MelSpectrogram CNN Autoencoder for Denoising

Introduction

In this project, we explore the application of convolutional neural networks (CNNs) for denoising mel-spectrograms. Mel-spectrograms are a representation of audio signals in the frequency domain, widely used in speech processing and audio analysis tasks. Denoising mel-spectrograms involves removing unwanted noise from audio signals, which is crucial for various applications such as speech recognition, music processing, and audio classification.

We leverage the concept of autoencoders, a type of neural network architecture capable of learning efficient representations of data by encoding input signals into a lower-dimensional space and then decoding them back to the original space. The autoencoder is trained in an unsupervised manner, meaning it learns to reconstruct the input data without explicit labels.

Dataset

The dataset utilized in this project comprises mel-spectrograms that I generated by converting audio recordings (.wav files) of spoken digits from the MNIST dataset **Audio MNIST** using the Librosa library. Each mel-spectrogram represents a single digit pronounced in English, ranging from 0 to 9. In the dataset we have 3000 mel-spectrograms in total, 300 for every digit. The dataset is split into training and testing sets, with 300 mel-spectrograms per digit in the training set and 30 mel-spectrograms per digit in the testing set (2700 - 300).

Convert audio (.wav) dataset to melspectrogram (.npy) dataset

In [22]:
```
import os
import librosa
import numpy as np
from sklearn.model_selection import train_test_split


# Melspectrogram parameters
sr = 22050
n_fft = 2048
hop_length = 512
n_mels = 128
fixed_length = 8000

# Original dataset path (.wav files)
```

```
audio_folder = 'recordings/'

# Function to convert audio to melspectrogram
def process_audio(file_path, sr=22050):
    y, sr = librosa.load(file_path, sr=sr)
    y = librosa.util.fix_length(y, size=fixed_length)
    mel = librosa.feature.melspectrogram(y=y, sr=sr, n_fft=n_fft, hop_length
    return mel

# List to store the melspectrograms
X = []

# Iterate over each audio file in the folder
for filename in os.listdir(audio_folder):
    if filename.endswith('.wav'):
        file_path = os.path.join(audio_folder, filename)
        mel = process_audio(file_path)
        X.append(mel)

X = np.array(X)
np.save('X.npy', X)

# Split the dataset into train set and test set, then save as .npy files
X_train, X_test = train_test_split(X, test_size=0.1, random_state=42)
np.save('train_data.npy', X_train)
np.save('test_data.npy', X_test)

# (2700, 128, 16), (300, 128, 16)
print("Shape of train_data:", X_train.shape)
print("Shape of test_data:", X_test.shape)

# Save the train set and test set as a .npz file
np.savez('dataset.npz', train_data=X_train, test_data=X_test)
```

```
Shape of train_data: (2700, 128, 16)
Shape of test_data: (300, 128, 16)
```

Pre-process and load data

In [75]:

```
import numpy as np

# Normalization and reshape
def preprocess(array: np.array):
    array = array.astype("float32")/255.0
    array = np.reshape(array, (len(array), 128, 16, 1))
    print("Final Shape:", array.shape)

    return array

# Add random noise to the numpy array (Gaussian noise)
def noise(array):
    noise_factor = 0.00000005
    noise_array = array + noise_factor * \
        np.random.normal(loc=0.0, scale=1, size=array.shape)

    return np.clip(noise_array, 0.0, 1.0)
```

```
# With this function we can load our data from dataset.npz, which has train_
def load_data(path="dataset.npz"):
    with np.load("dataset.npz", allow_pickle=True) as f:
        train_data, test_data = f['train_data'], f['test_data']

    print(train_data.shape)
    # (2700, 128, 16)
    print(test_data.shape)
    # (300, 128, 16)

    train_data = preprocess(train_data)
    test_data = preprocess(test_data)

    return train_data, test_data


# Load the data
train_data, test_data = load_data()

# Create a copy of the train and test data with noise, this is going to be i
noisy_train_data = noise(train_data)
noisy_test_data = noise(test_data)
```

```
(2700, 128, 16)
(300, 128, 16)
Final Shape: (2700, 128, 16, 1)
Final Shape: (300, 128, 16, 1)
```

Model Architecture

We design a CNN-based autoencoder architecture tailored for processing mel-spectrograms. The encoder part of the network consists of convolutional layers followed by max-pooling layers to progressively reduce the dimensionality of the input mel-spectrograms. The decoder part mirrors the encoder, using transposed convolutional layers to upsample the encoded features back to the original dimensions.

In [2]:

```
from tensorflow import keras
from keras import layers, models

# CNN Autoencoder model for processing melspectrograms (with (128, 16) shape
def build_model(input_shape=(128, 16, 1)):
    input = layers.Input(shape=input_shape)

    # Encoder
    x = layers.Conv2D(32, (3, 3), activation='relu', padding='same', name="C
    x = layers.MaxPooling2D((2, 2), padding='same', name='Pool1')(x)
    x = layers.Conv2D(64, (3, 3), activation='relu', padding='same', name='C
    x = layers.MaxPooling2D((2, 2), padding='same', name='Pool2')(x)

    # Decoder
    x = layers.Conv2DTranspose(64, (3, 3), strides=2, activation='relu', pad
    x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation='relu', pad
    output = layers.Conv2D(1, (3, 3), activation='sigmoid', padding='same',
```

```
    autoencoder = models.Model(input, output, name='AutoEncoder-Model')
    autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

    return autoencoder


# Build the model and show summary
model = build_model()
model.summary()
```

```
Model: "AutoEncoder-Model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_2 (InputLayer)        [(None, 128, 16, 1)]      0         
                                                                 
 Conv1 (Conv2D)              (None, 128, 16, 32)       320       
                                                                 
 Pool1 (MaxPooling2D)        (None, 64, 8, 32)         0         
                                                                 
 Conv2 (Conv2D)              (None, 64, 8, 64)         18496     
                                                                 
 Pool2 (MaxPooling2D)        (None, 32, 4, 64)         0         
                                                                 
 Conv1_transpose (Conv2DTra  (None, 64, 8, 64)         36928     
 nspose)                                                         
                                                                 
 Conv2_transpose (Conv2DTra  (None, 128, 16, 32)       18464     
 nspose)                                                         
                                                                 
 output_layer (Conv2D)       (None, 128, 16, 1)        289       
                                                                 
=================================================================
Total params: 74497 (291.00 KB)
Trainable params: 74497 (291.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Training

The autoencoder is trained using the noisy mel-spectrograms as input and the clean mel-spectrograms as the target output. We introduce random noise to the input mel-spectrograms to simulate real-world noisy audio signals. The model is trained using the Adam optimizer and binary cross-entropy loss function.

In [3]:
```
# Training of the model
def train_model(checkpoint_dir="tmp", monitor="val_loss"):
    autoencoder = build_model()
    autoencoder.summary()

    early_stopping = keras.callbacks.EarlyStopping(
        monitor=monitor,
        patience=5,
```

```
        restore_best_weights=True)

    model_checkpoint = keras.callbacks.ModelCheckpoint(
        checkpoint_dir,
        monitor=monitor,
        verbose=0,
        save_best_only=True,
        save_weights_only=False,
        mode="auto",
        save_freq="epoch",
        options=None)

    autoencoder.fit(
        x=noisy_train_data,
        y=train_data,
        epochs=20,
        batch_size=128,
        shuffle=True,
        validation_data=(noisy_test_data, test_data),
        callbacks=[early_stopping, model_checkpoint])

    autoencoder.save('saved_model')
```

Results

After training the autoencoder, we evaluate its performance by comparing the denoised mel-spectrograms generated by the model with the original clean mel-spectrograms. We visualize the results to assess the effectiveness of the denoising process and measure the quality of the reconstructed mel-spectrograms.

In [7]:

```
from matplotlib import pyplot as plt
import librosa

def display_melspectrogram(noisy_mel, denoised_mel, sr=22050, n=5):
    """
    Display multiple comparisons of melspectrograms with noise and denoised

    Args:
    - noisy_mel: Melspectrograms with noise (shape: [num_samples, 128, 16, 1
    - denoised_mel: Denoised melspectrograms (shape: [num_samples, 128, 16,
    - sr: Sample rate (default is 22050).
    - n: Number of comparisons to display.
    """

    # Select random indexes for showing random test data
    indices = np.random.randint(len(noisy_mel), size=n)

    fig, axes = plt.subplots(2, n, figsize=(16, 8))
    fig.suptitle('Comparison of Noisy and Denoised Melspectrograms', fontsiz

    for i, index in enumerate(indices):

        noisy_mel_dB = librosa.power_to_db(noisy_mel[index, :, :, 0], ref=np
        denoised_mel_dB = librosa.power_to_db(denoised_mel[index, :, :, 0],
```

```
        # Show noisy melspectrogram
        librosa.display.specshow(noisy_mel_dB, sr=sr, x_axis='time', y_axis=
        axes[0, i].set(title=f'Noisy {index+1}')

        # Show denoised melspectrogram
        librosa.display.specshow(denoised_mel_dB, sr=sr, x_axis='time', y_ax
        axes[1, i].set(title=f'Denoised {index+1}')

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()


def show_output():
    try:
        autoencoder = keras.models.load_model(
            "saved_model")  # Load model from 'tmp' folder
    except Exception:
        print("There is no model in the 'tmp' folder, please train the model

    predictions = autoencoder.predict(noisy_test_data[..., np.newaxis])
    display_melspectrogram(noisy_test_data, predictions)
```

In [9]:
```
train_model()
```

```
Model: "AutoEncoder-Model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_5 (InputLayer)        [(None, 128, 16, 1)]      0

 Conv1 (Conv2D)              (None, 128, 16, 32)       320

 Pool1 (MaxPooling2D)        (None, 64, 8, 32)         0

 Conv2 (Conv2D)              (None, 64, 8, 64)         18496

 Pool2 (MaxPooling2D)        (None, 32, 4, 64)         0

 Conv1_transpose (Conv2DTra  (None, 64, 8, 64)         36928
 nspose)

 Conv2_transpose (Conv2DTra  (None, 128, 16, 32)       18464
 nspose)

 output_layer (Conv2D)       (None, 128, 16, 1)        289

=================================================================
Total params: 74497 (291.00 KB)
Trainable params: 74497 (291.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/20
15/22 [===================>..........] - ETA: 0s - loss: 0.6478INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
```

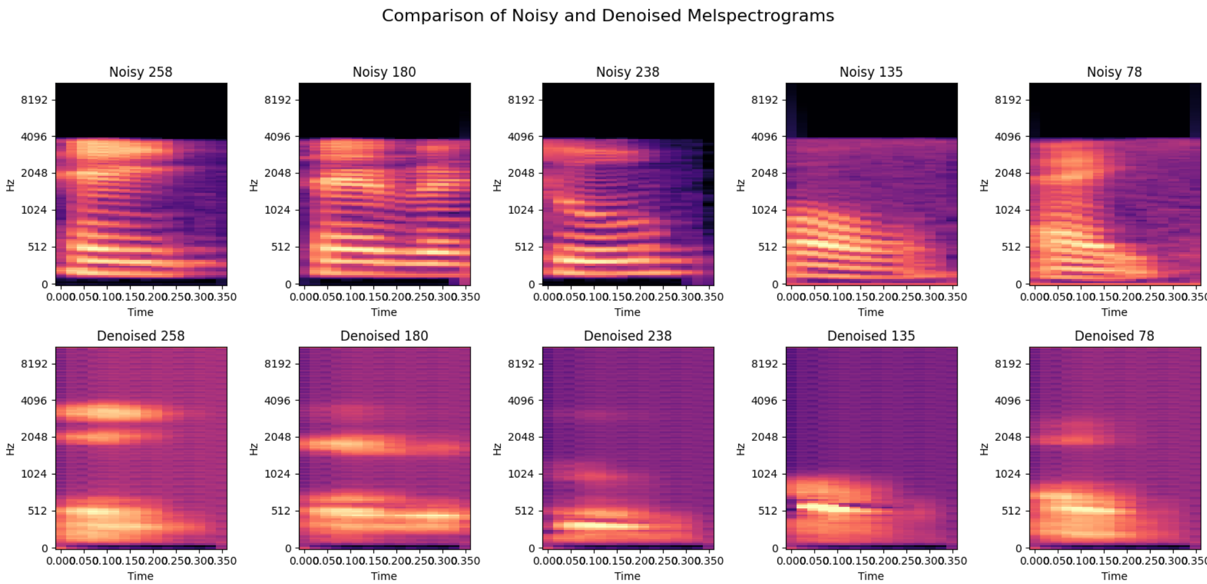
```
22/22 [==============================] - 1s 28ms/step - loss: 0.5680 - val_l
oss: 0.1307
Epoch 2/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0895INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 0s 23ms/step - loss: 0.0862 - val_l
oss: 0.0559
Epoch 3/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0441INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 30ms/step - loss: 0.0412 - val_l
oss: 0.0295
Epoch 4/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0262INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 25ms/step - loss: 0.0244 - val_l
oss: 0.0178
Epoch 5/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0169INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0164 - val_l
oss: 0.0146
Epoch 6/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0148INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0148 - val_l
oss: 0.0137
Epoch 7/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0139INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0141 - val_l
oss: 0.0132
Epoch 8/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0136INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0135 - val_l
oss: 0.0127
Epoch 9/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0132INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 31ms/step - loss: 0.0129 - val_l
oss: 0.0122
Epoch 10/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0124INFO:tensorfl
ow:Assets written to: tmp/assets
```

```
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0124 - val_l
oss: 0.0118
Epoch 11/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0122INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0120 - val_l
oss: 0.0114
Epoch 12/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0114INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0115 - val_l
oss: 0.0111
Epoch 13/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0113INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 25ms/step - loss: 0.0112 - val_l
oss: 0.0108
Epoch 14/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0106INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0108 - val_l
oss: 0.0105
Epoch 15/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0106INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0104 - val_l
oss: 0.0104
Epoch 16/20
16/22 [====================>.........] - ETA: 0s - loss: 0.0100INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 33ms/step - loss: 0.0099 - val_l
oss: 0.0100
Epoch 17/20
22/22 [==============================] - 0s 8ms/step - loss: 0.0094 - val_lo
ss: 0.0100
Epoch 18/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0097INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0089 - val_l
oss: 0.0095
Epoch 19/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0076INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
```

```
22/22 [==============================] - 1s 24ms/step - loss: 0.0080 - val_l
oss: 0.0089
Epoch 20/20
15/22 [===================>..........] - ETA: 0s - loss: 0.0074INFO:tensorfl
ow:Assets written to: tmp/assets
INFO:tensorflow:Assets written to: tmp/assets
22/22 [==============================] - 1s 24ms/step - loss: 0.0068 - val_l
oss: 0.0088
INFO:tensorflow:Assets written to: saved_model/assets
INFO:tensorflow:Assets written to: saved_model/assets
```

In [16]:
```python
show_output()
```

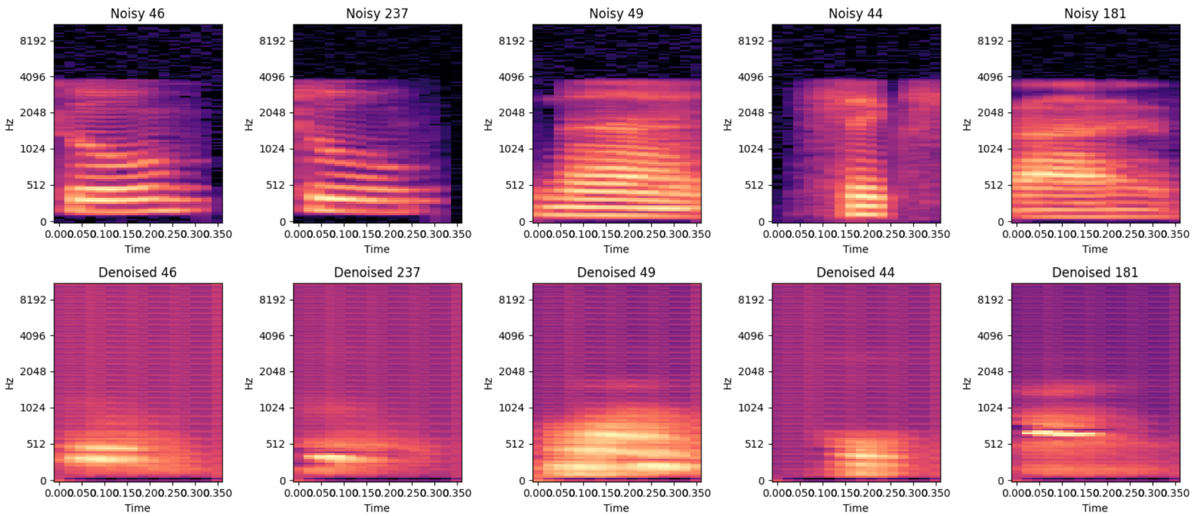
```
10/10 [==============================] - 0s 1ms/step
```



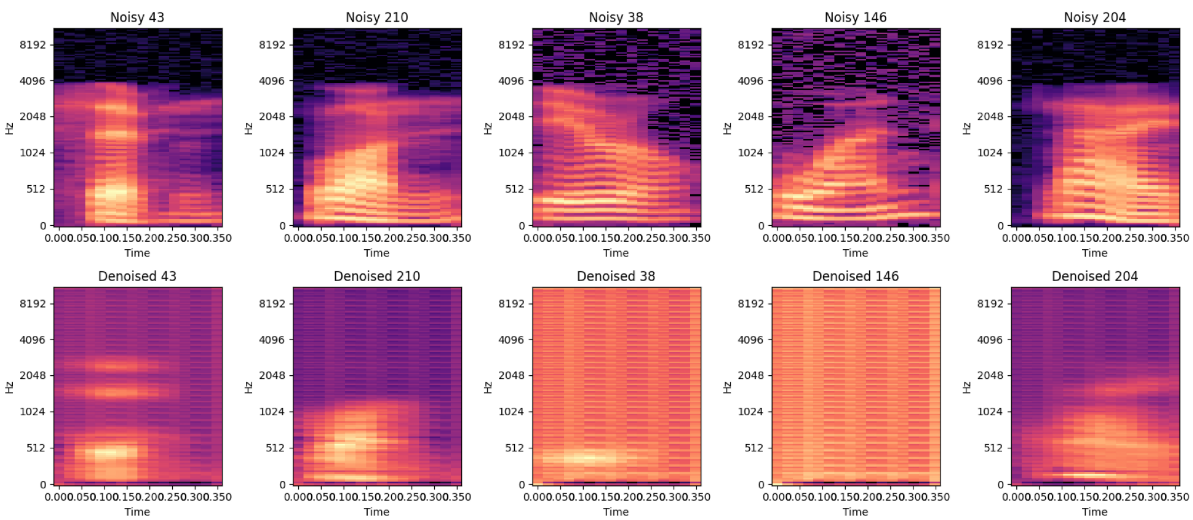
Some other results

In [17]:
```python
from matplotlib.image import imread

image_paths = ['Figure_5.png', 'Figure_4.png', 'Figure_3.png', 'Figure_2.png

plt.figure(figsize=(25, 50))

for i, image_path in enumerate(image_paths, start=1):
    plt.subplot(len(image_paths), 1, i)
    image = imread(image_path)
    plt.imshow(image)
    plt.axis('off')

plt.tight_layout()
plt.show()
```

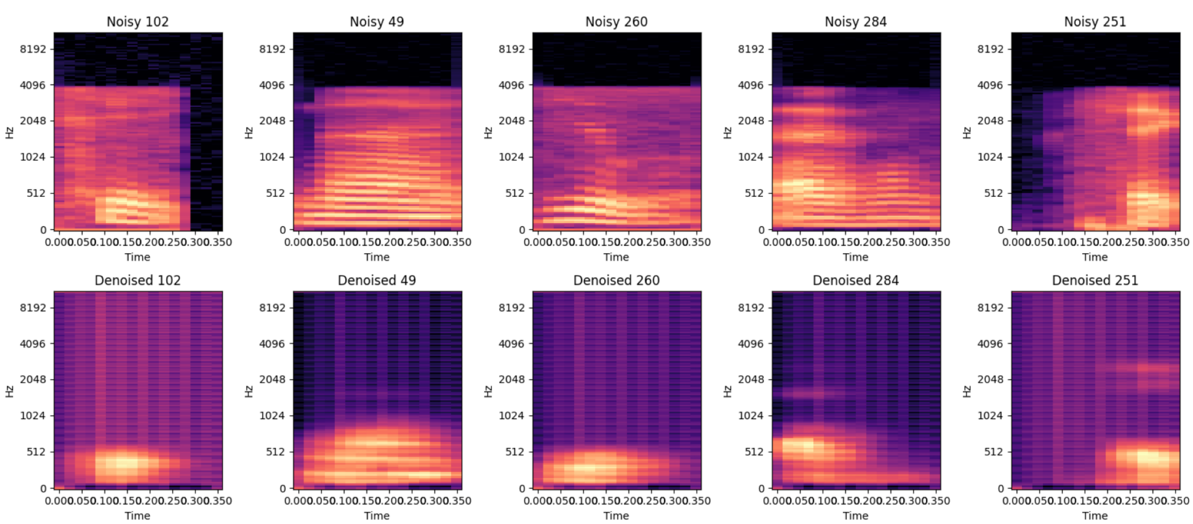
Comparison of Noisy and Denoised Melspectrograms



Comparison of Noisy and Denoised Melspectrograms

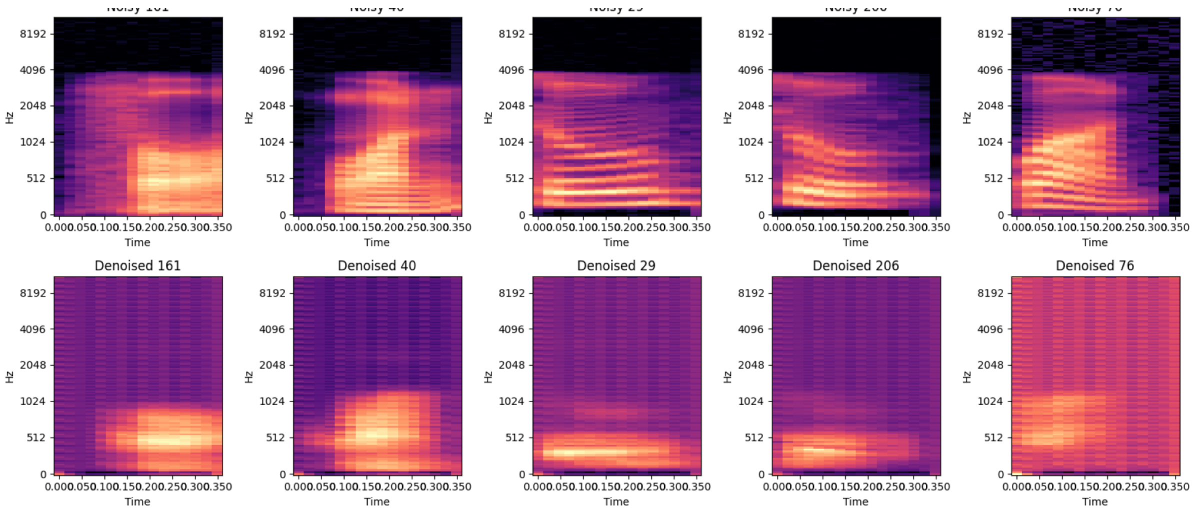


Comparison of Noisy and Denoised Melspectrograms

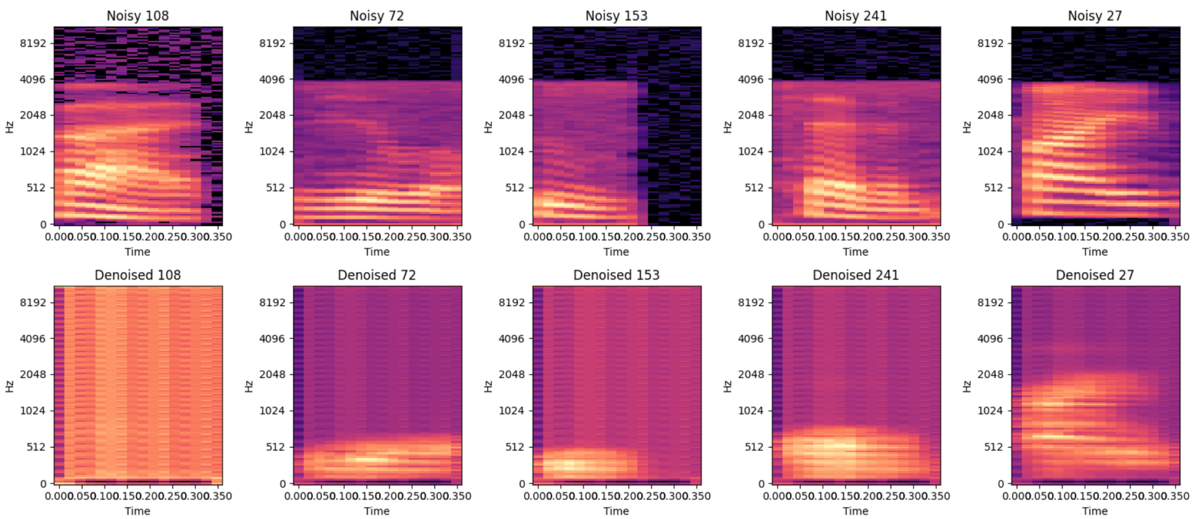


Comparison of Noisy and Denoised Melspectrograms

Noisy 161 Noisy 40 Noisy 29 Noisy 206 Noisy 76



Comparison of Noisy and Denoised Melspectrograms



Inference test for audio denoising

In [42]:
```
import IPython.display as ipd

audio, sr = librosa.load("recordings/0_george_0.wav")
ipd.Audio(audio, rate=sr)
```

Out[42]: 0:00 / 0:00

In [77]:
```
noisy_audio = noise(audio)
ipd.Audio(noisy_audio, rate = sr)
```

Out[77]: 0:00 / 0:00

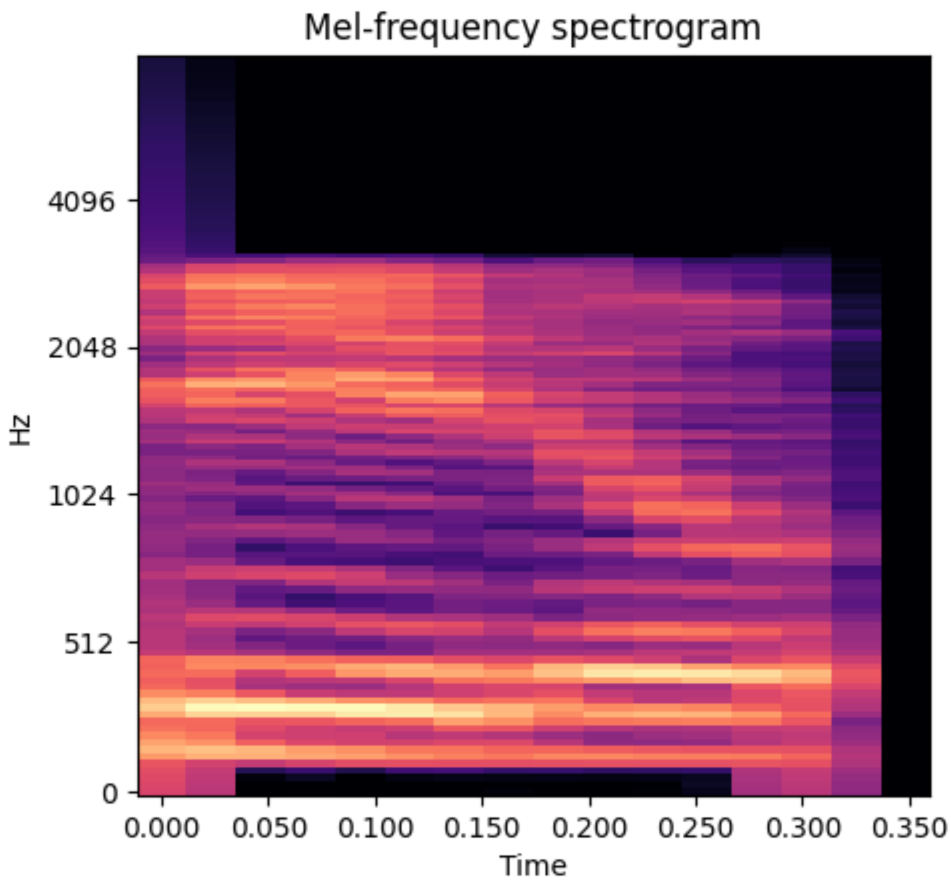
In [44]:
```
audio_to_mel = process_audio("recordings/0_george_0.wav")
```

In [45]:
```
audio_to_mel.shape
```

Out[45]:
```
(128, 16)
```

In [46]:
```
fig, ax = plt.subplots()
S_dB = librosa.power_to_db(audio_to_mel, ref=np.max)
img = librosa.display.specshow(S_dB, x_axis='time',
                               y_axis='mel', sr=sr,
                               fmax=8000, ax=ax)
fig.colorbar(img, ax=ax, format='%+2.0f dB')
ax.set(title='Mel-frequency spectrogram')
```

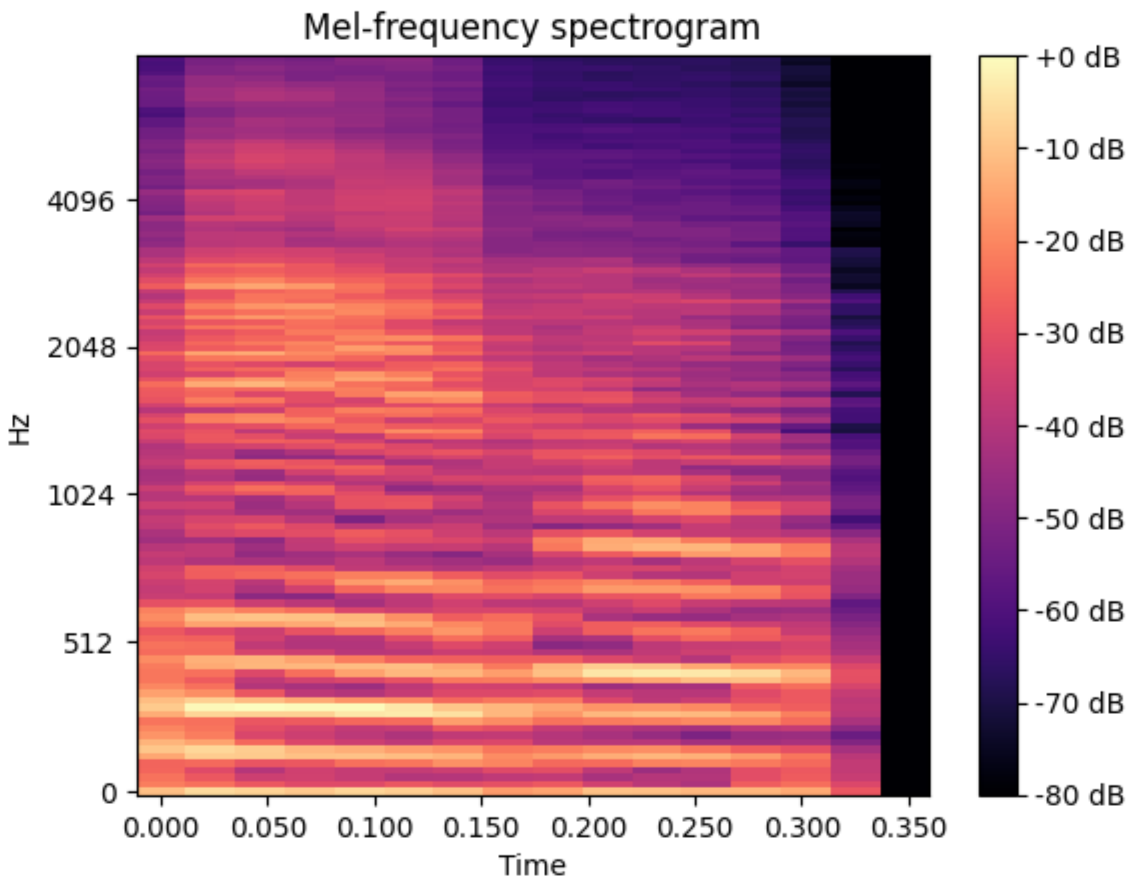
Out[46]:
```
[Text(0.5, 1.0, 'Mel-frequency spectrogram')]
```



In [47]:
```
noisy_audio = librosa.util.fix_length(noisy_audio, size=fixed_length)
noisy_audio_to_mel = librosa.feature.melspectrogram(y=noisy_audio, sr=sr, n_
```

In [48]:
```
fig, ax = plt.subplots()
S_dB = librosa.power_to_db(noisy_audio_to_mel, ref=np.max)
img = librosa.display.specshow(S_dB, x_axis='time',
                               y_axis='mel', sr=sr,
                               fmax=8000, ax=ax)
fig.colorbar(img, ax=ax, format='%+2.0f dB')
ax.set(title='Mel-frequency spectrogram')
```

Out[48]:
```
[Text(0.5, 1.0, 'Mel-frequency spectrogram')]
```



In [49]:
```
import tensorflow as tf
import numpy as np

noisy_audio_to_mel = np.expand_dims(noisy_audio_to_mel, axis=0)
prediction = autoencoder(noisy_audio_to_mel)
```

In [52]:
```
prediction.shape
```

Out[52]:
```
TensorShape([1, 128, 16, 1])
```

In [55]:
```
prediction = np.squeeze(prediction)
```

In [56]:
```
prediction.shape
```

Out[56]:
```
(128, 16)
```

In [76]:
```
# Original noisy audio
ipd.Audio(noisy_audio, rate = sr)
```

Out[76]:

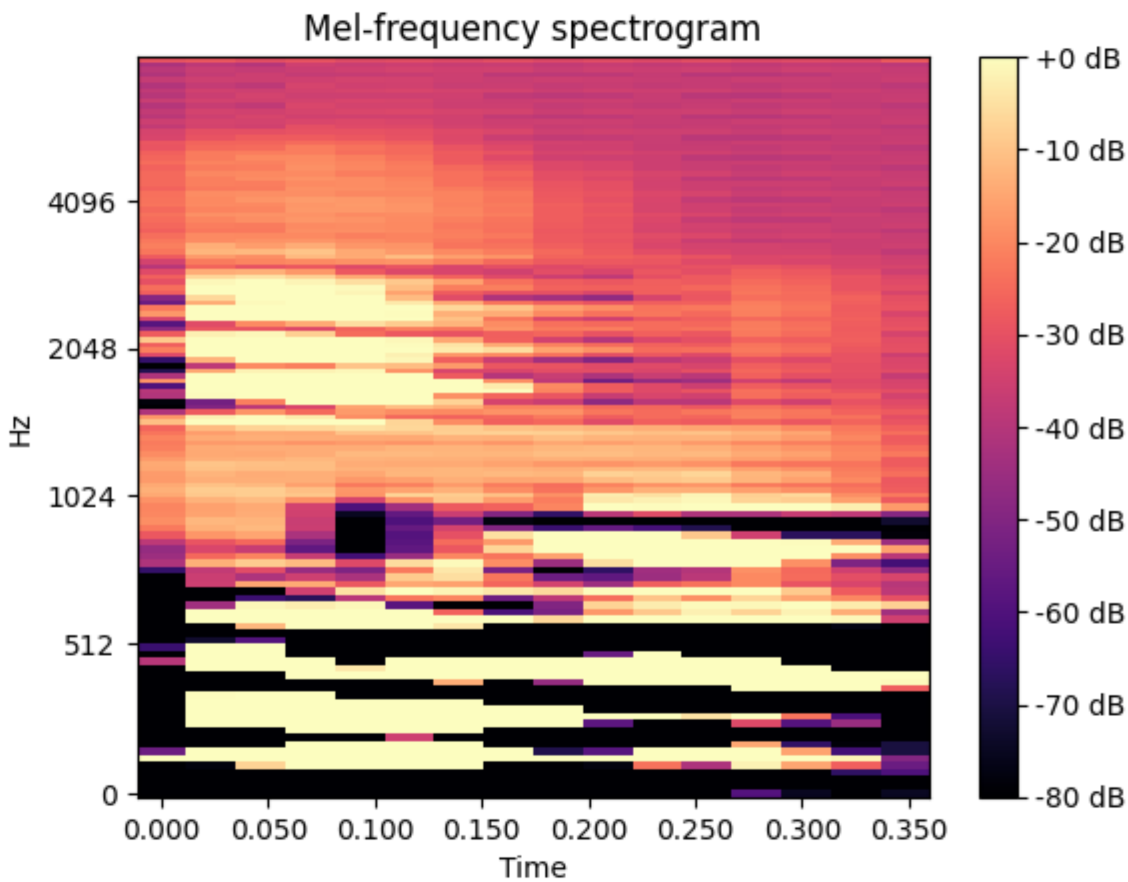
0:00 / 0:00

In [67]:
```
import soundfile as sf

def reconstruct_audio(mel, sr, hop_length, n_mels):
  mel_reconstructed = mel[:n_mels, :]
```

```
    reconstructed_audio = librosa.feature.inverse.mel_to_audio(mel_reconstruct
    sf.write('audio_reconstruido.wav', reconstructed_audio, sr)

    return reconstructed_audio

mel_to_audio = reconstruct_audio(prediction, sr, hop_length, n_mels)
```

In [57]:
```
fig, ax = plt.subplots()
S_dB = librosa.power_to_db(prediction, ref=np.max)
img = librosa.display.specshow(S_dB, x_axis='time',
                         y_axis='mel', sr=sr,
                         fmax=8000, ax=ax)
fig.colorbar(img, ax=ax, format='%+2.0f dB')
ax.set(title='Mel-frequency spectrogram')
```

Out[57]: [Text(0.5, 1.0, 'Mel-frequency spectrogram')]



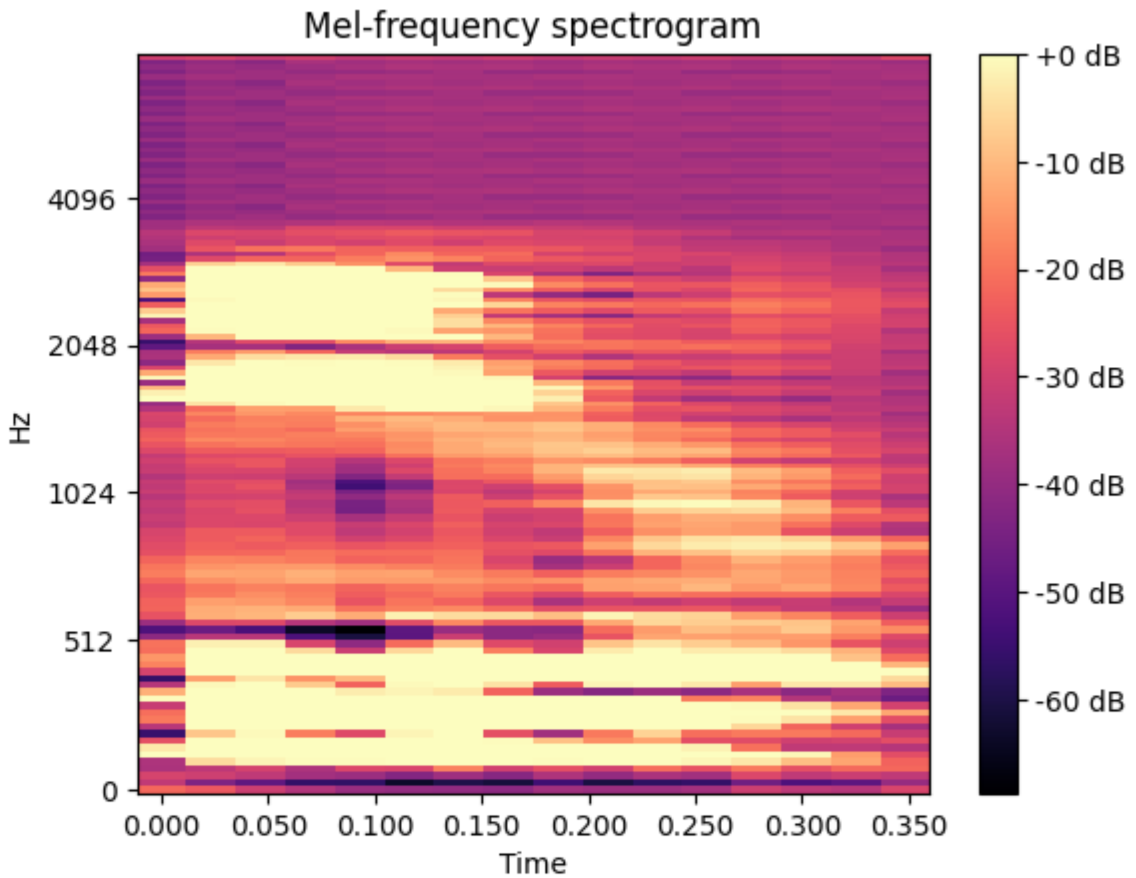
In [66]:
```
ipd.Audio(mel_to_audio, rate = sr)
```

Out[66]: 0:00 / 0:00

In [68]:
```
noisy_mel = noise(audio_to_mel)
noisy_mel = np.expand_dims(noisy_mel, axis=0)
denoised_mel = autoencoder(noisy_mel)
denoised_mel = np.squeeze(denoised_mel)

denoised_mel_to_audio = reconstruct_audio(denoised_mel, sr, hop_length, n_me
```

In [69]:
```
fig, ax = plt.subplots()
S_dB = librosa.power_to_db(denoised_mel, ref=np.max)
img = librosa.display.specshow(S_dB, x_axis='time',
                         y_axis='mel', sr=sr,
                         fmax=8000, ax=ax)
fig.colorbar(img, ax=ax, format='%+2.0f dB')
ax.set(title='Mel-frequency spectrogram')
```

Out[69]:
```
[Text(0.5, 1.0, 'Mel-frequency spectrogram')]
```



In [71]:
```
ipd.Audio(denoised_mel_to_audio, rate = sr)
```

Out[71]: 0:00 / 0:00

In [ ]: