# Emotions within speech

## Unearth the hidden language

Lin He , Ruilin Ma 6th, Dec., 2022

# A brief Intro

**What we have and what we do.**

- ➔ **The RAVDESS dataset**
  Ryerson Audio-Visual Database of Emotional **Speech** and Song. 24 actors, 60 trials per actor. 1440 files.
- ➔ **Eight distinct emotions**
  **neutral, calm, happy, sad, angry, fearful, disgust, surprised.** 96 neutral samples, 192 samples for each others.
- ➔ **A CNN approach**
  Build a CNN network to train the classifier and test its accuracy.

# How to distinguish these eight emotions effectively?

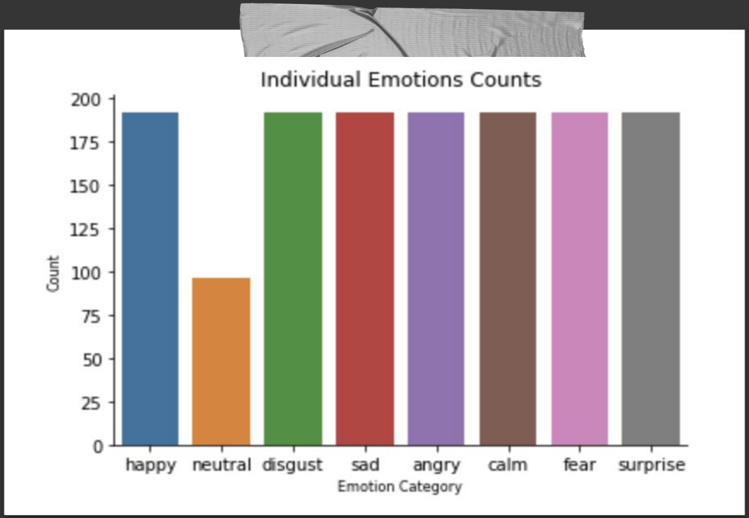



Figure showing the **emotion counts** of the investigated dataset.

# We tried two approaches.

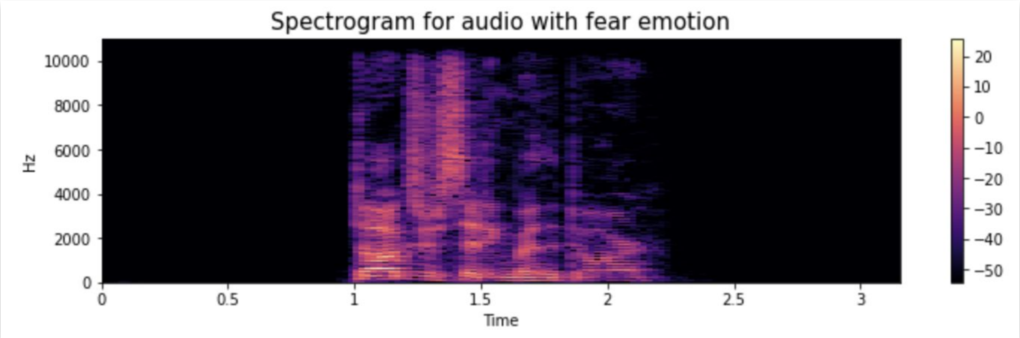
Based on Spectrogram

Based on Mel-Frequency Cepstral Coefficients (MFCCs)

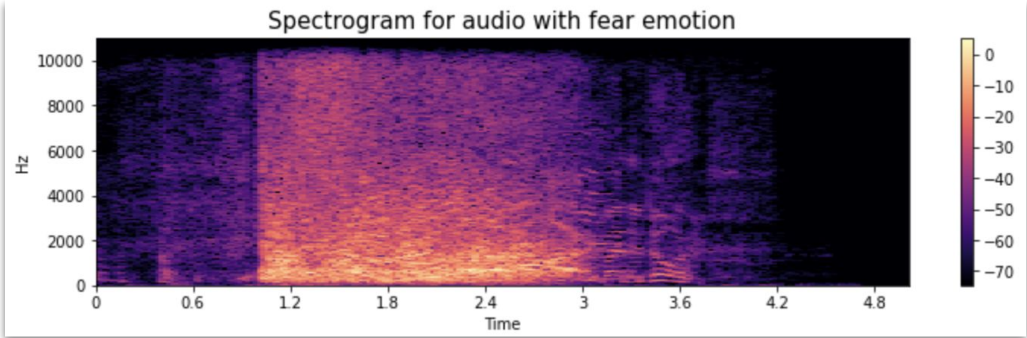
**Note**

We adopted the MFCCs to create figures used as the input data for the CNN networks, for the reason that **MFCC can reveal more features of a speech clip than the spectrogram**.

# **Spectrogram**: Merge merge merge!

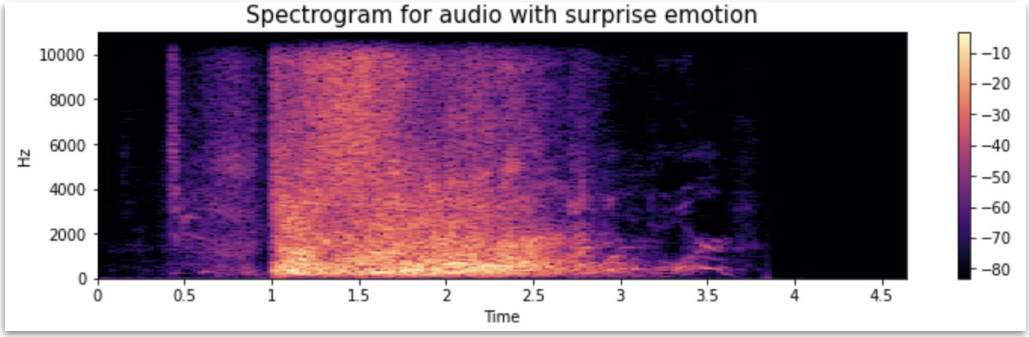



A spectrogram of **one speech clip** with a fear emotion.

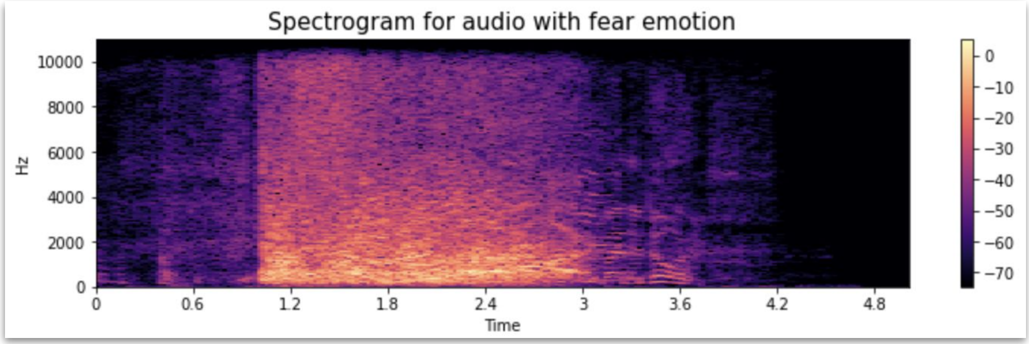



A spectrogram of the merging of **all speech clips** with a fear emotion.

# **Spectrogram**: Different, but too much noise to distinguish.




A spectrogram of the merging of all speech clips with a **surprise** emotion.




A spectrogram of the merging of all speech clips with a **fear** emotion.

# Data Transformation

**The process of transforming Audio waves to MFCC Spectrograms.**

- **Audio(.wav)**

  Time Domain
  Original Human Speech Data

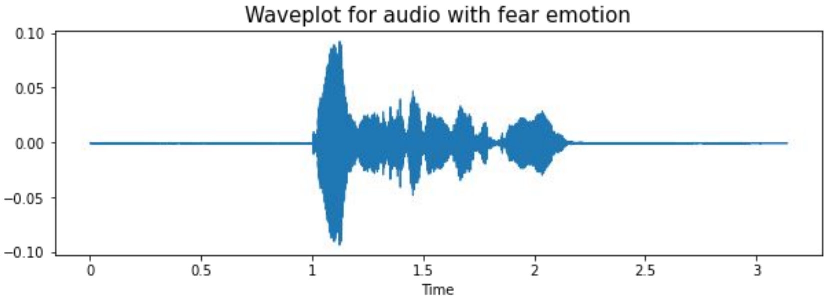
- **MFCC Spectrograms(.png)**

  Time Domain
  Image that contains all the features of the audio

# Audio Wave

## Normalization

Cut around all examples to 3 seconds




Example of a waveplot of an original audio file

### Why not use Frequency Spectrograms?

Frequency spectrograms also contains features. However, humans are not able to tell the difference between these frequency domain features.

Thus, we introduce MFCC.

# FFT

## Frequencies

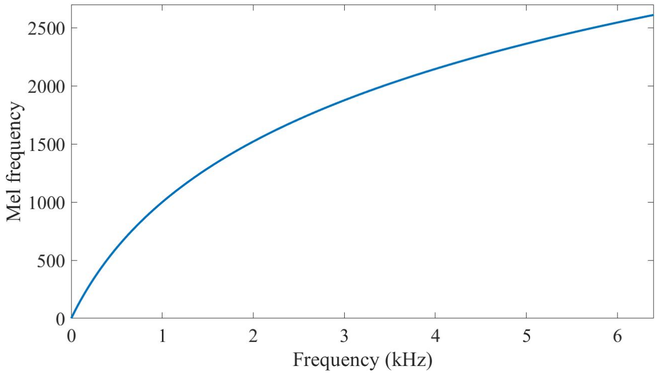
Transform all from time domain to frequency domain

Using STFT and calculating energy to generate Frequency Spectrograms

# MFCC

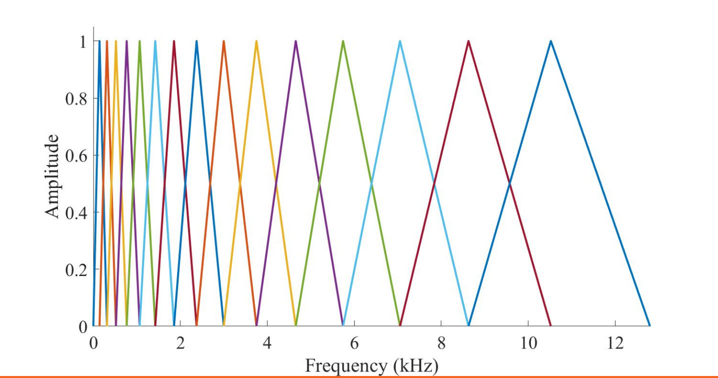
Mel-scale makes the spectrogram more human auditory-liked.

$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right).$$




*https://wiki.aalto.fi/display/ITSP/Cepstrum+and+MFCC*

Triangular overlapping windows also leave more low frequencies information.



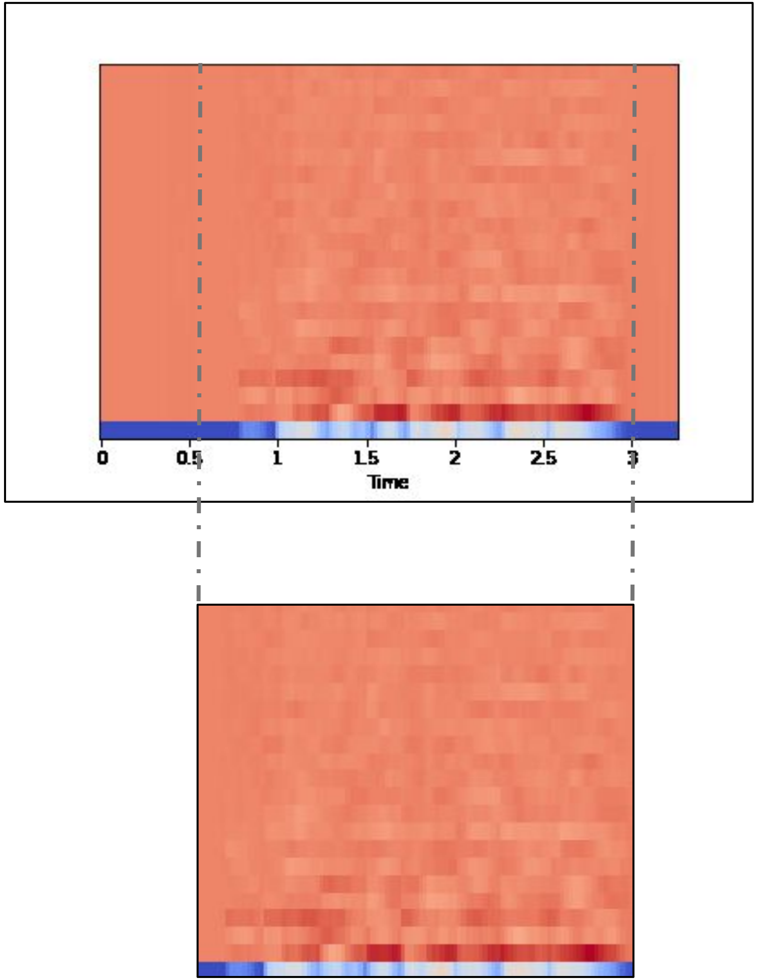

## Note

We directly use

`librosa.feature.mfcc( )`

to transform audio wave to mfcc matrix.

N_mfcc = 22




# Data Preparation

We cut down the spectrogram size from ( 432 x 288 x 3 ) to ( 240 x 210 x3 ).

Only reserve **the most dense information area** as CNN input.

**Split** the train set and test set with an ratio of 8 : 2.

# **CNN network**: Use more conv layers to reduce params count

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 210, 240, 32)      128

 conv2d_7 (Conv2D)           (None, 210, 240, 16)      4624

 dropout_5 (Dropout)         (None, 210, 240, 16)      0

 max_pooling2d_2 (MaxPooling  (None, 42, 48, 16)       0
 2D)

 conv2d_8 (Conv2D)           (None, 42, 48, 16)        2320

 dropout_6 (Dropout)         (None, 42, 48, 16)        0

 conv2d_9 (Conv2D)           (None, 42, 48, 16)        2320

 dropout_7 (Dropout)         (None, 42, 48, 16)        0

 conv2d_10 (Conv2D)          (None, 42, 48, 16)        2320

 dropout_8 (Dropout)         (None, 42, 48, 16)        0

 max_pooling2d_3 (MaxPooling  (None, 14, 16, 16)       0
 2D)

 conv2d_11 (Conv2D)          (None, 14, 16, 32)        4640

 dropout_9 (Dropout)         (None, 14, 16, 32)        0

 flatten_1 (Flatten)         (None, 7168)              0

 dense_1 (Dense)             (None, 8)                 57352

=================================================================
Total params: 73,704
Trainable params: 73,704
```

```
loss='categorical_crossentropy'
optimizer = Adam(learning_rate = 0.001),
metrics=['accuracy'])
batch_size = 16, epochs = 50
```

# **CNN network**: A model with accuracy of roughly 60 percent.

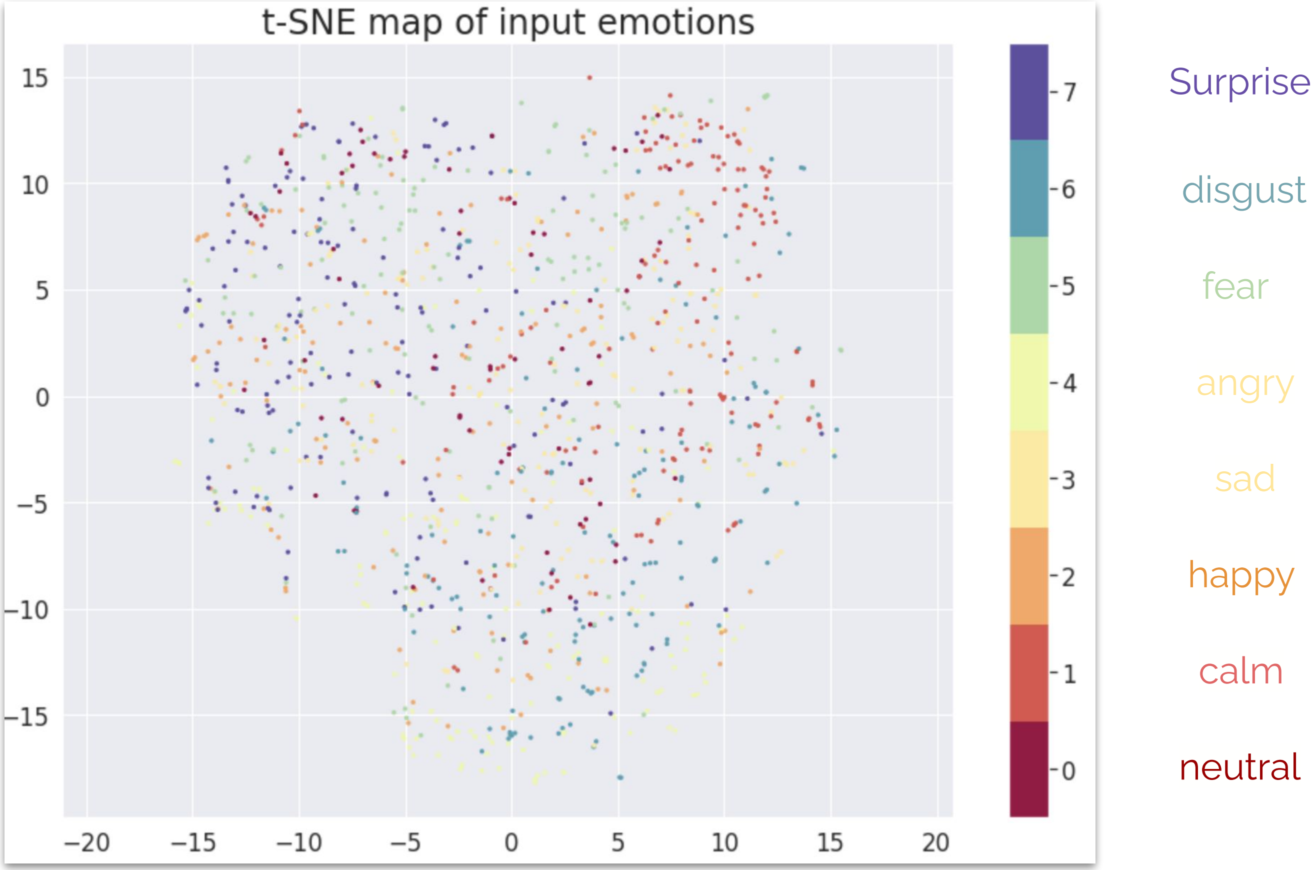
**3 independent runs** of the classifier, obtaining **a test accuracy of more than 60 percent**.
Stabilize below 70 percent as training budgets increase.
Unstable predicting correctness for now.

```
Epoch 50/50
72/72 [==============================] - 2s 34ms/step - loss: 0.3101 - accuracy: 0.9236 - val_loss: 1.3528 - val_accuracy: 0.6111
Test loss: 1.3528270721435547
Test accuracy: 0.6111111044883728
```

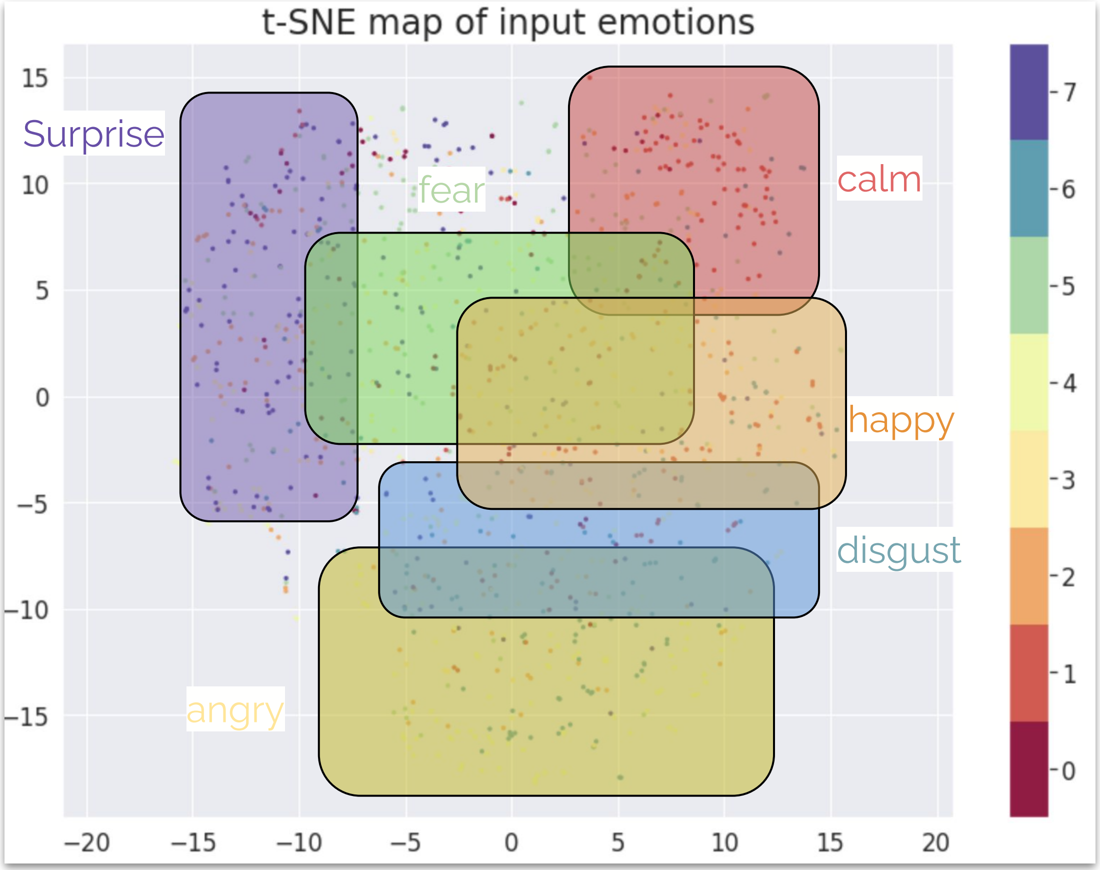
```
Epoch 50/50
72/72 [==============================] - 2s 32ms/step - loss: 0.2272 - accuracy: 0.9444 - val_loss: 1.2372 - val_accuracy: 0.6389
Test loss: 1.2371793985366821
Test accuracy: 0.6388888955116272
```

```
Epoch 50/50
72/72 [==============================] - 2s 34ms/step - loss: 0.2026 - accuracy: 0.9497 - val_loss: 1.5732 - val_accuracy: 0.6250
Test loss: 1.5732299089431763
Test accuracy: 0.625
```

# **Visualizing the boundary**: Pattern within chaos

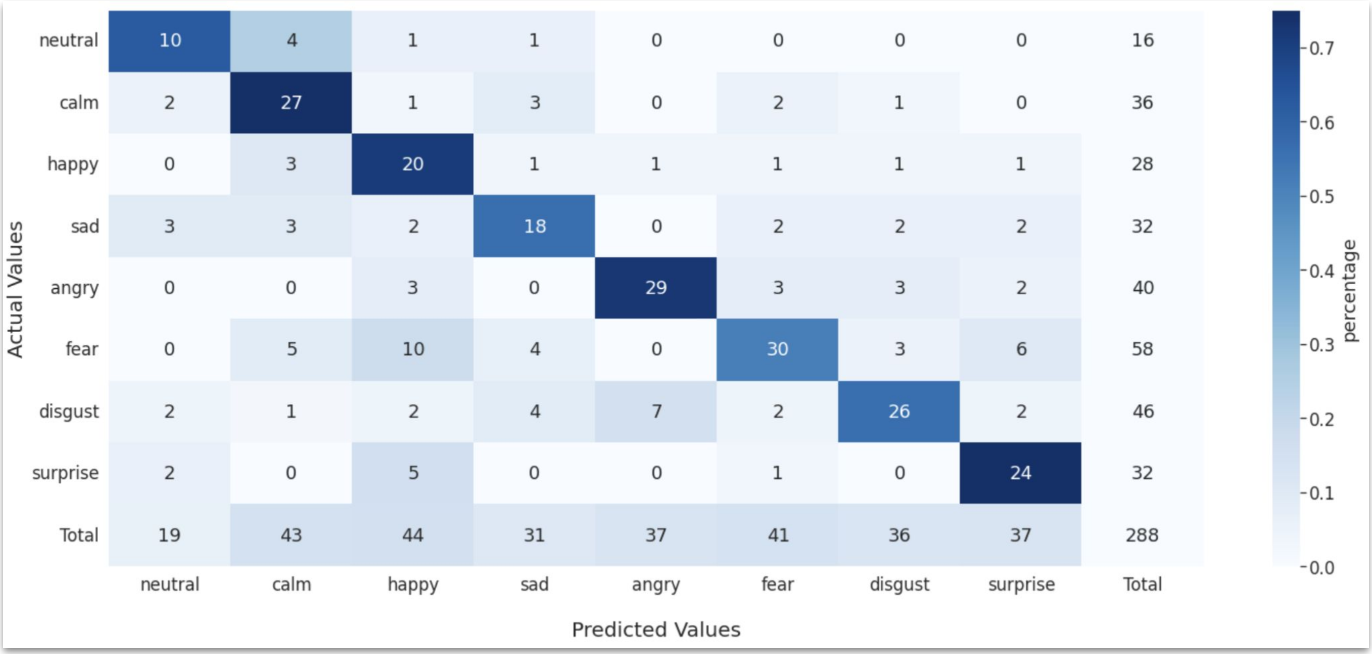


# **Visualizing the boundary**: Pattern within chaos



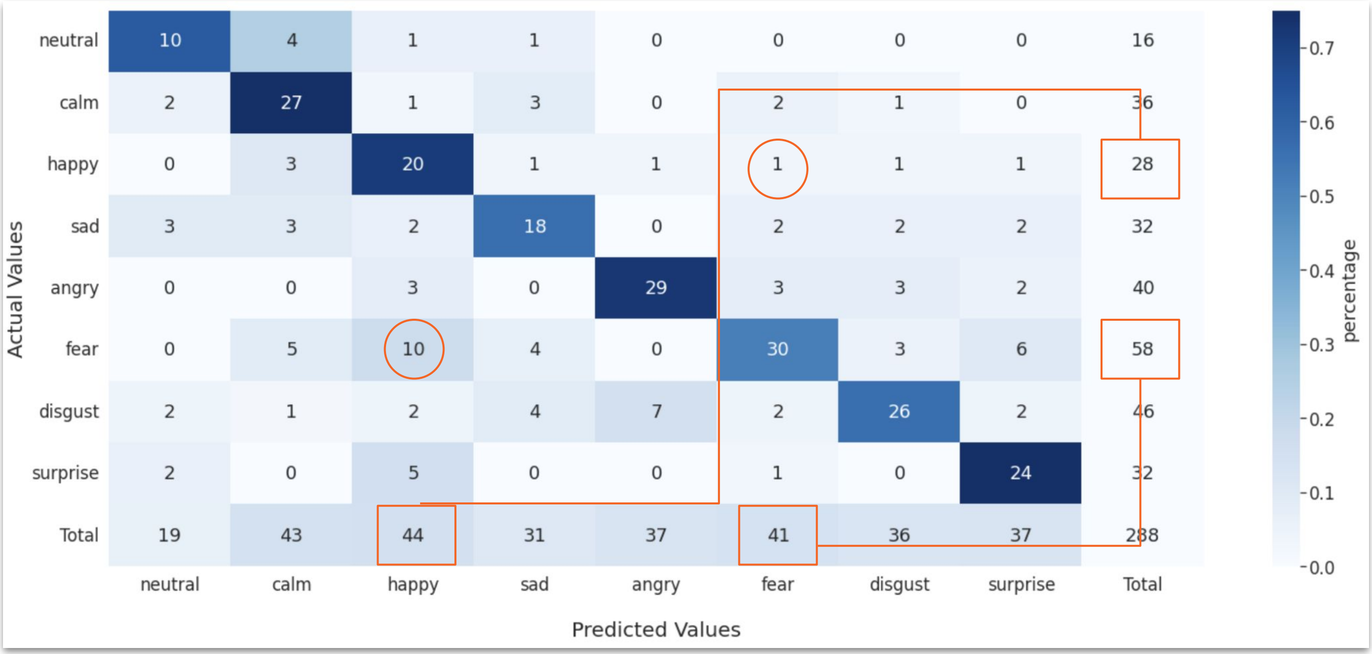
# **Confusion matrix**: How's prediction going?

**Surprise** and **calm** are most likely to be **correctly identified**.
**Fear** and **disgust** are most likely to be **misinterpreted**.



# **Confusion matrix**: How's prediction going?

Fear may sound like happy, but happy sounds unlikely to be fear.
The classifier have **a tendency for being happy and not being fearful.**




| | neutral | calm | happy | sad | angry | fear | disgust | surprise | Total |
|---|---|---|---|---|---|---|---|---|---|
| neutral | 10 | 4 | 1 | 1 | 0 | 0 | 0 | 0 | 16 |
| calm | 2 | 27 | 1 | 3 | 0 | 2 | 1 | 0 | 36 |
| happy | 0 | 3 | 20 | 1 | 1 | 1 | 1 | 1 | 28 |
| sad | 3 | 3 | 2 | 18 | 0 | 2 | 2 | 2 | 32 |
| angry | 0 | 0 | 3 | 0 | 29 | 3 | 3 | 2 | 40 |
| fear | 0 | 5 | 10 | 4 | 0 | 30 | 3 | 6 | 58 |
| disgust | 2 | 1 | 2 | 4 | 7 | 2 | 26 | 2 | 46 |
| surprise | 2 | 0 | 5 | 0 | 0 | 1 | 0 | 24 | 32 |
| Total | 19 | 43 | 44 | 31 | 37 | 41 | 36 | 37 | 288 |

# Conclusions

- Extract features from audio speech to MFCC spectrogram.
- A CNN model that makes prediction on emotions.

# Future Works

- Fine-Tune the CNN model.
- Finish the real-time prediction Interface.
- Test the emotion classification performance of the model on other languages.

# Thanks for Listening!

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Unearth the hidden language

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