Speech Emotion Recognition (SER)

Model: Long Short-Term Memory (LSTM)

Problem Statement:

The aim of this project is to construct and employ an LSTM classification model for SER.

GOAL:

Accurately assess the emotional state of speakers in audio recordings.

HOW:

Using the librosa library standardize and extract features voice signals from a dataset created for SER modeling and then build, train and test the SER model.

DELIVERABLE:

MVP - A functioning LSTM model

What is LSTM

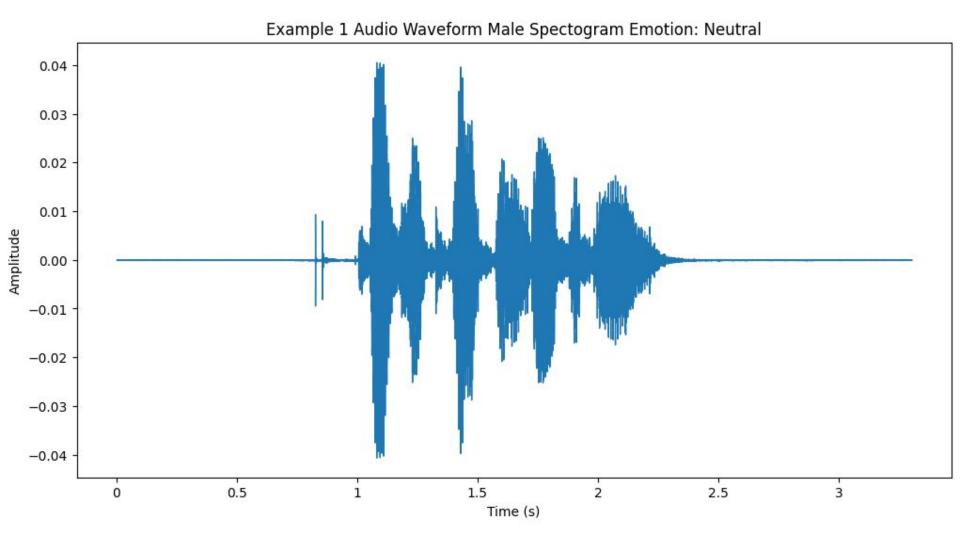
Data:

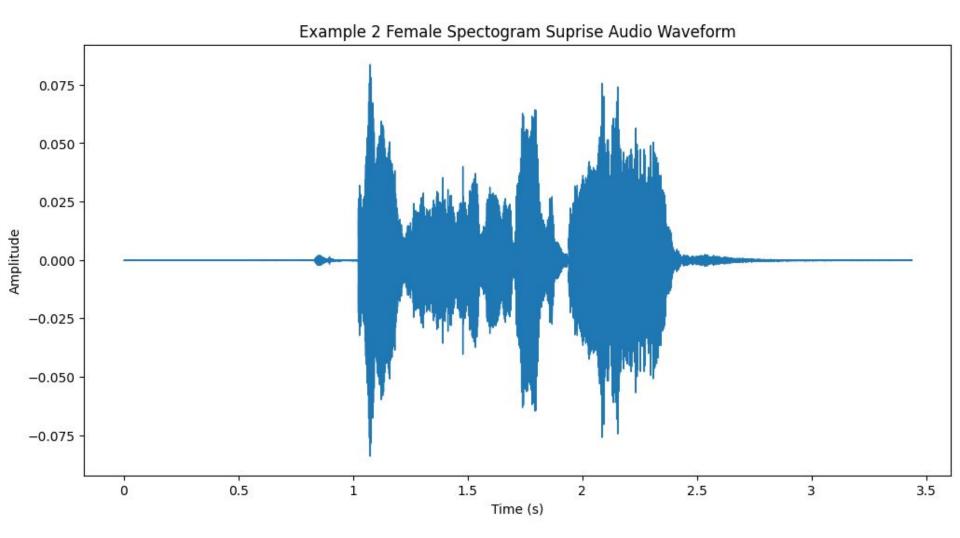
[Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS)](https://www.kaggle.com/datasets/uwrfkaggler/ravdess-emotional-speech-audio)

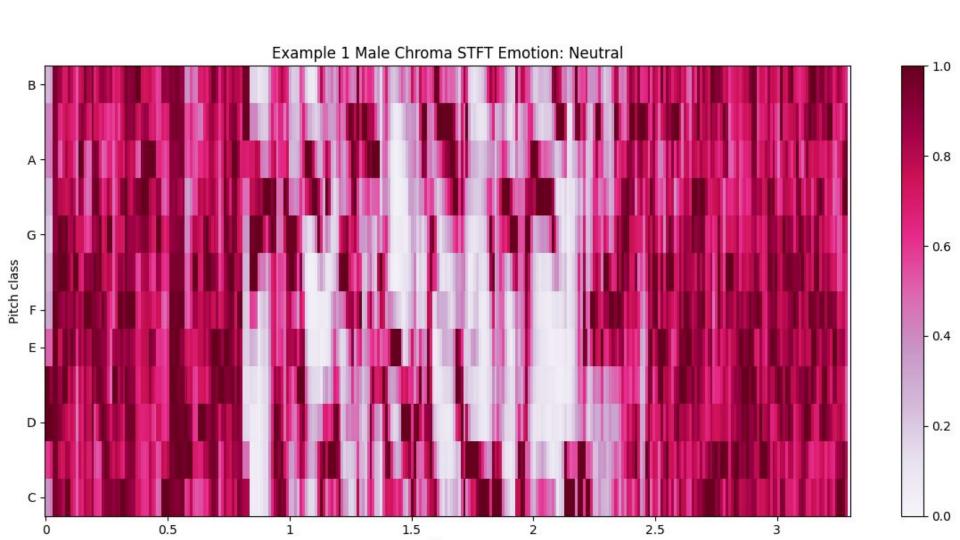
[Toronto emotional speech set (TESS)](https://www.kaggle.com/datasets/ejlok1/toronto-emotional-speech-set-tess)

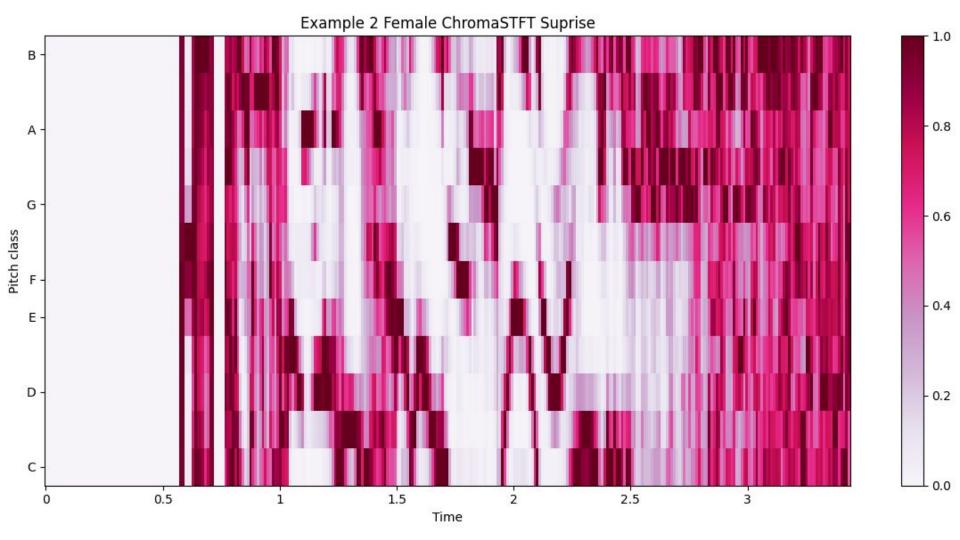
[Surrey Audio-Visual Expressed Emotion (SAVEE)](https://www.kaggle.com/datasets/ejlok1/surrey-audiovisual-expressed-emotion-savee)

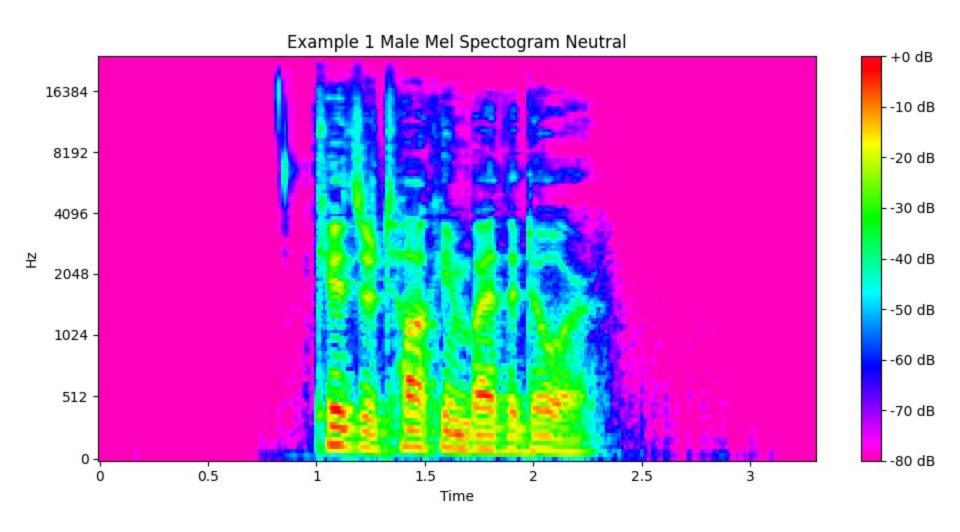
[Crowd Sourced Emotional Multimodal Actors Dataset (CREMA-D)](https://www.kaggle.com/datasets/ejlok1/cremad)

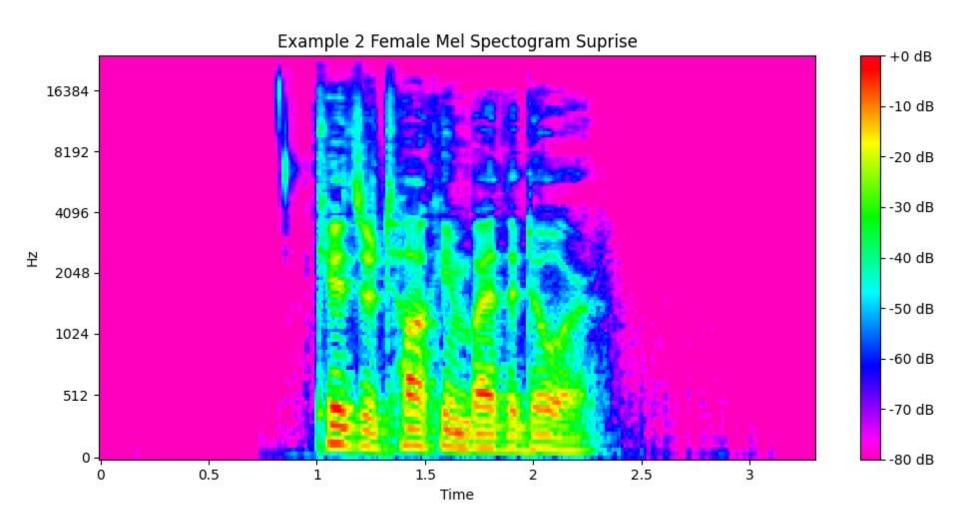








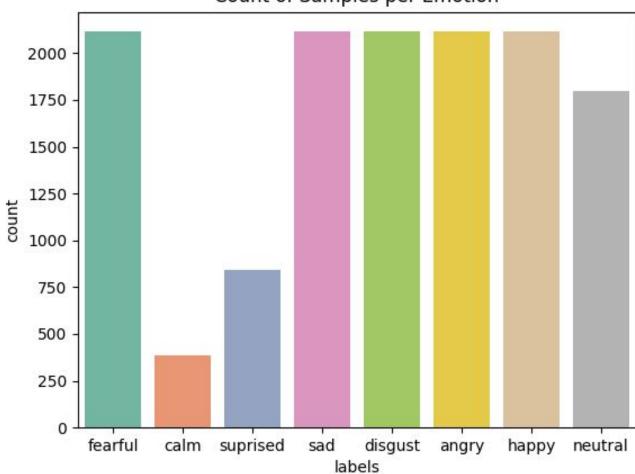


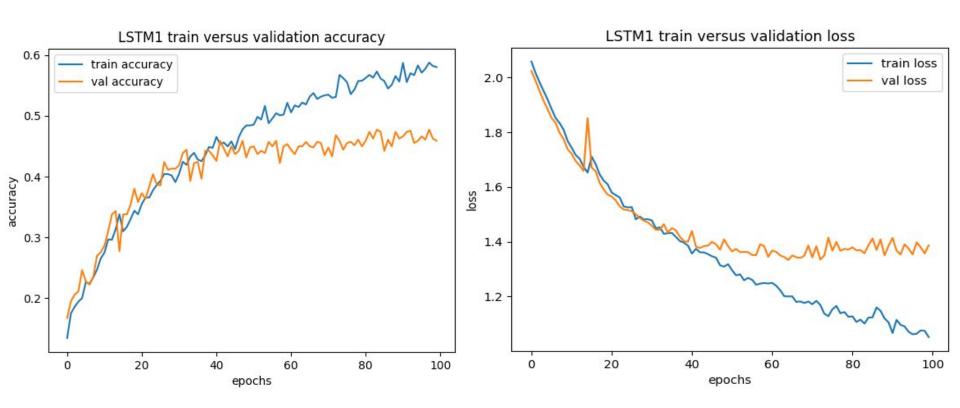


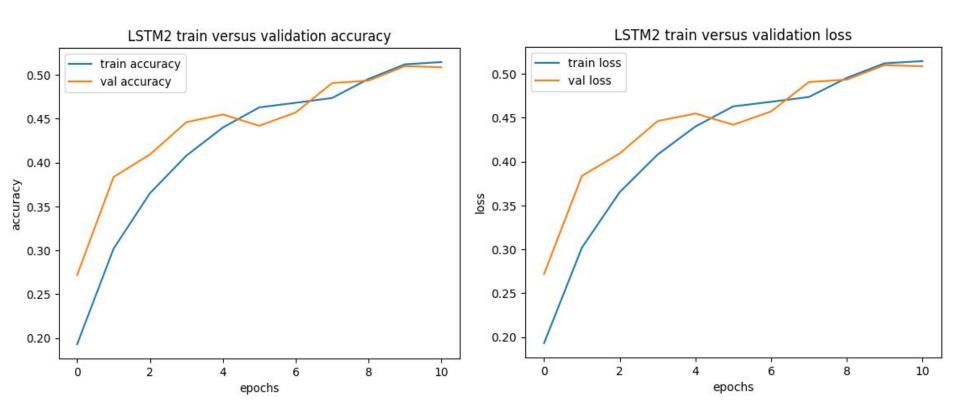
Example 1 Male Fourier Spectogram Emotion: Neutral - 10 20000 --1015000 -- -20 H 10000 -- -30 5000 -0 0.5 1.5 2.5 3 Time

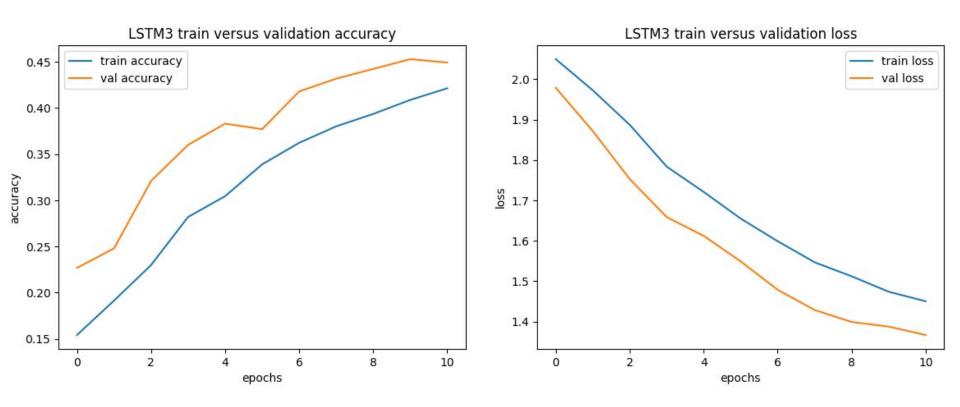
Example 2 Female Fourier Spectogram Suprise.png - 10 20000 --1015000 -- -20 H 10000 --305000 -0 0.5 1.5 2.5 3 Time

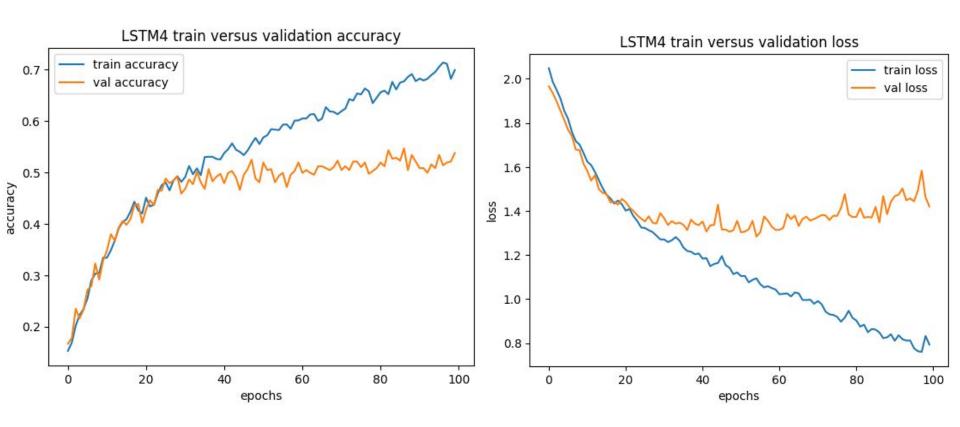












Outcomes

- Best model:

model_LSTM, 'first_lstm_model.h5'

- Best score:

accuracy: 0.6710 - loss: 0.8293 - val_accuracy: 0.6022 - val_loss: 1.1673

Future work:

- address class imbalances
- continue to tune and iterate or at least identify performance decline.
- Access other possible standardisations techniques, feature extraction and tuning methods.
- Utilize pretrained models such as Whisper, WavLM, and Wav2Vec 2.0, which can be fine-tuned for SER tasks.

Sources: