universität freiburg

Intelligent
Embedded
Systems Lab

Bowel Sound Pattern Spotting Fine Tuning using Active Learning

Master Project Presentation

M. Sc. Computer Science

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Background

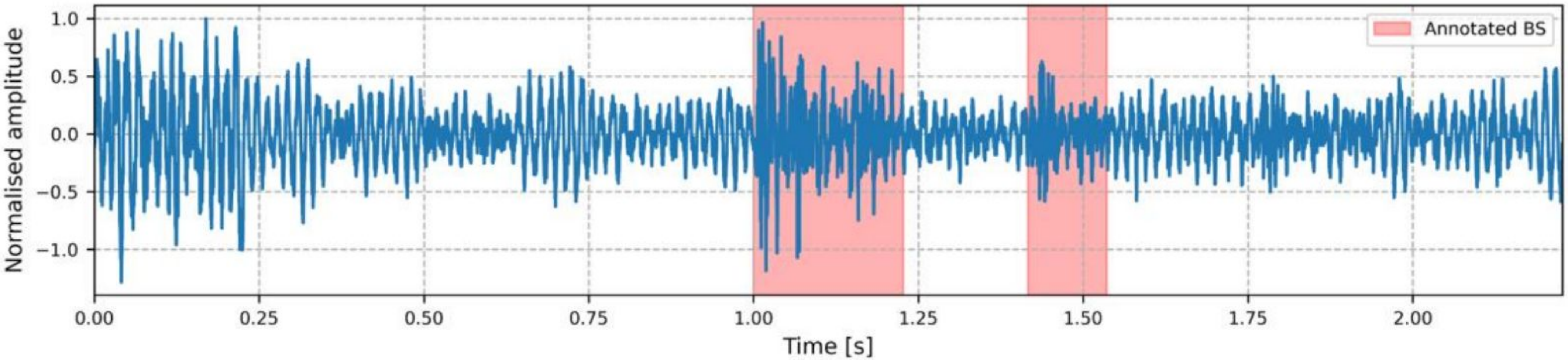
Bowel Sounds (BS) Spotting

- **Digestive disorders** evaluations are lengthy and usually invasive.
- **Auscultation** is a non-invasive option for monitoring gut health.
- **GastroDigitalShirt** [1] enables the recording of bowel sounds.
- **Deep Neural Networks** identify the onset and offset of BS patterns. [2]

GastroDigitalShirt [1]

Introduction to the Project

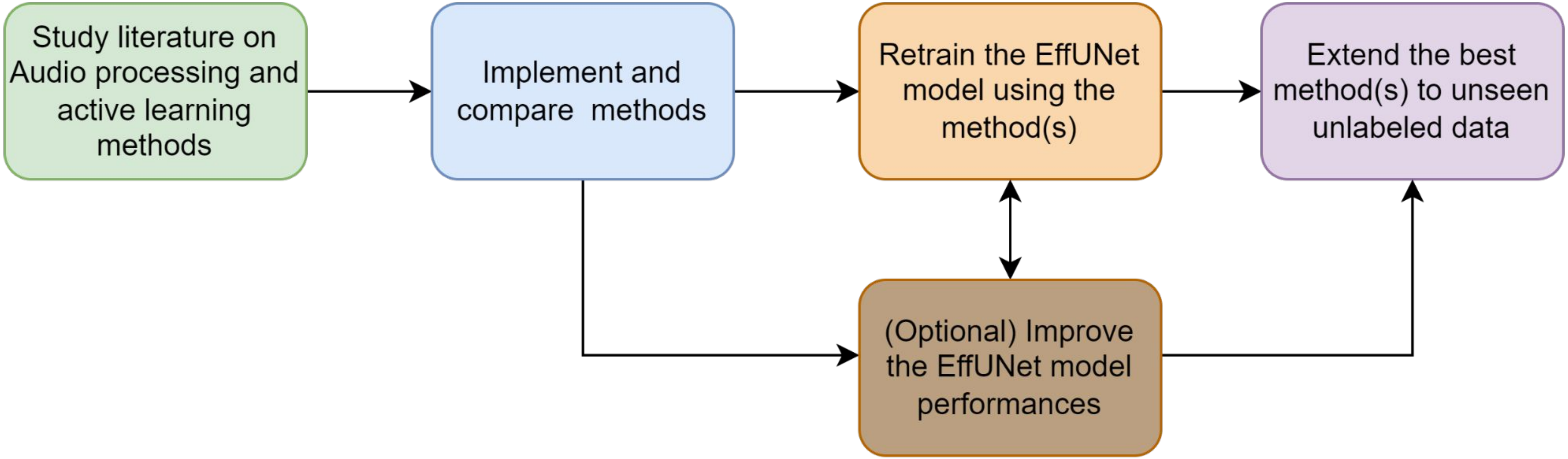
- Deep Neural Networks require **large amount of labeled data**
- 136 hours of audio data were labelled with 11482 BS events [2]
- On average, 1 hour of audio recording required **8-12 hours** for BS labelling [2]
- Various models tested and **EfficientUnet** [3] pretrained with transfer learning yielded the best results



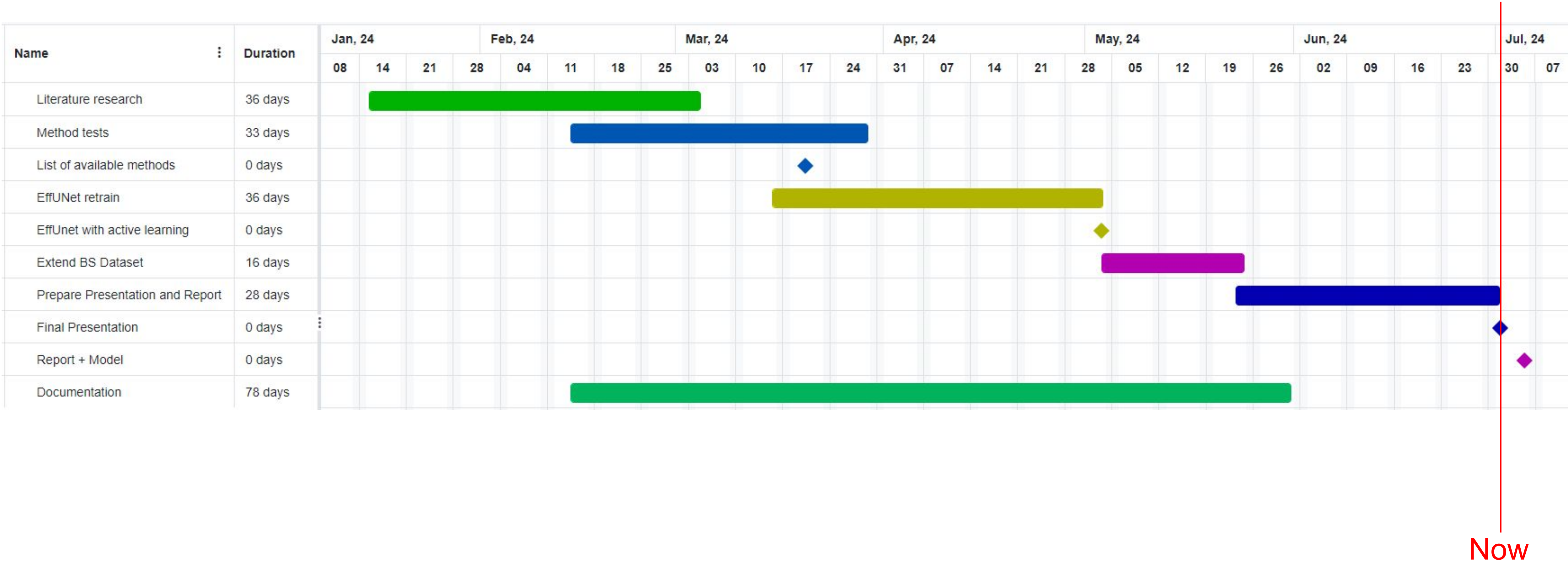
Representation of two expert-annotated BS events [2]

Project Goal and Tasks

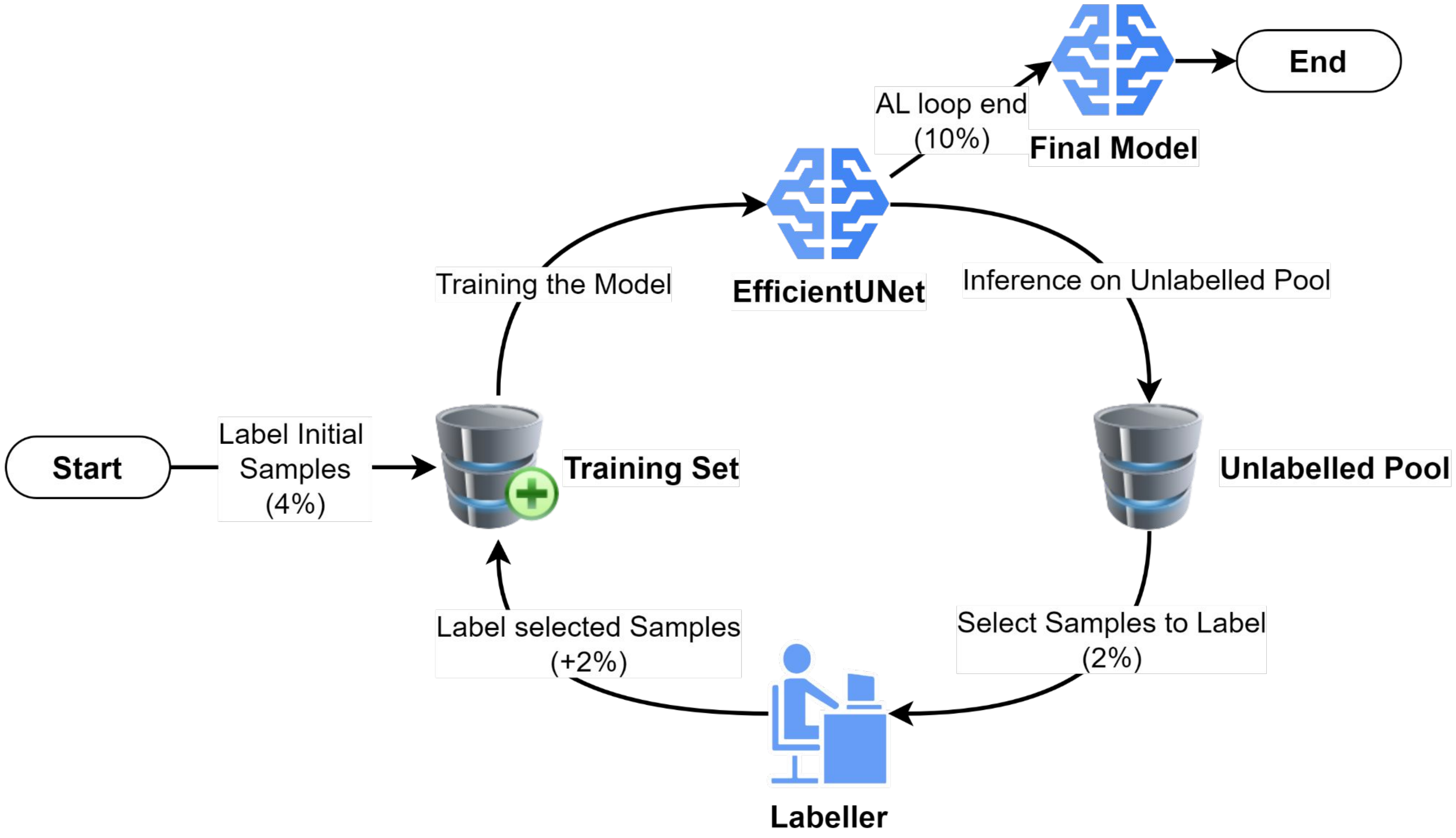
Goal of the project: **Achieve good performances with less labelled data**



Project Plan



Active Learning (AL) Process



(X%): Percentage of Labelled Data

Training Set: The labeled data used for training the model.

EfficientUNet: The deep learning model being trained.

Unlabelled Pool: The pool of unlabeled data from which new samples are selected.

Labeller: The process or person responsible for labeling the selected samples.

Final Model: The model after several iterations of active learning.

Active Learning Details

- **Samples selection process**:
  1. The current model **predicts** on the unlabeled dataset.
  2. The single predictions are a measure of **uncertainty.**
  3. **Heuristic** calculates the **uncertainty** for each sample. [4]
  4. Select **top samples** to label.

- **Initial Sampling**: Can be random or heuristic-based (only if using pretrained models).

Implementation

Built on Top of Existing GastroDigitalShirt Code

- **Language & Framework**: Python with Pytorch Lightning. [5]

Active Learning Integration

- **BAAL Library**: Leveraged Bayesian Active Learning techniques. [6]

Modifications:

- **Data Loader**: Customized to handle active learning queries.
- **Trainer**: Adapted to use BAAL's active learning cycle.
- **Model**: Kept EfficientUnet unchanged for consistency.
- **Pipeline:** Adapted to include Active Learning

Dataset and Model

Dataset:

- **Participants**: 27 (18 healthy and 9 patients with Inflammatory Bowel Disease).
- **Duration**: 136 hours of audio data.
- **Segmentation**: Split into non-overlapping 10-second segments.
- **Transformations**: Converted to Mel Spectrograms with a temporal resolution of 10 ms.
- **Data Imbalance**: BS ratio of 0.89%.

EfficientUnet Model:

- **Architecture**: Combines U-Net with EfficientNet as the encoder.
- **Pretraining**: Initially trained on AudioSet. [7]
- **Input**: Log Mel-spectrograms of shape 128 × 1056.
- **Output**: Binary detection mask indicating Bowel Sounds (BS) or Non-Bowel Sounds (NBS).

Overview of Experiments

- **Active Learning (AL) Parameters**:
  - **AL Start Percentage**: 2%, 4%, 10%, 20%.
  - **AL Step Percentage**: 1%, 2%, 3%, 5%, 10%.
  - **AL Number of Steps**: 3, 4, 5, 8, 10
  - **Heuristic**: Random, Entropy, Margin, BALD.
  - **Training Epochs**: 3, 5, 10, 20

- **Training Strategies:**
  - **From Scratch**: Retrained the model from scratch at each iteration to ensure fresh learning without any bias.
  - **Checkpoints**: Resumed training from the last checkpoint to save time and leverage previously learned features.

- **Model Hyperparameters**: Learning Rate, Loss, Optimizer, Warm-up.

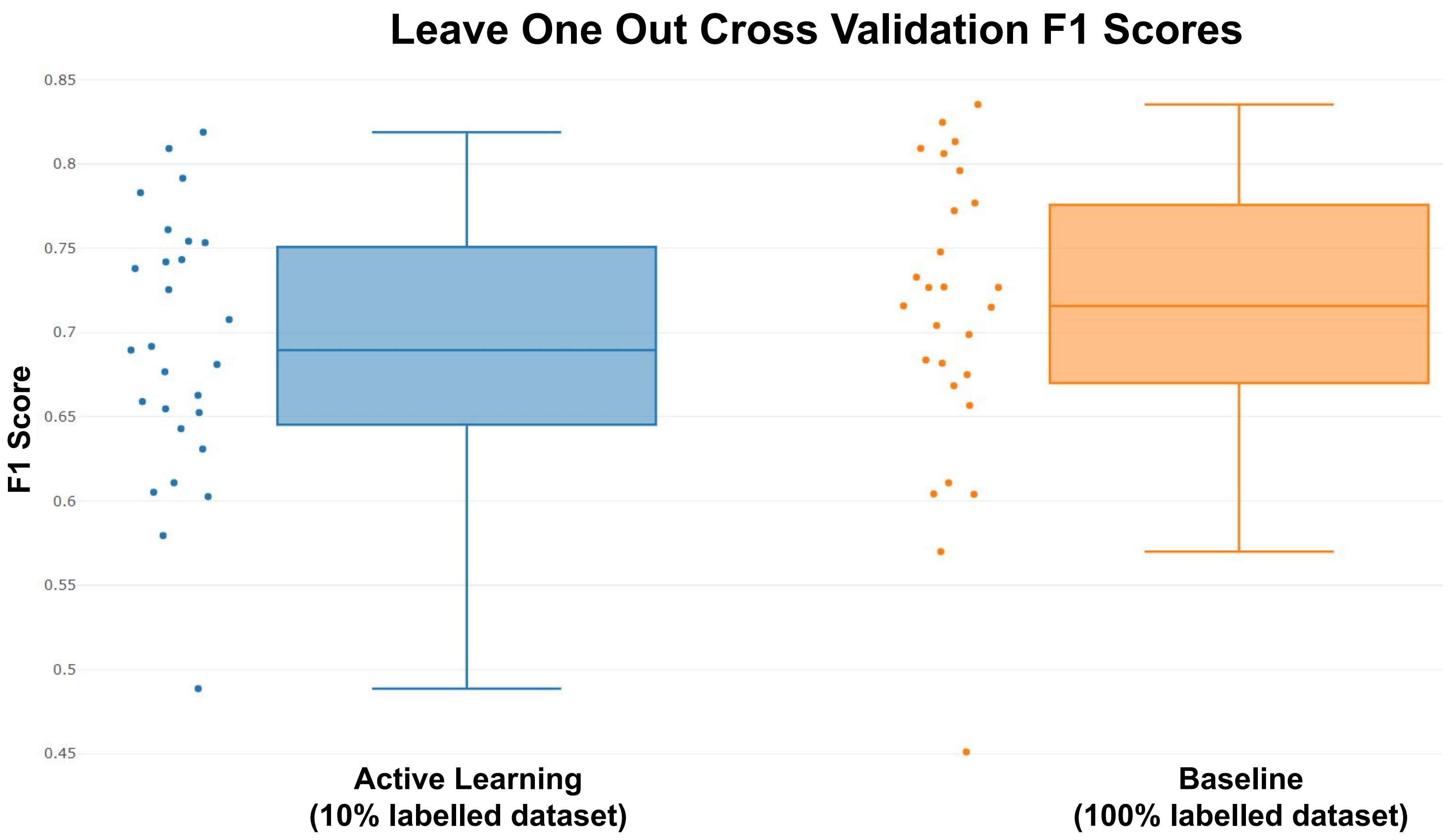
Best Result

Best trade-off configuration found:

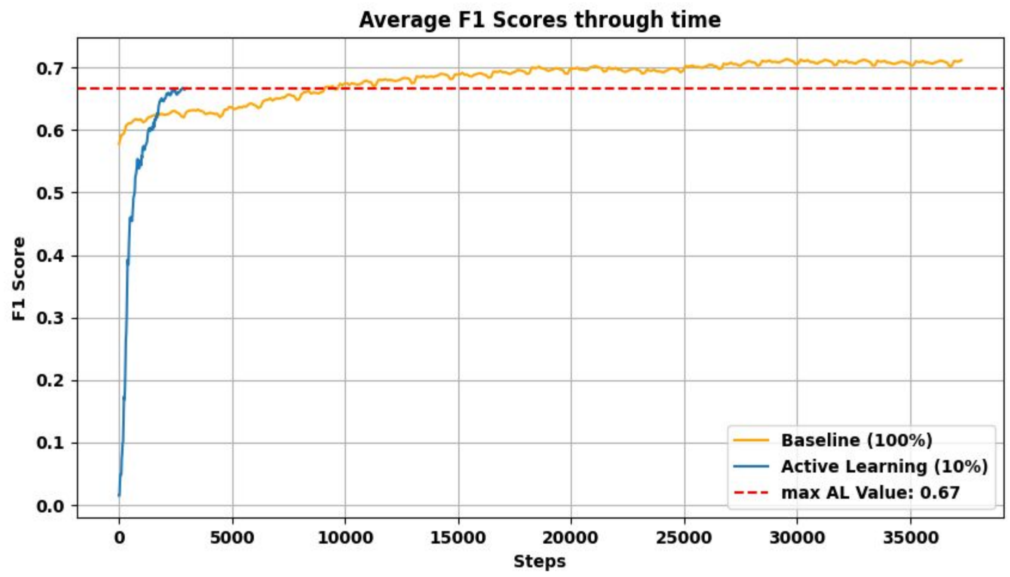
- AL Start Percentage: **4%**.
- AL Step Percentage: **2%**.
- AL Steps: **4**
- **Final Percentage: 10%**
- Heuristic: **Entropy**.
- Strategy: **From Scratch**
- Training Epochs: **10**
- Final Epochs: **25**

EfficientUnet Model (unchanged):

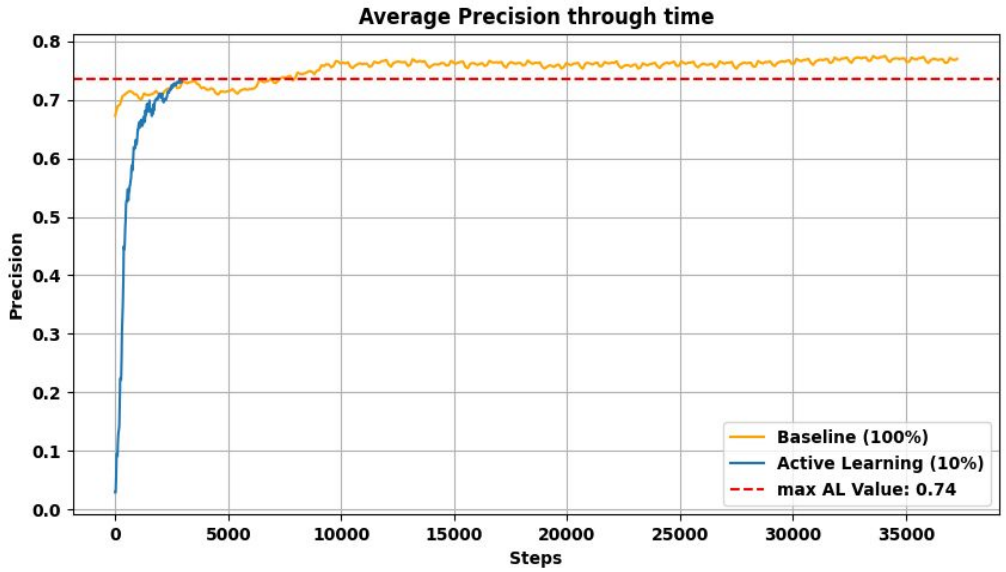
- LR: 0.0001
- Batch size: 32
- Optimizer: ADAM
- Loss: DCEL



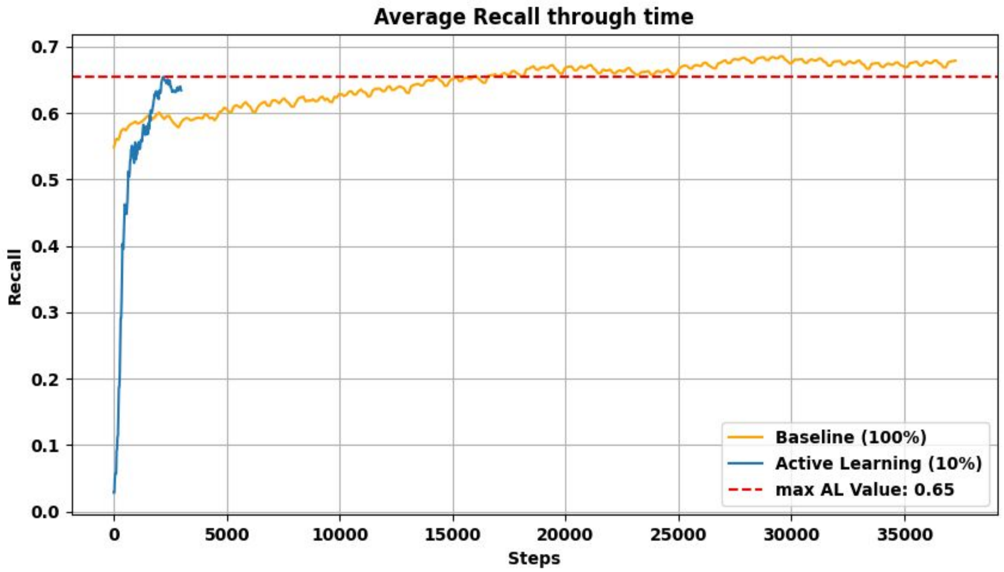
Results



Average F1 Scores through time
F1 Score
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
5000
10000
15000
20000
25000
30000
35000
Steps
Baseline (100%)
Active Learning (10%)
max AL Value: 0.67

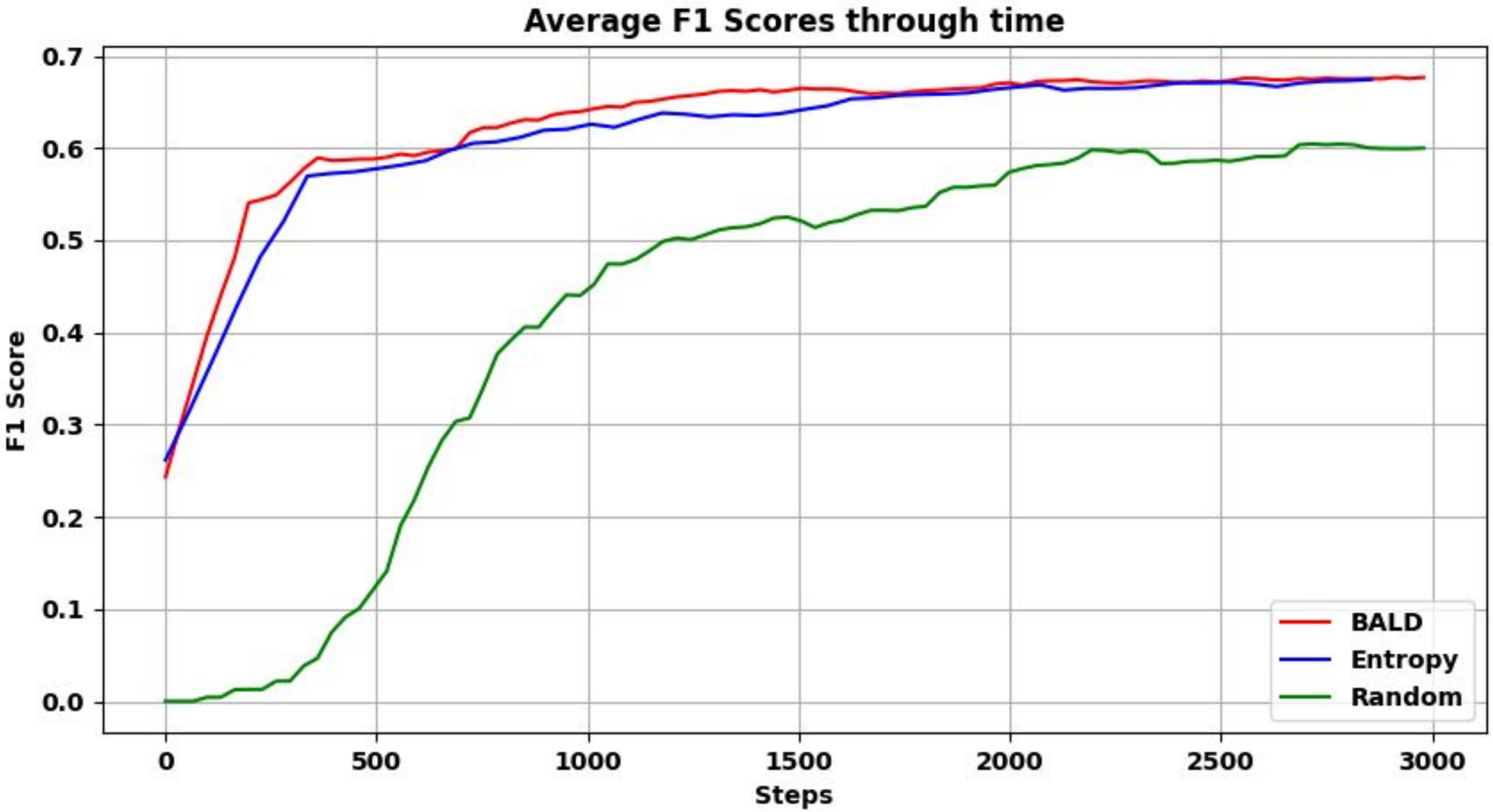


Average Precision through time
Precision
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
5000
10000
15000
20000
25000
30000
35000
Steps
Baseline (100%)
Active Learning (10%)
max AL Value: 0.74

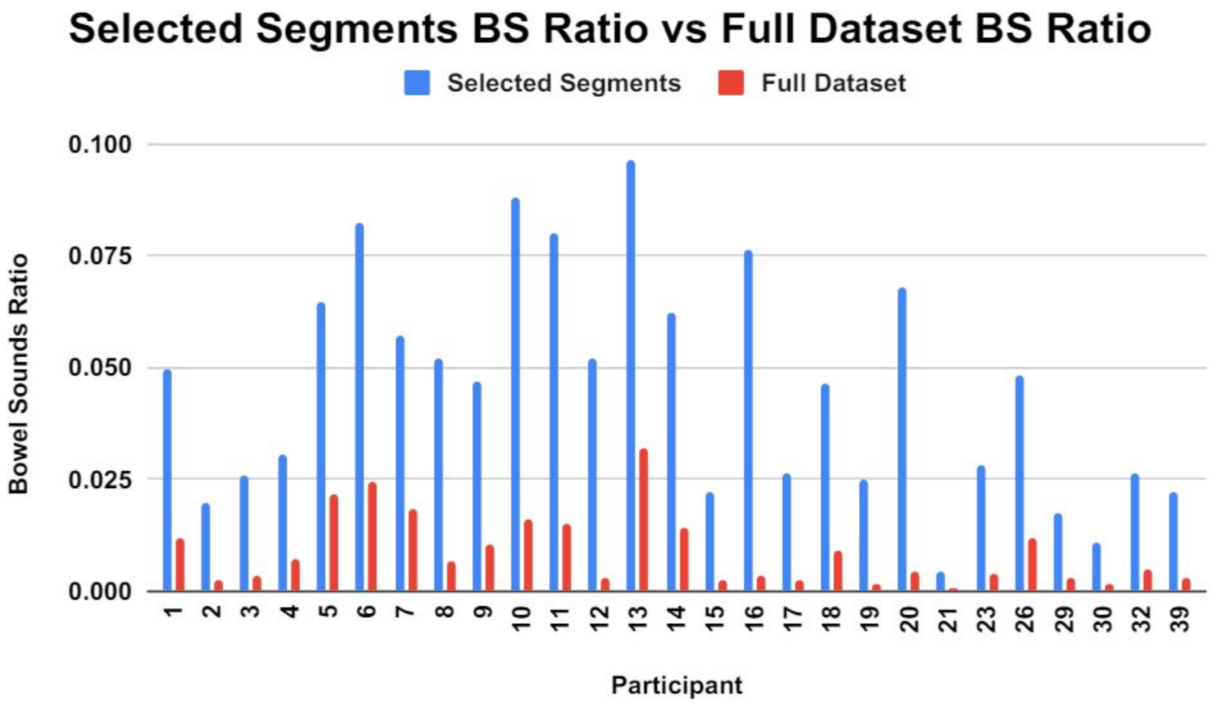


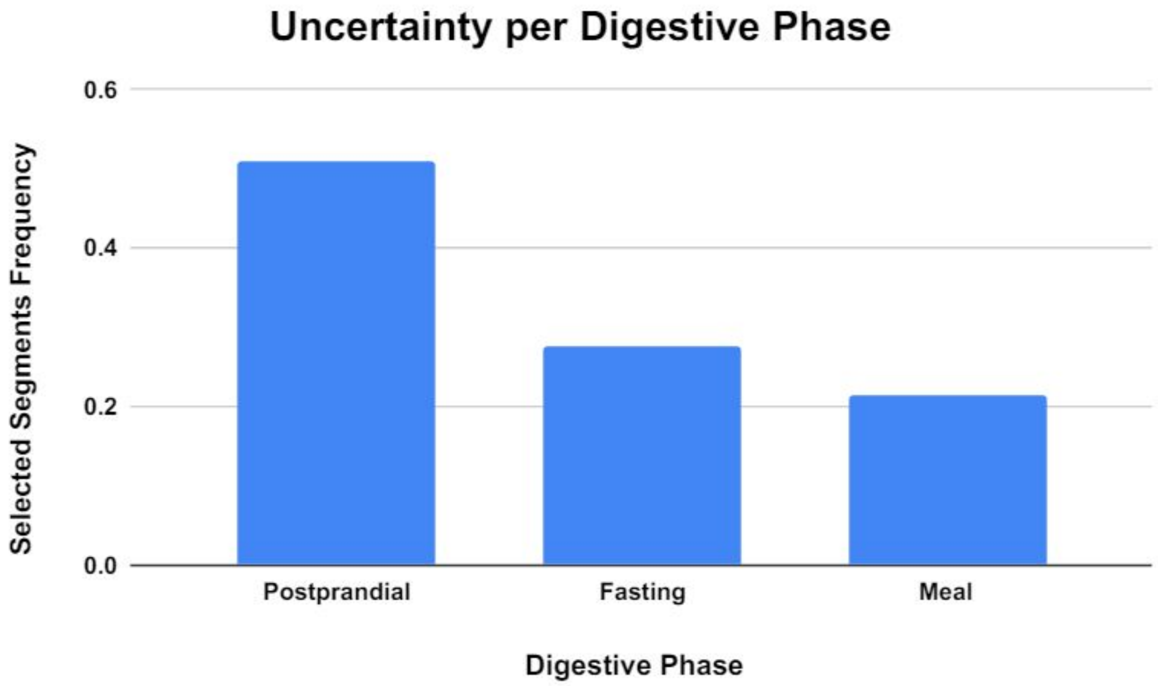
Average Recall through time
Recall
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
5000
10000
15000
20000
25000
30000
35000
Steps
Baseline (100%)
Active Learning (10%)
max AL Value: 0.65

Heuristics Results



Analysis on Selected 10s Audio Segments





Discussion

Why does the method work here?

1. **Unbalanced** dataset with a lot of noise. [2]

2. **High** labelling **costs.** [2]

3. Heuristics based on **Uncertainty.** [4]

4. The method selects segments with **many Bowel Sounds.**

Limitations

1. **Interactive Nature**: Necessity of repeated training and data labelling phases.
2. **Labeling Consistency**: Variability in human labeling can introduce inconsistencies.
3. **Initial Model Performance**: The effectiveness heavily depends on the initial model performance. [4]

Future Works

1. **Experiment with different models**: There might be better models for AL.
2. **Extend to new data**: Labelling new suggested data might further improve model performances.
3. **Implement Crowdsourcing**: Used for efficiently labelling new data. [8]

Conclusions

1. **Key concept:** Not all samples contribute equally to model performance. Samples with the highest uncertainty provide the most information gain.

2. **How it works:** AL algorithms select the most informative and uncertain samples from the dataset.

3. **When to use:** AL is particularly effective in datasets with significant noise or redundant samples.

In this project:

1. **Active Learning Efficiency**: Labelled data need reduced by **90%**.

2. **Time saving**: On average 10 h to label 1 h. The dataset has 136 h of labelled data →
   AL would have saved **1224 h** of data labelling, or **153 days** of 8 h.

References

[1] A. Baronetto, L. S. Graf, S. Fischer, M. F. Neurath, and O. Amft, “GastroDigitalShirt: A Smart Shirt for Digestion Acoustics Monitoring,” in ISWC ’20: Proceedings of the 2020 International Symposium on Wearable Computers, (Virtual Conference), pp. 17– 21, ACM, Sept. 2020

[2] A. Baronetto, L. S. Graf, S. Fischer, M. F. Neurath, and O. Amft, “Multi-scale Bowel Sound Event Spotting in Highly Imbalanced Wearable Monitoring Data,” under review

[3] B. Baheti, S. Innani, S. Gajre and S. Talbar, "Eff-UNet: A Novel Architecture for Semantic Segmentation in Unstructured Environment," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Seattle, WA, USA, 2020, pp. 1473-1481, doi: 10.1109/CVPRW50498.2020.00187

[4] Beck, Nathan, et al. "Effective evaluation of deep active learning on image classification tasks." arXiv preprint arXiv:2106.15324 (2021).

[5] https://github.com/Lightning-AI/pytorch-lightning

[6] Atighehchian, Parmida, Frédéric Branchaud-Charron, and Alexandre Lacoste. "Bayesian active learning for production, a systematic study and a reusable library." arXiv preprint arXiv:2006.09916 (2020).

[7] Gemmeke JF, Ellis DPW, Freedman D, Jansen A, Lawrence W, Moore RC, Plakal M, Ritter M. Audio Set: An ontology and human-labeled dataset for audio events. IEEE; 2017. p. 776–780. doi: 10.1109/ICASSP.2017.7952261

[8] S. Hantke, Z. Zhang, and B. Schuller, “Towards Intelligent Crowdsourcing for Audio Data Annotation: Integrating Active Learning in the Real World,” in Proceedings INTERSPEECH 2017, 18th Annual Conference of the International Speech Communication Association, ISCA. Stockholm, Sweden: ISCA, August 2017, pp. 3951–3955.

Questions

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