```
import pandas as pd
import numpy as np

import os
import sys

# librosa is a Python library for analyzing audio and music. It can be used to extract the data from the audio files we will see it later.
import librosa
import librosa.display
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import train_test_split

# to play the audio files
from IPython.display import Audio

import keras
from keras.callbacks import ReduceLROnPlateau
from keras.models import Sequential
from keras.layers import Dense, Conv1D, MaxPooling1D, Flatten, Dropout, BatchNormalization
from keras.utils import to_categorical
from keras.callbacks import ModelCheckpoint

import warnings
if not sys.warnoptions:
    warnings.simplefilter("ignore")
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import IPython                    # Play audio files.
import librosa                    # Music and audio analysis.
import librosa.display            # Data visualization
import matplotlib.pyplot as plt   # Data visualization.
import numpy as np                # Data wrangling.
import os                         # Manipulate operating system interfaces.
import pandas as pd               # Data handling.
import pickle                     # Python object serialization.
import plotly.express as px       # Data visualization
import plotly.graph_objects as go # Data visualization
import seaborn as sns             # Data visualization.
sns.set()
import warnings                   # Ignore all warnings.
warnings.filterwarnings('ignore')

!pip3 install antropy
from antropy import spectral_entropy             # Spectral entropy.               # Keras utilities.
from keras.utils import to_categorical  # Convert a class vector (integers) to binary class matrix.
from sklearn.preprocessing import LabelEncoder    # To encode target labels with value between 0 and n_classes-1.
from sklearn.preprocessing import StandardScaler # To perform standardization by centering and scaling.
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score, multilabel_confusion_matrix, precision_score, recall
from sklearn.model_selection import train_test_split # To split data in training/validating/testing.
from statistics import mode                         # Find the most likely predicted emotion.
from tensorflow.keras import models                 # Group layers into an object with training and inference features.
from tensorflow.keras import layers                 # Keras layers API.
from tensorflow.keras.callbacks import EarlyStopping     # Stop training when a monitored metric has stopped improving.
from tensorflow.keras.callbacks import ReduceLROnPlateau # Reduce learning rate when a metric has stopped improving.
from tensorflow.keras.models import load_model           # To load the model.
from tqdm.auto import tqdm                               # Progress bar.
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: antropy in /usr/local/lib/python3.10/dist-packages (0.1.5)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from antropy) (1.22.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from antropy) (1.10.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from antropy) (1.2.2)
Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-packages (from antropy) (0.56.4)
Requirement already satisfied: stochastic in /usr/local/lib/python3.10/dist-packages (from antropy) (0.7.0)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba->antropy
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from numba->antropy) (67.7.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->antropy) (1.2
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->antrop
```

```
classes = ['Angry', 'Happy', 'Neutral', 'Sad','Surprise']
```

Prediction Code

```
def predict_audio_class(audio_path):
    # Preprocess the audio

    # Make predictions

    predicted_class = classes[np.argmax(audio_path)]

    return predicted_class
```

```
Features = pd.read_csv('/content/drive/MyDrive/New_Features.csv')
Features.dropna(axis=0, inplace=True)
```

```
Features
```

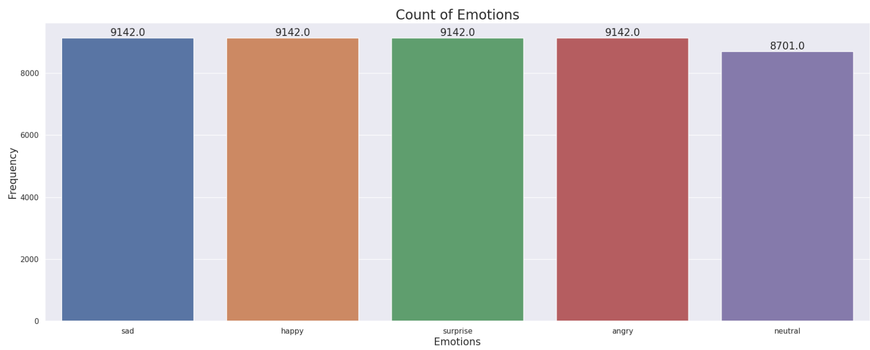
	0	1	2	3	4	5	6	7	8	9	...	49
0	-486.931915	115.747589	-25.467674	21.137320	1.408364	-17.748659	-5.206296	-11.816609	-23.193365	-10.483434	...	2.684004
1	-367.653098	51.456189	-7.431012	8.862830	3.618621	-9.529161	-3.643618	-8.304170	-15.196855	-7.301020	...	1.663208
2	-515.659546	122.350647	-35.442883	21.665054	1.273824	-19.084095	-5.192123	-11.303168	-24.574680	-9.924925	...	2.288218
3	-488.749237	117.429085	-26.239363	21.227299	1.340673	-17.568041	-5.151507	-11.720846	-23.201389	-10.467696	...	2.690360
4	-493.752899	112.388176	-30.887045	21.112549	-2.789590	-20.413330	-5.707886	-15.405882	-24.188908	-8.290537	...	0.317027
...	...	...	...	...	...	...	...	...	...	...	...	...
45264	-367.356323	59.965549	7.699082	10.579291	1.420210	-1.515012	-3.538505	0.960856	-7.773746	1.731510	...	1.201146
45265	-357.012695	59.367874	9.643609	13.521070	3.559073	-1.259370	-2.001130	2.180553	-7.028760	1.883122	...	0.804096
45266	-362.840332	59.882999	6.326694	8.220230	0.510714	-1.508667	-1.741256	1.716168	-5.908564	1.563138	...	1.874366
45267	-379.478882	69.366486	10.753653	12.303340	1.525899	-1.020674	-3.550493	1.462840	-8.037142	2.317529	...	0.326897
45268	-379.478882	69.366486	10.753653	12.303340	1.525899	-1.020674	-3.550493	1.462840	-8.037142	2.317529	...	0.326897

45269 rows × 59 columns

```
plt.figure(figsize=(22, 8))
ax = sns.countplot(x=Features.Emotions)

# Add total count labels to each bar
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width() / 2, height, height, ha='center', va='bottom',size = 15)

plt.ylabel('Frequency', size=15)
plt.xlabel('Emotions', size=15)
plt.title('Count of Emotions', size=20)
sns.despine(top=True, right=True, left=False, bottom=False)
plt.show()
```




```
X = Features.iloc[: ,:-1].values
Y = Features['Emotions'].values
```

```
Y
```

    array(['sad', 'sad', 'sad', ..., 'happy', 'happy', 'happy'], dtype=object)

```
emotions_classes = Features['Emotions'].unique()
```

```
emotions_classes = pd.DataFrame(emotions_classes)
```

```
emotions_classes
```

	0
0	sad
1	happy
2	surprise
3	angry
4	neutral

```
import matplotlib.pyplot as plt
```

```
yy2=pd.get_dummies(Y)
```

```
yy2
```

	angry	happy	neutral	sad	surprise
0	0	0	0	1	0
1	0	0	0	1	0
2	0	0	0	1	0
3	0	0	0	1	0
4	0	0	0	1	0
...	...	...	...	...	...
45264	0	1	0	0	0
45265	0	1	0	0	0
45266	0	1	0	0	0
45267	0	1	0	0	0
45268	0	1	0	0	0

45269 rows × 5 columns

```
encoder = OneHotEncoder()
Y_res = encoder.fit_transform(np.array(Y).reshape(-1,1)).toarray()
```

```
yy=pd.DataFrame(Y_res)
```

```
x_train, x_test, y_train, y_test = train_test_split(X, Y_res,test_size = 0.2, random_state=42, shuffle=True)
x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

    ((36215, 58), (36215, 5), (9054, 58), (9054, 5))

```
x_train = np.expand_dims(x_train, axis=2)
x_test = np.expand_dims(x_test, axis=2)
x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

    ((36215, 58, 1), (36215, 5), (9054, 58, 1), (9054, 5))

```
yy
```

	0	1	2	3	4
0	0.0	0.0	0.0	1.0	0.0
1	0.0	0.0	0.0	1.0	0.0
2	0.0	0.0	0.0	1.0	0.0
3	0.0	0.0	0.0	1.0	0.0
4	0.0	0.0	0.0	1.0	0.0
...	...	...	...	...	...
45264	0.0	1.0	0.0	0.0	0.0

Model - 1 (CNN)

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

from keras.callbacks import ReduceLROnPlateau, EarlyStopping
from keras.models import Sequential
from keras.layers import Dense, Conv1D, MaxPooling1D, Flatten, Dropout, BatchNormalization, LSTM, Bidirectional
from keras.callbacks import ModelCheckpoint
```

```
model = Sequential()
model.add(layers.Conv1D(512, kernel_size=5, strides=1,
                        padding="same", activation="relu",
                        input_shape=(x_train.shape[1], 1)))
model.add(layers.BatchNormalization())
model.add(layers.MaxPool1D(pool_size=5, strides=2, padding="same"))

model.add(layers.Conv1D(512, kernel_size=5, strides=1,
                        padding="same", activation="relu"))
model.add(layers.BatchNormalization())
model.add(layers.MaxPool1D(pool_size=5, strides=2, padding="same"))

model.add(layers.Conv1D(256, kernel_size=5, strides=1,
                        padding="same", activation="relu"))
model.add(layers.BatchNormalization())
model.add(layers.MaxPool1D(pool_size=5, strides=2, padding="same"))

model.add(layers.Conv1D(256, kernel_size=3, strides=1, padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling1D(pool_size=5, strides = 2, padding = 'same'))

model.add(layers.Conv1D(128, kernel_size=3, strides=1, padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling1D(pool_size=3, strides = 2, padding = 'same'))

model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Dense(5, activation="softmax"))


model.compile(optimizer = 'RMSprop' , loss = 'categorical_crossentropy' , metrics = ['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 58, 512)           3072

 batch_normalization (BatchN  (None, 58, 512)          2048
 ormalization)

 max_pooling1d (MaxPooling1D  (None, 29, 512)          0
 )

 conv1d_1 (Conv1D)           (None, 29, 512)           1311232

 batch_normalization_1 (Batc  (None, 29, 512)          2048
 hNormalization)

 max_pooling1d_1 (MaxPooling  (None, 15, 512)          0
 1D)

 conv1d_2 (Conv1D)           (None, 15, 256)           655616

 batch_normalization_2 (Batc  (None, 15, 256)          1024
 hNormalization)

 max_pooling1d_2 (MaxPooling  (None, 8, 256)           0
 1D)
```

```
 conv1d_3 (Conv1D)           (None, 8, 256)            196864

 batch_normalization_3 (Batc  (None, 8, 256)           1024
 hNormalization)

 max_pooling1d_3 (MaxPooling  (None, 4, 256)           0
 1D)

 conv1d_4 (Conv1D)           (None, 4, 128)            98432

 batch_normalization_4 (Batc  (None, 4, 128)           512
 hNormalization)

 max_pooling1d_4 (MaxPooling  (None, 2, 128)           0
 1D)

 flatten (Flatten)           (None, 256)               0

 dense (Dense)               (None, 512)               131584

 batch_normalization_5 (Batc  (None, 512)              2048
 hNormalization)

 dense_1 (Dense)             (None, 5)                 2565

=================================================================
Total params: 2,408,069
Trainable params: 2,403,717
Non-trainable params: 4,352
_________________________________________________________________
```

```
rlrp = ReduceLROnPlateau(monitor='val_accuracy',
                                            patience=3,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)
earlystopping = EarlyStopping(monitor ="val_accuracy",
                              mode = 'auto', patience = 5,
                              restore_best_weights = True)

history=model.fit(x_train, y_train, batch_size=64, epochs=70, validation_data=(x_test, y_test), callbacks=[rlrp,earlystopping])
```

```
Epoch 1/70
566/566 [==============================] - 39s 26ms/step - loss: 1.6899 - accuracy: 0.2393 - val_loss: 1.7842 - val_a
Epoch 2/70
566/566 [==============================] - 9s 16ms/step - loss: 1.5708 - accuracy: 0.2665 - val_loss: 1.5942 - val_ac
Epoch 3/70
566/566 [==============================] - 9s 15ms/step - loss: 1.5266 - accuracy: 0.2950 - val_loss: 1.5131 - val_ac
Epoch 4/70
566/566 [==============================] - 9s 16ms/step - loss: 1.4786 - accuracy: 0.3221 - val_loss: 1.5533 - val_ac
Epoch 5/70
566/566 [==============================] - 9s 16ms/step - loss: 1.4355 - accuracy: 0.3511 - val_loss: 1.4346 - val_ac
Epoch 6/70
566/566 [==============================] - 9s 16ms/step - loss: 1.3738 - accuracy: 0.3877 - val_loss: 1.3891 - val_ac
Epoch 7/70
566/566 [==============================] - 9s 16ms/step - loss: 1.3020 - accuracy: 0.4373 - val_loss: 1.3290 - val_ac
Epoch 8/70
566/566 [==============================] - 9s 16ms/step - loss: 1.2216 - accuracy: 0.4899 - val_loss: 1.2623 - val_ac
Epoch 9/70
566/566 [==============================] - 10s 17ms/step - loss: 1.1170 - accuracy: 0.5460 - val_loss: 1.3258 - val_a
Epoch 10/70
566/566 [==============================] - 11s 19ms/step - loss: 0.9992 - accuracy: 0.6041 - val_loss: 1.1286 - val_a
Epoch 11/70
566/566 [==============================] - 9s 17ms/step - loss: 0.8753 - accuracy: 0.6584 - val_loss: 0.9447 - val_ac
Epoch 12/70
566/566 [==============================] - 9s 16ms/step - loss: 0.7622 - accuracy: 0.7119 - val_loss: 0.9600 - val_ac
Epoch 13/70
566/566 [==============================] - 9s 16ms/step - loss: 0.6585 - accuracy: 0.7509 - val_loss: 0.7746 - val_ac
Epoch 14/70
566/566 [==============================] - 9s 16ms/step - loss: 0.5675 - accuracy: 0.7875 - val_loss: 0.7648 - val_ac
Epoch 15/70
566/566 [==============================] - 9s 16ms/step - loss: 0.4950 - accuracy: 0.8168 - val_loss: 0.7479 - val_ac
Epoch 16/70
566/566 [==============================] - 10s 17ms/step - loss: 0.4338 - accuracy: 0.8415 - val_loss: 0.6915 - val_a
Epoch 17/70
566/566 [==============================] - 9s 16ms/step - loss: 0.3906 - accuracy: 0.8610 - val_loss: 0.6510 - val_ac
Epoch 18/70
566/566 [==============================] - 10s 17ms/step - loss: 0.3469 - accuracy: 0.8752 - val_loss: 0.5830 - val_a
Epoch 19/70
566/566 [==============================] - 9s 16ms/step - loss: 0.3133 - accuracy: 0.8873 - val_loss: 0.5709 - val_ac
Epoch 20/70
566/566 [==============================] - 10s 18ms/step - loss: 0.2736 - accuracy: 0.9010 - val_loss: 0.5849 - val_a
Epoch 21/70
566/566 [==============================] - 10s 18ms/step - loss: 0.2541 - accuracy: 0.9087 - val_loss: 0.5519 - val_a
Epoch 22/70
566/566 [==============================] - 9s 16ms/step - loss: 0.2349 - accuracy: 0.9177 - val_loss: 0.5717 - val_ac
Epoch 23/70
566/566 [==============================] - 10s 17ms/step - loss: 0.2127 - accuracy: 0.9249 - val_loss: 0.5372 - val_a
Epoch 24/70
```

```
566/566 [==============================] - 10s 18ms/step - loss: 0.2012 - accuracy: 0.9294 - val_loss: 0.5068 - val_a
Epoch 25/70
566/566 [==============================] - 9s 16ms/step - loss: 0.1888 - accuracy: 0.9334 - val_loss: 0.5591 - val_ac
Epoch 26/70
566/566 [==============================] - 10s 17ms/step - loss: 0.1788 - accuracy: 0.9369 - val_loss: 0.5279 - val_a
Epoch 27/70
566/566 [==============================] - 9s 16ms/step - loss: 0.1684 - accuracy: 0.9406 - val_loss: 0.5047 - val_ac
```

```
preds = model.predict(x_test)
```

```
283/283 [==============================] - 26s 90ms/step
```

```
preds.shape
```

```
(9054, 5)
```

```
preds
```

```
array([[9.8562131e-13, 9.9999994e-01, 2.8186159e-10, 1.6682540e-08,
        4.4153183e-09],
       [1.6103312e-03, 5.9900002e-04, 3.9323657e-03, 9.9377388e-01,
        8.4416526e-05],
       [1.7406202e-07, 1.7350161e-06, 7.8732453e-05, 9.9991709e-01,
        2.0981809e-06],
       ...,
       [1.5594756e-13, 3.7762593e-09, 9.9988866e-01, 1.1128828e-04,
        2.3876820e-10],
       [1.1879481e-05, 9.9968839e-01, 2.5241452e-04, 4.6952006e-05,
        4.1180039e-07],
       [2.2854918e-08, 9.9999952e-01, 1.2899741e-09, 4.3786216e-07,
        5.0465114e-12]], dtype=float32)
```

```
np.sum(preds[:10],axis=1)
```

```
array([0.99999994, 1.        , 0.9999998 , 1.        , 0.99999994,
       0.9999999 , 0.99999994, 0.9999999 , 0.99999994, 0.99999994],
      dtype=float32)
```

```
y_pred = encoder.inverse_transform(preds)
y_tmp = encoder.inverse_transform(y_test)
```

```
y_pred.shape
```

```
(9054, 1)
```

```
# Calculate our accuracy score.
accuracy = accuracy_score(y_tmp, y_pred)

# Calculate our precision score.
precision = precision_score(y_tmp, y_pred, average = 'micro')

# Calculate our recall score.
recall = recall_score(y_tmp, y_pred, average = 'micro')

# Calculate our f1-score.
f1 = f1_score(y_tmp, y_pred, average = 'micro')

# Print each of our scores to inspect performance.
print('Accuracy Score: %f' % (accuracy * 100), '%', sep = '')
print('Precision Score: %f' % (precision * 100), '%', sep = '')
print('Recall Score: %f' % (recall * 100), '%', sep = '')
print('F1 Score: %f' % (f1 * 100), '%', sep = '')
```

```
Accuracy Score: 90.269494%
Precision Score: 90.269494%
Recall Score: 90.269494%
F1 Score: 90.269494%
```

```
y_pred[:100]
```

```
array([['happy'],
       ['neutral'],
       ['sad'],
       ['angry'],
       ['surprise'],
       ['sad'],
       ['neutral'],
       ['sad'],
       ['happy'],
       ['happy'],
       ['happy'],
       ['neutral'],
```

```
       ['surprise'],
       ['surprise'],
       ['angry'],
       ['surprise'],
       ['angry'],
       ['happy'],
       ['happy'],
       ['happy'],
       ['surprise'],
       ['angry'],
       ['surprise'],
       ['sad'],
       ['neutral'],
       ['angry'],
       ['sad'],
       ['neutral'],
       ['neutral'],
       ['angry'],
       ['sad'],
       ['neutral'],
       ['sad'],
       ['happy'],
       ['happy'],
       ['sad'],
       ['surprise'],
       ['happy'],
       ['surprise'],
       ['neutral'],
       ['sad'],
       ['surprise'],
       ['happy'],
       ['happy'],
       ['neutral'],
       ['sad'],
       ['angry'],
       ['surprise'],
       ['sad'],
       ['angry'],
       ['happy'],
       ['angry'],
       ['surprise'],
       ['happy'],
       ['surprise'],
       ['neutral'],
       ['sad'],
```

```
y_pred[0]
```

```
array(['happy'], dtype=object)
```

```
final_df = pd.DataFrame(columns=['PredictedLabels', 'ActualLabels'])
final_df['PredictedLabels'] = y_pred.flatten()
final_df['ActualLabels'] = y_tmp.flatten()

final_df
```

	PredictedLabels	ActualLabels
0	happy	happy
1	sad	happy
2	sad	sad
3	angry	angry
4	surprise	surprise
...	...	...
9049	neutral	neutral
9050	surprise	surprise
9051	neutral	neutral
9052	happy	happy
9053	happy	happy

9054 rows × 2 columns

```
modidf = final_df
classes = modidf.ActualLabels.unique()
classes
```

```
array(['happy', 'sad', 'angry', 'surprise', 'neutral'], dtype=object)
```

```
modidf.PredictedLabels.unique()
```

```
array(['happy', 'sad', 'angry', 'surprise', 'neutral'], dtype=object)
```

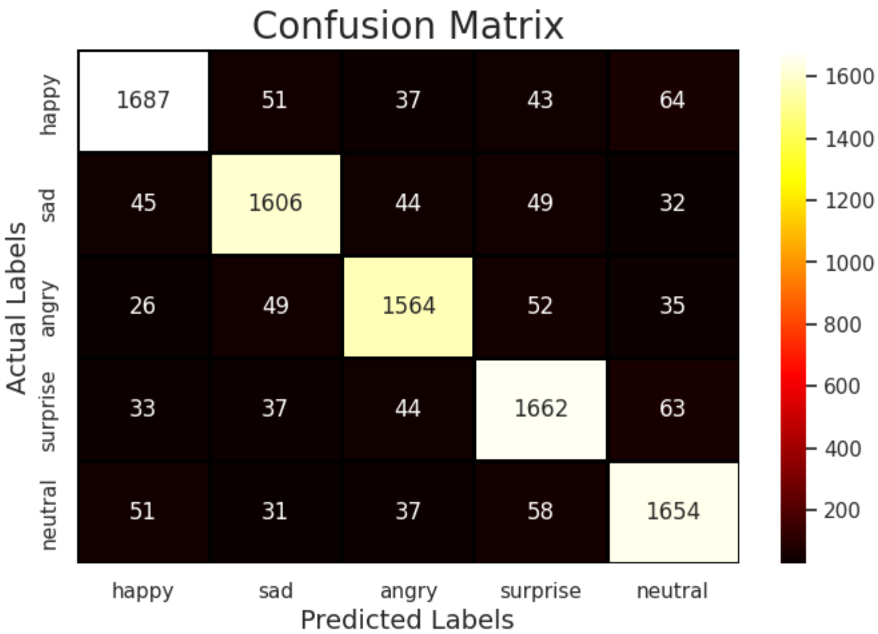
```
modidf = final_df


classes = modidf.ActualLabels.unique()


# Confusion matrix
c = confusion_matrix(modidf.ActualLabels, modidf.PredictedLabels)
print("Accuracy of our model on test data based on emotions: " ,round(accuracy_score(modidf.ActualLabels, modidf.PredictedLabels),2)*100,"%")

#cm = confusion_matrix(y_tmp, y_pred)
plt.figure(figsize = (8, 5))
c = pd.DataFrame(c , index = [i for i in modidf['ActualLabels'].unique()] , columns = [i for i in modidf['PredictedLabels'].unique()])
sns.heatmap(c, linecolor='Black', cmap='hot', linewidth=1, annot=True, fmt='')
plt.title('Confusion Matrix', size=20)
plt.xlabel('Predicted Labels', size=14)
plt.ylabel('Actual Labels', size=14)
plt.show()
```

```
Accuracy of our model on test data based on emotions:  90.0 %
```




```
print(y_pred[0])
```

```
['happy']
```

```
y_pred[1]
```

```
array(['neutral'], dtype=object)
```

```
model_name = 'Emotion_Model_conv1d.h5'
save_dir = os.path.join(os.getcwd(), 'saved_models')

if not os.path.isdir(save_dir):
    os.makedirs(save_dir)
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Save model and weights at %s ' % model_path)

# Save the model to disk
model_json = model.to_json()
with open("Emotion_Model_conv1d_gender_93.json", "w") as json_file:
    json_file.write(model_json)
```

```
Save model and weights at /content/saved_models/Emotion_Model_conv1d.h5
```

```
model.save('model.h5')
```

```
from keras.models import Sequential, model_from_json
```

```
json_file = open('/content/drive/MyDrive/Emotion_Model_conv1d_gender_93.json', 'r')
loaded_model_json = json_file.read()
json_file.close()
model = model_from_json(loaded_model_json)
```

```
# load weights into new model
model.load_weights("/content/drive/MyDrive/Emotion_Model_conv1d.h5")
print("Loaded model from disk")

# Keras optimiser
model.compile(optimizer = 'RMSprop' , loss = 'categorical_crossentropy' , metrics = ['accuracy'])
score = model.evaluate(x_test, y_test, verbose=0)
print("%s: %.2f%%" % (model.metrics_names[1], score[1]*100))
```

```
Loaded model from disk
accuracy: 90.27%
```

```
def noise(data):
    data = np.array(data, dtype=float)  # Convert data to a numeric array
    noise_amp = 0.04 * np.random.uniform() * np.amax(data)
    data = data + noise_amp * np.random.normal(size=data.shape[0])
    return data

def stretch(data, rate=0.70):
    return librosa.effects.time_stretch(data,rate=rate)

def shift(data):
    shift_range = int(np.random.uniform(low=-5, high = 5)*1000)
    return np.roll(data, shift_range)

def pitch(data, sampling_rate, pitch_factor=0.7):
    return librosa.effects.pitch_shift(data, sr=sampling_rate, n_steps=pitch_factor)

def higher_speed(data, speed_factor = 1.25):
    return librosa.effects.time_stretch(data,rate=speed_factor)

def lower_speed(data, speed_factor = 0.75):
    return librosa.effects.time_stretch(data,rate=speed_factor)
```

```
#sample_rate = 22050

def extract_features(data):

    result = np.array([])

    mfccs = librosa.feature.mfcc(y=data, sr=22050, n_mfcc=58)
    mfccs_processed = np.mean(mfccs.T,axis=0)
    result = np.array(mfccs_processed)

    return result

def get_features(path):
    # duration and offset are used to take care of the no audio in start and the ending of each audio files as seen above.
    data, sample_rate = librosa.load(path, duration=3, offset=0.5)

    #without augmentation
    res1 = extract_features(data)
    result = np.array(res1)

    #noised
    noise_data = noise(data)
    res2 = extract_features(noise_data)
    result = np.vstack((result, res2)) # stacking vertically

    #stretched
    stretch_data = stretch(data)
    res3 = extract_features(stretch_data)
    result = np.vstack((result, res3))

    #shifted
    shift_data = shift(data)
    res4 = extract_features(shift_data)
    result = np.vstack((result, res4))

    #pitched
    pitch_data = pitch(data, sample_rate)
    res5 = extract_features(pitch_data)
    result = np.vstack((result, res5))

    #speed up
    higher_speed_data = higher_speed(data)
    res6 = extract_features(higher_speed_data)
    result = np.vstack((result, res6))

    #speed down
    lower_speed_data = higher_speed(data)
    res7 = extract_features(lower_speed_data)
    result = np.vstack((result, res7))

    return result
```

```
sound_file_path = '/content/drive/MyDrive/M_03_ILIAS_S_7_SAD_3.wav'
features_test = sound_file_path
```

```
x_test2=get_features(features_test)
```

```
x_test2.shape
```

```
(7, 58)
```

```
x_test2 = np.expand_dims(x_test2, axis=2)
```

```
x_test2.shape
```

```
(7, 58, 1)
```

```
def predict(path):
    classes = ['Angry', 'Happy', 'Neutral', 'Sad','Surprise']  # Replace with your own class labels
    pred=(model.predict(path))
    y_pred = encoder.inverse_transform(pred)
    print(y_pred)
```

```
# Each audio data extraction has its own ndarray.
predict(x_test2)
```

```
1/1 [==============================] - 0s 381ms/step
[['sad']
 ['sad']
 ['sad']
 ['sad']
 ['sad']
 ['sad']
 ['sad']]
```

Model-2 (RNN-LSTM)

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
```

```
timesteps = x_train.shape[1]  # Number of time steps in each sequence
input_dim = x_train.shape[2]  # Number of features in each time step
output_dim = y_train.shape[1]
```

```
model = Sequential()

# Add the first LSTM layer with input shape (timesteps, input_dim)
model.add(LSTM(units=256, return_sequences=True, input_shape=(timesteps, input_dim)))
model.add(Dropout(0.2))

# Add additional LSTM layers
model.add(LSTM(units=256, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=256, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=256, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=256, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=256, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=256))
model.add(Dropout(0.2))

# Add a dense layer for output prediction
model.add(Dense(units=output_dim, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_8 (LSTM)               (None, 58, 256)           264192

 dropout_8 (Dropout)         (None, 58, 256)           0
```

```
 lstm_9 (LSTM)              (None, 58, 256)           525312

 dropout_9 (Dropout)        (None, 58, 256)           0

 lstm_10 (LSTM)             (None, 58, 256)           525312

 dropout_10 (Dropout)       (None, 58, 256)           0

 lstm_11 (LSTM)             (None, 58, 256)           525312

 dropout_11 (Dropout)       (None, 58, 256)           0

 lstm_12 (LSTM)             (None, 58, 256)           525312

 dropout_12 (Dropout)       (None, 58, 256)           0

 lstm_13 (LSTM)             (None, 58, 256)           525312

 dropout_13 (Dropout)       (None, 58, 256)           0

 lstm_14 (LSTM)             (None, 256)               525312

 dropout_14 (Dropout)       (None, 256)               0

 dense_3 (Dense)            (None, 5)                 1285

=================================================================
Total params: 3,417,349
Trainable params: 3,417,349
Non-trainable params: 0
_________________________________________________________________
```

```
rlrp = ReduceLROnPlateau(monitor='val_accuracy',
                                           patience=3,
                                           verbose=1,
                                           factor=0.5,
                                           min_lr=0.00001)
earlystopping = EarlyStopping(monitor ="val_accuracy",
                              mode = 'auto', patience = 5,
                              restore_best_weights = True)

history=model.fit(x_train, y_train, batch_size=64, epochs=200, validation_data=(x_test, y_test), callbacks=[rlrp,earlystopping])
```

```
Epoch 1/200
566/566 [==============================] - 26s 45ms/step - loss: 1.0528 - accuracy: 0.5511 - val_loss: 1.1676 - val_a
Epoch 2/200
566/566 [==============================] - 26s 45ms/step - loss: 1.0464 - accuracy: 0.5537 - val_loss: 1.1513 - val_a
Epoch 3/200
566/566 [==============================] - 26s 46ms/step - loss: 1.0343 - accuracy: 0.5592 - val_loss: 1.1532 - val_a
Epoch 4/200
566/566 [==============================] - 26s 45ms/step - loss: 1.0219 - accuracy: 0.5654 - val_loss: 1.1422 - val_a
Epoch 5/200
566/566 [==============================] - 25s 45ms/step - loss: 1.0077 - accuracy: 0.5732 - val_loss: 1.1387 - val_a
Epoch 6/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9999 - accuracy: 0.5767 - val_loss: 1.1408 - val_a
Epoch 7/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9868 - accuracy: 0.5804 - val_loss: 1.1122 - val_a
Epoch 8/200
566/566 [==============================] - 26s 45ms/step - loss: 0.9774 - accuracy: 0.5879 - val_loss: 1.1199 - val_a
Epoch 9/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9571 - accuracy: 0.6000 - val_loss: 1.1369 - val_a
Epoch 10/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9495 - accuracy: 0.6017 - val_loss: 1.1155 - val_a
Epoch 11/200
566/566 [==============================] - 26s 45ms/step - loss: 0.9380 - accuracy: 0.6094 - val_loss: 1.1058 - val_a
Epoch 12/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9232 - accuracy: 0.6152 - val_loss: 1.1177 - val_a
Epoch 13/200
566/566 [==============================] - 25s 45ms/step - loss: 0.9228 - accuracy: 0.6170 - val_loss: 1.0760 - val_a
Epoch 14/200
566/566 [==============================] - 26s 45ms/step - loss: 0.9009 - accuracy: 0.6280 - val_loss: 1.0548 - val_a
Epoch 15/200
566/566 [==============================] - 25s 45ms/step - loss: 0.8898 - accuracy: 0.6307 - val_loss: 1.0815 - val_a
Epoch 16/200
566/566 [==============================] - 26s 45ms/step - loss: 0.8748 - accuracy: 0.6387 - val_loss: 1.0526 - val_a
Epoch 17/200
566/566 [==============================] - 25s 45ms/step - loss: 0.8684 - accuracy: 0.6429 - val_loss: 1.0644 - val_a
Epoch 18/200
566/566 [==============================] - 26s 45ms/step - loss: 0.8499 - accuracy: 0.6533 - val_loss: 1.0478 - val_a
Epoch 19/200
566/566 [==============================] - 25s 45ms/step - loss: 0.8386 - accuracy: 0.6584 - val_loss: 1.0375 - val_a
Epoch 20/200
566/566 [==============================] - 26s 45ms/step - loss: 0.8379 - accuracy: 0.6589 - val_loss: 1.0445 - val_a
Epoch 21/200
566/566 [==============================] - 25s 45ms/step - loss: 0.8158 - accuracy: 0.6696 - val_loss: 1.0060 - val_a
Epoch 22/200
566/566 [==============================] - 25s 45ms/step - loss: 0.8009 - accuracy: 0.6716 - val_loss: 1.0100 - val_a
Epoch 23/200
566/566 [==============================] - 26s 45ms/step - loss: 0.7940 - accuracy: 0.6750 - val_loss: 1.0256 - val_a
```

```
Epoch 24/200
566/566 [==============================] - 26s 45ms/step - loss: 0.7829 - accuracy: 0.6852 - val_loss: 0.9858 - val_a
Epoch 25/200
566/566 [==============================] - 26s 45ms/step - loss: 0.7631 - accuracy: 0.6929 - val_loss: 0.9950 - val_a
Epoch 26/200
566/566 [==============================] - 26s 45ms/step - loss: 0.7540 - accuracy: 0.6981 - val_loss: 0.9846 - val_a
Epoch 27/200
566/566 [==============================] - 26s 45ms/step - loss: 0.7523 - accuracy: 0.6976 - val_loss: 0.9769 - val_a
```

```
print("Accuracy of our model on test data : " , round(model.evaluate(x_test,y_test)[1]*100,2) , "%")

epochs = [i for i in range(92)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
test_acc = history.history['val_accuracy']
test_loss = history.history['val_loss']

fig.set_size_inches(20,6)
ax[0].plot(epochs , train_loss , label = 'Training Loss')
ax[0].plot(epochs , test_loss , label = 'Testing Loss')
ax[0].set_title('Training & Testing Loss')
ax[0].legend()
ax[0].set_xlabel("Epochs")

ax[1].plot(epochs , train_acc , label = 'Training Accuracy')
ax[1].plot(epochs , test_acc , label = 'Testing Accuracy')
ax[1].set_title('Training & Testing Accuracy')
ax[1].legend()
ax[1].set_xlabel("Epochs")
plt.show()
```

```
283/283 [==============================] - 5s 16ms/step - loss: 0.7737 - accuracy: 0.8174
Accuracy of our model on test data :  81.74 %
```

Model-3 (Bi-LSTM)

```
from keras.models import Sequential
from keras.layers import LSTM, Bidirectional, Dense
```

```
# Define the number of hidden layers and units per layer
num_hidden_layers = 7
units_per_layer = 256

# Create the model
model = Sequential()

# Add the first Bi-LSTM layer with input_shape
model.add(Bidirectional(LSTM(units_per_layer, return_sequences=True), input_shape=(None, input_dim)))

# Add the remaining hidden layers
for _ in range(num_hidden_layers - 1):
    model.add(Bidirectional(LSTM(units_per_layer, return_sequences=True)))

# Add the output layer
model.add(Dense(output_dim, activation='softmax'))

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

```
# Print the model summary
model.summary()
```

```
print("Accuracy of our model on test data : " , round(model.evaluate(x_test,y_test)[1]*100,2) , "%")

epochs = [i for i in range(48)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
test_acc = history.history['val_accuracy']
test_loss = history.history['val_loss']

fig.set_size_inches(20,6)
ax[0].plot(epochs , train_loss , label = 'Training Loss')
ax[0].plot(epochs , test_loss , label = 'Testing Loss')
ax[0].set_title('Training & Testing Loss')
ax[0].legend()
ax[0].set_xlabel("Epochs")

ax[1].plot(epochs , train_acc , label = 'Training Accuracy')
ax[1].plot(epochs , test_acc , label = 'Testing Accuracy')
ax[1].set_title('Training & Testing Accuracy')
ax[1].legend()
ax[1].set_xlabel("Epochs")
plt.show()
```