THE BIOROBOTICS INSTITUTE

Sant'Anna School of Advanced Studies – Pisa

A Workflow for Developing Biohybrid Intelligent Sensing Systems

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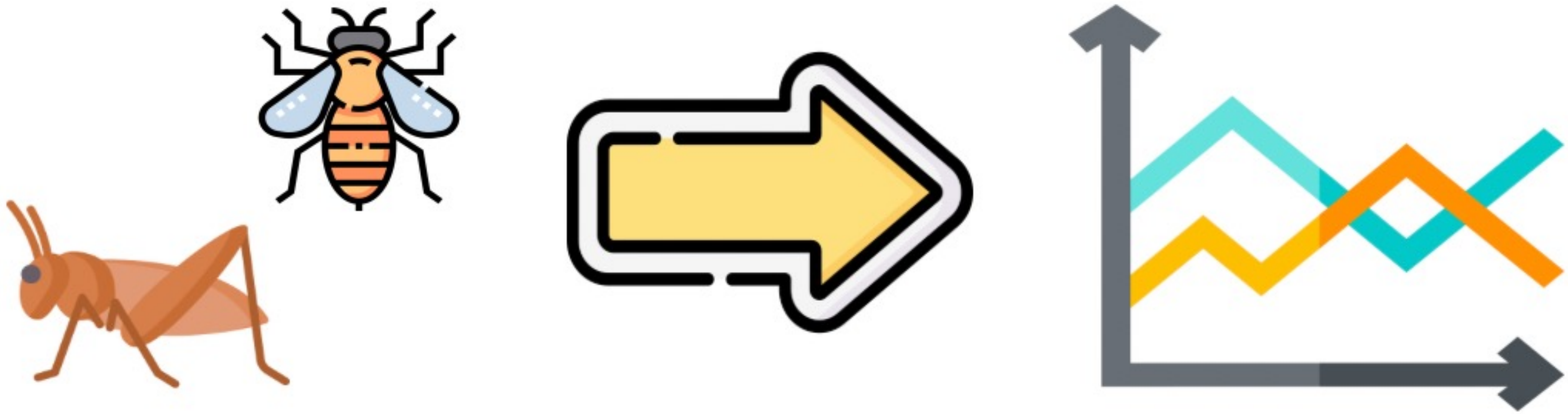
Introduction

Animal Biosensors are **analytical tools** that exploit animal olfactory capabilities to identify Volatile Organic Compounds (VOCs)



Introduction

Important because:

1. Animal sentitive olfactory system is beyond human capabilities and eletronic devices

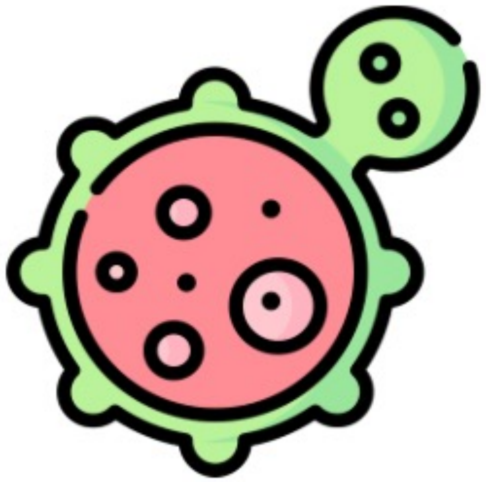
2. Portable, easy-to-use, *eco-friendly*, and do not need manufactory process for the analysis

3. Potential application in wide range of fields, from ecological studies to biomedical uses

Introduction

Already applied for:

Narcotics and explosives detection



Medical diagnosis

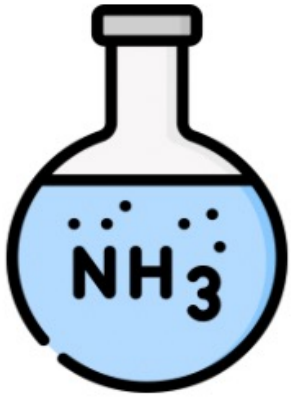
Early warning system

Introduction

This research focus on:

Classifying the type of response of crickets exposed to two chemical substances through the analysis of the movement of their antennae

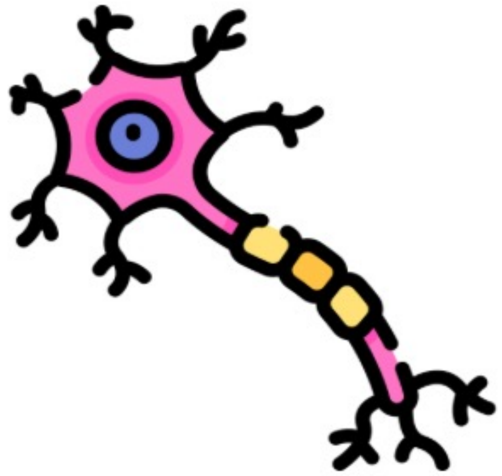
Paving the way for a workflow that developes *Biohybrid Intelligent Sensing Systems*



Introduction

This is important and innovative because previous studies relied on:

Human observer

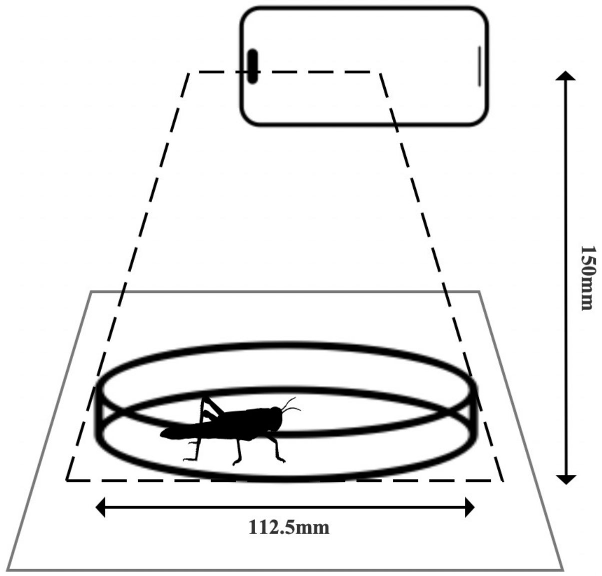


Direct nerve stimuli readings

Materials and Methods - Dataset

Adult crickets (*Acheta domesticus*) where used:

- Obtained 69 videos *(23 for each class)*
- Of length 3 minutes using an iPhone 14 Pro at 1080p and 30FPS
- Two periods:
  - Settling-in (*first minute*)
  - Interaction (*second and third minutes*)



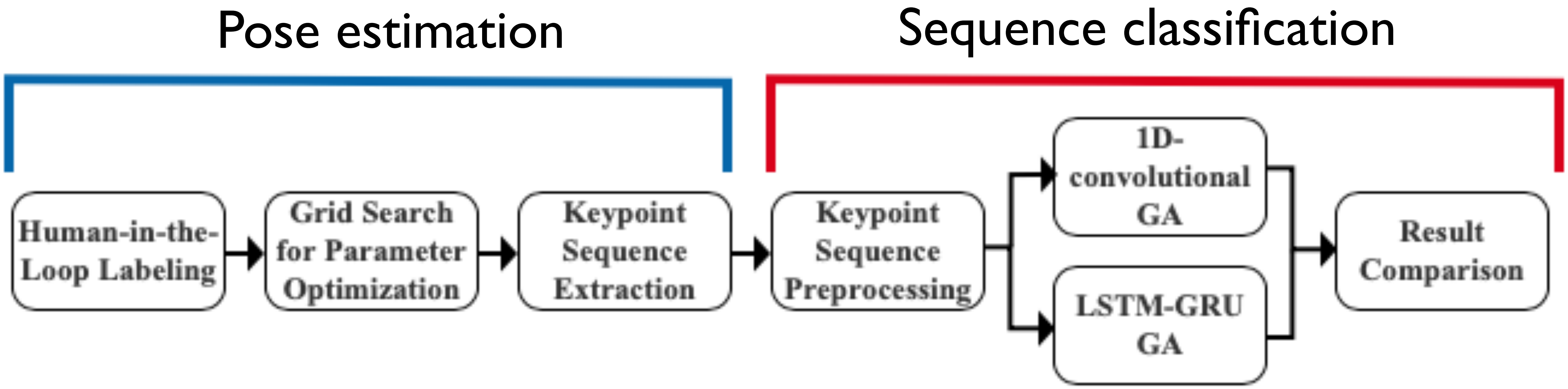
Materials and Methods - Dataset Preprocessing

Standardization of the videos:

- FPS reduced to 29
  - Interaction period bounded between frames 1740 and 5220 (3480 in total)

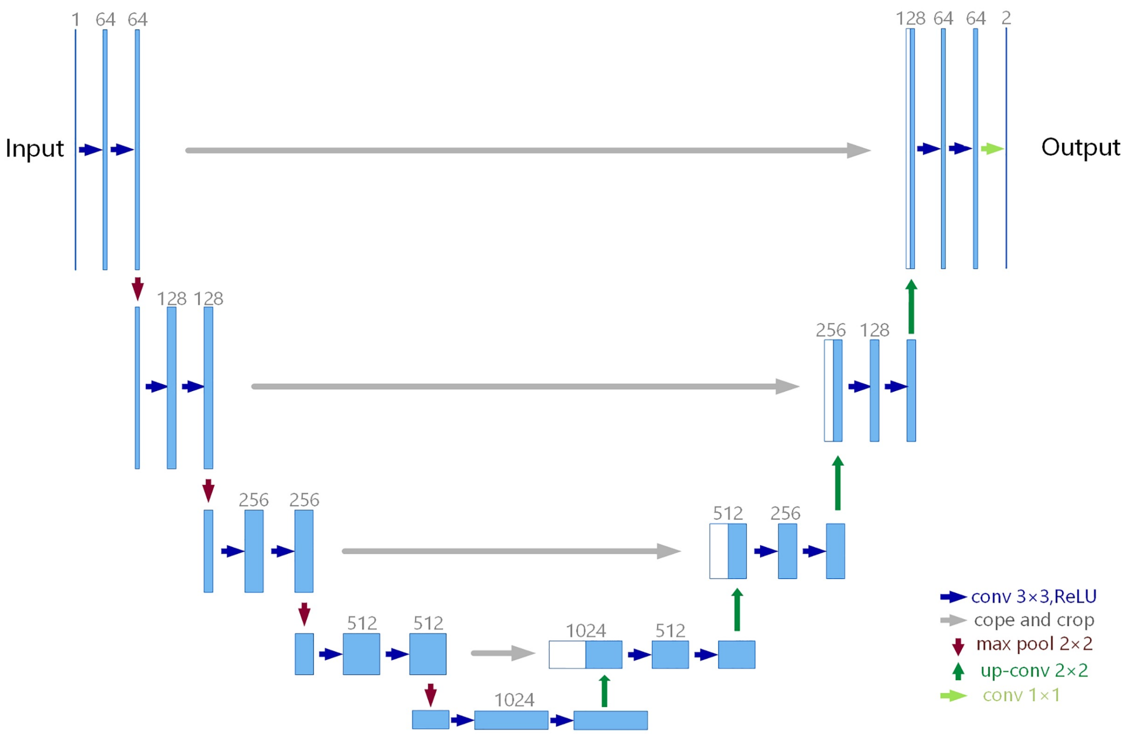
- Cropping centering the Petri dish generating videos of size 1080x1080

Materials and Methods - Workflow



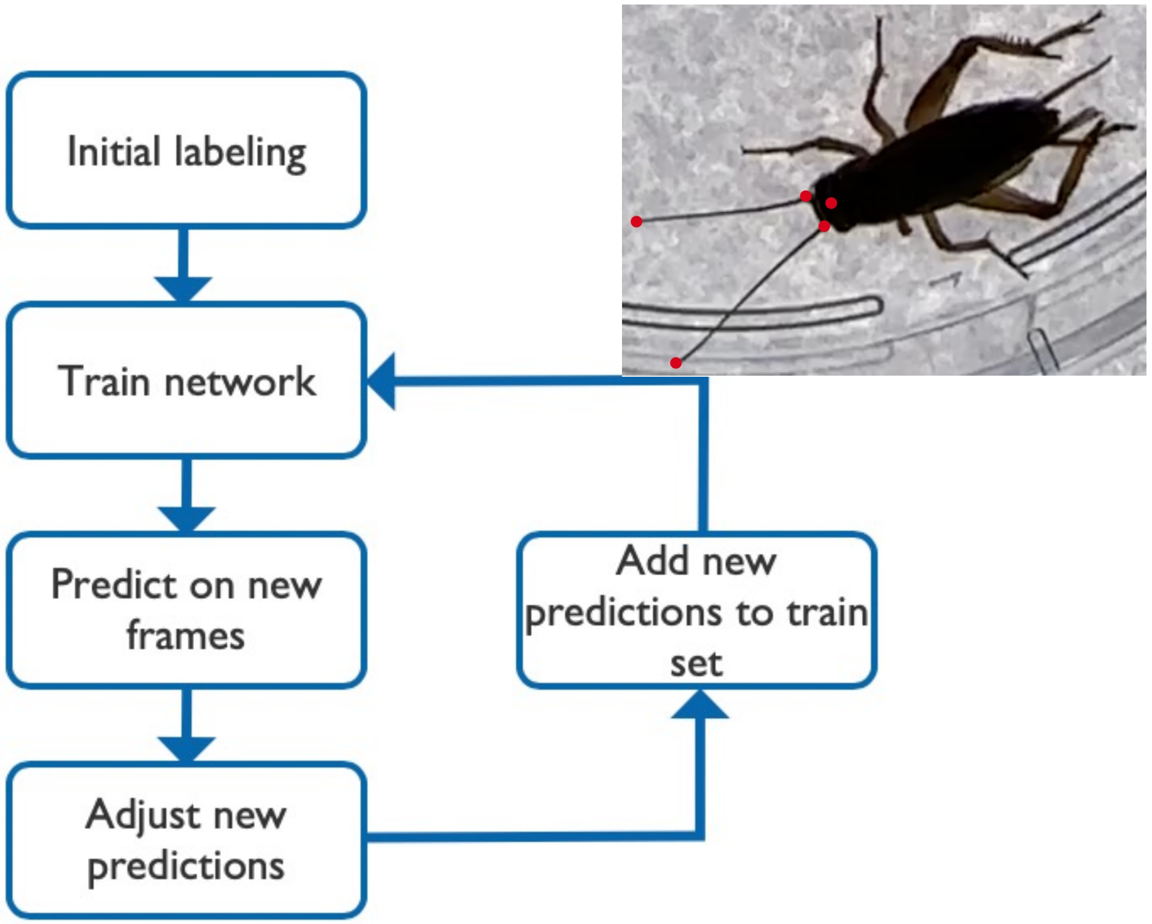
Pose Estimation - Model and Labeling

Model Used (SLEAP)



U-Net Backbone

Human-in-the-loop labeling



Pose Estimation – Grid Search

For the labeling phase, a network with max stride equals to 64, 64 initial filters, a filter rate of 2 and input scaling equals 0.7 was exploited

Search for a better network:

- Max stride
  - 32 - 64
- Initial number of filters
  - 32 - 64
- Input scaling
  - 0.7 - 0.8 - 0.9 - 1.0

Keypoint Sequence Extraction - Preprocessing

Extract keypoint location from every videos

- Obtaining sequences of shape *(#keypoints, #frames)*

Before training preprocessing is require:

- Filled NaN values using interpolation
- Positioned head as center of the Cartesian plane
  - Remove head from preprocessed sequences

GENETIC ALGORITH FOR ARCHITECTURE DEVELOPMENT

Two types of architecture where tested:

- One-dimensional convolutional neural network
- Recurrent neural network based on LSTM, GRU and bidirectional layer

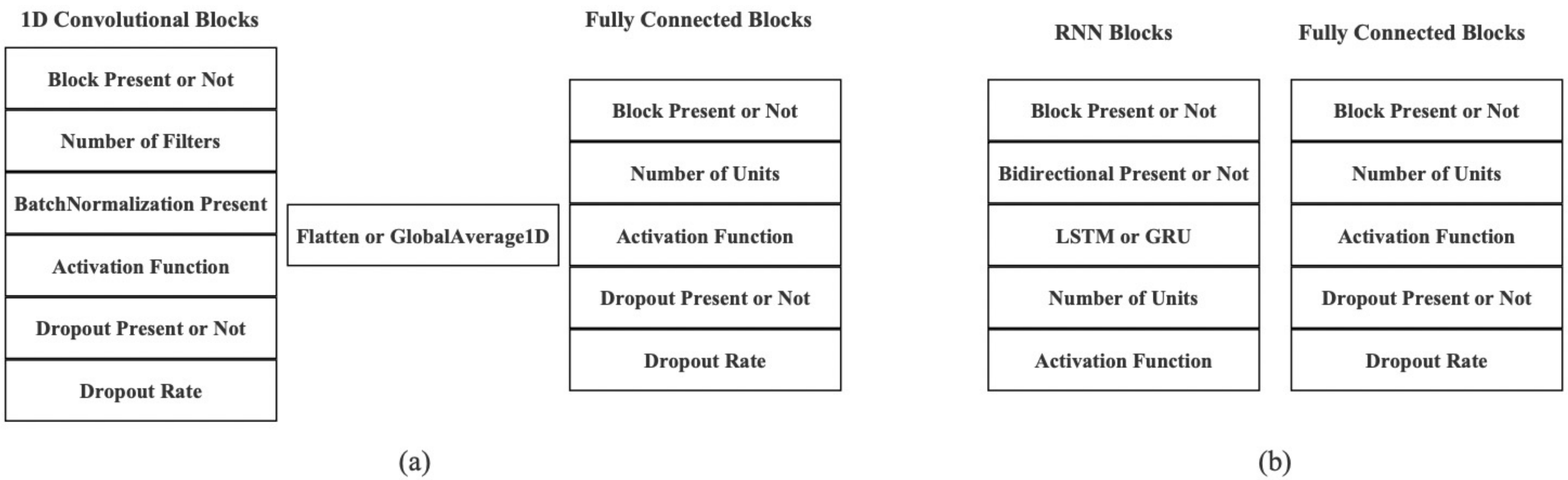
Why a genetic algorithm?

Codeiro et al. proved that the utilization of GA to search optimal architectures results in less cost than methods such as *greedy* and *random search*

GENETIC ALGORITH FOR ARCHITECTURE DEVELOPMENT

To work with a GA there the need to define some parameters:

- The chromosome structure



CNN RNN

GENETIC ALGORITH FOR ARCHITECTURE DEVELOPMENT

- Initial population
  - 250 (10 for elitism)
- Selection function:
  - *tournament selection*
- Crossover function:
  - *Bounded Simulated Binary Crossover (SBX)*
- Mutation function:
  - *Bounded Polynomial Mutation*

GENETIC ALGORITH FOR ARCHITECTURE DEVELOPMENT

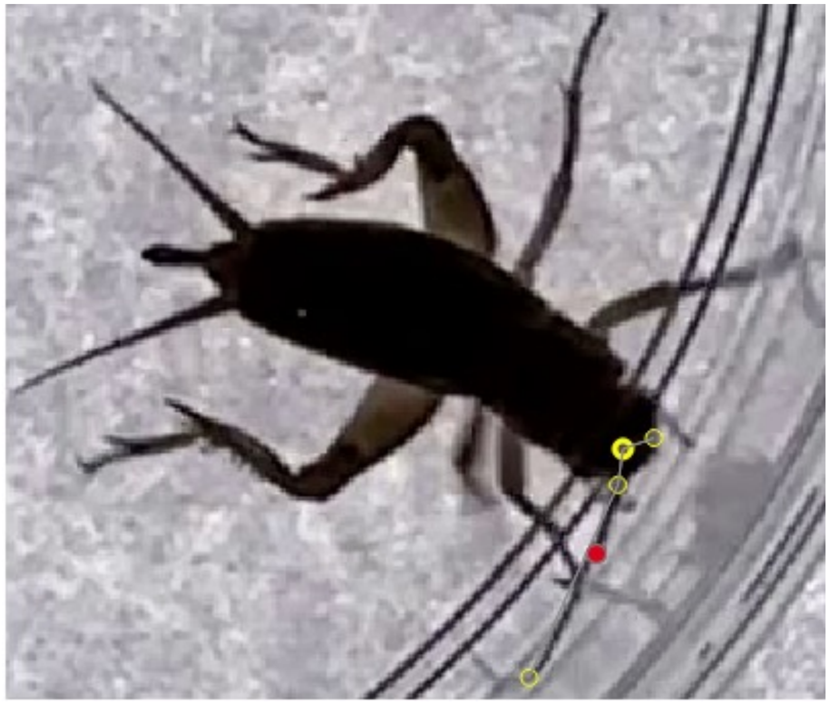
- Fitness function

$$fitness(gene) = \begin{cases} 10 \cdot (training\_accuracy - 1) & if\ training\_accuracy \leq 0.33 or\ validation\_accuracy \leq 0.33 or\ training\_accuracy < validation\_accuracy \\ -15 & if\ training\_accuracy \leq 0.1 \\ -20 & no\ convolutional\ or\ RNN\ layers\ present \\ -validation\_loss & otherwise \end{cases}$$

Results & Discussion – Pose Estimation

Grid search results as best model:

- Max stride: 64
- Initial number of filters: 64
- Input scaling: 1.0



Obtaining a *mean Average Precision* of 0.84 for the *validation set.*

Two problems:

- High complexity
- Could be improved leveraging the temporal information

Results & Discussion – Chemical Interaction Classification

The CNN proposed by the GA was:

- Conv layer 821 filters
- Batch normalization
- ELU activation layer
- Dropout (0.2)
- Conv layer: 483 filters
- Tanh activation layer
- Flatten

Obtaining 0.58 of accuracy

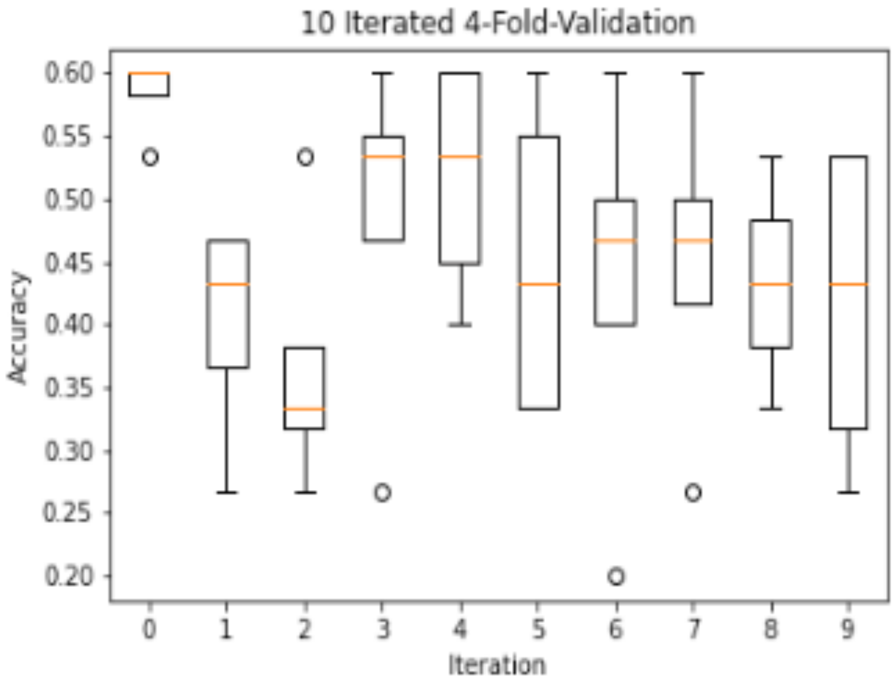
Results & Discussion – Chemical Interaction Classification

The RNN proposed by the GA was:

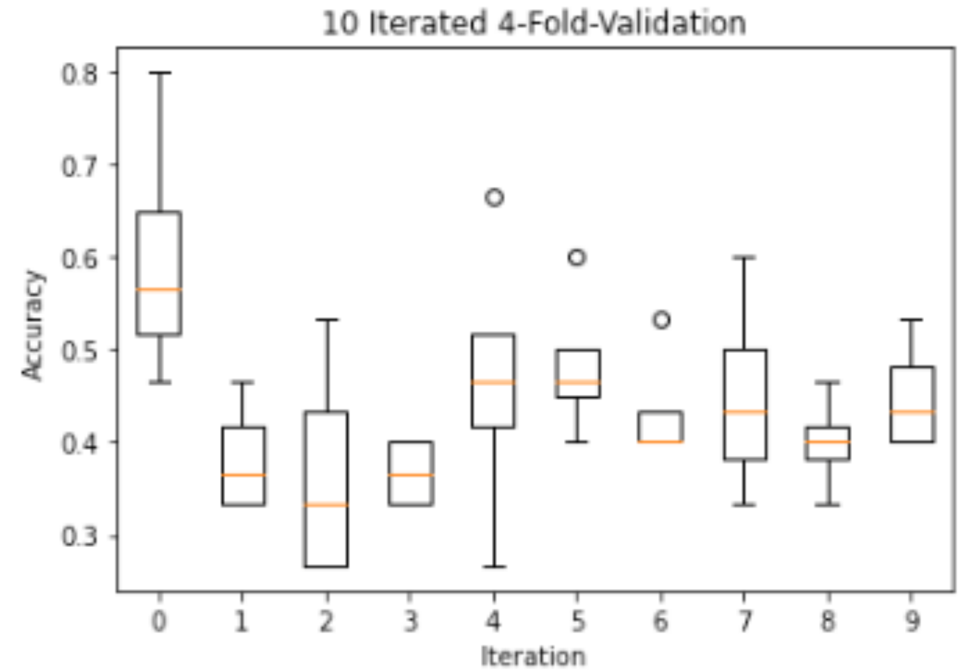
- Bidirectional LSTM: 707 units and ELU
- GRU: 660 units and leaky ReLU
- Bidirectional GRU: 469 and leaky ReLU
- Dense layer: 138 and GELU
- Dropout (0.2)
- Dense layer: 150 and leaky ReLU

Obtaining 0.5 of accuracy

Results & Discussion – Chemical Interaction Classification



(a)



(b)

CNN – 45.33% $\pm$ 5.85%

RNN – 44% $\pm$ 6.6%

Conclusion

Proposed a deep learning-based workflow for developing *Biohybrid Intelligent Sensing Systems (BISS)*

The motivation for this is to *enhance the performance and broaden the spectrum of potential applications of animal biosensors*

- In an ethical and environmentally sustainable way

For the future we hope to:

- Incorporate temporal information
- Train animals

THANK YOU!

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