

# Urban Sound Challenge

## Audio Classification with Deep Learning

From Feature Extraction to Recurrent Neural Networks

Micha Birklbauer, 2020

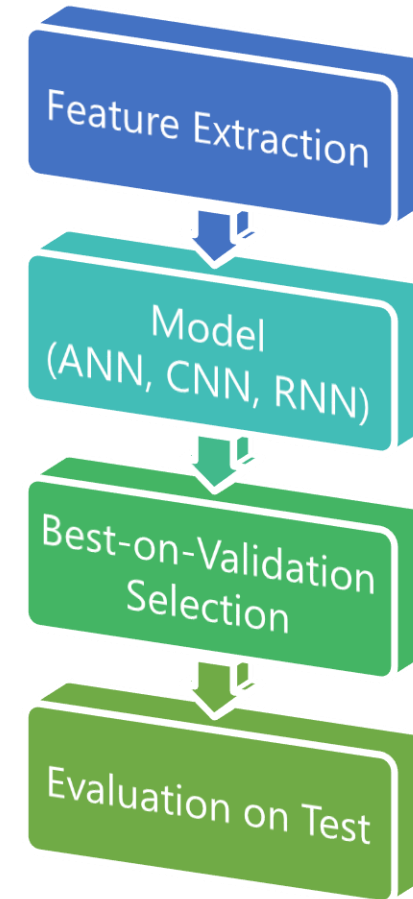
# Urban Sound Challenge – The Dataset

- Audio recordings of urban sounds
- 10 class multiclassification-problem
- 3673 samples with length of up to 4 seconds
- 3637 samples used for training
  - 70% of training samples used for training
  - 30% of training samples used for validation
- 33 samples used for testing (evaluation)
- 3 samples unused because of missing class
- Baseline:
  - siren: most frequent class – makes up 13.4% of total training samples
  - Therefore the baseline is an accuracy of >13.4%
- Classes (with Training Distribution):
  - air\_conditioner: 351 samples
  - car\_horn: 249 samples
  - children\_playing: 375 samples
  - dog\_bark: 433 samples
  - drilling: 468 samples
  - engine\_idling: 346 samples
  - gun\_shot: 151 samples
  - jackhammer: 377 samples
  - **siren: 488 samples (13.4% -> baseline)**
  - street\_music: 399 samples

# Pipeline

- Feature Extraction:
  - Mel-Frequency Cepstrum Coefficients (MFCC)
  - Chromagram
  - Melspectrogram
  - Spectral Contrast
  - Tonnetz
- Training with different Model Architectures:
  - Classical Feed-Forward Neural Networks
  - Convolutional Neural Networks
  - Recurrent Neural Networks
  - Recurrent Neural Networks with Gated Recurrent Units (GRU)
  - Recurrent Neural Networks with Long-Short Term Memory (LSTM)
- Best-on-Validation Selection:
  - Select model with highest validation accuracy
- Evaluation on Test Data:
  - 33 audio samples
- Model Architectures trained in total: 57

# Workflow



# Feature Extraction – Mel-Frequency Cepstrum Coefficients (MFCC)

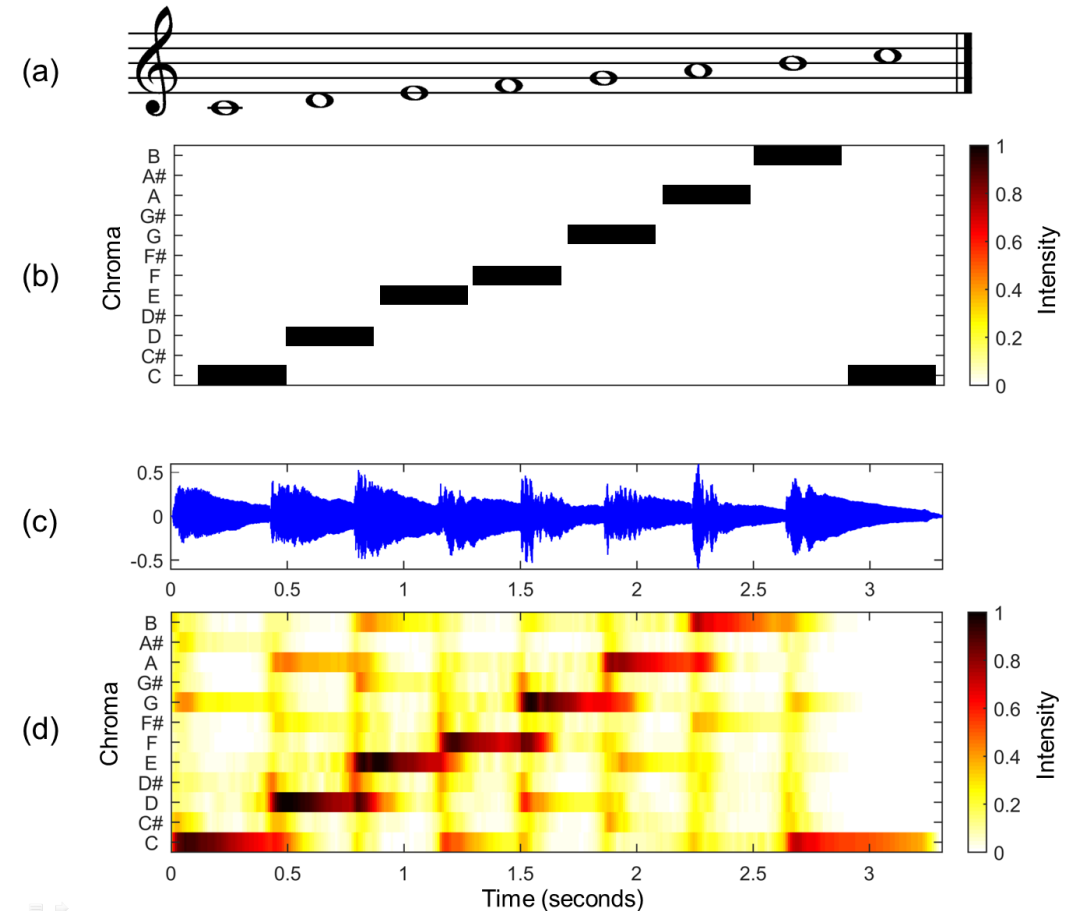
- Definitions:
  - **Power Spectrum:** Describes the distribution of power (=the energy that is transferred) as frequencies.
  - **Mel Scale:** Perceptual scale of pitches judged by listeners to be equal in distance from one another.
  - **Mel-Frequency Cepstrum:** Representation of the short-term power spectrum of a sound, based on the linear cosine transform of the log power spectrum on the mel scale.
- Mel-Frequency Cepstrum Coefficients (MFCC):  
Coefficients that collectively make up a Mel-Frequency Cepstrum.
- MFCC Usage:
  - Speech Recognition
  - Audio Classification
  - Audio Clustering
- MFCC Extraction:
  - Take the Fourier transform of (a window of) a signal.
  - Map the powers of the spectrum obtained onto the mel scale, using overlapping windows.
  - Take the logarithms of the powers for each of the mel frequencies.
  - Take the discrete cosine transform of the mel log powers.
  - The MFCCs are the amplitudes of the resulting spectrum.

Source: [Wikipedia](#)

# Feature Extraction – Chromagram

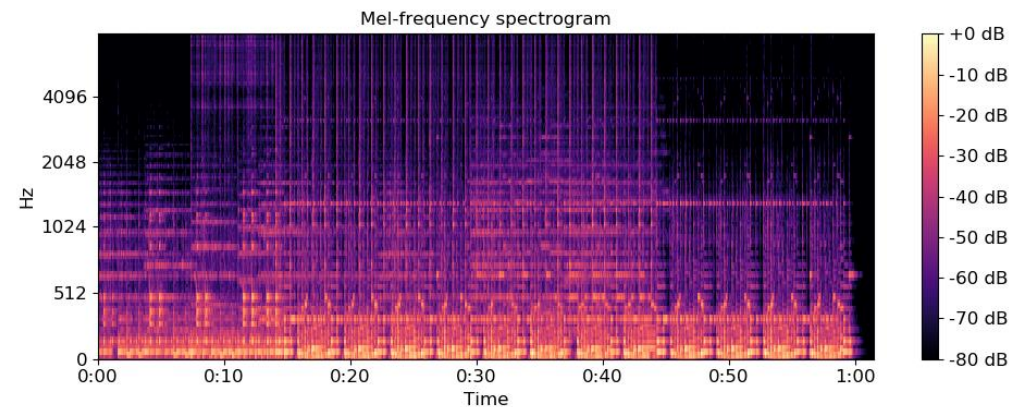
- A chromagram is a categorization for pitches of music or sound into usually 12 different categories. Typically a chromagram captures harmonic and melodic characteristics of music, while being robust to changes in timbre and instrumentation.
- The picture on the right illustrates:
  - A – the musical score of a C-major scale.
  - B – the chromagram obtained from the score.
  - C – audio recording of the C-major scale played on a piano.
  - D – chromagram obtained from the audio recording.

Source: [Wikipedia](https://en.wikipedia.org/wiki/Chromagram)



# Feature Extraction – Melspectrogram

- Definitions:
  - **Spectrogram:** Visual representation of the spectrum of frequencies of a signal as it varies with time.
  - **Mel Scale:** Perceptual scale of pitches judged by listeners to be equal in distance from one another.
- Melspectrogram:  
The mel-scaled spectrogram of an audio segment.

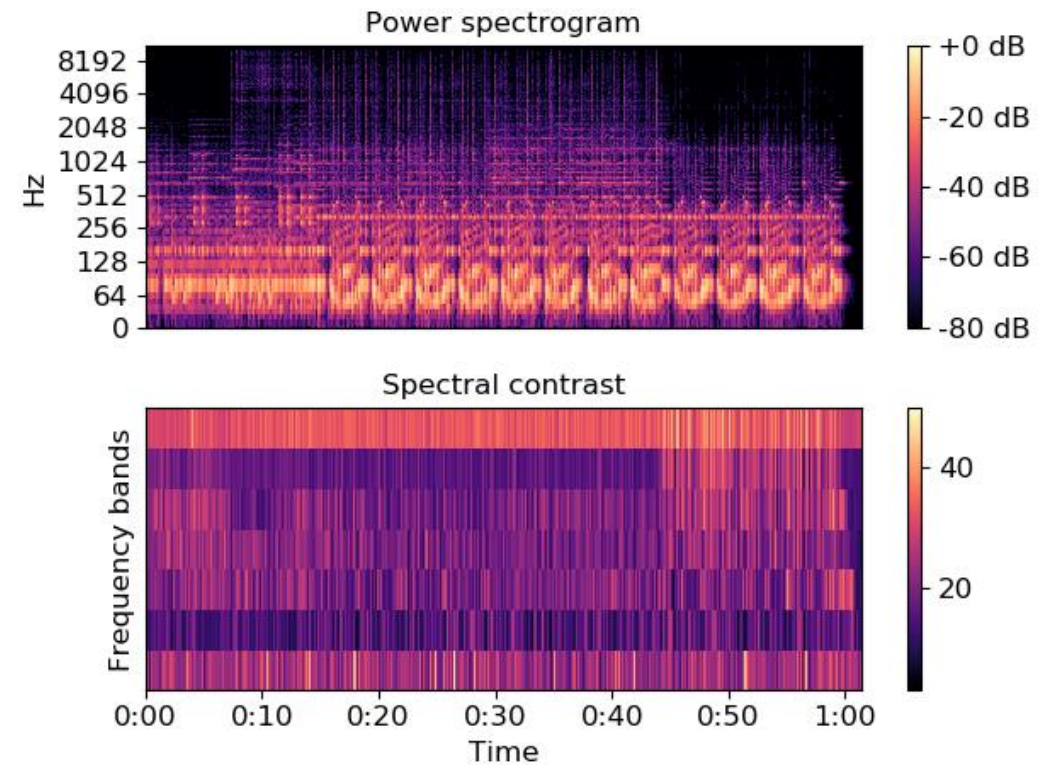


Source: [LibROSA](#)

Source: [Wikipedia](#)

# Feature Extraction – Spectral Contrast

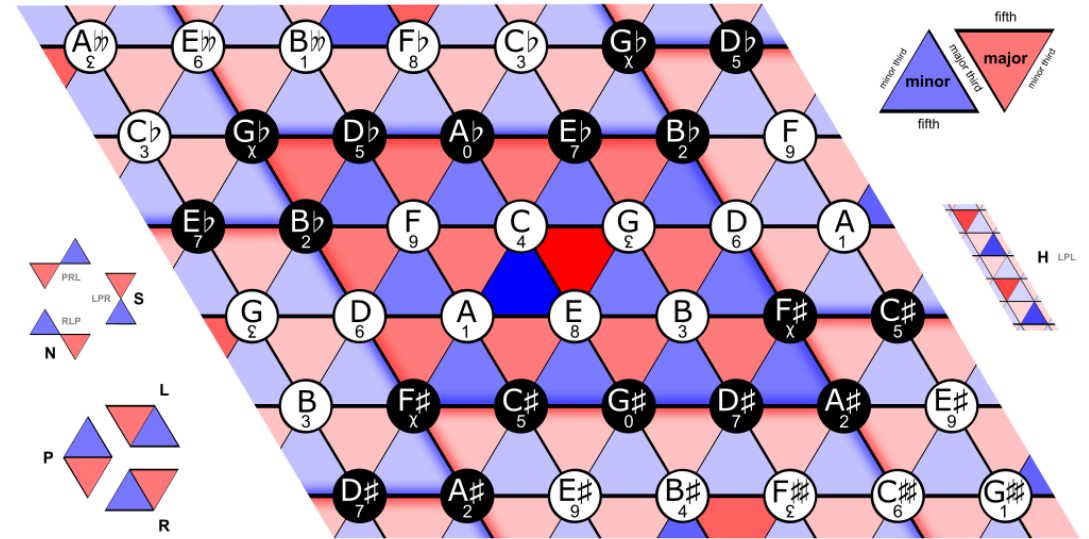
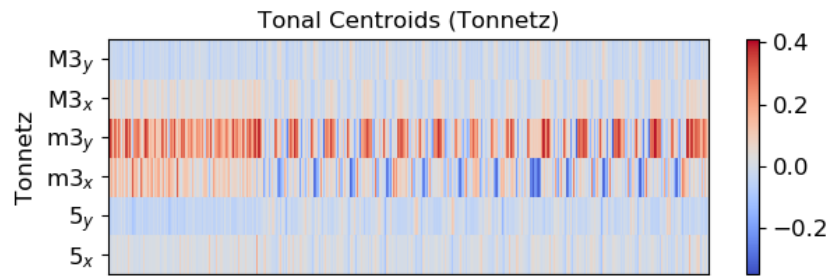
- Each frame of a power spectrogram is divided into bands. For each band, the energy contrast is estimated by comparing the mean energy in the top quantile (peak energy) to that of the bottom quantile (valley energy).



Source: [LibROSA](#)

# Feature Extraction – Tonnetz

- The Tonnetz is a conceptual lattice diagram representing tonal space. (left picture)
- In LibROSA represented as the 6 tonal centroid features at each timestep. (below picture)



Sources: [Wikipedia](#) / [LibROSA](#)



# Model Architectures

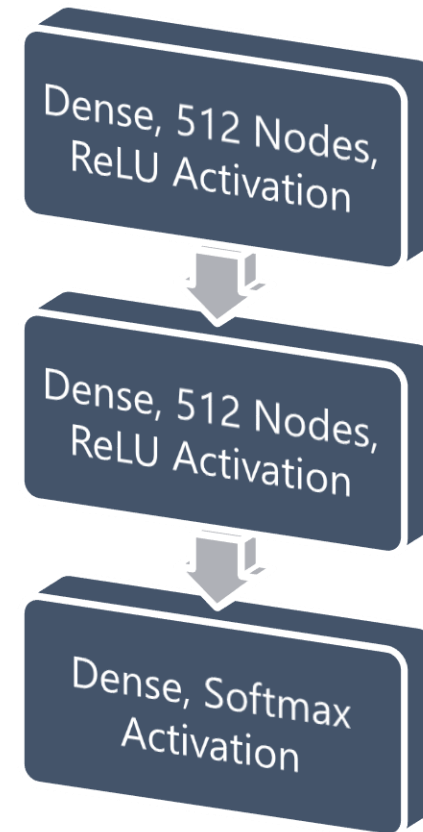
- Feed-Forward Neural Nets
- Convolutional Neural Nets
- Recurrent Neural Nets

# Feed-Forward Neural Networks – Architecture I

## Description & Results

- Simple 2 layer network with 512 nodes per layer and ReLU activation functions. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.907509**

## Architecture

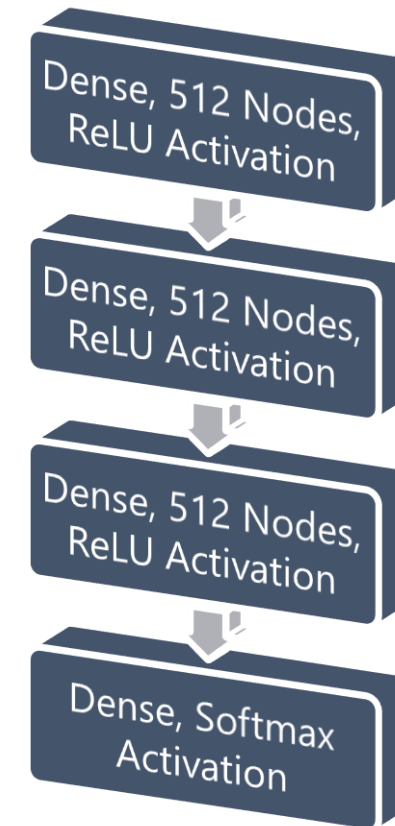


# Feed-Forward Neural Networks – Architecture II

## Description & Results

- 3 layer network with 512 nodes per layer and ReLU activation functions. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.912088**

## Architecture

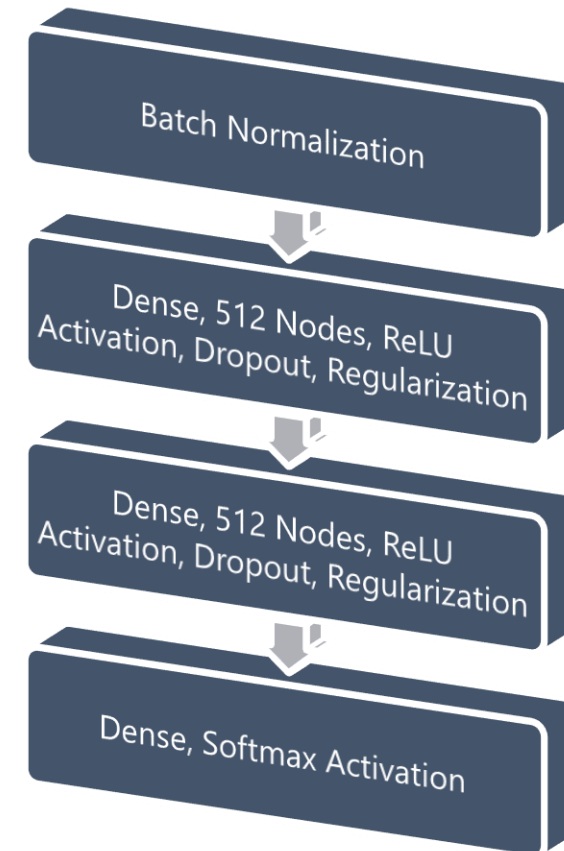


# Feed-Forward Neural Networks – Architecture III

## Description & Results

- 2 layer network with 512 nodes per layer and ReLU activation functions. Additionally layers have 0.3 dropout and 0.01 L2 kernel- and bias regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.946886**

## Architecture

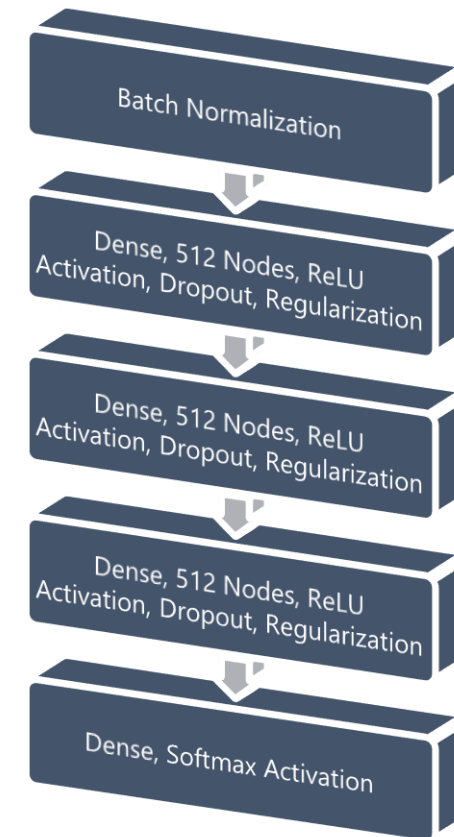


# Feed-Forward Neural Networks – Architecture IV

## Description & Results

- 3 layer network with 512 nodes per layer and ReLU activation functions. Additionally layers have 0.3 dropout and 0.01 L2 kernel- and bias regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.945971**

## Architecture

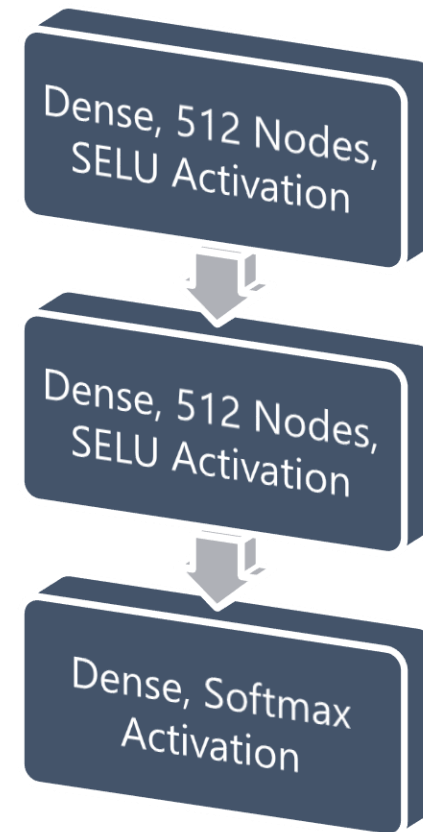


# Feed-Forward Neural Networks – Architecture V

## Description & Results

- 2 layer network with 512 nodes per layer and SELU activation functions. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.913004**

## Architecture

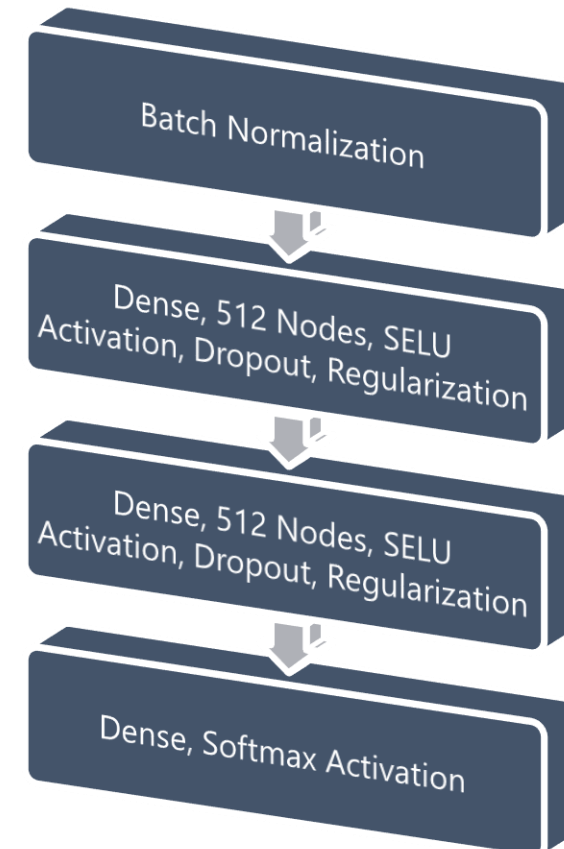


# Feed-Forward Neural Networks – Architecture VI

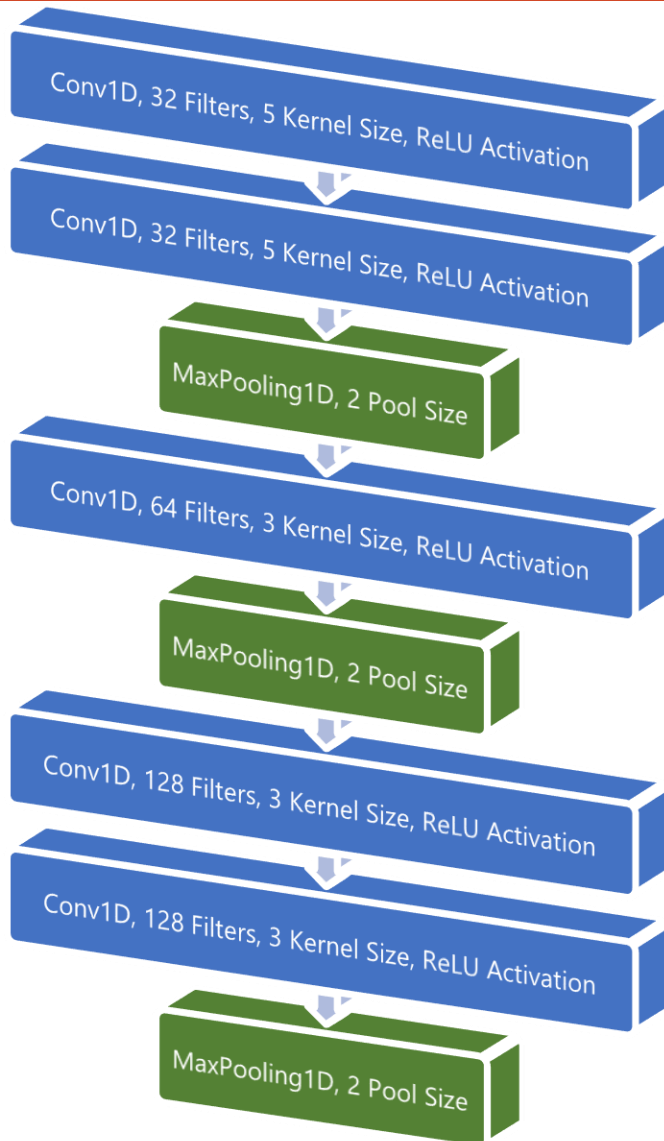
## Description & Results

- 2 layer network with 512 nodes per layer and SELU activation functions. Additionally layers have 0.3 dropout and 0.01 L2 kernel- and bias regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.874542**

## Architecture



# Convolutional Neural Networks – Architecture I



## Convolution – Description

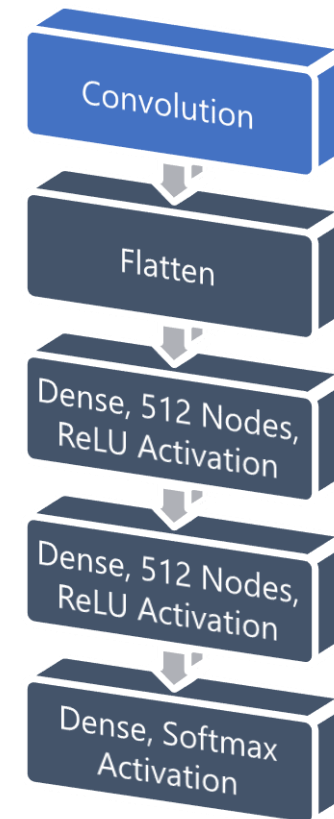
- 5 convolutional layers, all with ReLU activation functions.
- Different number of filters and varying kernel size in convolutional layers.
- 3 pooling layers doing max pooling with a pool size of 2.



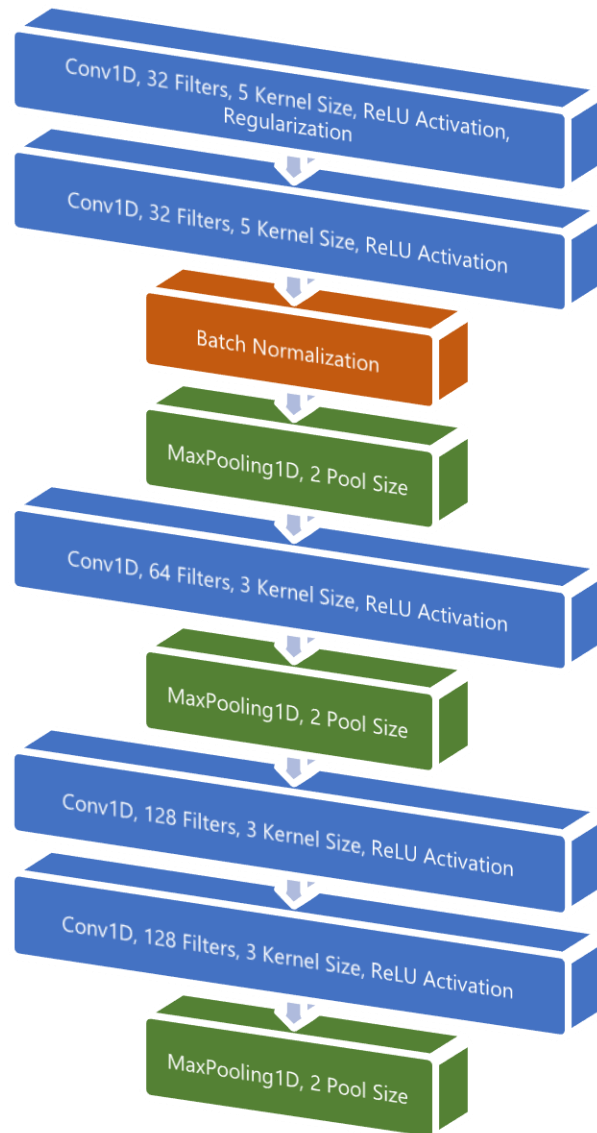
# Convolutional Neural Networks – Architecture I

## Feed-Forward Description & Results

- 2 layer network with 512 nodes per layer and ReLU activation functions. Convolution input is flattened. Output layer with softmax activation.
- Best Features for this Architecture:  
Combination of all
- Best-on-Validation Accuracy:  
**0.931319**



# Convolutional Neural Networks – Architecture II



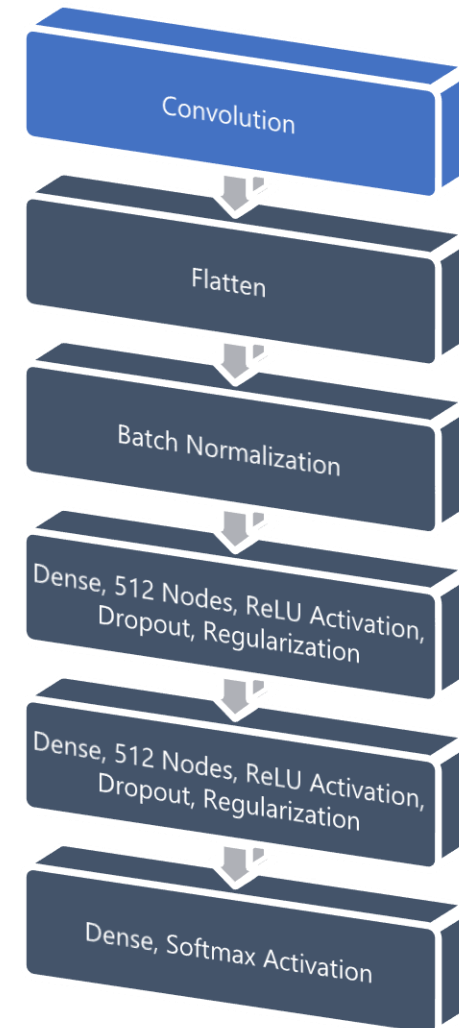
## Convolution – Description

- 5 convolutional layers, all with ReLU activation functions.
- Different number of filters and varying kernel size in convolutional layers.
- 0.01 kernel- and bias regularization in the first convolutional layer.
- Batch normalization before first pooling layer.
- 3 pooling layers doing max pooling with a pool size of 2.

# Convolutional Neural Networks – Architecture II

## Feed-Forward Description & Results

- 2 layer network with 512 nodes per layer and ReLU activation functions. Additionally layers have 0.3 dropout and 0.01 L2 kernel- and bias regularization. Convolution input is batch normalized and flattened. Output layer with softmax activation.
- Best Features for this Architecture: Combination of all
- Best-on-Validation Accuracy: **0.946886**

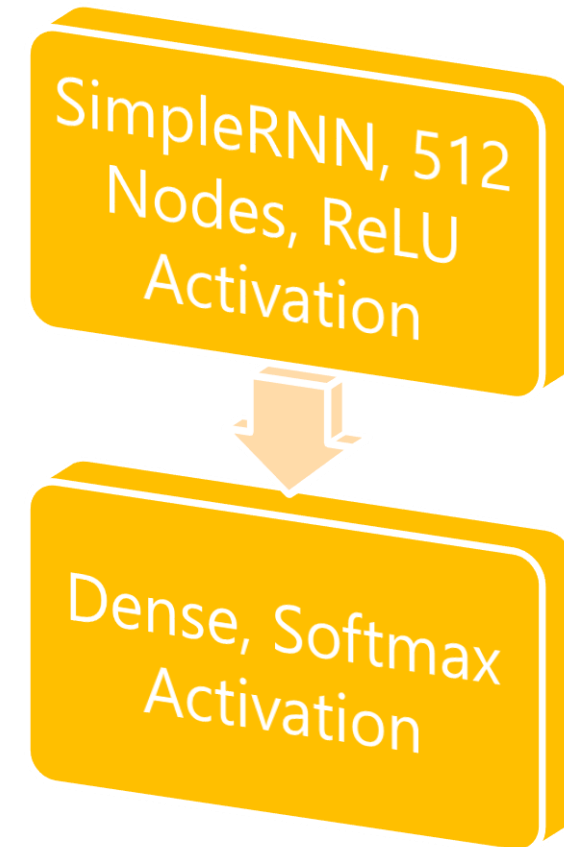


# Recurrent Neural Networks – Architecture I

## Description & Results

- Simple 1 layer RNN with 512 nodes and ReLU activation function. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs
- Best-on-Validation Accuracy:  
**0.901099**

## Architecture

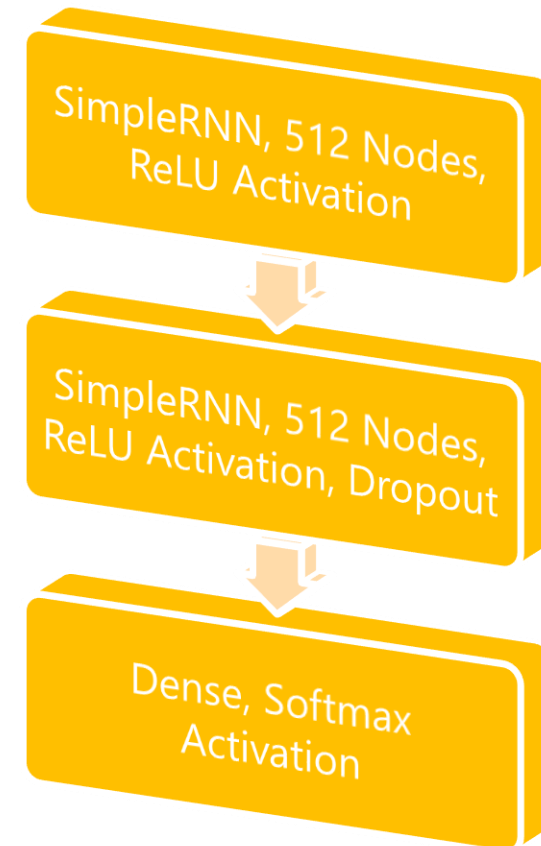


# Recurrent Neural Networks – Architecture II

## Description & Results

- 2 layer RNN with 512 nodes per layer and ReLU activation functions. The second layer also has 0.2 dropout and recurrent dropout. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs
- Best-on-Validation Accuracy:  
**0.880952**

## Architecture

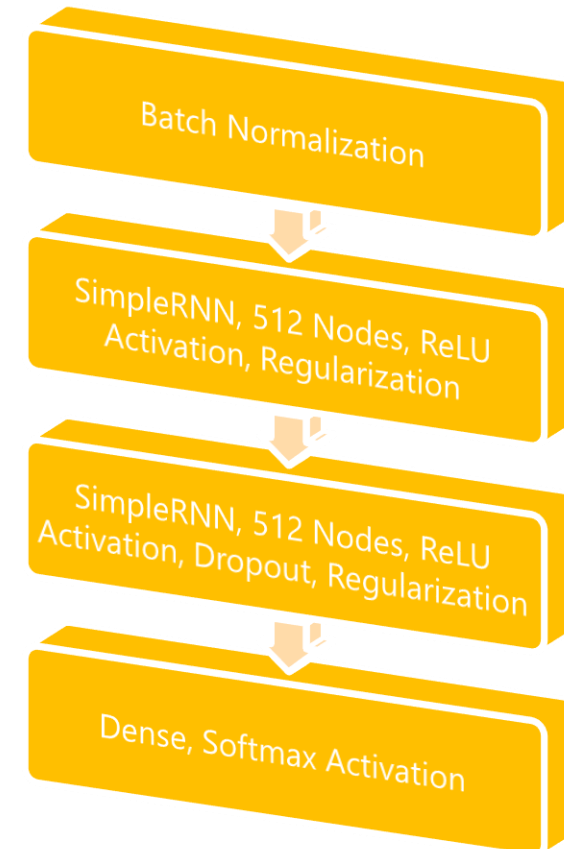


# Recurrent Neural Networks – Architecture III

## Description & Results

- 2 layer RNN with 512 nodes per layer and ReLU activation functions. The second layer also has 0.2 dropout and recurrent dropout. Additionally layers have 0.01 L2 kernel-, bias- and recurrent regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs (small sample size due to bad results)
- Best-on-Validation Accuracy:  
**0.326007**

## Architecture

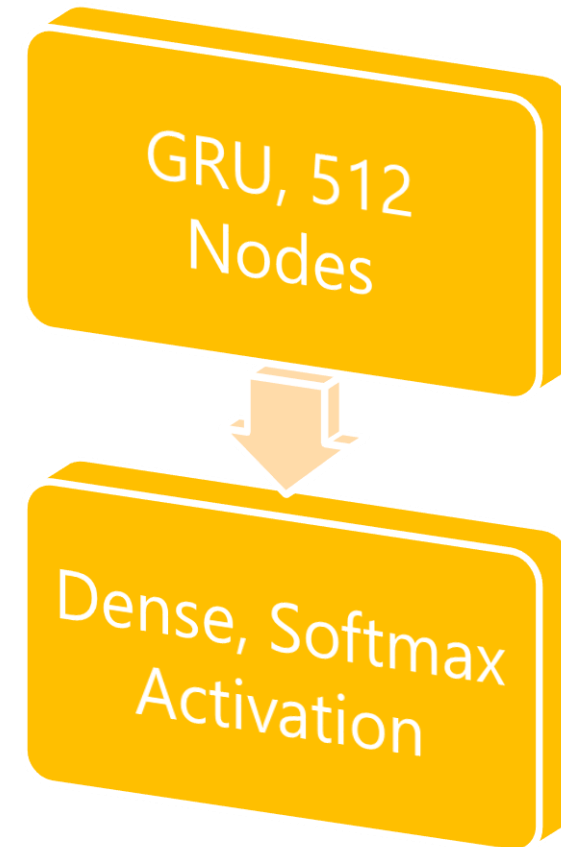


# Recurrent Neural Networks – Architecture IV (light)

## Description & Results

- Simple 1 layer Gated Recurrent Unit-RNN with 512 nodes. Output layer with softmax activation.
- Best Features for this Architecture: 40 MFCCs
- Best-on-Validation Accuracy: **0.578755**

## Architecture

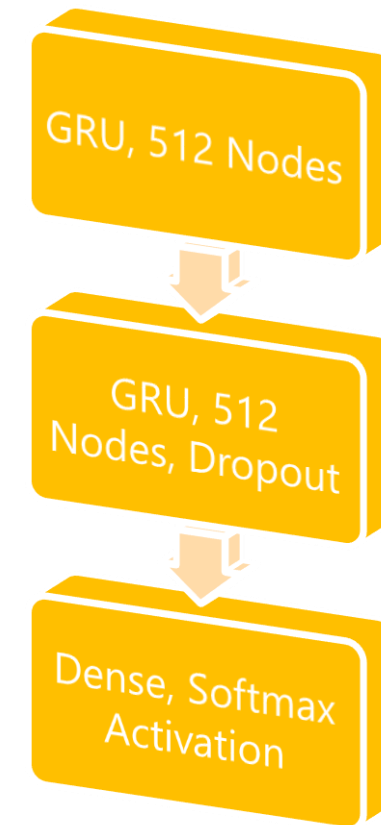


# Recurrent Neural Networks – Architecture IV

## Description & Results

- 2 layer Gated Recurrent Unit-RNN with 512 nodes per layer. The second layer also has 0.2 dropout and recurrent dropout. Output layer with softmax activation.
- Best Features for this Architecture: 40 MFCCs
- Best-on-Validation Accuracy: **0.769231**

## Architecture



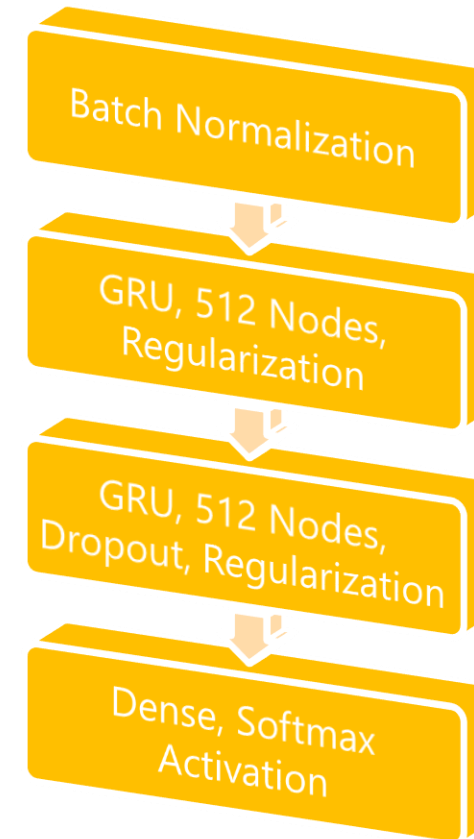


# Recurrent Neural Networks – Architecture V

## Description & Results

- 2 layer Gated Recurrent Unit-RNN with 512 nodes per layer. The second layer also has 0.2 dropout and recurrent dropout. Additionally layers have 0.01 L2 kernel-, bias- and recurrent regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs (small sample size due to bad results)
- Best-on-Validation Accuracy:  
**0.13461 (Baseline!)**

## Architecture

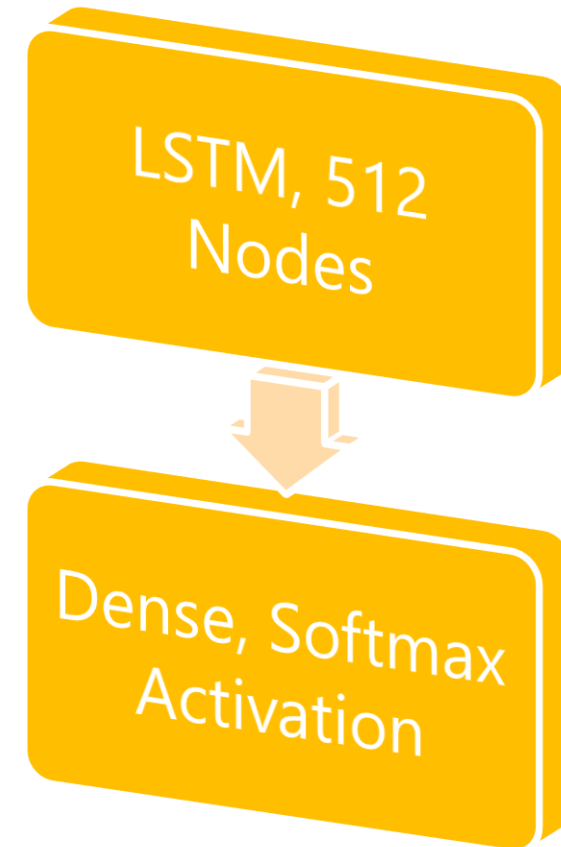


# Recurrent Neural Networks – Architecture VI (light)

## Description & Results

- Simple 1 layer Long-Short Term Memory-RNN with 512 nodes. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs
- Best-on-Validation Accuracy:  
**0.808608**

## Architecture



# Recurrent Neural Networks – Architecture VI

## Description & Results

- 2 layer Long-Short Term Memory-RNN with 512 nodes per layer. The second layer also has 0.2 dropout and recurrent dropout. Output layer with softmax activation.
- Best Features for this Architecture: 40 MFCCs
- Best-on-Validation Accuracy: **0.801282**

## Architecture

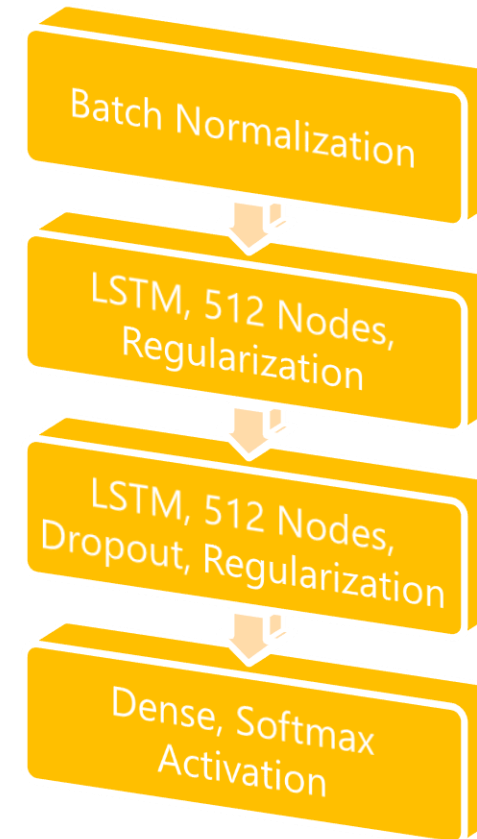


# Recurrent Neural Networks – Architecture VII

## Description & Results

- 2 layer Long-Short Term Memory-RNN with 512 nodes per layer. The second layer also has 0.2 dropout and recurrent dropout. Additionally layers have 0.01 L2 kernel-, bias- and recurrent regularization. Inputs are batch normalized. Output layer with softmax activation.
- Best Features for this Architecture:  
40 MFCCs (small sample size due to bad results)
- Best-on-Validation Accuracy:  
**0.13461 (Baseline!)**

## Architecture



# Results

- Overview
- Model Selection
- Evaluation on Test Data

# Results – Complete Overview

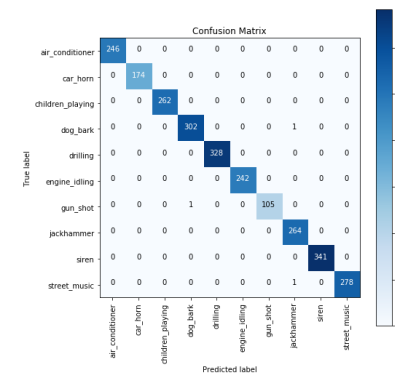
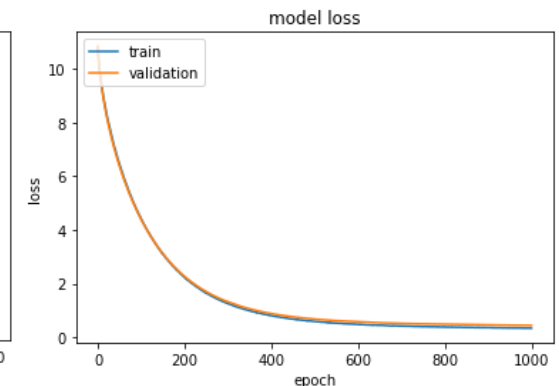
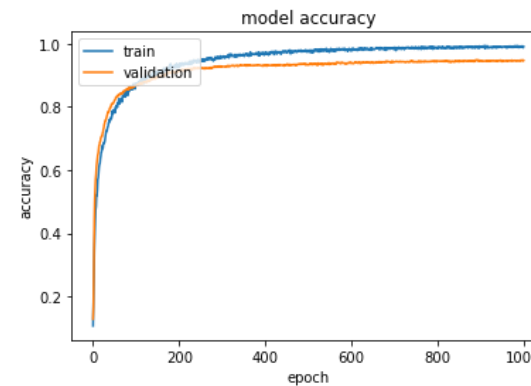
Feed-Forward Neural Networks			Convolutional Neural Networks			Recurrent Neural Networks		
	Models	Validation_Accuracy		Models	Validation_Accuracy		Model	Validation_Accuracy
14	mlp_3_all	0.946886	9	cnn_2_all	0.946886	0	mn_1_mfcc40	0.901099
15	mlp_4_all	0.945971	5	cnn_2_mfcc80	0.931319	1	mn_2_mfcc40	0.880952
8	mlp_3_mfcc80	0.929487	8	cnn_1_all	0.931319	8	mn_6light_mfcc40	0.808608
9	mlp_4_mfcc80	0.928571	3	cnn_2_mfcc60	0.930403	5	mn_6_mfcc40	0.801282
3	mlp_4_mfcc40	0.914835	1	cnn_2_mfcc40	0.923077	13	mn_6light_mfcc80	0.795788
16	mlp_5_all	0.913004	4	cnn_1_mfcc80	0.923077	14	mn_6_mfcc80	0.770147
13	mlp_2_all	0.912088	2	cnn_1_mfcc60	0.911172	3	mn_4_mfcc40	0.769231
2	mlp_3_mfcc40	0.911172	7	cnn_2_melspec	0.871795	9	mn_1_mfcc80	0.718864
12	mlp_1_all	0.907509	0	cnn_1_mfcc40	0.861722	7	mn_4light_mfcc40	0.713370
0	mlp_1_mfcc40	0.905678	6	cnn_1_melspec	0.713370	25	mn_6light_melspec	0.618132
7	mlp_2_mfcc80	0.905678	11	cnn_2_chroma	0.652930	10	mn_2_mfcc80	0.605311
4	mlp_5_mfcc40	0.899267	10	cnn_1_chroma	0.576007	16	mn_2_chroma	0.581502
10	mlp_5_mfcc80	0.892857				12	mn_4_mfcc80	0.579670
6	mlp_1_mfcc80	0.892857				11	mn_4light_mfcc80	0.578755
1	mlp_2_mfcc40	0.883700				15	mn_1_chroma	0.541209
17	mlp_6_all	0.874542				26	mn_6_melspec	0.509158
11	mlp_6_mfcc80	0.814103				17	mn_4light_chroma	0.359890
5	mlp_6_mfcc40	0.751832				18	mn_4_chroma	0.355311
						19	mn_6light_chroma	0.348901
						20	mn_6_chroma	0.334249
						2	mn_3_mfcc40	0.326007
						22	mn_2_melspec	0.271978
						24	mn_4_melspec	0.267399
						23	mn_4light_melspec	0.226190
						21	mn_1_melspec	0.187729
						6	mn_7_mfcc40	0.134615
						4	mn_5_mfcc40	0.134615

# Model Selection – Best-on-Validation

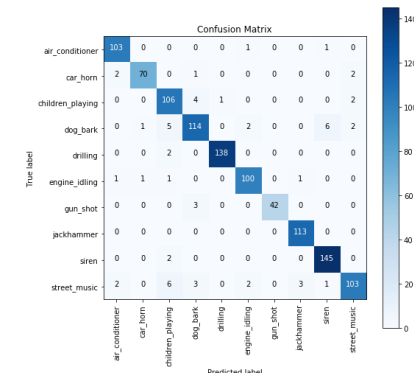
- Two models with **0.946886 accuracy** on validation set:
  - Feed-Forward Neural Network – Architecture III
  - Convolutional Neural Network – Architecture II
- Which one to choose?**  
The Convolutional Neural Network has slightly better training accuracy (about 1% improvement), however going by Occam's razor, the Feed-Forward Neural Network was chosen as it has a simpler network architecture and therefore generalization should be better!
- To recap – Feed-Forward Neural Network III:**  
2 layer network with 512 nodes per layer and ReLU activation functions. Additionally layers have 0.3 dropout and 0.01 L2 kernel- and bias regularization. Inputs are batch normalized. Output layer with softmax activation.  
Input: All features.

- Feed-Forward Neural Network III:**

- Training Accuracy: **0.998821**
- Validation Accuracy: **0.946886**



Training



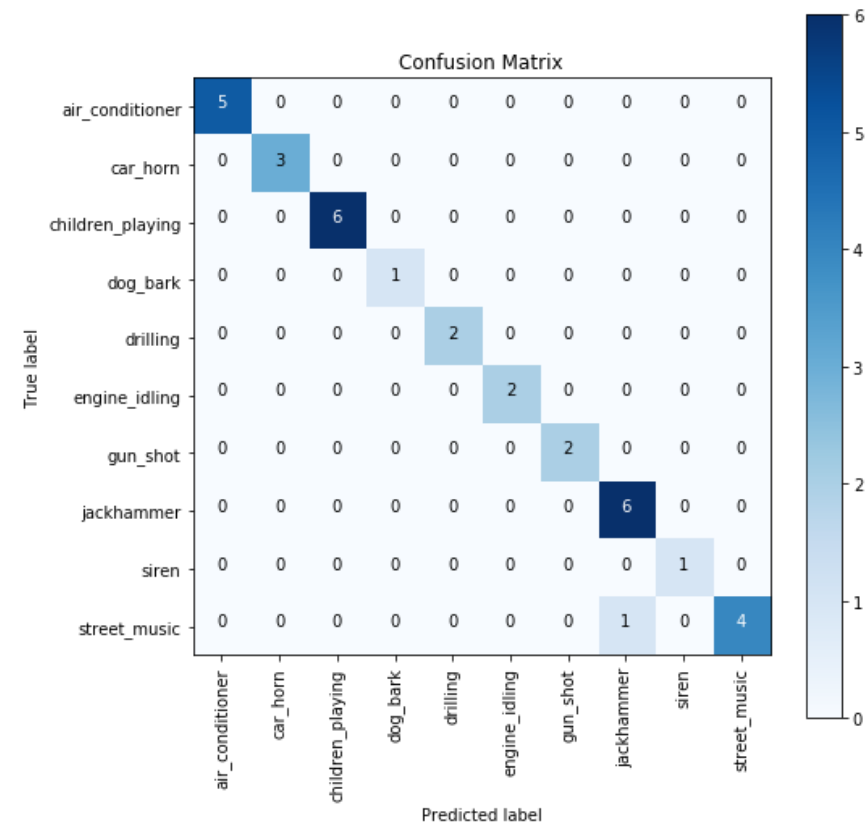
Validation

# Model Evaluation – Test Data

## Performance

- 33 samples predicted.
- 32 of the predictions are correct.
- Test Accuracy: **0.969697**

## Confusion Matrix





# Conclusion

- Discussion
- Take-aways
- Summary

# Discussion & Conclusion

## Discussion

- Both Feed-Forward and Convolutional architectures performed best when they had all features available (MFCCs, chromagram, melspectrogram, spectral contrast and tonnetz), closely followed by 80 MFCCs.
- Batch normalization, dropout and regularization improved validation performance for both network types.
- Recurrent Neural Network architectures worked best when using only 40 MFCCs as features.
- Batch normalization and/or regularization does not work very well in Recurrent architectures -> after some research it turns out batch normalization is probably the bottleneck, as batch normalization does not consider the recurrent part of the network. Technically it could be done but not with vanilla RNNs. [\[1\]](#)[\[2\]](#)

## Conclusion & Take-aways

- MFCCs work very well as features for all network architectures.
- One can easily top 90% accuracy already with simple Feed-Forward Neural Networks.
- It is possible to pass the 90% accuracy mark with all network architectures.
- In FFNNs and CNNs batch normalization is a good idea.
- In RNNs batch normalization is a bad idea (if RNNs are not adapted).
- Dropout is a good idea in all network architectures as it reduces overfitting.
- Regularization is a good idea for FFNNs and CNNs.

More?  
[Read here!](#)

Questions?

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