

Adaptive acoustic species classification in the field

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1 Species Classification

In recent years, the field of **computational sustainability** has striven to apply artificial intelligence techniques to solve ecological and environmental problems. In ecology, a key issue for the safeguarding of our planet is the monitoring of biodiversity. Automated acoustic recognition of species aims to provide a cost-effective method for biodiversity monitoring.

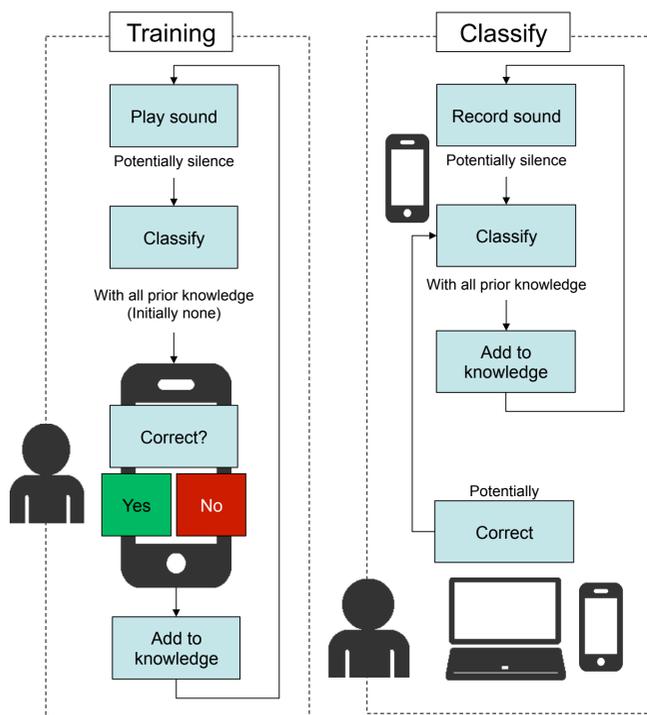


We investigate the development of a **generic smartphone-based acoustic classification system** that can be trained by ecologists with minimal effort and used in the field for the identification of virtually any species.

2 Mobile Classification System for Ecologists

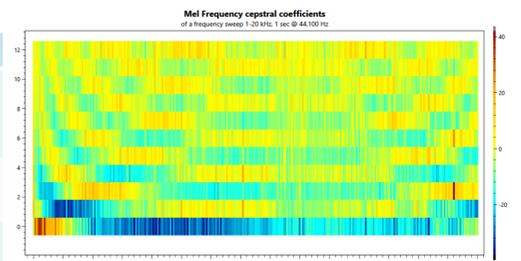
Automated detection and classification of animal sounds can be useful to determine the presence of particular species or individuals in a certain area. However, building an automated classifier can be time consuming. Therefore, we propose a system that:

- Can be
 - trained with minimal effort
 - deployed in the field at low cost
 - matches a sound to a training sample
- Doesn't require
 - Extremely high accuracy
 - Knowledge of the features to be extracted
 - Knowledge of machine learning algorithms



4 Feature extraction with MFCCs

Advantages	Disadvantages
Proven to match certain animals' hearing	Biased towards human hearing
Easy to cluster	Relatively expensive
Well established	



MFCCs pros and cons

Sample MFCCs from a frequency sweep.

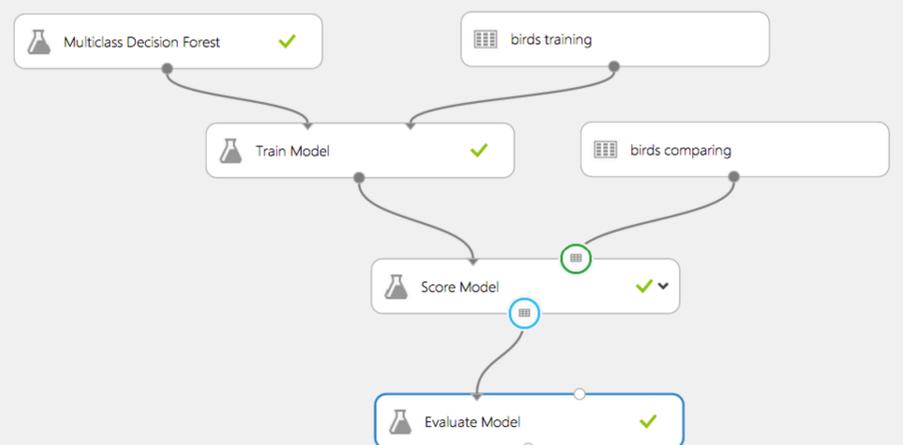
Firstly, we extract a number of features that are:

1. **Unbiased** to specific sounds
2. Sufficiently **inexpensive** to compute
3. **Independent** from volume

Mel Frequency Cepstral Coefficients (MFCCs) are an established technique from the speech recognition literature that represent the short-term power spectrum of a sound. They are calculated with the following steps:

- Compensate for any DC offset
- Frame and window the signal (with e.g. hamming window)
- Calculate the power density of the spectrum (DFT)
- Apply the mel filterbank to the spectrum and sum the energy
- Take the logarithm of mel filterbank energy
- Extract cepstral coefficients

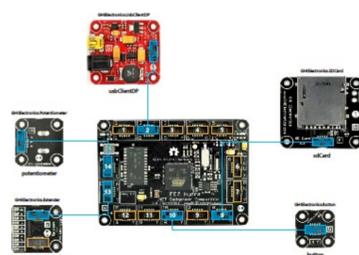
5 Classification on Azure ML



On Azure ML, a model can be trained with large datasets and on different classification algorithms. Results can then be easily evaluated in comparison to each other.

3 .NET Gadgeteer for quick prototyping

The .NET Gadgeteer simplifies hardware prototyping by providing a high-level C#/VB interface to several hardware components.



Prototype layout with FEZ Hydra motherboard

Advantages	Disadvantages
Quick to build	Slow high-level VM layer
Easy to deploy	Not very cheap
Low power	Max interrupt ~ 2 kHz

6 Deployment and future work

- System will be demonstrated on a sample elephant-recognition scenario.
- Elephants emit low-frequency calls (even subsonic)
- Deployment will be performed as a mobile phone application and on a .NET Gadgeteer board.
- System will be provided to other ecologists to train for different classes of sounds.
- Future applications could deviate from ecology.

