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CAS Applied Data Science University of Bern

Module 6 Deep Learning – Music vs Speech Classification

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Jupyter notebook on Github: Link

Objective & Data

Objective

> This project tries to implement a deep learning model that classifies audio samples in music or speech.

Data

> 128 audio files of 30 seconds each
  - 64 speech files
  - 64 music files

Data preparation, preprocessing and split

Split in train and test set

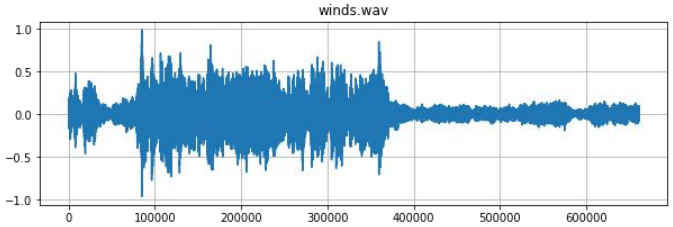
- Get directory of each audio file
- All audios from a category (i.e. speech or music) are split into a training (80%) and validation (20%) set

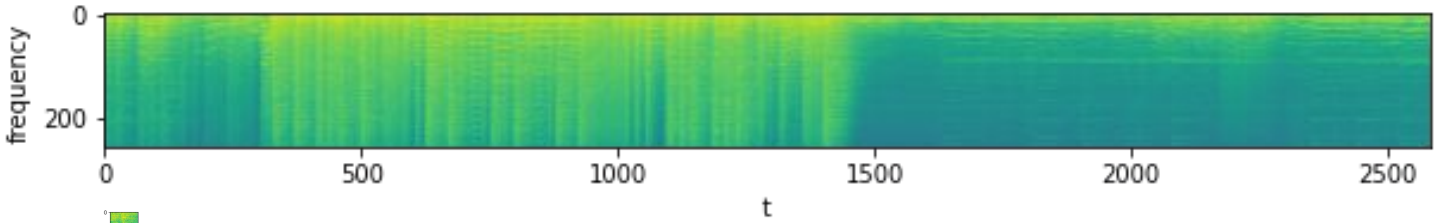
Data preprocessing

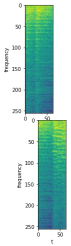
- Load audio files for music and speech datasets separately for training and validation
- Applying discrete Fourier Transformation
- Transform and cut into smaller slices (79 per audio)
- Put together samples of speech and music
- Add labels
- Results in:
  - Training set: 8’058
  -

Data preparation, preprocessing and split

Example of the **frequence** of a music file (winds.wav) including a **fourier transformation** and the first **slice**.





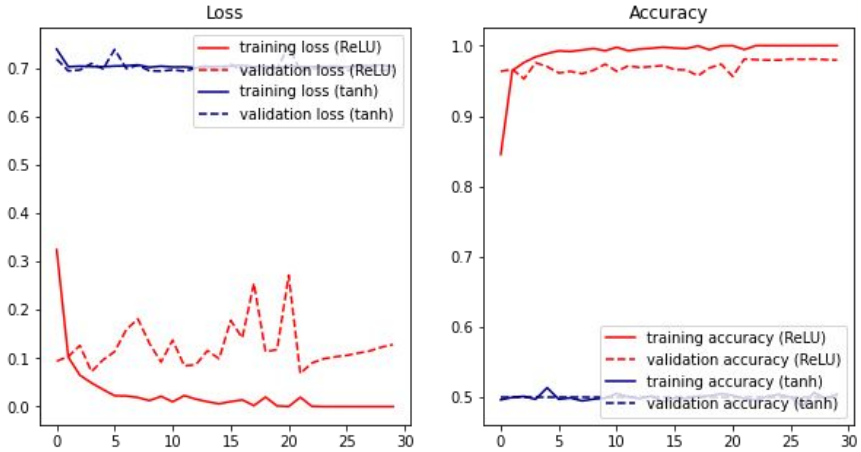


Model building

Model architecture

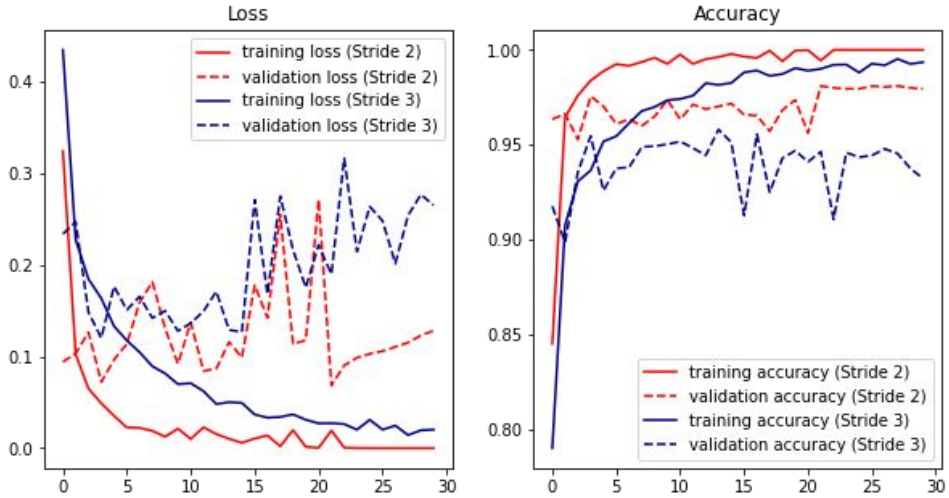
- With and without Pooling Layers
  - Epochs = 30
  - Batch Size = 10
- Testing different activations functions for hidden layers
  - ReLU and tanh
- Chose model based on accuracy
- Try different hyperparameters
  - Stride
  - Kernels
- Test Learnings rates
  - 0.0005
  - 0.001

Model building - only Convolutional Layers



- tanh activation function does not seem to work
- tanh activation function has some drawbacks
- One of the main limitations is the “vanishing gradient” problem.
- This makes it difficult for the model to learn and converge.

Model building - only Convolutional Layers



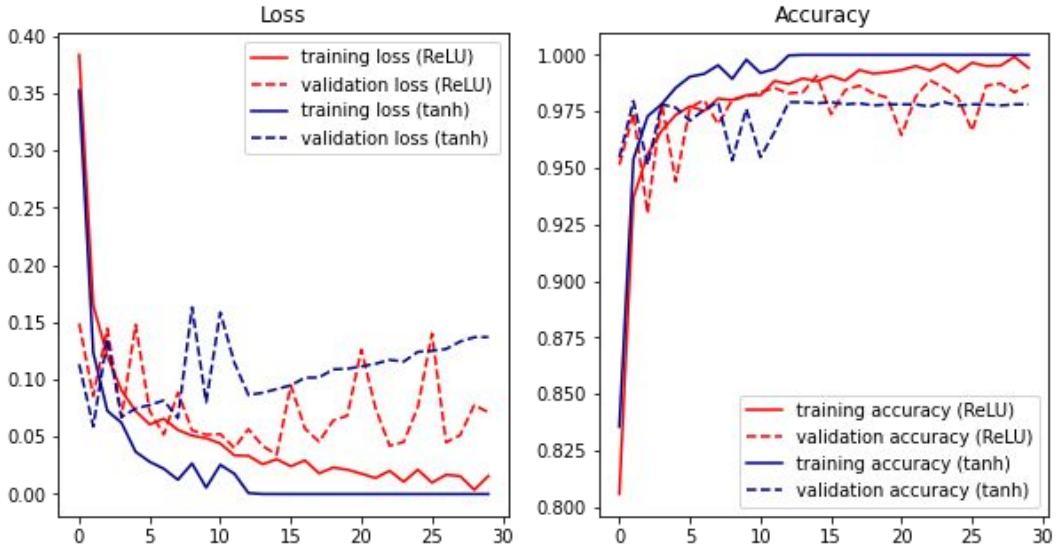
- Using a smaller stride value will result in a larger output volume which can increase the computational cost of the network.
- Using a larger stride can also result in a loss of information as some areas of the input may not be considered in the output.
- According to the plot implementing stride 2 leads to lower validation loss and better validation accuracy

Model building - only Convolutional Layers

Findings

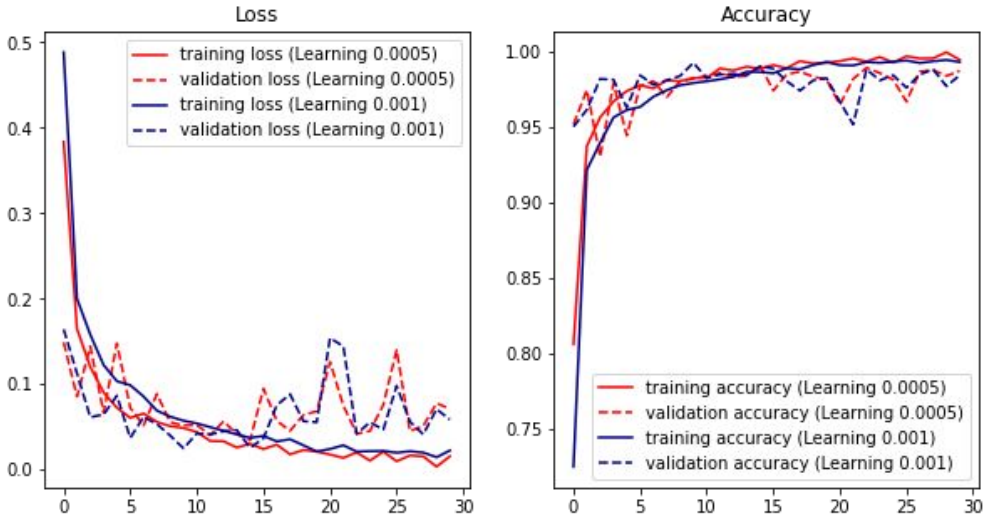
- tanh activation function does not seem to work
- Better implement ReLU activation function
- Stride of 2 leads to lower validation loss and better validation accuracy than stride of 3

Model building - with Pooling Layers



- ReLU activation function shows lower validation loss and better validation accuracy than tanh activation function

Model building - with Pooling Layers



- Testing model 1 with different learnings rates (0.0005 and 0.001)
- No visible difference with different learning rates

Model building - with Pooling Layers

- Testing different value for kernel size, stride and learning rate does not show strong differences in validation set.

- For the final model the following parameters will be implemented:
  - Activation function ReLU (Rectified Linear Unit)
  - Padding “same”
  - Kernel size = 2x2
  - Strides = 2
    - Higher strides does not work well with many layers
  - Learning rate = 0.0005

Model Comparison

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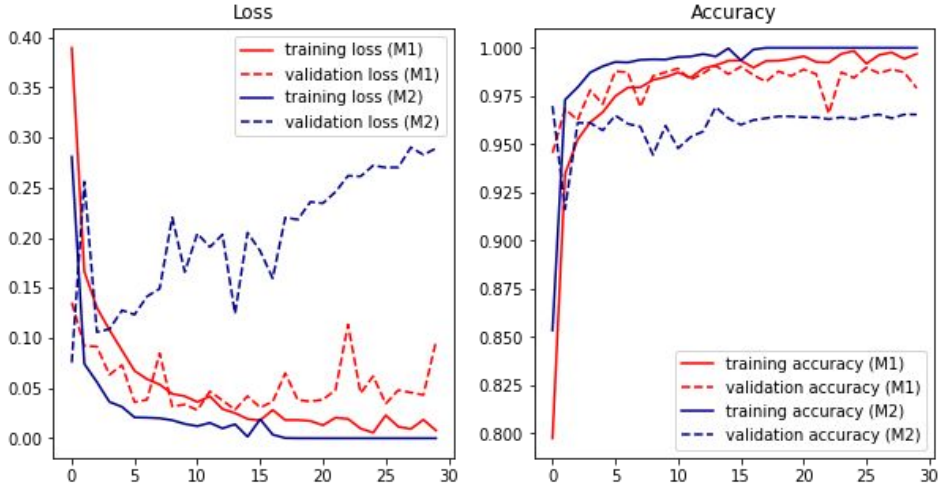
Model with pooling layer

```
Model: "sequential_14"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_56 (Conv2D)          (None, 128, 32, 32)       160

 max_pooling2d_28 (MaxPoolin  (None, 64, 16, 32)       0
 g2D)

 conv2d_57 (Conv2D)          (None, 64, 16, 64)        8256

 max_pooling2d_29 (MaxPoolin  (None, 32, 8, 64)        0
 g2D)

 conv2d_58 (Conv2D)          (None, 32, 8, 128)        32896

 max_pooling2d_30 (MaxPoolin  (None, 16, 4, 128)       0
 g2D)

 conv2d_59 (Conv2D)          (None, 16, 4, 256)        131328

 max_pooling2d_31 (MaxPoolin  (None, 8, 2, 256)        0
 g2D)

 flatten_14 (Flatten)        (None, 4096)              0

 dense_28 (Dense)            (None, 512)               2097664

 dense_29 (Dense)            (None, 2)                 1026

=================================================================
Total params: 2,271,330
Trainable params: 2,271,330
Non-trainable params: 0
_________________________________________________________________
```

Model only convolutional layer

```
Model: "sequential_15"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_60 (Conv2D)          (None, 128, 32, 32)       320

 conv2d_61 (Conv2D)          (None, 64, 16, 64)        18496

 conv2d_62 (Conv2D)          (None, 32, 8, 128)        73856

 conv2d_63 (Conv2D)          (None, 16, 4, 256)        295168

 flatten_15 (Flatten)        (None, 16384)             0

 dense_30 (Dense)            (None, 512)               8389120

 dense_31 (Dense)            (None, 2)                 1026

=================================================================
Total params: 8,777,986
Trainable params: 8,777,986
Non-trainable params: 0
_________________________________________________________________
```

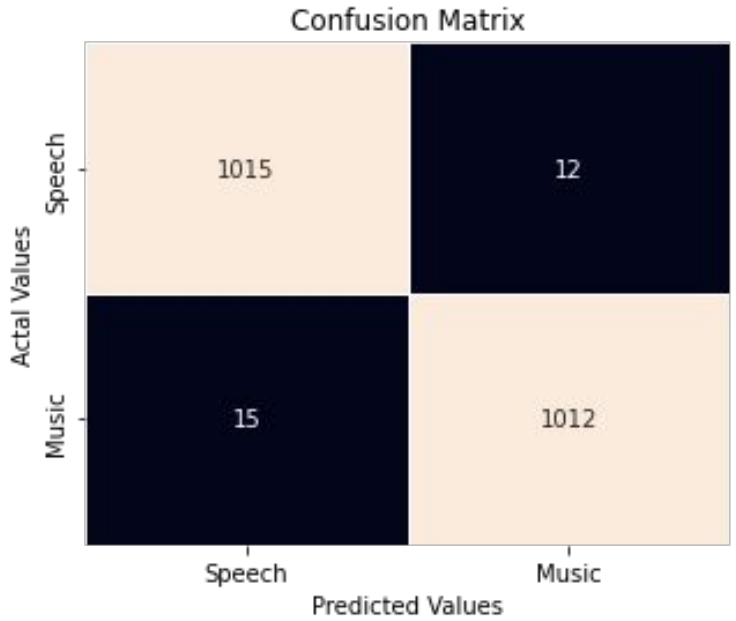
Comparison Model 1 & Model 2



- The comparison of the model with pooling layers and the model only with convolutional layers shows lower validation loss and better training accuracy with pooling layer.
- Apparently this is mainly due to the pooling layer which improves the performance with less trainable parameters

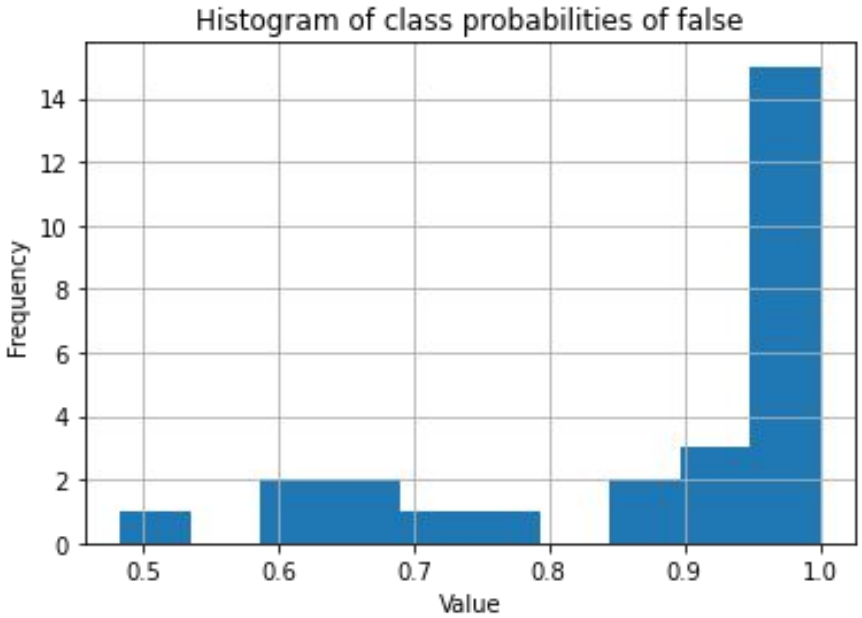
Evaluation - Confusion Matrix

- Validation accuracy: 98%
- Even distribution of wrong predicted classes

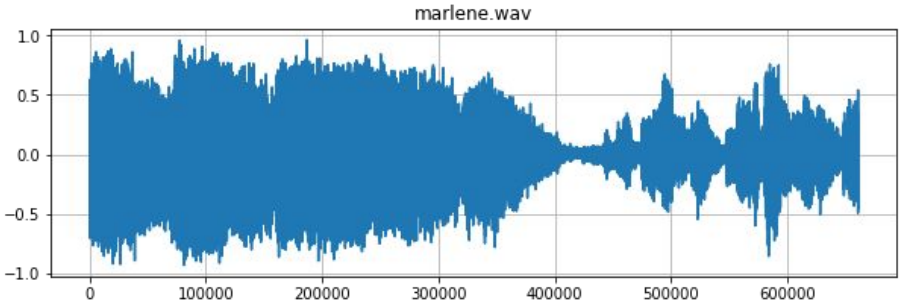


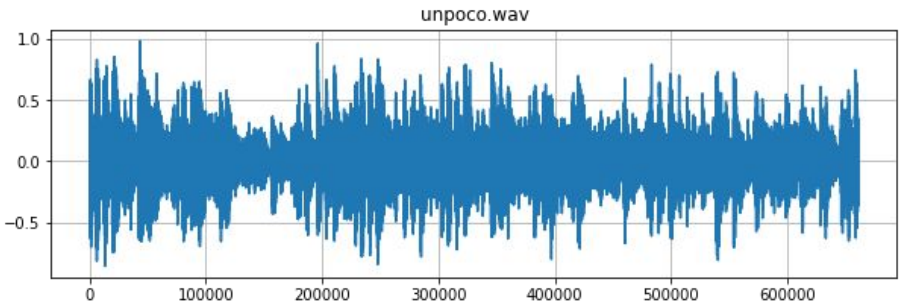
Evaluation - Probabilities and Audio Files

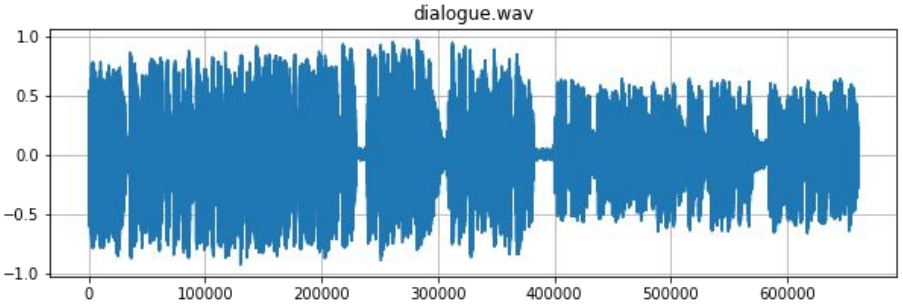
- Fairly high probabilities by wrong ones
- Remember: 79 slices per audio
  - Not whole song, only segment is wrongly predicted
- Names of wrong predicted audio files
  - ncherry.wav': 4,
  - gravity.wav': 8,
  - voices.wav': 1,
  - nj105.wav': 2,
  - dialogue1.wav': 2,
  - nj105a.wav': 2,
  - dialogue.wav': 6,
  - my_voice.wav': 2



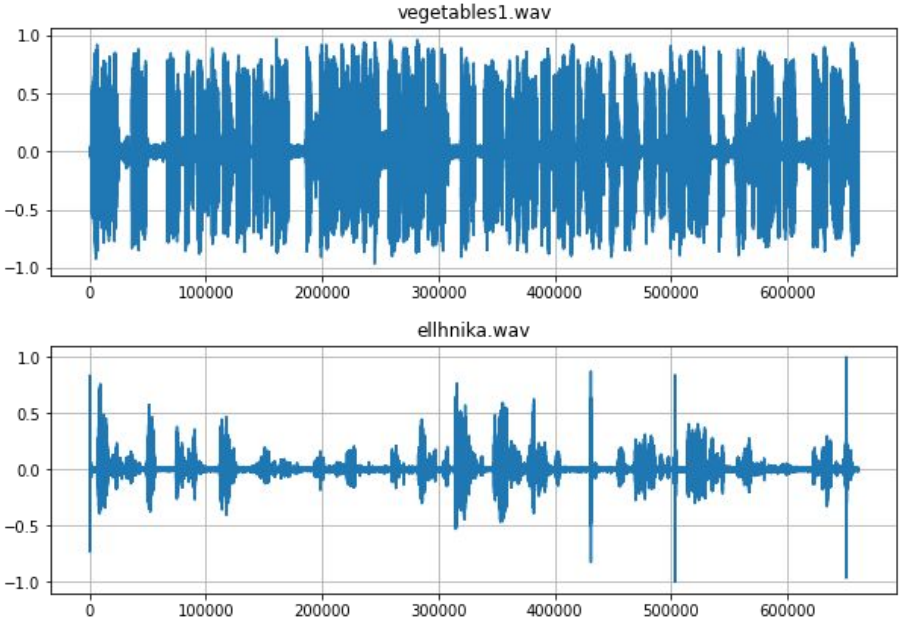
Evaluation - Speech recognized as Music

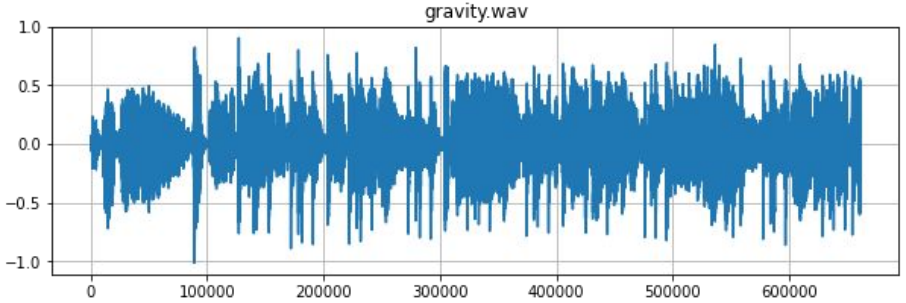






Evaluation - Music recognized as Speech





Conclusion

- Model works very good with moderate computational effort
- Pooling layers improved the performance with less trainable parameters
- Variation of model parameters would be better done by grid search