Emotion _Recognition_Model

March 5, 2025

Import Necessary Libraries

[1]:
```
import os
import pandas as pd
import librosa
import numpy as np
import librosa.display
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, LSTM, Dense,␣
↪Dropout, TimeDistributed
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
```

Load Dataset

[2]:
```
# Define EMO-DB emotion mapping
emotion_map = {
    'W': 'anger', 'L': 'boredom', 'E': 'disgust', 'A': 'fear',
    'F': 'happiness', 'T': 'sadness', 'N': 'neutral'
}

# Path to the dataset folder
DATASET_PATH = "/content/drive/MyDrive/wav"

# Collect file names and labels
data = []
for file in os.listdir(DATASET_PATH):
    if file.endswith(".wav"):
        emotion_code = file[5]  # 6th character in filename
        if emotion_code in emotion_map:
            emotion_label = emotion_map[emotion_code]
            data.append((os.path.join(DATASET_PATH, file), emotion_label))
```

```
# Create DataFrame
df = pd.DataFrame(data, columns=["filepath", "emotion"])
print(df.head())
```

```
                               filepath    emotion
0  /content/drive/MyDrive/wav/03a02Ta.wav    sadness
1  /content/drive/MyDrive/wav/03a02Fc.wav  happiness
2  /content/drive/MyDrive/wav/03a01Wa.wav      anger
3  /content/drive/MyDrive/wav/03a02Nc.wav    neutral
4  /content/drive/MyDrive/wav/03a01Fa.wav  happiness
```

[3]:
```
# Count files for each emotion
emotion_counts = df['emotion'].value_counts()
print("\nNumber of files per emotion:")
print(emotion_counts)
```

```

Number of files per emotion:
emotion
anger        127
boredom       81
neutral       79
happiness     71
fear          69
sadness       62
disgust       46
Name: count, dtype: int64
```

Preprocessing of Data

[4]:
```
def extract_features(file_path, max_pad_len=200):
    """Extract MFCC features from an audio file."""
    audio, sample_rate = librosa.load(file_path, sr=16000)  # Load with 16kHz
    mfccs = librosa.feature.mfcc(y=audio, sr=sample_rate, n_mfcc=40)  # Extract␣
↪40 MFCCs
    pad_width = max_pad_len - mfccs.shape[1]

    if pad_width > 0:
        mfccs = np.pad(mfccs, pad_width=((0, 0), (0, pad_width)),␣
↪mode='constant')
    else:
        mfccs = mfccs[:, :max_pad_len]

    return mfccs

# Extract features for all audio files
df["features"] = df["filepath"].apply(lambda x: extract_features(x))
```

[5]:
```
# Convert features to numpy array
X = np.array(df["features"].tolist())

# Encode labels
encoder = LabelEncoder()
y = encoder.fit_transform(df["emotion"])
y = to_categorical(y)  # One-hot encoding

# Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

Build the CNN-LSTM Model

[6]:
```
# Reshape input for CNN
X_train = X_train.reshape(X_train.shape[0], 40, 200, 1)
X_test = X_test.reshape(X_test.shape[0], 40, 200, 1)

# Build model
model = Sequential([
    # CNN Layers
    Conv2D(32, (3, 3), activation='relu', input_shape=(40, 200, 1)),
    MaxPooling2D((2, 2)),
    Dropout(0.2),

    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Dropout(0.2),

    TimeDistributed(Flatten()),  # Convert CNN output for LSTM
    LSTM(64, return_sequences=True),
    LSTM(64),

    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(y.shape[1], activation='softmax')  # Output layer
])

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

# Print summary
model.summary()
```

```
/usr/local/lib/python3.11/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
```

```
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

```
 Layer (type)                       Output Shape                          ␣
↪Param #

 conv2d (Conv2D)                    (None, 38, 198, 32)                       ␣
↪320

 max_pooling2d (MaxPooling2D)       (None, 19, 99, 32)                        ␣
↪  0

 dropout (Dropout)                  (None, 19, 99, 32)                        ␣
↪  0

 conv2d_1 (Conv2D)                  (None, 17, 97, 64)                     ␣
↪18,496

 max_pooling2d_1 (MaxPooling2D)     (None, 8, 48, 64)                         ␣
↪  0

 dropout_1 (Dropout)                (None, 8, 48, 64)                         ␣
↪  0

 time_distributed (TimeDistributed) (None, 8, 3072)                           ␣
↪  0

 lstm (LSTM)                        (None, 8, 64)                         ␣
↪803,072

 lstm_1 (LSTM)                      (None, 64)                             ␣
↪33,024

 dense (Dense)                      (None, 64)                              ␣
↪4,160

 dropout_2 (Dropout)                (None, 64)                                ␣
↪  0

 dense_1 (Dense)                    (None, 7)                                 ␣
↪455
```

Total params: 859,527 (3.28 MB)

Trainable params: 859,527 (3.28 MB)

Non-trainable params: 0 (0.00 B)

Train the Model

[7]:
```
# Train the model
history = model.fit(X_train, y_train, epochs=20, batch_size=16,␣
↪validation_data=(X_test, y_test))
```

```
Epoch 1/20
27/27                 15s 313ms/step -
accuracy: 0.1884 - loss: 1.9497 - val_accuracy: 0.2243 - val_loss: 1.8549
Epoch 2/20
27/27                 8s 223ms/step -
accuracy: 0.2508 - loss: 1.8638 - val_accuracy: 0.2991 - val_loss: 1.8019
Epoch 3/20
27/27                 10s 203ms/step -
accuracy: 0.2704 - loss: 1.8063 - val_accuracy: 0.3364 - val_loss: 1.7629
Epoch 4/20
27/27                 7s 275ms/step -
accuracy: 0.3553 - loss: 1.7028 - val_accuracy: 0.4206 - val_loss: 1.6157
Epoch 5/20
27/27                 6s 204ms/step -
accuracy: 0.3757 - loss: 1.5451 - val_accuracy: 0.4393 - val_loss: 1.5274
Epoch 6/20
27/27                 6s 239ms/step -
accuracy: 0.4435 - loss: 1.4603 - val_accuracy: 0.4486 - val_loss: 1.4144
Epoch 7/20
27/27                 9s 207ms/step -
accuracy: 0.5227 - loss: 1.3633 - val_accuracy: 0.5234 - val_loss: 1.3222
Epoch 8/20
27/27                 7s 271ms/step -
accuracy: 0.4583 - loss: 1.3137 - val_accuracy: 0.4766 - val_loss: 1.4256
Epoch 9/20
27/27                 6s 209ms/step -
accuracy: 0.5553 - loss: 1.1543 - val_accuracy: 0.5140 - val_loss: 1.3464
Epoch 10/20
27/27                 11s 233ms/step -
accuracy: 0.5889 - loss: 1.0612 - val_accuracy: 0.5047 - val_loss: 1.3421
Epoch 11/20
27/27                 6s 214ms/step -
accuracy: 0.5711 - loss: 1.0676 - val_accuracy: 0.4673 - val_loss: 1.4629
```

```
Epoch 12/20
27/27              10s 200ms/step -
accuracy: 0.6093 - loss: 1.0420 - val_accuracy: 0.5140 - val_loss: 1.4074
Epoch 13/20
27/27              11s 208ms/step -
accuracy: 0.5734 - loss: 1.0755 - val_accuracy: 0.5607 - val_loss: 1.2911
Epoch 14/20
27/27              12s 282ms/step -
accuracy: 0.6593 - loss: 1.0187 - val_accuracy: 0.5607 - val_loss: 1.3380
Epoch 15/20
27/27              8s 212ms/step -
accuracy: 0.6303 - loss: 0.8721 - val_accuracy: 0.4953 - val_loss: 1.4226
Epoch 16/20
27/27              10s 199ms/step -
accuracy: 0.6181 - loss: 0.9628 - val_accuracy: 0.5421 - val_loss: 1.3738
Epoch 17/20
27/27              10s 202ms/step -
accuracy: 0.6649 - loss: 0.9221 - val_accuracy: 0.5607 - val_loss: 1.4456
Epoch 18/20
27/27              12s 270ms/step -
accuracy: 0.7054 - loss: 0.8318 - val_accuracy: 0.5514 - val_loss: 1.2939
Epoch 19/20
27/27              12s 327ms/step -
accuracy: 0.6646 - loss: 0.8627 - val_accuracy: 0.4860 - val_loss: 1.4756
Epoch 20/20
27/27              9s 263ms/step -
accuracy: 0.6671 - loss: 0.9864 - val_accuracy: 0.4673 - val_loss: 1.3212
```

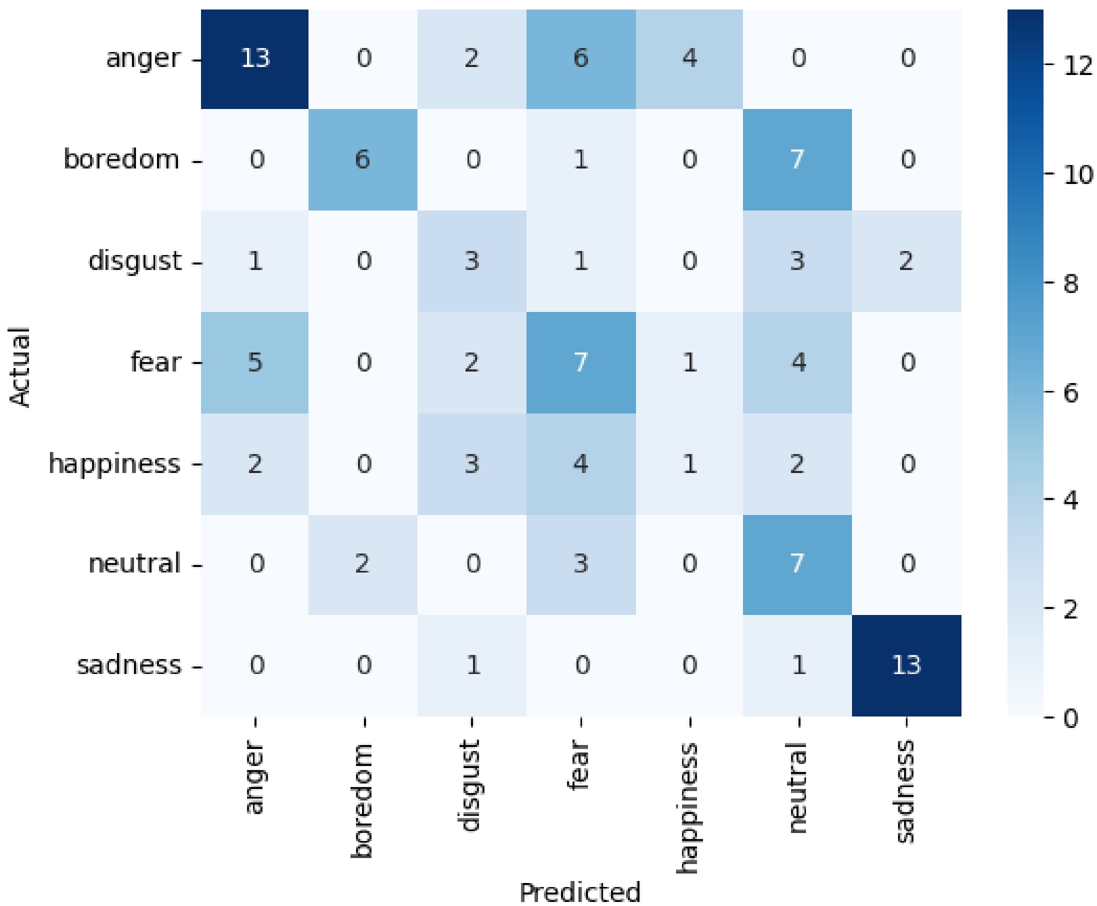
Evaluate the Model

[8]:
```
# Evaluate on test data
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.2f}")

# Plot the loss and accuracy curves
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Loss Curve')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
```

```
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Accuracy Curve')
plt.legend()

plt.tight_layout()
plt.show()


# Predict and display confusion matrix
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

cm = confusion_matrix(y_true_classes, y_pred_classes)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=encoder.
    ↪classes_, yticklabels=encoder.classes_)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
4/4              1s 297ms/step -
accuracy: 0.4817 - loss: 1.3092
Test Accuracy: 0.47
```


```
4/4              3s 474ms/step
```


anger
boredom
disgust
fear
happiness
neutral
sadness
Actual
Predicted
13 0 2 6 4 0 0
0 6 0 1 0 7 0
1 0 3 1 0 3 2
5 0 2 7 1 4 0
2 0 3 4 1 2 0
0 2 0 3 0 7 0
0 0 1 0 0 1 13
0
2
4
6
8
10
12