speech-recognition-assignment

May 15, 2023

Name1: Ali Hassan Ali Ahmed ElSharawy - ID1: 19016013

Name2: Ziad Mohamed Abuelkher - ID2: 19015733

Name3: Youssef Magdy Helmy - ID3: 19016937

[ ]:
```python
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np
import os
from scipy.io import wavfile
# ! pip install pydub
import matplotlib.pyplot as plt
import librosa.display
from pydub import AudioSegment
import IPython
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Conv1D, MaxPooling1D, Flatten,␣
↪Dense, Dropout, Activation, BatchNormalization
from sklearn.preprocessing import StandardScaler
from tensorflow import keras
from tensorflow.keras.layers import *
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.regularizers import l2
```

walk through the dataset

[ ]:
```python
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

useful function to treat with data

```
[3]: def read_audio(filepath):
         data, sampling_rate = librosa.load(filepath, sr=None)
         return data, sampling_rate


     def plot_audio(filepath):
         data, sampling_rate = read_audio(filepath)
         plt.figure(figsize=(15, 5))
         plt.title('Waveform plot')
         plt.xlabel('Time (seconds)')
         plt.ylabel('Amplitude')
         librosa.display.waveshow(data, sr=sampling_rate)

     def plot_audio_data(data):
         plt.figure(figsize=(15, 5))
         plt.title('Waveform plot')
         plt.xlabel('Time (seconds)')
         plt.ylabel('Amplitude')
         librosa.display.waveshow(data)


     def play_audio(filepath):
         return IPython.display.Audio(filepath)
```

read files and sort directory list

```
[4]: path = '/kaggle/input/speech-emotion-recognition-en/Crema'
     dir_list = os.listdir(path)
     dir_list.sort()
     print(dir_list[0:10])
```

```
['1001_DFA_ANG_XX.wav', '1001_DFA_DIS_XX.wav', '1001_DFA_FEA_XX.wav',
'1001_DFA_HAP_XX.wav', '1001_DFA_NEU_XX.wav', '1001_DFA_SAD_XX.wav',
'1001_IEO_ANG_HI.wav', '1001_IEO_ANG_LO.wav', '1001_IEO_ANG_MD.wav',
'1001_IEO_DIS_HI.wav']
```

define emotions in data set

```
[5]: emotions = []
     for filename in dir_list:
         emotions.append(filename.split('_')[2])
     print(set(emotions))
```

```
{'NEU', 'DIS', 'ANG', 'FEA', 'HAP', 'SAD'}
```

we have 6 different emothions in our dataset: * ANG : angry * NEU : neutral * HAP : happy * SAD : sad * DIS : disgust * FEA : fear map every emotion to number

[6]:
```python
dic = {'ANG' : 0, 'NEU' : 1, 'HAP' : 2, 'SAD' : 3, 'DIS' : 4, 'FEA' : 5}
```

read data from data set and store in lists : data, sample_rate, labels and extract labels from files name

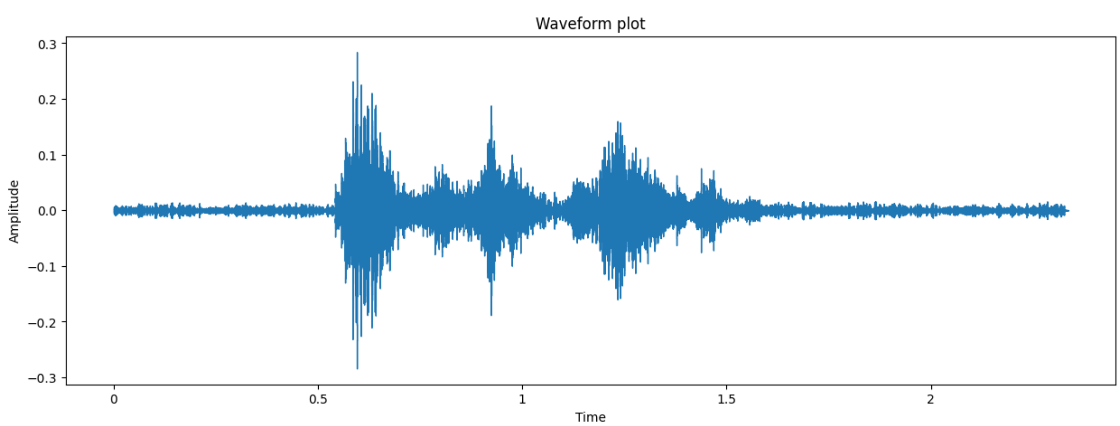
[7]:
```python
data = []
sample_rate = []
labels = []
for filename in dir_list:
    record, s = read_audio(path+'/'+filename)
    sample_rate.append(s)
    data.append(record)
    labels.append(dic[filename.split('_')[2]])
```

get familiar with data and try to chane i to get different samples and look at different features

[8]:
```python
i = 1   # free to change it to display different audio and see wave form
p = path+'/'+dir_list[i]
emotion = dir_list[i].split('_')
print("emotion : ", emotion[2])
plot_audio(p)
IPython.display.Audio(p)
```

```
emotion :  DIS
```

[8]:
```
<IPython.lib.display.Audio object>
```

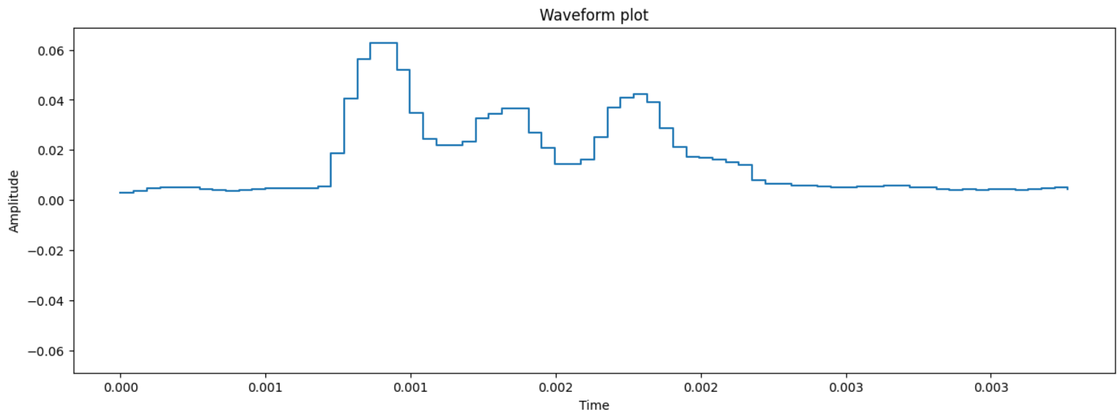


default rms in librose package

[9]:
```python
energy = librosa.feature.rms(y=data[i])
plot_audio_data(energy)
print(energy.shape)
```

```
print(data[i].shape)
```

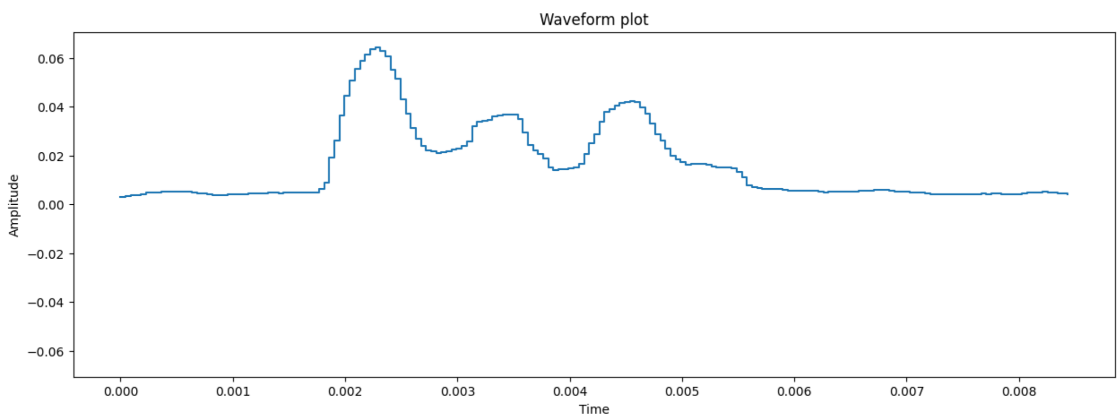
```
(1, 73)
(37371,)
```



we need to get optimal values of frame_length, hop_length to get features of data good enough for training and don't lose information

```
[10]: energy = librosa.feature.rms(y=data[i],frame_length=2048,hop_length=200)
plot_audio_data(energy)
print(energy.shape)
```

```
(1, 187)
```

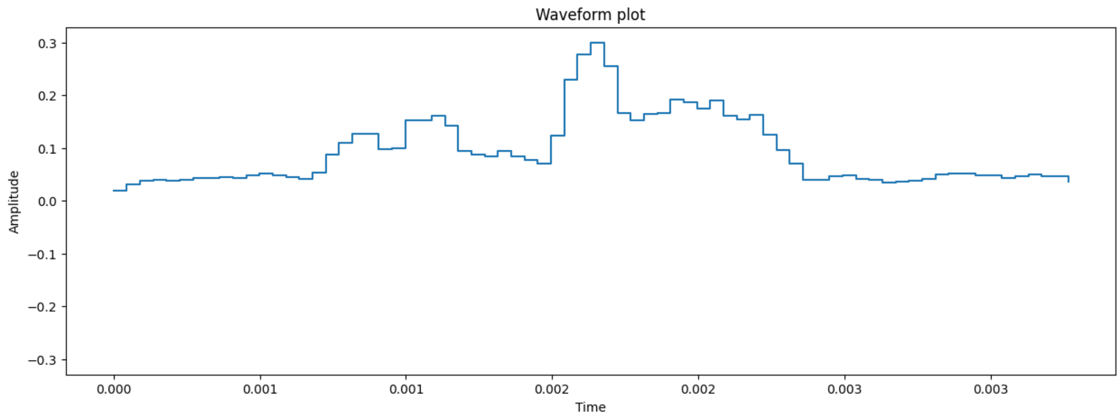


default zero crossing rate

```
[11]: zrc = librosa.feature.zero_crossing_rate(y=data[i])
plot_audio_data(zrc)
```

```
print(zrc.shape)
```

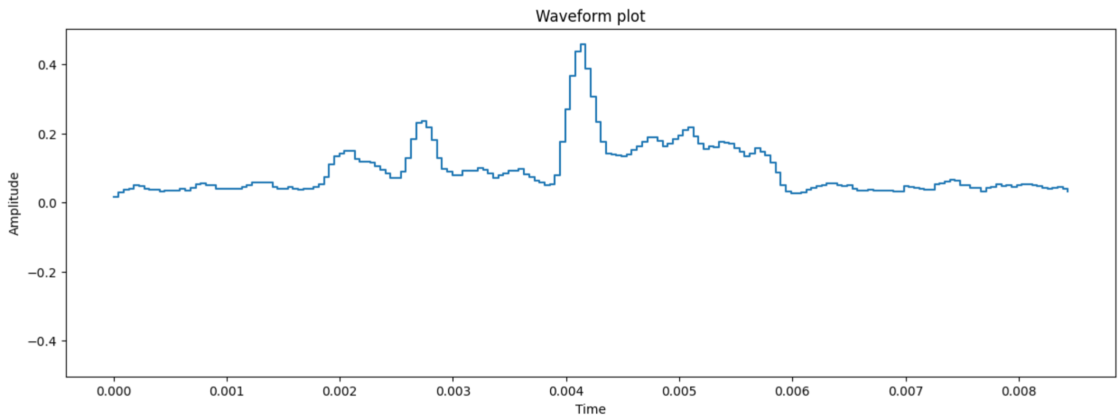
```
(1, 73)
```



we need to get optimal values of frame_length, hop_length to get features of data good enough for training and don't lose information

[12]:
```
zrc = librosa.feature.
 ↪zero_crossing_rate(y=data[i],frame_length=1000,hop_length=200)
plot_audio_data(zrc)
print(zrc.shape)
```

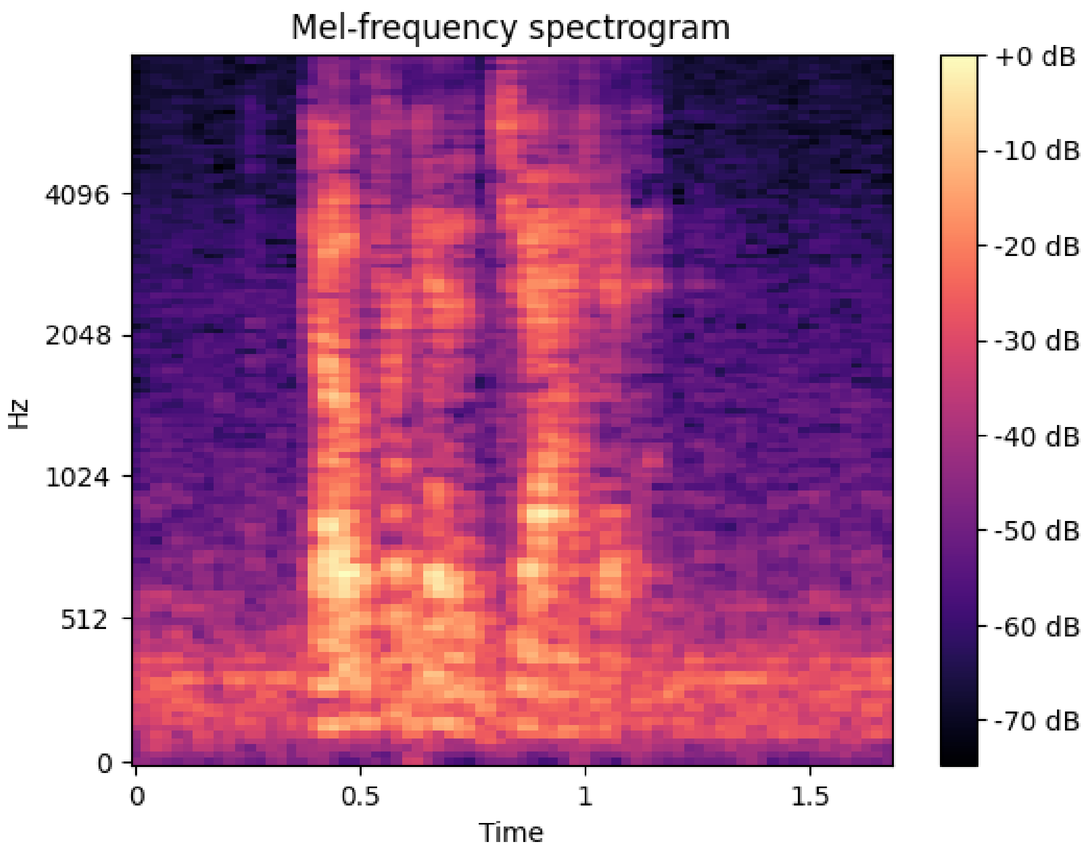
```
(1, 187)
```



melspectrogram in librosa package

[13]:
```
S = librosa.feature.melspectrogram(y=data[i], n_mels=128, fmax=8000,␣
 ↪n_fft=2048, hop_length=512)
```

```
# Convert to decibels
S_dB = librosa.power_to_db(S, ref=np.max)

# Display Mel spectrogram
librosa.display.specshow(S_dB, x_axis='time', y_axis='mel', fmax=8000)
plt.colorbar(format='%+2.0f dB')
plt.title('Mel-frequency spectrogram')
plt.show()
print(S_dB.shape)
```




```
(128, 73)
```

we need to make all data has same length to be able to train data and do different operation on it

get max data file size to make all files has same lenght by padding we add zeros from back

[14]:
```
max_len = 0
min_len = float('inf')

# loop over the list and update max and min lengths
```

```python
for arr in data:
    length = len(arr)
    if length > max_len:
        max_len = length
    if length < min_len:
        min_len = length

print("Max length:", max_len)
print("Min length:", min_len)
```

```
Max length: 80080
Min length: 20287
```

[15]:
```python
padded_data = []
for signal in data:
    pad_width = max_len - len(signal)
    padded_signal = np.pad(signal, (0, pad_width), mode='constant')
    padded_data.append(padded_signal)
```

we store data in padded form so all data has same size

[16]:
```python
IPython.display.Audio(padded_data[8], rate = 20000)
```

[16]: <IPython.lib.display.Audio object>

[17]:
```python
IPython.display.Audio(padded_data[13], rate = 20000)
```

[17]: <IPython.lib.display.Audio object>

Creare Featues Space from data

[18]:
```python
data_rms = []
data_zcr = []
data_mel = []

for audio in padded_data:
    data_rms.append(librosa.feature.
 ↪rms(y=audio,frame_length=2048,hop_length=200))

for audio in padded_data:
    data_zcr.append(librosa.feature.
 ↪zero_crossing_rate(y=audio,frame_length=1000,hop_length=200))

for audio in padded_data:
    S = librosa.feature.melspectrogram(y=audio, n_mels=128, fmax=8000,␣
 ↪n_fft=2048, hop_length=512)
    S_dB = librosa.power_to_db(S, ref=np.max)
    data_mel.append(S_dB)
```

split data into trainig, test and validation

[19]:
```
data_train_val_rms, data_test_rms, label_train_val_rms, label_test_rms = train_test_split(data_rms, labels, test_size=0.3, random_state=42)
data_train_val_zcr, data_test_zcr, label_train_val_zcr, label_test_zcr = train_test_split(data_zcr, labels, test_size=0.3, random_state=42)
data_train_val_mel, data_test_mel, label_train_val_mel, label_test_mel = train_test_split(data_mel, labels, test_size=0.3, random_state=42)

data_train_rms, data_val_rms, label_train_rms, label_val_rms = train_test_split(data_train_val_rms, label_train_val_rms, test_size=0.05, random_state=42)
data_train_zcr, data_val_zcr, label_train_zcr, label_val_zcr = train_test_split(data_train_val_zcr, label_train_val_zcr, test_size=0.05, random_state=42)
data_train_mel, data_val_mel, label_train_mel, label_val_mel = train_test_split(data_train_val_mel, label_train_val_mel, test_size=0.05, random_state=42)
```

[20]:
```
sample_train_val, sample_test, label_train_val_sample, label_test_sample = train_test_split(sample_rate, labels, test_size=0.3, random_state=42)
sample_train, sample_val, label_train_sample, label_val_sample = train_test_split(sample_train_val, label_train_val_sample, test_size=0.05, random_state=42)
```

normalize data and convert to numpy array

[21]:
```
data_train_rms = np.array(data_train_rms)
data_test_rms = np.array(data_test_rms)
label_train_rms = np.array(label_train_rms)
label_test_rms = np.array(label_test_rms)
data_val_rms = np.array(data_val_rms)
label_val_rms = np.array(label_val_rms)


data_train_zcr = np.array(data_train_zcr)
data_test_zcr = np.array(data_test_zcr)
label_train_zcr = np.array(label_train_zcr)
label_test_zcr = np.array(label_test_zcr)
data_val_zcr = np.array(data_val_zcr)
label_val_zcr = np.array(label_val_zcr)

train_data_mel = np.array(data_train_mel)
data_test_mel = np.array(data_test_mel)
train_label_mel = np.array(label_train_mel)
label_test_mel = np.array(label_test_mel)
cv_data_mel = np.array(data_val_mel)
```

```
cv_label_mel = np.array(label_val_mel)
```

we will use sample rate as feature

[22]:
```
sample_train = np.array(sample_train)
sample_val = np.array(sample_val)
label_train_sample = np.array(label_train_sample)
label_val_sample = np.array(label_val_sample)

sample_test = np.array(sample_test)
label_test_sample = np.array(label_test_sample)
```

[23]:
```
print(sample_train.shape)
print(sample_val.shape)
print(sample_test.shape)
```

```
(4948,)
(261,)
(2233,)
```

normalize data

normalize rms feature

[24]:
```
rms_train_reshape = data_train_rms.reshape(data_train_rms.
 ↪shape[0],data_train_rms.shape[2])
rms_val_reshape = data_val_rms.reshape(data_val_rms.shape[0],data_val_rms.
 ↪shape[2])
rms_test_reshape = data_test_rms.reshape(data_test_rms.shape[0],data_test_rms.
 ↪shape[2])

scaler_rms = StandardScaler()
data_train_rms_norm = scaler_rms.fit_transform(rms_train_reshape)
data_train_rms_norm = scaler_rms.transform(rms_train_reshape)
data_test_rms_norm = scaler_rms.transform(rms_test_reshape)
data_val_rms_norm = scaler_rms.transform(rms_val_reshape)
```

[25]:
```
print(data_train_rms_norm.shape)
print(data_test_rms_norm.shape)
print(data_val_rms_norm.shape)
```

```
(4948, 401)
(2233, 401)
(261, 401)
```

[26]:
```
data_train_rms_norm = data_train_rms_norm.reshape((data_train_rms_norm.
 ↪shape[0],data_train_rms_norm.shape[1],1))
data_test_rms_norm = data_test_rms_norm.reshape((data_test_rms_norm.
 ↪shape[0],data_test_rms_norm.shape[1],1))
```

```
data_val_rms_norm = data_val_rms_norm.reshape((data_val_rms_norm.
  ↪shape[0],data_val_rms_norm.shape[1],1))
```

normalize zcr feature

[27]:
```
zcr_train_reshape = data_train_zcr.reshape(data_train_zcr.
  ↪shape[0],data_train_zcr.shape[2])
zcr_val_reshape = data_val_zcr.reshape(data_val_zcr.shape[0],data_val_zcr.
  ↪shape[2])
zcr_test_reshape = data_test_zcr.reshape(data_test_zcr.shape[0],data_test_zcr.
  ↪shape[2])

scaler_zcr = StandardScaler()
data_train_zcr_norm = scaler_zcr.fit_transform(zcr_train_reshape)
data_train_zcr_norm = scaler_zcr.transform(zcr_train_reshape)
data_test_zcr_norm = scaler_zcr.transform(zcr_test_reshape)
data_val_zcr_norm = scaler_zcr.transform(zcr_val_reshape)
```

[28]:
```
print(data_train_zcr_norm.shape)
print(data_test_zcr_norm.shape)
print(data_val_zcr_norm.shape)
```

```
(4948, 401)
(2233, 401)
(261, 401)
```

[29]:
```
data_train_zcr_norm = data_train_zcr_norm.reshape((data_train_zcr_norm.
  ↪shape[0],data_train_zcr_norm.shape[1],1))
data_test_zcr_norm = data_test_zcr_norm.reshape((data_test_zcr_norm.
  ↪shape[0],data_test_zcr_norm.shape[1],1))
data_val_zcr_norm = data_val_zcr_norm.reshape((data_val_zcr_norm.
  ↪shape[0],data_val_zcr_norm.shape[1],1))
```

[30]:
```
print(data_train_zcr_norm.shape)
print(data_test_zcr_norm.shape)
print(data_val_zcr_norm.shape)
```

```
(4948, 401, 1)
(2233, 401, 1)
(261, 401, 1)
```

normalize mel spectogram feature

[33]:
```
mel_train_reshape = train_data_mel.reshape(train_data_mel.
  ↪shape[0],train_data_mel.shape[1]*train_data_mel.shape[2])
mel_cv_reshape = cv_data_mel.reshape(cv_data_mel.shape[0],cv_data_mel.
  ↪shape[1]*cv_data_mel.shape[2])
```

```
mel_test_reshape = data_test_mel.reshape(data_test_mel.shape[0],data_test_mel.
 ↪shape[1]*data_test_mel.shape[2])
print(cv_data_mel.shape)
```

```
(261, 128, 157)
```

[34]:
```
scaler_mel = StandardScaler()
data_train_mel_norm = scaler_mel.fit_transform(mel_train_reshape)
data_train_mel_norm = scaler_mel.transform(mel_train_reshape)
data_test_mel_norm = scaler_mel.transform(mel_test_reshape)
data_cv_mel_norm = scaler_mel.transform(mel_cv_reshape)
```

[35]:
```
print(data_train_mel_norm.shape)
print(data_test_mel_norm.shape)
print(data_cv_mel_norm.shape)
data_train_mel_norm = data_train_mel_norm.reshape((data_train_mel_norm.
 ↪shape[0],train_data_mel.shape[1],train_data_mel.shape[2]))
data_test_mel_norm = data_test_mel_norm.reshape((data_test_mel_norm.
 ↪shape[0],data_test_mel.shape[1], data_test_mel.shape[2]))
data_cv_mel_norm = data_cv_mel_norm.reshape((data_cv_mel_norm.
 ↪shape[0],cv_data_mel.shape[1],cv_data_mel.shape[2]))
print(data_train_mel_norm.shape)
print(data_test_mel_norm.shape)
print(data_cv_mel_norm.shape)
```

```
(4948, 20096)
(2233, 20096)
(261, 20096)
(4948, 128, 157)
(2233, 128, 157)
(261, 128, 157)
```

concatinate data to get time domain feature

[36]:
```
train_time = np.concatenate((data_train_rms_norm, data_train_zcr_norm), axis =␣
 ↪-1)
val_time = np.concatenate((data_val_rms_norm, data_val_zcr_norm), axis = -1)
test_time = np.concatenate((data_test_rms_norm, data_test_zcr_norm), axis = -1)
```

[37]:
```
train_time = train_time.reshape(train_time.shape[0], -1, 1)
val_time = val_time.reshape(val_time.shape[0], -1, 1)
test_time = test_time.reshape(test_time.shape[0], -1, 1)
```

add sample rate as second channel

[ ]:
```
# sample_train = sample_train.reshape(-1,1,1)
# sample_test = sample_test.reshape(-1,1,1)
# sample_val = sample_val.reshape(-1,1,1)
```

[ ]:
```
# print(sample_train.shape)
# print(train_time.shape)
```

[ ]:
```
# train_time = np.concatenate((train_time, sample_train), axis = 1)
# val_time = np.concatenate((val_time, sample_val), axis = 1)
# test_time = np.concatenate((test_time, sample_test), axis = 1)
```

[39]:
```
# print(train_time.shape)
# print(label_time_train.shape)
```

RMSE model

build model

[40]:
```
model_time = Sequential()
alpha = 0.000001
model_time.add(Conv1D(64, 16, padding='same',input_shape=(train_time.
 ↪shape[1],1)))

model_time.add(LeakyReLU(alpha=alpha))
model_time.add(BatchNormalization())

model_time.add(Conv1D(64, 16, padding='same'))

model_time.add(LeakyReLU(alpha=alpha))
model_time.add(Conv1D(64, 16, padding='same'))

model_time.add(LeakyReLU(alpha=alpha))

model_time.add(Conv1D(64, 16, padding='same'))

model_time.add(LeakyReLU(alpha=alpha))
model_time.add(Conv1D(64, 16, padding='same'))

model_time.add(LeakyReLU(alpha=alpha))

model_time.add(MaxPooling1D(pool_size=(8)))
model_time.add(Conv1D(64, 16, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(Conv1D(64, 8, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(BatchNormalization())
model_time.add(Conv1D(128, 8, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))
model_time.add(Conv1D(128, 8, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))
```

```
model_time.add(Dropout(0.2))
model_time.add(Conv1D(256, 8, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(MaxPooling1D(pool_size=(8)))
model_time.add(BatchNormalization())
model_time.add(Conv1D(256, 8, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(Conv1D(256, 4, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(Conv1D(512, 4, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))
model_time.add(Conv1D(512, 4, padding='same'))
model_time.add(LeakyReLU(alpha=alpha))

model_time.add(Flatten())
model_time.add(Dense(128, activation='relu', kernel_regularizer=l2(0.01)))
model_time.add(Dense(64, activation='relu', kernel_regularizer=l2(0.01)))
model_time.add(Dense(6, activation='softmax'))
model_time.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 802, 64)           1088

 leaky_re_lu (LeakyReLU)     (None, 802, 64)           0

 batch_normalization (BatchN  (None, 802, 64)          256
 ormalization)

 conv1d_1 (Conv1D)           (None, 802, 64)           65600

 leaky_re_lu_1 (LeakyReLU)   (None, 802, 64)           0

 conv1d_2 (Conv1D)           (None, 802, 64)           65600

 leaky_re_lu_2 (LeakyReLU)   (None, 802, 64)           0

 conv1d_3 (Conv1D)           (None, 802, 64)           65600

 leaky_re_lu_3 (LeakyReLU)   (None, 802, 64)           0
```

```
conv1d_4 (Conv1D)           (None, 802, 64)           65600

leaky_re_lu_4 (LeakyReLU)   (None, 802, 64)           0

max_pooling1d (MaxPooling1D  (None, 100, 64)          0
)

conv1d_5 (Conv1D)           (None, 100, 64)           65600

leaky_re_lu_5 (LeakyReLU)   (None, 100, 64)           0

conv1d_6 (Conv1D)           (None, 100, 64)           32832

leaky_re_lu_6 (LeakyReLU)   (None, 100, 64)           0

batch_normalization_1 (Batc  (None, 100, 64)          256
hNormalization)

conv1d_7 (Conv1D)           (None, 100, 128)          65664

leaky_re_lu_7 (LeakyReLU)   (None, 100, 128)          0

conv1d_8 (Conv1D)           (None, 100, 128)          131200

leaky_re_lu_8 (LeakyReLU)   (None, 100, 128)          0

dropout (Dropout)           (None, 100, 128)          0

conv1d_9 (Conv1D)           (None, 100, 256)          262400

leaky_re_lu_9 (LeakyReLU)   (None, 100, 256)          0

max_pooling1d_1 (MaxPooling  (None, 12, 256)          0
1D)

batch_normalization_2 (Batc  (None, 12, 256)          1024
hNormalization)

conv1d_10 (Conv1D)          (None, 12, 256)           524544

leaky_re_lu_10 (LeakyReLU)  (None, 12, 256)           0

conv1d_11 (Conv1D)          (None, 12, 256)           262400

leaky_re_lu_11 (LeakyReLU)  (None, 12, 256)           0

conv1d_12 (Conv1D)          (None, 12, 512)           524800
```

```
 leaky_re_lu_12 (LeakyReLU)  (None, 12, 512)           0

 conv1d_13 (Conv1D)          (None, 12, 512)           1049088

 leaky_re_lu_13 (LeakyReLU)  (None, 12, 512)           0

 flatten (Flatten)           (None, 6144)              0

 dense (Dense)               (None, 128)               786560

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 6)                 390

=================================================================
Total params: 3,978,758
Trainable params: 3,977,990
Non-trainable params: 768
_________________________________________________________________
```

concatinate label data

[41]:
```python
from keras.utils import to_categorical

label_time_train = to_categorical(label_train_rms, 6)
label_time_test = to_categorical(label_test_rms, 6)
label_time_val = to_categorical(label_val_rms, 6)
```

[42]:
```python
print(train_time.shape)
print(val_time.shape)
```

```
(4948, 802, 1)
(261, 802, 1)
```

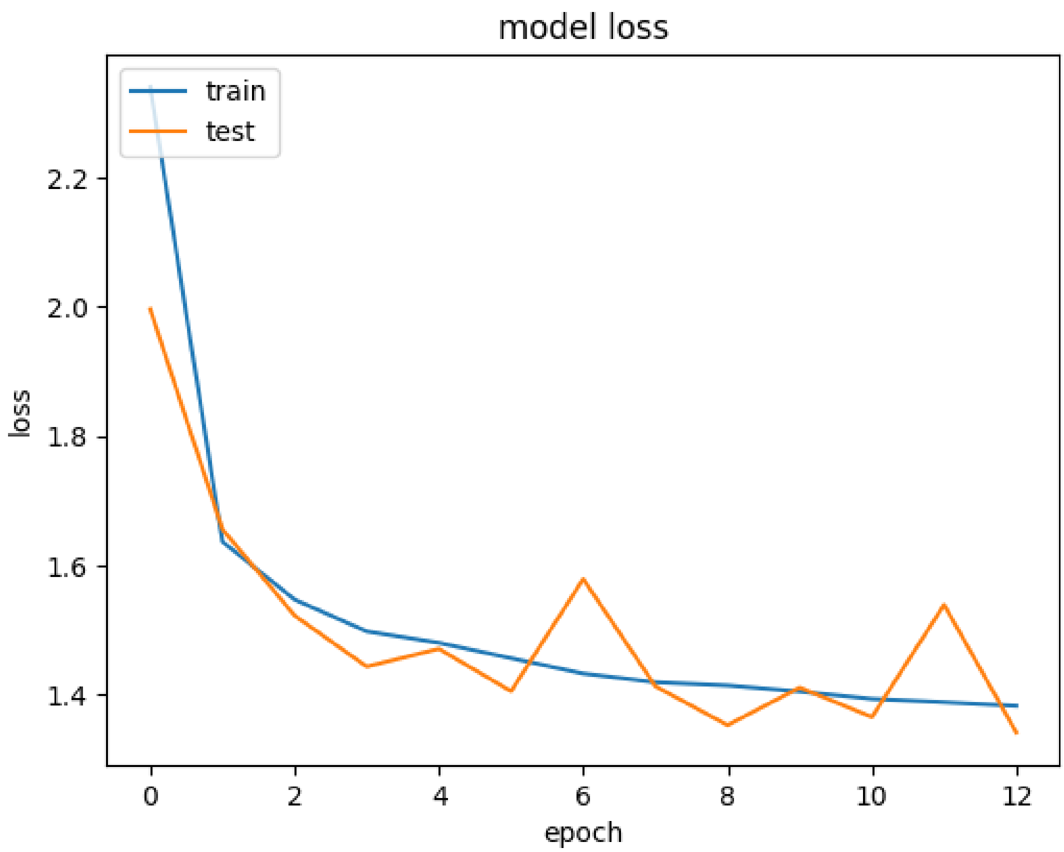
[44]:
```python
from tensorflow.keras.callbacks import EarlyStopping

early_stopping_callback = EarlyStopping(monitor='val_accuracy', patience=5)

model_time.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
model_history=model_time.fit(train_time, label_time_train, batch_size=32,␣
 ↪epochs=100,
                        validation_data=(val_time, label_time_val),␣
 ↪callbacks=[early_stopping_callback])

# model.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
```

```python
# model_history=model.fit(train_time, label_time_train, batch_size=32,
epochs=20,
#                          validation_data=(val_time, label_time_val))
```

```
Epoch 1/100
155/155 [==============================] - 18s 31ms/step - loss: 2.3396 -
accuracy: 0.3333 - val_loss: 1.9958 - val_accuracy: 0.2605
Epoch 2/100
155/155 [==============================] - 4s 23ms/step - loss: 1.6364 -
accuracy: 0.3824 - val_loss: 1.6556 - val_accuracy: 0.3678
Epoch 3/100
155/155 [==============================] - 4s 24ms/step - loss: 1.5467 -
accuracy: 0.4131 - val_loss: 1.5220 - val_accuracy: 0.3908
Epoch 4/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4974 -
accuracy: 0.4258 - val_loss: 1.4430 - val_accuracy: 0.4444
Epoch 5/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4798 -
accuracy: 0.4274 - val_loss: 1.4704 - val_accuracy: 0.4521
Epoch 6/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4560 -
accuracy: 0.4323 - val_loss: 1.4050 - val_accuracy: 0.4598
Epoch 7/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4322 -
accuracy: 0.4351 - val_loss: 1.5785 - val_accuracy: 0.4406
Epoch 8/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4189 -
accuracy: 0.4434 - val_loss: 1.4125 - val_accuracy: 0.4751
Epoch 9/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4139 -
accuracy: 0.4378 - val_loss: 1.3525 - val_accuracy: 0.4368
Epoch 10/100
155/155 [==============================] - 4s 24ms/step - loss: 1.4044 -
accuracy: 0.4460 - val_loss: 1.4105 - val_accuracy: 0.4291
Epoch 11/100
155/155 [==============================] - 4s 23ms/step - loss: 1.3930 -
accuracy: 0.4483 - val_loss: 1.3651 - val_accuracy: 0.4674
Epoch 12/100
155/155 [==============================] - 4s 23ms/step - loss: 1.3878 -
accuracy: 0.4507 - val_loss: 1.5386 - val_accuracy: 0.4291
Epoch 13/100
155/155 [==============================] - 4s 24ms/step - loss: 1.3822 -
accuracy: 0.4535 - val_loss: 1.3412 - val_accuracy: 0.4559
```

evalute model performance

[45]:
```
plt.plot(model_history.history['loss'])
plt.plot(model_history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



[47]:
```
pred = model_time.predict(test_time)
```

```
70/70 [==============================] - 1s 9ms/step
```

[48]:
```
print(pred)
```

```
[[6.54770017e-01 6.02504704e-04 1.72963589e-01 4.95522516e-04
  2.90141385e-02 1.42154217e-01]
 [1.96295306e-02 2.63427854e-01 1.15780577e-01 2.98779100e-01
  1.39243722e-01 1.63139209e-01]
 [3.87055129e-02 1.47476450e-01 1.86895311e-01 1.10940345e-01
  2.53588766e-01 2.62393653e-01]
```

```
 …
 [1.71514899e-02 3.19855750e-01 1.08466461e-01 2.87581831e-01
  1.34053141e-01 1.32891387e-01]
 [2.88596991e-02 3.50182027e-01 1.53114676e-01 1.41299054e-01
  1.36858702e-01 1.89685851e-01]
 [7.56240590e-03 5.93177676e-02 5.88369817e-02 3.32595825e-01
  2.77759373e-01 2.63927639e-01]]
```

[50]:
```python
pred_time = np.argmax(pred, axis=1)

print(pred_time)
label_time_test_time = np.argmax(label_time_test, axis=1)
print(label_time_test_time)
```

```
[0 3 5 … 1 1 3]
[5 3 4 … 3 1 4]
```

[51]:
```python
from sklearn.metrics import f1_score

f1 = f1_score(label_time_test_time, pred_time, average='weighted')
print("f score measure : ", f1)
```

```
f score measure :  0.4329533463971103
```

[73]:
```python
print(label_time_test)
```

```
[[0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0.]
 …
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 1. 0.]]
```

[53]:
```python
score = model_time.evaluate(test_time, label_time_test, verbose=0)
print("accuracy measure : ",score[1])
print("loss measure : ",score[0])
```

```
accuracy measure :  0.45991939306259155
loss measure :  1.3897926807403564
```

```
=====================================================================
```

mel spectrogram mdel

[59]:
```python
model_mel = Sequential()
model_mel.add(Conv2D(32, kernel_size=(3, 3), activation='relu',␣
 ↪input_shape=(data_train_mel_norm.shape[1],data_train_mel_norm.shape[2],1)))
model_mel.add(MaxPooling2D(pool_size=(2, 2)))
```

```
model_mel.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model_mel.add(MaxPooling2D(pool_size=(2, 2)))
model_mel.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model_mel.add(MaxPooling2D(pool_size=(2, 2)))
model_mel.add(Flatten())
model_mel.add(Dense(128, activation='relu'))
model_mel.add(Dense(64, activation='relu'))
model_mel.add(Dense(6, activation='softmax'))
model_mel.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 126, 155, 32)      320

 max_pooling2d_6 (MaxPooling  (None, 63, 77, 32)       0
 2D)

 conv2d_7 (Conv2D)           (None, 61, 75, 64)        18496

 max_pooling2d_7 (MaxPooling  (None, 30, 37, 64)       0
 2D)

 conv2d_8 (Conv2D)           (None, 28, 35, 128)       73856

 max_pooling2d_8 (MaxPooling  (None, 14, 17, 128)      0
 2D)

 flatten_3 (Flatten)         (None, 30464)             0

 dense_9 (Dense)             (None, 128)               3899520

 dense_10 (Dense)            (None, 64)                8256

 dense_11 (Dense)            (None, 6)                 390

=================================================================
Total params: 4,000,838
Trainable params: 4,000,838
Non-trainable params: 0
_________________________________________________________________
```

convert to hot code label

[60]:
```
from keras.utils import to_categorical
cat_train_label = to_categorical(train_label_mel, 6)
cat_cv_label = to_categorical(cv_label_mel)
```

```python
print(cat_train_label.shape)
print(cat_cv_label.shape)
```

```
(4948, 6)
(261, 6)
```

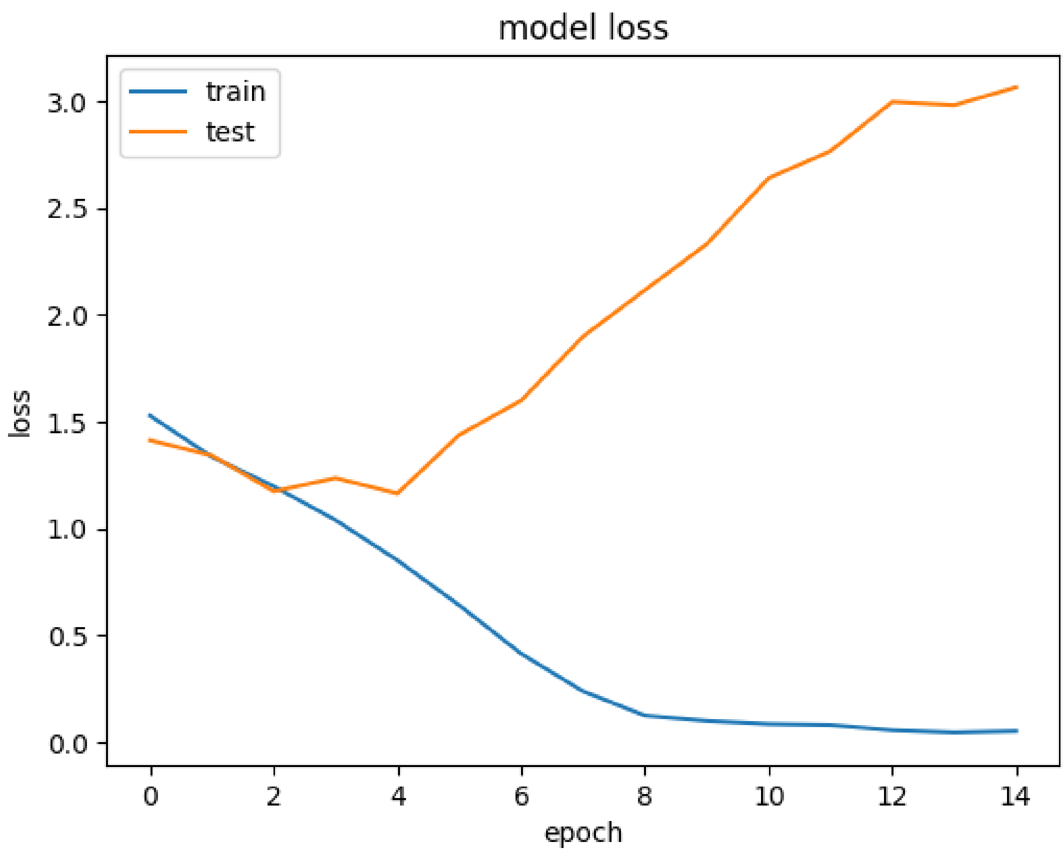
train model

[61]:
```python
from tensorflow.keras.callbacks import EarlyStopping
early_stopping_callback = EarlyStopping(monitor='val_accuracy', patience=10)
model_mel.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])
model_history=model_mel.fit(data_train_mel_norm, cat_train_label,␣
↪batch_size=32, epochs=100, validation_data=(data_cv_mel_norm,␣
↪cat_cv_label),callbacks=[early_stopping_callback])
```

```
Epoch 1/100
155/155 [==============================] - 4s 15ms/step - loss: 1.5282 -
accuracy: 0.3771 - val_loss: 1.4126 - val_accuracy: 0.4789
Epoch 2/100
155/155 [==============================] - 2s 15ms/step - loss: 1.3358 -
accuracy: 0.4733 - val_loss: 1.3421 - val_accuracy: 0.5057
Epoch 3/100
155/155 [==============================] - 2s 13ms/step - loss: 1.1980 -
accuracy: 0.5325 - val_loss: 1.1746 - val_accuracy: 0.5517
Epoch 4/100
155/155 [==============================] - 2s 13ms/step - loss: 1.0401 -
accuracy: 0.6051 - val_loss: 1.2360 - val_accuracy: 0.5249
Epoch 5/100
155/155 [==============================] - 2s 13ms/step - loss: 0.8521 -
accuracy: 0.6750 - val_loss: 1.1646 - val_accuracy: 0.5939
Epoch 6/100
155/155 [==============================] - 2s 13ms/step - loss: 0.6420 -
accuracy: 0.7565 - val_loss: 1.4382 - val_accuracy: 0.5096
Epoch 7/100
155/155 [==============================] - 2s 13ms/step - loss: 0.4157 -
accuracy: 0.8486 - val_loss: 1.5988 - val_accuracy: 0.5441
Epoch 8/100
155/155 [==============================] - 2s 13ms/step - loss: 0.2400 -
accuracy: 0.9129 - val_loss: 1.8979 - val_accuracy: 0.5517
Epoch 9/100
155/155 [==============================] - 2s 13ms/step - loss: 0.1266 -
accuracy: 0.9572 - val_loss: 2.1149 - val_accuracy: 0.5134
Epoch 10/100
155/155 [==============================] - 2s 13ms/step - loss: 0.1017 -
accuracy: 0.9658 - val_loss: 2.3297 - val_accuracy: 0.5517
Epoch 11/100
155/155 [==============================] - 2s 13ms/step - loss: 0.0871 -
```

```
accuracy: 0.9701 - val_loss: 2.6384 - val_accuracy: 0.5364
Epoch 12/100
155/155 [==============================] - 2s 13ms/step - loss: 0.0824 -
accuracy: 0.9733 - val_loss: 2.7644 - val_accuracy: 0.5249
Epoch 13/100
155/155 [==============================] - 2s 13ms/step - loss: 0.0580 -
accuracy: 0.9826 - val_loss: 2.9949 - val_accuracy: 0.5211
Epoch 14/100
155/155 [==============================] - 2s 15ms/step - loss: 0.0475 -
accuracy: 0.9840 - val_loss: 2.9795 - val_accuracy: 0.5709
Epoch 15/100
155/155 [==============================] - 2s 14ms/step - loss: 0.0538 -
accuracy: 0.9844 - val_loss: 3.0624 - val_accuracy: 0.5211
```

[62]:
```python
plt.plot(model_history.history['loss'])
plt.plot(model_history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



evalute model performance

[64]:
```
pred = model_mel.predict(data_test_mel_norm)
print(pred)
```

```
70/70 [==============================] - 0s 6ms/step
[[9.99955535e-01 1.13819287e-22 3.78458826e-05 1.54699739e-13
  2.75636565e-16 6.62365983e-06]
 [1.80216812e-04 5.32235026e-01 8.40027269e-07 4.66214150e-01
  2.08244001e-05 1.34900946e-03]
 [7.17388320e-05 4.05109931e-05 5.35217300e-03 4.60997717e-06
  1.20479278e-01 8.74051690e-01]
 …
 [2.83548841e-04 3.98541195e-03 8.54643166e-01 1.40758500e-01
  2.91849894e-04 3.74945193e-05]
 [1.21240455e-05 9.94802952e-01 1.22962518e-07 5.18436916e-03
  3.95581793e-07 8.43647499e-08]
 [2.14086685e-04 7.08788320e-06 3.71561535e-02 1.01014669e-03
  8.66688728e-01 9.49238539e-02]]
```

[67]:
```
pred_mel = np.argmax(pred, axis=1)

print(pred_mel)
print(label_test_mel)
```

```
[0 1 5 … 2 1 4]
[5 3 4 … 3 1 4]
```

[69]:
```
f1 = f1_score(label_test_mel, pred_mel, average='weighted')
print("f score measure : ", f1)
```

```
f score measure :  0.5342704134448267
```

[74]:
```
print(to_categorical(label_test_mel, 6))
```

```
[[0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0.]
 …
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 1. 0.]]
```

[75]:
```
score = model_mel.evaluate(data_test_mel_norm, to_categorical(label_test_mel),␣
 ↪verbose=0)
print("accuracy measure : ",score[1])
print("loss measure : ",score[0])
```

```
accuracy measure :  0.5396327972412109
loss measure :  3.205275058746338

==============================================================================
```

confusion matrix

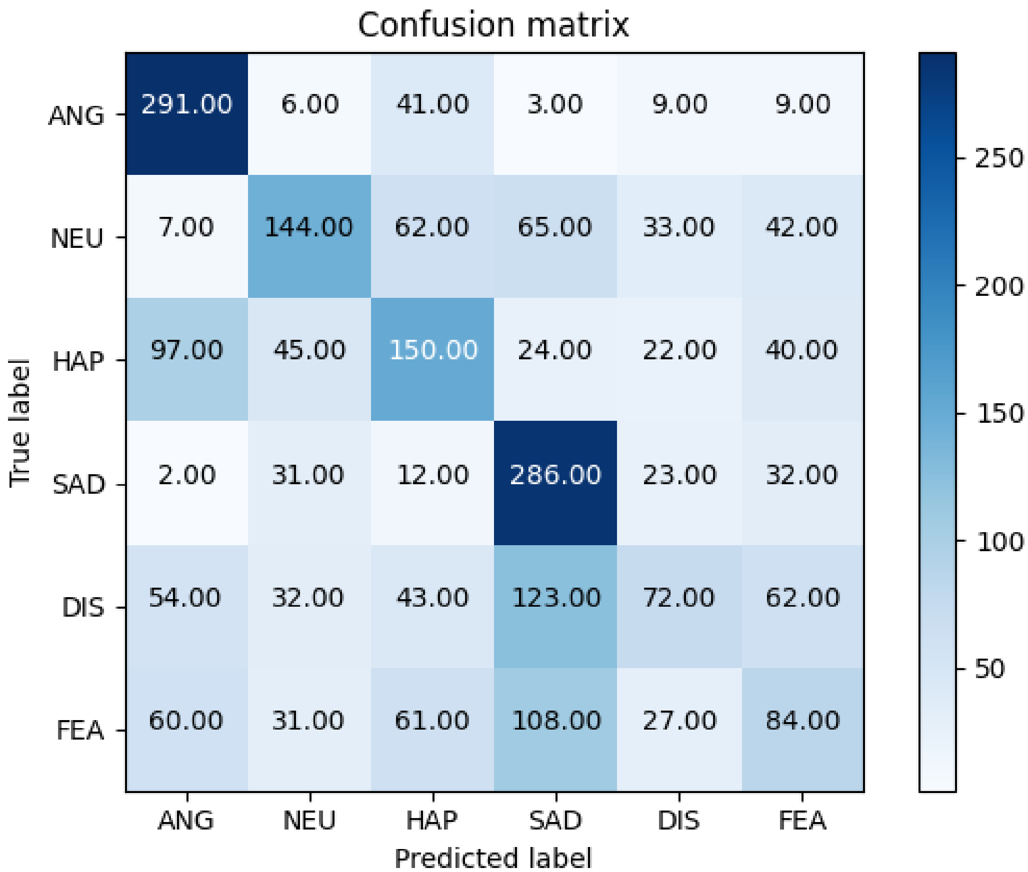
[76]:
```python
from sklearn.metrics import confusion_matrix

def get_confusion_matrix(actual, predicted):
    # create confusion matrix using sklearn's confusion_matrix function
    cm = confusion_matrix(actual, predicted)

    print(cm)
    return cm

def confusing_classes(conf_matrix, threshold, categories):
    pairs_numbers = []

    for i in range(len(conf_matrix)):
        for j in range(len(conf_matrix[i])):
            if i != j:
                misclassifications = conf_matrix[i][j] + conf_matrix[j][i]

                if misclassifications > threshold:
                    pairs_numbers.append(((categories[i], categories[j]),␣
↪misclassifications))

    pairs_numbers.sort(key=lambda x: x[1], reverse=True)

    return pairs_numbers

def plot_confusion_matrix(cm, classes):
    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title('Confusion matrix')
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes)
    plt.yticks(tick_marks, classes)
    fmt = '.2f'
    thresh = cm.max() / 2.
    for i, j in np.ndindex(cm.shape):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

```
    plt.show()
```

confusion matrix for time feature

[77]:
```
conf_matrix = get_confusion_matrix(label_time_test_time, pred_time)
classes = [0, 1, 2, 3, 4, 5]

reverse_dic = {value: key for key, value in dic.items()}
category_list = [reverse_dic[value] for value in classes]
# print(category_list)

plot_confusion_matrix(conf_matrix, category_list)
threshold=100
confused_classes = confusing_classes(conf_matrix, threshold, category_list)
print(f"Confused classes with more than {threshold} misclassifications are:")
i=0
for pair, value in confused_classes:
    if(i%2==0):
        print(f"Classes ({pair[0]} , {pair[1]}) --> {value}")
    i+=1
```

```
[[291   6  41   3   9   9]
 [  7 144  62  65  33  42]
 [ 97  45 150  24  22  40]
 [  2  31  12 286  23  32]
 [ 54  32  43 123  72  62]
 [ 60  31  61 108  27  84]]
```




```
Confused classes with more than 100 misclassifications are:
Classes (SAD , DIS) --> 146
Classes (SAD , FEA) --> 140
Classes (ANG , HAP) --> 138
Classes (NEU , HAP) --> 107
Classes (HAP , FEA) --> 101
```

confusion matrix for mel spectrogram

conf_matrix = get_confusion_matrix(label_test_mel, pred_mel) classes = [0, 1, 2, 3, 4, 5]

reverse_dic = {value: key for key, value in dic.items()} category_list = [reverse_dic[value] for value in classes] # print(category_list)

plot_confusion_matrix(conf_matrix, category_list) threshold=100 confused_classes = confusing_classes(conf_matrix, threshold, category_list) print(f"Confused classes with more than {threshold} misclassifications are:") i=0 for pair, value in confused_classes: if(i%2==0): print(f"Classes ({pair[0]} , {pair[1]}) –> {value}") i+=1