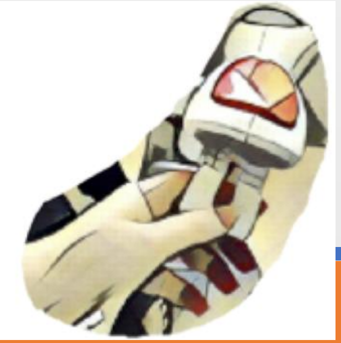
On Deep Learning for Computational Ethology

MARINA AGUILAR-MORENO

MANUEL GRAÑA

COMPUTATIONAL INTELLIGENCE GROUP

UNIVERSITY OF THE BASQUE COUNTRY (UPV/EHU) SAN SEBASTIAN, SPAIN



CybSPEED, Donostia, 18th of July 2023

Outline

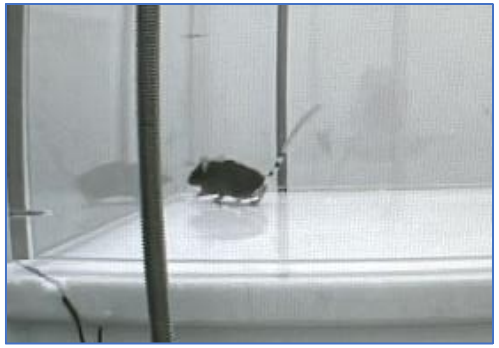
1. Introduction
   - Computational Ethology
   - State of the art in CE
2. Research Question
3. Material and Methods
   - Animals and Experimentation
   - Behavioral Data Processing
   - Model Training and Evaluation
4. Results
   - Results with the Chronux library
   - Results with Sonic Visualizer
5. Conclusion and Future Work

1. Introduction
1.1 Computational Ethology

Behavior: The set of muscular responses of a living being because of an external stimulus and internal motivation.

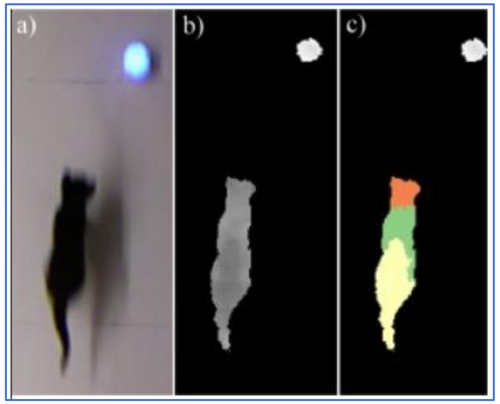
Computational Ethology (CE):

- Discipline that studies the animal behavior
- Using the advances in Computer Vision and Artificial Intelligence.
- Focused on the natural behavior to perform real-world tasks
- In unrestricted environments
- Quantitative behavior characterization.



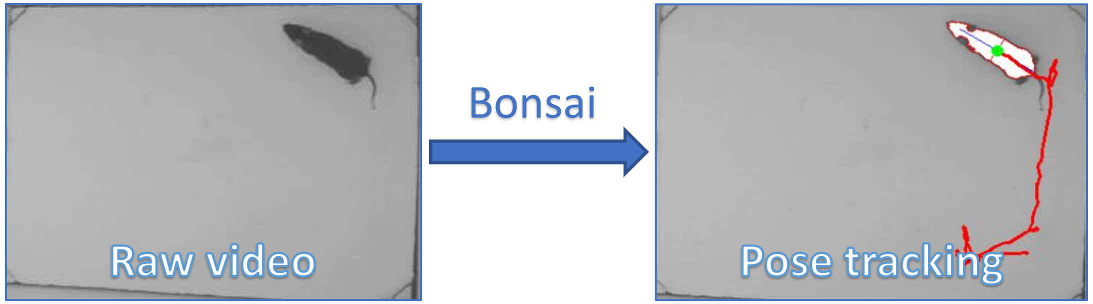
Pharmacological point of view: CE is useful to test new medicines comparing the effect on different subjects, obtained by genetic modifications.

1. Introduction
1.2 State of the art in Computational Ethology



Sensors:
- RGB / depth / infrared cameras
- Pressure sensors
- Inertial sensors
- Microphones

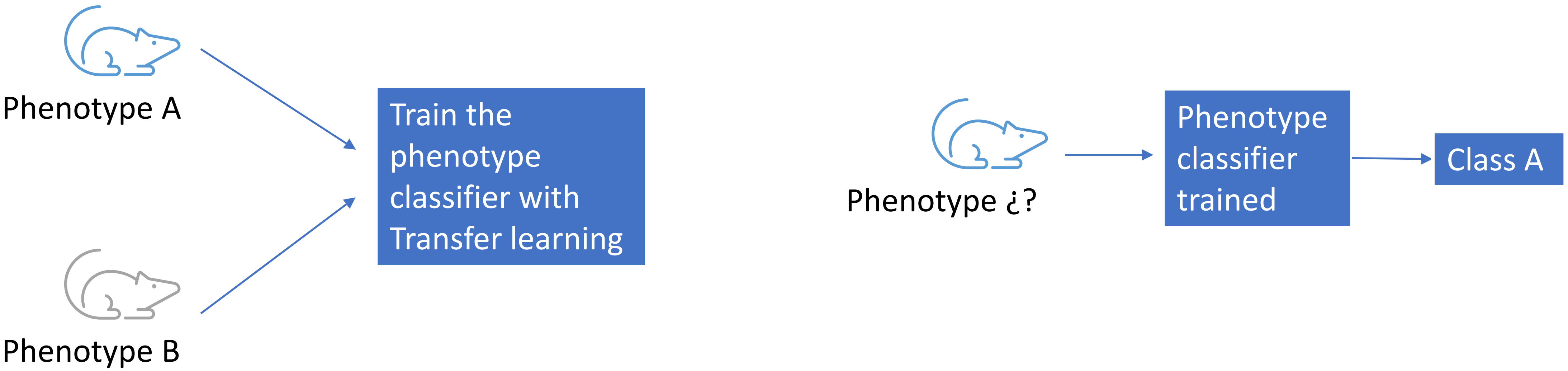
Applications based on Artificial Intelligence:
- Tracking applications: DeepLabCut, Bonsai, SLEAP, …
- Behavior classification: JAABA, DeepEthogram, VAME, …
- Strain classification: SVM, k-NN



2. Research Question

Is it possible to implement a **strain classifier** from **pressure signal** and images by applying **pre-trained models** and **transfer learning?**

We focus on comparing spectrogram images from piezoelectric sensor during **locomotion periods.**



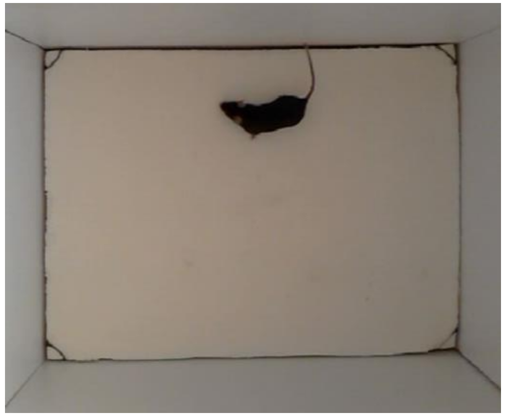
3. Materials and Methods
3.1 Animals and Experimentation

12 mice with 2 different strains:
- 7 wild-type (WT): non-mutated gene
- 5 transgenic Fmr1-knockout (Fmr1-KO): animal model to study Fragile X Syndrome

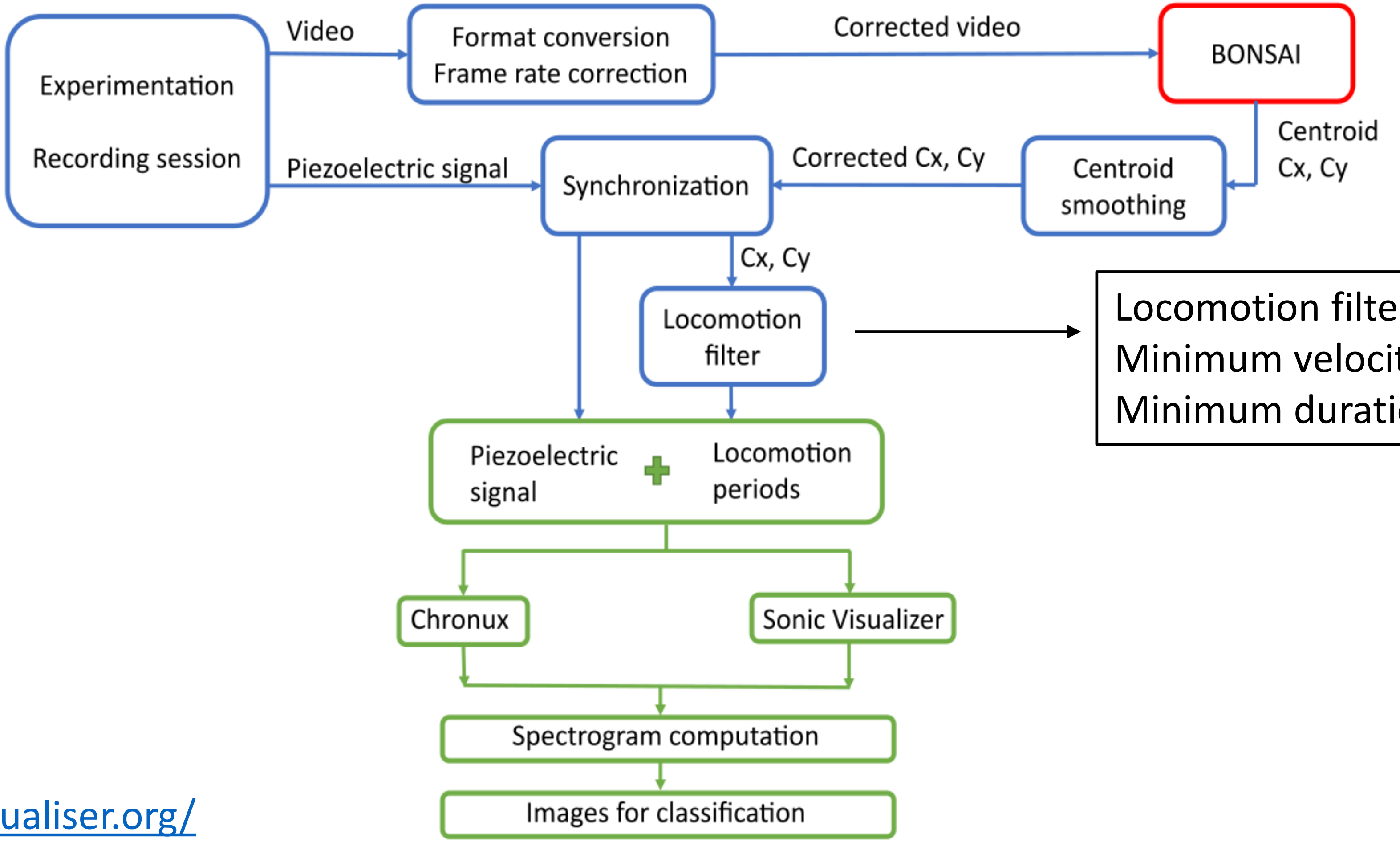
Recording system:
- Opaque-walled cage
- Base: piezoelectric platform with 3 sensors (20 kHz)
- Top video camera (25 fps)
- Computer with the Spike software to record piezoelectric signal

Animals introduced individually.

Procedure in accordance with EU directives for animal protection.



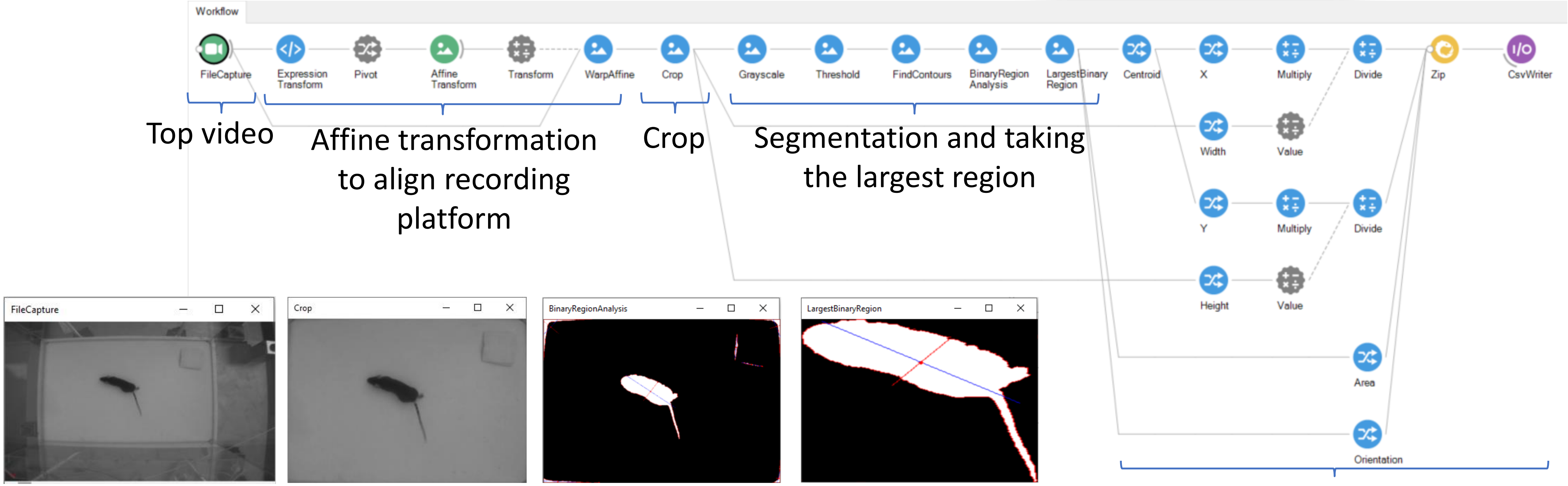
3. Materials and Methods
3.2 Behavioral Data Processing



Locomotion filter:
Minimum velocity of 2.5 cm/s
Minimum duration of 2500 ms

http://chronux.org/
https://www.sonicvisualiser.org/

3. Materials and Methods
3.2 Behavioral Data Processing



Top video

Affine transformation to align recording platform

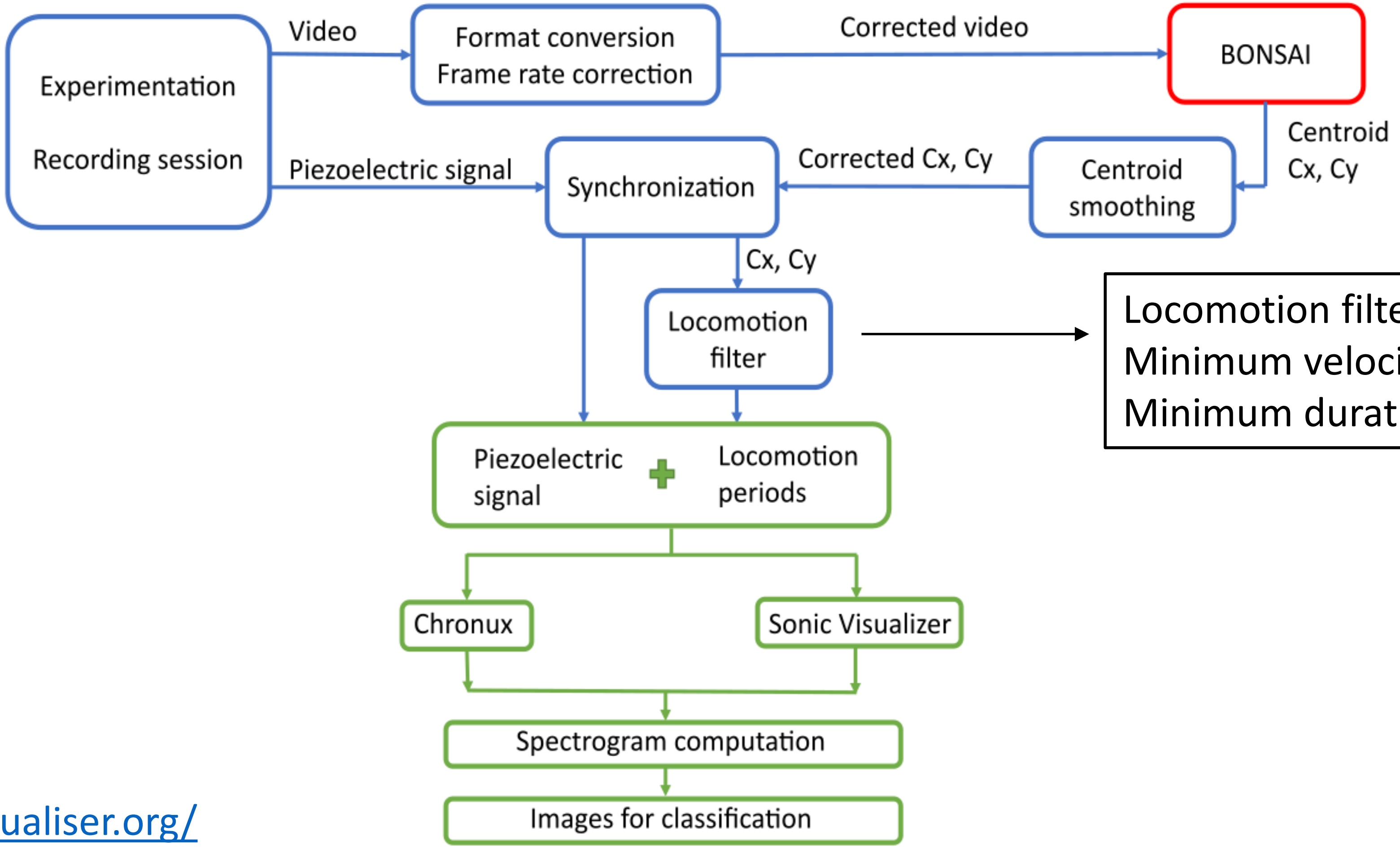
Crop

Segmentation and taking the largest region

Save centroid (*x*, *y*) in a *.csv file*

https://bonsai-rx.org/

3. Materials and Methods
3.2 Behavioral Data Processing



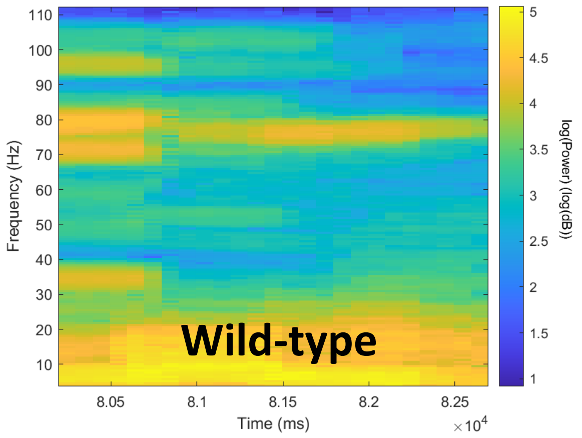
Locomotion filter:
Minimum velocity of 2.5 cm/s
Minimum duration of 2500 ms

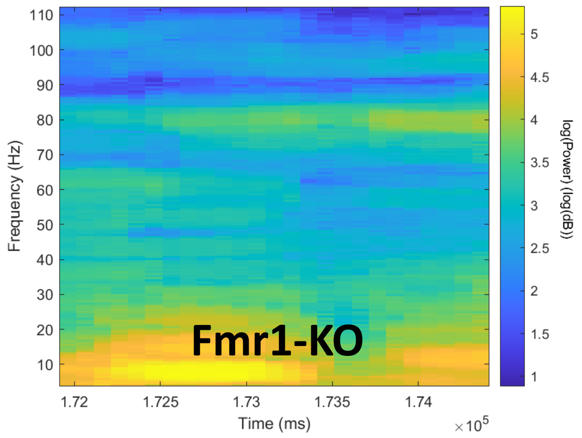
http://chronux.org/
https://www.sonicvisualiser.org/

3. Materials and Methods
3.2 Behavioral Data Processing

Table 1. Parameters for spectrogram computation with Chronux library.

Parameters	Value 1	Value 2	Default values
Window size (s)	1	2	-
Windows step (s)	0.1	0.2	-
Tapers	[4, 2]	[3, 5]	[3, 5]: A numeric vector [TW K] where TW is the time-bandwidth product and K is the number of tapers, less than or equal to 2TW-1
Frequency of interest (Hz)	[1.5 - 40]	[4 - 112]	[0 - Fs/2] (Fs: sampling frequency)

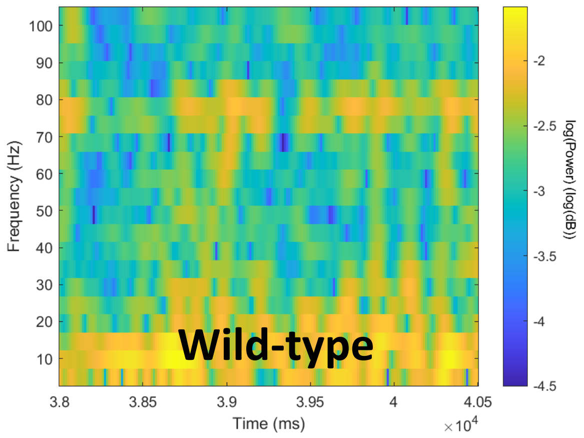


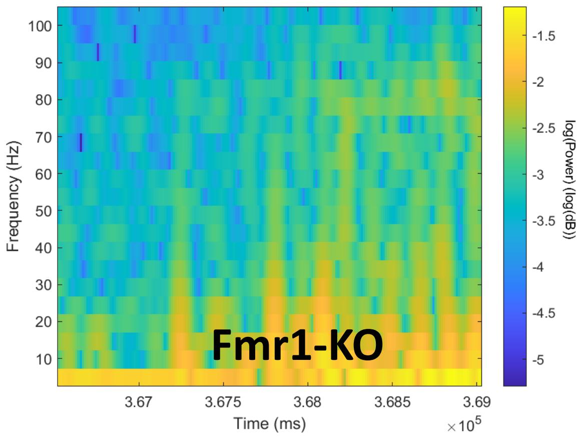


3. Materials and Methods
3.2 Behavioral Data Processing

Table 2. Parameter for spectrogram computation with Sonic Visualizer.

Parameter	Value	Range of values
Colour	Green	[Green, Sunset, ... , Wasp, Ice, ...]
Scale	dB	[Linear, Meter, dB^2, dB, Phase]
Window size	256	[32, 64, 128, 256, 512, ... , 16384, 32768]
Overlap	93.75%	[none, 25%, 50%, 75%, 87.5%, 93.75%]
Show	All bins	[All Bins, Peak Bins, Frequencies]
Scale	Linear	[Linear, Log]





3. Materials and Methods
3.3 Model Training and Evaluation

Binary classification problem to discriminate two phenotypes: WT (class 0) and Fmr1-KO (class 1)

Transfer learning to spectrogram images during locomotion with:
- Alexnet
- GoogLeNet
- ResNet50

Dataset divided into two parts:
- 80% train set
- 20% test set

5-fold cross-validation

Accuracy, Recall, Precision, F1 score.

Parameter	Value
Solver	Adam
Learning rate	0.0001
Mini batch size	52
L2 Regularization	0.0001
Folds for Cross-validation	5

Algorithm	Execution time	Layers	Total learnables
AlexNet	$\approx$ 35min	25 (depth 8)	56 876 418
ResNet50	$\approx$ 4h	177 (depth 50)	23 538 690
GoogLeNet	$\approx$ 2h	144 (depth 22)	5 975 602

4. Results
4.1 Results for Spectrogram computed with Chronux library

1 second window size and 0.1 seconds window step

Tapers	3 - 5				4 - 2			
	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score
AlexNet	98.40%	1.00	0.97	0.98	**100.00%**	**1.00**	**1.00**	**1.00**
GoogLeNet	**99.47%**	**0.99**	**1.00**	**0.99**	99.47%	1.00	0.99	0.99
ResNet50	**99.47%**	**0.99**	**1.00**	**0.99**	99.47%	0.99	1.00	0.99

2 seconds window size and 0.5 seconds window step

Tapers	3 - 5				4 - 2			
	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score
AlexNet	98.93%	0.98	1.00	0.99	96.79%	0.93	1.00	0.97
GoogLeNet	97.86%	0.97	0.99	0.98	97.33%	0.97	0.98	0.97
ResNet50	**99.47%**	**0.99**	**1.00**	**0.99**	**97.86%**	**0.97**	**0.99**	**0.98**

4. Results
4.2 Results for Spectrogram computed with Sonic Visualizer

Window size - overlap	256 - 93.75%			
	Accuracy	Precision	Recall	F1 score
AlexNet	**100.00%**	**1.00**	**1.00**	**1.00**
GoogLeNet	96.26%	0.93	0.99	0.96
ResNet50	96.79%	0.95	0.98	0.97

5. Conclusion and Future Work

Introduction of Computational Ethology and its state of the art.

Research question: Is it possible to discriminate phenotypes with pressure signals and images using transfer learning?

Binary classification problem with 2 different animal models:

- Wild-type
- Fmr1-KO

Spectrogram images from the piezoelectric pressure signal during locomotion periods.

Yes, we can differentiate phenotypes with high accuracy, precision, recall and F1 score.

Future work: apply this approach to an experimental study about healthy ageing in elderly to detect gait anomalies with recordings from an electroencephalogram (EEG) and a walking platform.

Acknowledgments

Grant PRE2018-085294 funded by MCIN/AEI 10.13039/501100011033 and by “ESF Investing in your future”.

Grant from University Research group of excellence of the Basque Government.

Prof. Xavier Leinekugel for sharing the data to test our approach

MINISTERIO DE CIENCIA E INNOVACIÓN

UNIÓN EUROPEA
Fondo Social Europeo
El FSE invierte en tu futuro

AGENCIA ESTATAL DE INVESTIGACIÓN

eman ta zabal zazu

Universidad del País Vasco

Euskal Herriko Unibertsitatea

Thank you for your attention

MARINA AGUILAR-MORENO

MANUEL GRAÑA

COMPUTATIONAL INTELLIGENCE GROUP

UNIVERSITY OF THE BASQUE COUNTRY (UPV/EHU) SAN SEBASTIAN, SPAIN

MARINA.AGUILAR@EHU.EUS