



Speech Recognition

Comparison of Neural Networks

CSIT687 Masters Project– Spring 2020

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Project Phases



DATA PREPARATION

Identify a good data set for speech recognition. Prepare the data for better feature extractions.



FEATURE IDENTIFICATION

Identify good feature representations for training data. Identify optimization techniques for the features



BUILD MODELS

Build different deep neural network models. Choose between various activation functions and optimizers



TEST MODELS

Test models with prepared data set to evaluate the loss and performance of the models



COMPARE

Compare the training and validation losses and draw conclusions

LibriSpeech Data Stats

Subset	Hours	Per-speaker Minutes	Female Speakers	Male Speakers	Total Speakers
dev-clean	5.4	8	20	20	40
test-clean	5.4	8	20	20	40
dev-other	5.3	10	16	17	33
test-other	5.1	10	17	16	33
train-clean-100	100.6	25	125	126	251
train-clean-360	363.6	25	439	482	921
train-other-500	496.7	30	564	602	1166

LENGTH

1000 hours

of noise free English speech data

SAMPLE RATE

16kHz

Frequency range in the normal conversation spectrum

MALE : FEMALE SPEAKERS

1:1

Ratio of male and female speakers

Environment



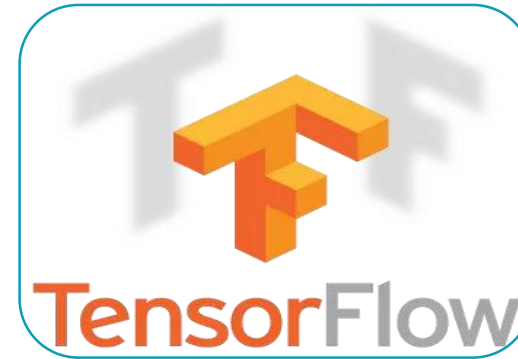
Jupyter Notebook

- Interactive environment for python



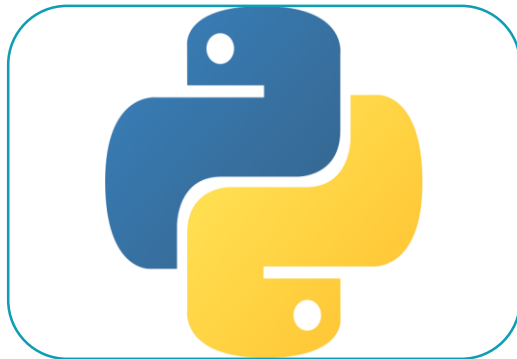
Keras 2.3.1

- Part of TensorFlow 2
- Allows easy layering of neural networks



TensorFlow 2.1.0

- Powerful framework for neural network
- Easy integration with GPU



Python 3.6

- Programming language with wrapper modules for several frameworks and visualizations



CUDA 10.1

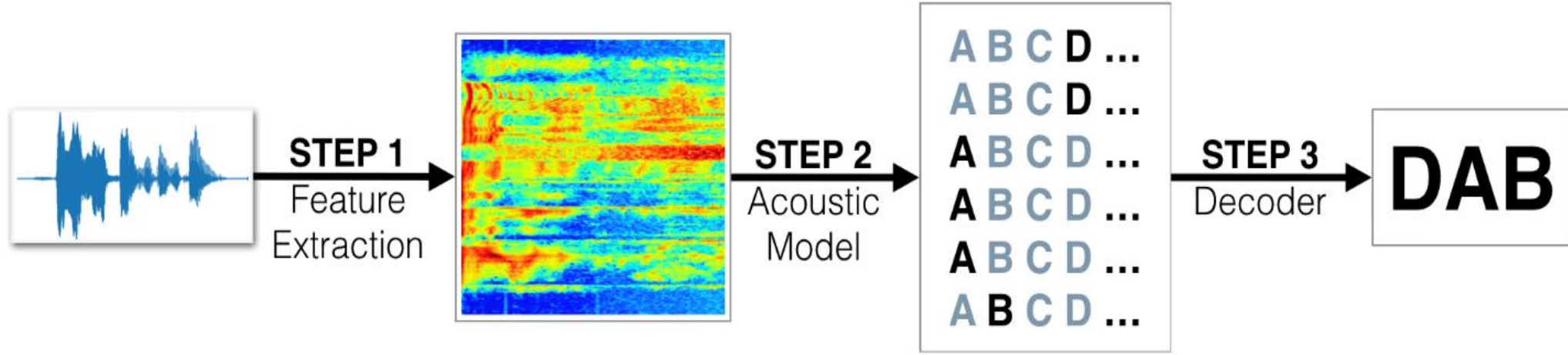
- NVIDIA GPU Compute Framework



Ubuntu 18.04

- Linux Distribution which supports all major frameworks.

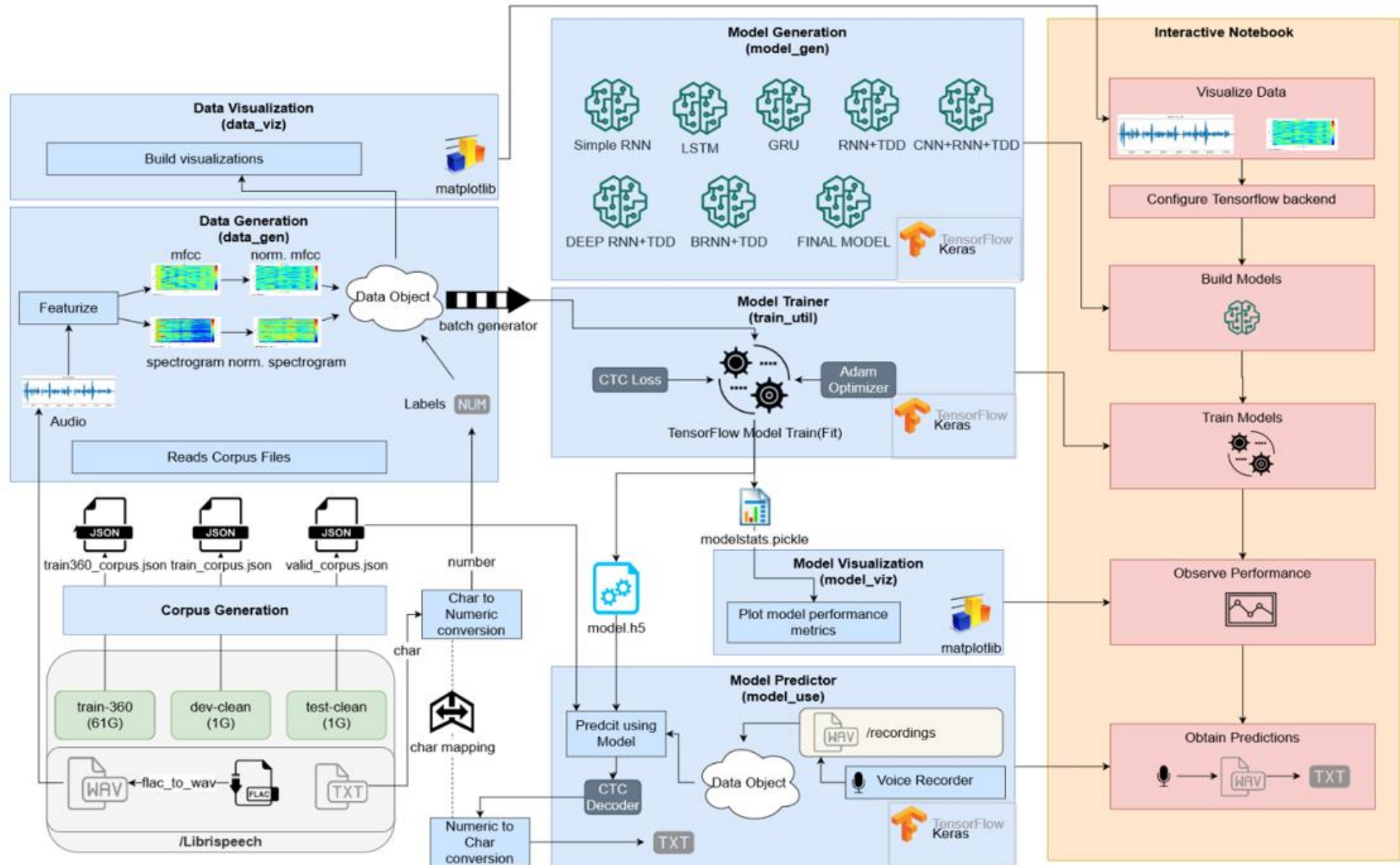
Overall Pipeline



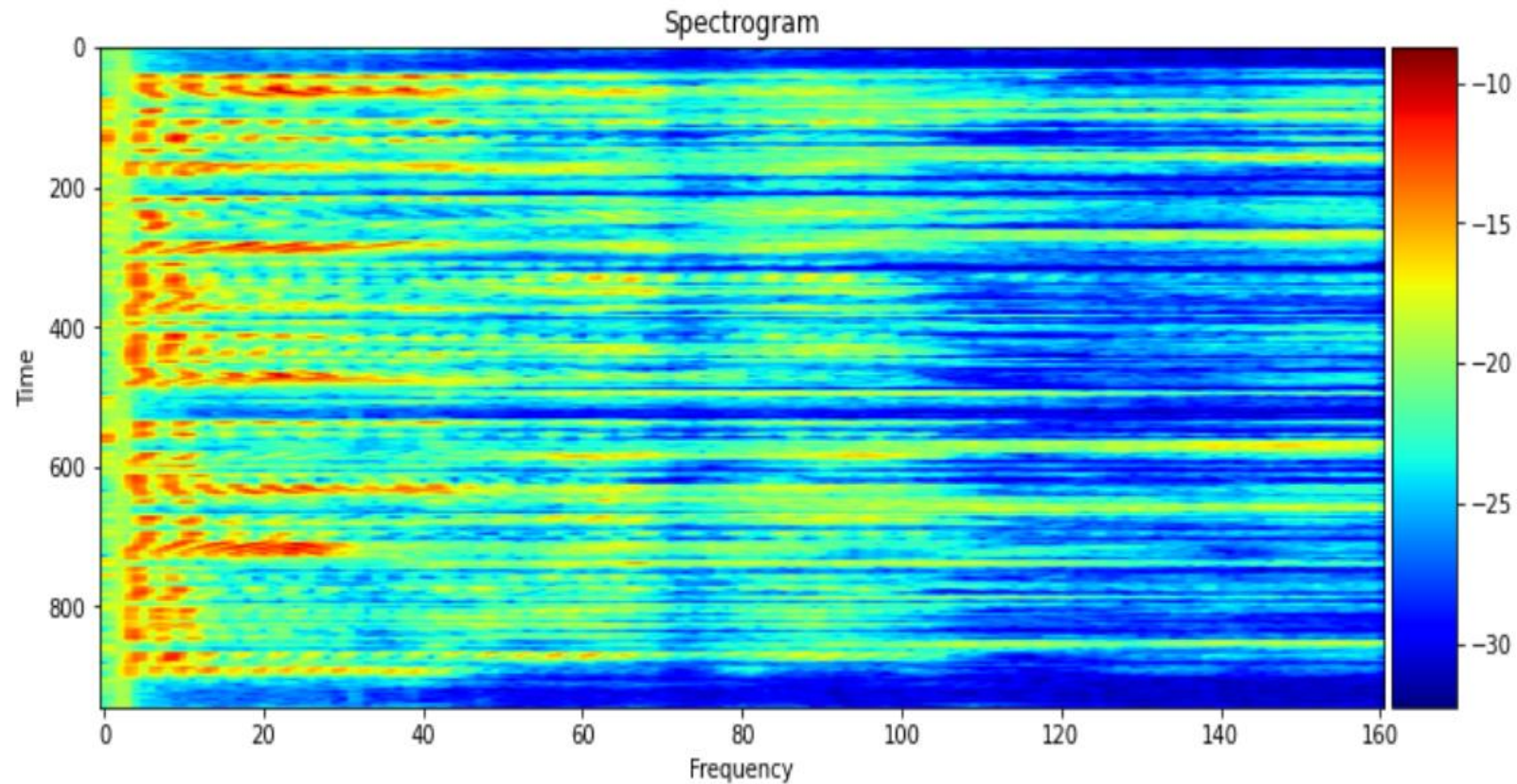
Label Encoding

'	SPACE	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27

Overall Architecture



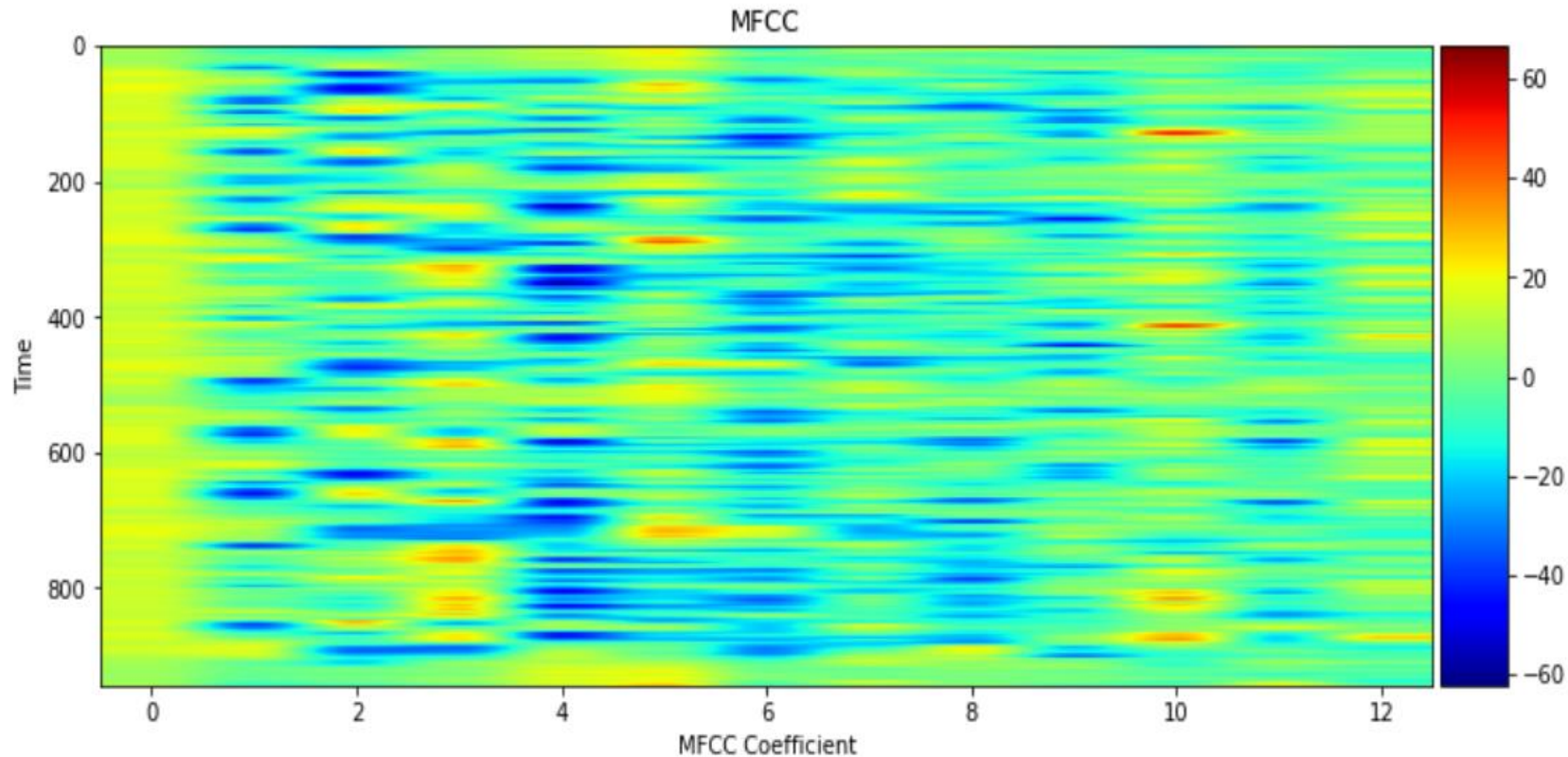
Features – Spectrogram



Shape of Spectrogram : (944, 161)

- A visual representation of the spectrum of frequencies of a signal as it varies with time.
- Represented as a 2D tensor of shape (X,161) where X is the length of the speech.

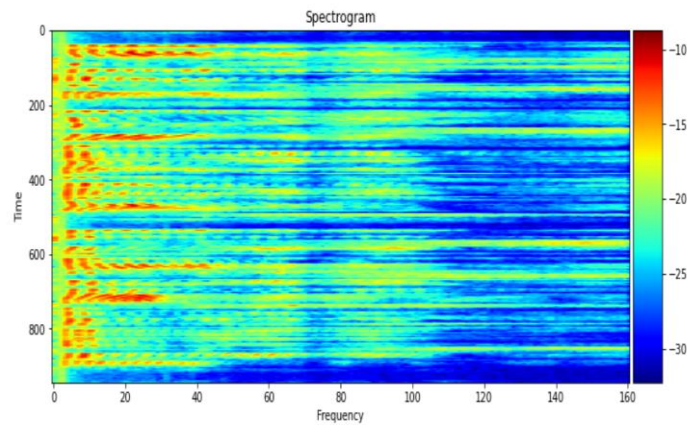
Features – MFCC



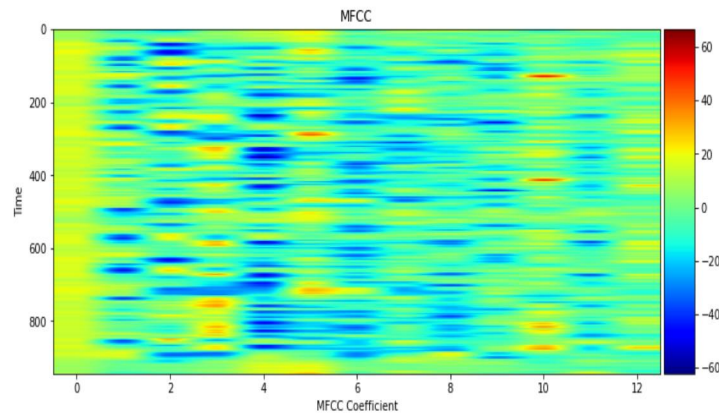
Shape of MFCC : (944, 13)

- Mel-Frequency Cepstral Coefficients of a signal are small set of features which describe the overall shape of a spectral envelope.
- Represented as a 2D tensor of shape (X,13) where X is the length of the speech.

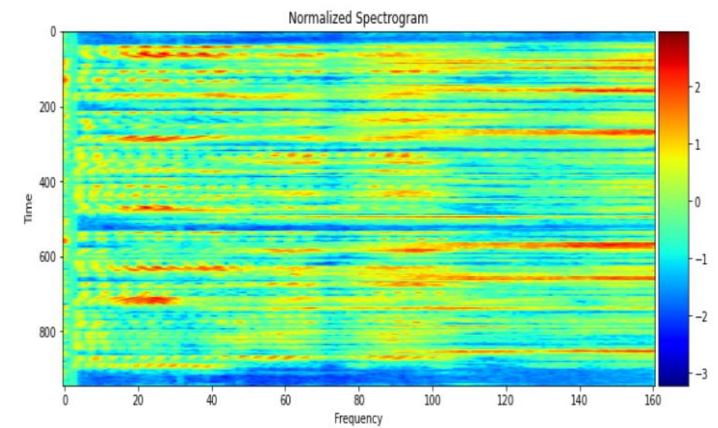
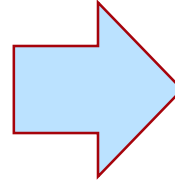
Features – Normalization



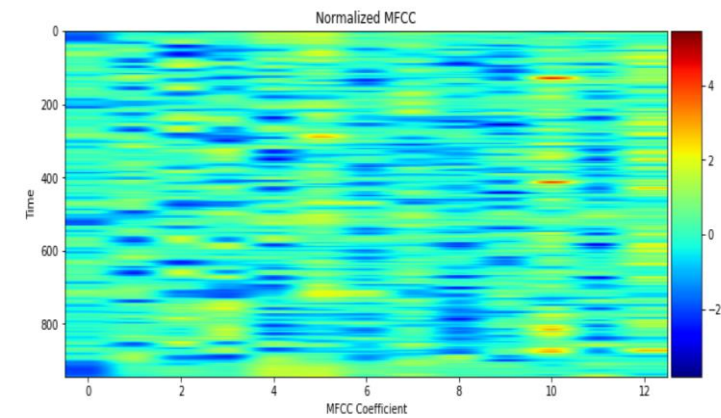
Shape of Spectrogram : (944, 161)



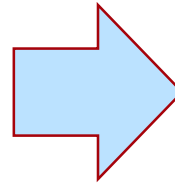
Shape of MFCC : (944, 13)



Shape of Spectrogram : (944, 161)

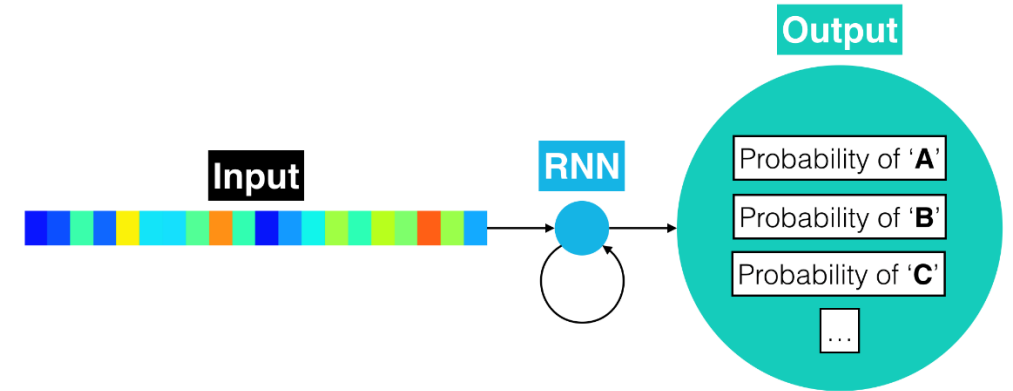
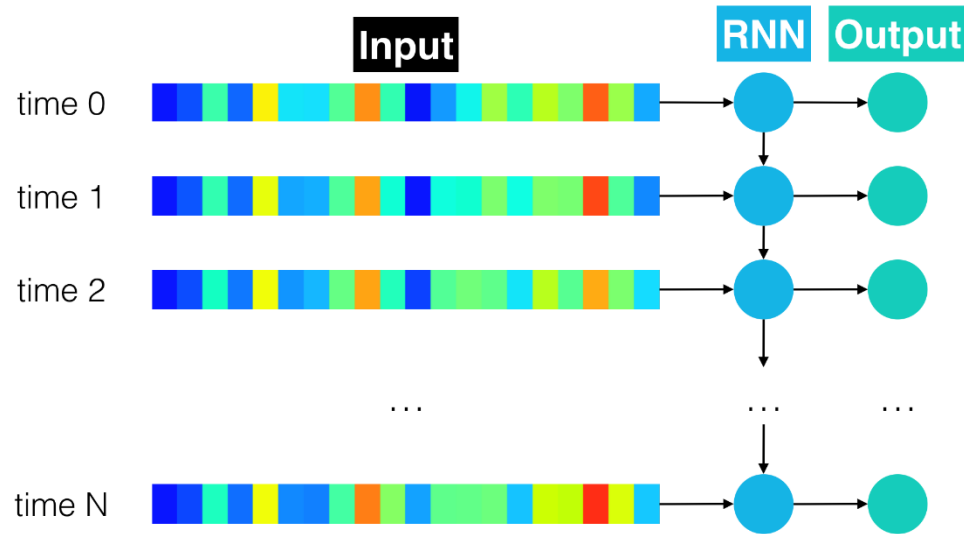


Shape of MFCC : (944, 13)



- Speeds up convergence
- Reduces the impact of noise in the data

Models – Single Layer RNN – Arch



- Simplest RNN Layer where Input is directly fed to RNN
- Implemented on SimpleRNN , LSTM and GRU

Models – Single Layer RNN – Summary

MFCC Models

Model: "simple_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
rnn (SimpleRNN)	(None, None, 29)	1247
softmax (Activation)	(None, None, 29)	0

Total params: 1,247
Trainable params: 1,247
Non-trainable params: 0

Model: "lstm_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
rnn (LSTM)	(None, None, 29)	4988
softmax (Activation)	(None, None, 29)	0

Total params: 4,988
Trainable params: 4,988
Non-trainable params: 0

Model: "gru_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
rnn (GRU)	(None, None, 29)	3828
softmax (Activation)	(None, None, 29)	0

Total params: 3,828
Trainable params: 3,828
Non-trainable params: 0

Models – Single Layer RNN – Summary

Spectrogram Models

Model: "simple_spectrogram"

Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 161)]	0
rnn (SimpleRNN)	(None, None, 29)	5539
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 5,539		
Trainable params: 5,539		
Non-trainable params: 0		

Model: "lstm_spectrogram"

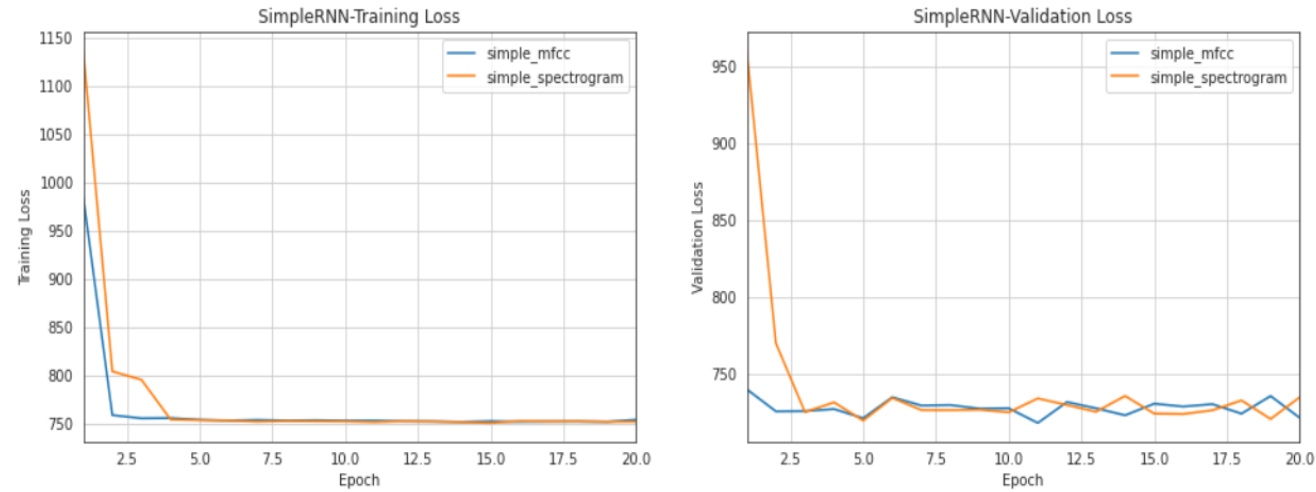
Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 161)]	0
rnn (LSTM)	(None, None, 29)	22156
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 22,156		
Trainable params: 22,156		
Non-trainable params: 0		

Model: "gru_spectrogram"

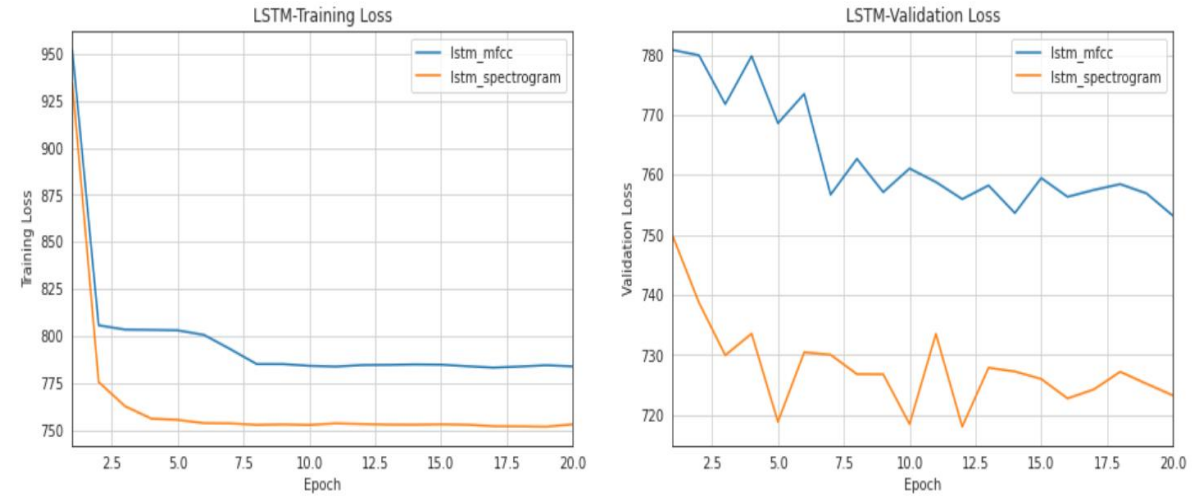
Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 161)]	0
rnn (GRU)	(None, None, 29)	16704
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 16,704		
Trainable params: 16,704		
Non-trainable params: 0		

Models – Single Layer RNN – Result

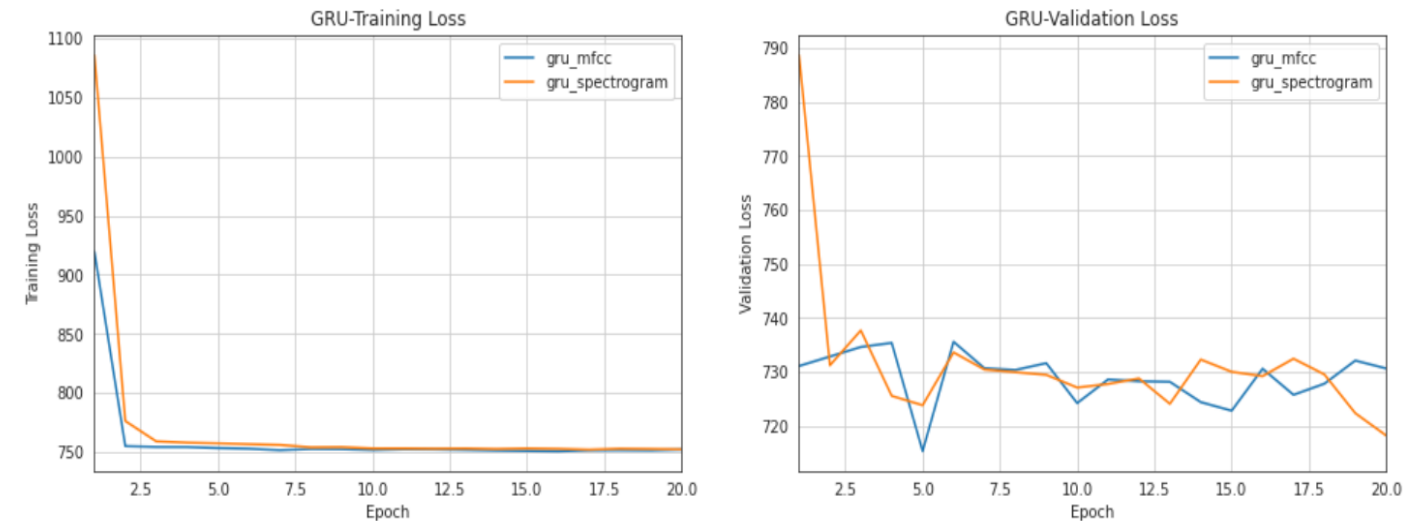
SimpleRNN



LSTM

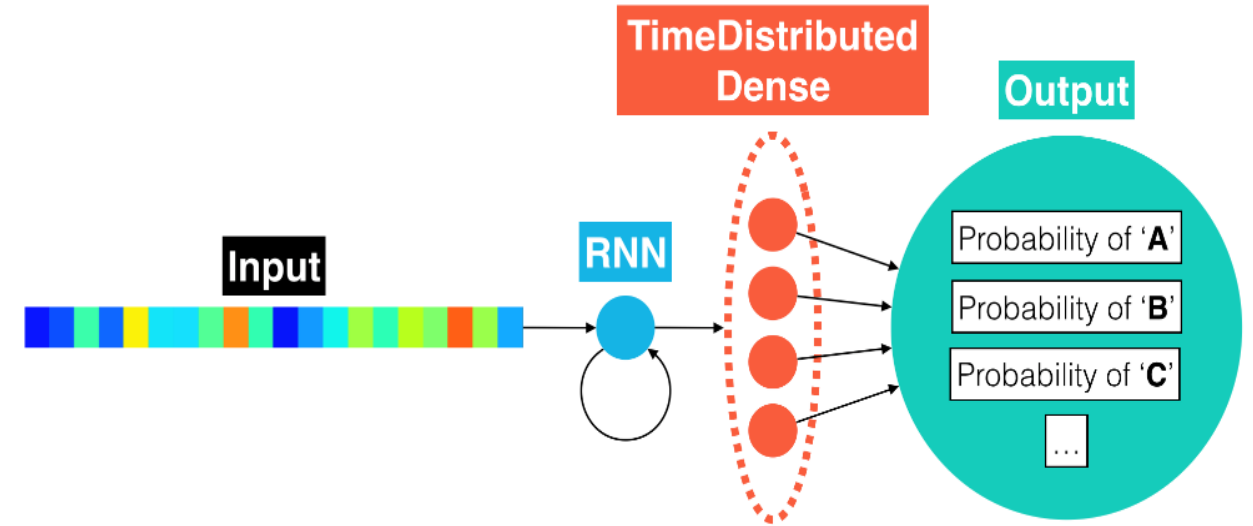
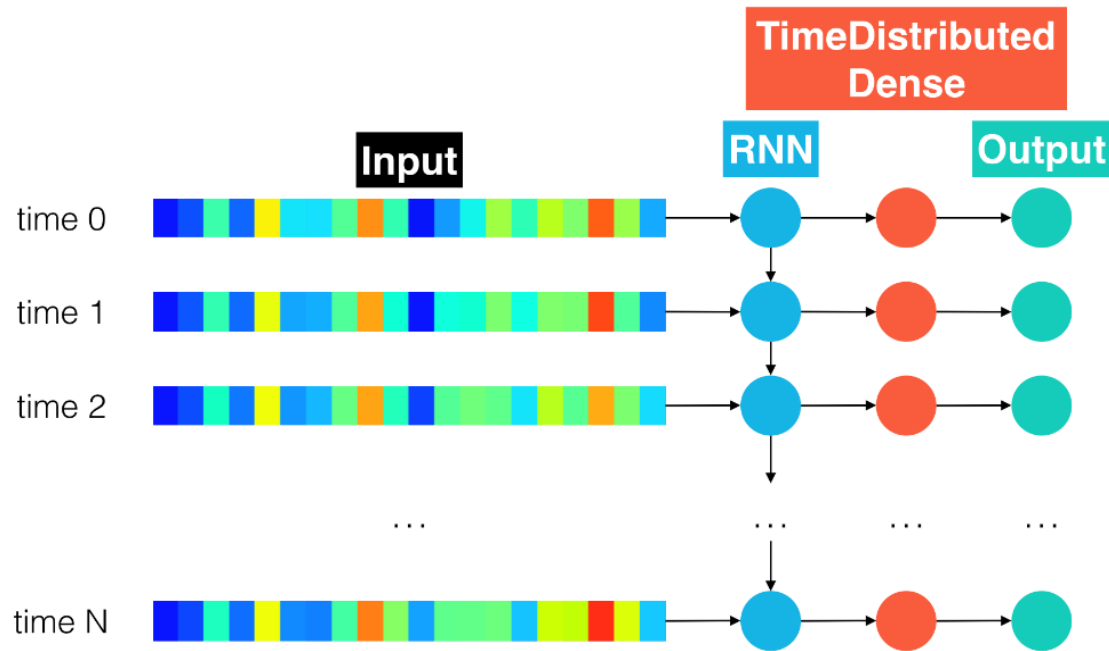


GRU



Model	Feature	Training Loss	Validation Loss
SimpleRNN	MFCC	754	721
	Spectrogram	752	735
LSTM	MFCC	783	753
	Spectrogram	752	723
GRU	MFCC	752	730
	Spectrogram	752	718

Models – RNN + TDD – Arch



- TimeDistributed Dense wrapper and the BatchNormalization layer are applied to the GRU RNN layer
- Batch Normalization reduces training times
- Time Distributed layer helps find more complex patterns in the data set. Speeds up RNN, but is more memory intensive

Models – RNN + TDD – Summary

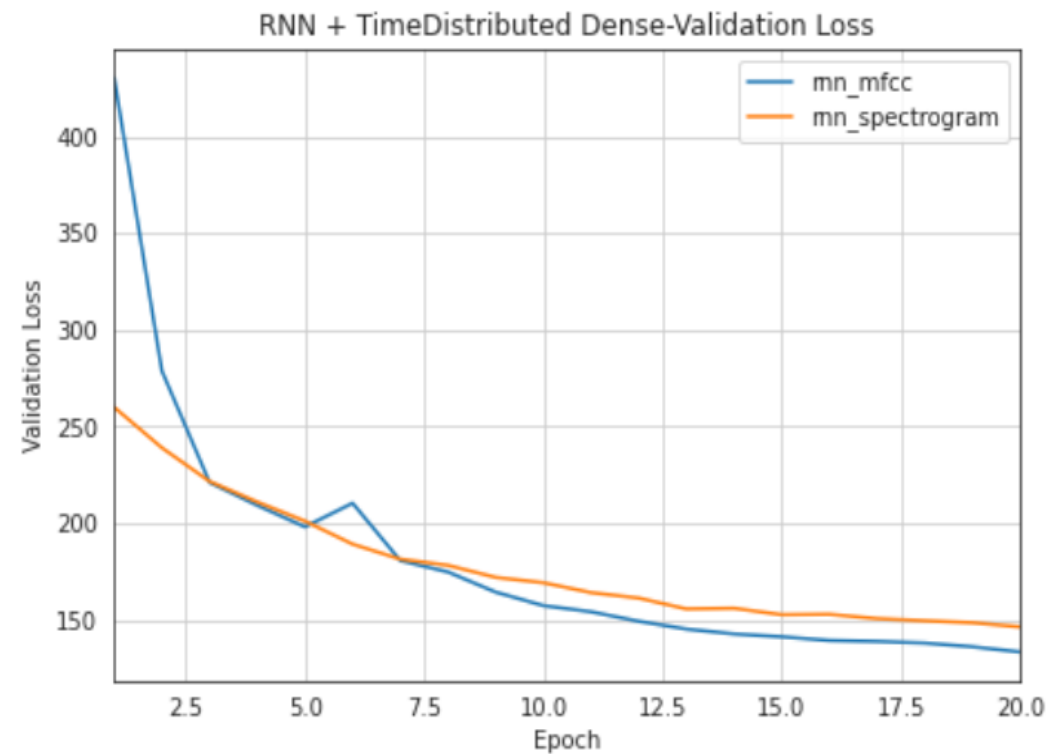
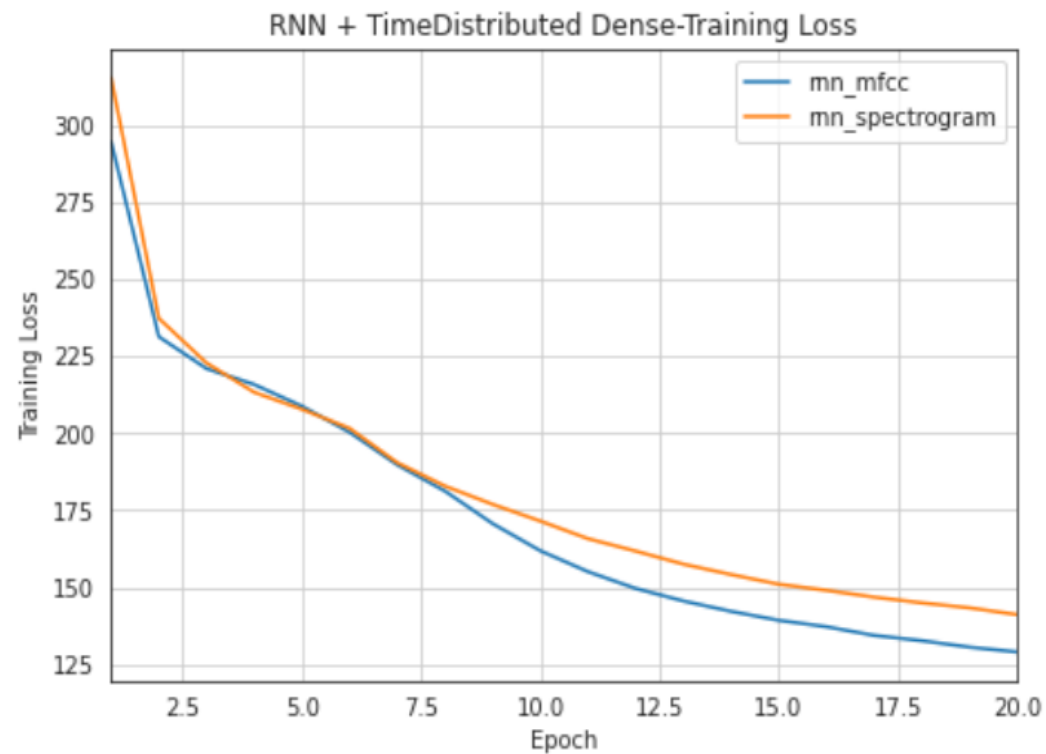
Model: "rnn_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
rnn (GRU)	(None, None, 200)	129000
bn_rnn_1d (BatchNormalizatio	(None, None, 200)	800
time_distributed_2 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0
Total params: 135,629		
Trainable params: 135,229		
Non-trainable params: 400		

Model: "rnn_spectrogram"

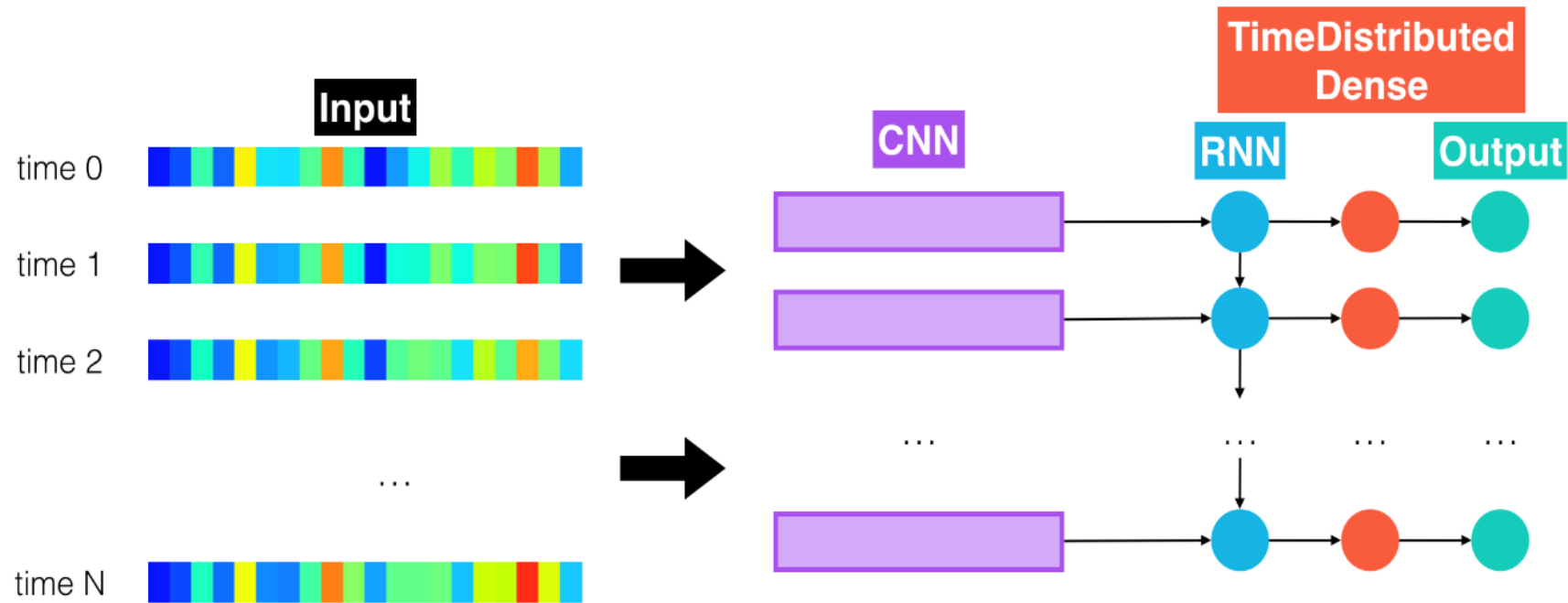
Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 161)]	0
rnn (GRU)	(None, None, 200)	217800
bn_rnn_1d (BatchNormalizatio	(None, None, 200)	800
time_distributed_3 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0
Total params: 224,429		
Trainable params: 224,029		
Non-trainable params: 400		

Models – RNN + TDD – Result



Feature	Training Loss	Validation Loss
MFCC	128	133
Spectrogram	141	146

Models – CNN + RNN + TDD – Arch



- Additional 1-D Convolutional Layer is added to increase the level of complexity

Models – CNN + RNN + TDD – Summary

Model: "cnn_rnn_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
conv1d (Conv1D)	(None, None, 200)	28800
bn_conv_1d (BatchNormalizati	(None, None, 200)	800
rnn (GRU)	(None, None, 200)	241200
gru_rnn (BatchNormalization)	(None, None, 200)	800
time_distributed_4 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0

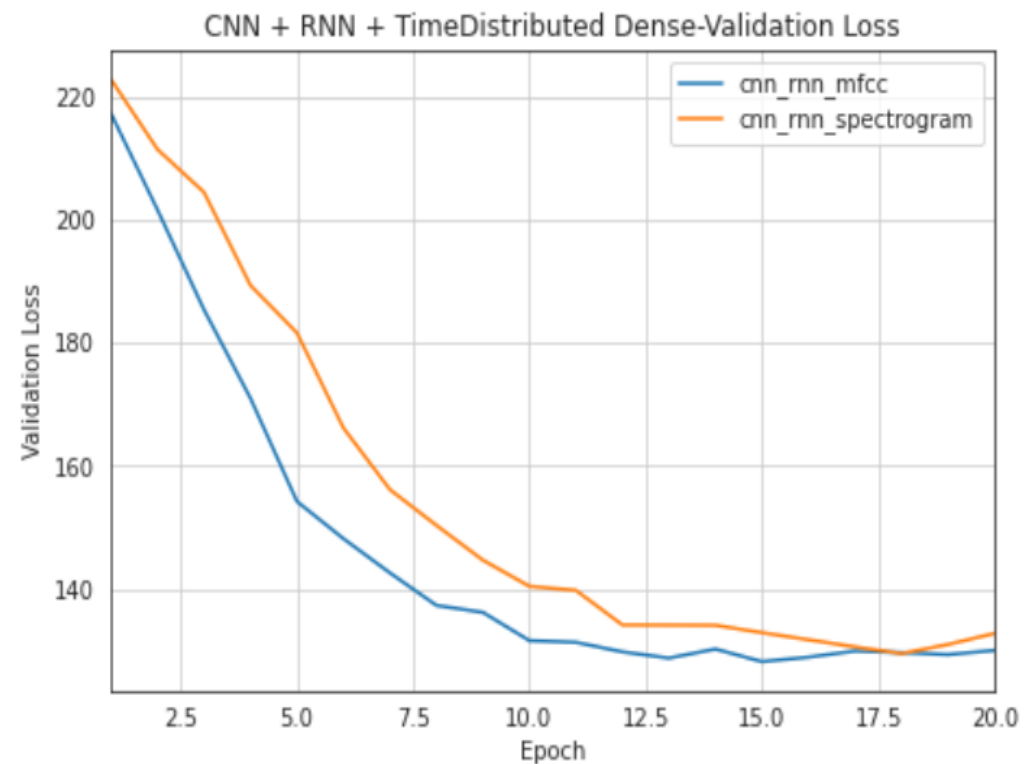
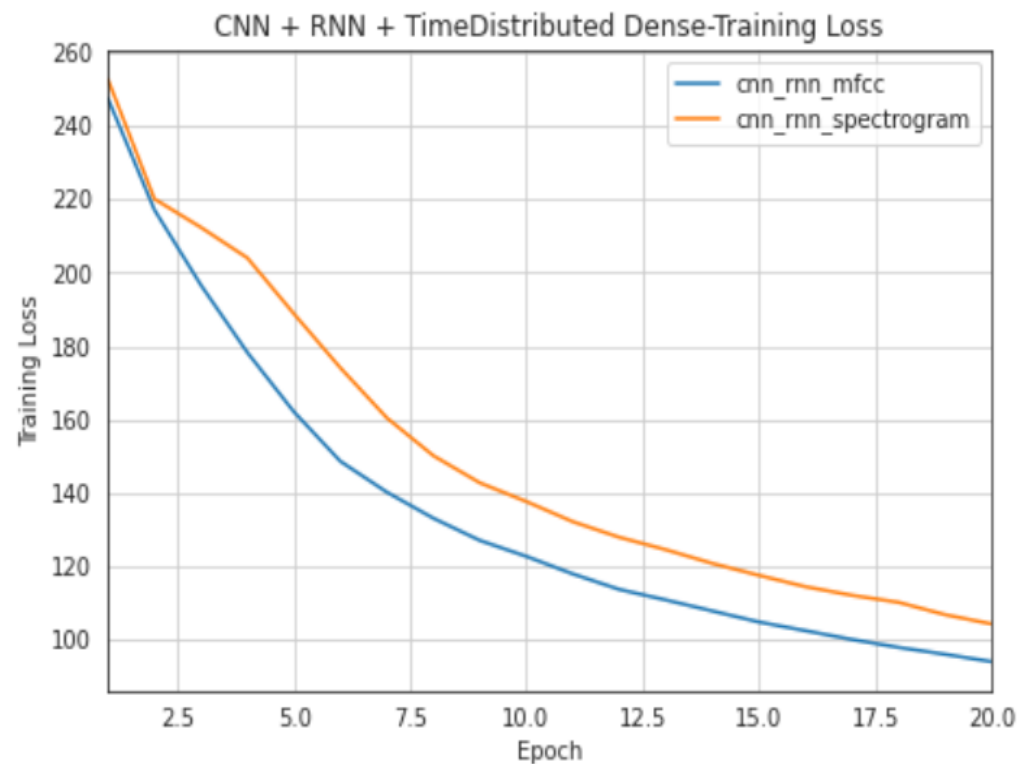
Total params: 277,429
Trainable params: 276,629
Non-trainable params: 800

Model: "cnn_rnn_spectrogram"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 161)]	0
conv1d (Conv1D)	(None, None, 200)	354400
bn_conv_1d (BatchNormalizati	(None, None, 200)	800
rnn (GRU)	(None, None, 200)	241200
gru_rnn (BatchNormalization)	(None, None, 200)	800
time_distributed_5 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0

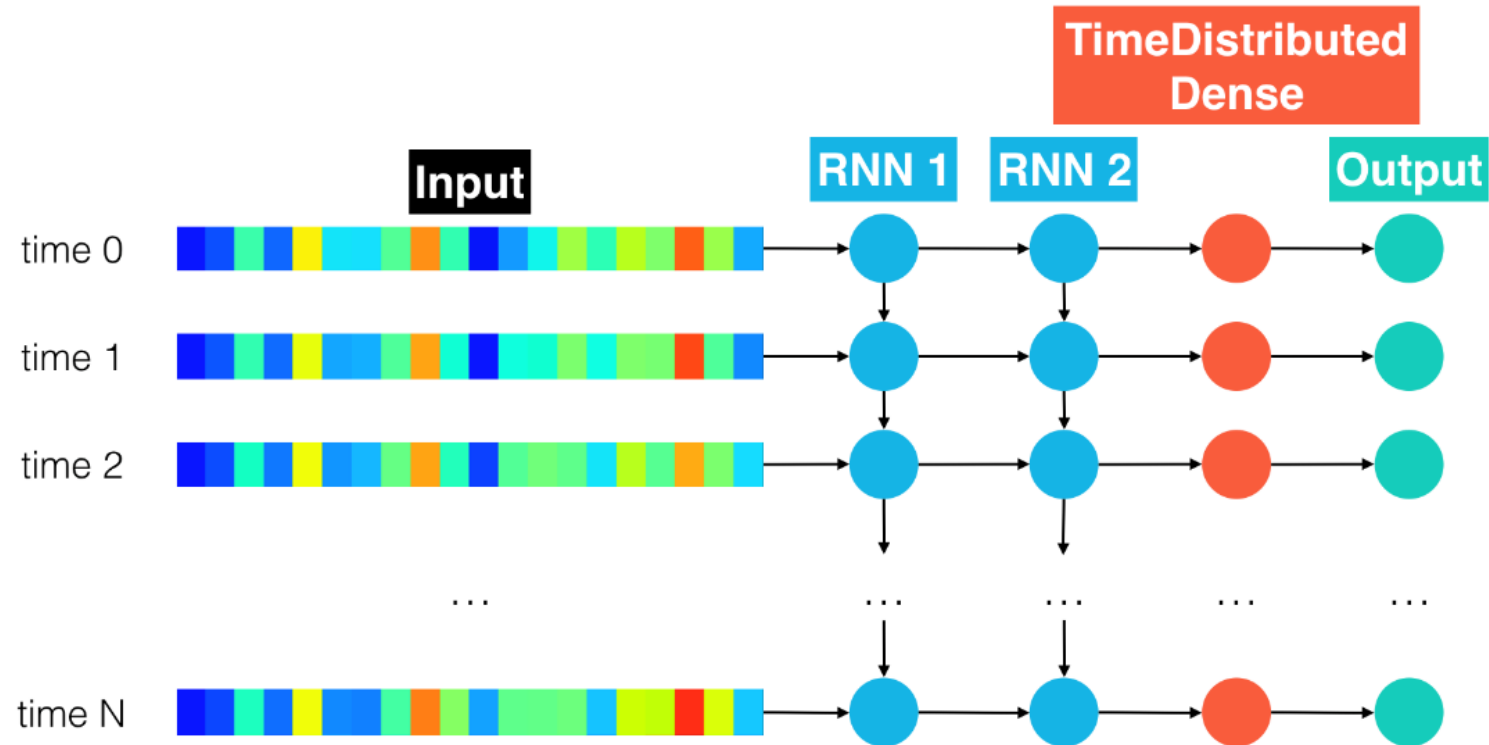
Total params: 603,029
Trainable params: 602,229
Non-trainable params: 800

Models – CNN + RNN + TDD – Result



Feature	Training Loss	Validation Loss
MFCC	94	129
Spectrogram	104	132

Models – Deep RNN + TDD – Arch



- A number of GRU to be added back to back which can process long sequences and interdependencies

Models – Deep RNN + TDD – Summary

Model: "deep_rnn_mfcc"

Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 13)]	0
gru (GRU)	(None, None, 200)	129000
bt_rnn_1 (BatchNormalization)	(None, None, 200)	800
gru_1 (GRU)	(None, None, 200)	241200
bt_rnn_last_rnn (BatchNormal	(None, None, 200)	800
time_distributed_6 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0
=====		

Total params: 377,629

Trainable params: 376,829

Non-trainable params: 800

Model: "deep_rnn_spectrogram"

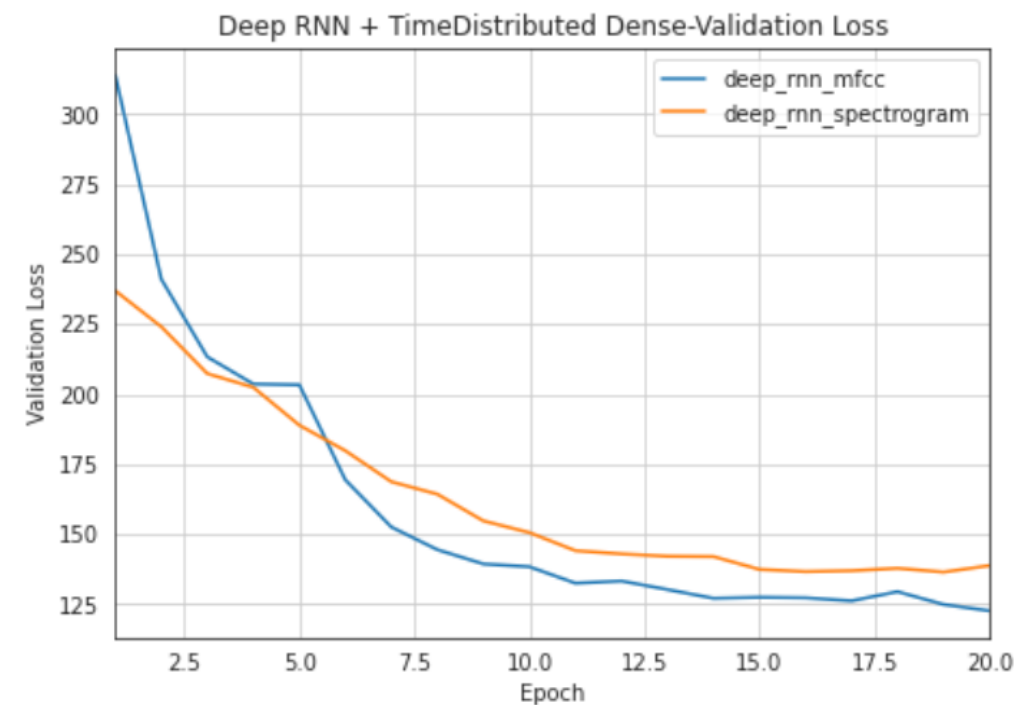
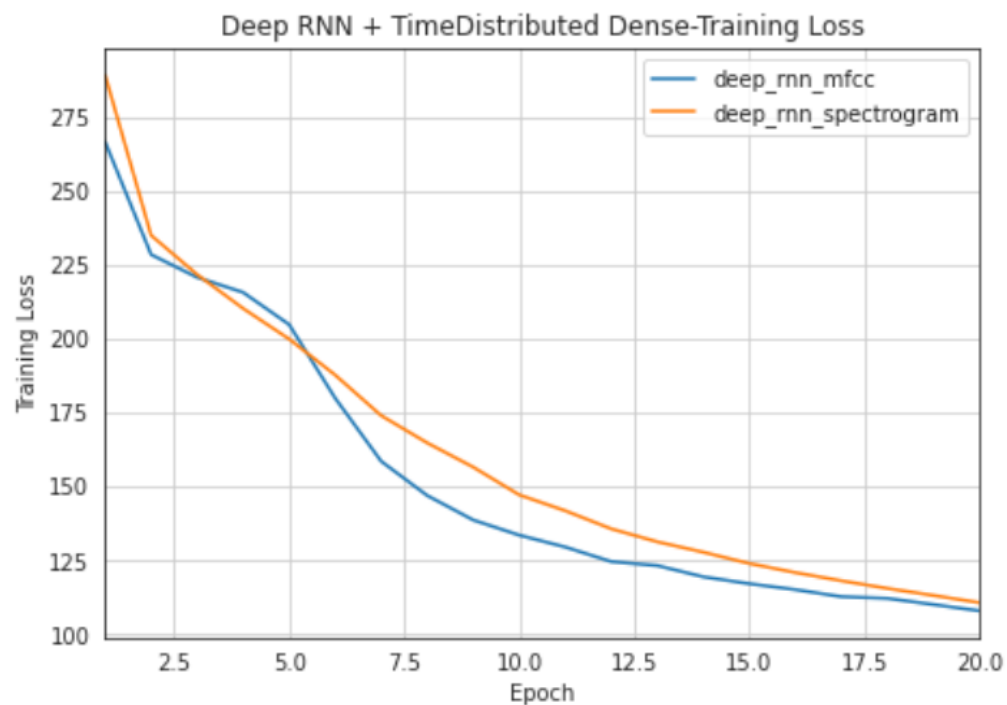
Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 161)]	0
gru_2 (GRU)	(None, None, 200)	217800
bt_rnn_1 (BatchNormalization)	(None, None, 200)	800
gru_3 (GRU)	(None, None, 200)	241200
bt_rnn_last_rnn (BatchNormal	(None, None, 200)	800
time_distributed_7 (TimeDist	(None, None, 29)	5829
softmax (Activation)	(None, None, 29)	0
=====		

Total params: 466,429

Trainable params: 465,629

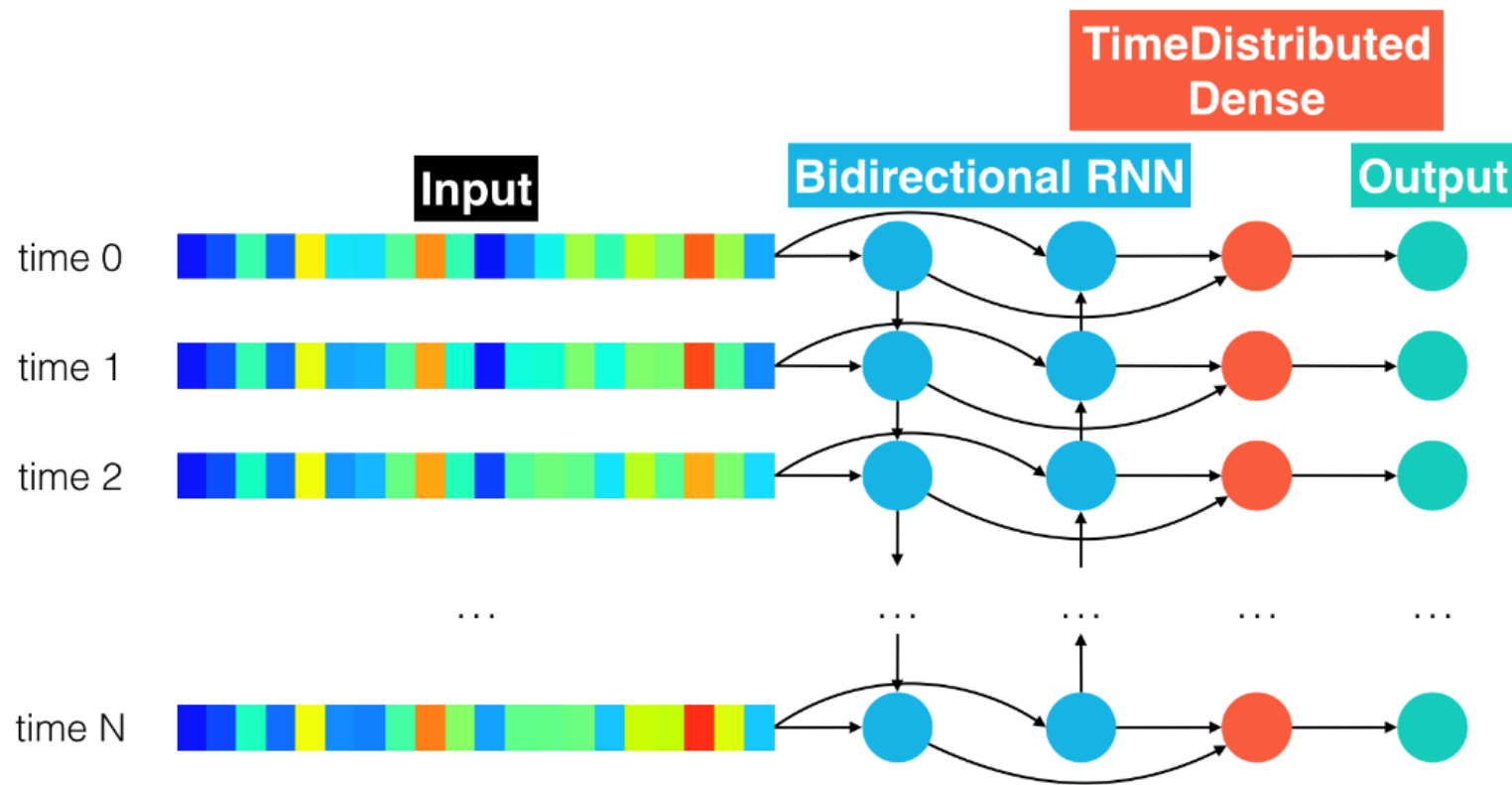
Non-trainable params: 800

Models – Deep RNN + TDD – Result



Feature	Training Loss	Validation Loss
MFCC	108	122
Spectrogram	110	138

Models – Bidirectional RNN + TDD – Arch



- Processes the data in both directions (forward and backward)
- Allows to assess future context.

Models – Bidirectional RNN + TDD – Summary

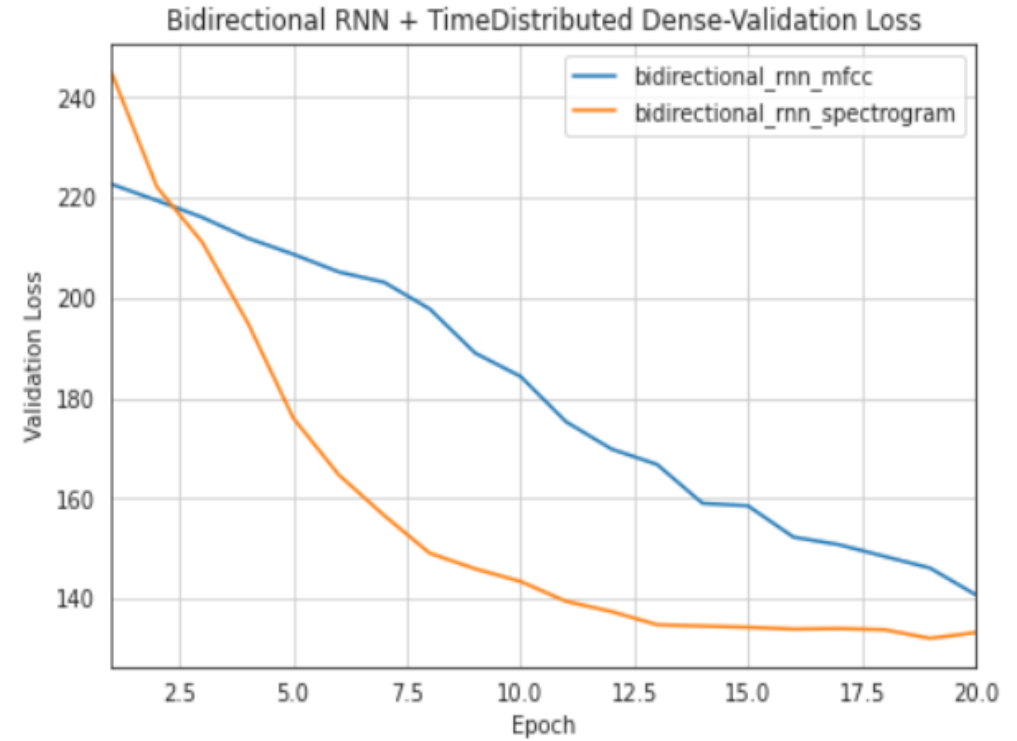
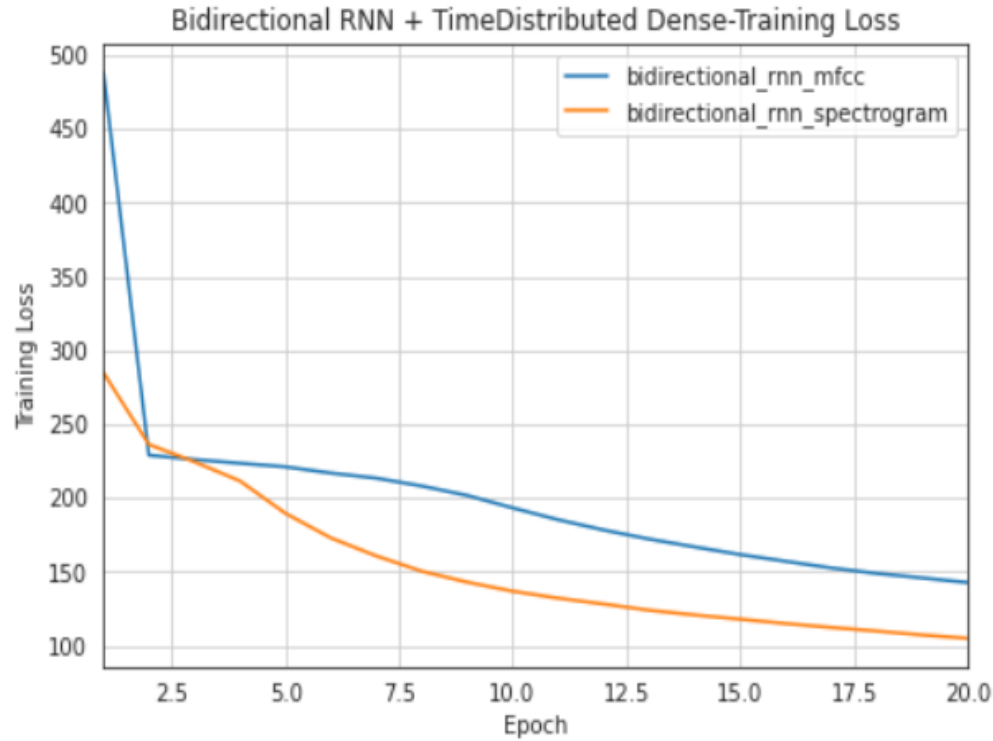
Model: "bidirectional_rnn_mfcc"

Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 13)]	0
=====		
bidirectional (Bidirectional)	(None, None, 400)	258000
=====		
time_distributed_8 (TimeDist)	(None, None, 29)	11629
=====		
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 269,629		
Trainable params: 269,629		
Non-trainable params: 0		

Model: "bidirectional_rnn_spectrogram"

Layer (type)	Output Shape	Param #
=====		
the_input (InputLayer)	[(None, None, 161)]	0
=====		
bidirectional_1 (Bidirectional)	(None, None, 400)	435600
=====		
time_distributed_9 (TimeDist)	(None, None, 29)	11629
=====		
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 447,229		
Trainable params: 447,229		
Non-trainable params: 0		

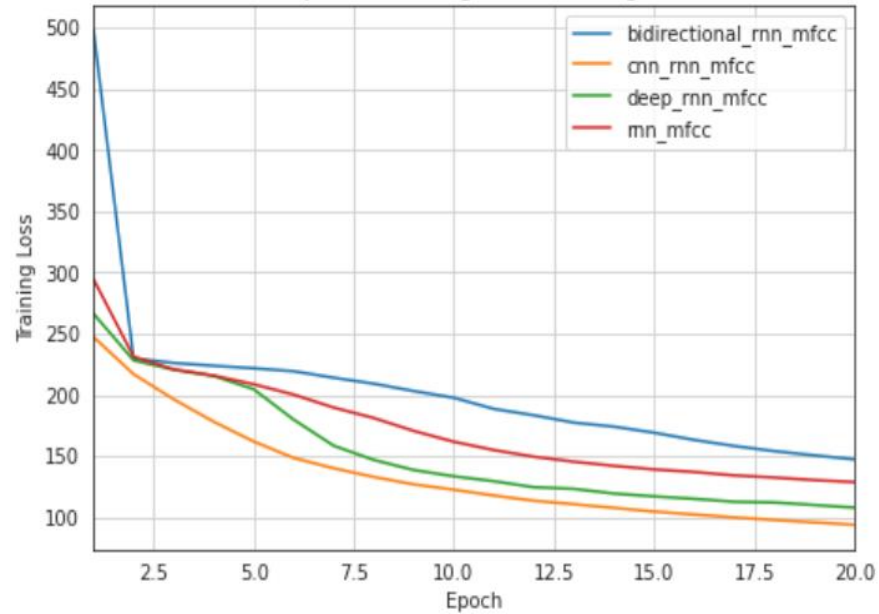
Models – Bidirectional RNN + TDD – Result



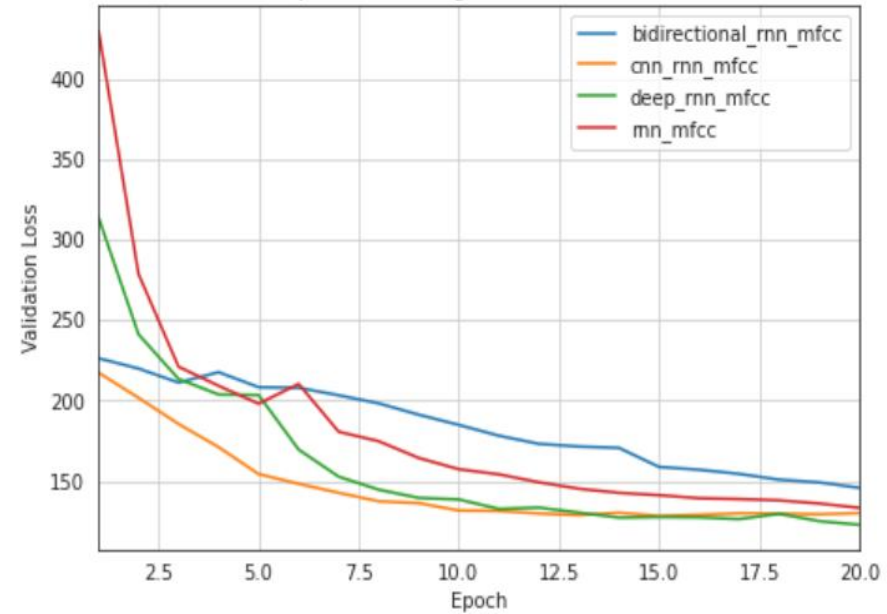
Feature	Training Loss	Validation Loss
MFCC	147	145
Spectrogram	109	130

Models – Comparison

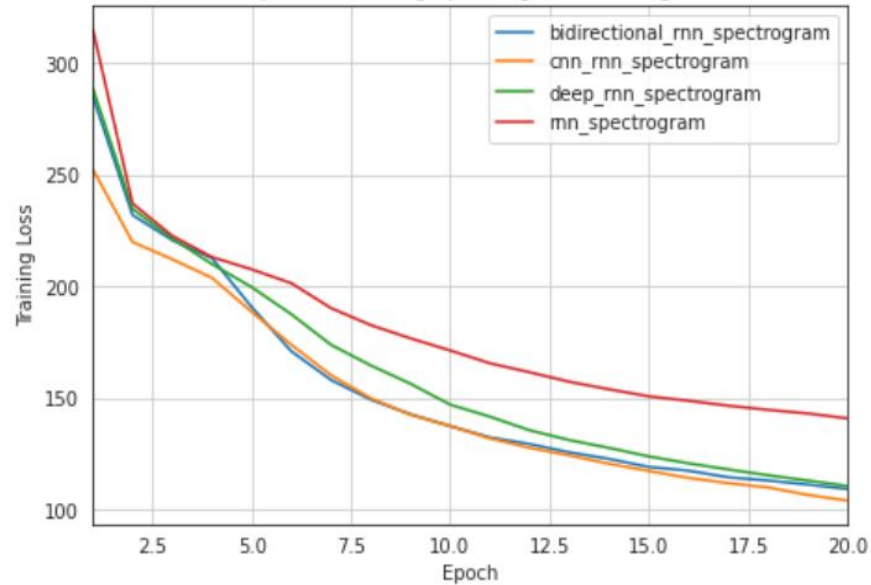
Comparison among MFCC-Training Loss



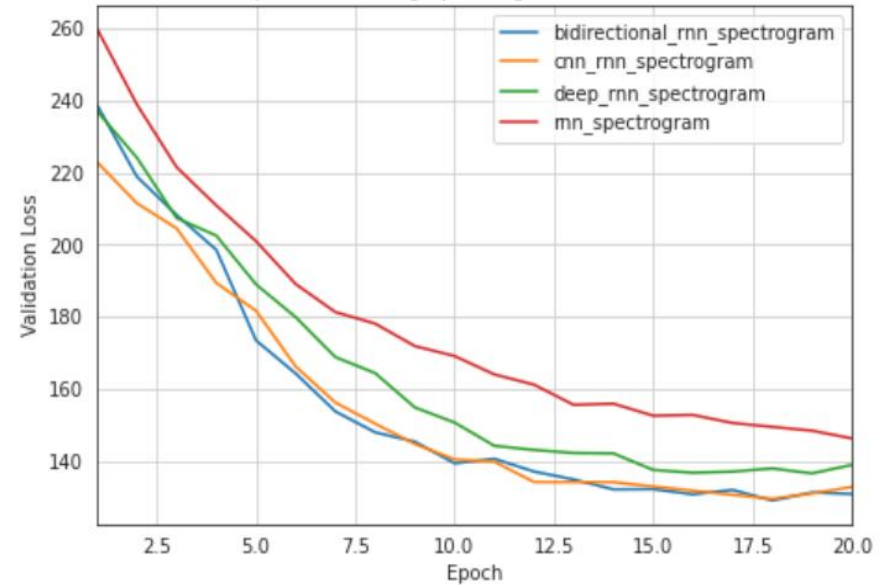
Comparison among MFCC-Validation Loss



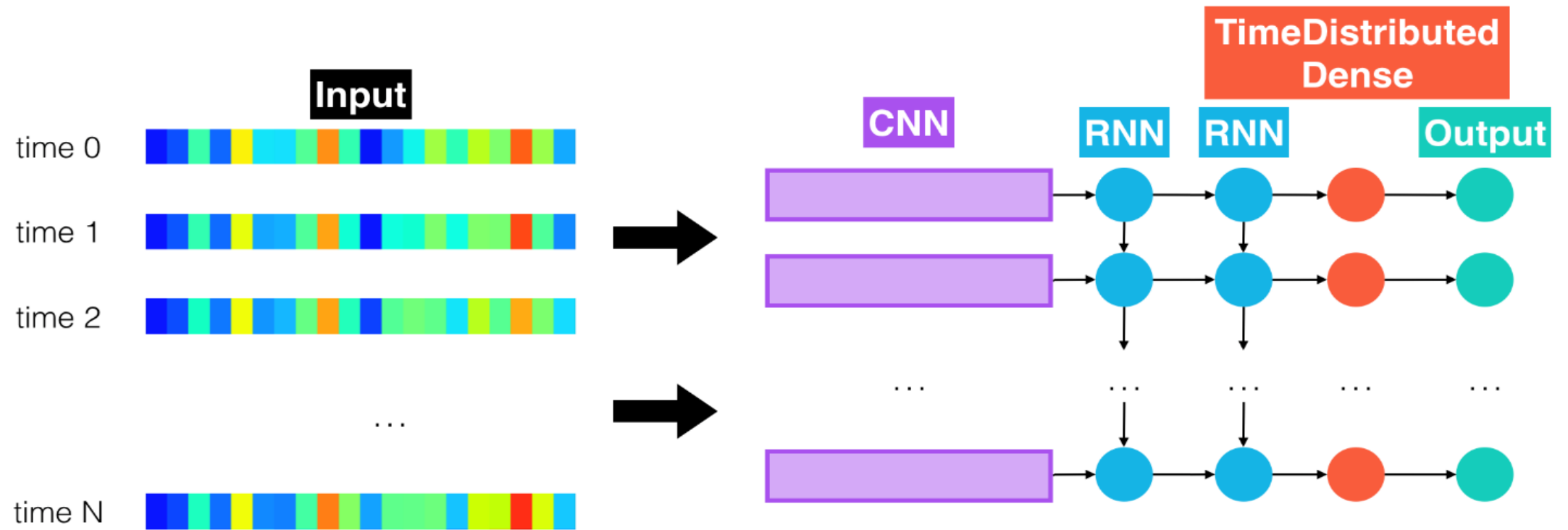
Comparison among spectrogram-Training Loss



Comparison among spectrogram-Validation Loss



Models – Final – Arch



- Combination of CNN & Deep RNN with TimeDistributed Dense layer

Models – Final – Summary

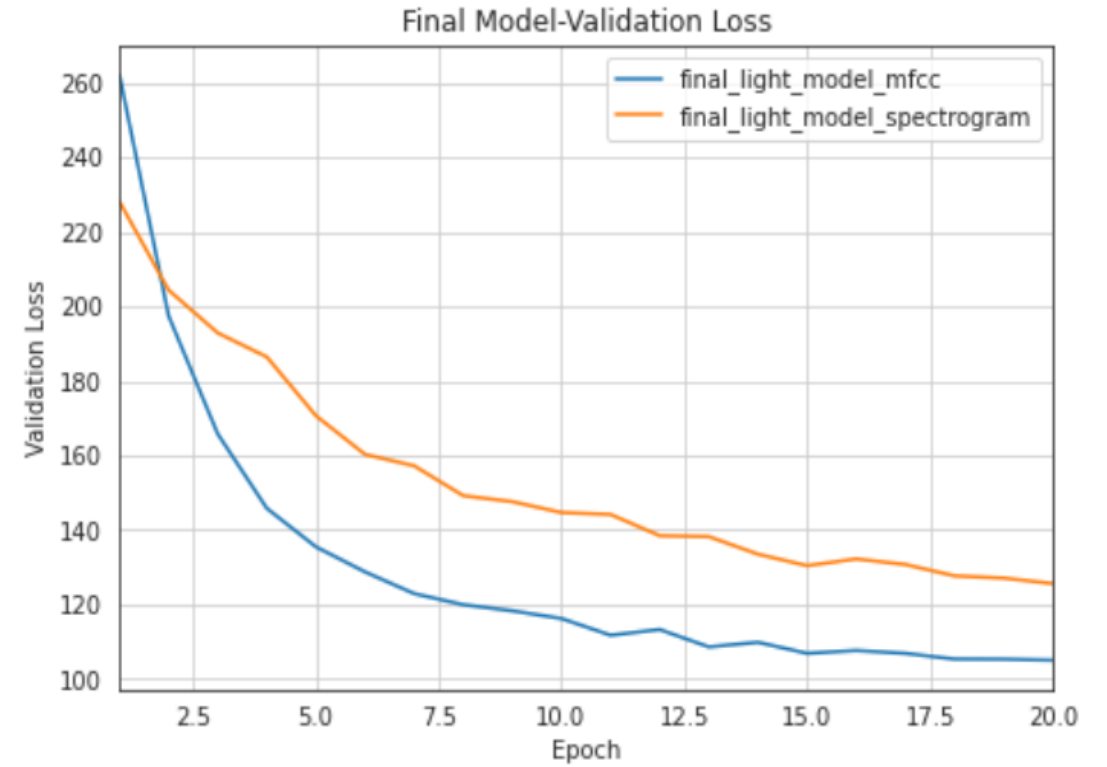
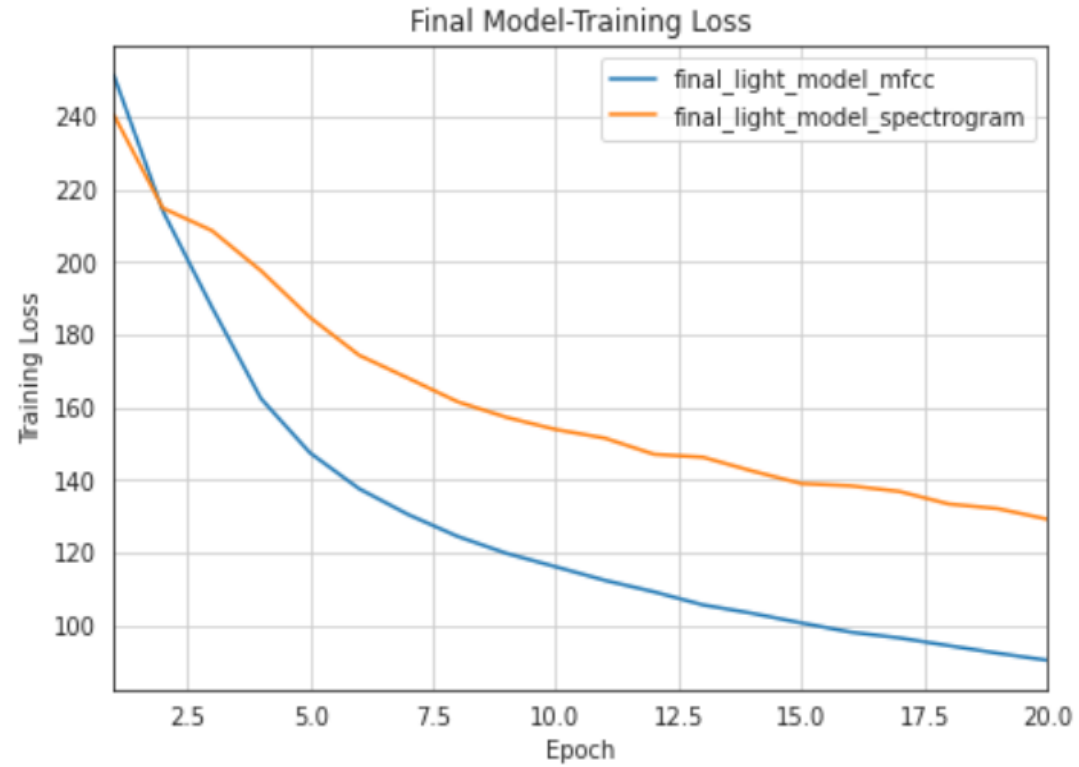
Model: "final_model_mfcc"

Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 13)]	0
layer_1_conv (Conv1D)	(None, None, 200)	28800
conv_batch_norm (BatchNormal	(None, None, 200)	800
rnn_1 (GRU)	(None, None, 250)	339000
bt_rnn_1 (BatchNormalization	(None, None, 250)	1000
final_layer_of_rnn (GRU)	(None, None, 250)	376500
bt_rnn_final (BatchNormaliza	(None, None, 250)	1000
time_distributed (TimeDistri	(None, None, 29)	7279
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 754,379		
Trainable params: 752,979		
Non-trainable params: 1,400		

Model: "final_model_spectrogram"

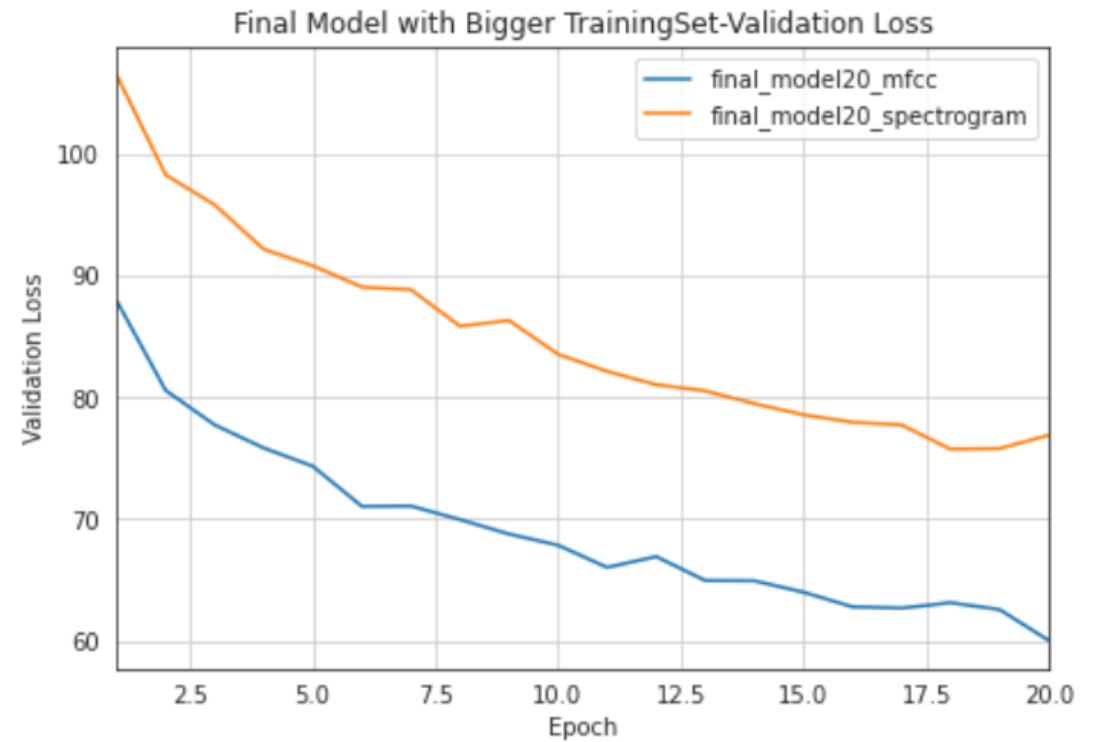
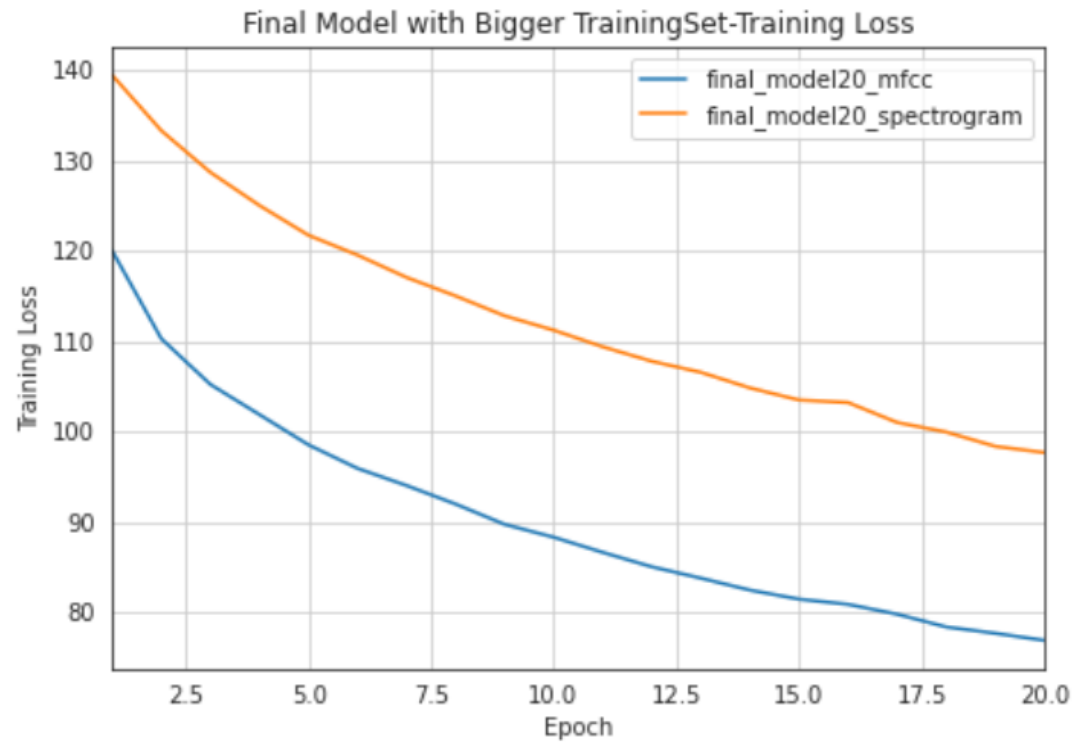
Layer (type)	Output Shape	Param #
the_input (InputLayer)	[(None, None, 161)]	0
layer_1_conv (Conv1D)	(None, None, 200)	354400
conv_batch_norm (BatchNormal	(None, None, 200)	800
rnn_1 (GRU)	(None, None, 250)	339000
bt_rnn_1 (BatchNormalization	(None, None, 250)	1000
final_layer_of_rnn (GRU)	(None, None, 250)	376500
bt_rnn_final (BatchNormaliza	(None, None, 250)	1000
time_distributed_1 (TimeDist	(None, None, 29)	7279
softmax (Activation)	(None, None, 29)	0
=====		
Total params: 1,079,979		
Trainable params: 1,078,579		
Non-trainable params: 1,400		

Models – Final – Result



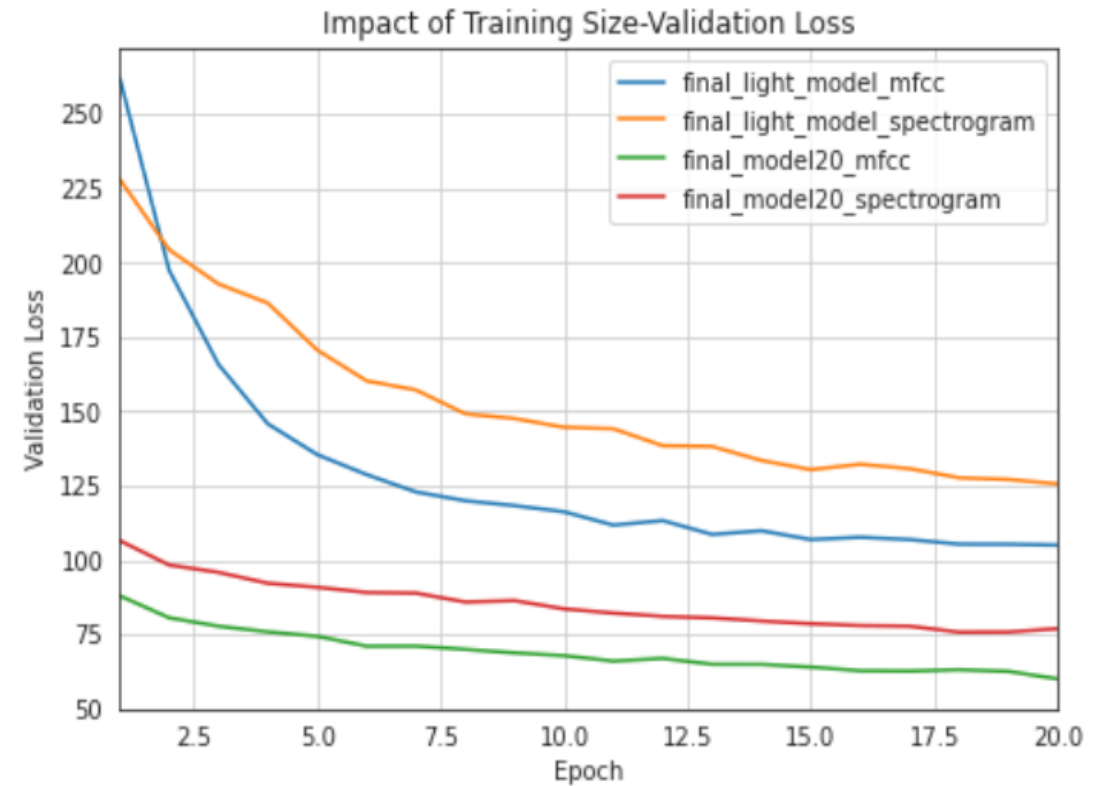
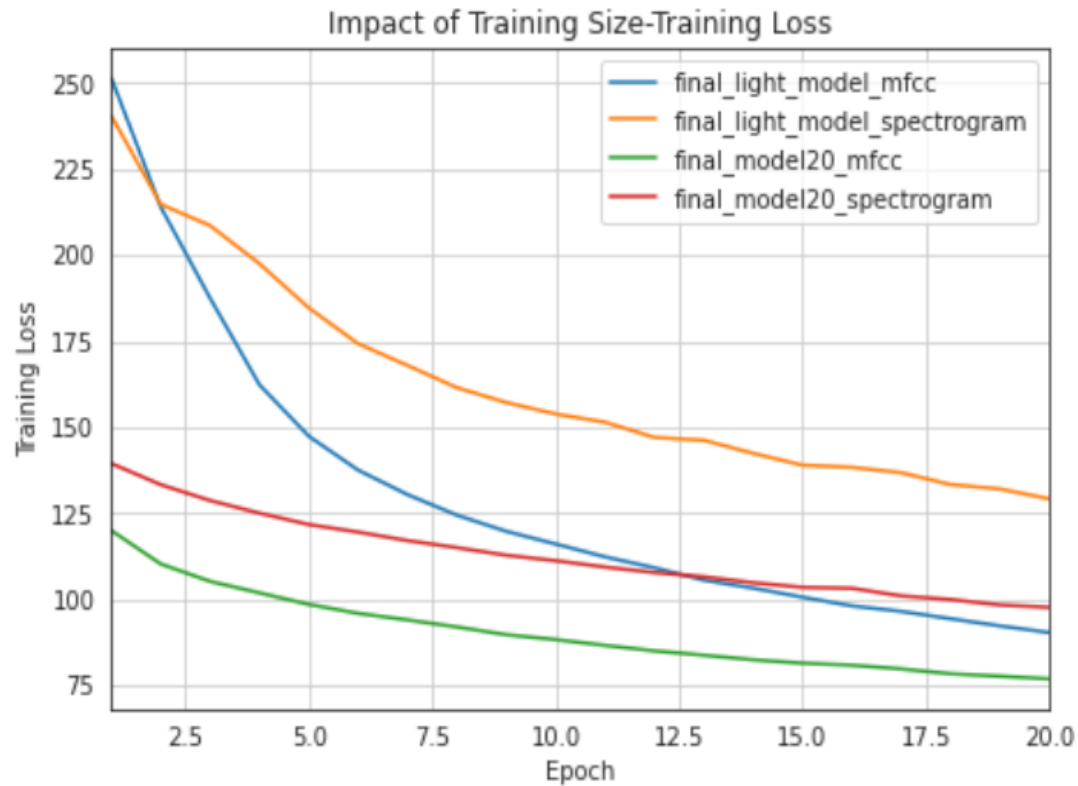
Feature	Training Loss	Validation Loss
MFCC	90	105
Spectrogram	129	125

Models – Final - with train-360-clean



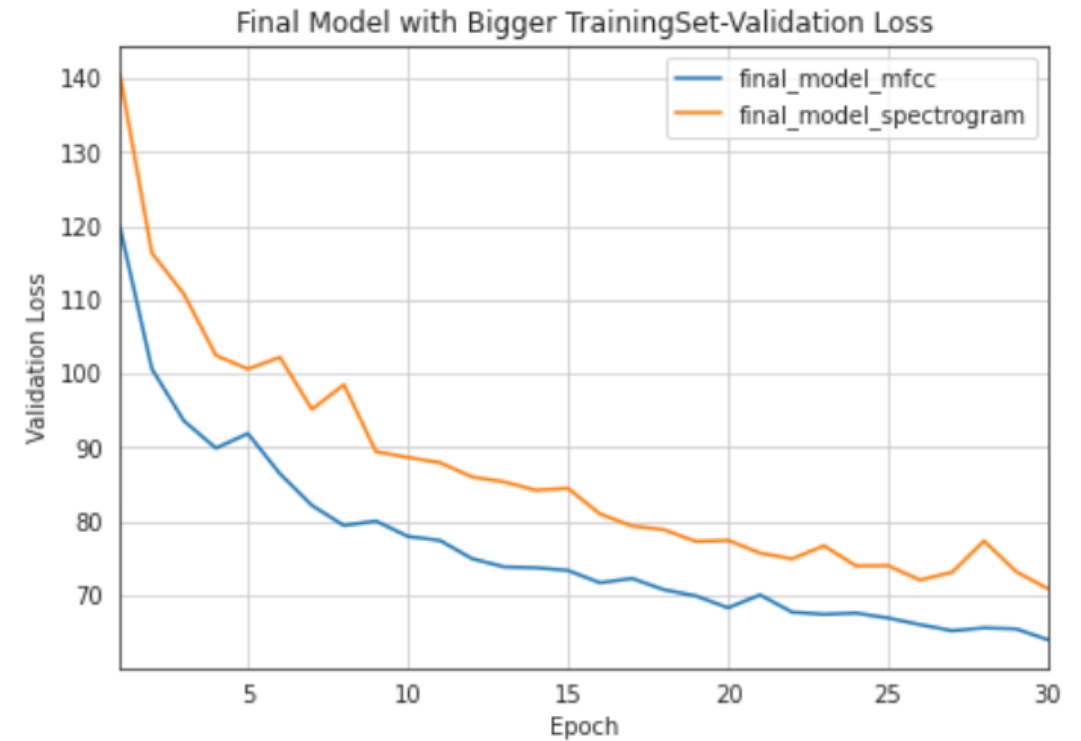
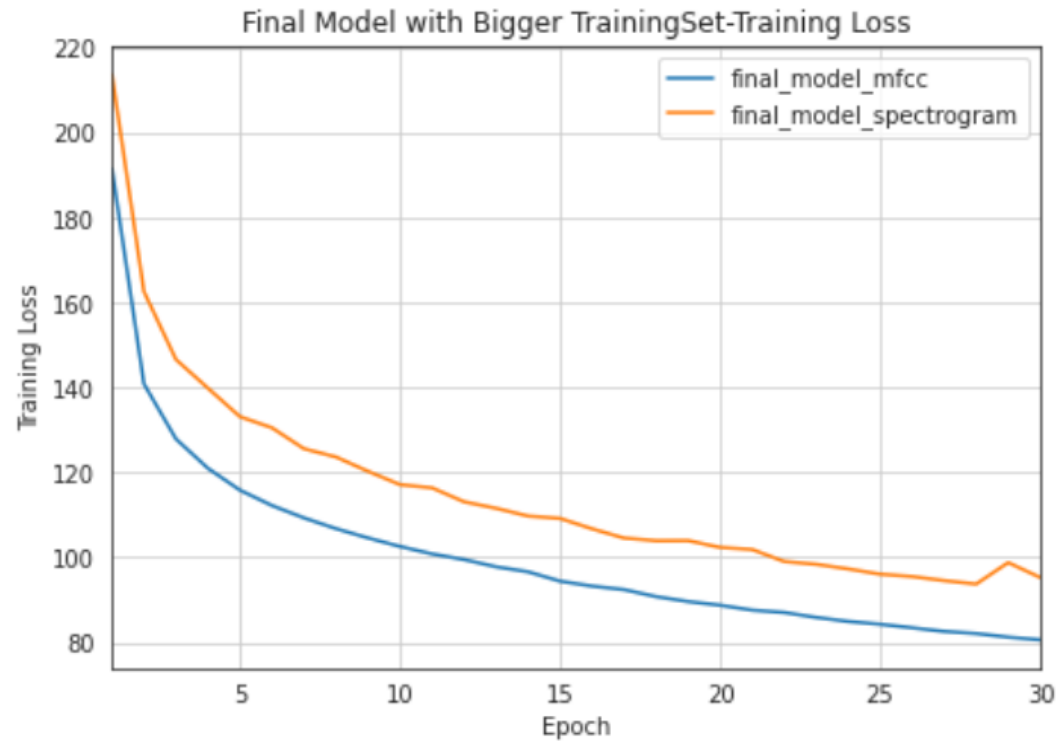
Feature	Training Loss	Validation Loss
MFCC	77	60
Spectrogram	98	77

Models – Final- Impact of Training Size



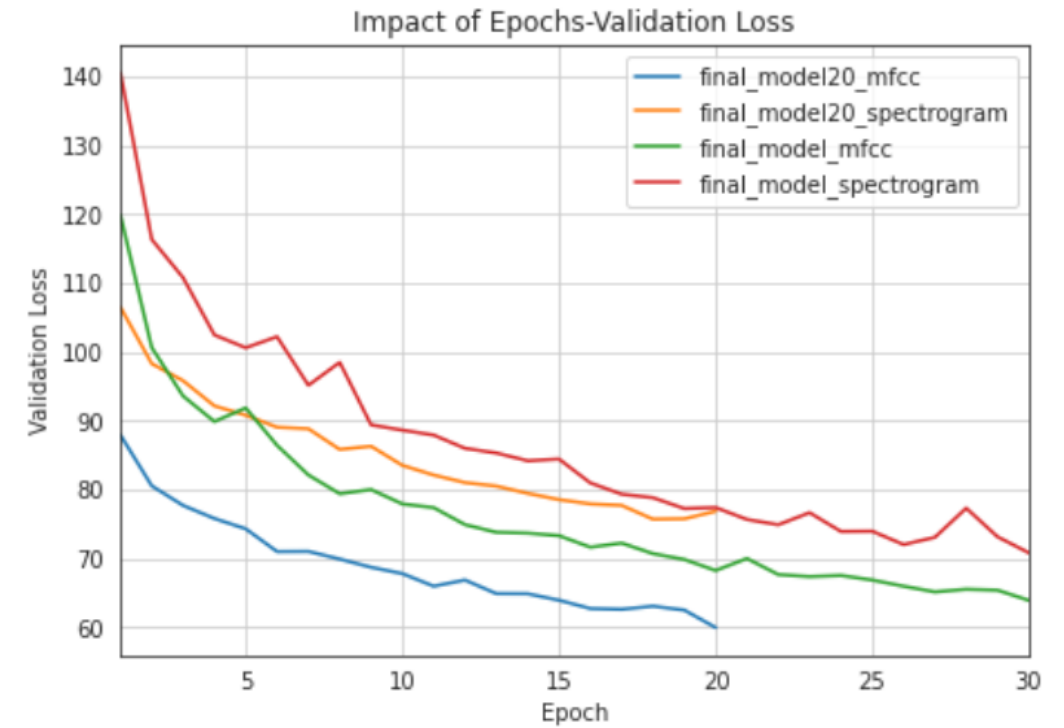
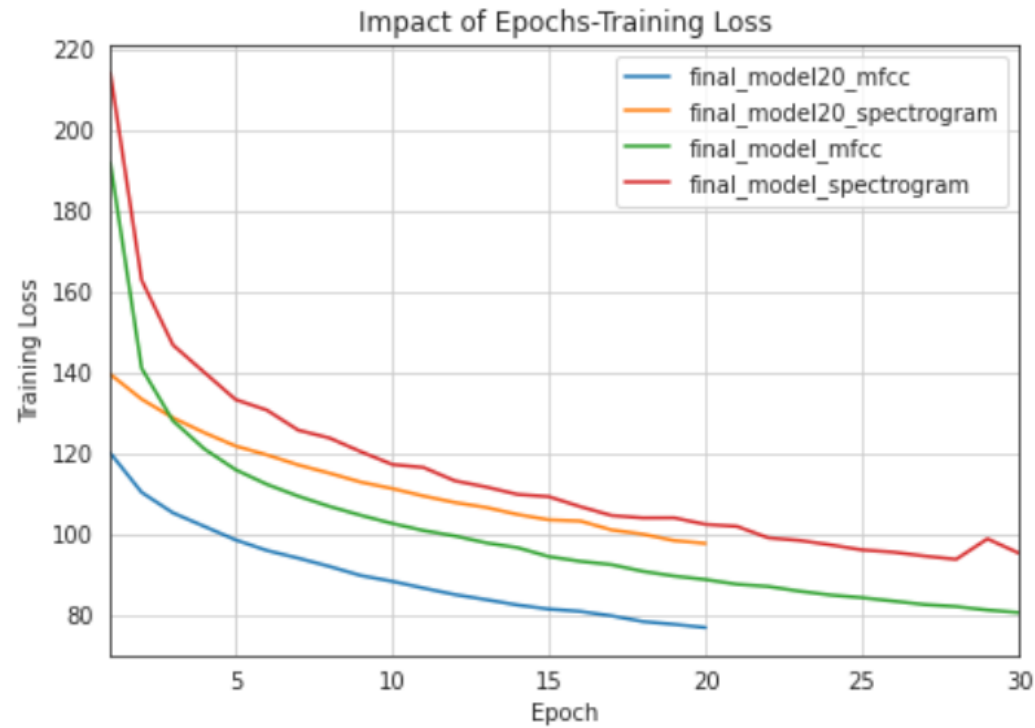
- Loss reduced with increase of training size

Models – Final- with train-360 and 30 epochs



Feature	Training Loss	Validation Loss
MFCC	80	64
Spectrogram	95	71

Models – Final- Impact of Epochs



- Slight decrease in loss when number of epochs increased (yet to reach plateau)

Predictions using Final Model

```
from model_use import ModelPredictor
predictor = ModelPredictor(input_to_softmax=final_model_mfcc,model_path='results/final_model_mfcc.h5')
from IPython.display import Audio

# display the true and predicted transcriptions and show the audio file
predictor.get_predictions_index(index=0,
                                partition='train',
                                spectrogram = False)
print('-'*80)
Audio(predictor.audio_path)
```

True transcription:

and now it had come to pass that his sole remaining ally mister samuel bozzle the ex policeman was becoming weary of his service

Predicted transcription:

ands now had com to pas atd his so remaning oli mister san no bossl the axpilisemen was becomeing wear yef his servace


```
from model_use import ModelPredictor
predictor = ModelPredictor(input_to_softmax=final_model_mfcc,model_path='results/final_model_mfcc.h5')
from IPython.display import Audio

# display the true and predicted transcriptions and show the audio file
predictor.get_predictions_index(index=0,
                                partition='validation',
                                spectrogram = False)
print('-'*80)
Audio(predictor.audio_path)
```

miss lake declined the carriage to night

Predicted transcription:

misrak to cines te cargad to mat

Real-Time Prediction Engine

```
from model_use import ModelPredictor
from IPython.display import Audio
from voice_rec import voice_record

predictor = ModelPredictor(input_to_softmax=final_model_mfcc,model_path='results/final_model_mfcc.h5')
voice_record(path='recordings/demo_mfcc.wav')
# display the true and predicted transcriptions and show the audio file
predictor.get_predictions_recorded(spectrogram = False,recordingpath='recordings/demo_mfcc.wav')
print('-'*80)
Audio(predictor.audio_path)
```

please speak into the microphone
done - result written to recordings/demo_spectro.wav

Predicted transcription:

lis go

"Let's go"

```
from model_use import ModelPredictor
from IPython.display import Audio
from voice_rec import voice_record

predictor = ModelPredictor(input_to_softmax=final_model_spectrogram,model_path='results/final_model_spectrogram.h5')
# record your voice
voice_record(path='recordings/demo_spectro.wav')
# display the true and predicted transcriptions and show the audio file
predictor.get_predictions_recorded(spectrogram = True,recordingpath='recordings/demo_spectro.wav')
print('-'*80)
Audio(predictor.audio_path)
```

please speak into the microphone
done - result written to recordings/demo_spectro.wav

Predicted transcription:

a a you

"How are you"

Conclusions

MFCC as a feature outperforms Spectrogram in accuracy of the models.

CNN layer ahead of GRU RNN improved the accuracy significantly.

Increasing the depth of RNN layer also increased accuracy.

Combining the best performing models (CNN+RNN+TDD and Deep RNN + TDD) further reduced the loss values.

Model quality can be further improved by training with bigger training set and increasing the number of epochs.

Adam optimizer provide a better stability for training deep learning network due to its self-stabilizing nature.

Future Work

Assessment of additional layers

- Additional combinations of Keras layers can be tried to further expand the possibility of a better model. An example would be to use deep bidirectional RNNs.

Beam Size Impact

- Controlling the beam size for CTC batch can be analyzed to see the impact of beam size on accuracy.

Noise reduction

- Noise reduction code can be implemented in the voice recording module to generate better real-time recognitions.

Lexicon Language Model

- Lexicon language model provided in the Librispeech can be used as the Labels for training. This will get a better recognition rate for words in dictionary.

References & Improvements



Base code : <https://github.com/udacity/AIND-VUI-Capstone>

Data set : <http://www.openslr.org/12/>



Features added to base code:

- Added Various Model Codes
- Voice Recording Module
- Tensor board integration
- Upgraded to latest versions of
 - TensorFlow
 - Python Packages
 - CUDA
- Visualization modules



GitHub Link: https://github.com/lithathampan/speech_recognition_nn_comparison.git



Thank You