import numpy as np

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import librosa
import cv2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout, Cony2D, MaxPooling2D, Flatten, Input
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
from collections import defaultdict
from google.colab import drive
# 스펙트로그램 생성 함수 (리사이즈 적용)
def extract_spectrogram_segment(y, sr, start, duration=10, n_mels=128):
   오디오 신호에서 시작 시간부터 일정 기간의 스펙트로그램을 생성하고 리사이즈.
   y_segment = y[int(start * sr):int((start + duration) * sr)] # 특정 구간의 샘플 추출
   if len(y_segment) < duration * sr: # 10초보다 짧은 구간 제외
       return None # 작은 구간은 None 반환
   spectrogram = librosa.feature.melspectrogram(y=y_segment, sr=sr, n_mels=n_mels)
   spectrogram_db = librosa.power_to_db(spectrogram, ref=np.max)
   # 스펙트로그램을 128x128 크기로 리사이즈 (OpenCV 활용)
   spectrogram_resized = cv2.resize(spectrogram_db, (128, 128), interpolation=cv2.INTER_CUBIC)
   return spectrogram_resized
# 데이터 로드 항수 (파일 단위로 나누기)
def load_data_by_files(data_path, labels, segment_duration=10):
   오디오 파일별로 스펙트로그램 데이터를 생성하고 라벨을 매핑.
   data_by_files = defaultdict(list)
   for label in labels:
       genre_folder = os.path.join(data_path, label)
       for file in os.listdir(genre_folder):
           if file.endswith('.wav'): # .wav 파일만 처리
               file_path = os.path.join(genre_folder, file)
               try:
                  y, sr = librosa.load(file_path, sr=22050) # 오디오 파일 로드 (샘플링 레이트: 22050)
                  total_duration = librosa.get_duration(y=y, sr=sr)
                  # 10초 단위로 데이터를 나눠 스펙트로그램 생성
                  for start in range(0, int(total_duration), segment_duration):
                      spectrogram = extract_spectrogram_segment(y, sr, start, duration=segment_duration)
                      if spectrogram is not None: # 유효한 스펙트로그램만 추가
                         data_by_files[file].append((spectrogram, label))
               except Exception as e:
                  print(f"Error processing {file_path}: {e}")
   return data_by_files
# 데이터 로드
drive.mount('/content/drive')
DATA_PATH = '/content/drive/My Drive/DataSet/genres_original'
CLASS_LABELS = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal', 'pop', 'reggae', 'rock']
print("Extracting features from audio files...")
data_by_files = load_data_by_files(DATA_PATH, CLASS_LABELS, segment_duration=10)
# 파일 이름 기반으로 데이터 분리
file_names = list(data_by_files.keys())
train_files, test_files = train_test_split(file_names, test_size=0.2, random_state=42)
# 훈련 및 테스트 데이터 구성
X_train, y_train = [], []
X_test, y_test = [], []
for file in train files:
   for spectrogram, label in data_by_files[file]:
       X_train.append(spectrogram)
       y_train.append(label)
for file in test_files:
   for spectrogram, label in data_by_files[file]:
       X_test.append(spectrogram)
       y_test.append(label)
X_train = np.array(X_train)[..., np.newaxis] # CNN 입력을 위한 채널 차원 추가 (128, 128, 1)
X_train = np.repeat(X_train, 3, axis=-1) # VGG16은 3채널 이미지를 필요로 하므로 채널 복제 (128, 128, 3)
X_test = np.array(X_test)[..., np.newaxis]
X_test = np.repeat(X_test, 3, axis=-1)
# 라벨 인코딩
label_encoder = LabelEncoder()
v train encoded = label encoder.fit transform(v train)
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\verb|y_train_encoded| = to_categorical(y_train_encoded, num_classes=len(CLASS_LABELS))|
y_test_encoded = label_encoder.transform(y_test)
y_test_encoded = to_categorical(y_test_encoded, num_classes=len(CLASS_LABELS))
# 사전 학습된 VGG16 모델 로드
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(128, 128, 3))
for layer in base_model.layers:
    layer.trainable = False # 사전 학습된 가중치를 고정
# 분류 계층 추가
x = base_model.output
x = GlobalAveragePooling2D()(x) # GAP 계층 추가
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(len(CLASS_LABELS), activation='softmax')(x)
# 새 모델 정의
model = Model(inputs=base_model.input, outputs=predictions)
# 모델 컨파잌
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy'
              metrics=['accuracy'])
Exprise already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
     Extracting features from audio files...
# 모델 학습
history = model.fit(X train. v train encoded, epochs=5, batch size=32, validation data=(X test. v test encoded))
# 모델 평가
test_loss, test_accuracy = model.evaluate(X_test, y_test_encoded, verbose=2)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
# 학습 과정 시각화
import matplotlib.pyplot as plt
def plot_history(history):
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
   plt.legend()
    plt.title('Accuracy')
   plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Train Loss')
   plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.legend()
   plt.title('Loss')
   plt.show()
plot_history(history)
 € Epoch 1/5
     75/75 -
                                                    649s 9s/step - accuracy: 0.1788 - loss: 4.2707 - val_accuracy: 0.4197 - val_loss: 1.6659
     Epoch 2/5
     75/75
                                                    651s 9s/step - accuracy: 0.4458 - loss: 1.6271 - val_accuracy: 0.5117 - val_loss: 1.4047
     Epoch 3/5
     75/75
                                                    682s 9s/step - accuracy: 0.5113 - loss: 1.4202 - val_accuracy: 0.5585 - val_loss: 1.2915
     Epoch 4/5
     75/75
                                                    622s 8s/step - accuracy: 0.5606 - loss: 1.2428 - val_accuracy: 0.5585 - val_loss: 1.2243
     Epoch 5/5
     75/75
                                                   - 678s 8s/step - accuracy: 0.5803 - loss: 1.1525 - val_accuracy: 0.5669 - val_loss: 1.1827
      19/19 - 133s - 7s/step - accuracy: 0.5669 - loss: 1.1827
     Test Accuracy: 56.69%
                                     Accuracy
                                                                                                               Loss
       0.60
                                                                               2.8
                                                                                                                               Train Loss
                                                                                                                              Validation Loss
                                                                               2.6
       0.55
                                                                               2.4
       0.50
                                                                               2.2
       0.45
                                                                               2.0
       0.40
                                                                               1.8
       0.35
                                                                               1.4
       0.30
                                                   Train Accuracy
                                                                               1.2
                                                   Validation Accuracy
       0.25
              0.0
                    0.5
                           1.0
                                  1.5
                                        2.0
                                                      3.0
                                                                    4.0
                                                                                     0.0
                                                                                            0.5
                                                                                                  1.0
                                                                                                         1.5
                                                                                                               2.0
                                                                                                                      2.5
                                                                                                                                           4.0
                                               2.5
                                                             3.5
                                                                                                                             3.0
                                                                                                                                    3.5
# 간단한 CNN 모델 정의
model = Sequential([
    # Conv Block 1
    Input(shape=(128, 128, 3)), # 입력 크기 지정
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Conv2D(32, (3, 3), activation='relu', padding='same'),

다음 단계: 오류 설명

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# Conv Block 2
    Conv2D(64, (3, 3), activation='relu', padding='same'),
    # Conv Block 3
    Conv2D(128, (3, 3), activation='relu', padding='same'),
    # Conv Block 4
    Conv2D(128, (3, 3), activation='relu', padding='same'),
    # Flatten and Dense Layers
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(len(CLASS_LABELS), activation='softmax')
])
# 모델 컴파일
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(X_train, y_train_encoded, epochs=10, batch_size=32, validation_data=(X_test, y_test_encoded))
# 모델 평가
test_loss, test_accuracy = model.evaluate(X_test, y_test_encoded, verbose=2)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
# 학습 과정 시각화
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    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.legend()
    plt.title('Accuracy')
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.legend()
    plt.title('Loss')
    plt.show()
plot_history(history)
출 숨겨진 출력 표시
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 $https://colab.research.google.com/drive/1jW8wtHChO57Z-h3GdVtDAw6_HQga1oaD? authuser=0\#scrollTo=QbwzPp8bPK2x$