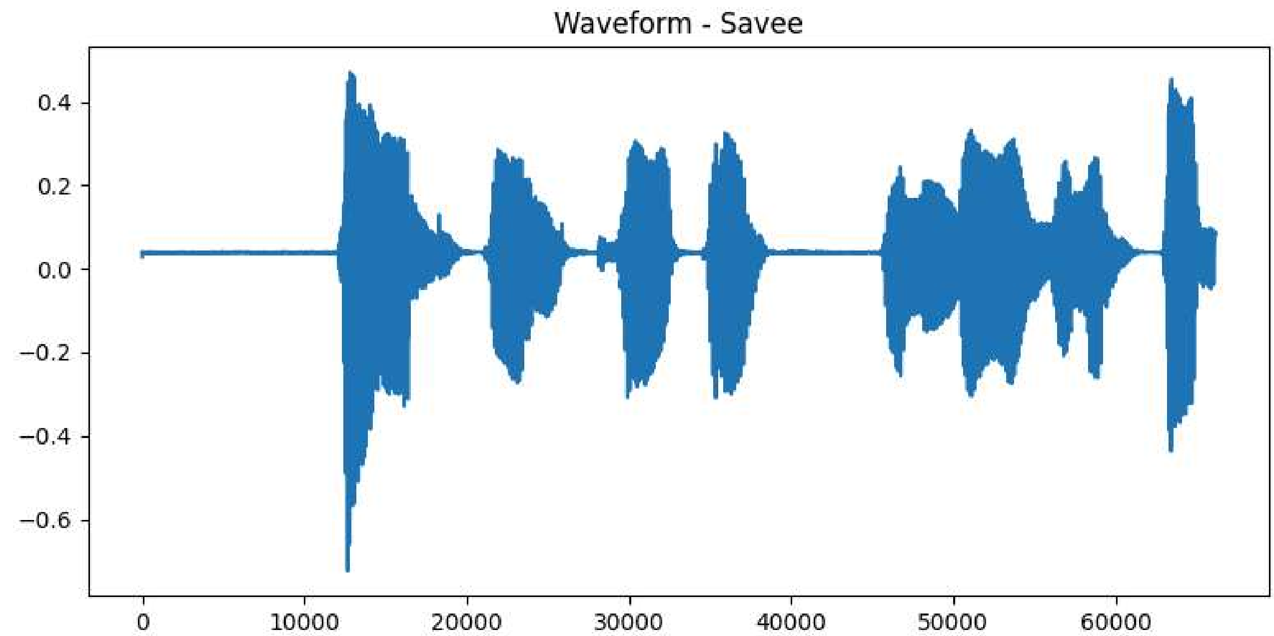
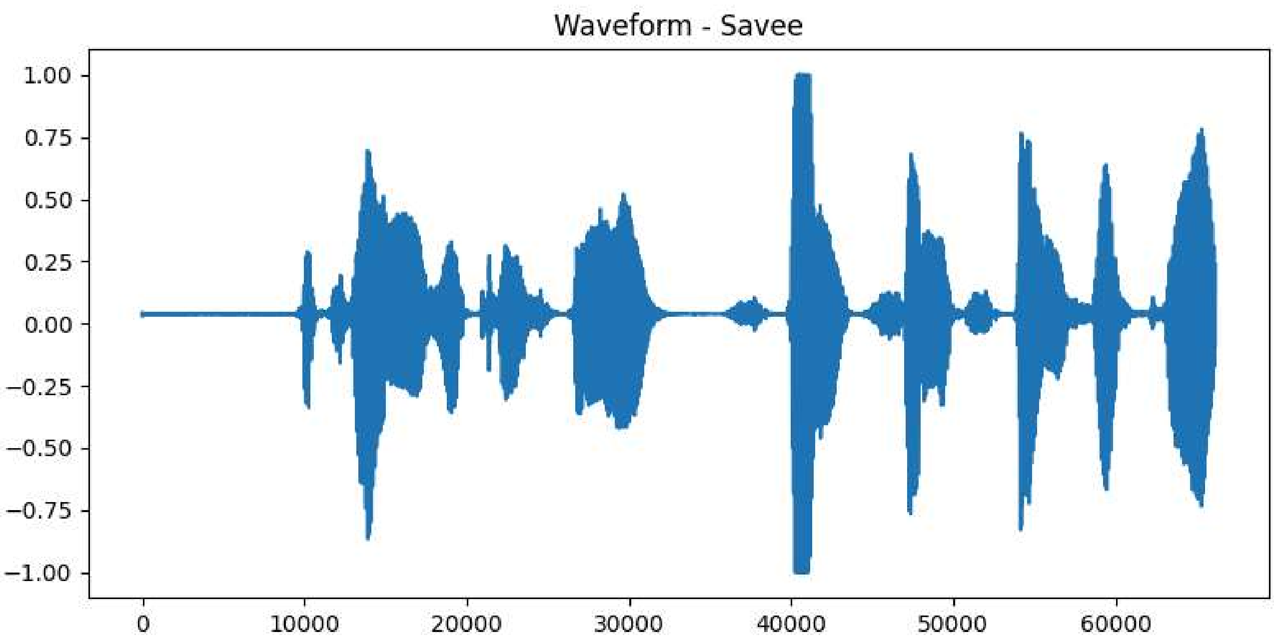
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import sys
from IPython.display import Audio
import librosa
import librosa.display

from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

import tensorflow as tf
from tensorflow.keras.models import Sequential
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout


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


data_dir = '/content/Savee.zip'


import zipfile
import os

# Assuming your zip file is in '/content/Savee.zip'
zip_file_path = '/content/Savee.zip'
extract_dir = '/content/Savee'  # Choose your desired extraction directory

# Extract the zip file
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

# Update the data_dir variable to point to the extracted directory
data_dir = extract_dir

# Now, the rest of your code should work
features = []
labels = []
for folder in os.listdir(data_dir):
    folder_path = os.path.join(data_dir, folder)
```

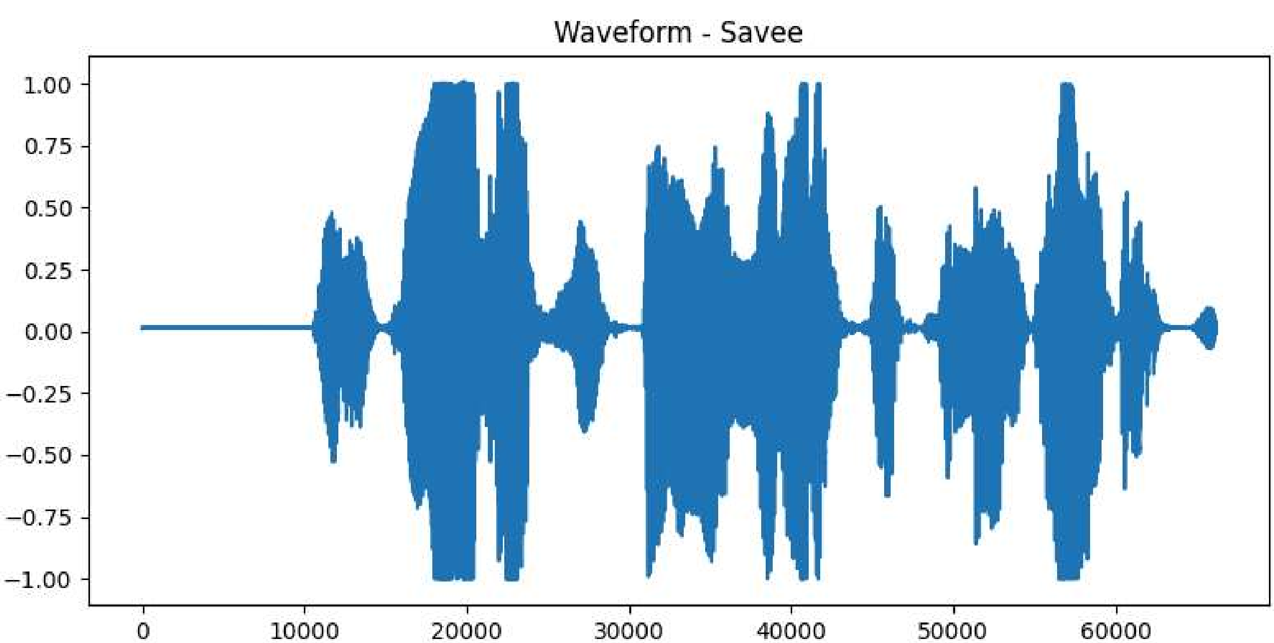
```
    if os.path.isdir(folder_path):
        emotion_label = folder.split('_')[-1]  # Extract the emotion label from the folder r

        for file_name in os.listdir(folder_path):
            file_path = os.path.join(folder_path, file_name)
            if file_path.endswith('.wav'):
                # Load the audio file and extract features
                audio, sr = librosa.load(file_path, duration=3)  # Adjust the duration as ne
                mfcc = librosa.feature.mfcc(y=audio, sr=sr, n_mfcc=13)
                mfcc_mean = np.mean(mfcc, axis=1)
                features.append(mfcc_mean)
                labels.append(emotion_label)


features = np.array(features)
labels = np.array(labels)


label_encoder = LabelEncoder()
labels_encoded = label_encoder.fit_transform(labels)


# Define the emotions and the number of samples to select from each emotion
emotions = ['angry', 'disgust', 'fear', 'happy', 'neutral', 'sad']
num_samples_per_emotion = 3
# Initialize empty lists for storing the selected samples
selected_samples = []


import zipfile
import os
import librosa
import numpy as np
from sklearn.preprocessing import LabelEncoder

# Assuming your zip file is in '/content/Savee.zip'
zip_file_path = '/content/Savee.zip'
extract_dir = '/content/Savee'  # Choose your desired extraction directory

# Extract the zip file
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

# Update the data_dir variable to point to the extracted directory
data_dir = extract_dir

# Now, the rest of your code should work
features = []
labels = []
for folder in os.listdir(data_dir):
    folder_path = os.path.join(data_dir, folder)
    if os.path.isdir(folder_path):
```

```
        # Assuming emotion label is the last part of the folder name,
        # but adapt this based on your actual folder structure
        emotion_label = folder.split('_')[-1]

        for file_name in os.listdir(folder_path):
            file_path = os.path.join(folder_path, file_name)
            if file_path.endswith('.wav'):
                # Load the audio file and extract features
                audio, sr = librosa.load(file_path, duration=3)  # Adjust the duration as ne
                mfcc = librosa.feature.mfcc(y=audio, sr=sr, n_mfcc=13)
                mfcc_mean = np.mean(mfcc, axis=1)
                features.append(mfcc_mean)
                labels.append(emotion_label)

features = np.array(features)
labels = np.array(labels)

label_encoder = LabelEncoder()
labels_encoded = label_encoder.fit_transform(labels)

# Define the emotions based on the actual folder names
# Adjust 'emotions' list to match the folder structure
# Example: emotions = ['DC', 'JE', 'JK', 'KL'] # Replace with actual folder names
emotions = [folder.split('_')[0] for folder in os.listdir(data_dir) if os.path.isdir(os.path

num_samples_per_emotion = 3

# Initialize empty lists for storing the selected samples
selected_samples = []

# Iterate through the emotions and select samples
for emotion in emotions:
    # Construct the emotion directory path based on your actual folder structure
    emotion_dir = os.path.join(data_dir, f'{emotion}')  # Modified to match actual folder st

    if os.path.exists(emotion_dir):  # Check if the directory exists
        audio_files = os.listdir(emotion_dir)
        selected_files = np.random.choice(audio_files, size=num_samples_per_emotion, replace

        for file_name in selected_files:
            file_path = os.path.join(emotion_dir, file_name)
            audio, sr = librosa.load(file_path, duration=3)
            selected_samples.append((audio, sr, emotion))
    else:
        print(f"Warning: Emotion directory not found: {emotion_dir}")  # Print a warning if



# Plot the selected samples
num_samples = len(selected_samples)
plt.figure(figsize=(8, 4 * num_samples))
```

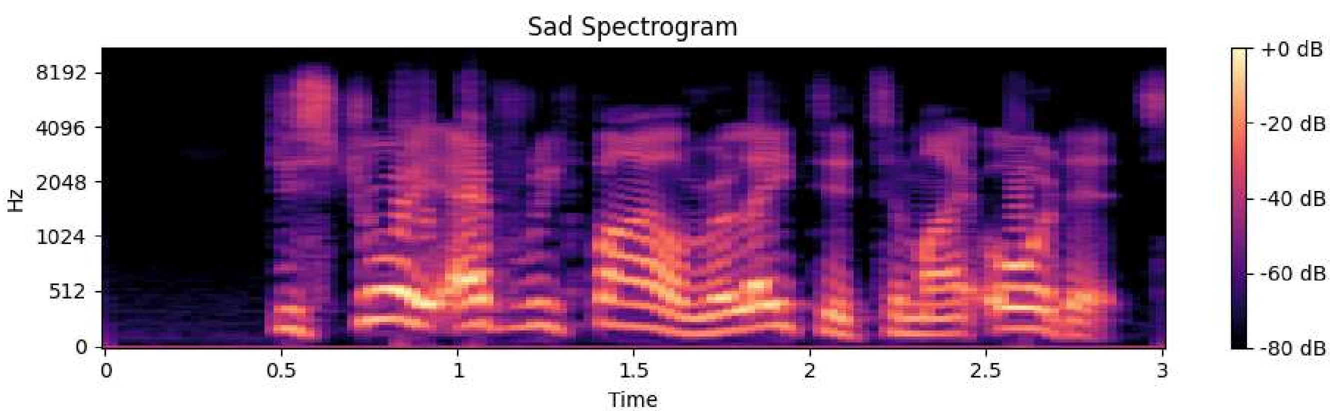
```
for i, (audio, sr, emotion) in enumerate(selected_samples):
    plt.subplot(num_samples, 1, i + 1)
    plt.plot(audio)
    plt.title(f'Waveform - {emotion}')

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


Waveform - Savee
0.4
0.2
0.0
−0.2
−0.4
−0.6
0
10000
20000
30000
40000
50000
60000


Waveform - Savee
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
10000
20000
30000
40000
50000
60000


Waveform - Savee
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
10000
20000
30000
40000
50000
60000

```
# Calculate the spectrogram
spectrogram = librosa.feature.melspectrogram(y=audio, sr=sr)

# Convert power spectrogram to dB scale
spectrogram_db = librosa.power_to_db(spectrogram, ref=np.max)

# Plot the spectrogram
plt.figure(figsize=(10, 3))
librosa.display.specshow(spectrogram_db, sr=sr, x_axis='time', y_axis='mel')
plt.colorbar(format='%+2.0f dB')
plt.title('Sad Spectrogram')
plt.tight_layout()
plt.show()
Audio(file_path)
```



0:03 / 0:03

```
# Apply audio transformations (e.g., noise addition, time stretching, pitch shifting)
augmented_features = []
augmented_labels = []
```

```
for feature, label in zip(features, labels):
    augmented_features.append(feature)
    augmented_labels.append(label)

    # Apply noise addition
    noise = np.random.randn(len(feature))
    augmented_features.append(feature + 0.005 * noise)  # Adjust the noise magnitude as neec
    augmented_labels.append(label)

    # Apply time stretching
    # Reshape time_stretch output to match original feature shape
    stretched_feature = librosa.effects.time_stretch(feature, rate=1.2)
    # Pad or trim the stretched feature to match the original feature length
    stretched_feature = np.pad(stretched_feature, (0, len(feature) - len(stretched_feature))

    augmented_features.append(stretched_feature)
    augmented_labels.append(label)

    # Apply pitch shifting (Assuming the pitch function is defined elsewhere)
    # pitched_feature = pitch(feature, sr, pitch_factor=0.7)
    # pitched_feature = pitched_feature[:feature.shape[0]]  # Trim or pad to original length
    # augmented_features.append(pitched_feature)
    # augmented_labels.append(label)

# Convert the augmented lists to NumPy arrays
augmented_features = np.array(augmented_features)
augmented_labels = np.array(augmented_labels)

# Print the number of original and augmented samples
print('Original samples:', len(features))
print('Augmented samples:', len(augmented_features))
```

```
/usr/local/lib/python3.10/dist-packages/librosa/core/spectrum.py:266: UserWarning: n_fft
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/librosa/core/spectrum.py:266: UserWarning: n_fft
  warnings.warn(
Original samples: 480
Augmented samples: 1440
```

```
# Define a list to store the preprocessed data
preprocessed_data = []
file_list = os.listdir(data_dir)
# Iterate over the files
for filename in file_list:
    file_path = os.path.join(data_dir, filename)

    # Skip non-audio files
    if not filename.endswith('.wav'):
        continue
```

```
    # Load the audio file and obtain the waveform and sample rate
    waveform, sr = librosa.load(file_path, sr=None, dtype=np.float32)

    # Resample the audio if needed
    if sr != 22050:
        waveform = librosa.resample(waveform, sr, 22050)
        sr = 22050



# Encode the emotion labels
label_mapping = {'angry': 0, 'disgust': 1, 'fear': 2, 'happy': 3, 'neutral': 4, 'sad': 5}
encoded_labels = np.array([label_mapping.get(label, -1) for label in labels])

# Filter out any samples with unknown emotion labels
valid_indices = np.where(encoded_labels != 1)[0]  # Get the indices from the tuple
features = features[valid_indices]
encoded_labels = encoded_labels[valid_indices]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, encoded_labels, test_size=0.2,

# Reshape the input features
X_train = X_train.reshape((*X_train.shape, 1))
X_test = X_test.reshape((*X_test.shape, 1))


# Convert the emotion labels to categorical format
num_classes = len(label_mapping)
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)


print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (384, 13, 1)
y_train shape: (384, 6)
X_test shape: (96, 13, 1)
y_test shape: (96, 6)
```

```
#Build the cnn model architeture
model = Sequential()

# Add the first convolutional layer
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(13, 1, 1), padding='same'))

# Flatten the output
```

```
model.add(Flatten())

# Add a dense layer0
model.add(Dense(32, activation='relu'))

# Add the output layer
model.add(Dense(6, activation='softmax'))

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

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 13, 1, 32)	320
flatten (Flatten)	(None, 416)	0
dense (Dense)	(None, 32)	13,344
dense_1 (Dense)	(None, 6)	198

Total params: 13,862 (54.15 KB)

```
history = model.fit(X_train, y_train, batch_size=64, epochs=10, validation_data=(X_test, y_t

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)

print("Test loss:", loss)
print("Test accuracy:", accuracy)
```

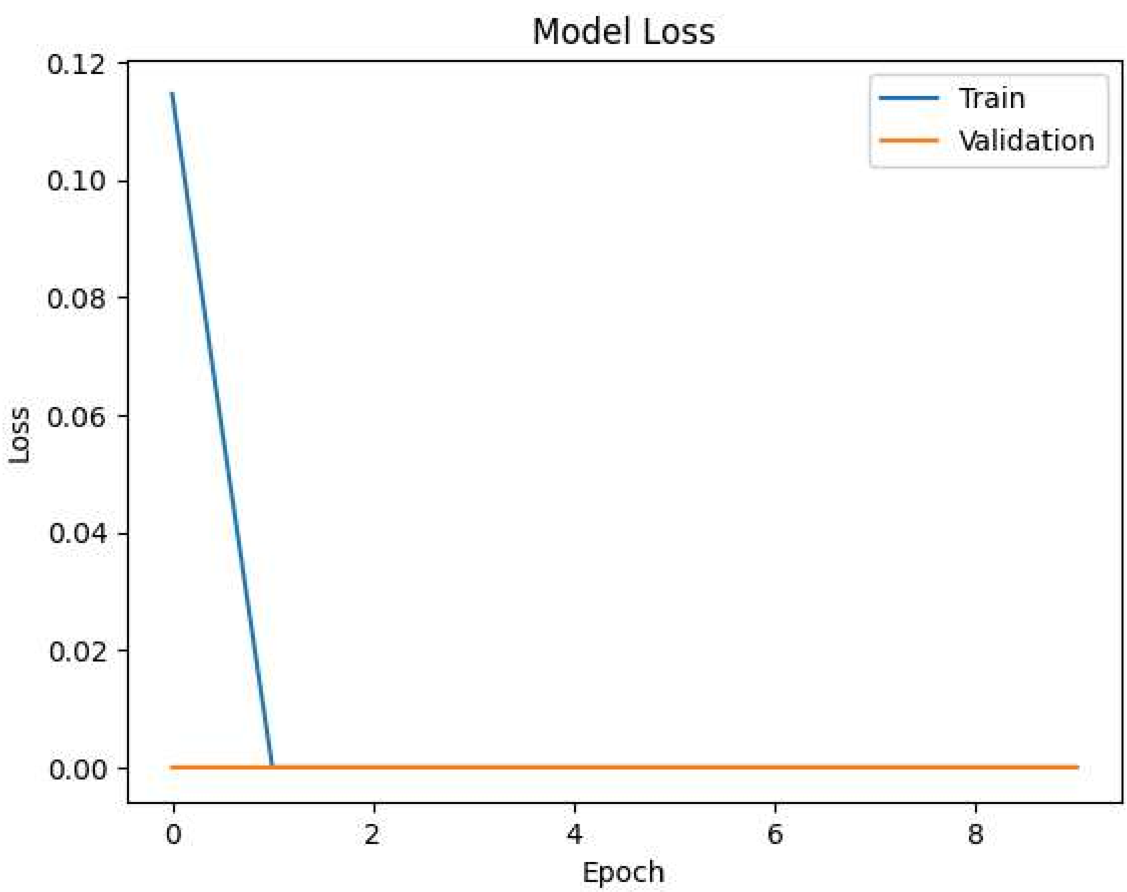
```
Epoch 1/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 2s 50ms/step - accuracy: 0.8423 - loss: 0.2547 - val_accuracy:
Epoch 2/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 1.0000 - loss: 2.1069e-06 - val_accura
Epoch 3/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 1.0000 - loss: 9.2263e-08 - val_accura
Epoch 4/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 1.0000 - loss: 1.6192e-08 - val_accura
Epoch 5/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 1.0000 - loss: 7.5615e-09 - val_accura
Epoch 6/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 1.0000 - loss: 4.1910e-09 - val_accura
Epoch 7/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - accuracy: 1.0000 - loss: 3.7918e-09 - val_accura
Epoch 8/10
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 1.0000 - loss: 3.2197e-09 - val_accura
Epoch 9/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 1.0000 - loss: 2.1687e-09 - val_accurac
Epoch 10/10
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 1.0000 - loss: 2.0001e-09 - val_accura
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 1.0000 - loss: 2.1731e-09
Test loss: 2.4835264955669345e-09
Test accuracy: 1.0
```

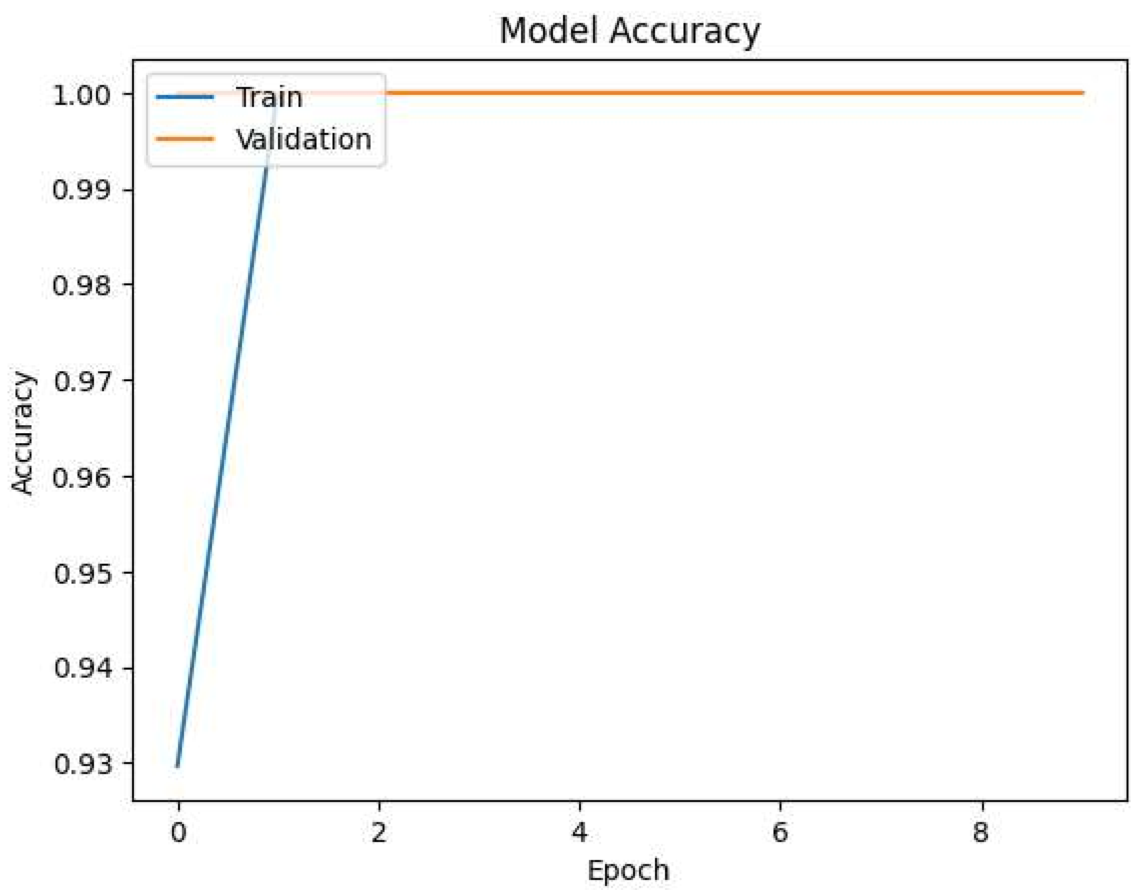
```
print("Accuracy of our model on test data : " , model.evaluate(X_test,y_test)[1]*100 , "%")
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 1.0000 - loss: 2.1731e-09
Accuracy of our model on test data :  100.0 %
```

```
# Plot the training and validation loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
```



```
# Plot the training and validation accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```




```
# Get the predicted labels for the test set
y_pred = model.predict(X_test)
y_pred_labels = np.argmax(y_pred, axis=1)  # Convert one-hot encoded predictions to labels

# Convert the true labels from one-hot encoding to labels
y_true_labels = np.argmax(y_test, axis=1)

# Generate the confusion matrix
cm = confusion_matrix(y_true_labels, y_pred_labels)

class_names = ['angry', 'disgust', 'fear', 'happy', 'neutral', 'sad']  # Replace with your a
report = classification_report(y_true_labels, y_pred_labels, target_names=class_names, label

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=clas
plt.title('Confusion Matrix')
```

```
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.show()
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:409: UserWarr
  warnings.warn(
```

```
print(report)
```

```
              precision    recall  f1-score   support

       angry       0.00      0.00      0.00         0
     disgust       0.00      0.00      0.00         0
        fear       0.00      0.00      0.00         0
       happy       0.00      0.00      0.00         0
     neutral       0.00      0.00      0.00         0
         sad       1.00      1.00      1.00        96

    accuracy                           1.00        96
   macro avg       0.17      0.17      0.17        96
weighted avg       1.00      1.00      1.00        96

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: Undefin
```

```
history = model.fit(X_train, y_train, validation_split=0.3, epochs=10, batch_size=64)
```

```
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - accuracy: 1.0000 - loss: 4.4786e-09 - val_accura
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 1.0000 - loss: 3.6508e-09 - val_accura
Epoch 3/10
```