



Classification for Basic Voice Commands

HOW CAN DEEP LEARNING IMPACT SPEECH RECOGNITION ?

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1. INTRODUCTION



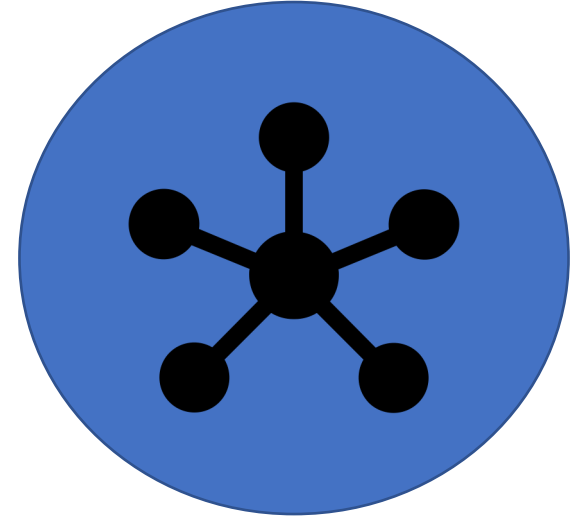
ORIGINAL MESSAGE :

Have you tried scaling your data using a MinMaxScaler ?

2. PROBLEM STATEMENT : Context




Rising demand
for smart devices
and voice-controlled
applications



Need for **efficient** and **accurate**
speech recognition technology


3. OUR PROJECT

Kaggle Competition (ended Jan - 2018)

 Featured Prediction Competition

TensorFlow Speech Recognition Challenge

Can you build an algorithm that understands simple speech commands?

 Google Brain · 1,313 teams · 6 years ago

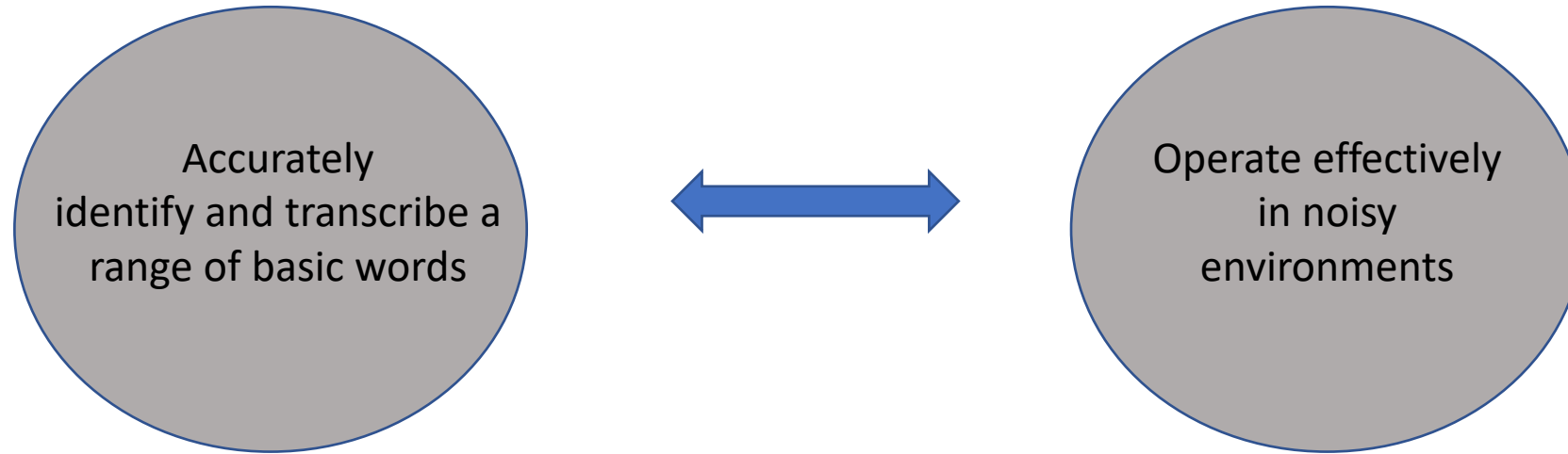
\$25,000

Prize Money

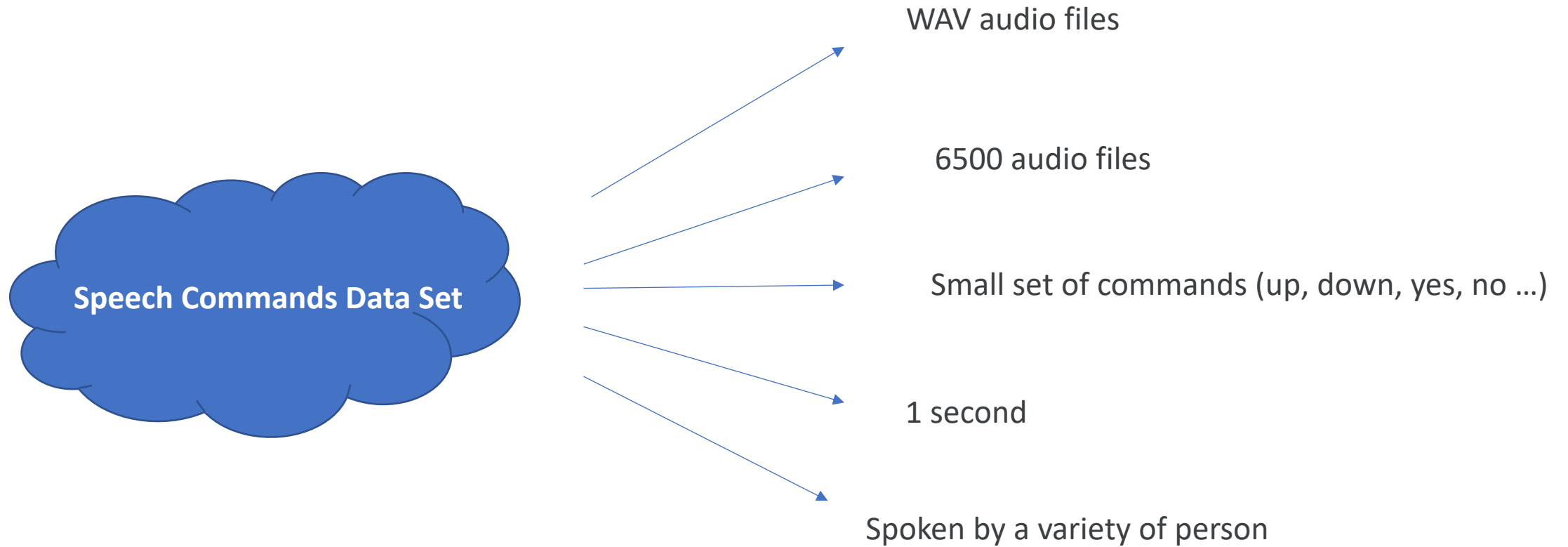
[Overview](#) [Data](#) [Code](#) [Discussion](#) [Leaderboard](#) [Rules](#) [Team](#)

[Submissions](#) [Late Submission](#) [...](#)

3. OUR PROJECT: Goals



4. DATA COLLECTION AND PREPROCESSING



4. DATA COLLECTION AND PREPROCESSING

13 commands

(yes, no, one, two, three, four, five, six, seven, eight, nine, up, down)



500 audio files for each command



Added Background Noise

4. DATA COLLECTION AND PREPROCESSING: RAW AUDIO



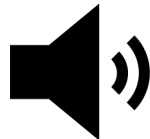
STOP Audio File



TWO Audio File



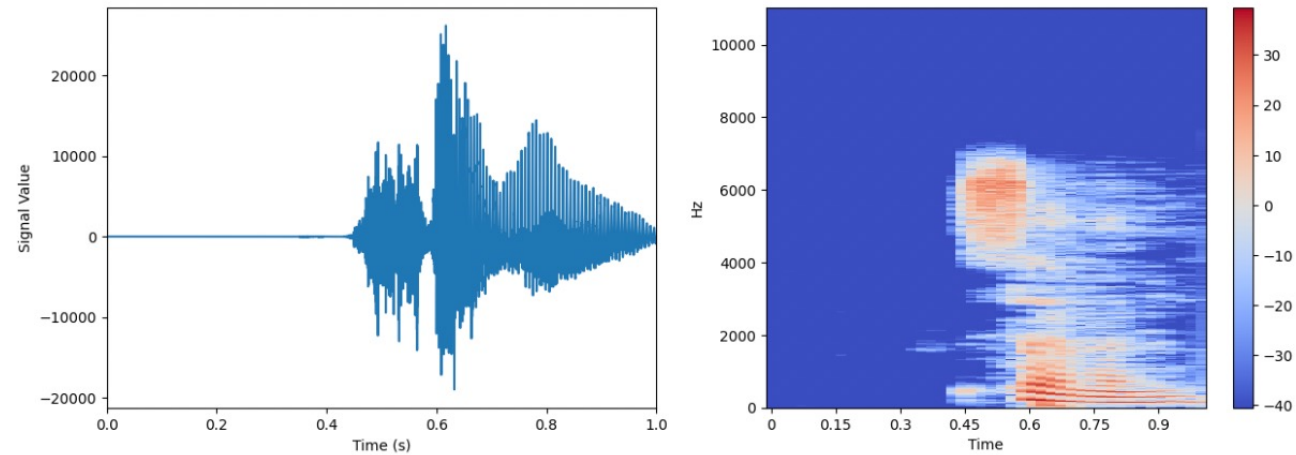
UP Audio File



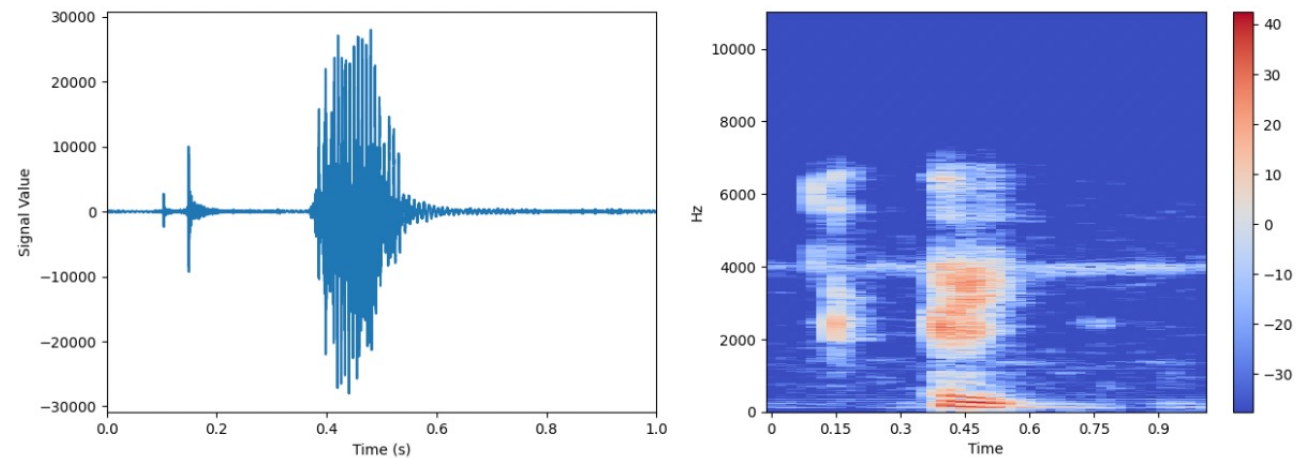
4. DATA COLLECTION AND PREPROCESSING: Waveform and Spectrogram

STFT (Short-Time Fourier Transform)

Audio : 6b81fead_nohash_0.wav, Class: seven, Length: 1.0 secs

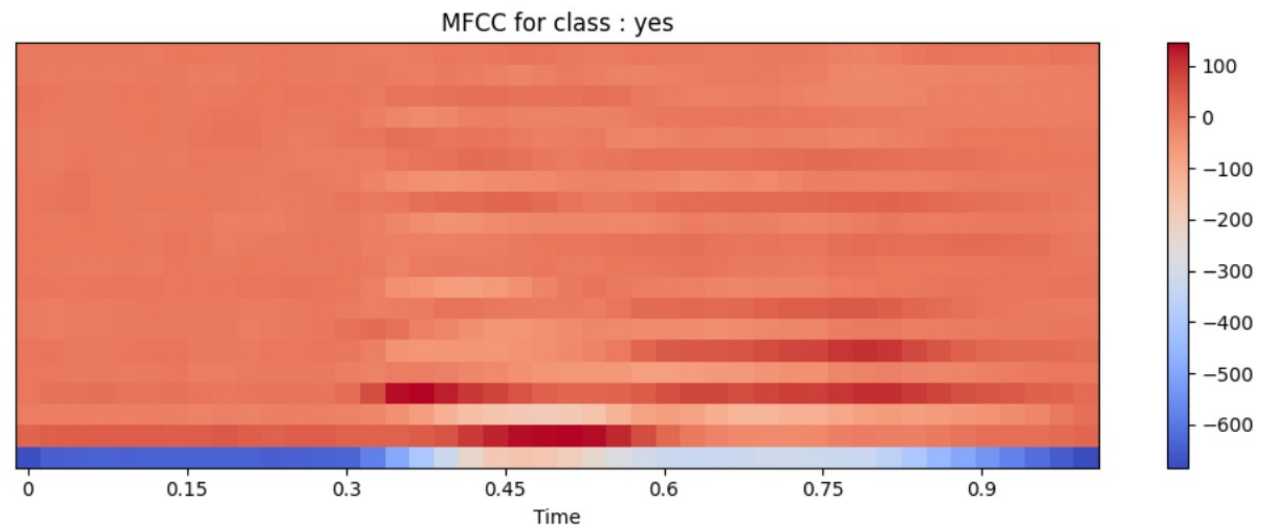
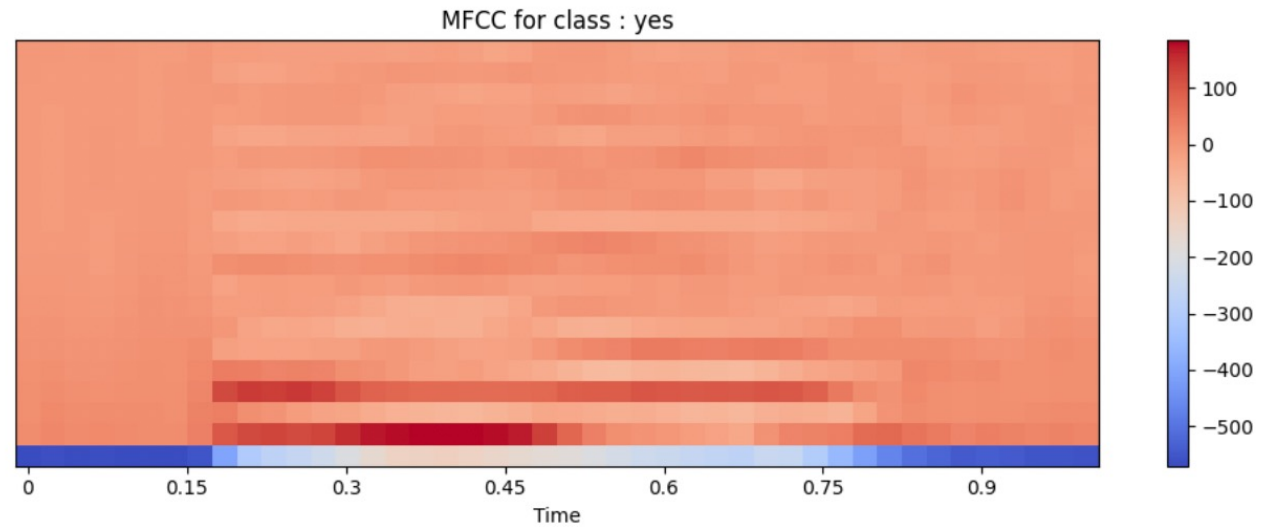


Audio : c634a189_nohash_3.wav, Class: eight, Length: 1.0 secs



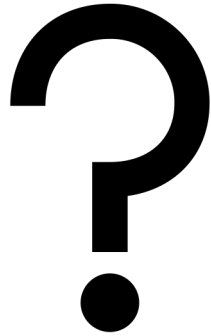
4. DATA COLLECTION AND PREPROCESSING: MFCC

MFCC (Mel Frequency Cepstral Coefficients)



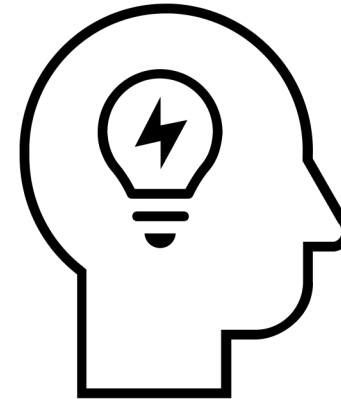
4. DATA COLLECTION AND PREPROCESSING: Challenges

PROBLEM



Initial Pre-processing

SOLUTION



LIBROSA library

5. MODEL DEVELOPMENT: TRAINING PROCESS

GENERAL INFO:

- Training Set, Validation Set, Test Set
- 50 epochs
- Accuracy Metric
- Adam Optimizer
- Learning Rate: 0.001

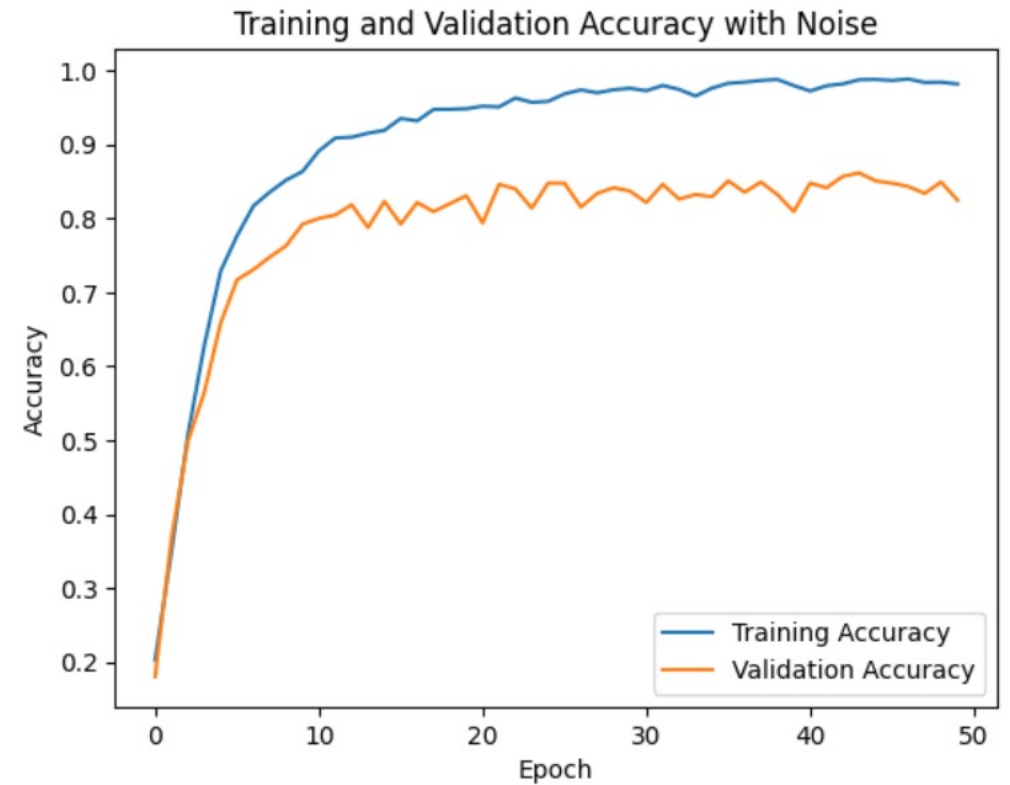
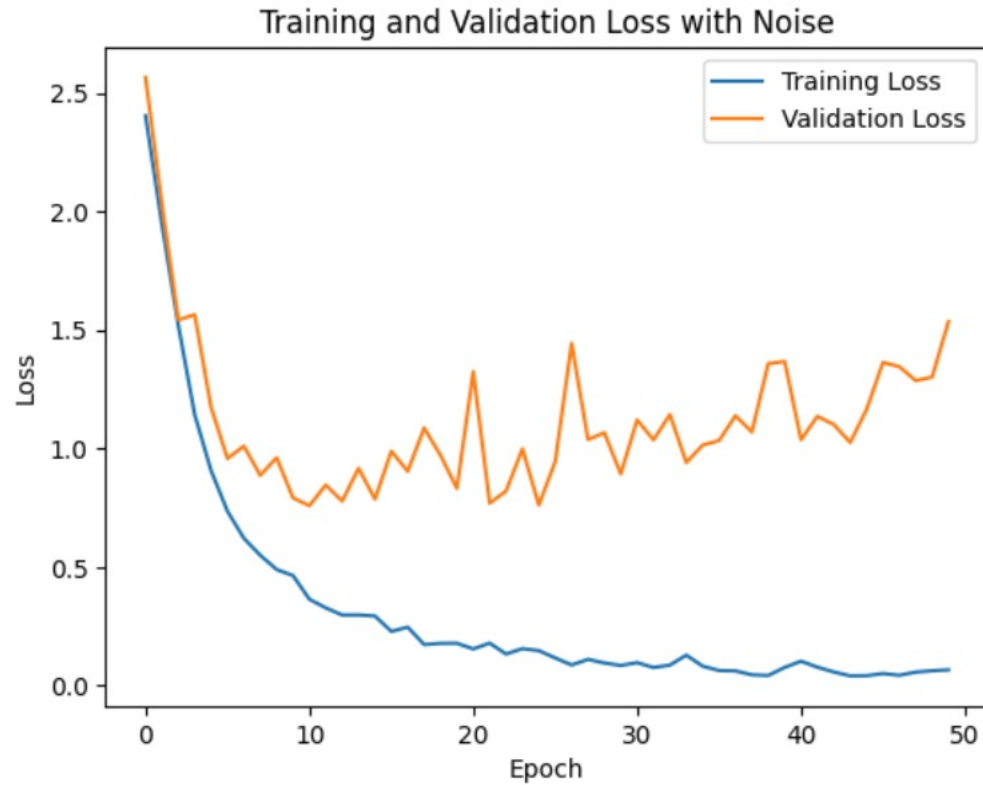
OUR MODEL:

- Sequential model architecture
- Reshape, Conv2D, MaxPooling2D, Flatten, Dense, and Dropout layers
- Smaller number of layers compared to AlexNet
- Fewer trainable parameters compared to AlexNet

Model: "sequential_4"

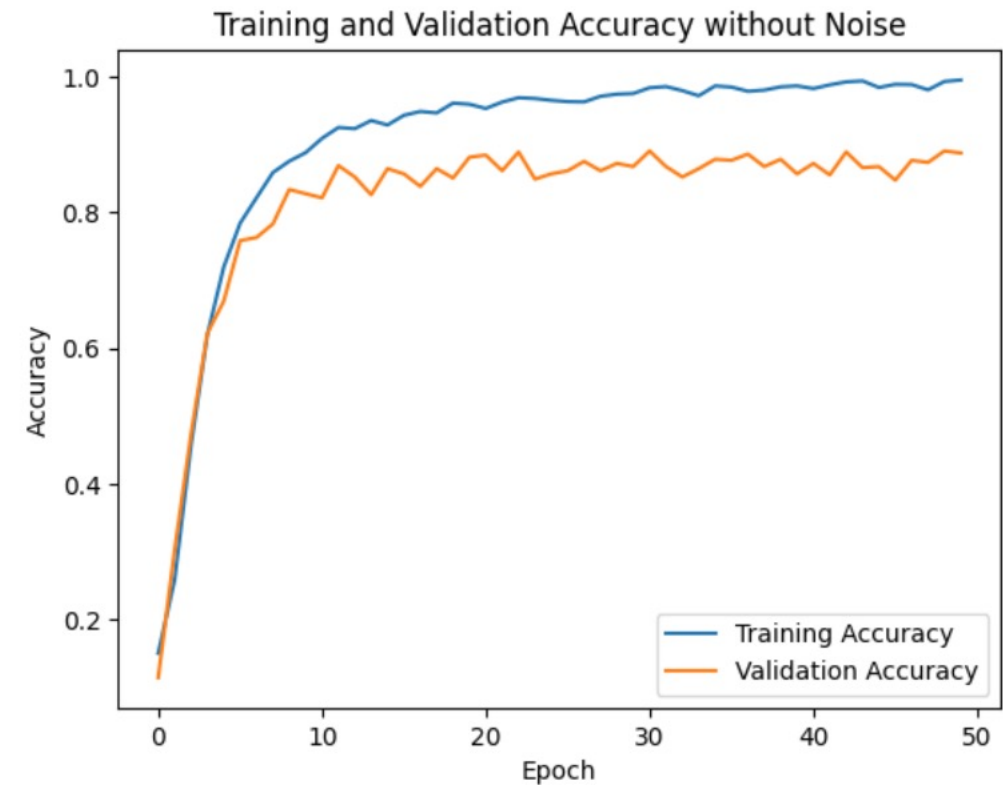
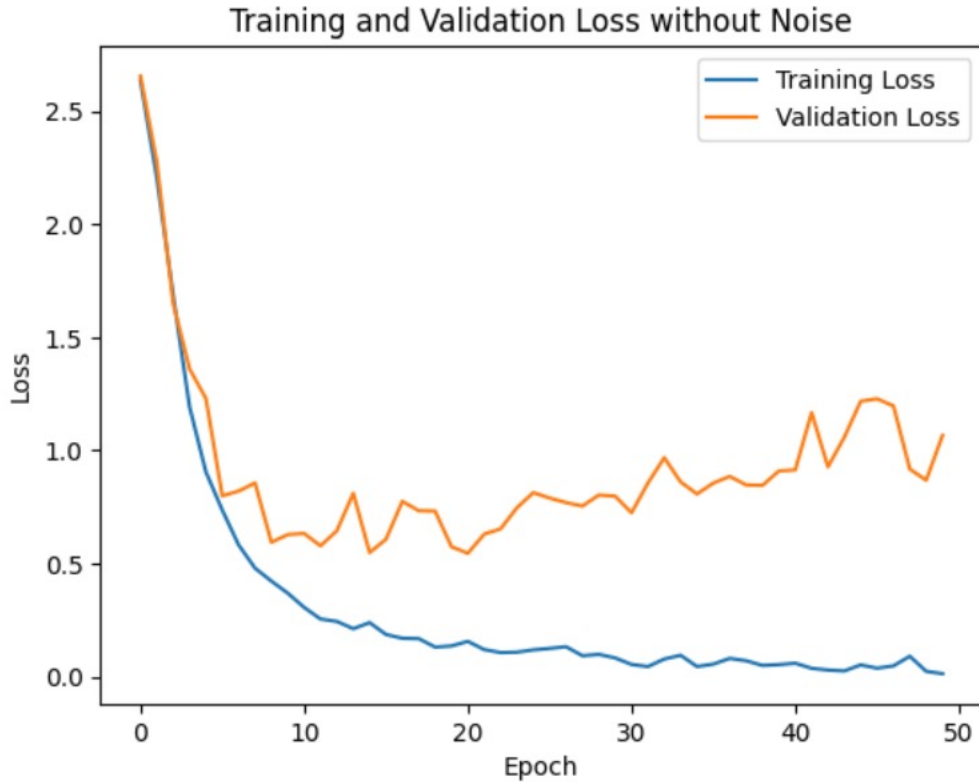
Layer (type)	Output Shape	Param #
reshape_4 (Reshape)	(None, 20, 32, 1)	0
conv2d_12 (Conv2D)	(None, 18, 30, 32)	320
max_pooling2d_9 (MaxPooling2D)	(None, 9, 15, 32)	0
conv2d_13 (Conv2D)	(None, 7, 13, 64)	18496
max_pooling2d_10 (MaxPooling2D)	(None, 3, 6, 64)	0
conv2d_14 (Conv2D)	(None, 1, 4, 128)	73856
flatten_4 (Flatten)	(None, 512)	0
dense_12 (Dense)	(None, 128)	65664
dropout_8 (Dropout)	(None, 128)	0
dense_13 (Dense)	(None, 64)	8256
dropout_9 (Dropout)	(None, 64)	0
dense_14 (Dense)	(None, 13)	845
Total params: 167,437		
Trainable params: 167,437		
Non-trainable params: 0		

6. RESULTS AND EVALUATION : MFCC with noise



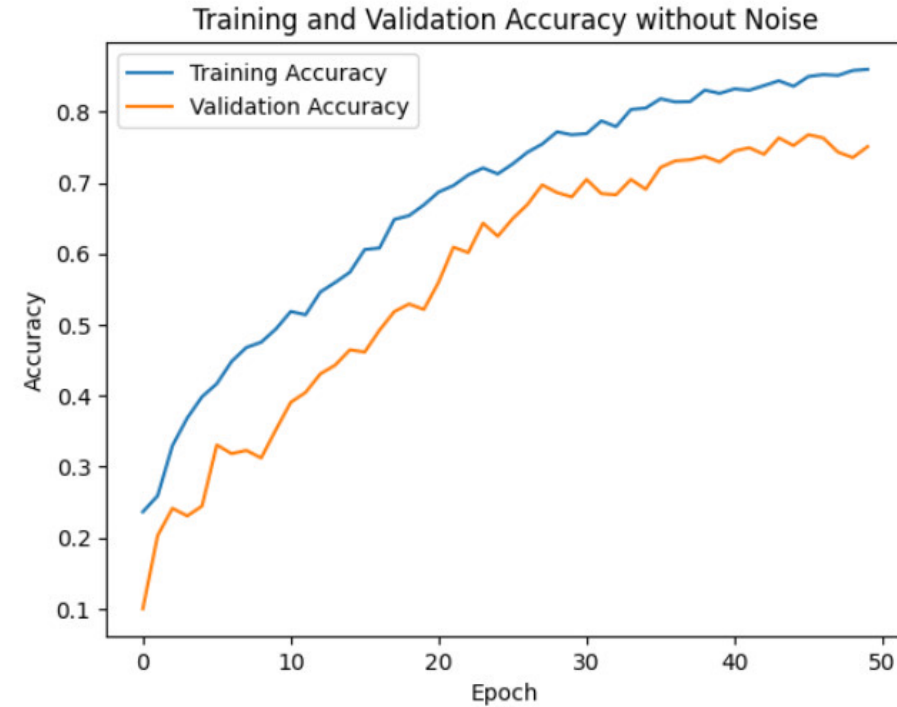
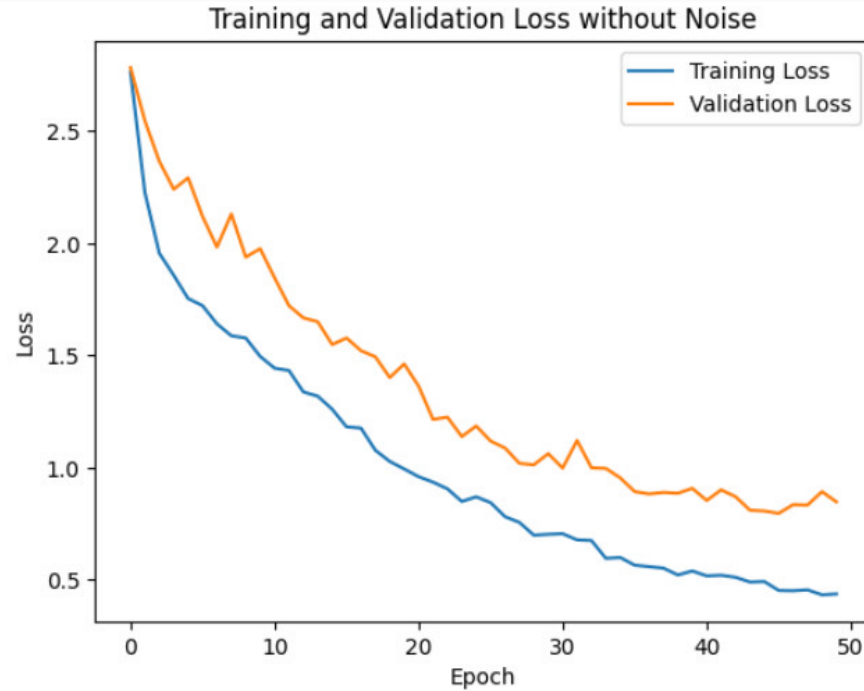
Validation Accuracy achieved: 0.86

6. RESULTS AND EVALUATION : MFCC without noise



Validation Accuracy achieved: 0.88

6. RESULTS AND EVALUATION : Spectrograms



Validation Accuracy achieved: 0.70

7. DEMO



<http://172.16.0.57:8501/>

8. REAL-WORLD APPLICATIONS



**VOICE
ASSISTANT**



**SMART
HOME**



CARS



GAMING

9. CONCLUSION

RESULTS

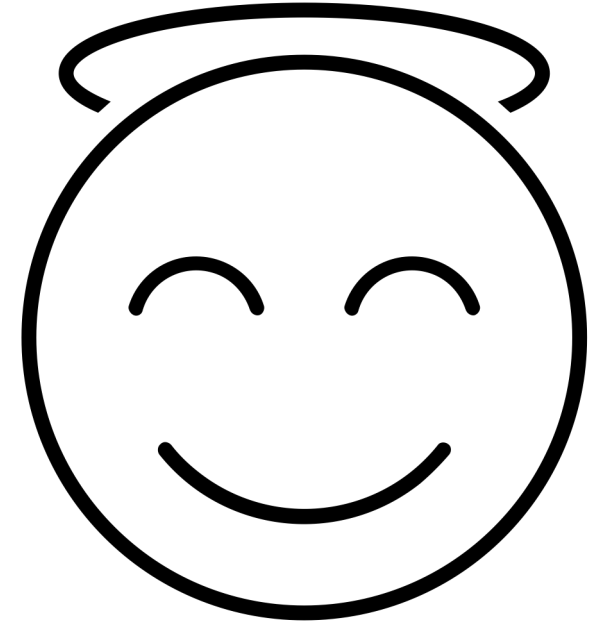
- Achieved very good accuracy with noise BUT overfits ...
- Very inspiring project !

NEXT STEPS

- Increase the different commands
- Try with sentences
- Increase background noise

Last Word !

- Wav2Vec (META)

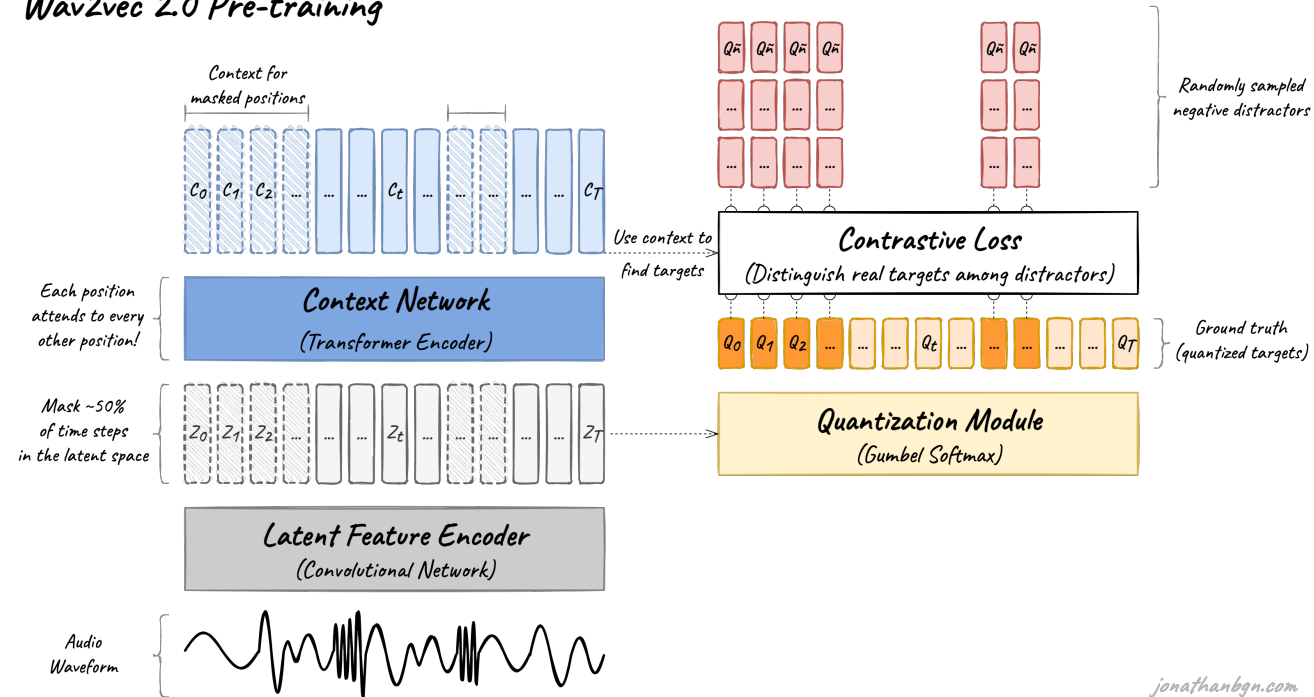


ANNEXES

MODEL DEVELOPMENT: WAV2VEC

- Deep learning model for speech recognition and speech-related tasks
- State-of-the-art results in speech recognition benchmarks
- Handles raw audio data directly, no manual feature extraction needed
- Uses transformers to process CNN output for feature extraction
- Transformer models capture long-range dependencies and contextual information in audio sequences
- Pre-trained: 72% results

Wav2vec 2.0 Pre-training

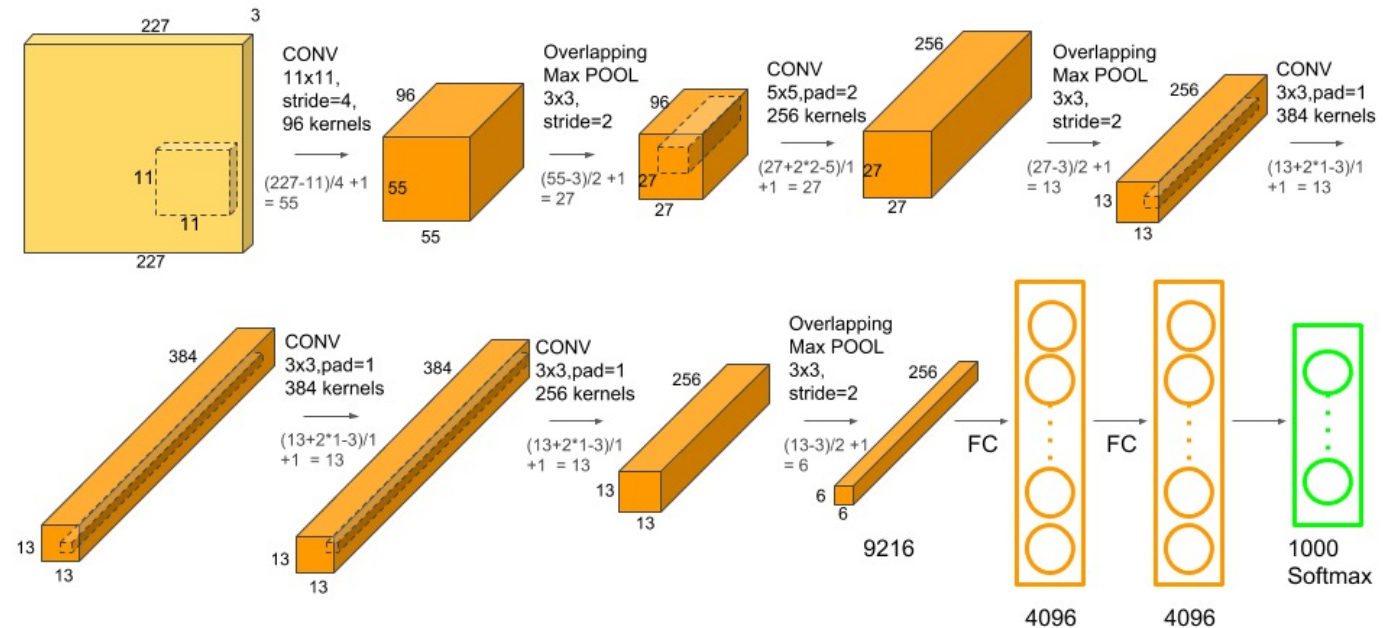


jonathanbgn.com

KEY METRIC: Levenshtein

MODEL DEVELOPMENT: AlexNet CNN

- Deep convolutional neural network architecture
- Multiple layers: convolutional, max-pooling, and fully connected
- Eight layers in total, with the first five being convolutional
- Convolutional layers extract low-level features
- Max-pooling layers downsample feature maps
- Fully connected layers serve as classifier
- ReLU activation functions used
- Dropout regularization implemented



KEY METRIC: Accuracy