Indoor Location Sensing Using Smartphone Acoustic System

What kind of dataset should be collected and evaluated for training the deep model?How to process the captured indoor acoustic signals for efficient and accurate indoor location sensing?

01 Introduction

Imagine being in a huge building with dozens of rooms and suddenly an emergency arises. Now it might be essential for other people where you exactly are within the building. Currently, the most popular location technique, GPS, would not help much since inside the walls this technology fall a bit short. What we need is a system for indoor location sensing that can accurately classify the room that you are in at any given moment.

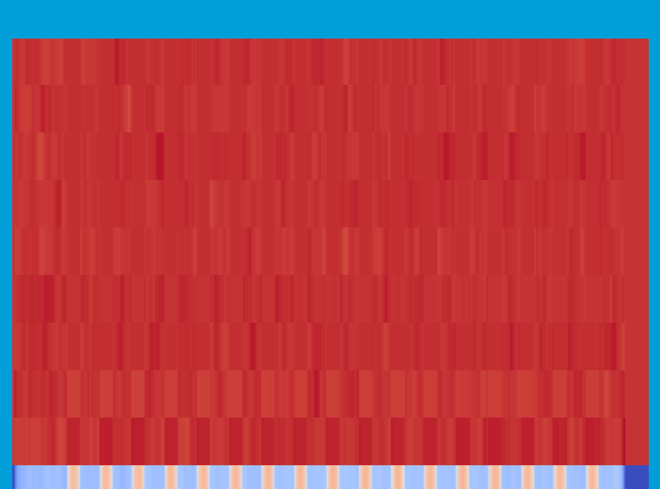
This research aims to further investigate a new technology using acoustic sounds from a smartphone to allow for this classification. Specifically, what kind of dataset is to be collected for training AI to do this classification for us.

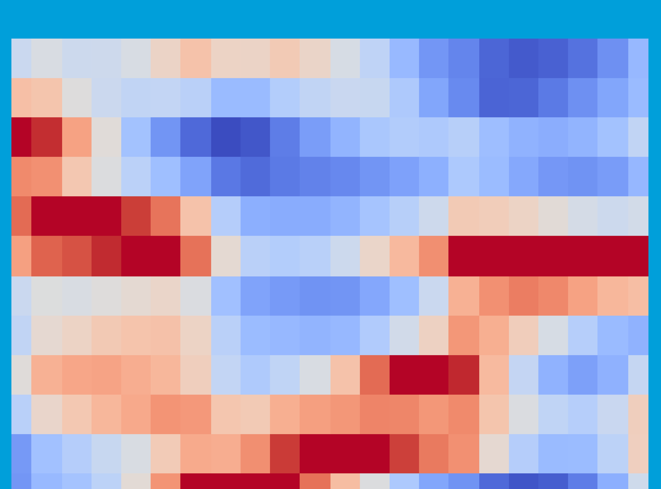
02 Objective

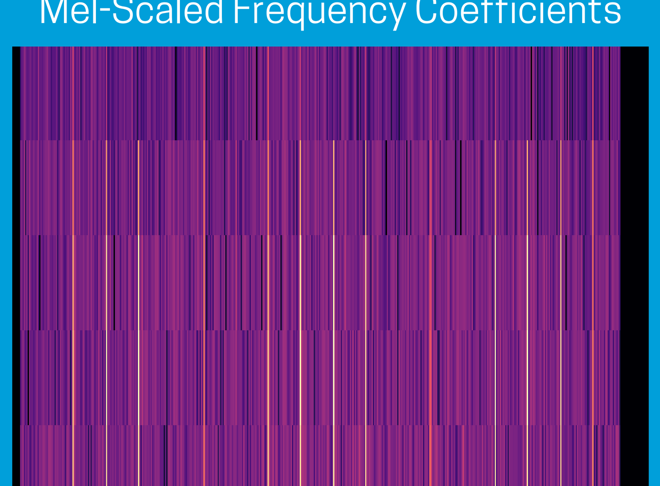
To find the feature extraction method with the best performance in terms of accuracy.

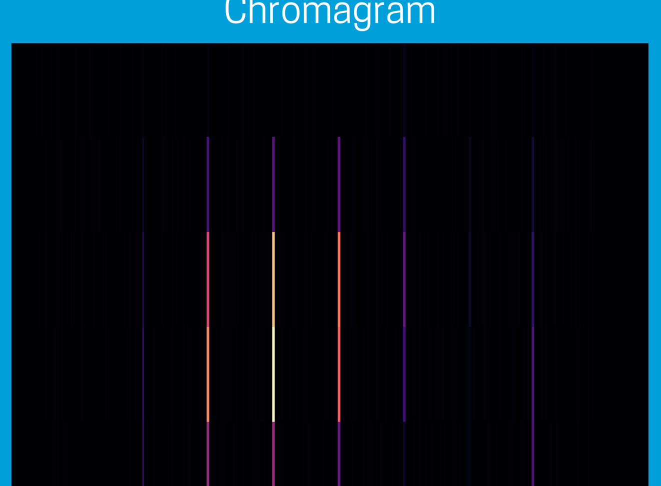
03 Methodology

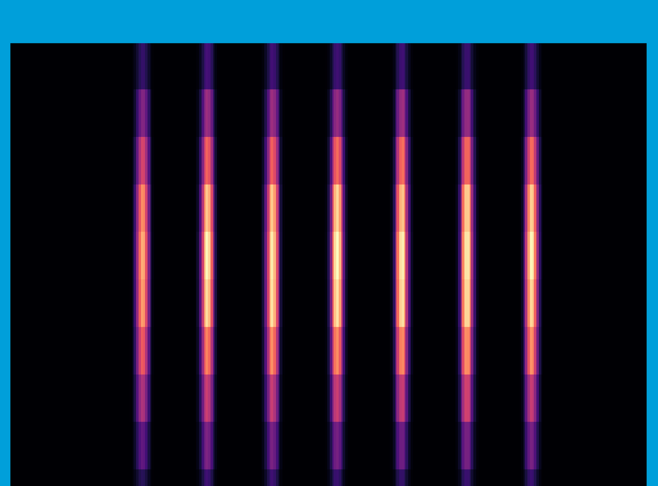
- Record data on 7 different locations
- Process the recorded data using 6 different Feature Extraction Methods (FET)
- Train the same deep model on each FET
- Record the results and show these results in two different visuals:
  - A history graph showing the performance during the training
  - A confusion matrix showing the tested accuracy with a new data set.


Mel-Scaled Frequency Coefficients

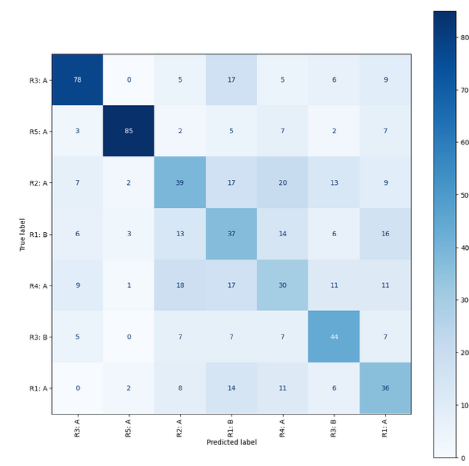

Chromagram

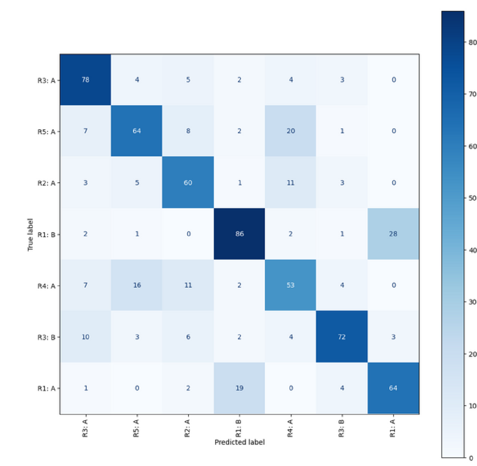

Linear standard spectrogram

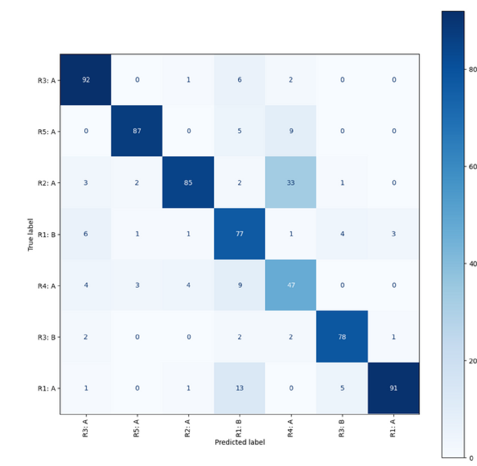

Standard Spectrogram

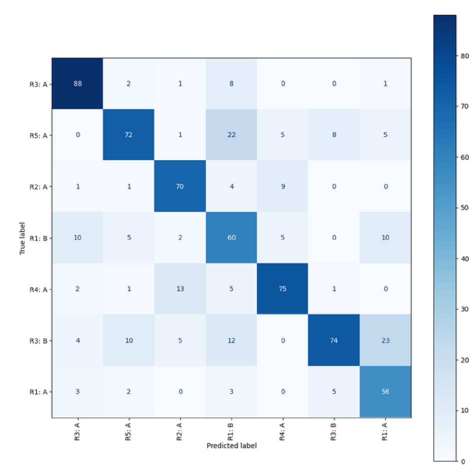

Mel-Scaled spectrogram

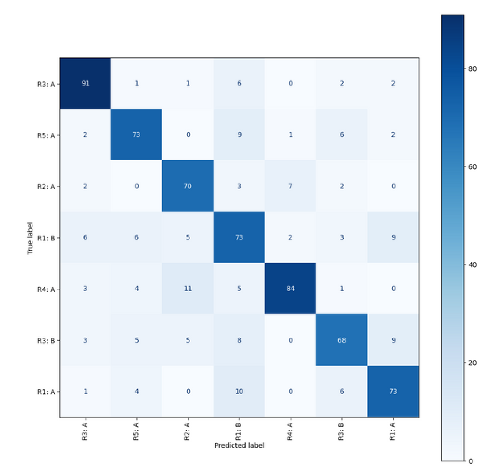
05 Results/Findings

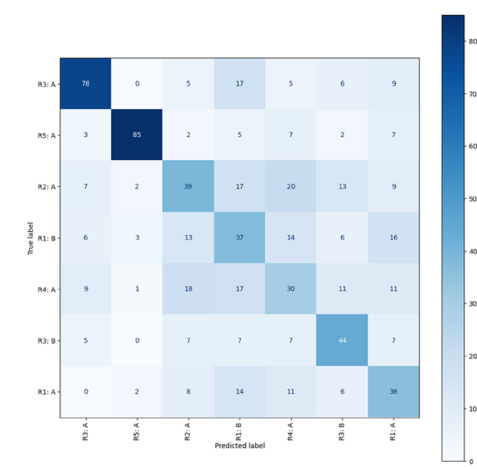

Chromagram

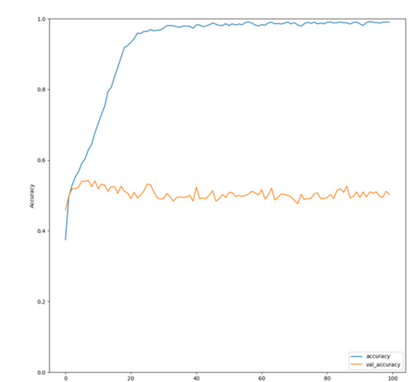

Filtered Chromagram

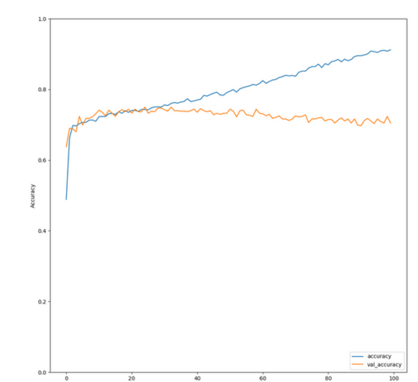

Mel-Scaled Spectrogram

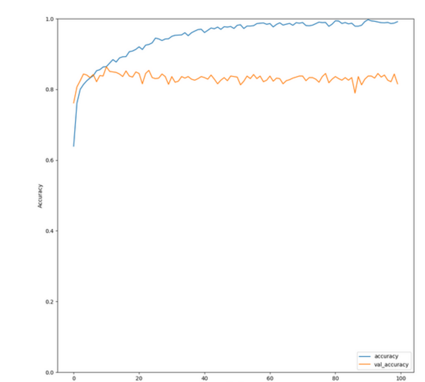

Linear Standard Spectrogram

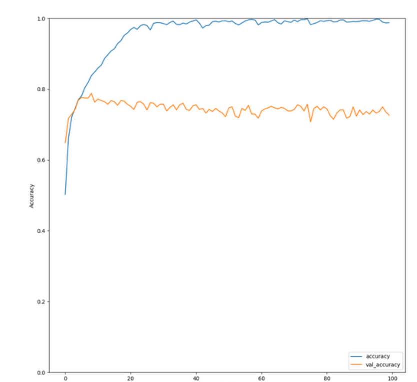

Standard Spectrogram

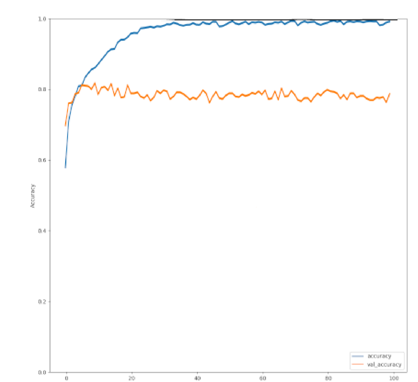

Mel-Scaled Frequency Coefficients

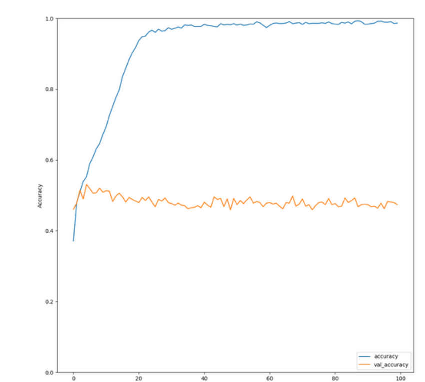

Chromagram

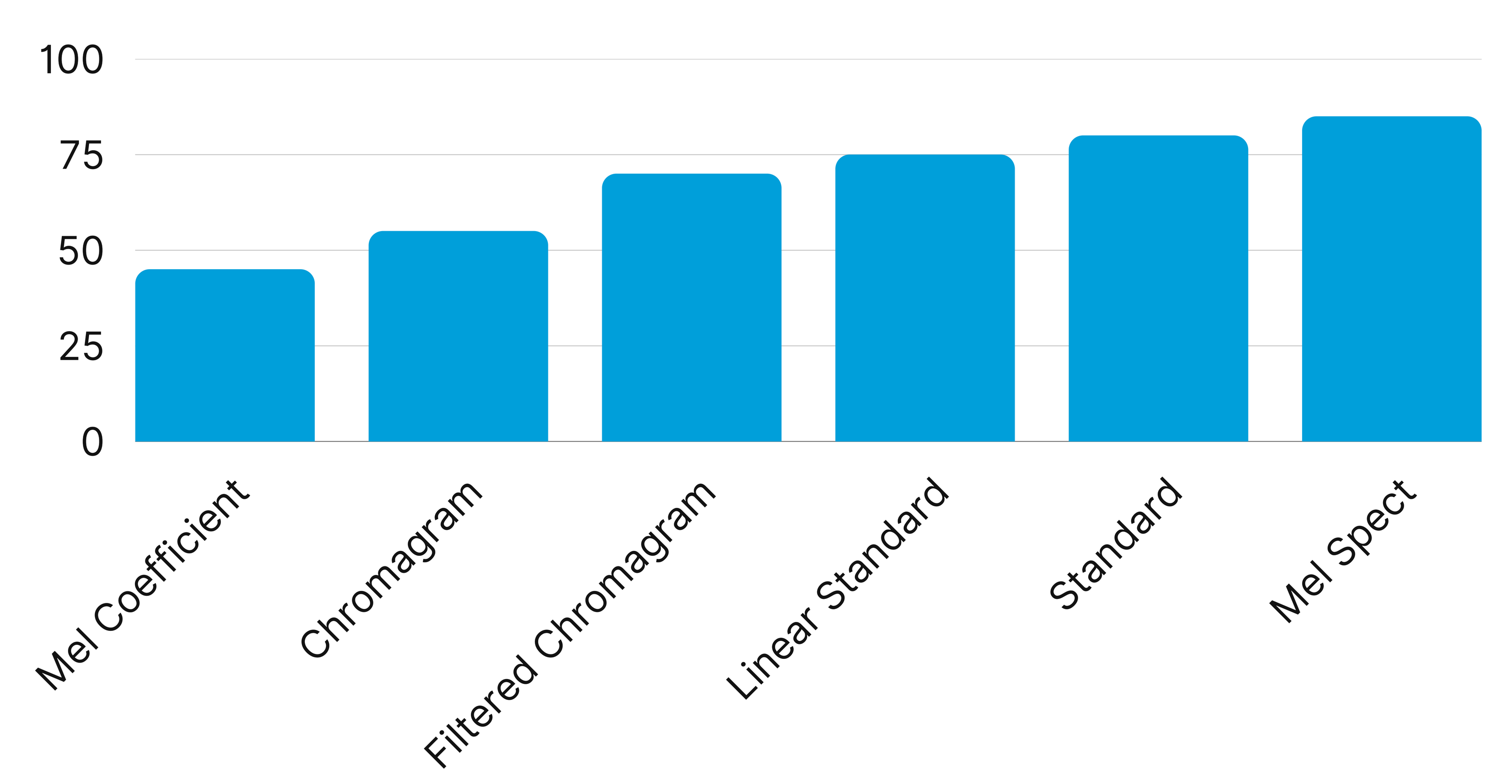

Filtered Chromagram


Mel-Scaled Spectrogram


Linear Standard Spectrogram


Standard Spectrogram


Mel-Scaled Frequency Coefficients



1. Unfiltered chromagram and mfcc performed significantly worse with the mfcc performing slightly worse
2. Accuracy ranged between 45% and 85%
3. Standard spectrogram and linear standard spectrogram have similar accuracies of which the non-linear standard spectrogram performed slightly better
4. Mel-Scaled spectrogram had the highest performance with the two versions of the standard spectrograms being just below the Mel-Scaled spectrograms
5. Location R4 A and R5 A seem to have higher accuracy on average than the other locations despite the FET

06 Conclusions

- *For the chromagrams, a high pass filter severely improves performance*
- *The Mel-Scaled spectrogram has the best perforance with 85%*
- *The standard spectrograms have the most accurate confusion matrix*

Related literature

[1] Qun Song, Chaojie Gu, and Rui Tan. Deep room recognition using inaudible echos. ACM. 2018.
[2] B. Zhou; M. Elbadry; R. Gao; F. Ye. Batmapper: Acoustic sensing based indoor floor plan construction using smartphones. page 14. Stony Brook University, Beijing Jiaotong University, 2017
[3] Q. Song; C. Gu; R. Tan. Deep room recognition using inaudible echos. page 28. Nanyang Technological University, 2018.
[4] K. Liu; X. Liu; L. Xie; X. Li. Towards accurate acoustic localization on a smartphone. page 5. University of Florida, 2013.
[5] H. Murakami; M. Nakamura; S. Yamasaki; H. Hashizume; M. Sugimoto. Smartphone localization using active–passive acoustic sensing. page 8. Stony Brook University, Beijing Jiaotong University, 2018.
[6] S. P. Tarzia; P. A. Dinda; R. P. Dick; Gokhan Memik. Indoor localization without infrastructure using the acoustic background spectrum. page 14. Northwestern University, University of Michigan, 2011.

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