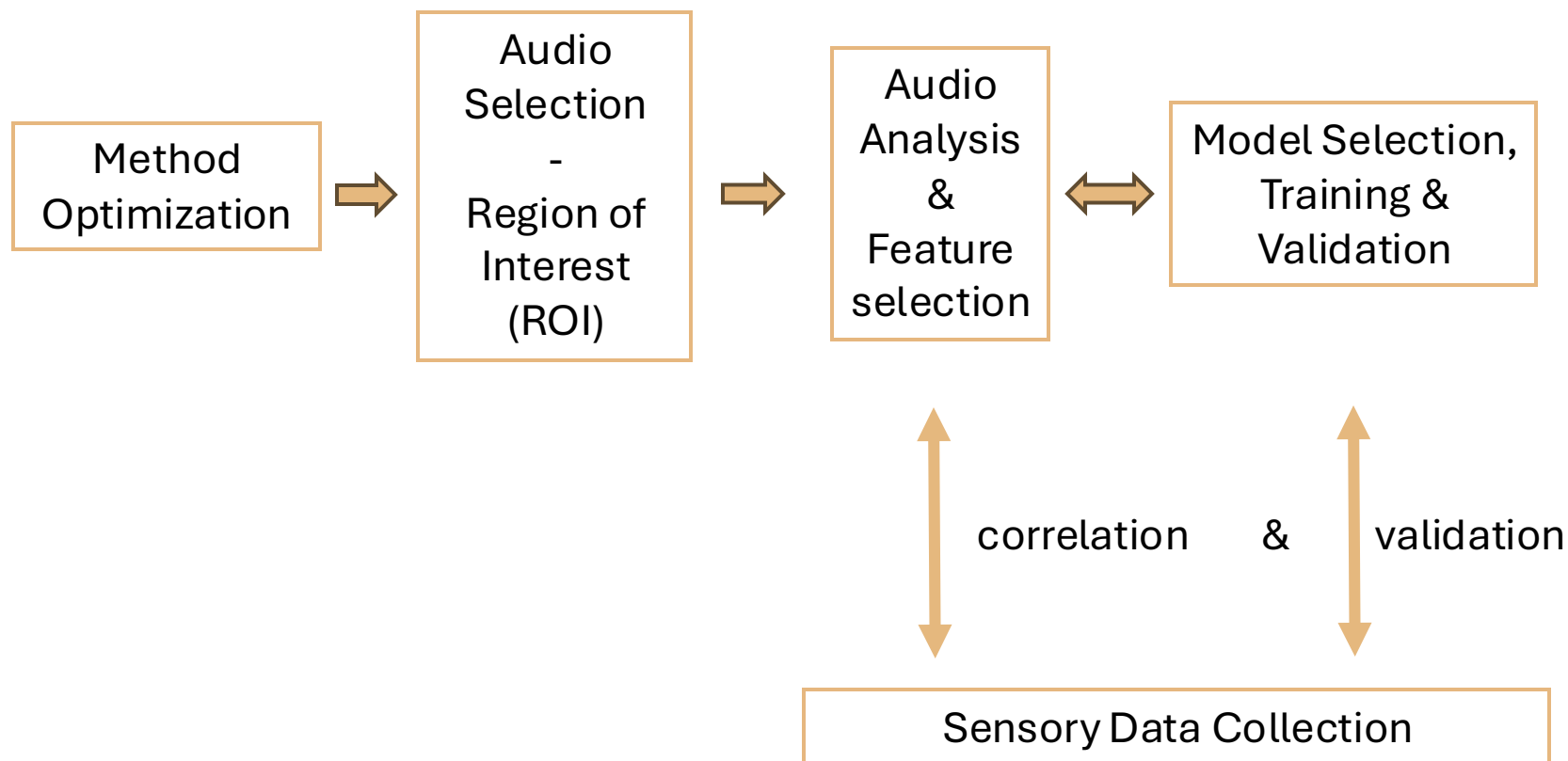
-4-  
Bread  
(Baguette)

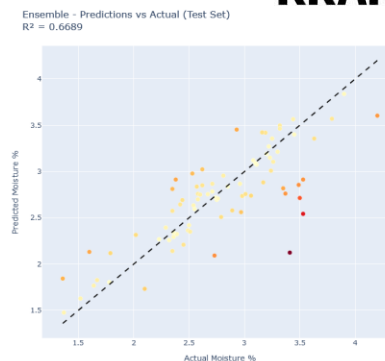
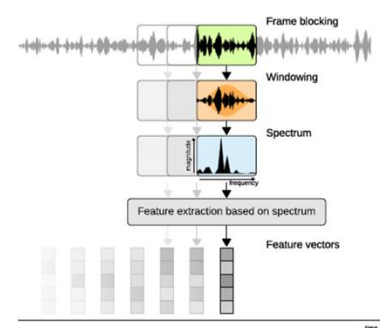
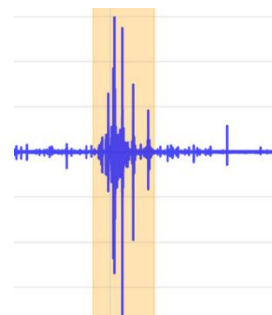


-5-  
Chocolate



-6-  
Breaded &  
Battered  
products





-3-  
Cookies



Method  
Optimization

Probe  
Speed  
Distance  
Orientation

Audio  
Selection  
-  
Region of  
Interest  
(ROI)

Audio  
Analysis  
&  
Feature  
selection

Model Selection,  
Training &  
Validation

correlation & validation

Sensory Data Collection



-1-  
Chips

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# Model Case 5 Chips

## EXPERIMENTAL VARIABLES

Five types of chips will be evaluated:

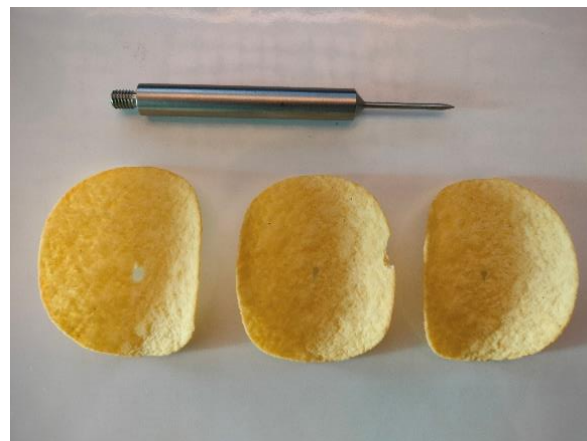
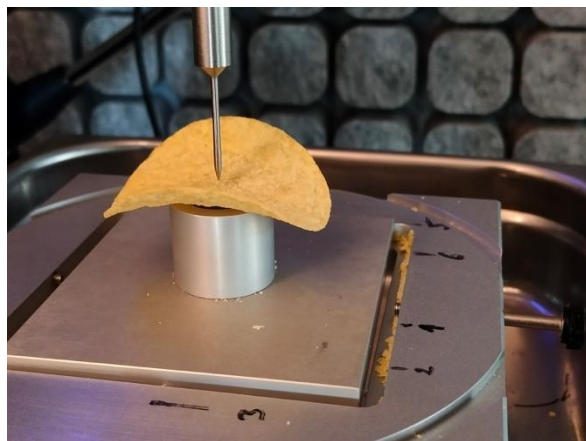
Raw, Soft, Reference, Hard, Burnt



Variables	Type	Values
Sample		
Type	<u>Categorical</u>	5 types (Raw, Soft, Reference, Hard, Burnt)
Protocol		
Speed	<u>Continuous</u>	(0.2 <u>mm.s<sup>-1</sup></u> , 1 <u>mm.s<sup>-1</sup></u> and 2 <u>mm.s<sup>-1</sup></u> )
Type of <u>breaking</u>	<u>categorical</u>	1/ Hole* 2/Split** 3/Crush***

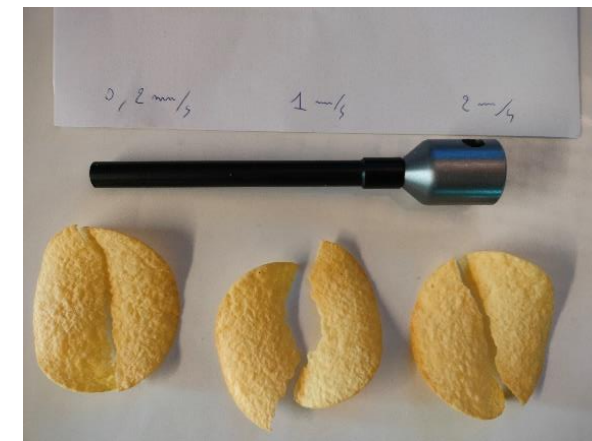
**\*Hole**

Needle Probe (1,75mm) stop test at 3mm, chips convex on chip stand



**\*\*Split**

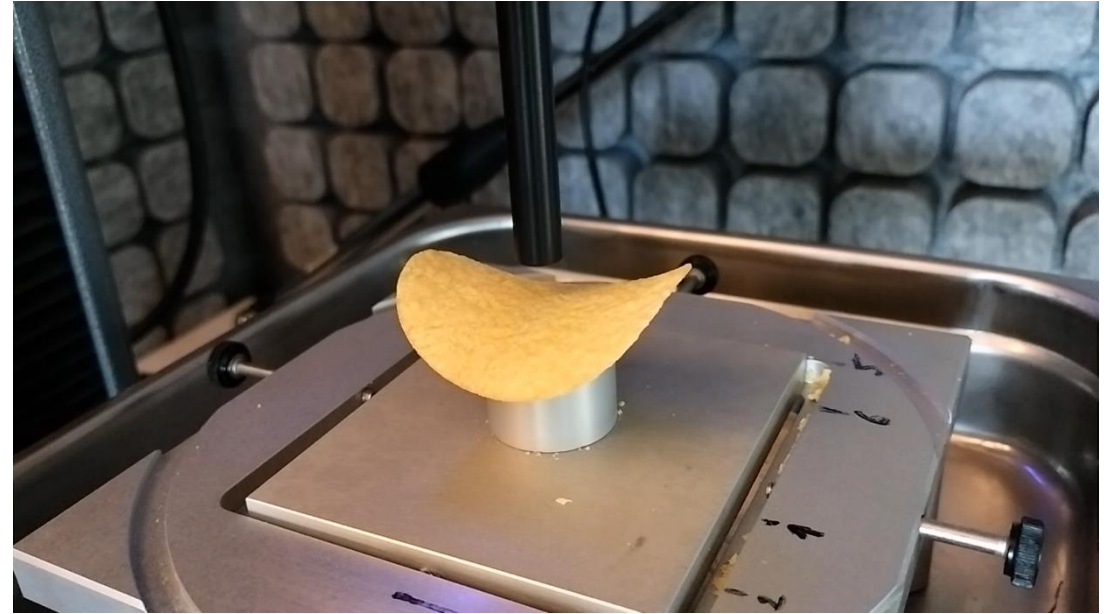
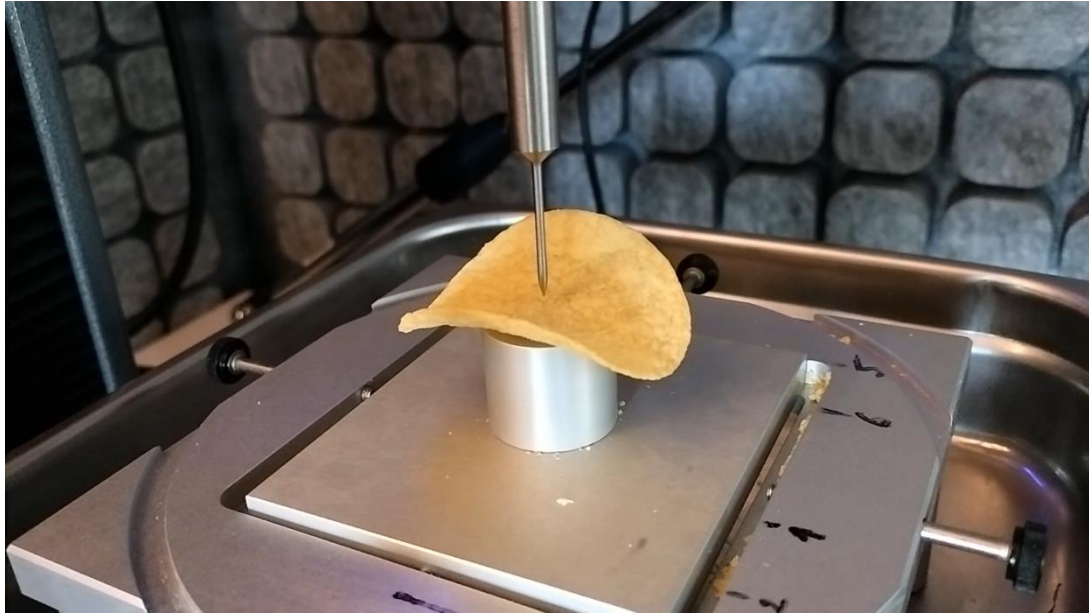
Puncture probe (9,4mm), plastic, stop test at 3mm, chip concave on chip stand

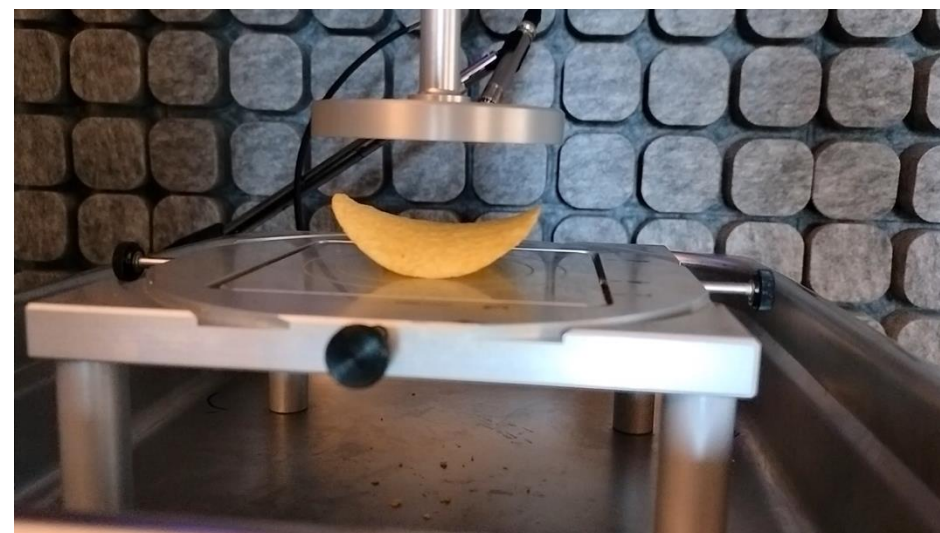
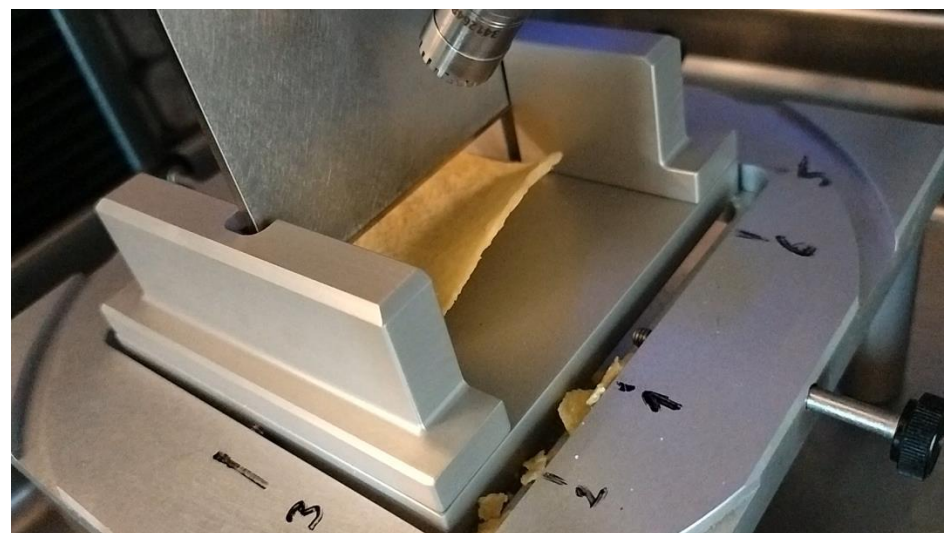


**\*\*\*Crush**

Kramer cell, 5 blades, stop test at 10mm



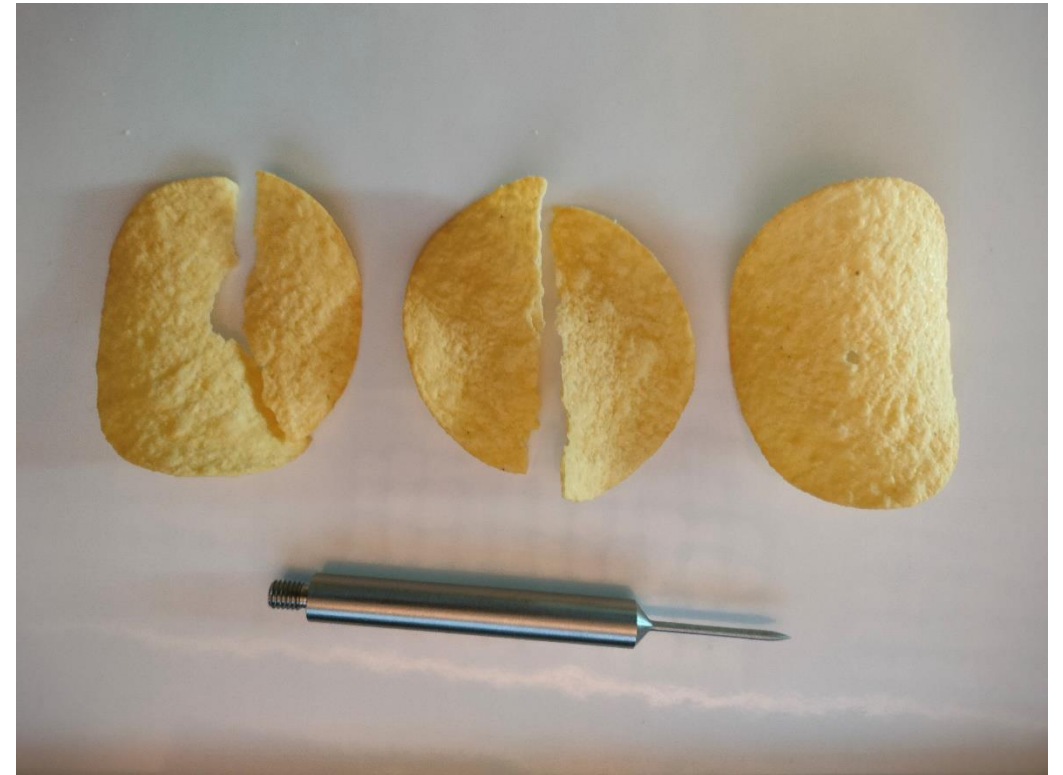
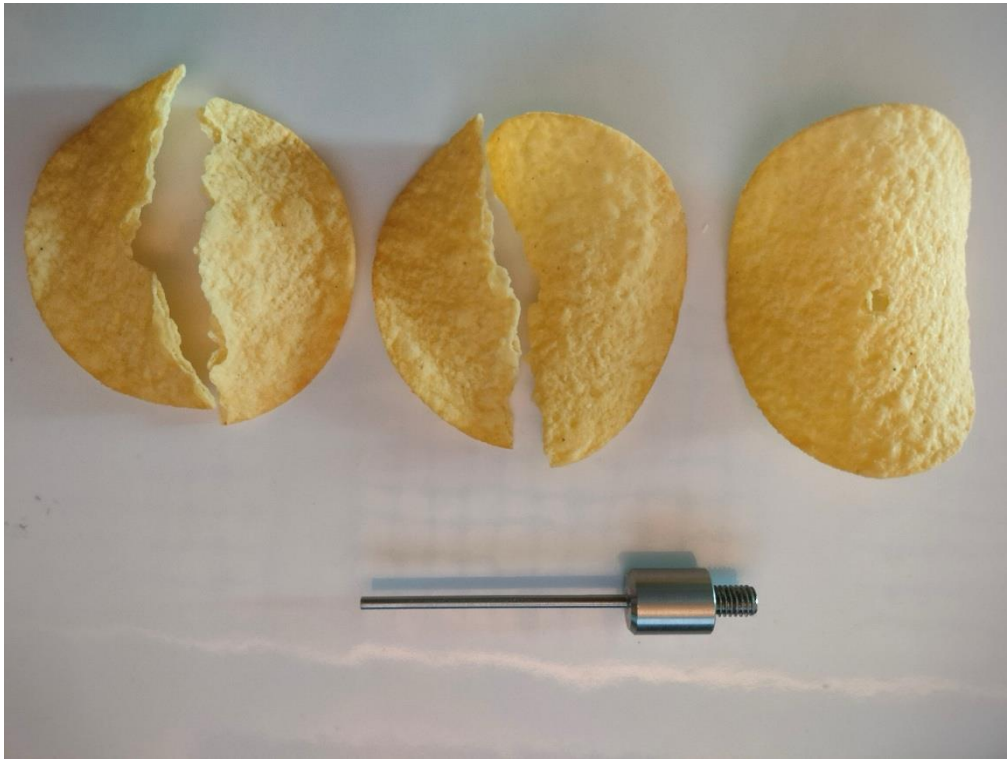




**Other probes gave no even breaking**

# ORIENTATION

Concave

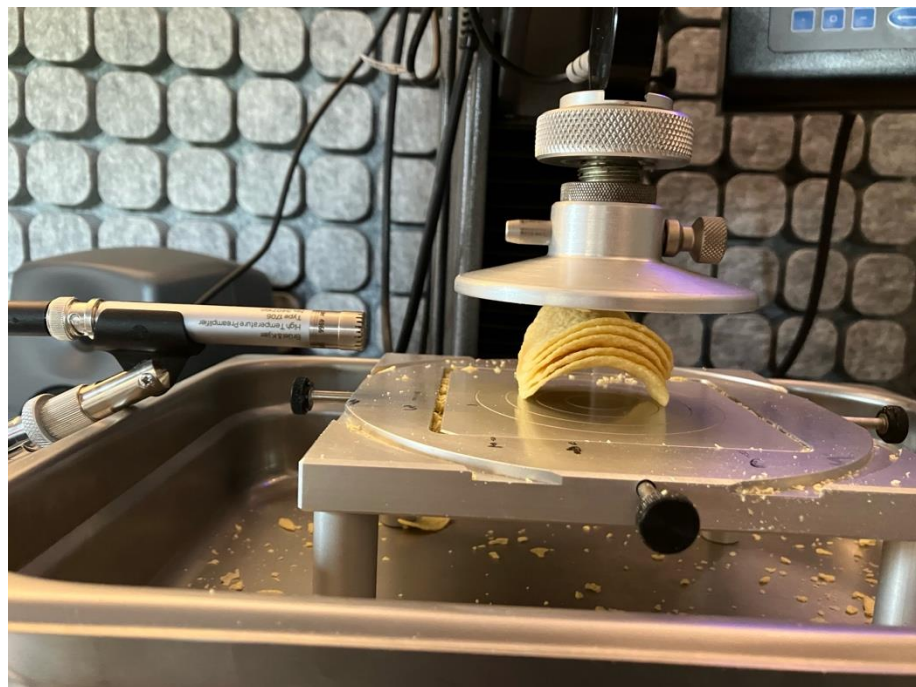


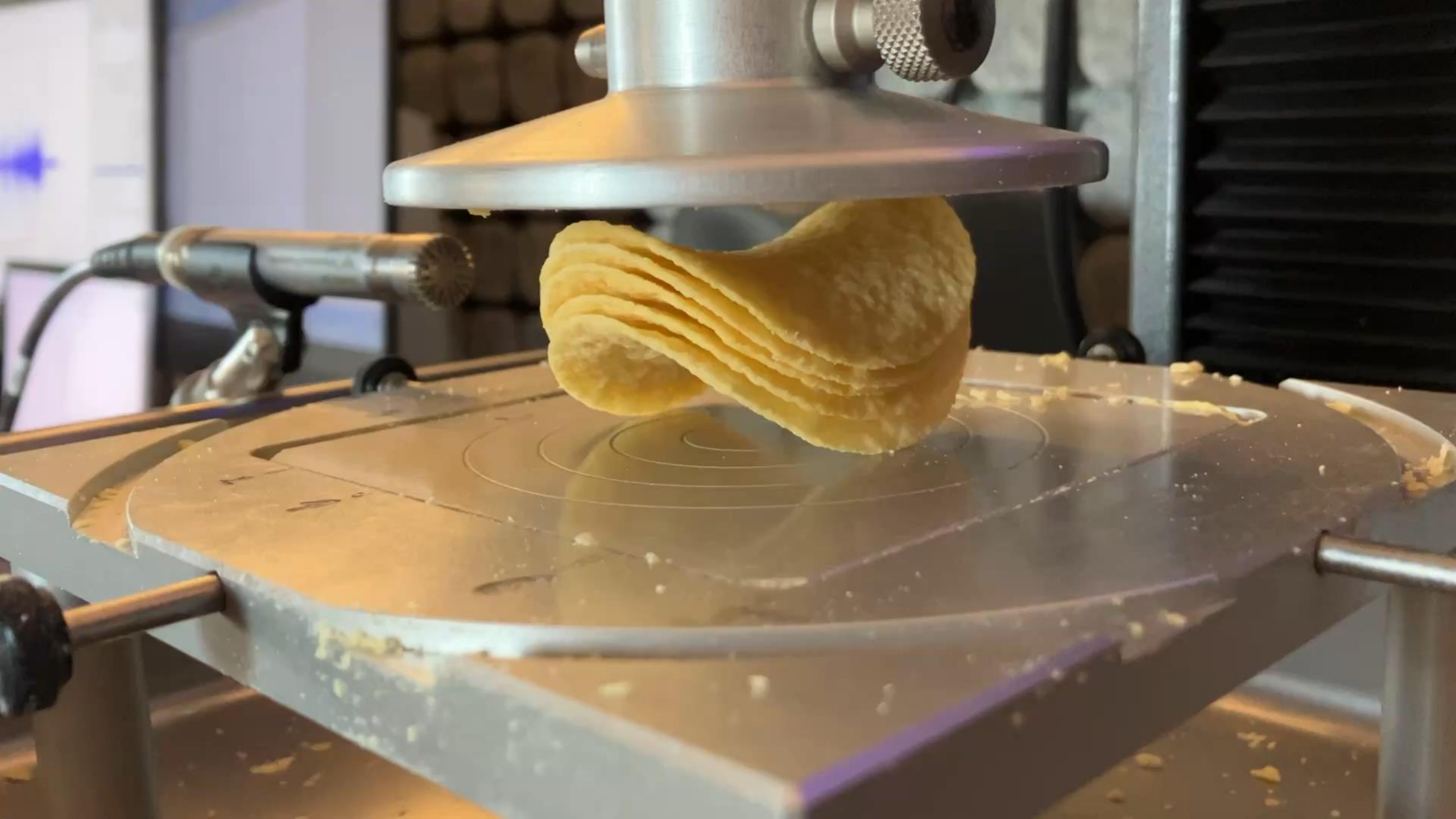
Type	Method	Speed	Repeats	3x total experiment
			6	3 cans
	Needle		1	
			2	
			3	
1 Break			1	
			2	
			3	
Crush			1	
			2	
			3	
		9 experiments per type		
		x5 types -->		
>		<b>45 experiments</b>	<b>270 measurements</b>	

Experiment Number	Type	Method	Speed (mm/s)	Can number
1	Raw	Needle	0,2	1
2	Raw	Needle	0,2	2
3	Raw	Needle	0,2	3
4	Raw	Needle	0,2	1
5	Raw	Needle	0,2	2
6	Raw	Needle	0,2	3
7	Raw	Needle	1	1
8	Raw	Needle	1	2
9	Raw	Needle	1	3
10	Raw	Needle	1	1
11	Raw	Needle	1	2
12	Raw	Needle	1	3
13	Raw	Needle	2	1
14	Raw	Needle	2	2
15	Raw	Needle	2	3
16	Raw	Needle	2	1
17	Raw	Needle	2	2
18	Raw	Needle	2	3
19	Raw	Break	0,2	1
20	Raw	Break	0,2	2
21	Raw	Break	0,2	3
22	Raw	Break	0,2	1
23	Raw	Break	0.2	2

\*Compression

Compression Plate (100mm) stop test at load of 350N, 5 chips stacked, concave





# Perimeter calculation of broken chips fragments



Filename	Num_Objects	Total_Perimeter_mm	Mean_Perimeter_mm
Chips_Sample_1.jpeg	11	165.20	15.01
Chips_Sample_2.jpeg	11	159.17	14.47

-2-  
French  
Fries



Variables	Type	Values
<b>SAMPLE</b>		
<b>DM Packed Product</b>	Continuous	Q1: DM (high) Q3: DM (Low)
<b>Frying time</b>	Continuous	3.5min 4.5min 5.5min
<b>PROTOCOL</b>		
<b>Speed</b>	Continuous	Speed 1= 0.5 mm/s Speed 2 = 1 mm/s Speed 3 = 4mm/s
<b>Probe</b>	Categorical	1/ Knife  2/ Fork

\*Cut through

Knife probe (1.75mm) stop test at 15 mm, 6 fries in a row

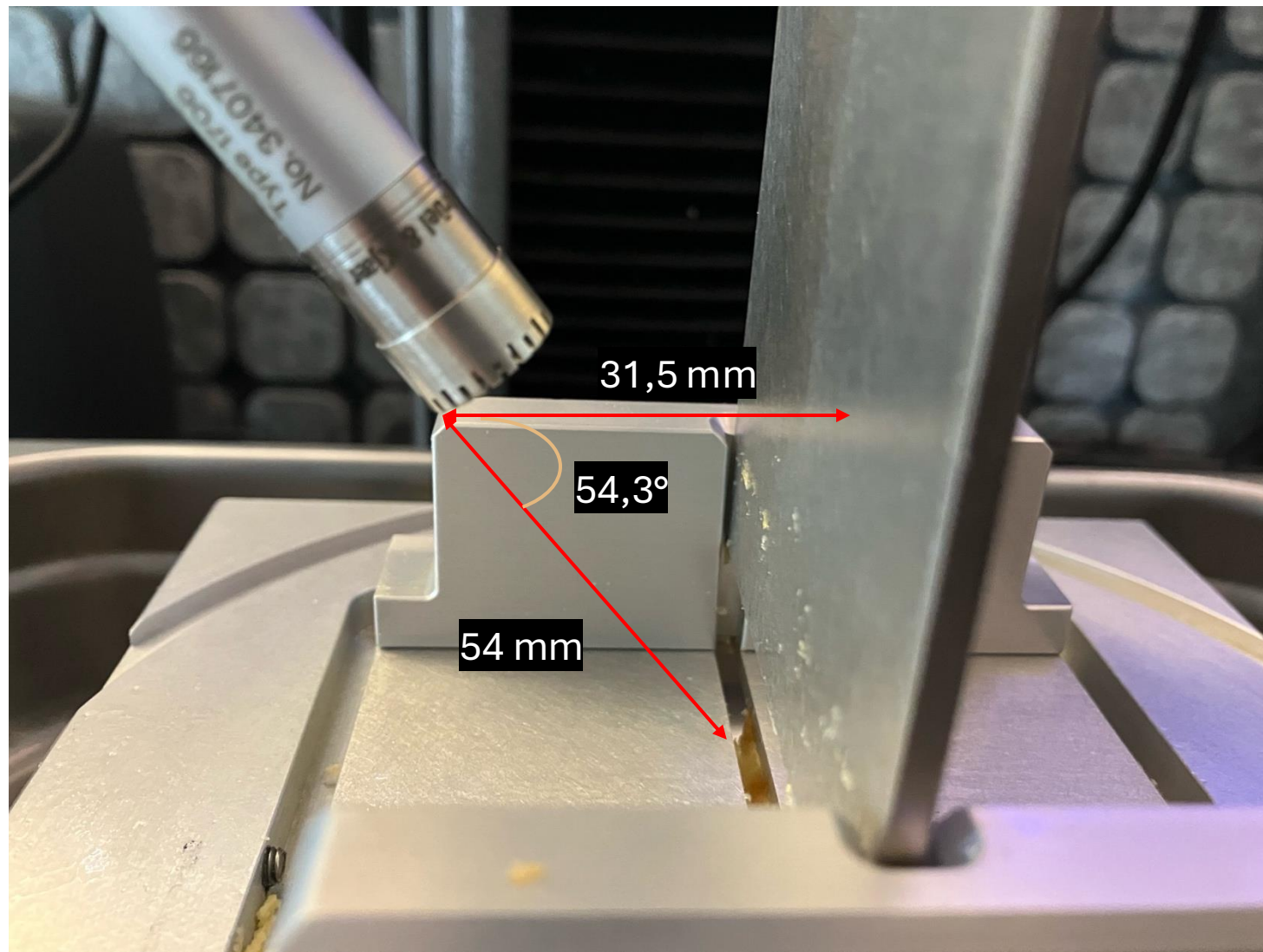


\*\*Puncture

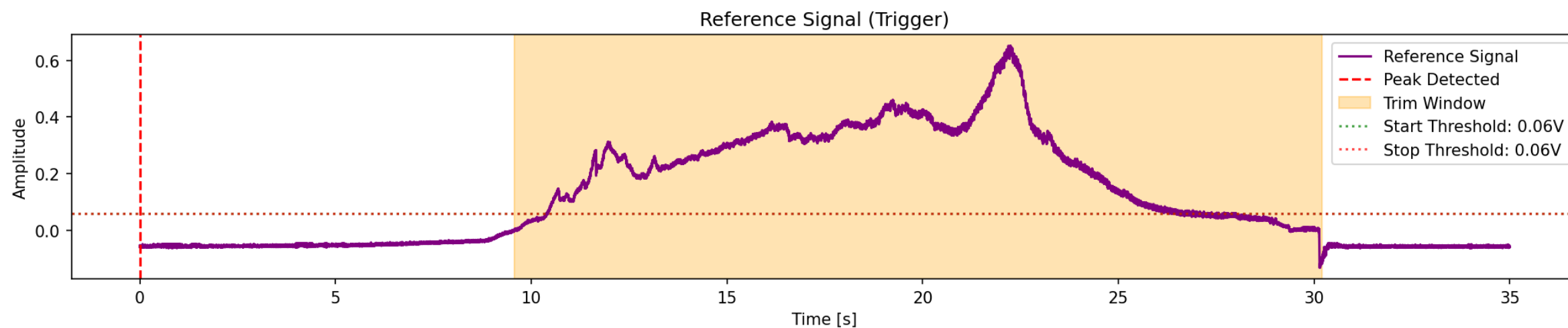
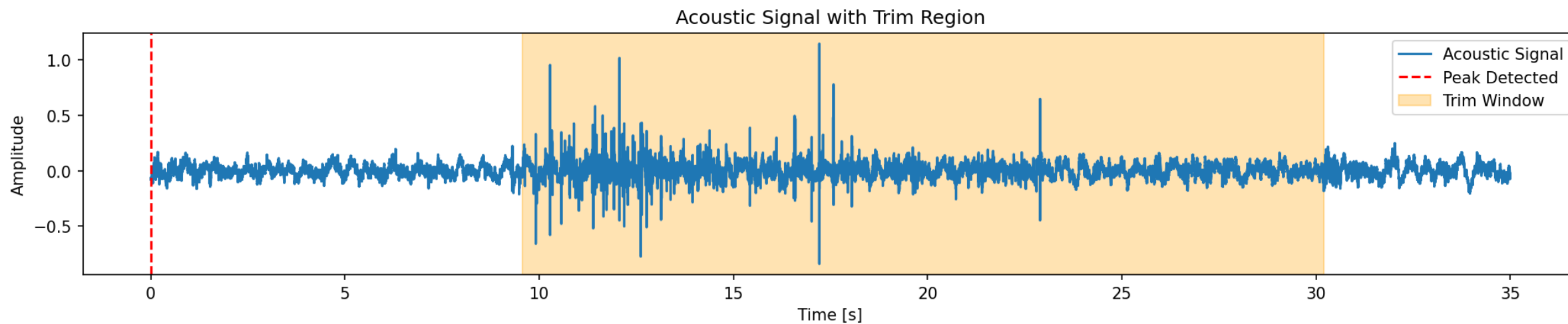
Needles probe (10 needles of 1.75 mm), stop test at 5 mm, 5 fries in a row



# Microphone setup



# Audio output



Quality 1

Quality 3

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DEC 2026

3,5 min



4,5 min



5,5 min



Quality 1

Quality 3

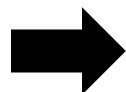
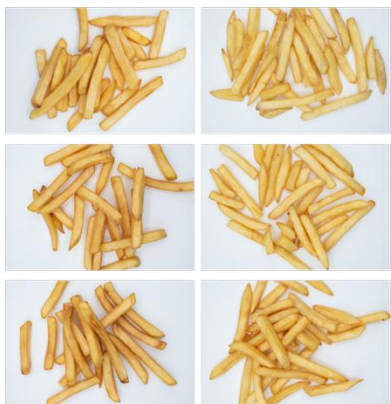
3,5 min



4,5 min



5,5 min



## Bake Samples Overview (sorted by Composite Score: low → high)

frietjes-Q3-3,5.tif  
Composite=39.73



frietjes-Q3-4,5.tif  
Composite=40.51



frietjes-Q1-3,5.tif  
Composite=44.11



frietjes-Q3-5,5.tif  
Composite=44.77



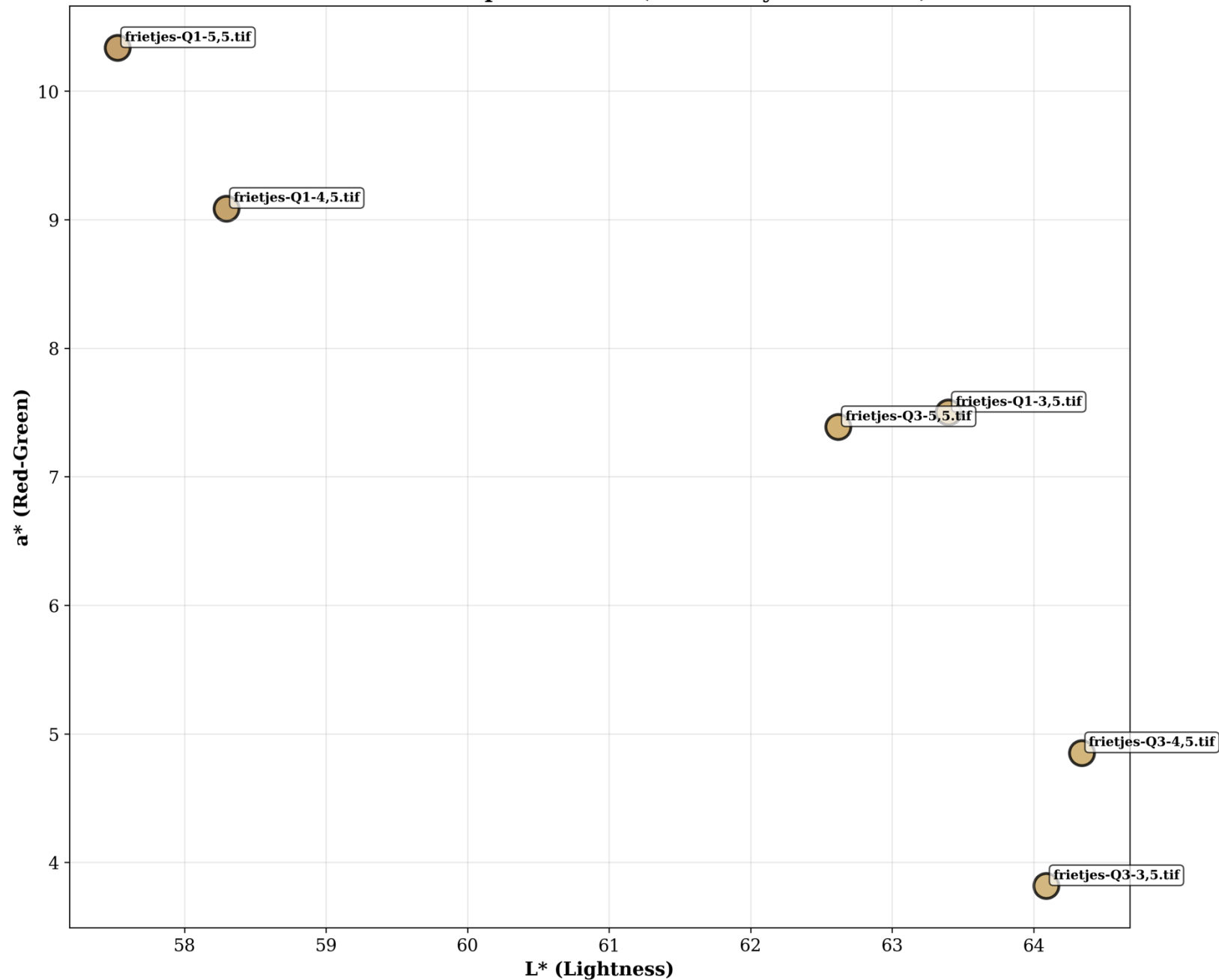
frietjes-Q1-4,5.tif  
Composite=50.79



frietjes-Q1-5,5.tif  
Composite=52.81



# Enhanced Scatterplot L\* vs a\* (colored by actual RGB)



-3-  
Cookies



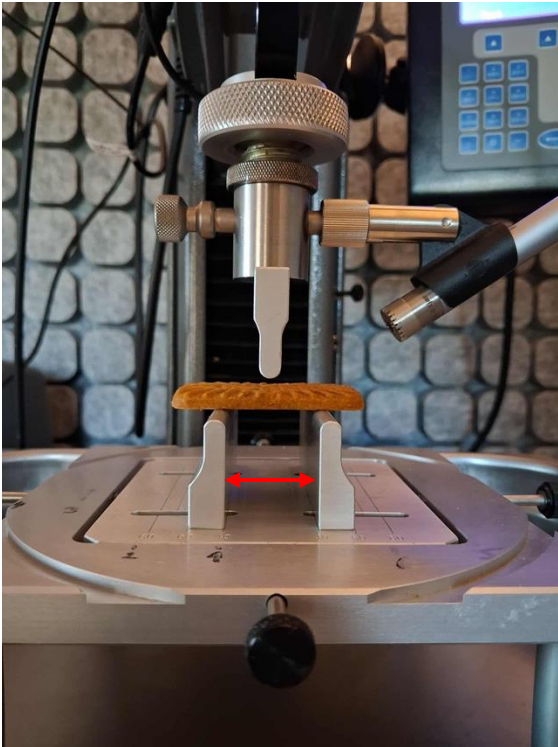
Variables	Type	Values
Moisture	Continuous	L1: 0-2% L2: 2-3% L3: 3-5%
Speed	Continuous	0,2 mm/s 1 mm/s 2 mm/s
Distance	Continuous	1,5 cm (only vertical) 2,5 cm 3,5 cm 4,5 cm
Orientation	Categorical	Horizontal Vertical

# Moisture

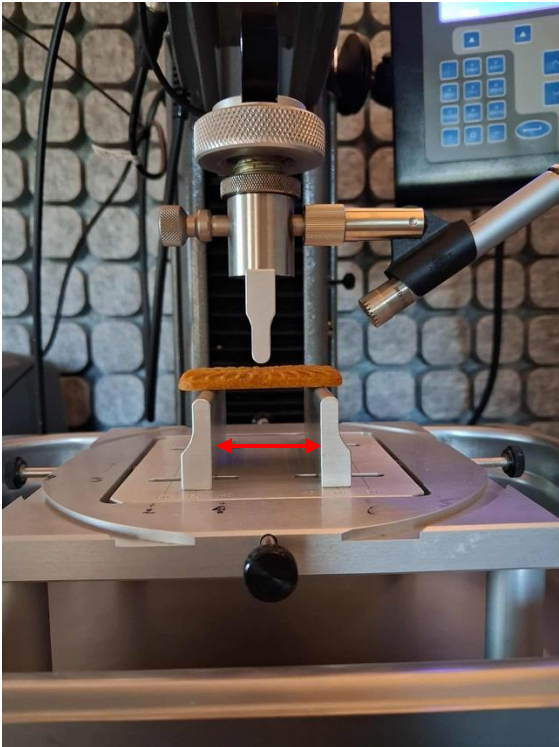
- Main parameter to determine the quality
- Hard to control
  - Climate chamber
    - Almost instant absorption of the moisture in the chamber → cookie too soft to break
  - Open air
    - Gradual moisture uptake → easy to follow up by weight
      - Fresh cookie = ±1,5% moisture → L1
      - After 2 hours open air +1% = ±2,5% → L2
      - After 4 hours open air +2% = ±3,5% → L3

# Orientation

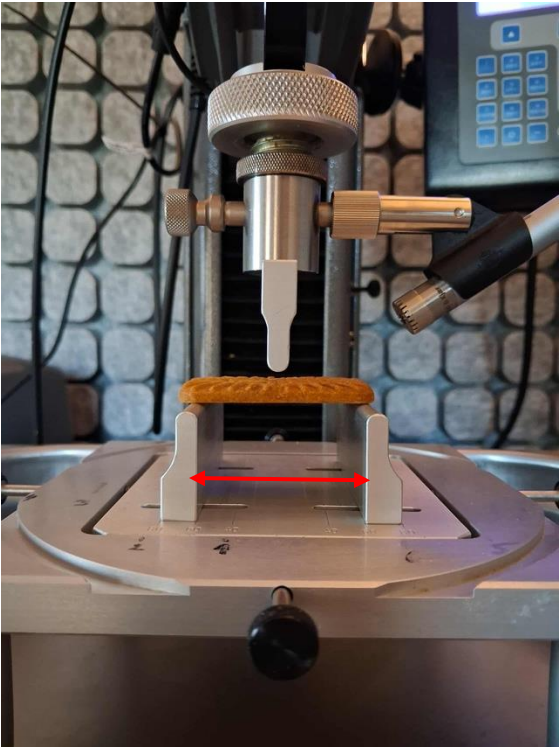
2,5 cm



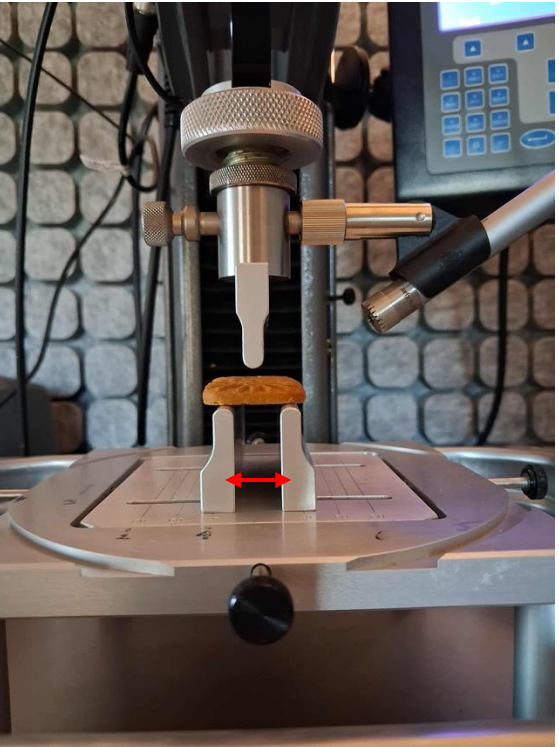
3,5 cm



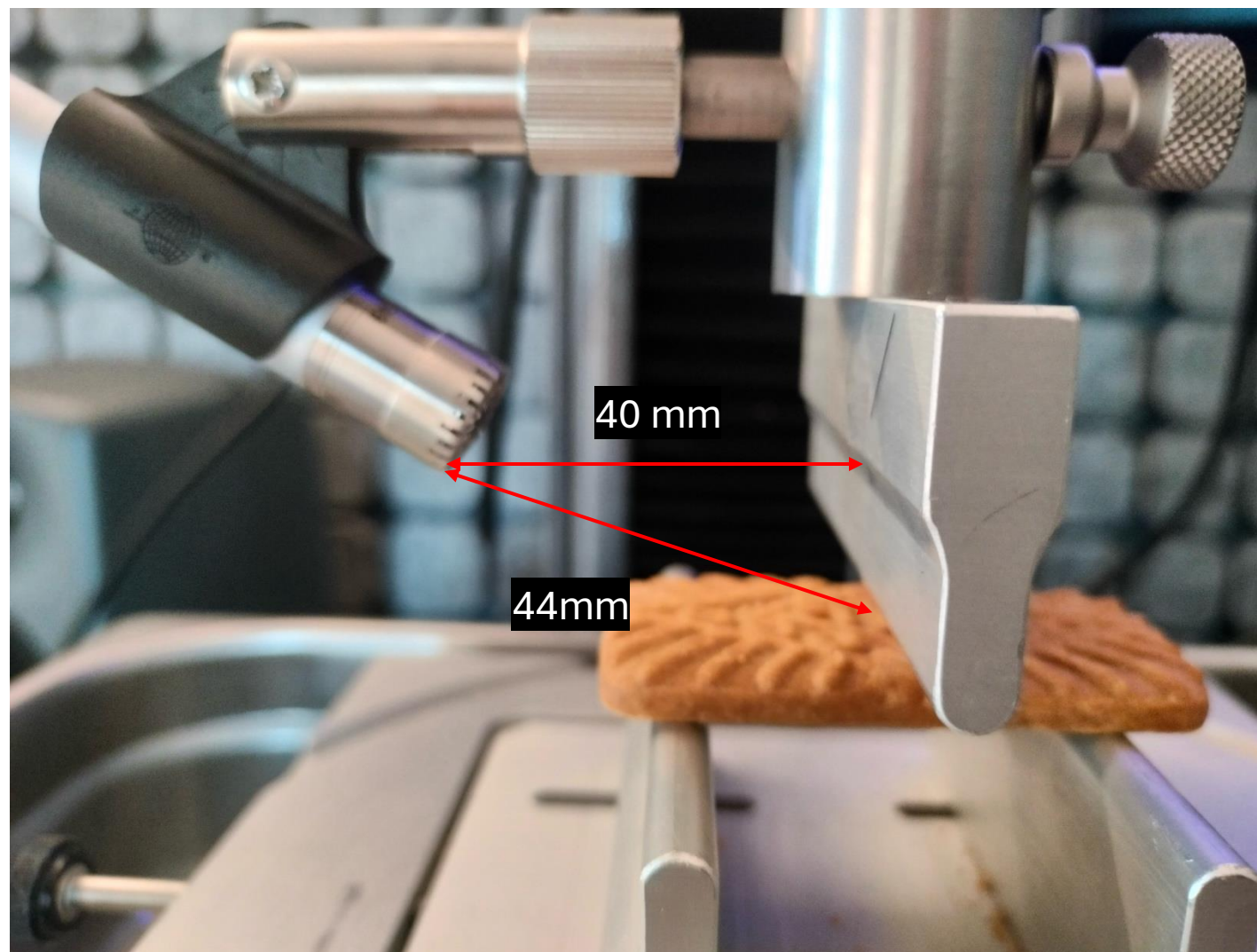
4,5 cm



1,5 cm



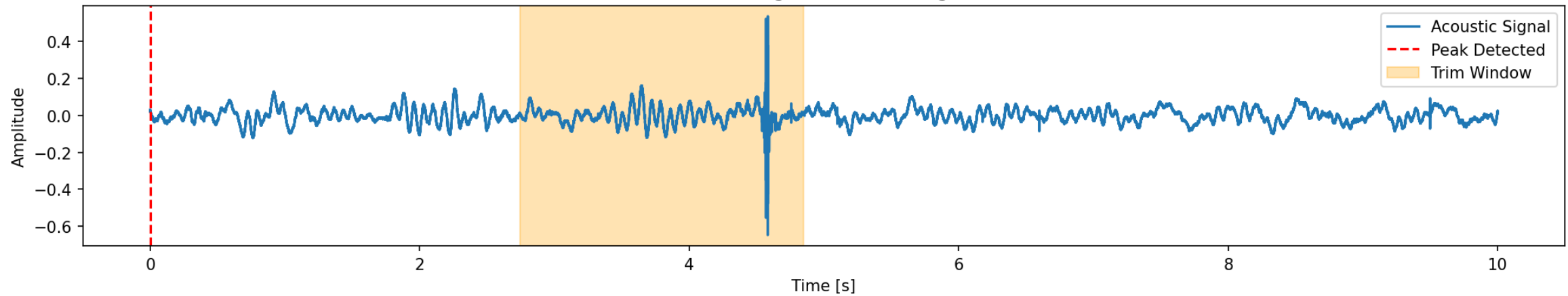
# Microphone setup



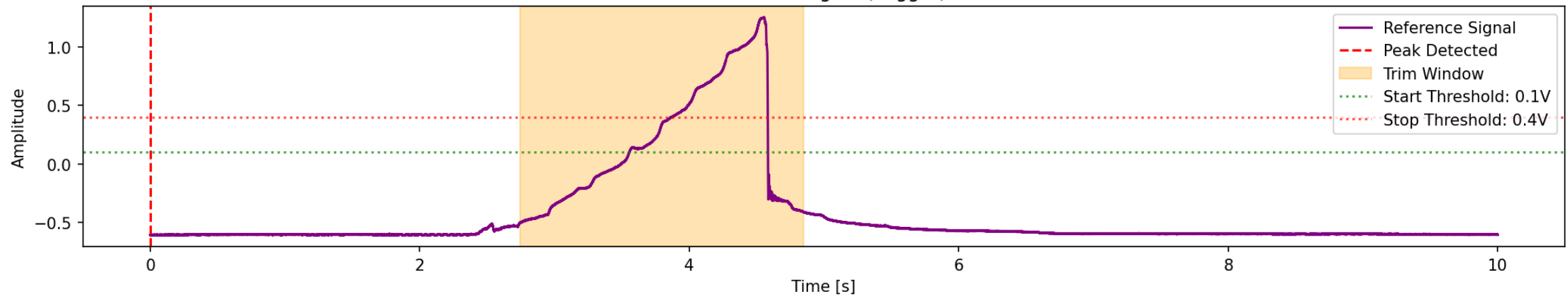
# Audio output

## Crack

Acoustic Signal with Trim Region



Reference Signal (Trigger)



-4-  
Bread  
(Baguette)



## Baguette Crust

### Visual & Texture Profile

The crust is the bread's **sensory calling card**

#### VISUAL ATTRIBUTES

**Darkness:** degree of browning from light to deep golden-brown

**Thickness:** sidewall crust thickness, driven by oven temperature and bake time

**Irregularity:** color variation, blisters, and cracks

**Distribution:** top thicker; sides/bottom thinner

#### TEXTURE ATTRIBUTES

**Crispiness:** cracks/snaps on touch or bite

**Toughness:** resistance when biting through the crust

**Cohesiveness:** structural integrity without excessive crumbling

#### Physicochemical markers:

Water activity ( $A_w$ ) of crust: 0.522–0.540

Moisture: thick crust  $\approx$  11%; thin crust  $\approx$  9.67%

Mechanical transition around  $A_w$  0.68–0.69: brittle  $\rightarrow$  tough (glass  $\rightarrow$  rubbery)

Puncture test most widely used (radius: 2mm – 40mm)

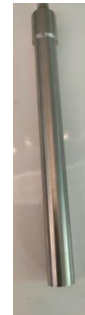
Measuring on **side** → least variation, even surface

Measuring crust over **time**: 30 min - 4h after baking

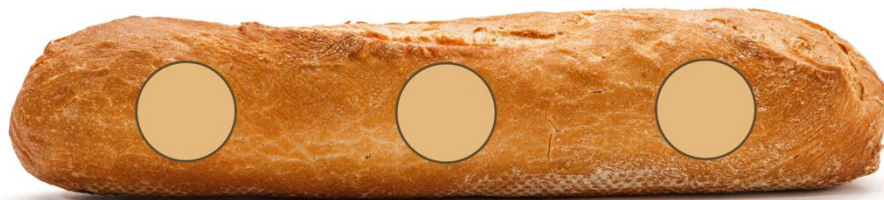
Different zones tip, side, center



Bread probe ( Ø 35,5mm)



Puncture probe ( Ø 10mm)





-5-  
Chocolate

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## Chocolate

### =SNAP

**Method:** protocol available for texture testing  
Measure hardness value / max breaking force

## Ingredients

More cocoa butter in dark chocolate → ‘better snap’  
→ What is a better snap in terms of **audio features**?

Knowledge from fracture tests available  
Different shapes possible → thick tablet gives best measurement results

## Research questions

**Ingredient** influence on snap?  
Effect of chocolate **thickness**?

-6-

# Breaded & Battered products

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## **Breadcrumbs – Crispiness Evaluation**

### **Crispiness under realistic conditions**

Assess crispiness evolution after preparation

→ *warm holding, delivery, serving* conditions

### **Characterization of breadcrumbs**

Compare different breadcrumb types (panko, big crumbs, extra baked, dense crumbs)

Open question: measure baked on standard substrate *or* unbaked (as such)?

Investigate which audio features are linked to

→ breadcrumb type / structure

→ crispiness loss during warm holding

**Sensory attributes:** crispiness, brittleness, hardness

# 2. Measurement System Optimization Methodology

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# Methodology

## Step 1: Optimize the method (Setup protocol)

In our experiments, we test different configurations of our method and use the audio data to find the optimal configuration for which we expect the audio signals for the crunchy and non-crunchy food to be as different as possible.

Taking the cookies as an example, we want to find the optimal method (Distance, Orientation, Speed) that produces the largest difference in the audio signals between the soft and hard cookies.

## The optimal configuration for cookies:

For the cookie dataset, when modeling the **number of peaks**, we discovered an interaction effect between **Speed** and **Moisture %**.

Distance (cm)	Orientation (Short/Long)	Speed (mm/s)	Difference in number of peaks predicted for low and high moisture %
-	Short	0.2	3.50
-	Short	2.0	2.37

# Methodology

## Step 2: Optimize the model (Prediction protocol)

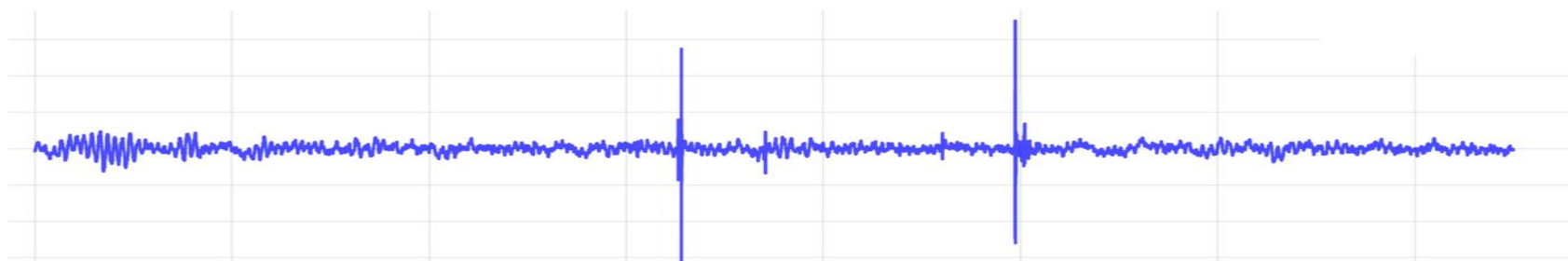
Using the "optimal method" discovered in step 1, collect more data by only varying levels of the crunchy/crispy parameter, and find a mathematical model that best correlates the variance in the audio due to the change in the crunchy/crispy parameter.

# Methodology

Our goal:



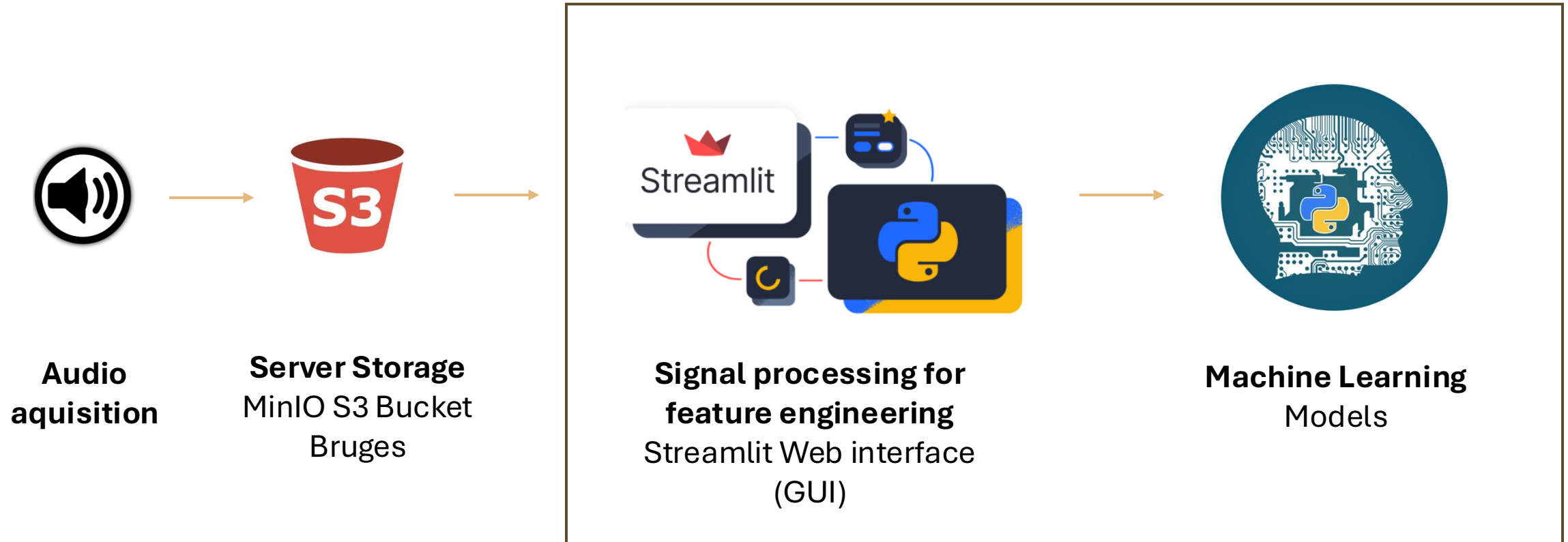
# 2. Audio Acquisition & Analysis



# 3 approaches

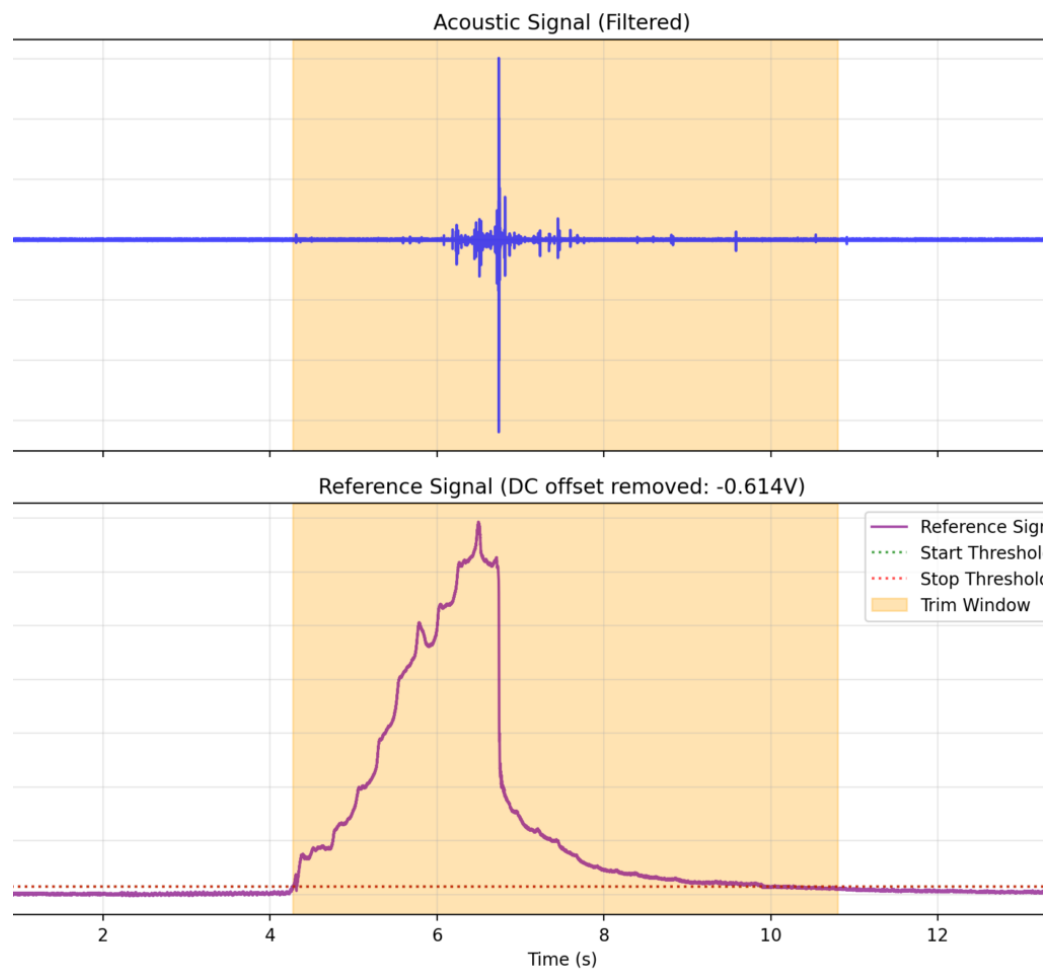
- With audio signal processing expertise
- Use of deep learning pre-trained audio neural networks
- Making own deep learning model

# Data flow: Audio signal processing

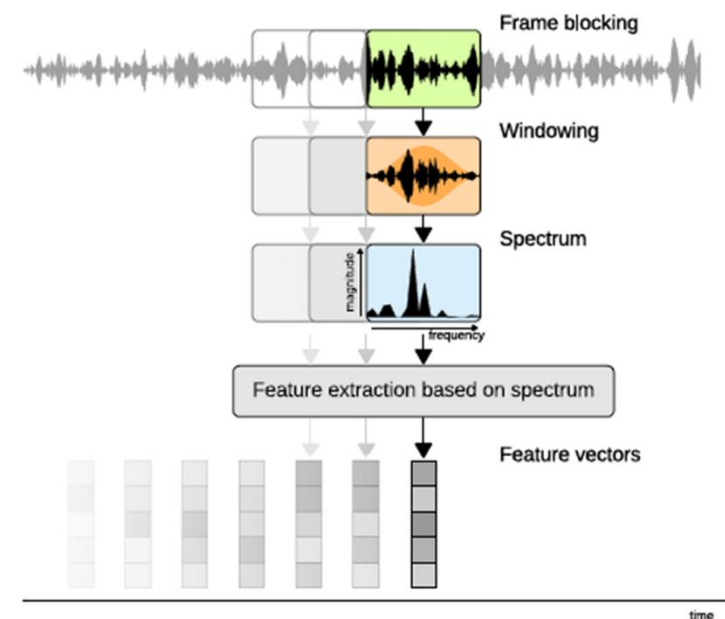
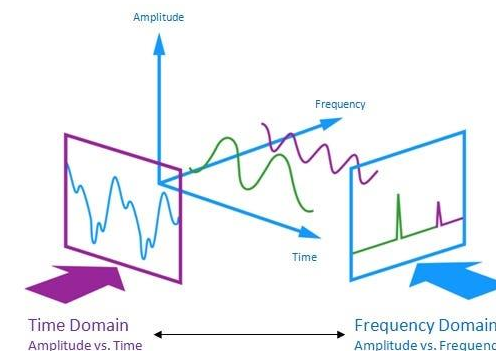


# Signal processing (Streamlit web interface)

## 1. Analysis window



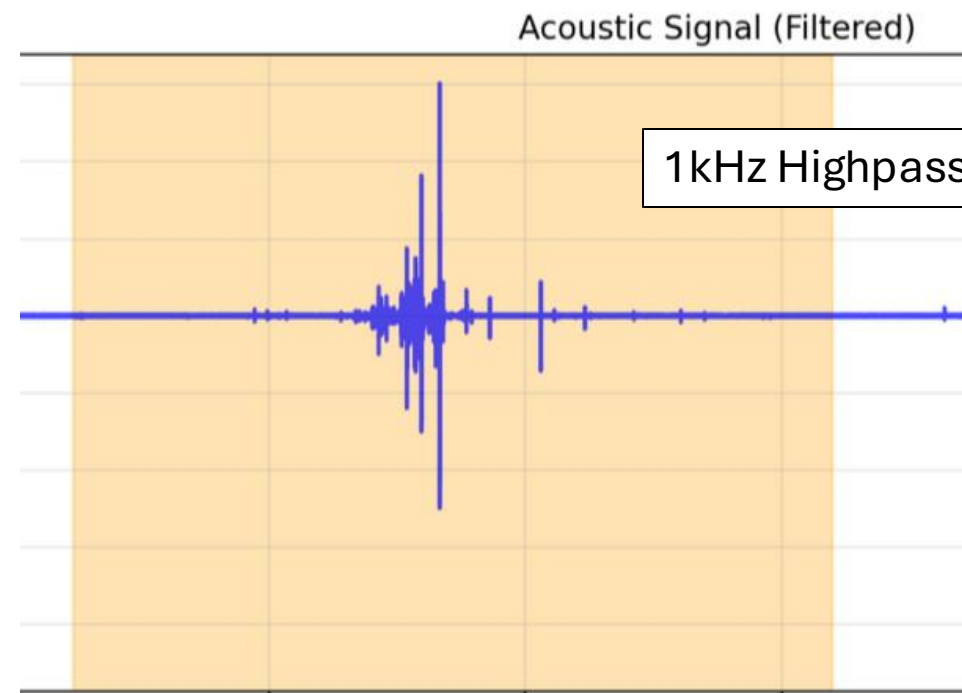
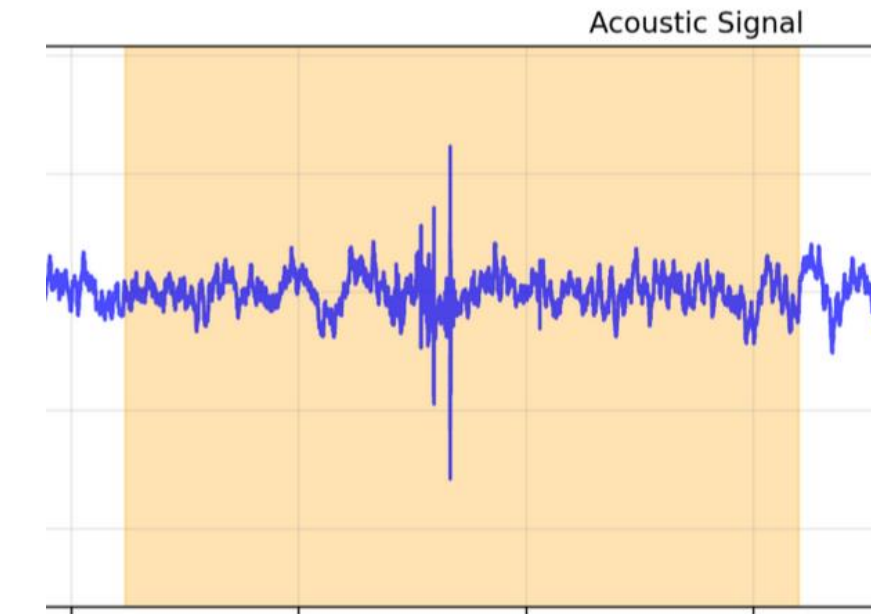
## 2. Feature extraction



# Signal processing

## 1. Analysis window

- Automated method
  - Visual inspection
  - Audio inspection
- Filtered/unfiltered

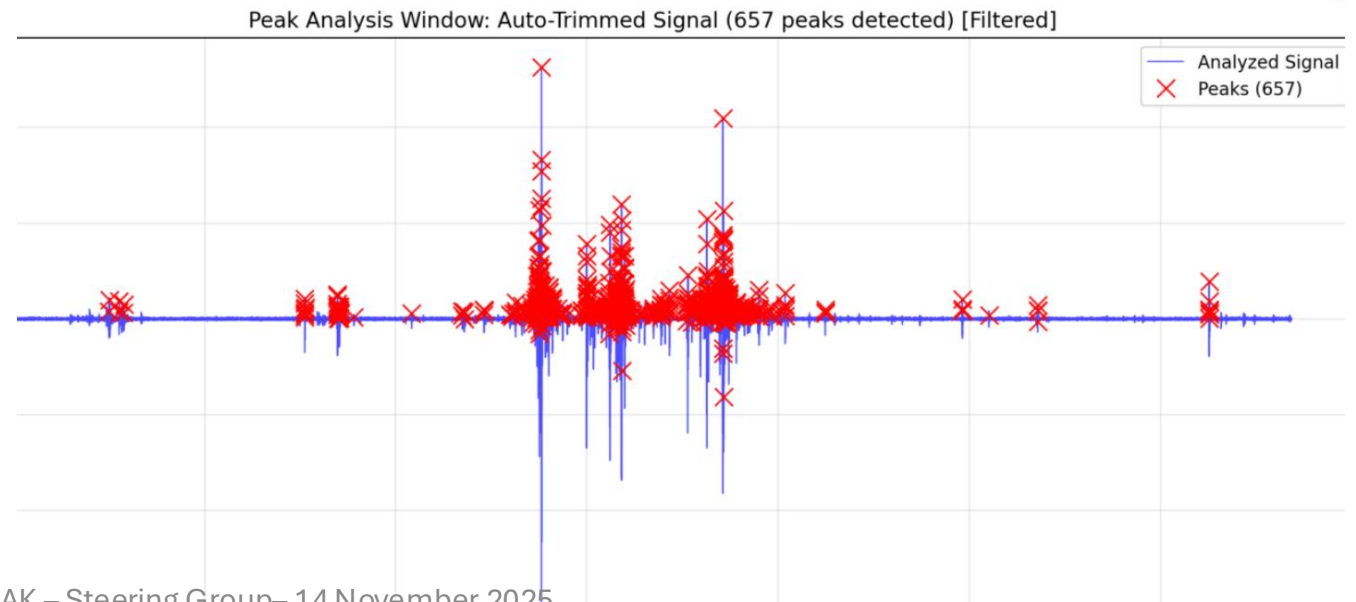
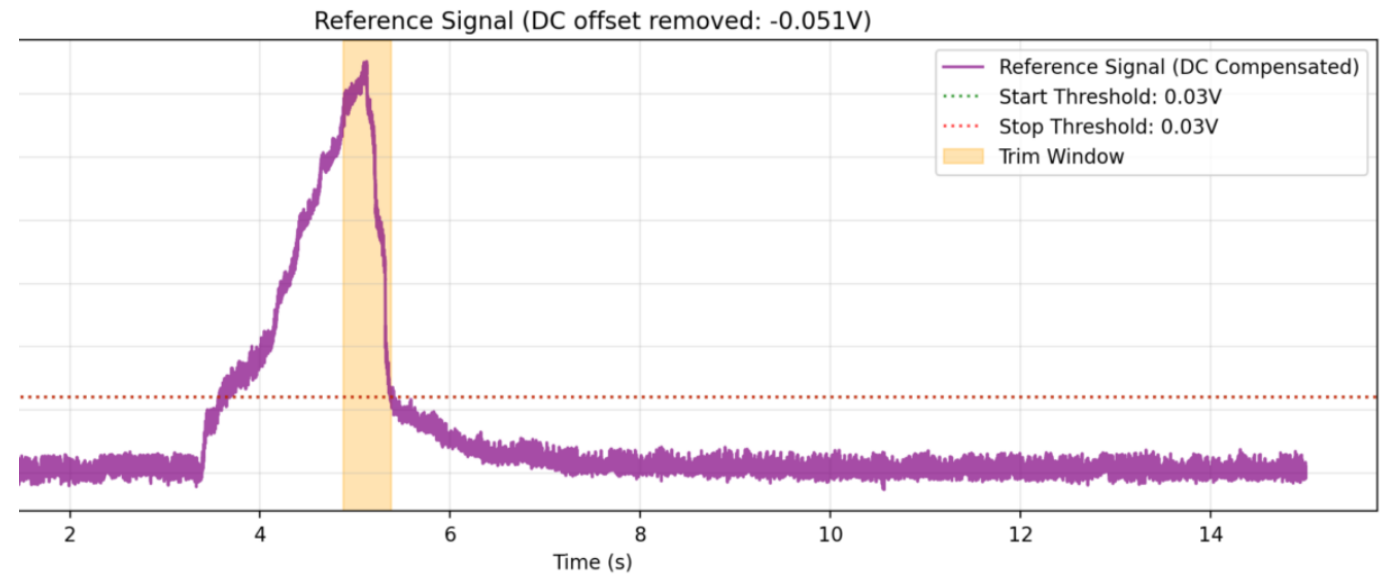


# Signal processing

## 1. Analysis window

- Automated method:
  - Loadcell Data:
    - Thresholds
    - Sharp decline

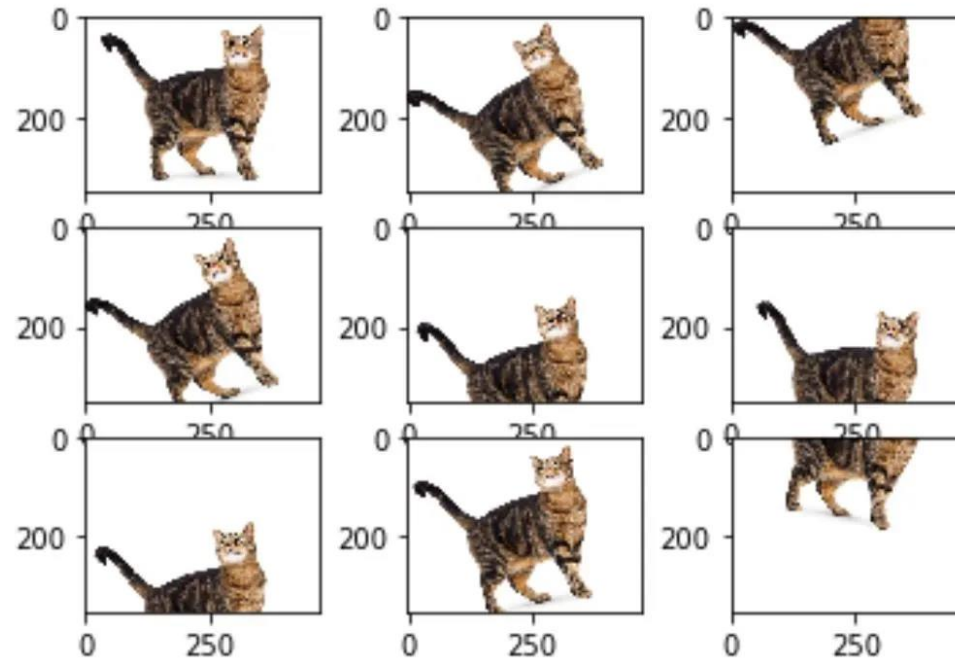
- Audio Data:
  - Peaks



# Signal processing

## 1. Analysis window

- Different ways of looking at the data
- Augment the number of usefull features



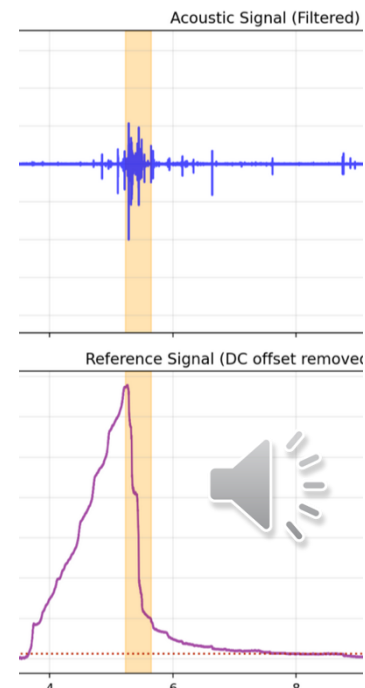
## 1. Analysis window

- **Different analysis windows: focus on different aspects of the audio signal**

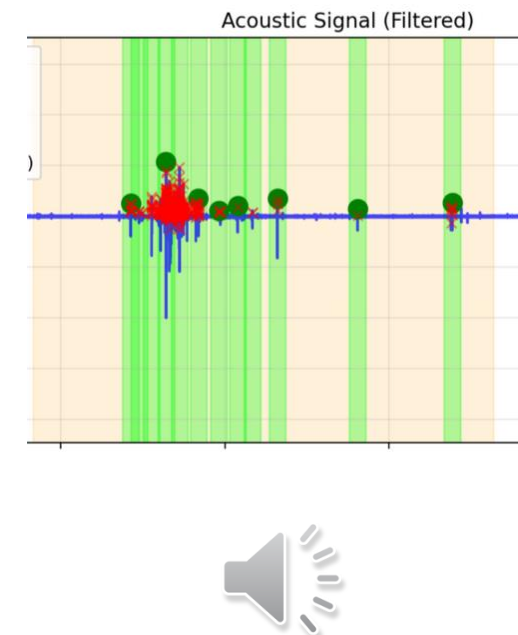
broad: first to last peak  
(within loadcell thresholds)



focused: main cracking  
(loadcell decline + audio peak)



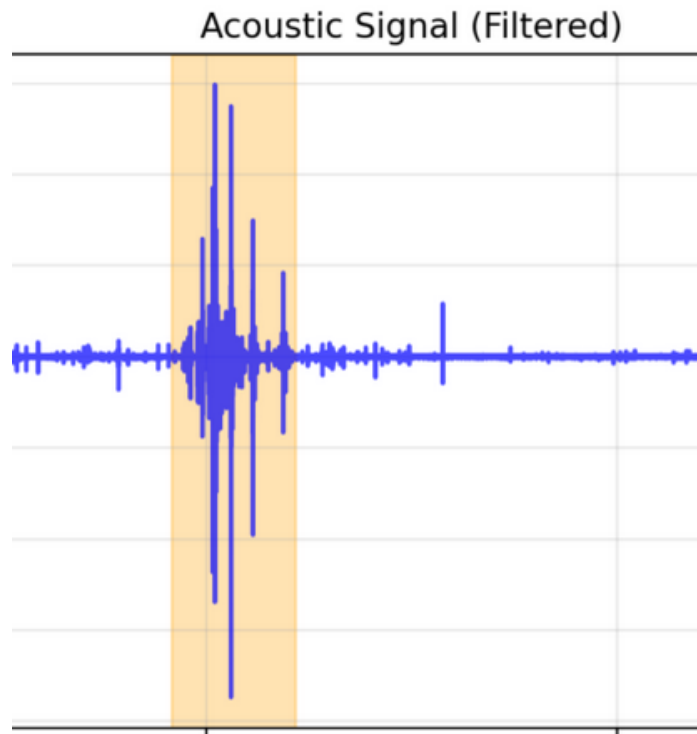
focused: audio peaks  
(statistical features)



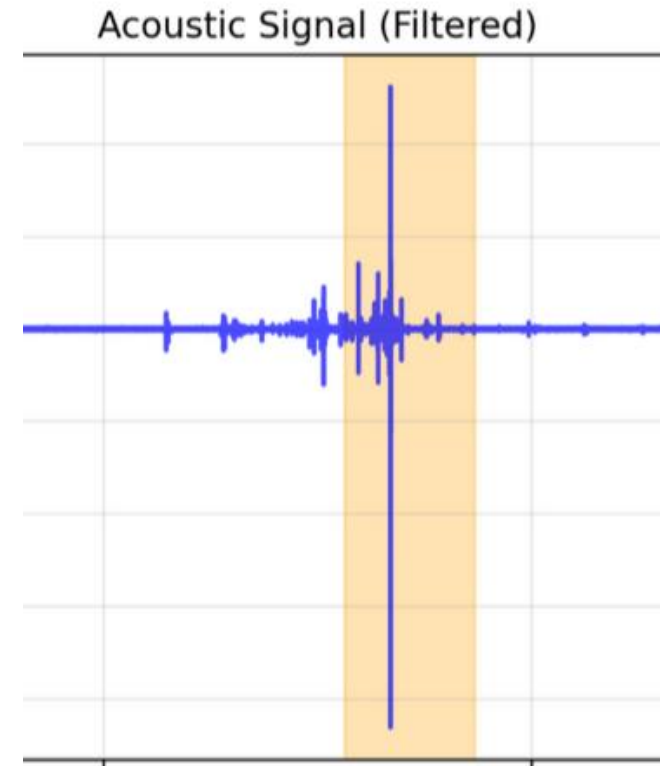
# Signal processing

## Audio examples: cookie

### 'Crunchy'



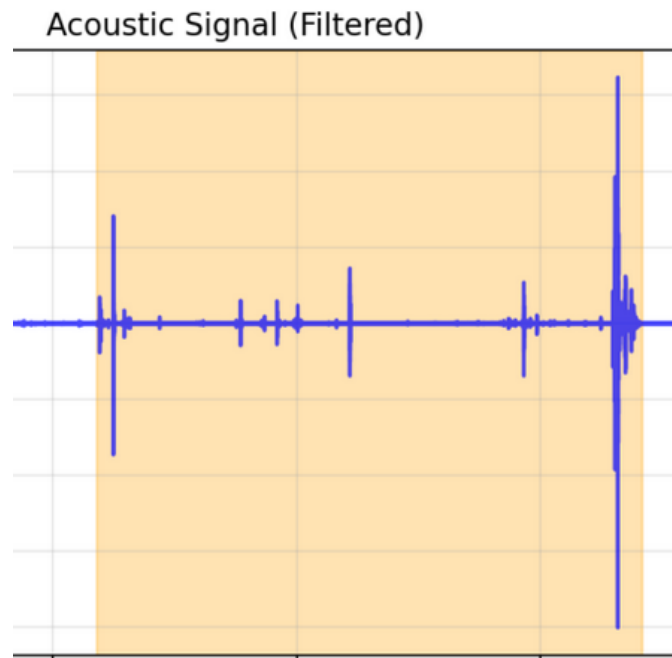
### 'Moist'



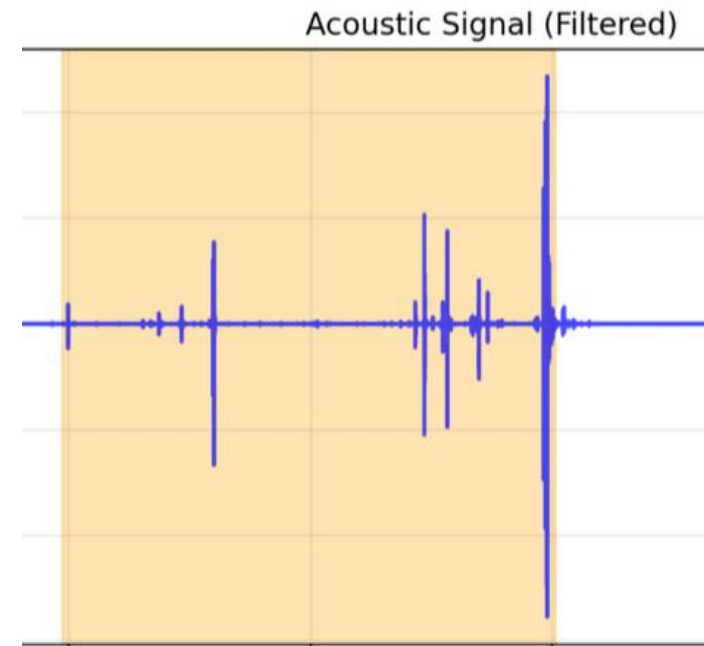
# Signal processing

## Audio examples: chips (single)

**Crunch: low**



**Crunch: high**

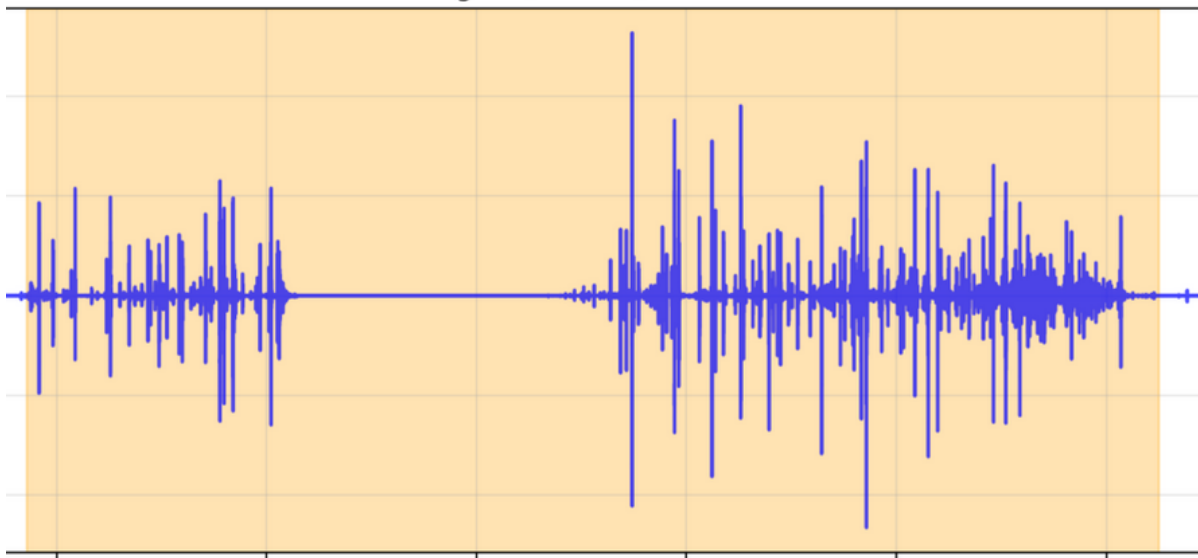


# Signal processing

## Audio examples: chips (stacked)

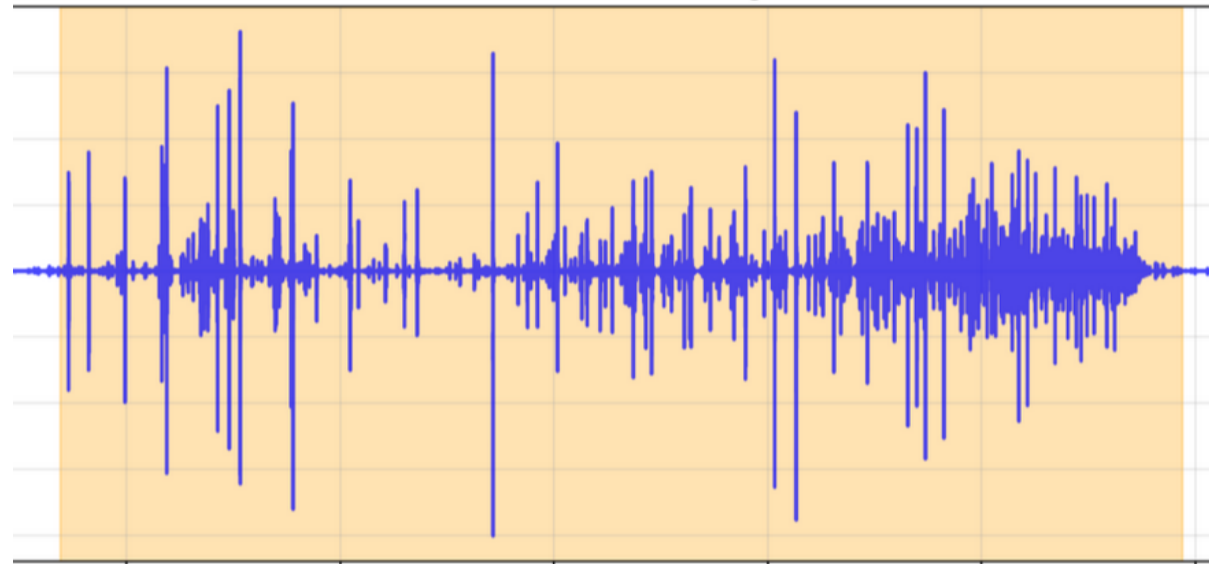
**Crunch: low**

Acoustic Signal (Filtered)



**Crunch: high**

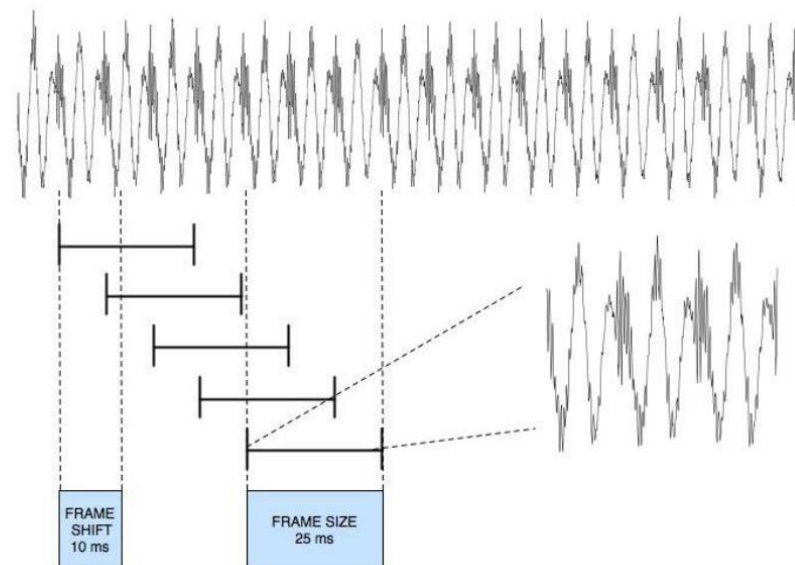
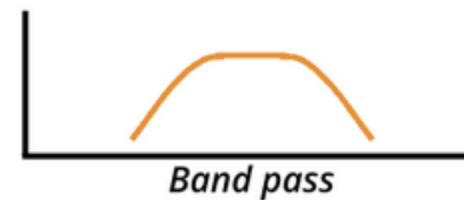
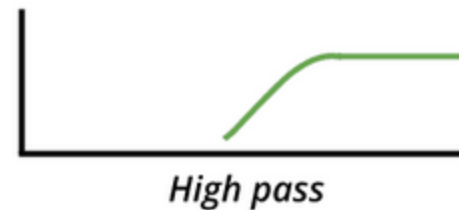
Acoustic Signal (Filtered)



# Signal processing

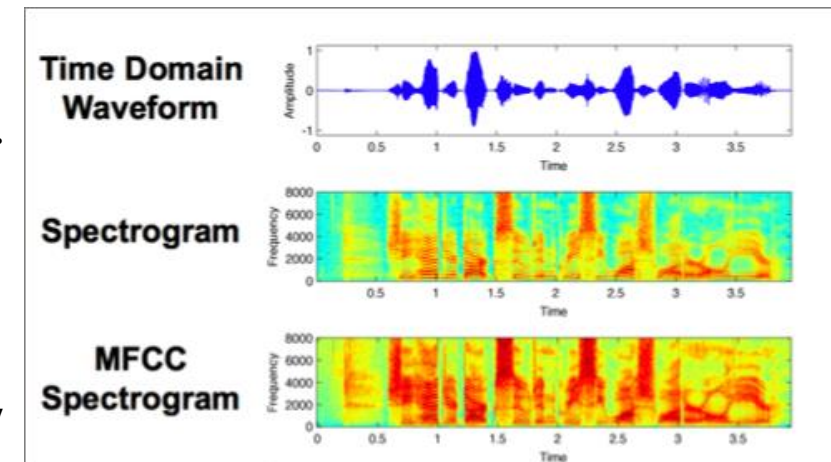
## 2. Feature extraction

- Trimmed analysis window: always unfiltered data
- Feature extraction:
  - Multiple audio filters:
    - High pass
    - Band pass
  - Multiple settings:
    - Frame size
    - Frame shift



## 2. Feature Types: general features

- Time domain:
  - Energy of the signal, distribution of energy over the signal
  - Peaks: number of peaks per time, sharpness of peaks, peak heights, ...
- Frequency domain:
  - Distribution of energy over the spectrum
  - Peakedness, randomness, symmetry, peaks vs valleys, ...
- Mel frequency domain:
  - MFCCs (short-term spectral shape info in several logarithmic frequency bands)
  - + derivatives: velocity and acceleration of changes in spectral shape



## 2. Feature Types: more sophisticated features

- Chroma features:
  - Energy per tone (music: 12 tones)
- Impulse response/transient features:
  - Onset, transient, ... analysis: number of “attacks” in the signal, how long their effect lasts, ..
- Impact and crack related features:
  - Impact sharpness (abruptness of spike, time between cracks, ...)
- Knock related features
- Speech features:
  - intensity, duration of the explosive part of a /p/, /b/, /t/ etc
  - Pitch, voicing ratio, tempo, ...
  - Formant analysis (which frequencies are observed together per sound? → dominant resonances + bandwidth (energy damping per resonance frequency))



# Data science time!

- Many feature sets x many frequency bands x many trimming methods = **many features!** (around 20.000)
- We have limited data (max. around 400 samples, first around 70)
  - 20000 features is too much!
  - Not all models are suitable
- How to know which features to use? → feature selection!
- Which modelling technique to choose? → model selection!

# Feature selection funnel

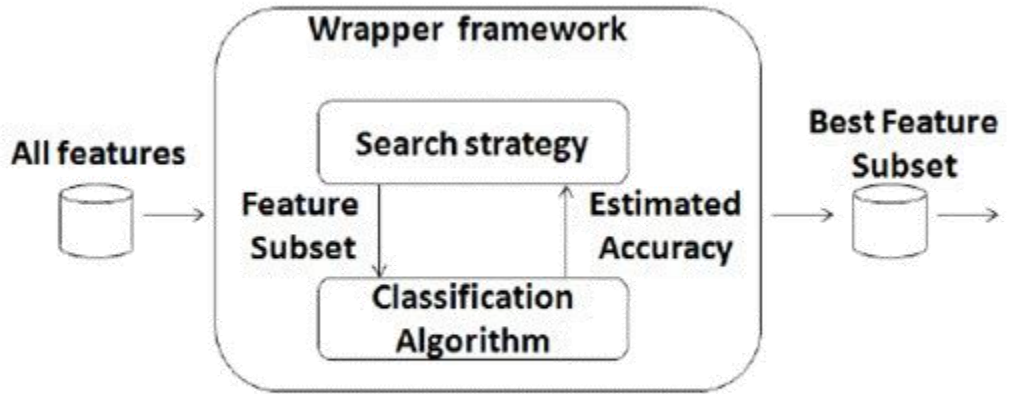
1. Remove low-variance features/  
remove correlated features

Filter methods (purely statistical)  
Pearson correlation >0,85  
Spearman correlation >0,90

2. Remove features  
with no correlation  
with moisture

3. Keep  
features  
which  
increase  
the  
predictive  
power of  
the ML  
model

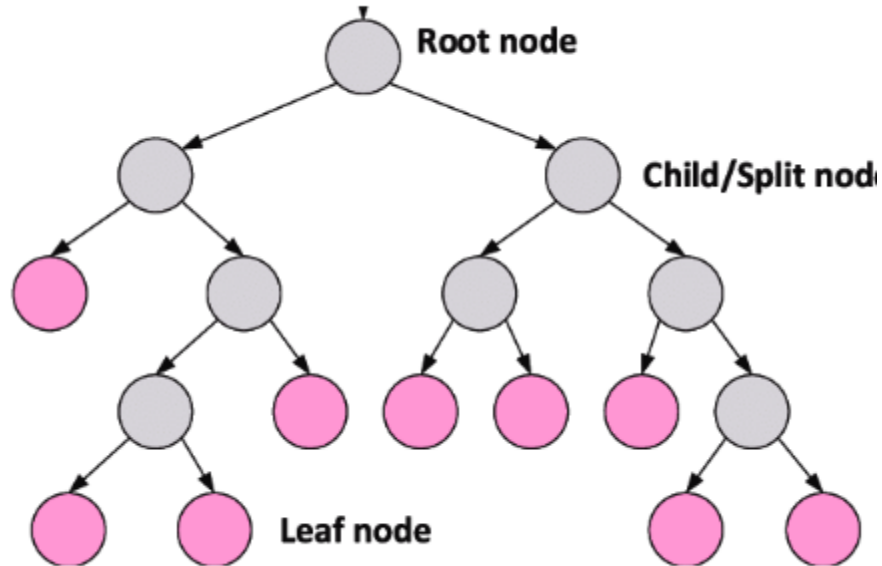
Wrapper/embedded methods (Machine Learning)



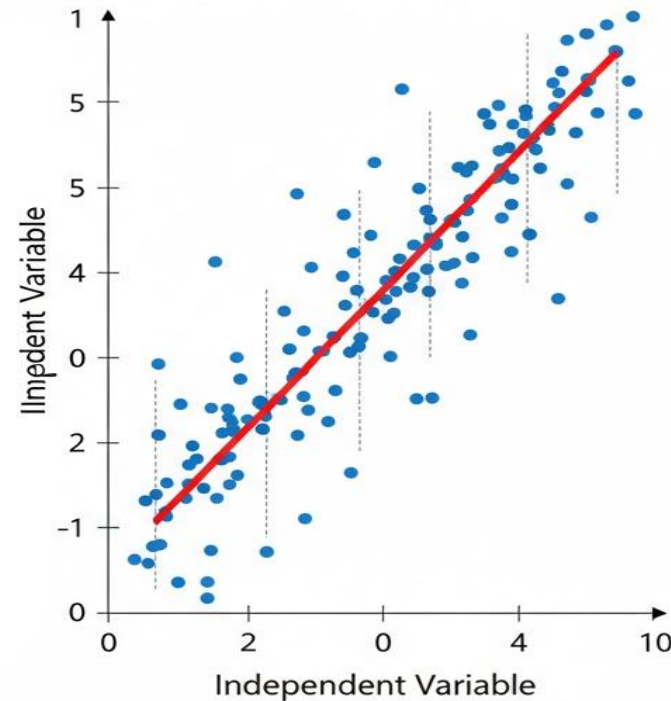
# Model selection: start from simple models

Decision tree / regression tree

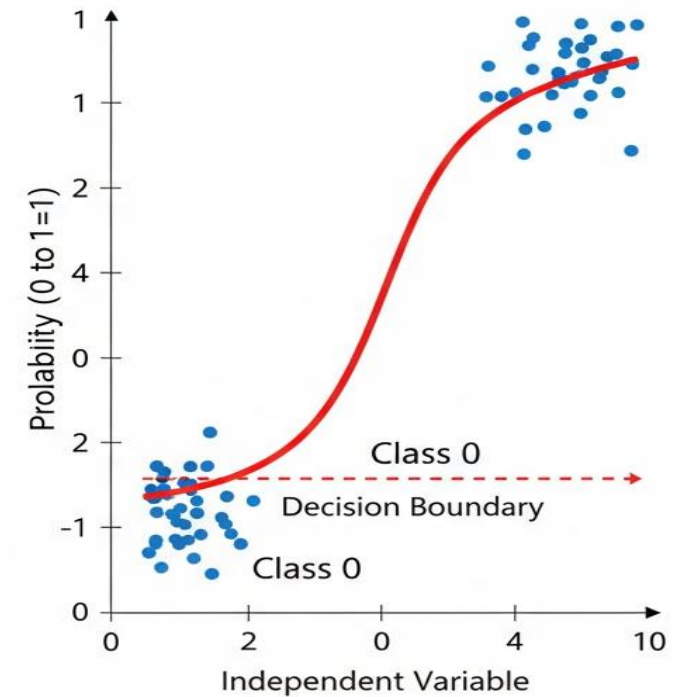
logistic / linear regression



Linear Regression



Logistic Regression

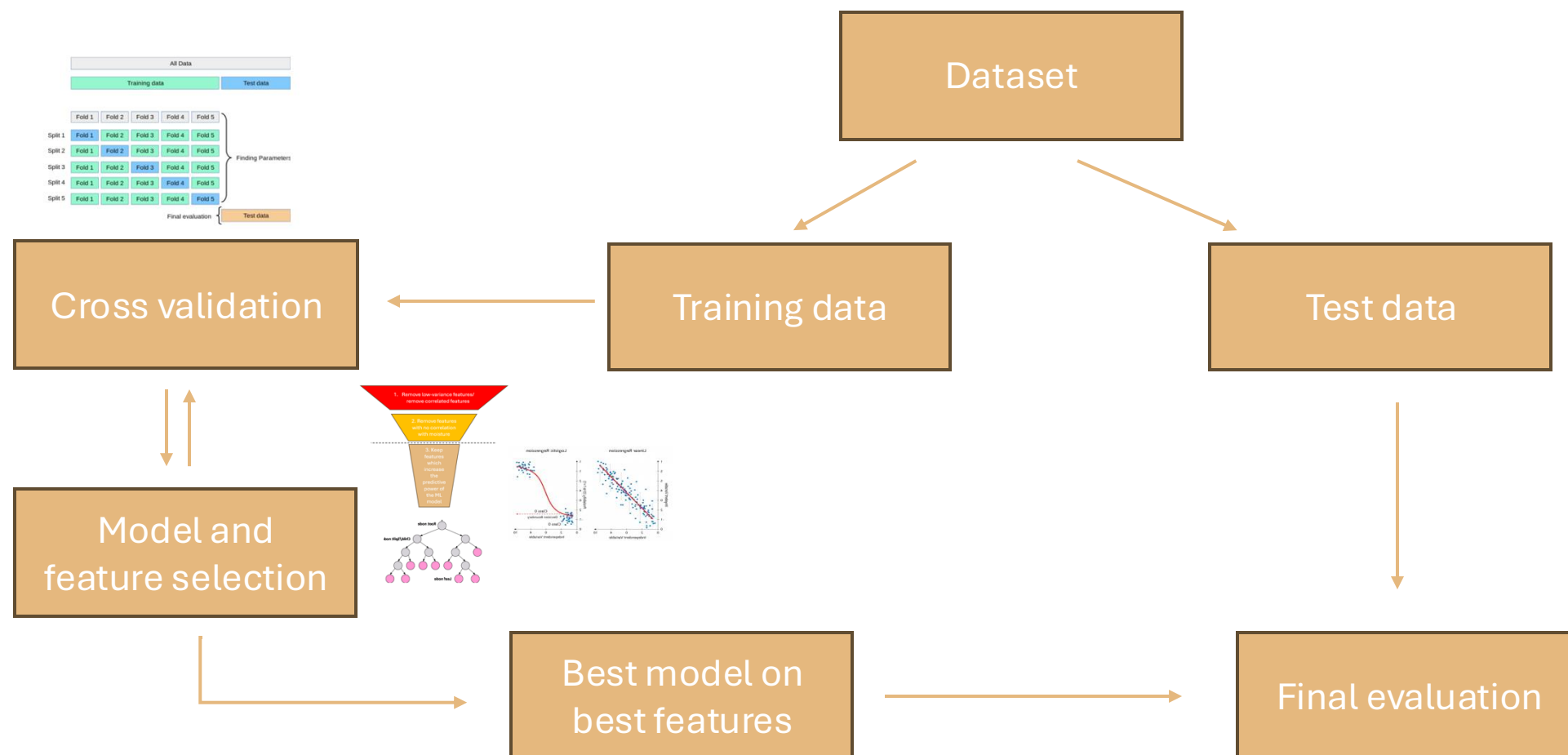


# Model selection: start from simple models

... and combine many into an ensemble model!

- Every model trained on a slightly different dataset: different samples, different feature subsets, different model type, ...
- Two well-known ensemble models:
  - XGBoost (combination of decision trees)
  - Ensemble linear regression with Elastic Net (combination of linear regression models + extra feature selection)

# Model validation: experimental setup

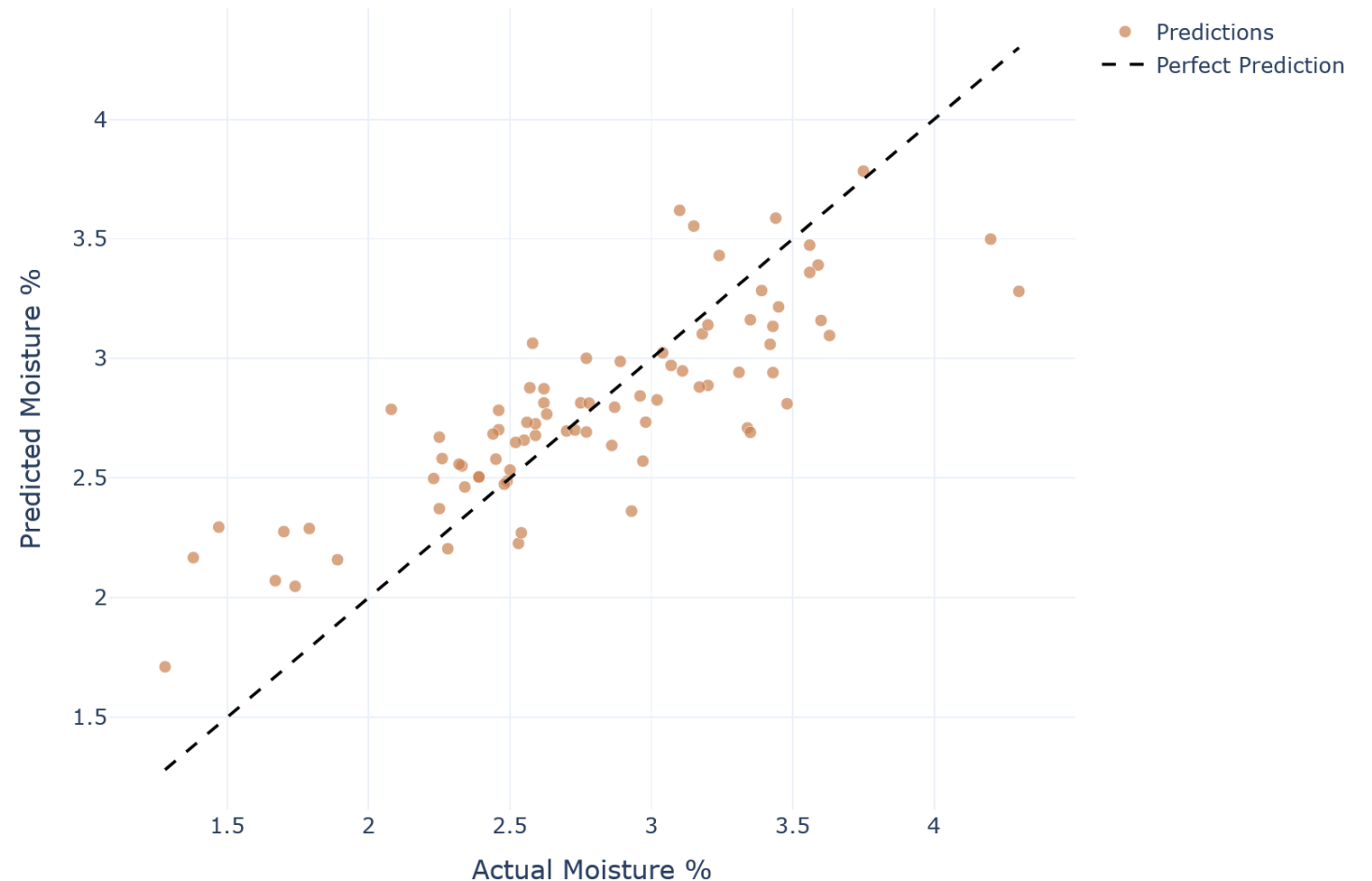


# Machine learning

## 3. Results

- Model test on new data
- Model combined from models created with different analysis windows
- Further finetuning:
  - Better feature selection methods
  - Examine outliers ?
  - Feature combinations for nonlinear relationships
- **Dataset:**
  - Orientation: horizontal
  - Speed: 0.2mm/s

Ensemble - Predictions vs Actual (Test Set)  
 $R^2 = 0.6661$



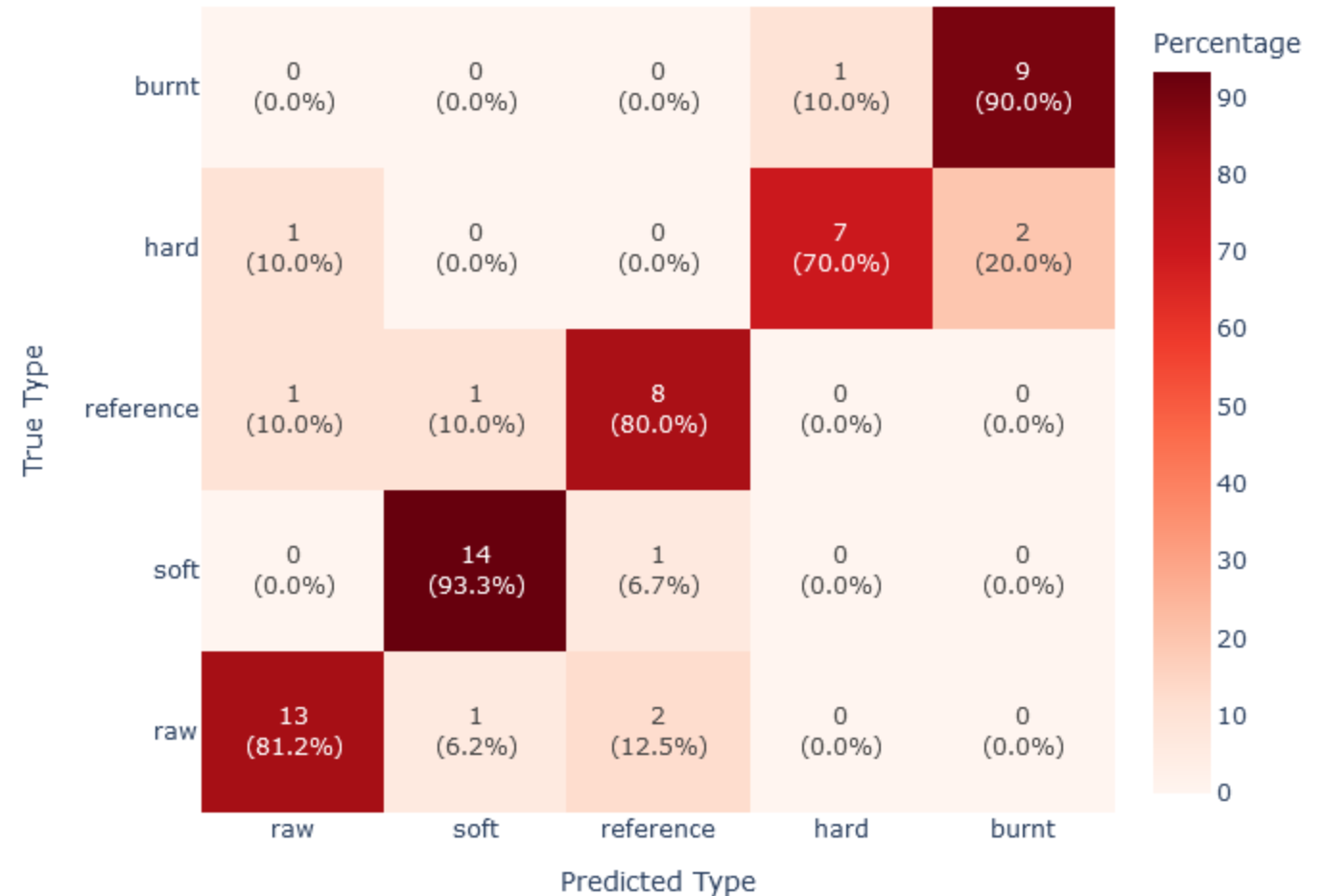
# Machine learning

## 3. Results

- Chips predicted quality vs real quality (classification)
- Model test on new data (not previously seen by model)
- Ensemble model from different analysis windows
- Overall accuracy: 83%
- **Dataset:**
  - Method: Break
  - Speed: 0.2mm/s

### Confusion Matrix (Test Set)

Ensemble (soft\_voting\_ensemble, 4 models)



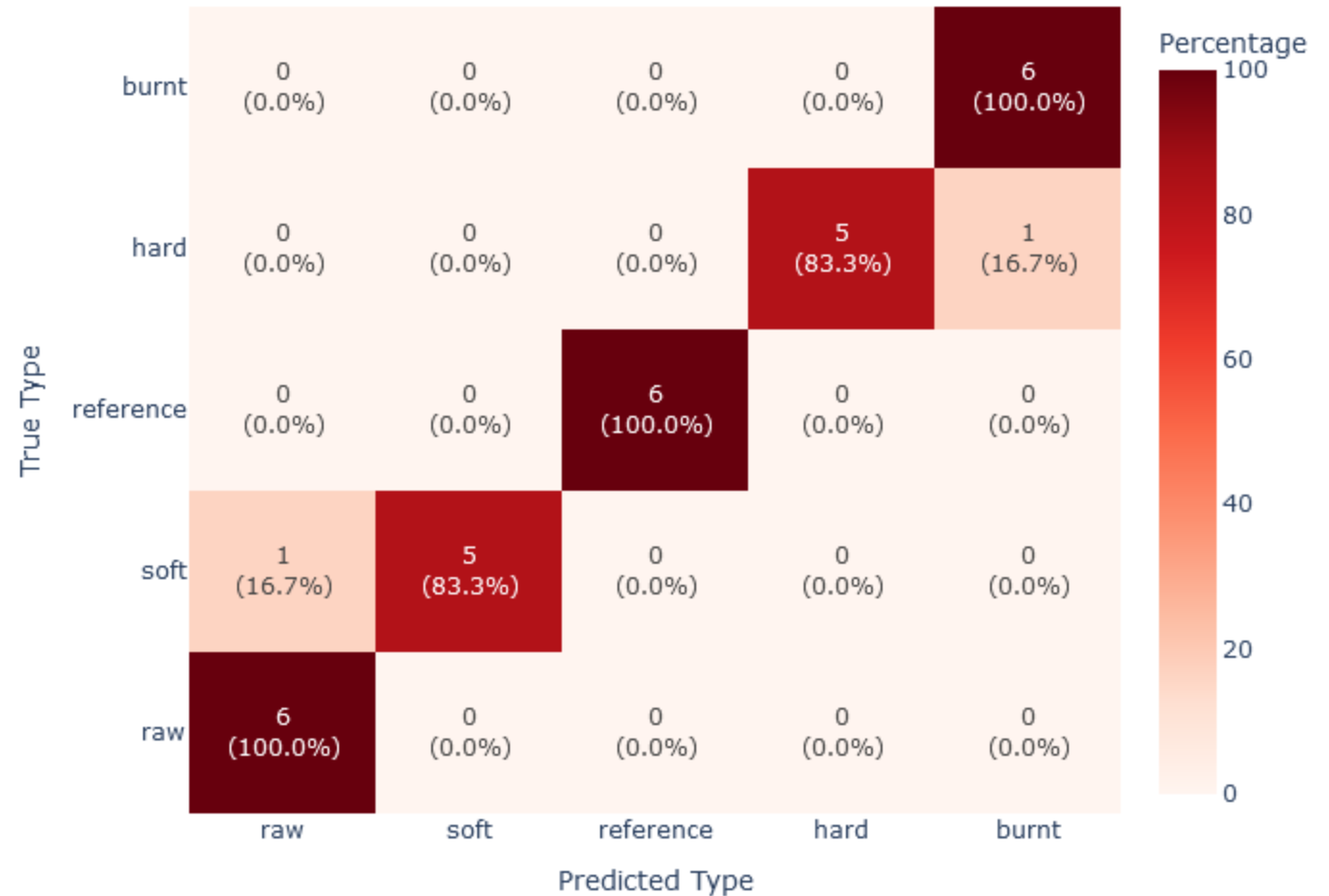
# Machine learning

## 3. Results

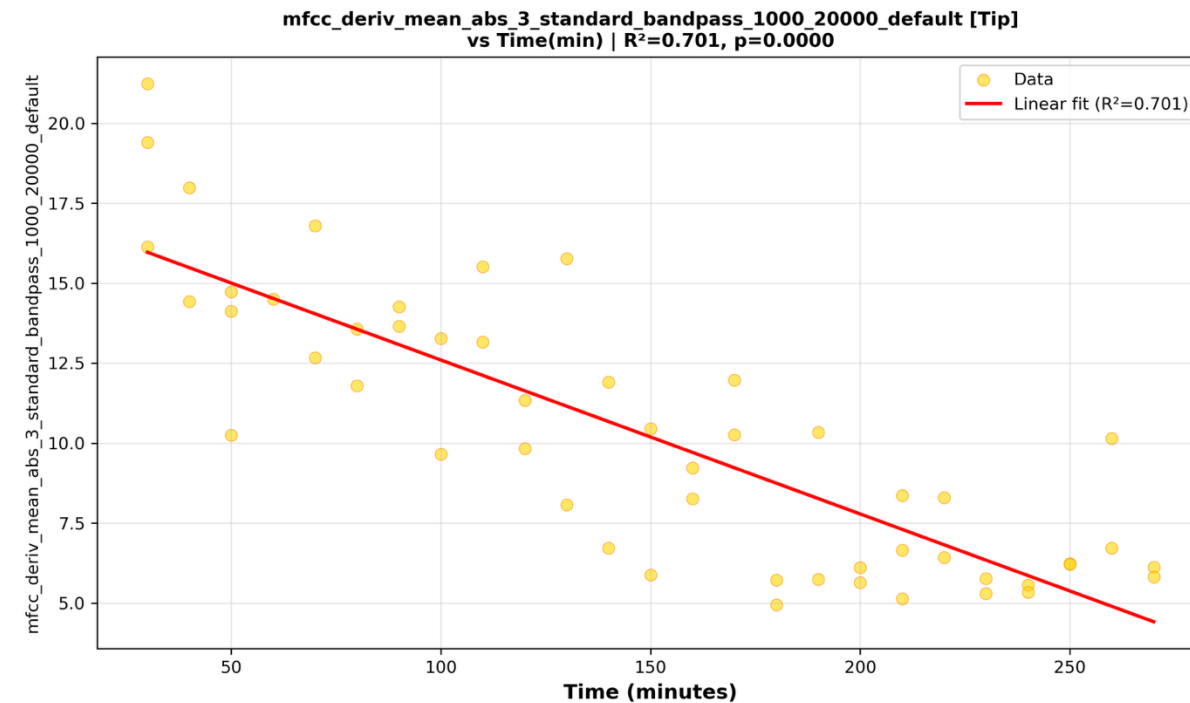
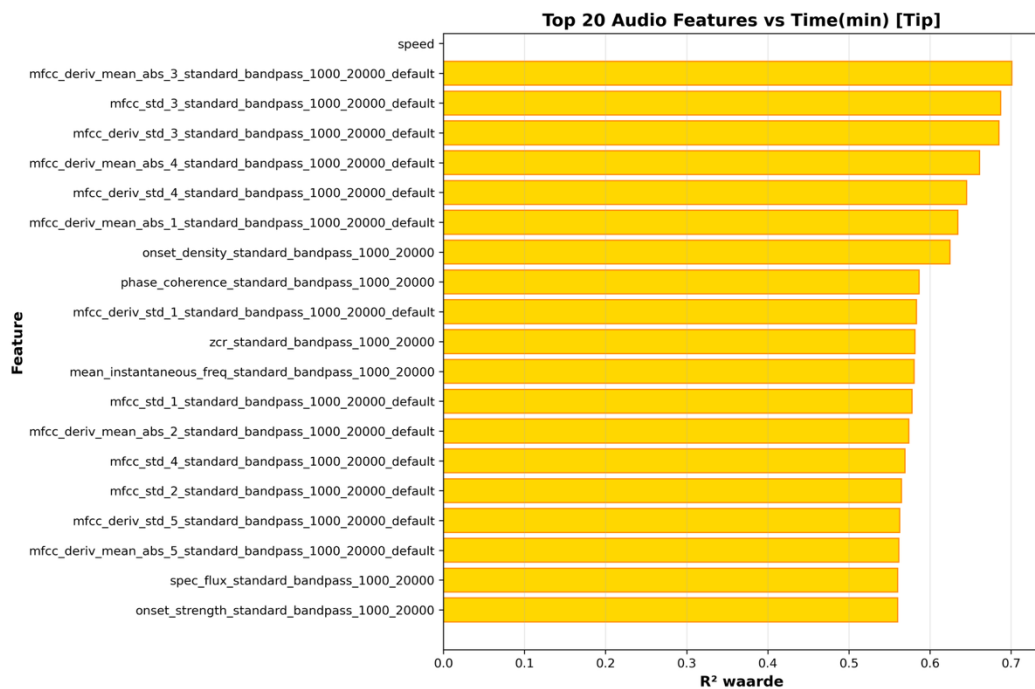
- Chips predicted quality vs real quality (classification)
- Model test on new data (not previously seen by model)
- First model: Finetuning possible
  - Feature selection
  - Combining different models from different analysis windows
- Overall accuracy: 93%
- **Dataset:**
  - Method: **STACKED**
  - Speed: 2mm/s

Confusion Matrix (Test Set)

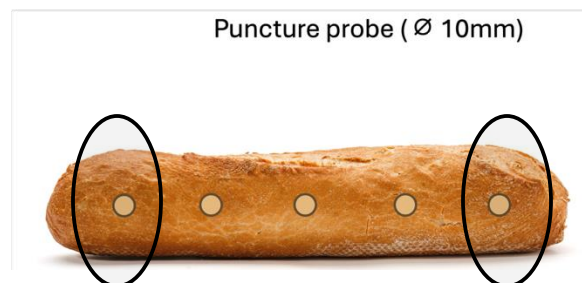
ElasticNet



## Crispiness over time : Tip, Puncture probe

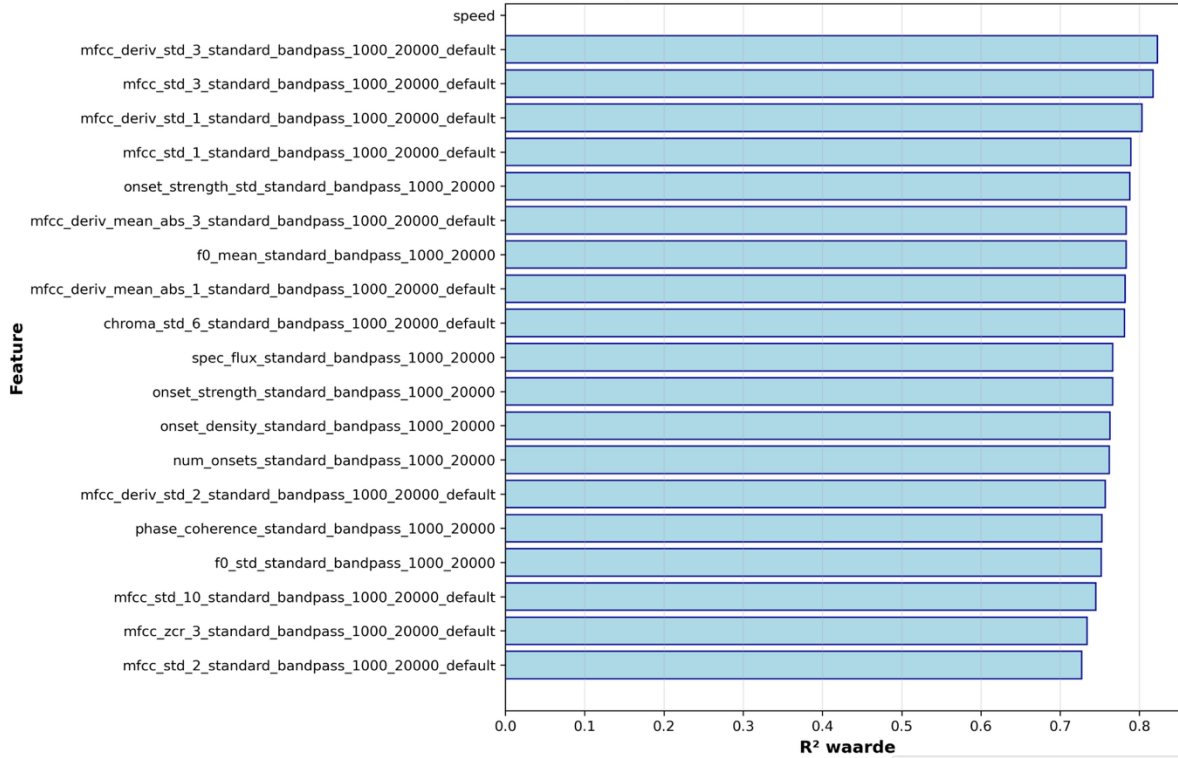


-4-  
Bread  
(Baguette)

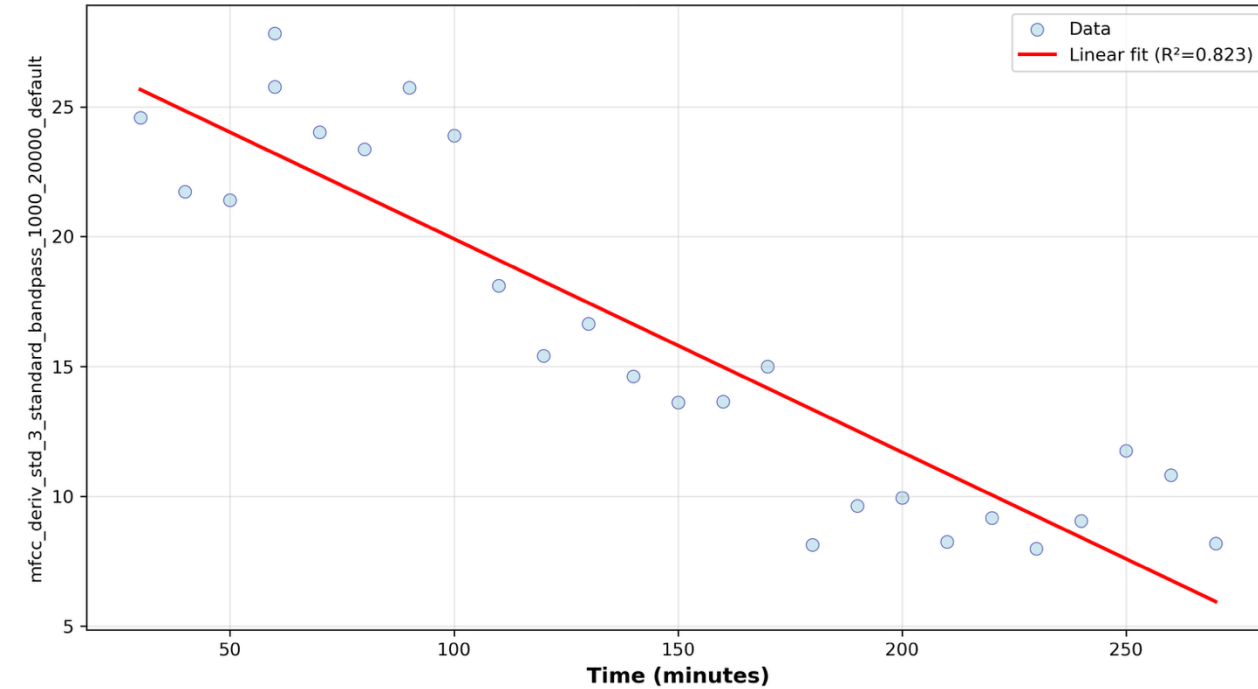


## Crispiness over time : Middle, Puncture probe

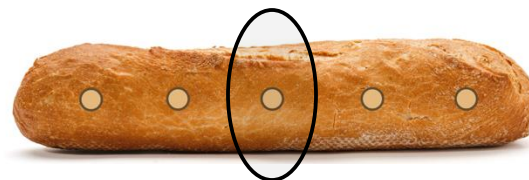
Top 20 Audio Features vs Time(min) [Middle]



mfcc\_deriv\_std\_3\_standard\_bandpass\_1000\_20000\_default [Middle]  
vs Time(min) | R²=0.823, p=0.0000



Puncture probe (Ø 10mm)



# Which features were selected the most for the cookies?

Feature Type	Acoustic Meaning	Moisture Connection
Spectral entropy	Spread of energy	Cracking = broadband noise
Peak density / num peaks	Transient density	Cracking = many small impacts
MFCC regularity/range	Spectral envelope variation	Cracking = irregular fine structure
F <sub>0</sub> std / range	Unstable resonances	Cracking = multiple microfractures
Chroma std	Frequency irregularity	Cracking = scattered spectral content
Impact sharpness	Steep attack	Cracking = sharp onsets
High-band energy (10–20 kHz)	Brightness	Cracking = high-frequency content

# Which features were selected the most for the chips?

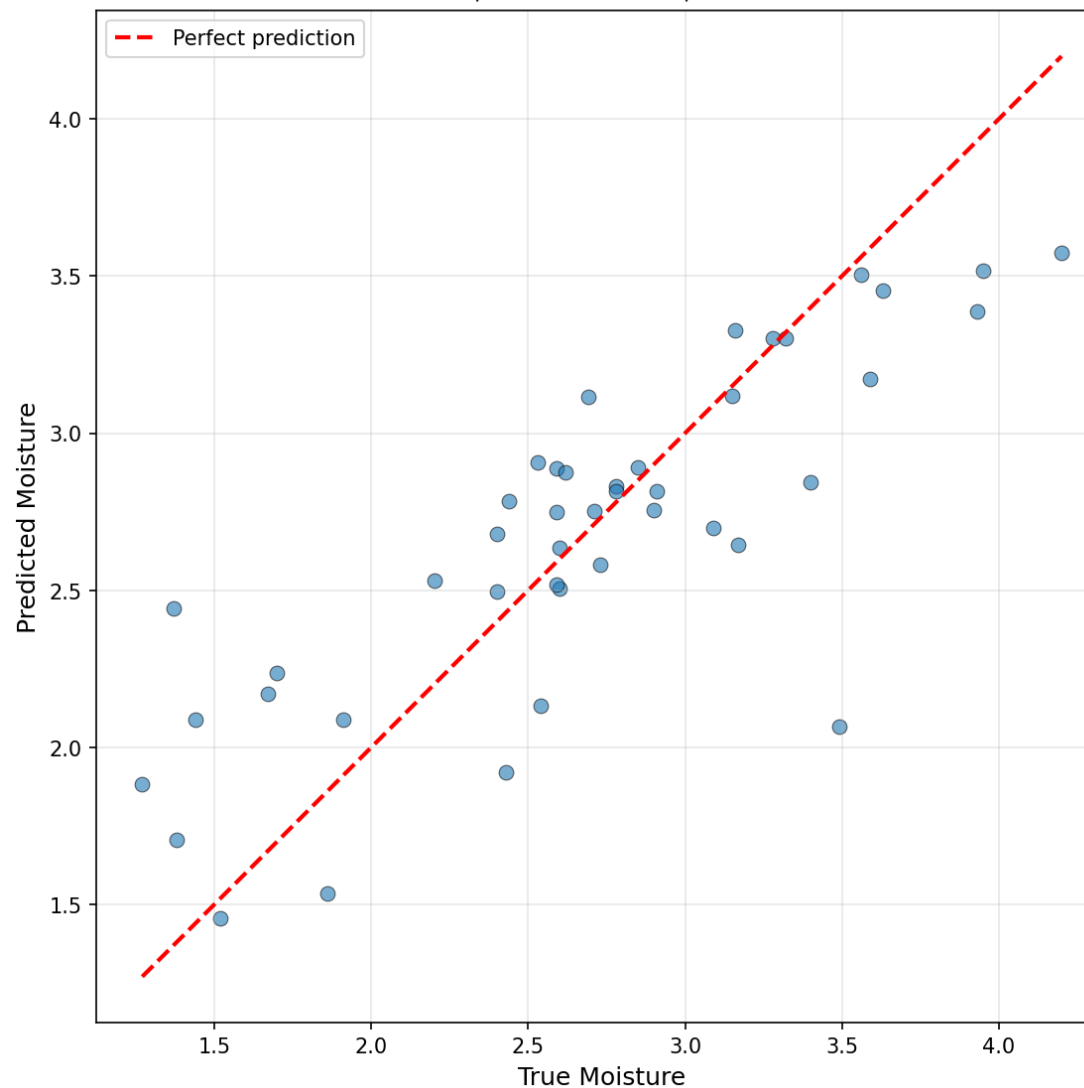
Feature Type	Acoustic Meaning	Crunchiness Connection
Spectral Entropy	Spread of energy	Cracking = broadband noise
Chroma Std	Frequency irregularity	Cracking = scattered spectral content
Peak Density / Num Peaks	Transient density	Cracking = many small impacts
F <sub>0</sub> Range / Std / Mean	Unstable resonances	Cracking = multiple microfractures
MFCC Regularity / Std / Range	Spectral envelope variation	Cracking = irregular fine structure
High-Frequency Energy (10–25 kHz)	Brightness.	Cracking = high-frequency content
Impact Sharpness	Steepness of attack	Cracking = sharp onsets
Formant Variability (F <sub>4</sub> -std)	Variability in resonance peaks	Cracking = high variability in resonance
ZCR (Zero-Crossing Rate)	Frequency of waveform sign changes	Cracking = high ZCR (many small impacts)
Energy Percentiles (p95)	Energy at high percentile of amplitude distribution.	Cracking = high energy bursts

# An alternative approach: Deep Learning

- Can we start from alternative features without using our audio-knowledge?
  - Use of deep learning pre-trained audio neural networks
  - Training own deep-learning network



YAMNet Ensemble Predictions  
 $R^2 = 0.656$ , RMSE = 0.424, MAE = 0.316



!Preliminary results on cookies!  
 Appels vs pears: other test set,  
 other dataset (only 220 data  
 points)

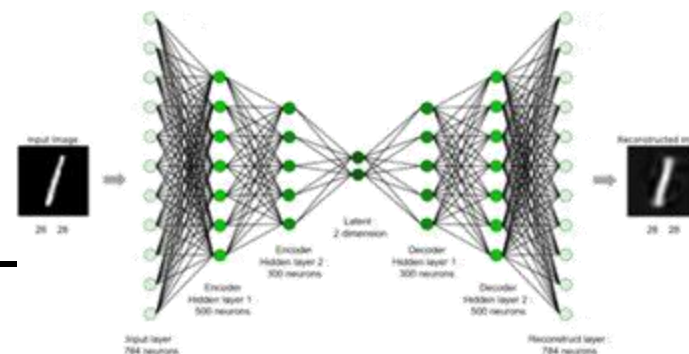


# Denoising autoencoder

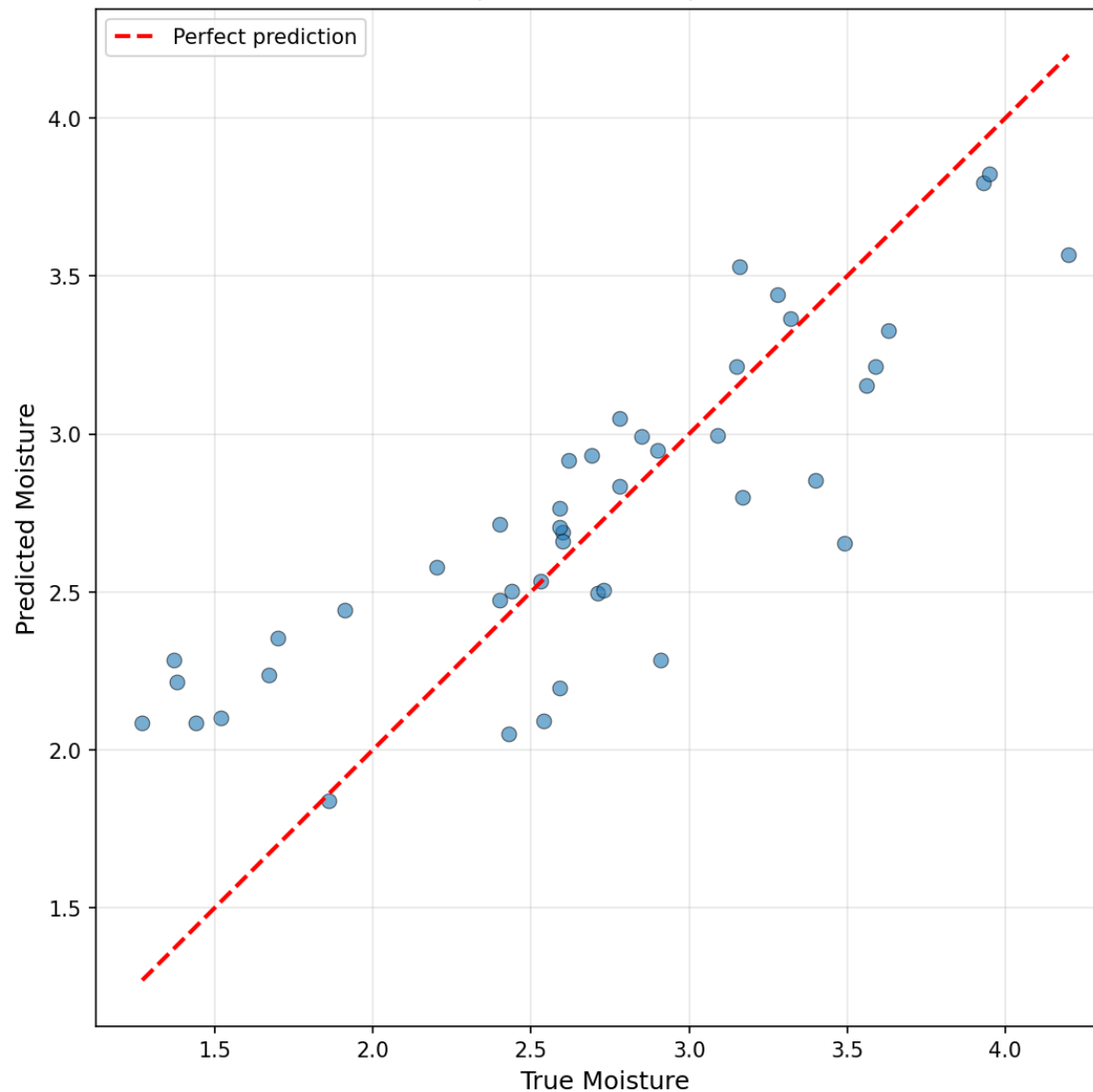
- Step 1: download 10 hours of ASMR (mukbang) crunchy audio
- Step 2: add noise to the audio
- Step 3: train an autoencoder to predict the original audio from the audio with noise
- Step 4: latent space (256 dim) should capture good crunchy features
- Simple statistics (std, mean, ...) → file-level features
- Same approach as before: feature & model selection



+ noise



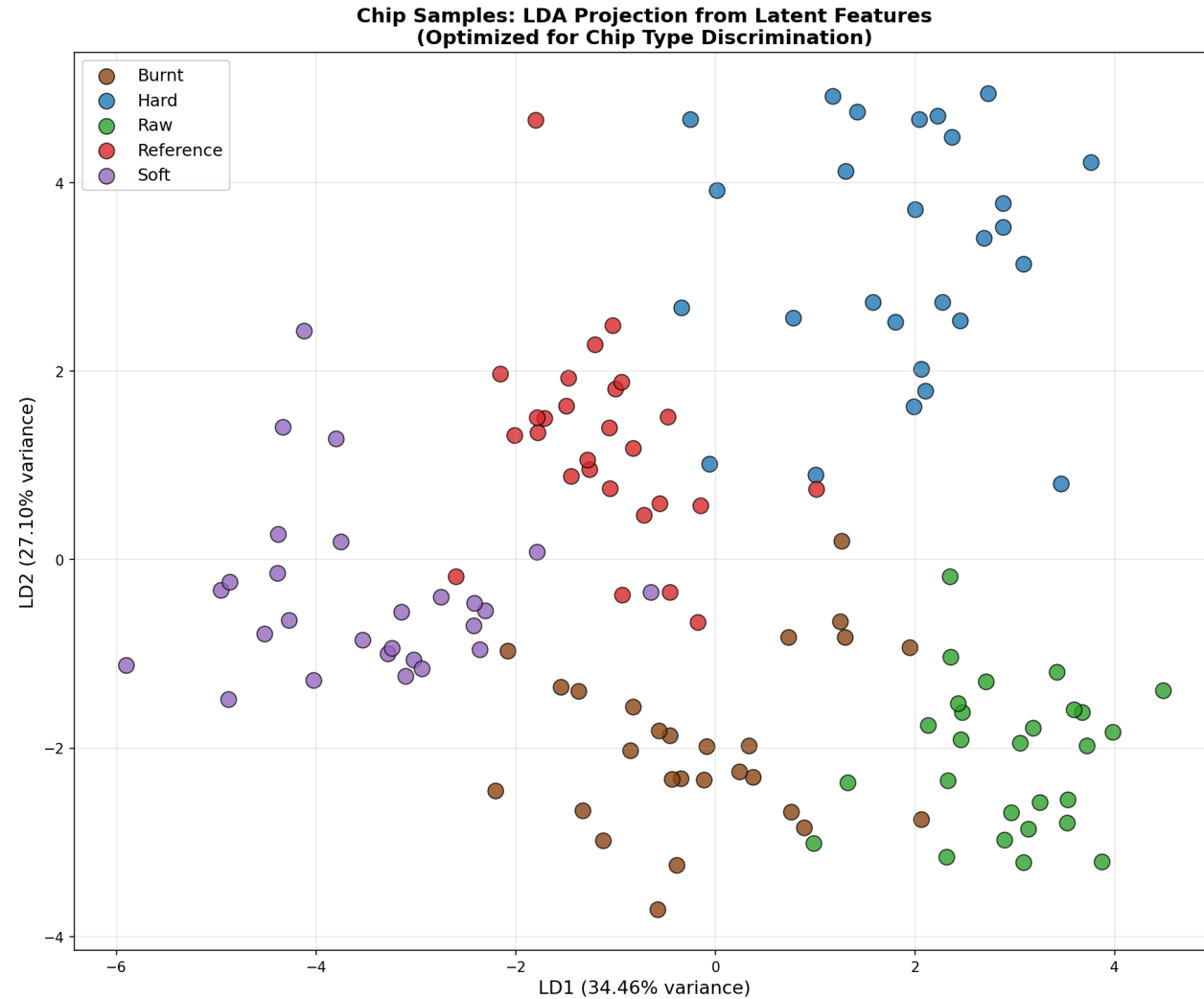
Autoencoder Ensemble Predictions  
 $R^2 = 0.668$ , RMSE = 0.417, MAE = 0.333



!Preliminary results on cookies!  
Appels vs pears: other test set,  
other dataset (only 220 data  
points)



# Next to do: classify the chips using DNN



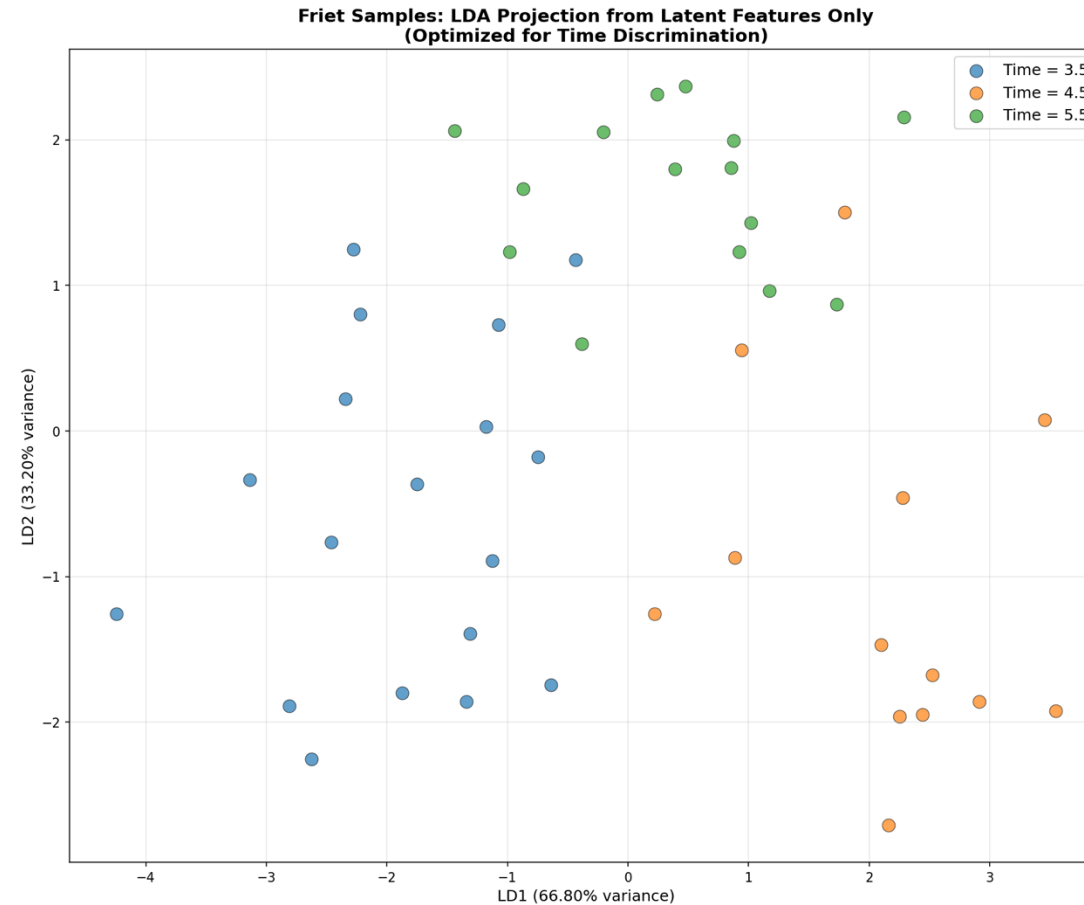
-1-  
Chips



# Conclusions

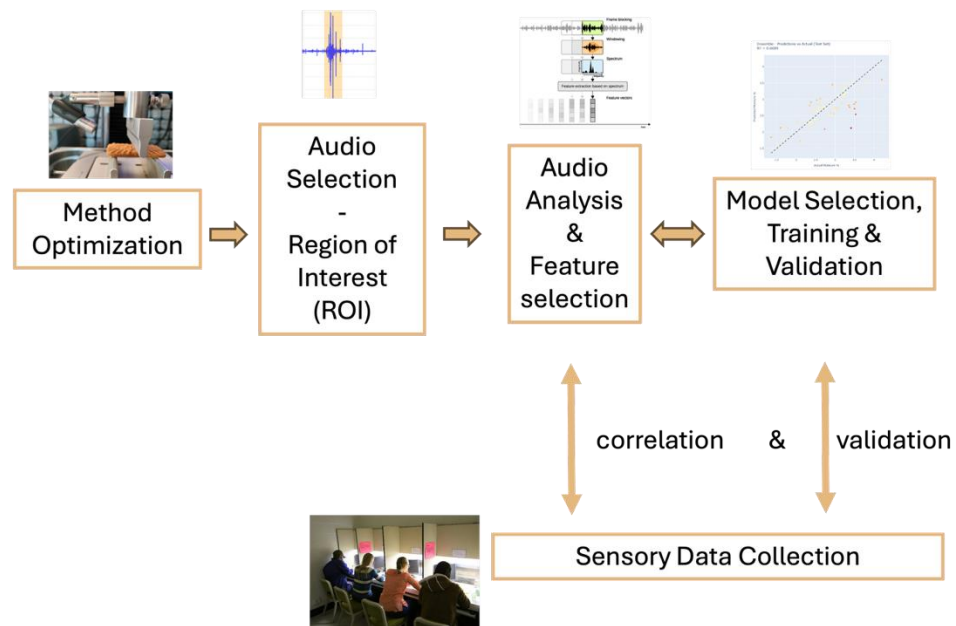
- We **seem** to have 3 methods to tackle the audio analysis
- No table with comparison on speed, performance, simplicity, cost etc yet → first more experiments + same test setup

# Next on our list...



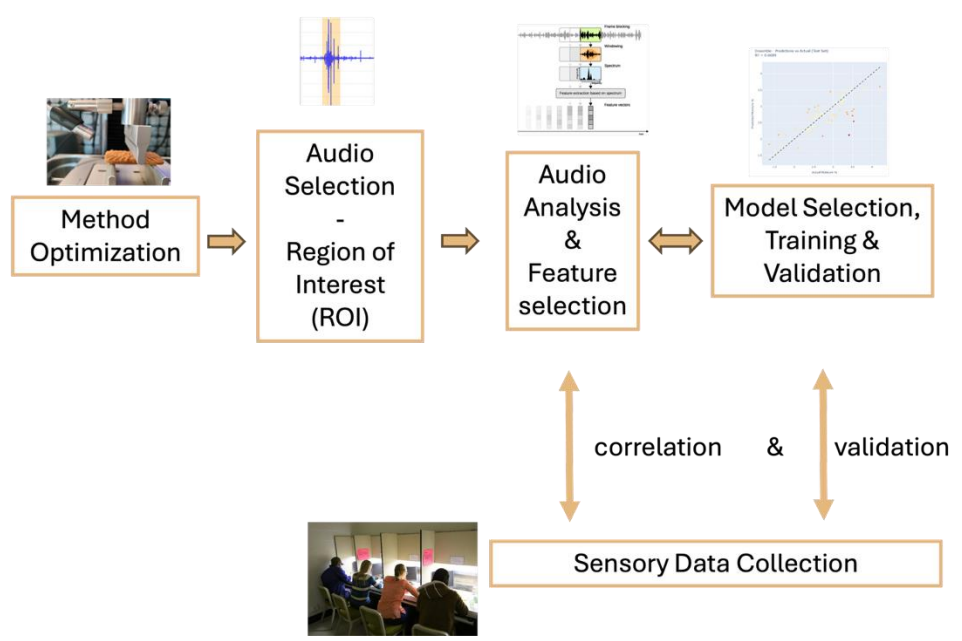
# 4. Wrap up.

---

-1-  
Chips-2-  
French  
Fries-3-  
Cookies-4-  
Bread  
(Baguette)-5-  
Chocolate-6-  
Breaded &  
Battered  
products

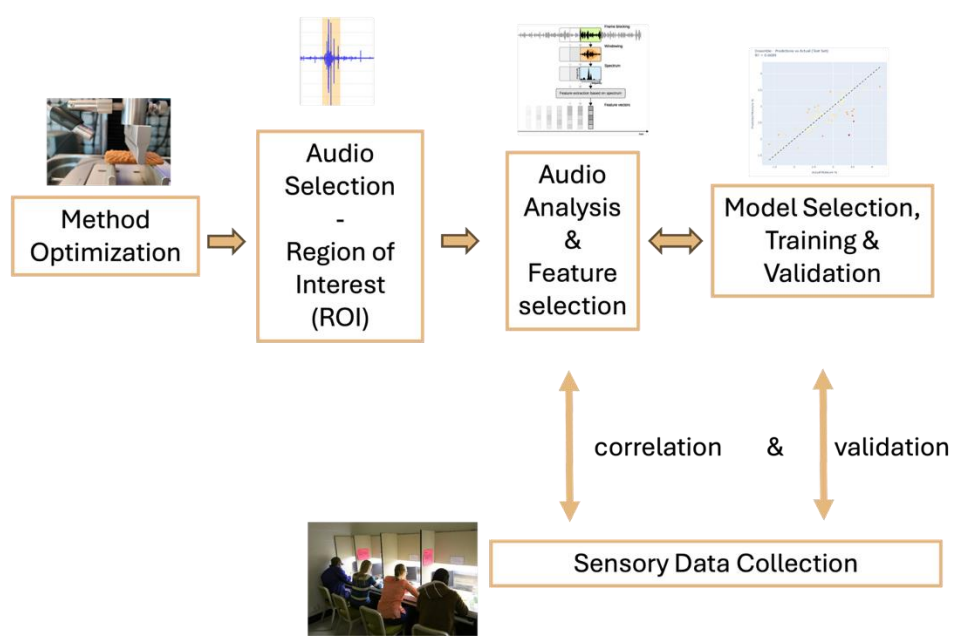
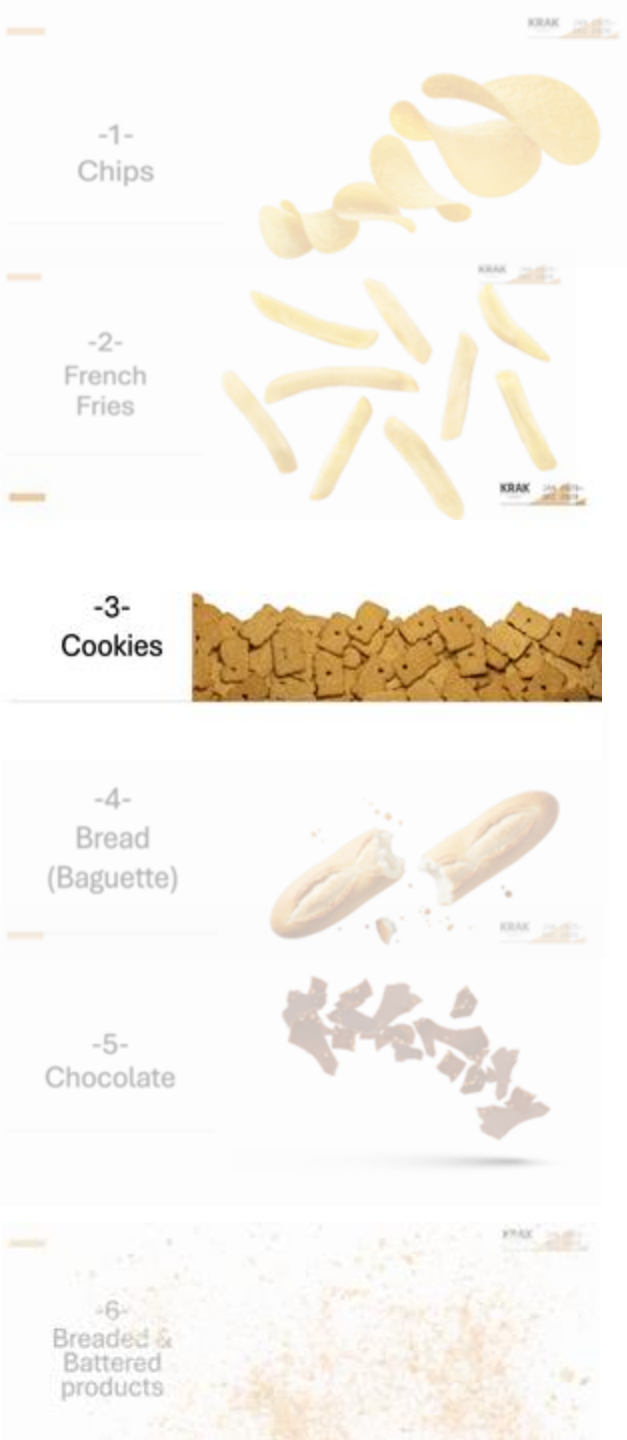
- Different methods tested and evaluated
- Breaking method --> model to predict crispiness
  - Raw, Soft, Reference, Hard, Burnt (accuracy 83%)
- Main audio features determined (Spectral entropy, MFCC regularity/range etc.)

→ Next steps: more crisps at one time, sensory correlation



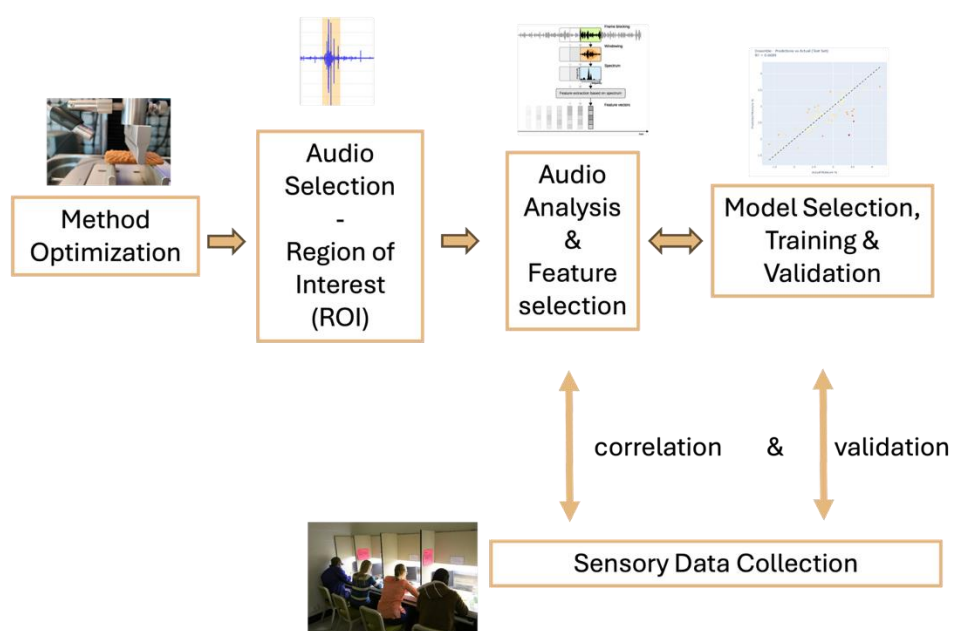
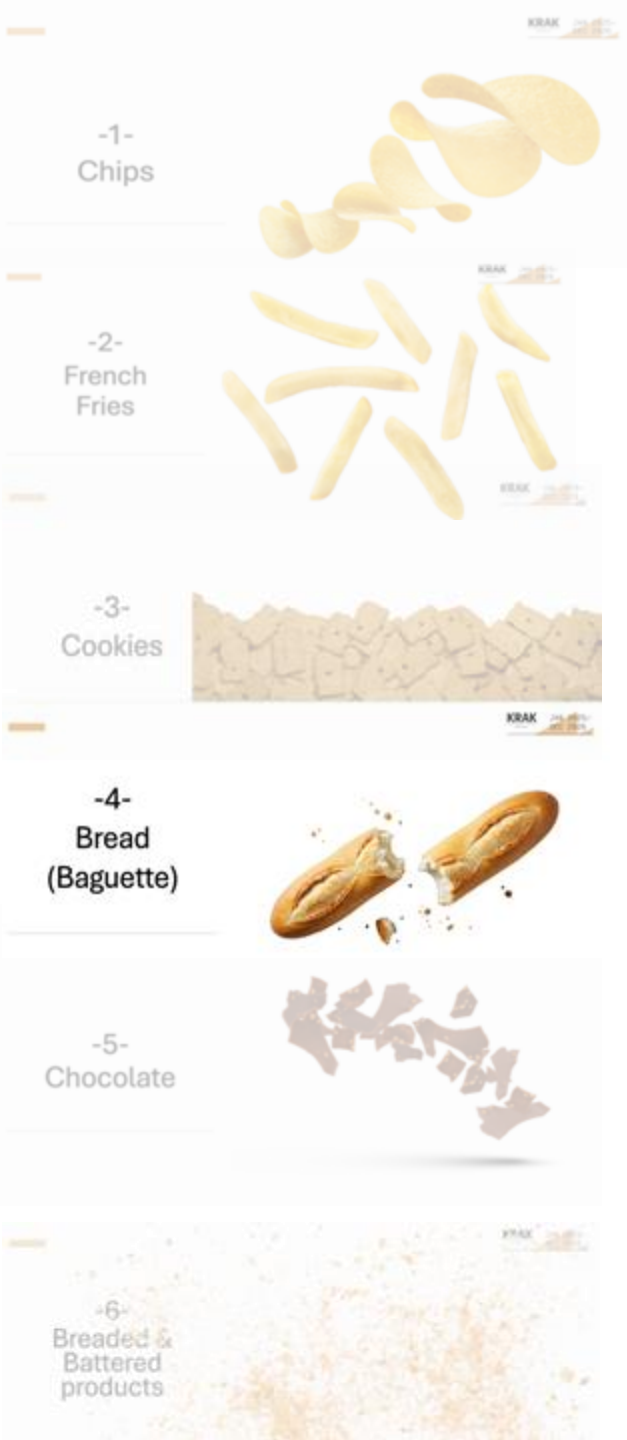
- Different methods tested
- Differentiate baking times

→ Next steps: method evaluation, differentiate “qualities”, sensory correlation



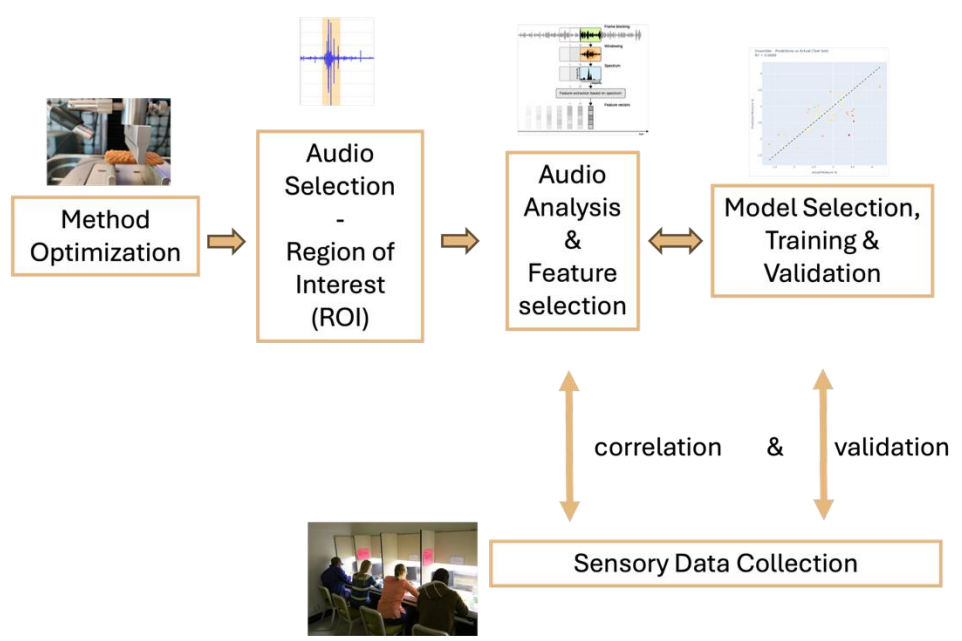
- Different methods tested and evaluated (DOE) → low speed
- Main audio features determined (Spectral entropy, MFCC regularity/range etc.)
- Moisture level correlation with audio driven predicted value (Model)

→ Next steps: validation & sensory correlation



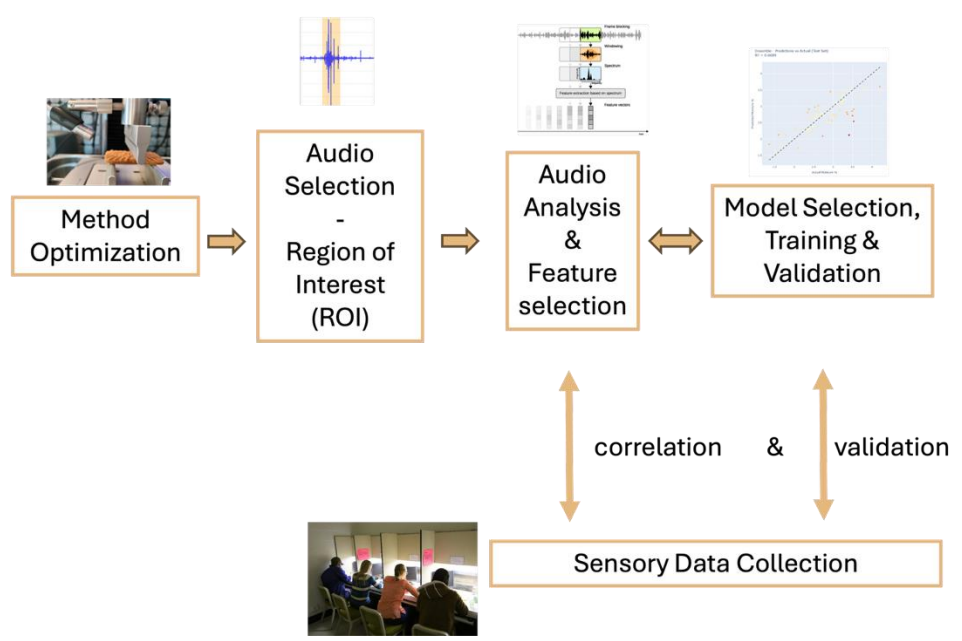
- Different methods tested
- Different zones (side, center) evaluated
- First audio feature correlations with crispiness over time

→ Next steps: method evaluation, model training, sensory correlation



- **1 method:** protocol available for texture testing

→ **Next steps:** feature extraction (different cocoa butter levels), model training, sensory correlation



→ **Next steps:** determining measurement protocols

# 5. Did you hear about KRAK?

---

← Programma

# HOE KLINTK JOW FAVORIETE SNACK?

ZATERDAG — DOORLOPEND ♡ Jungle

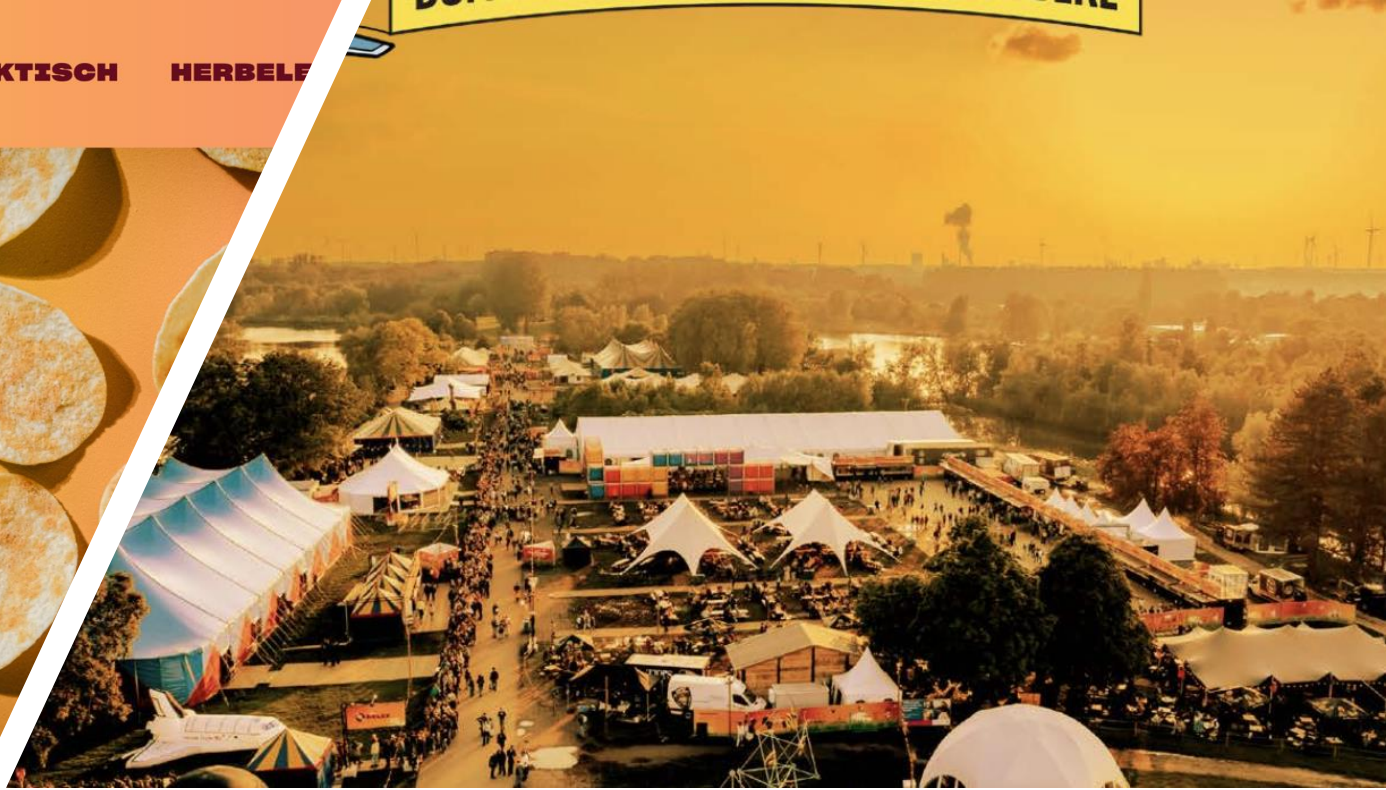
ZONDAG — DOORLOPEND ♡ Jungle

MAANDAG — DOORLOPEND ♡ Jungle



EXPERIENCE

KINDVRIENDELIJK



\*CRUNCH\* Wist je dat het geluid van een knapperige croissant je smaakbeleving compleet kan veranderen? Bij Hogeschool Vrije Universiteit Brussel nemen ze crunch serieus en onderzoeken ze hoe geluid onze manier van eten beïnvloedt. En jij mag meedoen! Met AI analyseren ze geluidsgolven naar hun ultieme smaakervaring. Klinkt cool, euh, lekker toch? In dit workshop-stap je in de smaakhokjes, proef je met je oren én je ogen hoe technologie en smaak samensmelten in een land van smaak. Snacken voor de wetenschap!

Experience in samenwerking met Hogeschool Vrije Universiteit Brussel





# KRAK @ Nerdland Festival

7, 8, 9 juni 2025



KRAK @ Academische opening  
Hogeschool VIVES

23 september 2025



# KRAK @ Dag van het Onderzoek

3 oktober 2025



## CARDBOARDS EN DEMOSSIES

Tijdens de poster- en demossies kwam het onderzoek pas echt tot leven. Door een speling van het logistieke lot, ditmaal geen klassieke roll-up banners, maar strakke cardboards. Met veel enthousiasme en gedrevenheid gaven diverse onderzoekers het beste van zichzelf. Gewapend met grafieken, tabellen en infographics stonden ze collega-onderzoekers te woord. En ook aan de demotafels was er heel wat animo:

- KRAK serveerde een krokant onderzoek rond smaakbeleving
- Preisnijden met AI zorgde voor pretoogjes
- De VR-app Bandenmonteur leerde ons digitaal sleutelen aan wagens
- Dankzij e-learning klonk kindzorg bijna kinderlijk eenvoudig
- Bij FONEMI weerklonk de kracht van klank voor taalontwikkeling



KRAK @ 'Voedingsquiz'  
Technopolis voor studenten  
3de graad secundair

oktober 2025

**TECHN  
POLIS**



Ik ben onderzoeker aan  
de VIVES Hogeschool.

# 6. What's next?

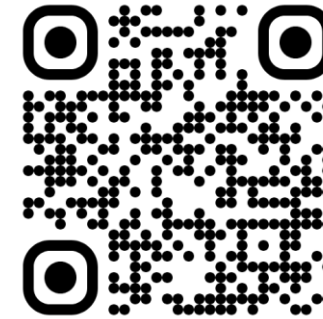
---

- Optimization of the modeling protocols
- Sensory correlation (start with cookies)
- Bread, Chocolate & Breadcrumbs → method optimization
- Software development



## Join the Flemish STEM Olympiad

### Inspire the next generation of innovators



- ✓ A VIVES initiative supported by universities, the Flemish Government & industry partners
- ✓ Fun, hands-on & smart challenges for pupils (ages 10–14)
- ✓ Over **60.000 young minds** take part each year!
- ✓ Goal: **inspire young students** to choose STEM studies
- ✓ We're looking for **food industry partners** to collaborate and co-create this and next editions

Learn more: [www.stemolympiade.be](http://www.stemolympiade.be)

Contact: [koen.malfait@vives.be](mailto:koen.malfait@vives.be)

# FABRIEKEN VOOR DE TOEKOMST

POM

**KRAK**  
OP ZOEK NAAR DE PERFECTE  
CRUNCH

JAN 2025-  
DEC 2026



2 12 2025

**Inspiratiesessie 'Efficiënt en kwalitatief bakken  
met nieuwe technologieën'**

Food Innovation Park



<https://www.menti.com/alnueeon5bmw>



# KRAK

OP ZOEK NAAR DE PERFECTE  
CRUNCH

JAN 2025–  
DEC 2026

## TETRA PROJECT

BEPALING VAN DE PRODUCTKWALITEIT VAN VOEDING  
AAN DE HAND VAN GEAVANCEERDE GELUIDSANALYSE



MET DE STEUN VAN

AGENTSCHAP  
INNOVEREN &  
ONDERNEMEN



Vlaanderen  
is ondernemen

FF

FLANDERS  
FOOD

EEN SAMENWERKING TUSSEN

KU LEUVEN

hogeschool  
**vives**

# Feedback?

**Michaël Verlinden**

Michael.Verlinden@vives.be

KRAK – Steering Group– 14 November 2025

hogeschool  
**vives**

RESEARCH GROUP  
FOOD PROCESSING

# KRAK

OP ZOEK NAAR DE PERFECTE  
CRUNCH

JAN 2025–  
DEC 2026

## TETRA PROJECT

BEPALING VAN DE PRODUCTKWALITEIT VAN VOEDING  
AAN DE HAND VAN GEAVANCEERDE GELUIDSANALYSE



MET DE STEUN VAN

AGENTSCHAP  
INNOVEREN &  
ONDERNEMEN



Vlaanderen  
is ondernemen



FLANDERS'  
FOOD



EEN SAMENWERKING TUSSEN



[www.project-krak.be](http://www.project-krak.be)

HBC.2024.0136

KRAK – Steering Group– 14 November 2025