Midterm Progress Report

AudioT - Team EUT

An audio classification approach to assess bird transportation welfare

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1. Introduction - The chicken industry

Every year, the USA ranks in the **top 3 countries for chicken consumption** per capita[2].

Concurrently, **animal welfare** is a growing consumer, industry and public administration concern[3].

Transportation stress is known to have an impact on **meat quality**, with duration and conditions impacting pH and cortisol levels, glycogen in muscles and the development of PSE (Pale, Soft, and Exudative) meat, undesirable in the industry[4,5,6,7,8].

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1. Introduction - AudioT

AudioT specializes in leveraging **acoustics**, **machine learning** and **signal processing** expertise to **monitor poultry farms**.

AudioT solutions enable industry actors to **detect anomalies** including intrusion, sickness, equipment failures, and changes in chicken behavior, ranging from hatching to transport to the processing facilities.

2. Project details - Objectives

The objective of the Eurotruck project (EUT) is to build upon AudioT's knowledge and insights regarding vocalizations from late-stage broiler flocks, and **apply it to the birds during transport** in order to **detect** and measure **distress events**.

The underlying idea is to detect, measure and analyze **flock activity**, assuming that **a quiet flock is a good flock**.

2. Project details - Recordings

Just like for its poultry farms monitoring, AudioT relies on microphones to generate its primary source of data: **recordings of bird vocalizations**.

Recordings can then be analyzed, labeled and used to train models able to distinguish between **different types of vocalizations** and alert in case of distress.

Microphones were therefore placed in trucks to record flock activity for future analysis and processing.

2. Project details - Recording process

Two different types of trucks were used:

- **Regular trailer** (the most common ones in the US)
- **Aircool trailer**

Six trips were recorded in total, and **five different microphones** were used. Times provided are in CET.

- **EUT1** - Trip 1 (single trip on Aug 30, 6:30 to 8:10 AM)
  - Mic 2
  - Mic 9
- **EUT2** - Trip 2 (single trip on Aug 30, 12:48 to 17:37)
  - Mic 2
  - Mic 8
- **EUT3** - Trip 3 (out and back on Nov 29, 8:25 to 15:28)
  - Mic 2 (failed)

- **EUT1** - Trip 1 (single trip on Oct 27, 7:30 to 10:49 AM)
  - Mic 2
  - Mic 10
- **EUT2** - Trip 2 (single trip on Oct 27, 10:50 to 13:48)
  - Mic 2
  - Mic 10
- **EUT4** - Trip 3 (out and back twice on Nov 29, 8:23 to 16:23)
  - Mic 2

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2. Project details - Recording process

Regular trailer

Aircool truck

3. State of data

The data consists of **one minute audio segments** of the recordings mentioned previously. These segments are available in the form of `.flac` files (free of compression).

The data comes from:

- Different **trips**
- Different **trucks**
- Different **microphones**
- Different **microphone placements** in trucks

These are the source of **variability** in the data quality.

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3. State of data

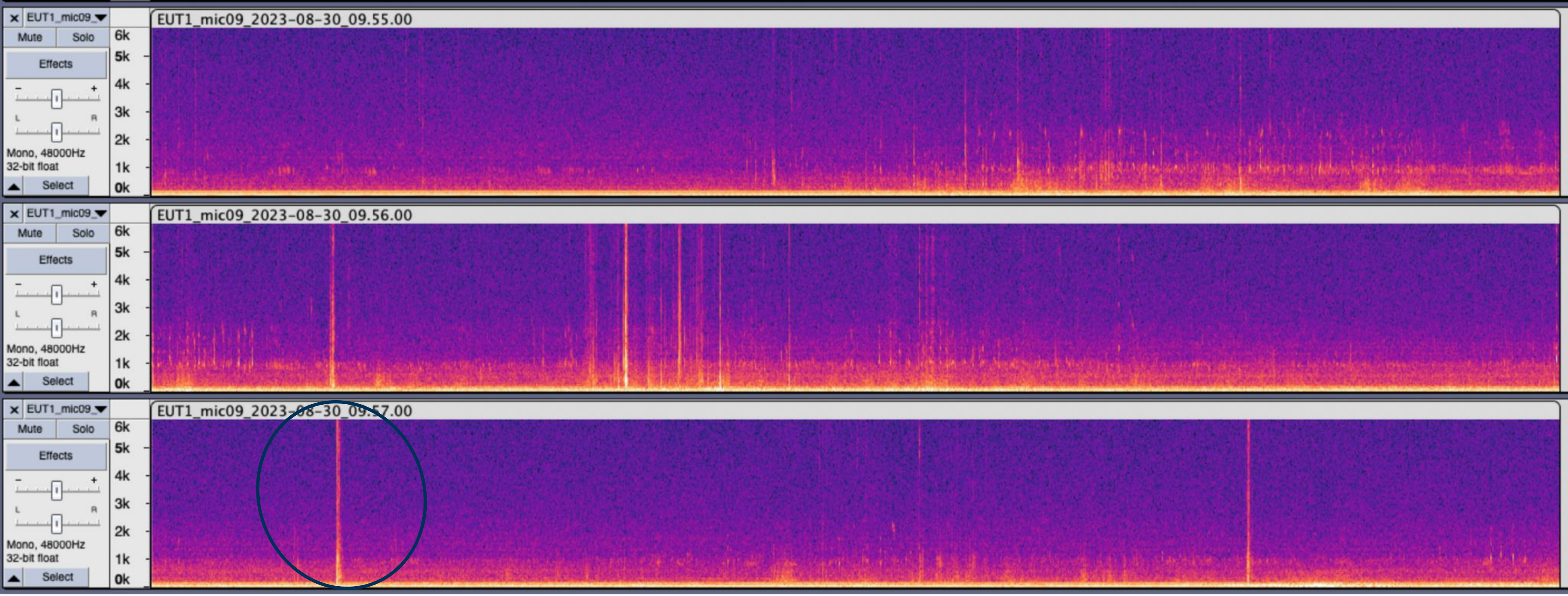
The `.flac` files provided have a standard naming convention.

- **Example: `EUT1_mic02_2023-08-30_07.00.00.flac`**
- **Decoding the naming structure:**
  - `EUT1` matches the legend on slide 7, indicating this is from trip EUT1, an aircool trailer trip on 8/30/2023.
  - `mic02` indicates that the audio is from Mic 2
  - `2023-08-30` indicates the date, though this is redundant with information provided on the legend
  - `07.00.00` indicates the minute in GMT, so an hour needs to be added for it to match the legend, which is in CET (i.e., 8:00 CET.)
    - This is particularly important, as there are audio files of the trucks when chickens are not present.

3. State of data - Processing

We rely on **audio and visual analysis** (spectrogram, wavelength) to **label the data** in Audacity. The final result, on top of the features contained in the audio file itself, are a timestamp and corresponding labels, and the presence or absence of labels in itself.

We need to identify interesting segments, label them accurately and enough of them to have a solid training dataset. Audacity lets us listen and visually analyze several files at the same time.



The 3 audio data files here shows **EUT truck 1 (Aircooled) on 08/30/2023 from 9:55 AM - 9:57 AM CET** using **microphone #9**. Visually, the warmer coloured tones (yellow/orange/red) shows audio captured through the microphone. When identifying bird vocalization, they are generally identified to be up to the 3000 Hz frequencies. For any above that range - as identified with the circle above, that audio is most likely a “truck” noise (rustling, clanking, brushing of the microphone).

3. State of data - Processing

Bird vocalizations can be labeled in different fashions, and we **collaborate** with another AudioT team (Team AW6) working on **late stage vocalization** (right before they get transported). Such vocalizations can be labeled as cooing, cackling, chirping, trilling, coughing…

In transport, **a lot of other noises are recorded** as well, but shouldn’t be mixed up for bird activity. Such noises are air vents, crates rattling or rustling, wind blowing, road bumping, etc.

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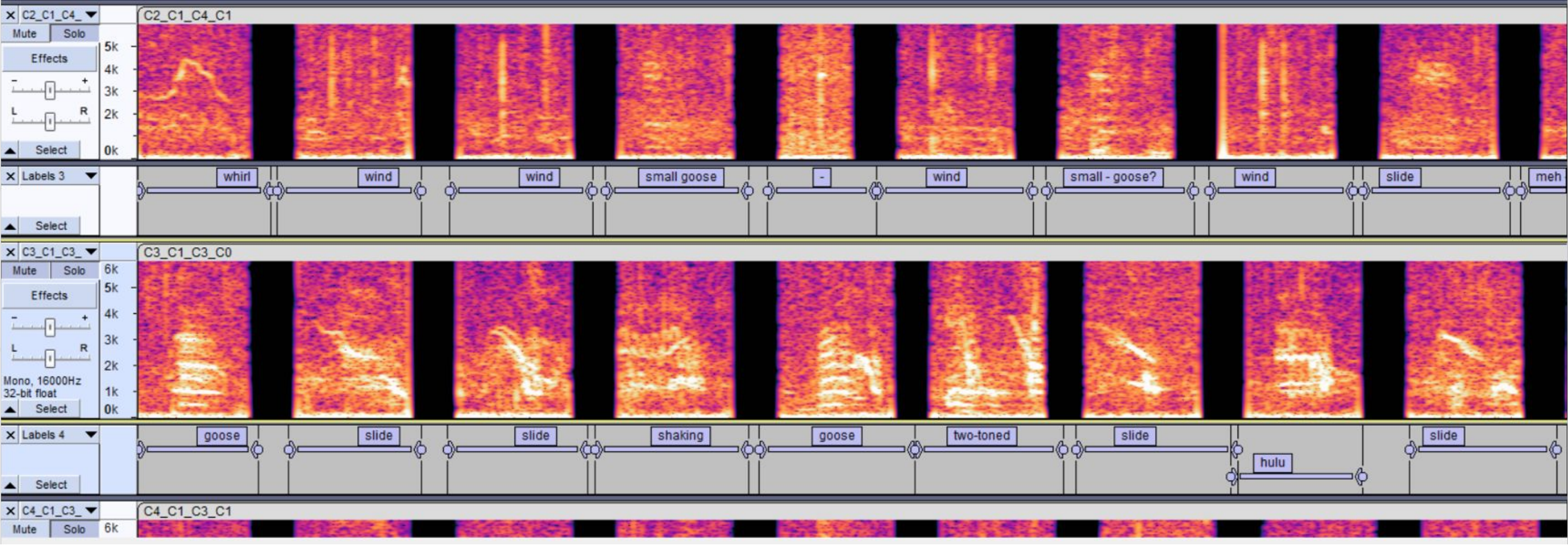


An example of existing AudioT taxonomy, presenting a dictionary matching specific sound patterns and audio cues to visual patterns on the corresponding spectrogram. Our initial effort will focus on binary classification (detecting flock activity vs none). However, such a taxonomy can help bring variance to the training dataset and improve model accuracy in a multiclass classification approach (more on this point in Part 6).

4. Data preparation challenges

- Labeling sounds accurately on the **timeframe**
- Labeling sounds accurately (our interpretation of the sound is **subjective**)
- Finding one-minute segment with **enough activity to learn from**
- **Balancing segments** with quiet flock, segments with active flocks and segments without flock
- Potential **imbalance** (distress events are hopefully rare)

4. Data preparation challenges

- Selecting quality segments **without biasing** the training set
- Working with microphones in **real-life conditions** (close to an air vent, on the exterior of the truck, obstructed by crates)
- Agreeing and deciding on the **label dictionary** (binary - activity / no activity, or more precise for multi-classification, bringing more variance to learn from but potentially more data to train on)
- Dealing with **some low quality recordings** (we can't just increase the sound, because noise also increases)
- Noise reduction vs filtering lower frequencies

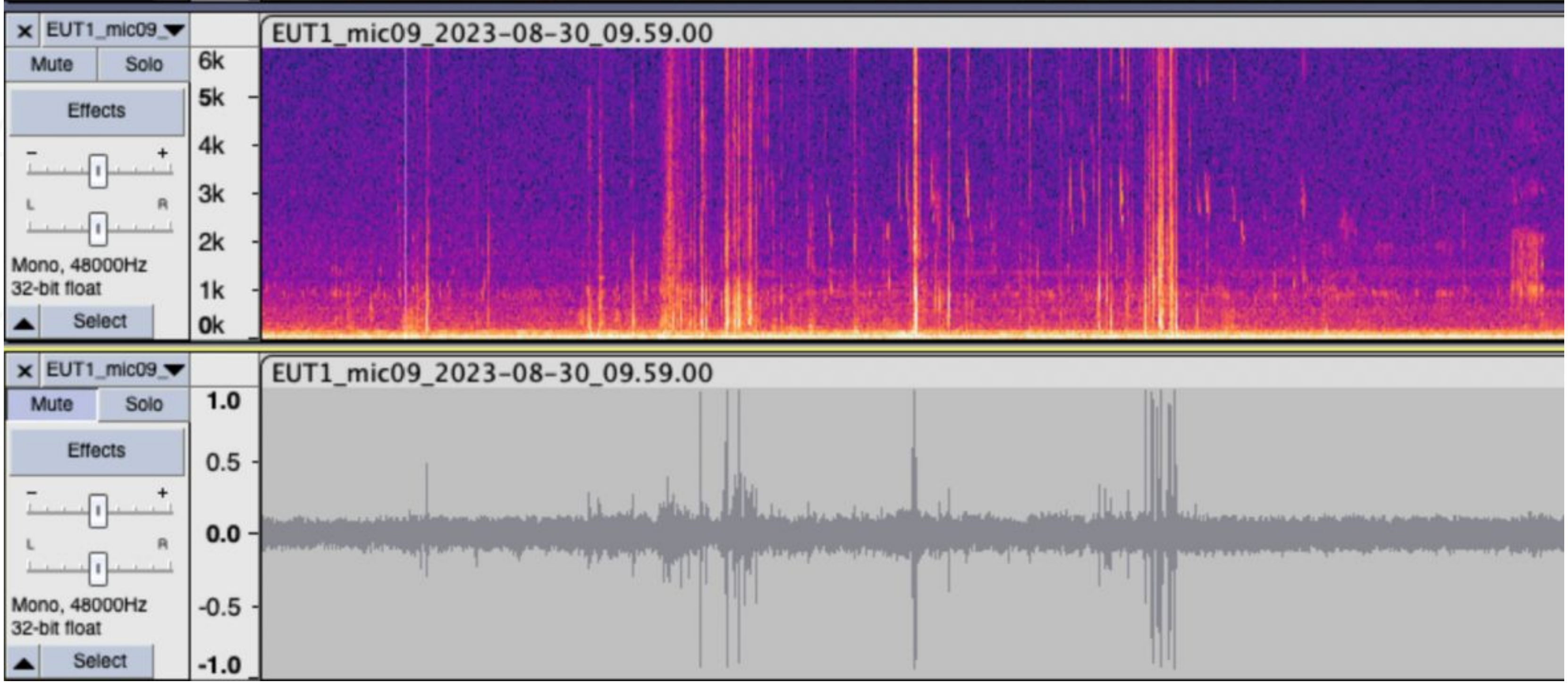
4. Data preparation challenges

Due to fan noise, road noise, and other external factors, extra noise in the data is a challenge. Two potential ways of addressing this are **noise reduction** and **filtering**.

- **Noise Reduction** involves identifying a noise profile of the noise to remove and then applying it to the audio file
- **Filtering** involves attenuating (reducing) specific frequencies:
  - **Low-pass filters** attenuate frequencies above a specific cutoff
  - **High-pass filters** attenuate frequencies below a specific cutoff
- For our project, a filtering approach is more appropriate, as noise reduction leads to loss of bird vocalizations due to shared frequencies

5. Data features

- Truck
- Trip number
- Microphone used
- Timestamp
- Presence or absence of labels
- Statistical summaries of mean and variance of spectrogram coefficients from Mel spectrogram (frequency) and MCFF (timber)
- Spectral contrast
- Chroma features

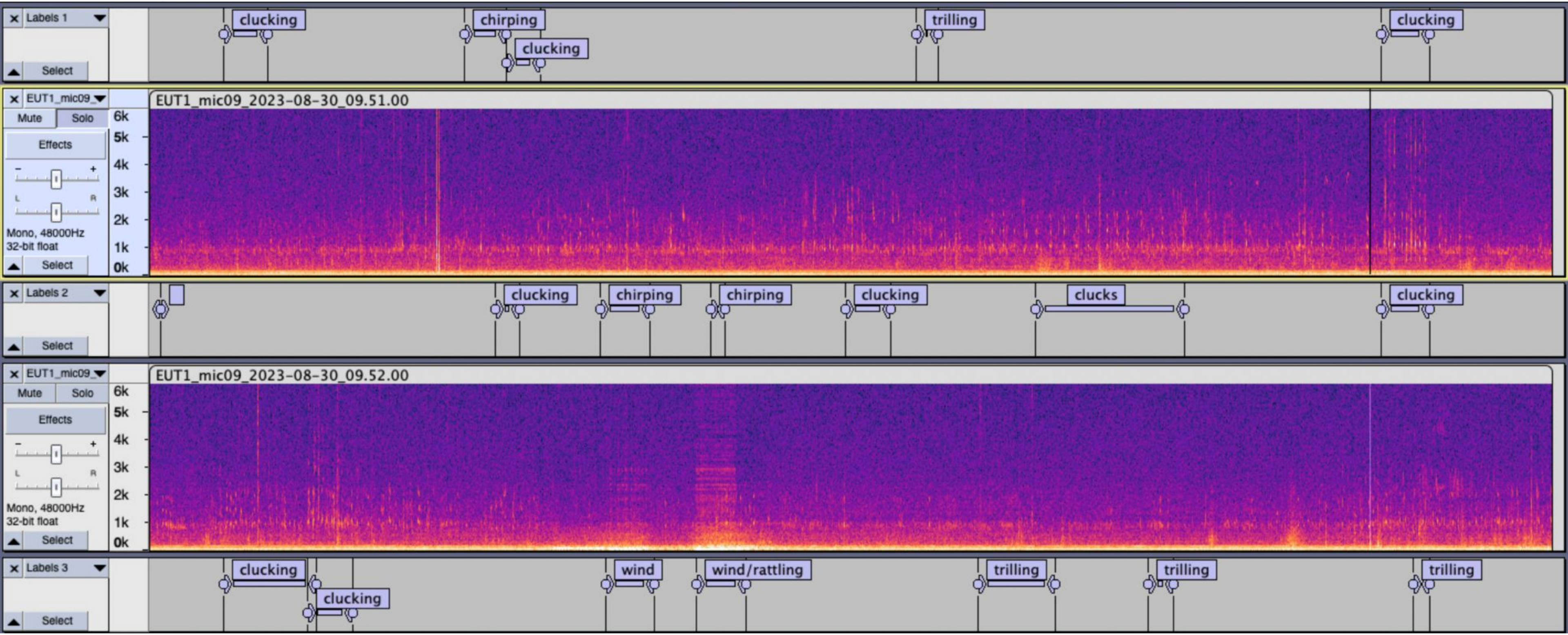


The same audio file in spectrogram and waveform views. "Spectrogram view provides a visual indication of how the energy in different frequency bands changes over time" - here set with a minimum frequency of 0 Hz and a maximum frequency of 6000 Hz. Below the waveform view provides a "linear vertical scale running from -1.0 (negative values) to +1.0 (positive values), centered on zero." The +1 denotes the maximum possible loudness when positive and the -1 denotes the maximum possible when negative. Within waveform view, there is also a decibel scale available.

5. Data features

In terms of labeling, **three different approaches** are possible:

- **Binary** labeling (flock activity vs everything else)
- **Multiclass** labeling (classifying flock and other noises more accurately, e.g. the taxonomy dictionary mentioned in Part 3)
- **Multilabel** labeling (each team member labels each sound based on a common taxonomy)



The 3 audio files **EUT truck 1 (Aircooled) on 08/30/2023 from 9:55 AM - 9:57 AM CET** using **microphone #9**, with labels. It is important to note that the audio files from the transportation of the birds have much lower amounts of bird activity. This is a positive outcome as there are no sounds of distress. From the data that has been labelled, we have found only positive bird activity including clucks, trilling/coos, and chirping.

6. Feature selection

- Mel spectrogram for feature selection
  - Emphasizes **frequency** content
  - Matches the human auditory system's sensitivity, especially in the lower frequency range
  - Helps identify frequency **patterns specific to certain sounds**
- Mel-Frequency Cepstral Coefficients (MCFF) for feature selection
  - Emphasizes **timber**
  - Helps **distinguish between sounds** with different textures despite **having similar frequencies**
- Random Forest, CNN or RNN for frame-based approach

6. Feature selection

→ *A **Mel Spectrogram** can help us identify segments of high activity*

→*A **MCFF** approach can complement this by helping distinguish between sounds within this segment of high activity*

7. Modeling approaches

- **Frame-based** approach
  - Audio is analyzed in short, overlapping frames
  - Efficient in detecting short-term events and sound characteristics
  - Increases computational complexity
  - Sensitive to noise (requires noise reduction preprocessing)
- **Segment-based** approach
  - Better suited for capturing the overall activity level or the presence of sustained sounds
  - Reduces computational complexity
  - Lower temporal resolution (may miss short-lived sounds or rapide changes)
  - Choice of segment length impacts specific event detection

7. Modeling approaches

→ *A **segment-based** approach seems more appropriate to our **flock activity detection** objective*

→*A **frame-based** approach could complement the segment-based approach, intervening only within active segments:*

- *To **ensure activity is indeed flock activity** and not noise: a current issue at AudioT is some models detecting crates rattling in empty trucks before loading or after unloading as flock activity*
- *To assess the **nature** of the flock activity: are we hearing **comfort** chirping or **distress** chirping?*

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7. Modeling approaches

- ***Logistic regression, SVM and Random Forest*** *could help in binary classification*
- ***CNN, RNN and gradient boosting machines*** *could help in multiclass classification*
- ***Binary relevance*** *(with Logistic Regression, SVMs, or Random Forests),* ***classifier trains and neural networks with multiple outputs layers*** *could help in multilabel classification*

Tools used: Audacity for labeling, scikit learn and librosa for modeling

7. Modeling approaches - simple to complex

- Establish **baselines** using simpler approaches (binary classification, segment-based only)
- Increase **model complexity** with **classification complexity** (move to multiclass and multilabel, merge segment and frame-based approaches)
- Revise feature engineering and hyperparameter tuning as needed based on **continuous learning**
- Consider **ensemble models** if we discover several well-performing models, potentially weighing them on their respective accuracy on flock vs non-flock detection

Sources

1. Title slide picture: Chicken by Cassie, Flickr, https://flic.kr/p/9uUefi, Licence CC BY-NC-SA 2.0 DEED, changed tone to sepia.
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4. Grandin, T. (1997). "Assessment of Stress during Handling and Transport." Journal of Animal Science, 75(1), 249-257.
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6. Knowles, T. G., et al. (1999). "Effects of road transport on indices of stress in sheep." Veterinary Record, 144(15), 418-422.
7. Fazio, E., & Ferlazzo, A. (2003). "Evaluation of stress during transport." Veterinary Research Communications, 27(1), 519-524.
8. Swanson, J. C., & Morrow-Tesch, J. (2001). "Cattle transport: Historical, research, and future perspectives." Journal of Animal Science, 79(E-Suppl), E102-E109.

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