Exploring Generative Models (Variational Autoencoders) for Audio Generation

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Presentation Outline

- Introduction
- Methodology
- Results
- References

Introduction

- Speech is a unique to human trait
- Allows to express thoughts, ideas, and emotions
- But, what about Human-Computer Interaction?
  - Computers can recognize human speech
  - However, the responses are pre-recorded and not as dynamic
- This project will explore the area of generative AI to synthesize voices for such systems.

Methodology

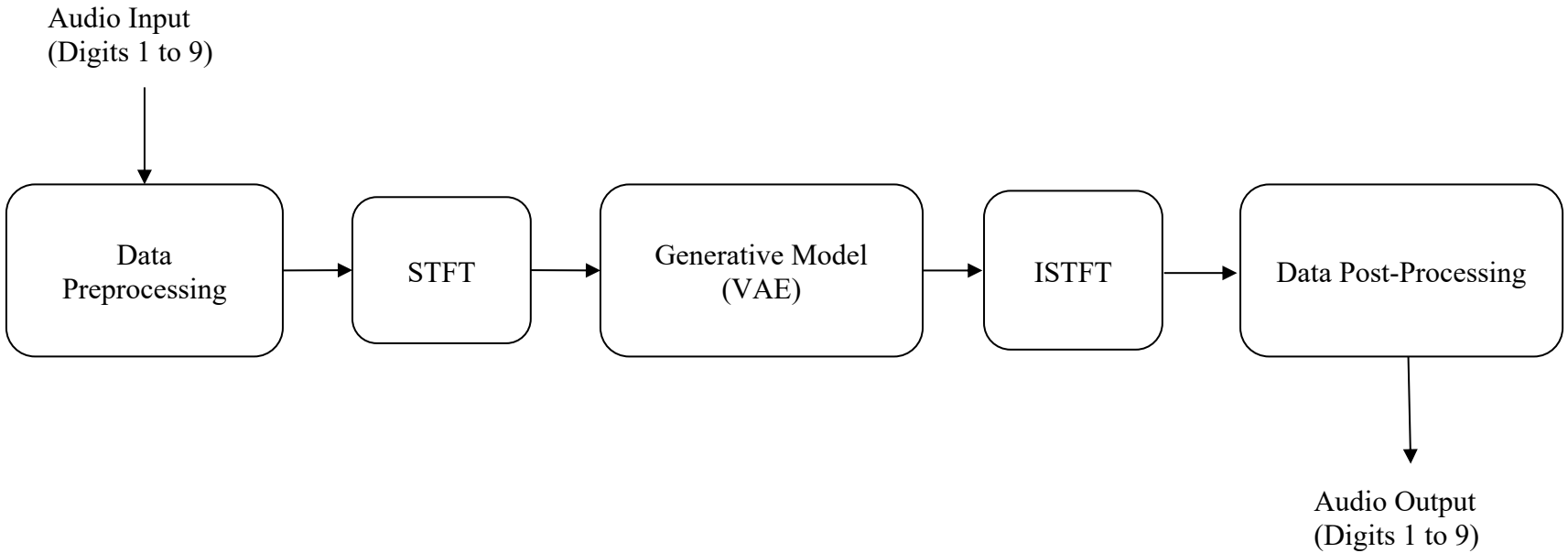
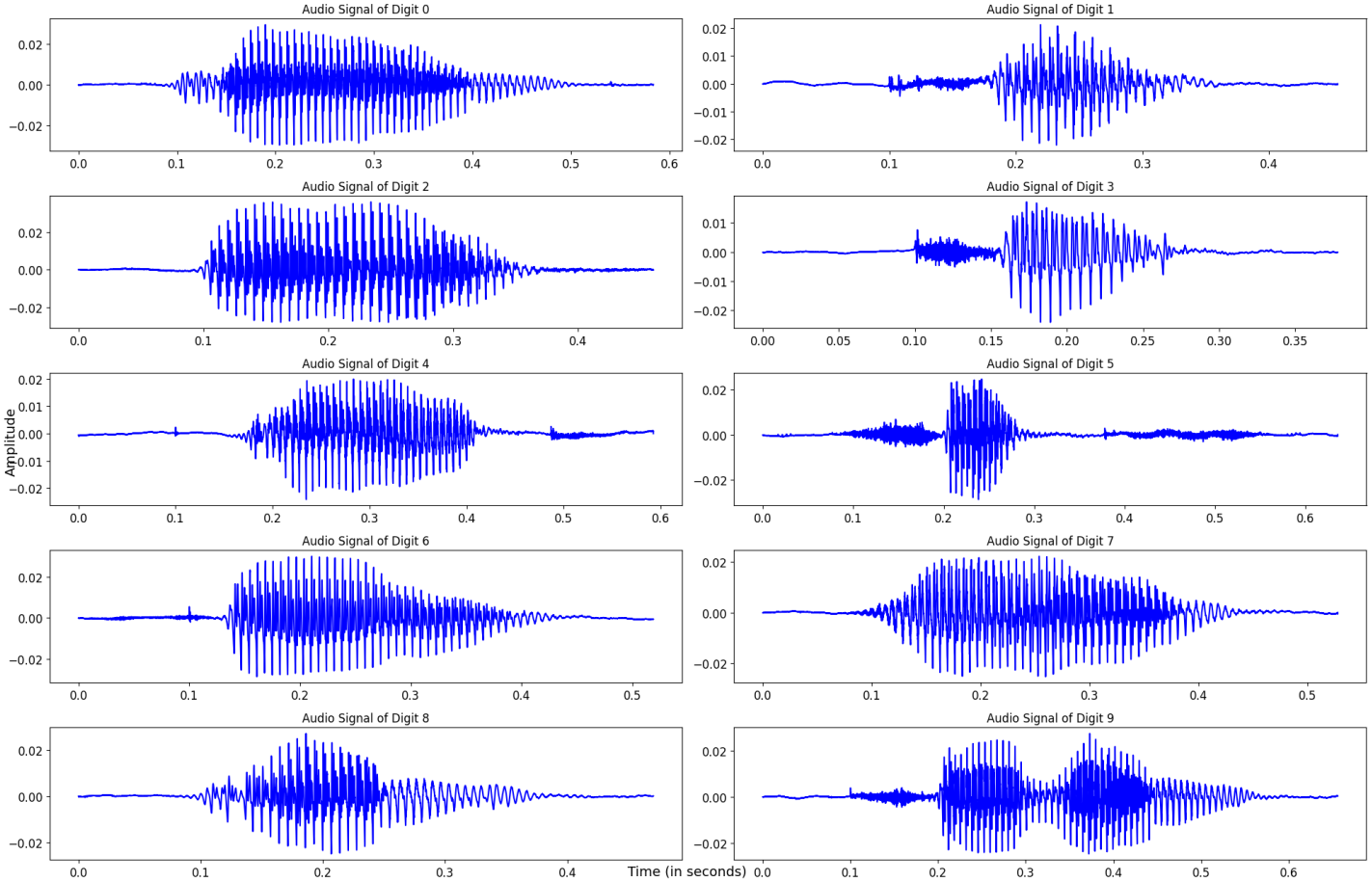
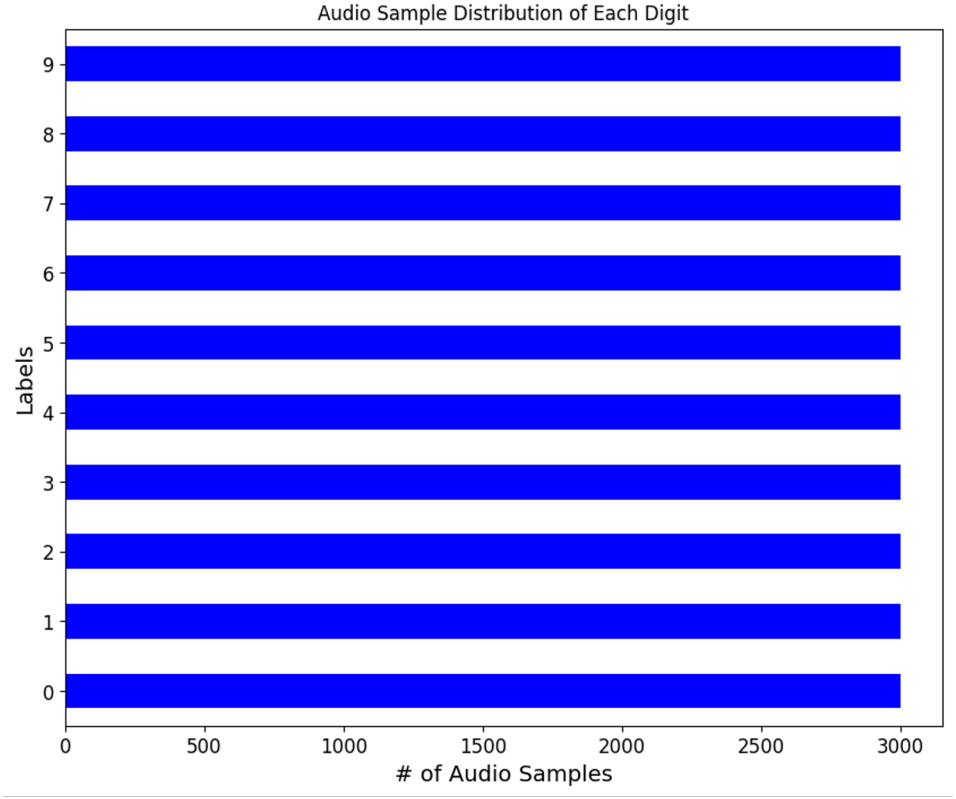


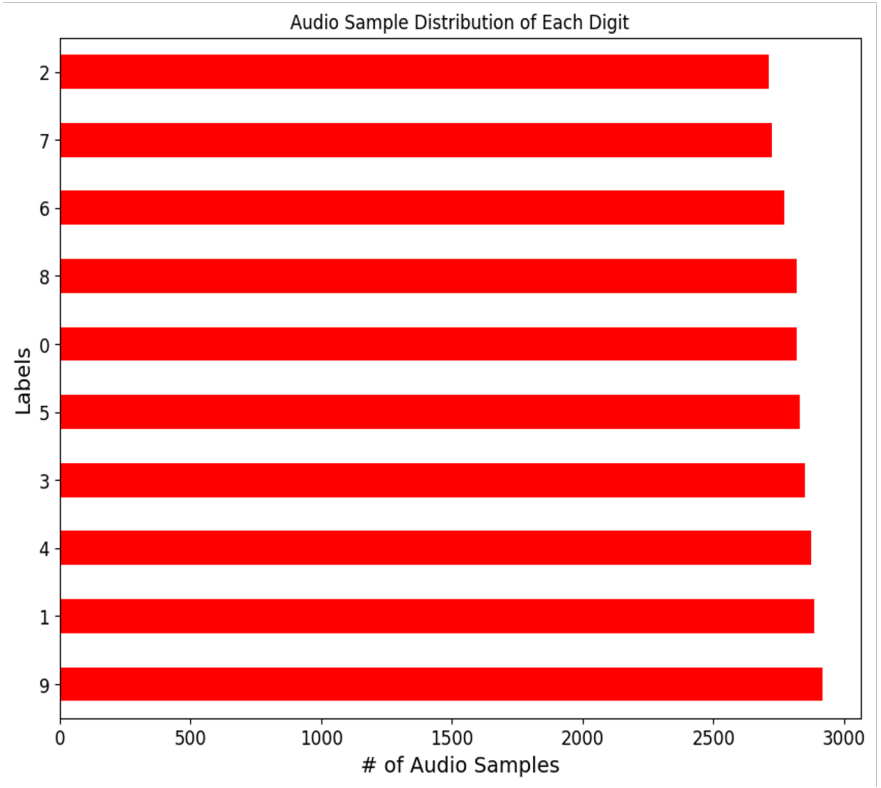
Fig: Block Diagram for the Training Phase of the Proposed Audio Generation System

Input Signal

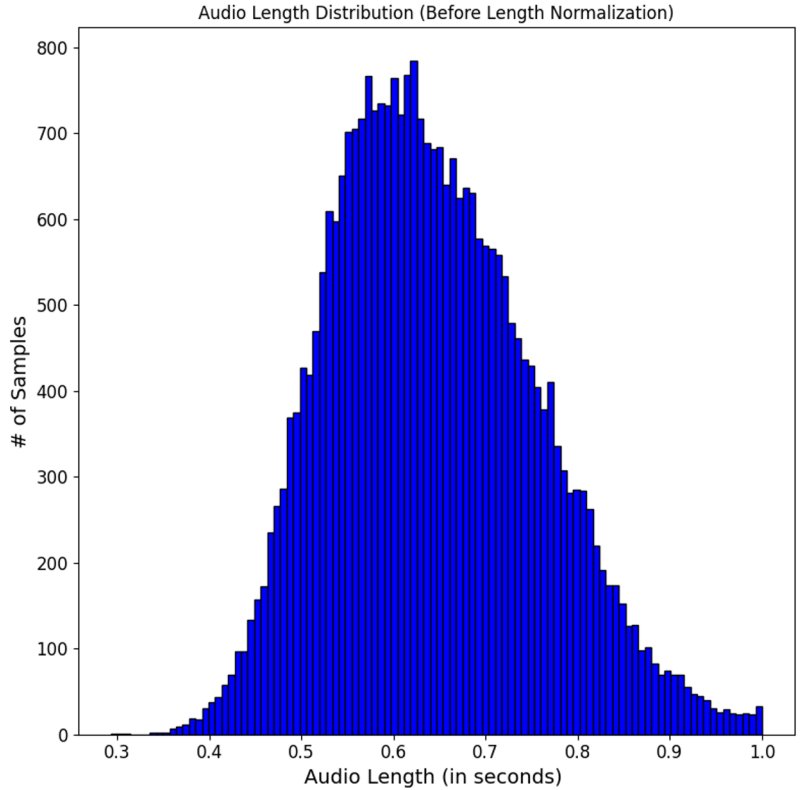


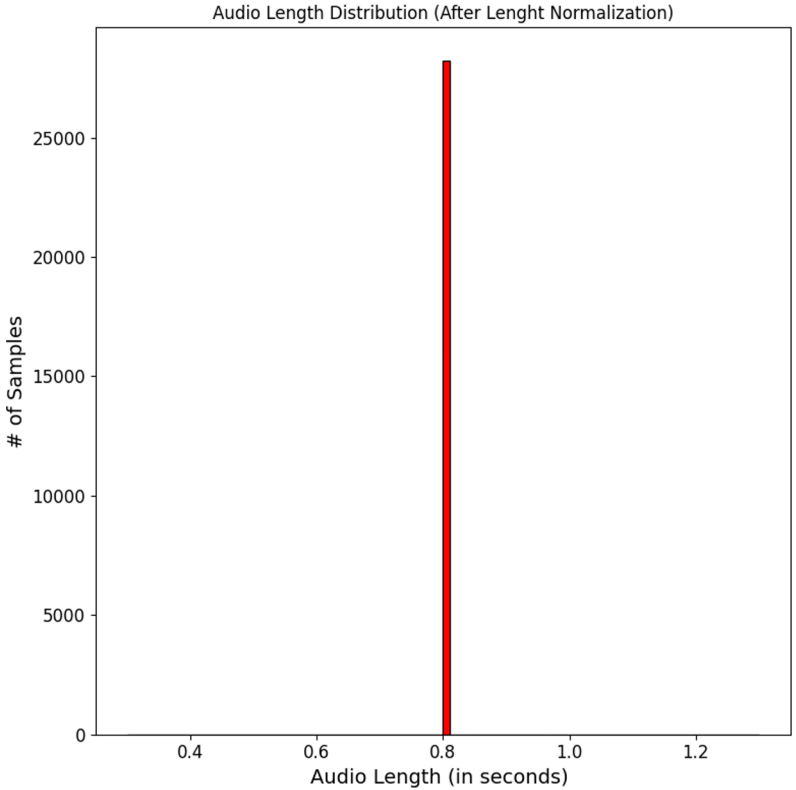
Data Preprocessing [Filtering Unusable Samples]



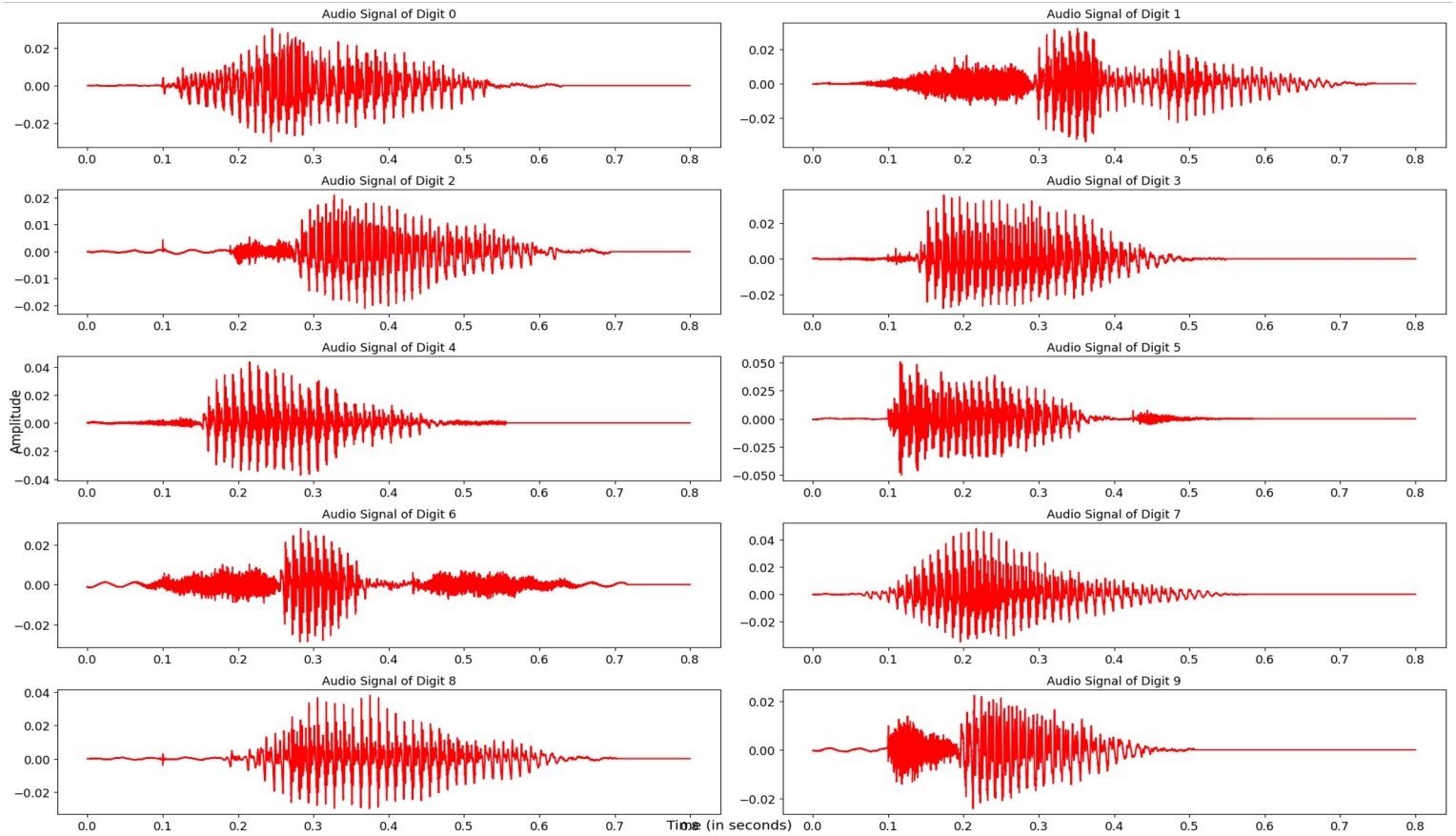


Data Preprocessing [Length Normalization]

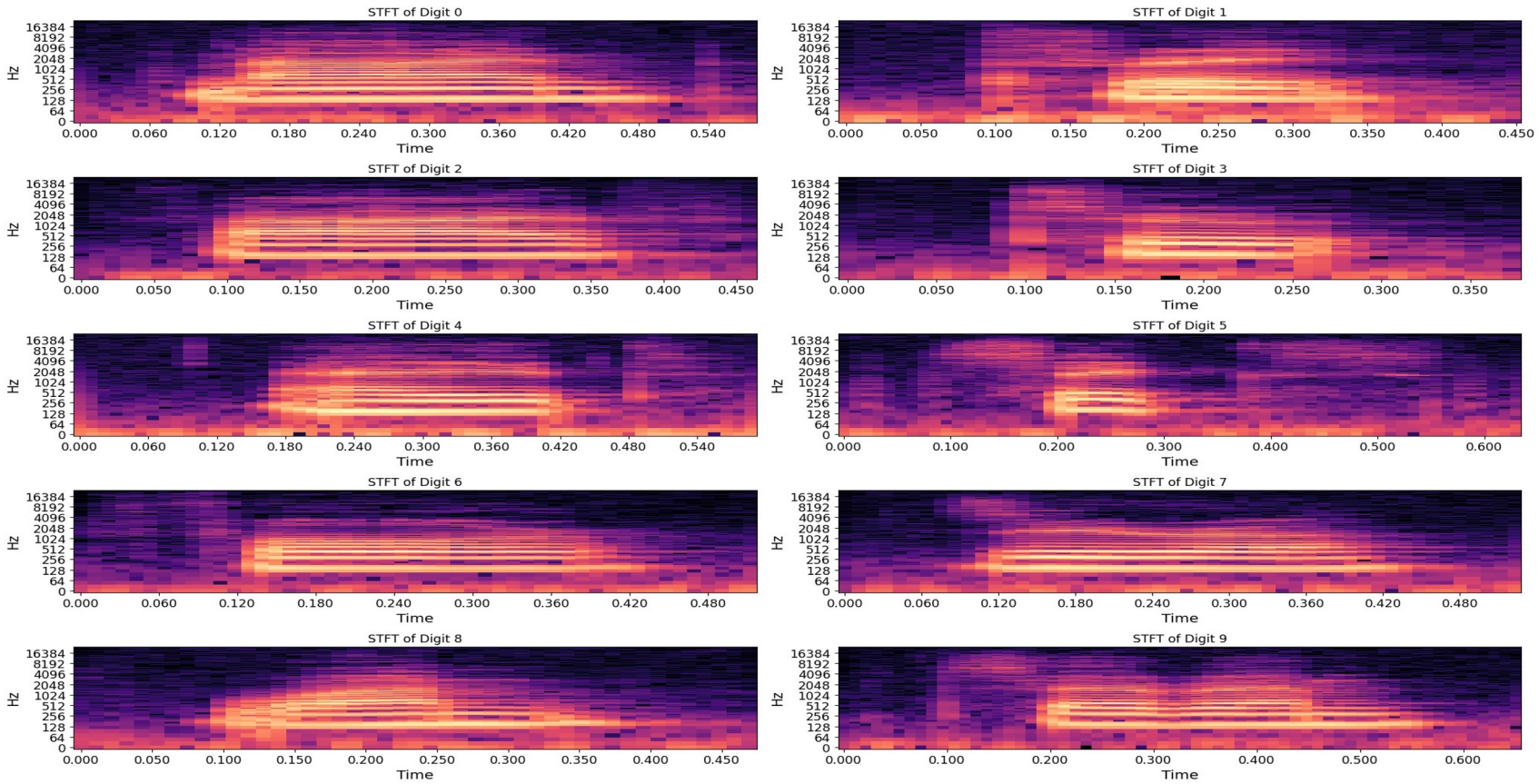




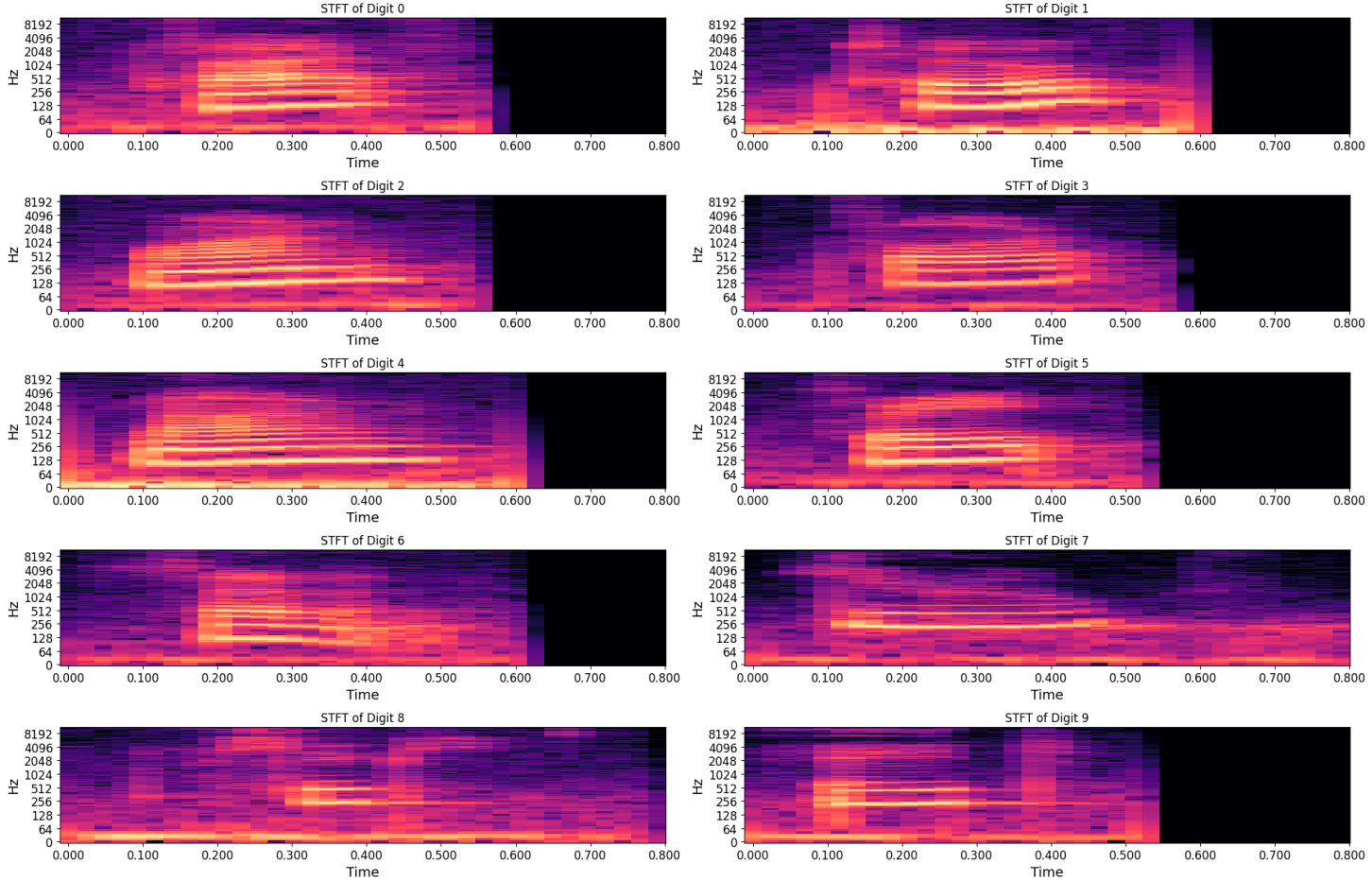
Data Preprocessing [Length Normalization]



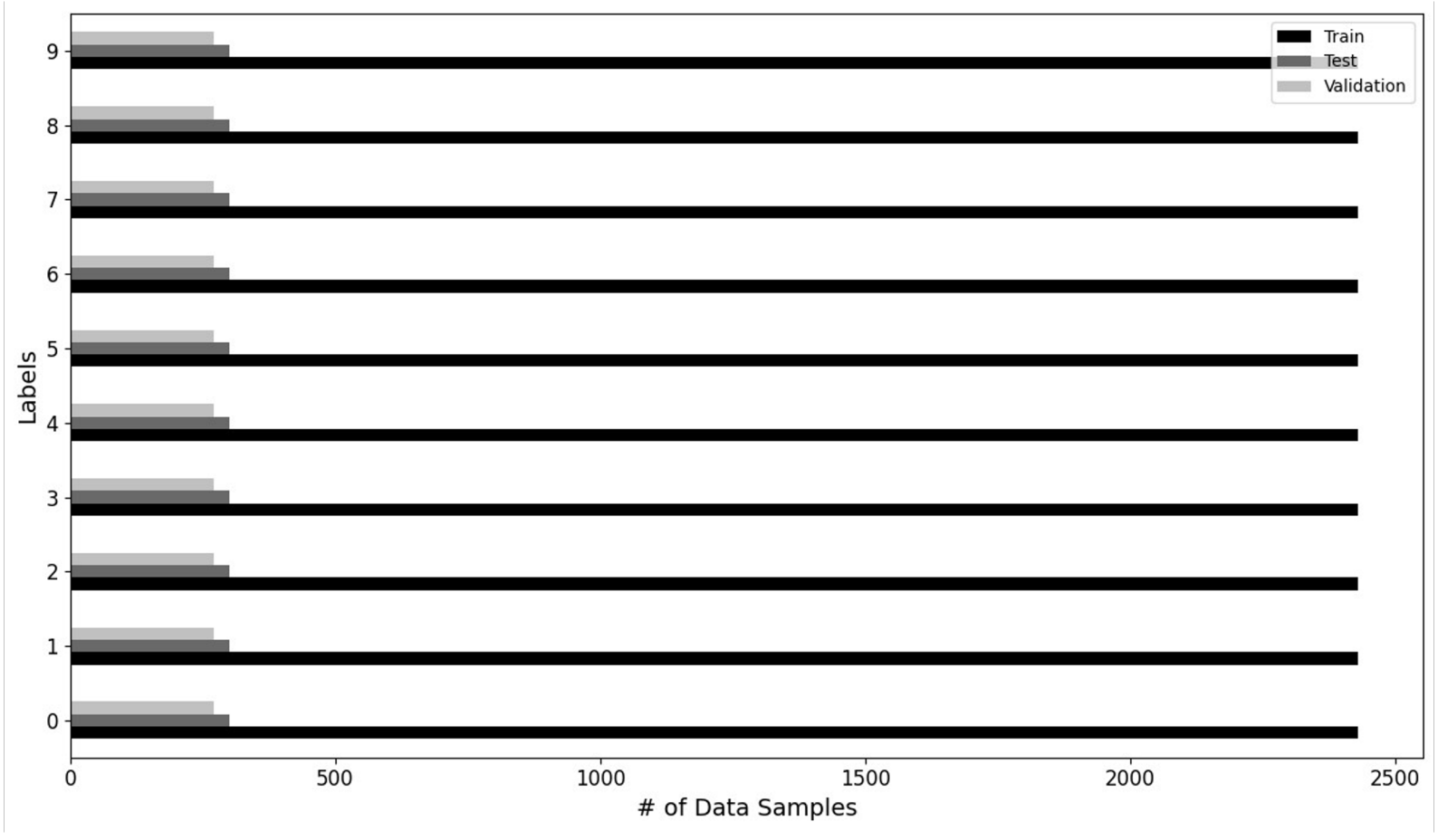
Feature Extraction (STFT – Raw Data)



Feature Extraction (STFT – Normalized Data)

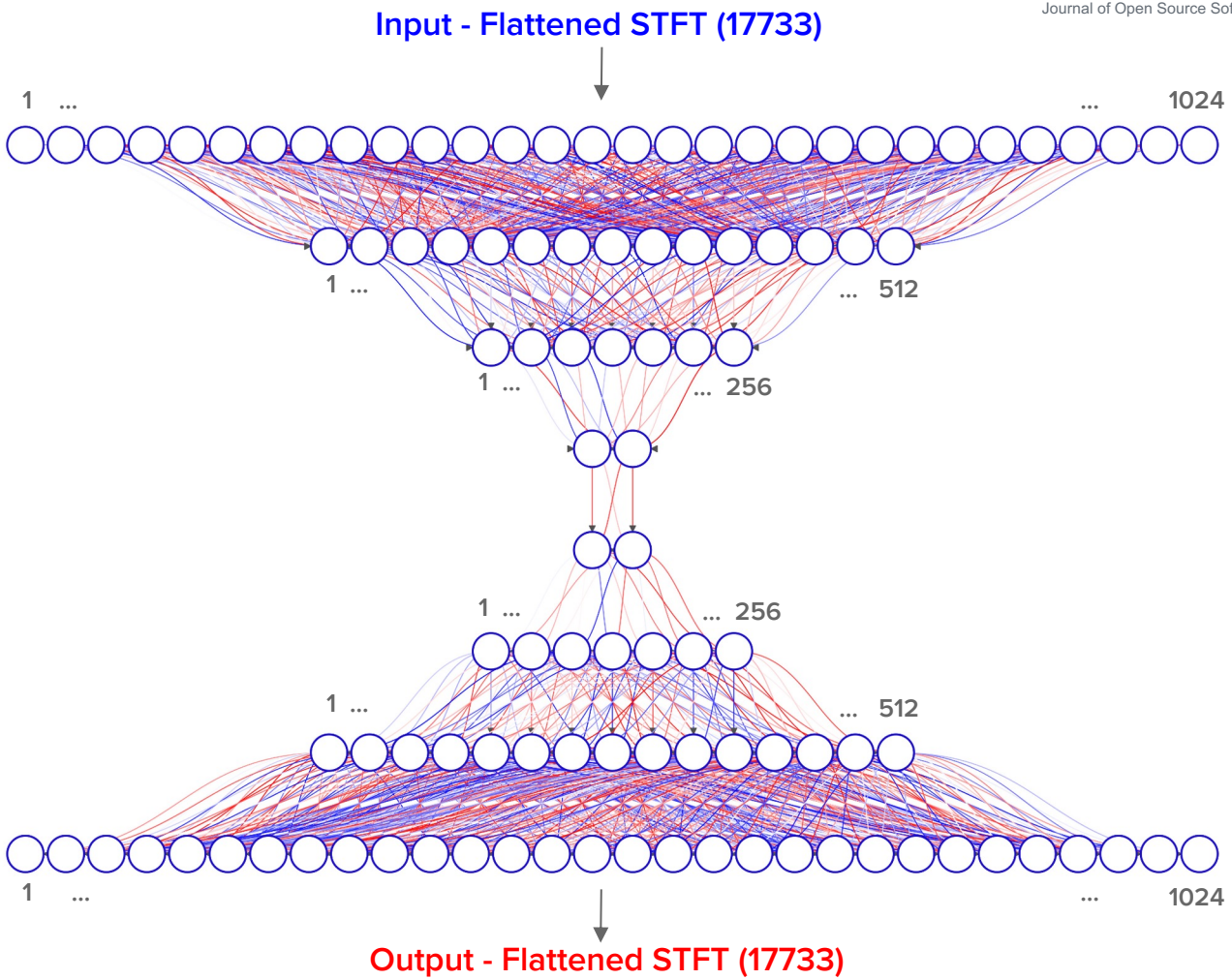


Dataset Split



LeNail, (2019). NN-SVG: Publication-Ready Neural Network Architecture Schematics.
Journal of Open Source Software, 4(33), 747, https://doi.org/10.21105/joss.00747

VAE (with MLP) Architecture



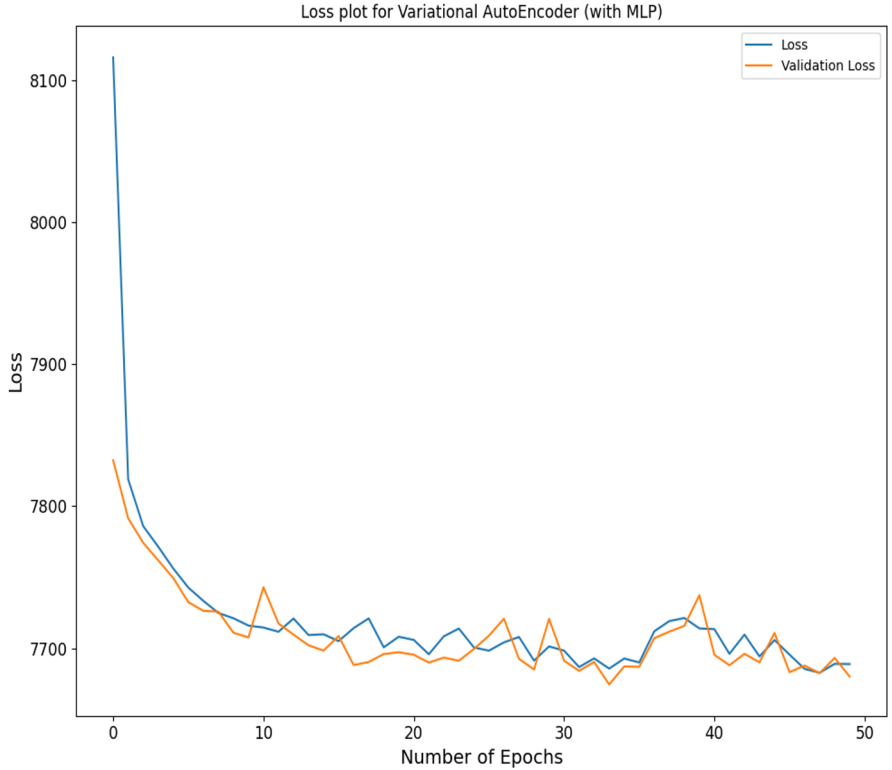
Encoder Layer

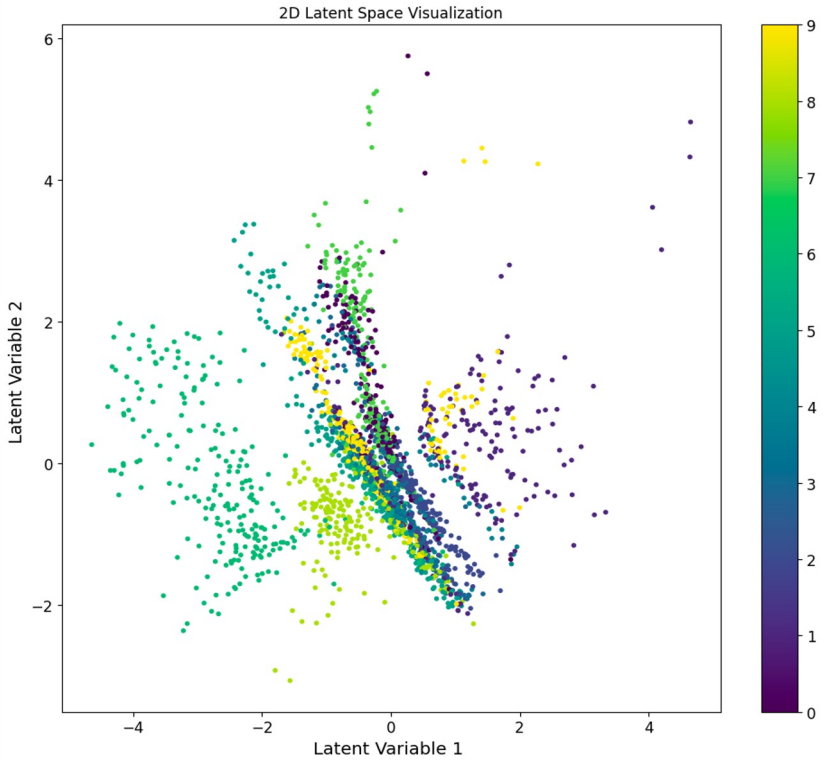
Latent Layer

Decoder Layer

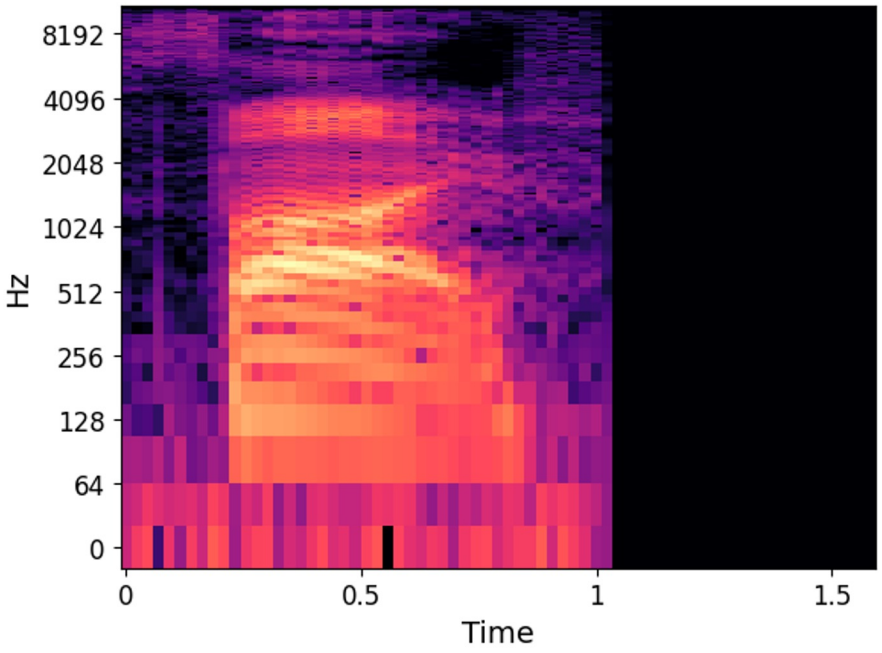
Results [Model Performance]

Training Loss	Validation Loss	Test Loss
7673.74	7667.33	7692.69

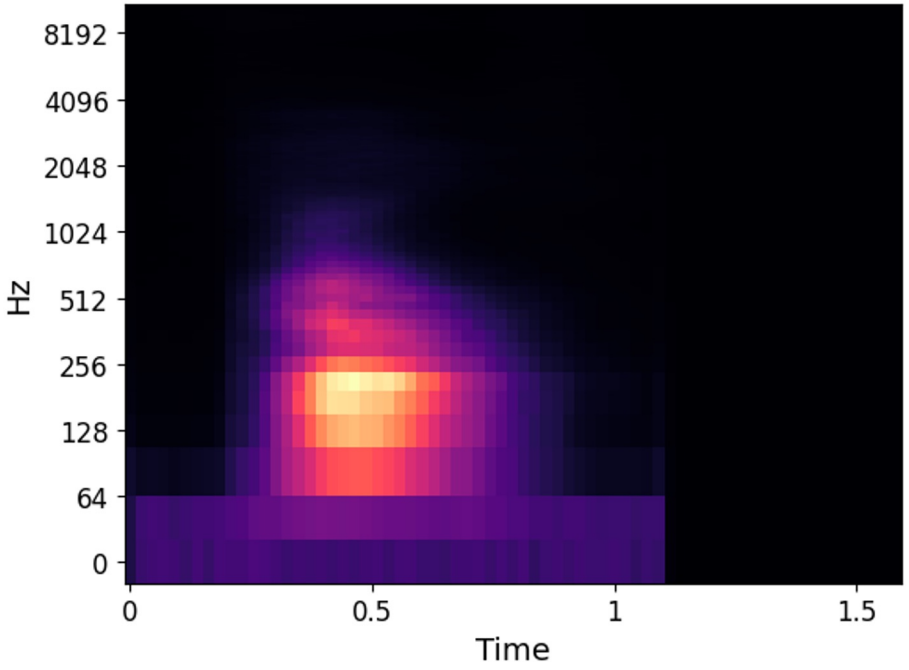




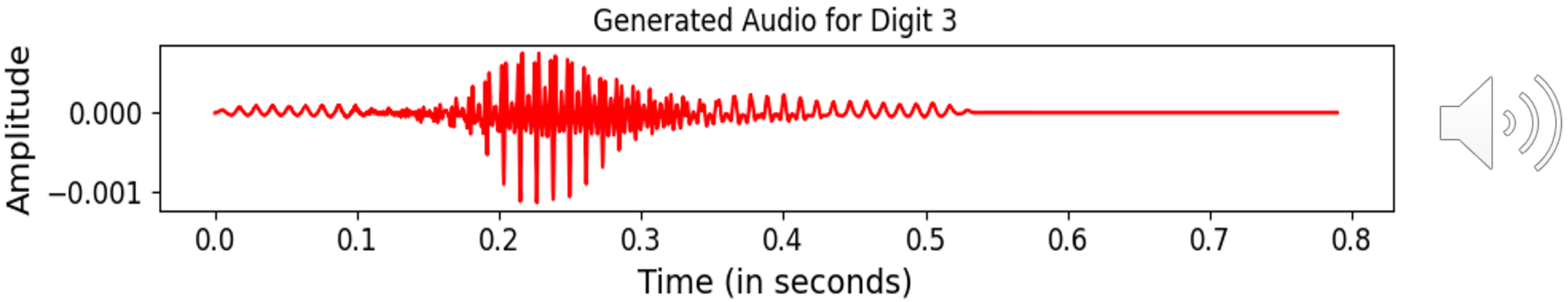
Results [Comparison of Generated STFT]

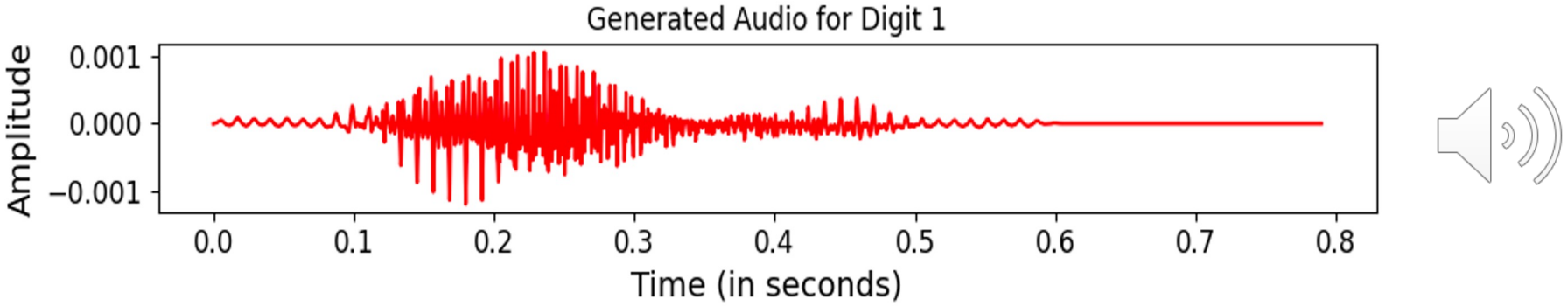


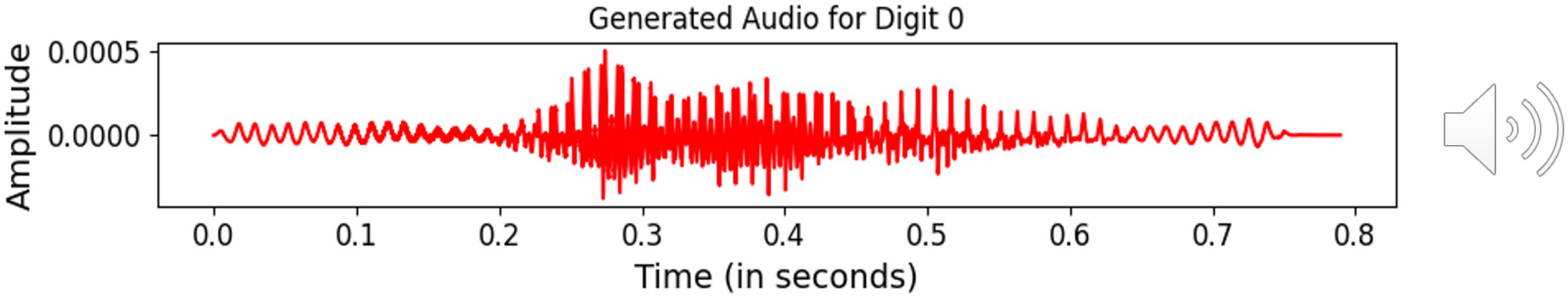
Input STFT for Digit 5

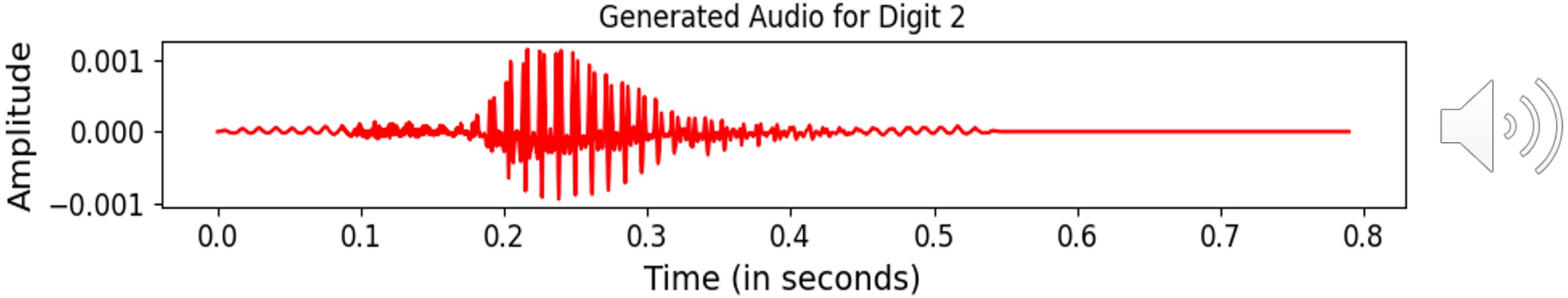


Generated STFT for Digit 5


Generated Audio for Digit 3
Amplitude
0.000
−0.001
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Time (in seconds)


Generated Audio for Digit 1
Amplitude
0.001
0.000
−0.001
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Time (in seconds)


Generated Audio for Digit 0
Amplitude
0.0005
0.0000
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Time (in seconds)


Generated Audio for Digit 2
Amplitude
0.001
0.000
−0.001
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Time (in seconds)

Further Works

- Train Model for more epochs
- Fine tune model hyperparameters and add regularization
- Work on Audio Post-processing to enhance clarity
- Train VAE with CNN and compare against VAE with MLP

THANK YOU !

REFERENCES

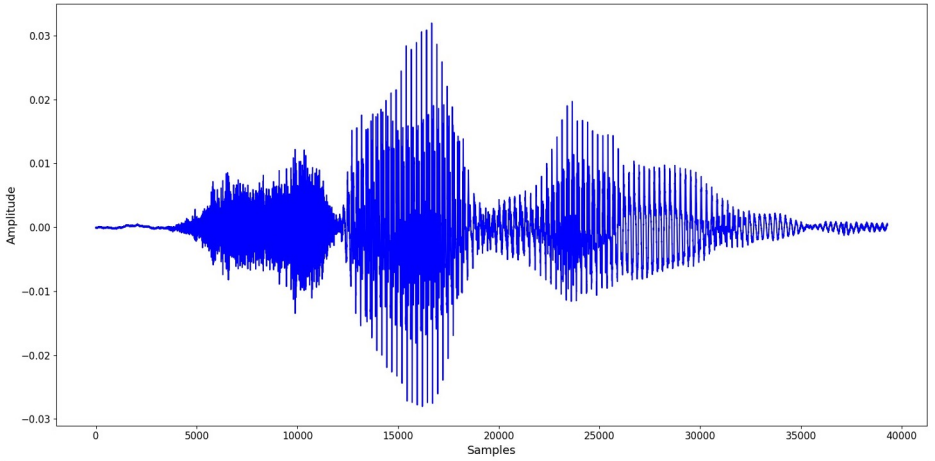
[1] L. Weng, “From Autoencoder to Beta-VAE,” Lil’Log, Aug. 12, 2018. https://lilianweng.github.io/posts/2018-08-12-vae/ (accessed Sep. 30, 2023).

[2] S. Becker, M. Ackermann, S. Lapuschkin, K.-R. Müller, and W. Samek, “Interpreting and Explaining Deep Neural Networks for Classification of Audio Signals,” arXiv.org, Jul. 09, 2018. https://arxiv.org/abs/1807.03418

Appendix

AudioMNIST Dataset

- AudioMNIST Dataset has an audio recording of all the digits (from 0 to 9), from a total of 60 speakers, totaling 30,000 samples. [2]
- 9.5 hours long and is recorded from speakers with a broad range of accents, including both native and non-native speakers.
- The recorded sample is 16-bit single-channel audio, sampled at 48KHz.



MODEL ARCHITECTURE

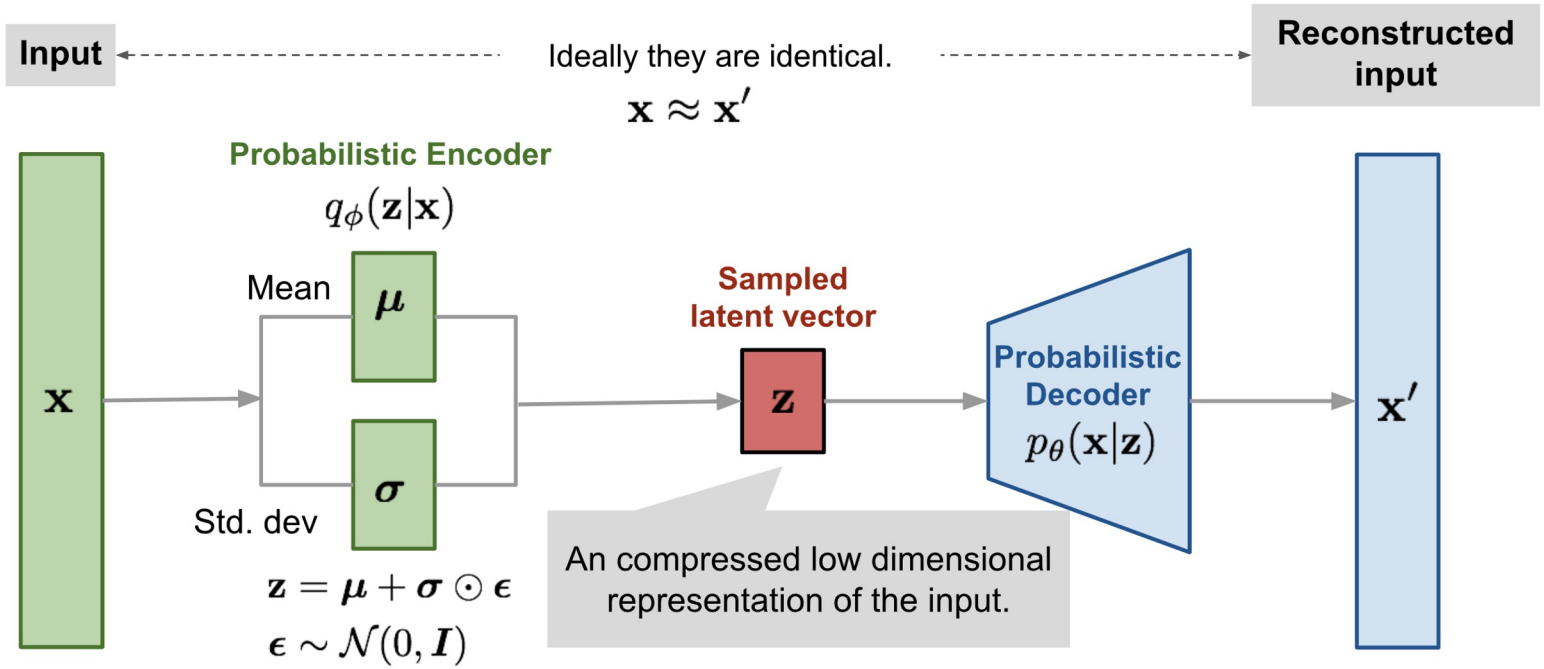


Fig 3: Architecture of Variational AutoEncoders [1]

Code Snippets [Extracting Data and Length Normalization]

Normalize Data Lengths

```
sample_len = [len(x) for x in audios]
print("1st Percentile: ",np.percentile(sample_len,1))
print("3rd Percentile: ",np.percentile(sample_len,3))
print("5th Percentile: ",np.percentile(sample_len,5))
print("10th Percentile: ",np.percentile(sample_len,10))
print("95th Percentile: ",np.percentile(sample_len,95))
print("97th Percentile: ",np.percentile(sample_len,97))
```

```
1st Percentile:  9391.94
3rd Percentile:  10150.0
5th Percentile:  10535.0
10th Percentile:  11168.0
95th Percentile:  18502.0
97th Percentile:  19185.03
```

```
def fetch_data(**kwargs):
    audio = []
    labels = []
    for file in tqdm.tqdm(files,desc="Reading Data ... "):
        _audio, SR = librosa.load(file,sr=22050,dtype=np.float32)

        if(kwargs):
            length = kwargs["length"]
            min_allowed_len = kwargs["min"]
            max_allowed_len = kwargs["max"]
            if((len(_audio) > min_allowed_len) and (len(_audio) < max_allowed_len)):
                if(len(_audio)>length):
                    trim_front = math.floor((len(_audio) - length) / 2 )
                    trim_back = math.ceil((len(_audio) - length) / 2)
                    _audio = _audio[trim_front:-trim_back]
                elif(len(_audio)<length):
                    _audio = np.pad(_audio,(0,length-len(_audio)),constant_values=(0.0,0.0))
            else:
                continue
        audio.append(_audio)
        labels.append(os.path.split(file)[-1][0])
    return audio,SR,labels
```

Code Snippets [Encoder & Decoder]

```
# see encoder summary
encoder.summary()
```

✓ 0.0s

```
Model: "encoder"
__________________________________________________________________________________________________
 Layer (type)                Output Shape              Param #   Connected to
==================================================================================================
 input_2 (InputLayer)        [(None, 17733)]           0         []

 dense_7 (Dense)             (None, 1024)              18159616  ['input_2[0][0]']

 dense_8 (Dense)             (None, 512)               524800    ['dense_7[0][0]']

 dense_9 (Dense)             (None, 256)               131328    ['dense_8[0][0]']

 z_mean (Dense)              (None, 2)                 514       ['dense_9[0][0]']

 z_log_var (Dense)           (None, 2)                 514       ['dense_9[0][0]']

 z (Lambda)                  (None, 2)                 0         ['z_mean[0][0]',
                                                                  'z_log_var[0][0]']

==================================================================================================
Total params: 18816772 (71.78 MB)
Trainable params: 18816772 (71.78 MB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
```

```
# see decoder summary
decoder.summary()
```

✓ 0.0s

```
Model: "decoder"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 decoder_input (InputLayer)  [(None, 2)]               0

 dense_10 (Dense)            (None, 256)               768

 dense_11 (Dense)            (None, 512)               131584

 dense_12 (Dense)            (None, 1024)              525312

 dense_13 (Dense)            (None, 17733)             18176325

=================================================================
Total params: 18833989 (71.85 MB)
Trainable params: 18833989 (71.85 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Code Snippets [MLP VAE Architecture]

```python
# Encoder network
inputs = Input(shape=(X_train.shape[1],))

x = Dense(1024, activation='relu')(inputs)
x = Dense(512, activation='relu')(x)
x = Dense(256, activation='relu')(x)

z_mean = Dense(latent_dim, name='z_mean')(x)
z_log_var = Dense(latent_dim, name='z_log_var')(x)


def sampling(args):
    z_mean, z_log_var = args
    batch_size = K.shape(z_mean)[0]
    epsilon = K.random_normal(shape=(batch_size, latent_dim), mean=0., stddev=1.)
    return z_mean + K.exp(0.5 * z_log_var) * epsilon

z = Lambda(sampling, output_shape=(latent_dim,), name='z')([z_mean, z_log_var])

# Decoder network
decoder_inputs = Input(shape=(latent_dim,), name='decoder_input')
x = Dense(256, activation='relu')(decoder_inputs)
x = Dense(512, activation='relu')(x)
x = Dense(1024, activation='relu')(x)
outputs = Dense(17733, activation='sigmoid')(x)

# Define the encoder and decoder models
encoder = Model(inputs, [z_mean, z_log_var, z], name='encoder')
decoder = Model(decoder_inputs, outputs, name='decoder')
```

✓ 0.0s

```python
# Define the loss function for VAE
def vae_loss(inputs, x_decoded_mean):
    recon_loss = original_dim * binary_crossentropy(inputs, x_decoded_mean)
    kl_loss = -0.5 * K.sum(1 + z_log_var - K.square(z_mean) - K.exp(z_log_var), axis=-1)
    return K.mean(recon_loss + kl_loss)
```

✓ 0.0s

```python
# VAE model
outputs = decoder(encoder(inputs)[2])
dense_vae = Model(inputs, outputs, name='vae')
dense_vae.compile(optimizer='adam', loss=vae_loss)
dense_vae.summary()
```

✓ 0.0s

```
Model: "vae"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 17733)]           0

 encoder (Functional)        [(None, 2),               18816772
                              (None, 2),
                              (None, 2)]

 decoder (Functional)        (None, 17733)             18833989

=================================================================
Total params: 37650761 (143.63 MB)
Trainable params: 37650761 (143.63 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Code Snippets [Amplitude Normalization using MinMax]

```python
def MinMaxScaler(features):
    scaled = []
    min_max_values = []
    for f in features:
        min_val = np.min(f)
        max_val = np.max(f)
        f_normalized = (f - min_val) / (max_val - min_val)
        min_max_values.append((min_val,max_val))
        scaled.append(f_normalized)
    return np.array(scaled),np.array(min_max_values)
```

✓ 0.0s

```python
def MinMaxUnScaler(features, min_max_values):
    unscaled = []
    for f,min_max in zip(features,min_max_values):
        f = f.reshape(257,69)
        unscaled_feature = (f * (min_max[1] - min_max[0])) + min_max[0]
        unscaled_feature = librosa.db_to_amplitude(unscaled_feature)
        unscaled.append(unscaled_feature)
    return np.array(unscaled)
```

✓ 0.0s

Code Snippets [Feature Extraction (STFT)]

Feature Extraction

```
def extract_stft(audios):
    stft_features = []
    for audio in tqdm.tqdm(audios,desc="Extracting Features ... "):
        stft = librosa.amplitude_to_db(np.abs(librosa.stft(audio,n_fft=512,hop_length=256)), ref=np.max)
        stft  = stft.reshape((*stft.shape, 1))  # Add channel dimension

        stft_features.append(stft)
    return np.array(stft_features)
```

```
X_train_features = extract_stft(X_train)
X_test_features = extract_stft(X_test)
X_val_features = extract_stft(X_val)
```

```
Extracting Features ... : 100%|██████████| 22840/22840 [00:15<00:00, 1502.06it/s]
Extracting Features ... : 100%|██████████| 2820/2820 [00:02<00:00, 1265.28it/s]
Extracting Features ... : 100%|██████████| 2538/2538 [00:02<00:00, 1167.23it/s]
```

Code Snippets [iSTFT]

Invserse STFT

```
def ISTFT(feature):
    audios = []
    for f in tqdm.tqdm(feature,desc="Appling inverse STFT ..."):
        audio = librosa.istft(f,hop_length=256)
        audios.append(audio)
    return np.array(audios)
```

✓ 0.0s

```
decoded_istft = ISTFT(decoded_stft)
```

✓ 1.4s

```
Appling inverse STFT ...: 100%|██████████| 2538/2538 [00:01<00:00, 1818.40it/s]
```

MODEL ARCHITECTURE

- **Unsupervised Learning:** VAE is an unsupervised learning method designed to comprehend the data distribution and generate new data points.
- **Architecture:** The VAE comprises two vital components - **an encoder and a decoder.** These components collaborate to minimize the reconstruction error between the encoded-decoded data and the initial dataset.
- **Encoder:** The encoder maps the dataset into a latent representation, creating a **joint probability distribution of the samples**. This representation serves as the foundation for generating new, meaningful data.
- **Decoder: A random sample from this latent space** is fed into the decoder, reconstructing the data. The reconstruction error, calculated between the input and reconstructed data, guides the training process.
- **Objective:** VAE is trained to minimize this reconstruction error, ensuring that the generated data closely resembles the original dataset, capturing its essential features.
- **Loss** = **Reconstruction_loss** (error in reconstruction) + **KL_Divergence** (latent space to conform to a specific desired distribution)

Code Snippets [Train-Test-Val Split]

Train test split

```
# Perform an initial split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(audios, labels, test_size=0.1, random_state=42, stratify=labels)

# Perform an second split into train and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.1, random_state=42, stratify=y_train)

print("Shape of training data: ", X_train.shape)
print("Shape of test data: ", X_test.shape)
print("Shape of validation data: ", X_val.shape)
```

```
Shape of training data:  (22840, 17640)
Shape of test data:  (2820, 17640)
Shape of validation data:  (2538, 17640)
```

Methodology

Input Data: Audio samples of spoken digits are used as input to the system.

Data Preprocessing: Raw audio data undergoes preprocessing to eliminates this inconsistency in data samples making them uniform in amplitude, length, etc.

Feature Extraction: STFT is a way of observing the frequency and phase content of a signal over time. It is applied to extract relevant features from the preprocessed audio data.

Generative Model: The STFT of audio signals are fed into a Variational Autoencoder (VAE), a generative model, to generate new STFT representations for the audio data.

Inverse Short Time Fourier Transform (ISTFT): The generated STFT data is converted back into an audio signal using Inverse Short Time Fourier Transform(ISTFT), reconstructing the audio waveform.

Data Post-Processing: The reconstructed audio signal undergoes post-processing, including amplitude adjustment, frequency conversion, and other necessary enhancements.

Output: The final output is a properly generated audio signal, retaining the natural nuances of human speech.