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M.Sc. *Computer Engineering*
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Audio Source Separation

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Keywords: *STFT (Short-Time Fourier Transform), DPRNN (Dual-Path Recurrent Neural Network)*

Objectives

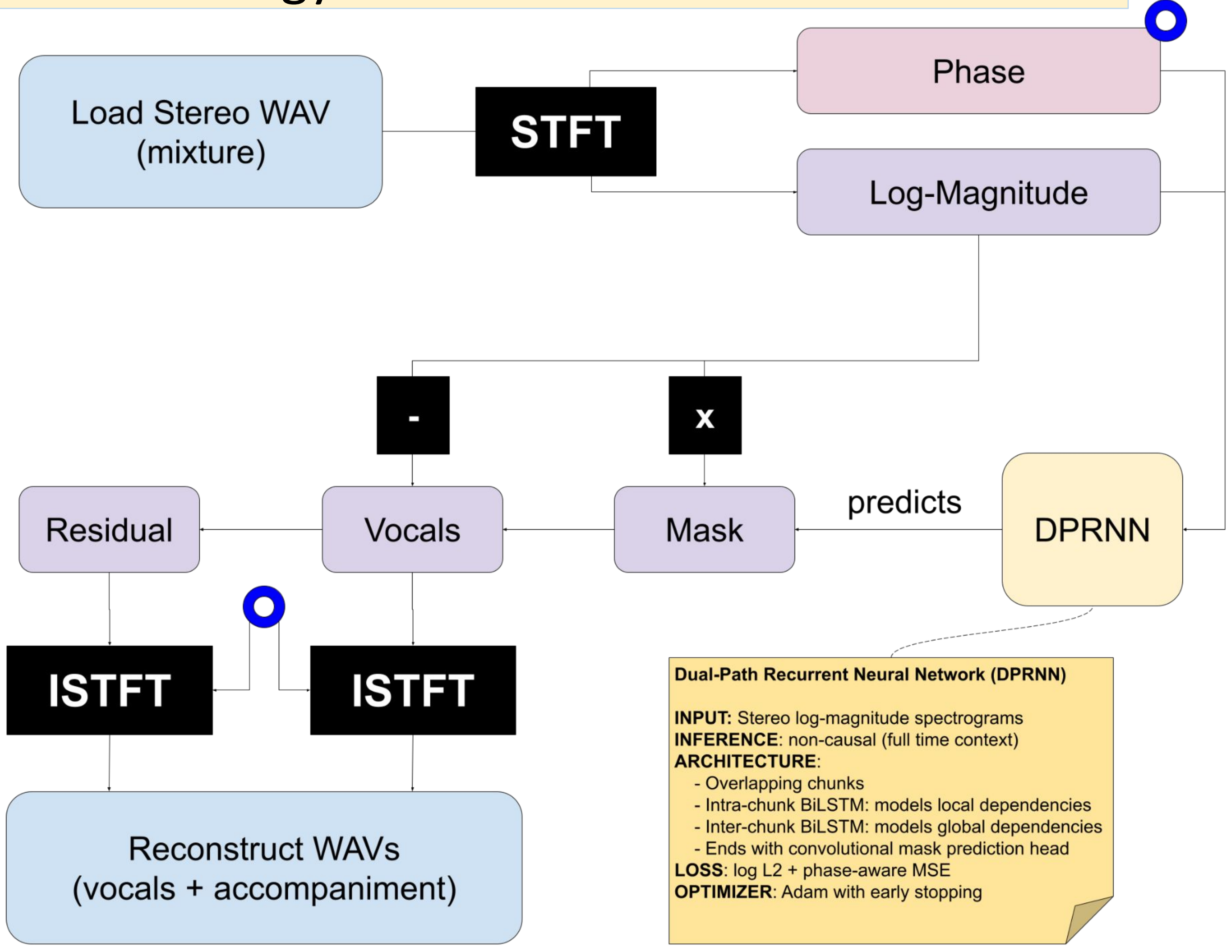
- **Build** and **evaluate** a **deep learning system** to **separate components of an audio track**: vocals and accompaniment.
- **Compare** our developed model with a popular **pre-trained model** (**Open-Unmix UMXHQ**) through the use of standard **separation metrics** that evaluate the quality of the separation as well as the lack of unwanted sources and distortions.

Problem

- **Audio source separation** is the process of isolating specific sounds from an original audio source containing a mixture of multiple elements, namely instruments and vocals.
- For example, we might want to separate the instrumental of a song from its vocals to make a karaoke track or isolate a specific instrument from a song so a musician can learn that part.
- In this type of task, we usually have 2 main models:

1. **Time-Frequency Domain**, using *STFT* to separate sources based on magnitude/phase or by predicting a mask to isolate target sources from the mixture.
   Drawbacks: Phase reconstruction can limit quality; resolution trade-offs (time vs. frequency).
2. **Time-Domain**, by learning to map raw waveforms directly to separated sources (*end-to-end*).
   Drawbacks: Often more complex, require more training data and compute resources.

Methodology



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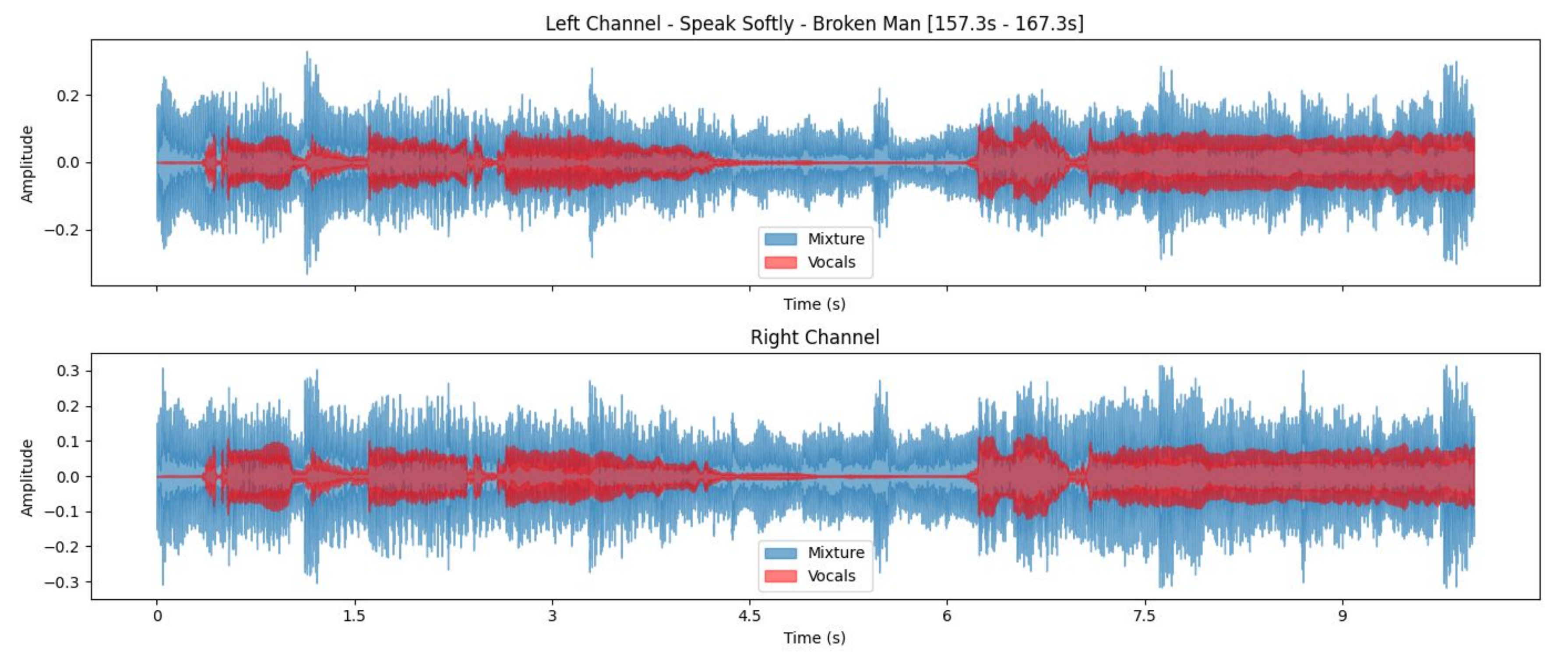
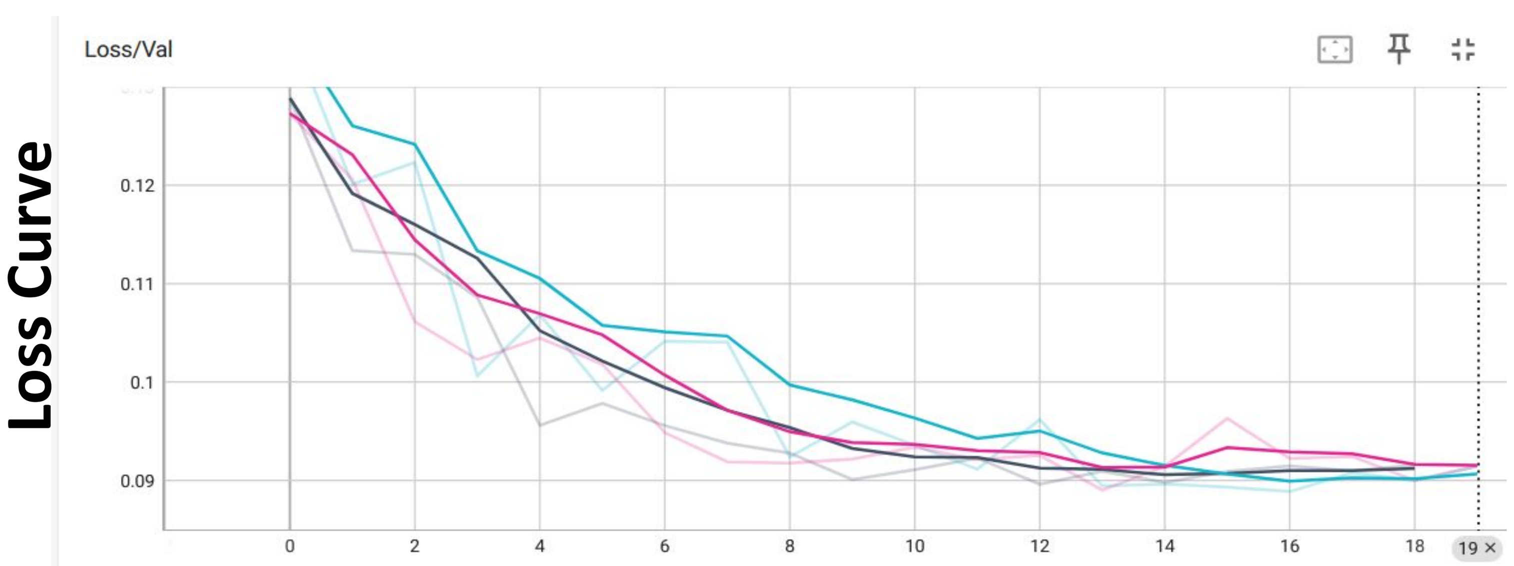
Datasets

- **MUSDB18-HQ**, an industry standard dataset, was used.
  - 150 full-length **stereo** tracks (~10 hours) of different genres split into 86 train tracks, 50 test tracks and 14 validation tracks.
  - Each track comes pre-split into **mixture**, **bass**, **drums**, **vocal** and **other** *.wav* files, of which we used the **vocal** and **mixture** files.
- Example **waveform plot** of one of the tracks (10 seconds):

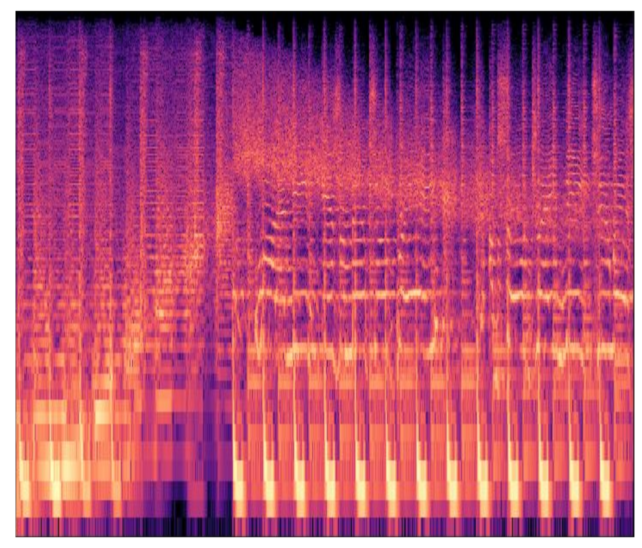


Results

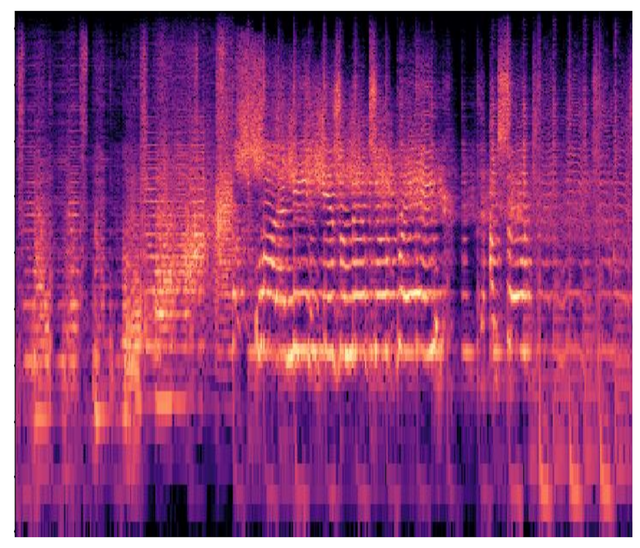
Loss Curve



Mixture Spec



Pred Vocals Spec



- Comparison of industry standard metrics between the **2 models**, tested on **30 second** chunks of **25 random** tracks:

Target	Model	SDR	SIR	ISR	SAR
Vocals	*Open-Unmix*	5.259	12.508	14.385	6.607
Accompaniment	*Open-Unmix*	**12.951**	19.901	**21.255**	**14.464**
Vocals	DPRNN-ass	2.516	5.445	9.482	6.011
Accompaniment	DPRNN-ass	6.094	**22.865**	6.941	8.449

Conclusions

- Our project demonstrates that **it is suitable to use a DPRNN-based** deep learning approach in the time-frequency domain for the audio source separation task, because the **dual intra/inter chunk RNN** balances **local** and **global context**.
- Adding the **phase-aware loss helped a lot**, even if we **don't yet have results comparable to the state of the art**.
- **Future directions** could include
  - Exploring **time-domain** architectures and **multi-target sep.**
  - Exploring more advanced **data augmentation** techniques like **pitch shifting** or **time stretching** before *STFT* and **parameter tuning** with *GridSearch*

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