

# rim\_trad\_music\_recognizer (9)

May 20, 2024

<span style = “font-family : ‘Times New Roman’ ; font-size: 28pt ; line-height: 1.5”

Classification et Reconnaissance des Notes (Maqamat) de Musique Traditionnelle Mauritanienne à l’aide d’un LSTM

Zeinebou TAKI Ahmed Bezeid Moulaye Ahmed Mohamed BRAHIM

Le 17 Mai 2024

#

## INTRODUCTION ET OBJECTIFS DU PROJET

#

### Introduction

La musique traditionnelle mauritanienne est riche en histoire, en culture et en diversité. Au cœur de cette musique se trouve un instrument emblématique appelé le tidinit, qui produit une variété de notes et de mélodies. Pour classer ces mélodies et faciliter les relations du joueur avec l’instrument ainsi qu’avec la gamme musicale, les musiciens mauritaniens utilisent un système appelé les “maqamat”. Les maqamat sont des séquences de signes musicaux organisés selon certaines dimensions et règles établies, permettant de classer les mélodies musicales de manière systématique.

Cependant, malgré l’importance des maqamat dans la musique mauritanienne, leur classification et leur reconnaissance manquent souvent de précision et nécessitent une expertise approfondie. Actuellement, il n’existe pas de méthode efficace pour automatiser cette classification complexe, ce qui limite la compréhension et l’analyse précises de la musique mauritanienne.

#

### Objectifs et utilité du projet

Notre objectif principal est de développer un modèle de deep learning basé sur un LSTM capable de recevoir des enregistrements audio de musique traditionnelle mauritanienne contenant des notes de tidinit, et de les classer avec précision en fonction de leur maqam. En fournissant un outil automatisé pour analyser la musique basée sur les maqamat, nous visons à faciliter la compréhension et l’étude de ce patrimoine musical riche et complexe.

Utilité et Impact : Ce projet présente plusieurs avantages :

Préservation Culturelle : En automatisant la classification des maqamat, notre modèle contribuera à préserver et à documenter de manière précise la musique traditionnelle mauritanienne, facilitant ainsi sa transmission aux générations futures. Accessibilité : En fournissant un outil automatisé pour reconnaître les maqamat, notre modèle rendra la musique mauritanienne plus accessible aux

musiciens et aux chercheurs du monde entier, favorisant ainsi l'échange culturel et la diversité musicale. Enrichissement de la Pratique Musicale : En facilitant l'identification précise des maqamat, notre modèle aidera les musiciens mauritaniens à explorer de nouvelles avenues créatives et à enrichir leur pratique musicale.

En combinant les traditions musicales anciennes avec les technologies modernes de deep learning, notre projet vise à ouvrir de nouvelles perspectives pour l'étude, la préservation et la diffusion de la musique traditionnelle mauritanienne, en particulier en ce qui concerne la classification des maqamat. Nous croyons fermement que notre modèle LSTM contribuera à enrichir la compréhension et l'appréciation de ce riche patrimoine culturel pour les générations présentes et futures.

#

DATA PREPARATION

#

Chargement des packages & Importation des donnees

```
[140]: import os
import librosa
import math
import json
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Usual Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn

# Librosa (the mother of audio files)
import librosa
import librosa.display
import IPython.display as ipd
import warnings
warnings.filterwarnings('ignore')
```

## 1 Convertission des extenction :

```
[4]: pip install pydub
```

Requirement already satisfied: pydub in  
c:\users\hp\appdata\local\programs\python\python311\lib\site-packages (0.25.1)  
Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 23.3.2 -> 24.0

[notice] To update, run: python.exe -m pip install --upgrade pip

```
[7]: import os

# Chemin vers le dossier contenant les fichiers audio
input_folder = r'C:\Users\hp\Downloads\My_Projects\traditional music_
↳generator\music dataset'

# Parcourir tous les genres et tous les fichiers audio pour vérifier leur
↳existence
for genre_folder in os.listdir(input_folder):
    genre_path = os.path.join(input_folder, genre_folder)
    if os.path.isdir(genre_path):
        for filename in os.listdir(genre_path):
            file_path = os.path.join(genre_path, filename)
            if os.path.isfile(file_path):
                print(f"Found: {file_path}")
            else:
                print(f"Missing: {file_path}")
```

```
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\karr_guitar.mp3
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\karr_guitar2.mp3
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\khal karr 2.unknown
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\khall_karr.dat.unknown
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\khall_karr2.opus
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\karr\seyni_karr.opus
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\byad_lebteyt.opus
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\khal_lebteyt.opus
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\lebteyt 3.unknown
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\lebteyt.dat.unknown
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\lebteyt_guitar.mp3
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebteyt\lebteyt_guitar2.mp3
Found: C:\Users\hp\Downloads\My_Projects\traditional music generator\music
dataset\lebyad\lbyad3.unknown
```

Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad.dat.unknown  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad2.opus  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad\_guitar.mp3  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad\_guitar2.mp3  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lleyin.opus  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lkhall\lk7all3.unknown  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lkhall\lk7all\_guitar.mp3  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lkhall\lkhall.dat.unknown  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lkhall\lkhall2.opus  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lkhall\lkhall\_guitar2.mp3  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\byad\_va9ou(te7rar).opus  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\khal va9ou.unknown  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\khal\_va9ou.wav.unknown  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\va9ou2.opus  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\va9ou\_guitar.mp3  
Found: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\va9ou\va9ou\_guitar2.mp3

```
[142]: import os
import subprocess

def convert_to_wav(input_file, output_file):
    command = ['C:\\Users\\hp\\Downloads\\ffmpeg-7.0-essentials_build\\ffmpeg-7.0-essentials_build\\bin\\ffmpeg.exe', '-i', input_file, output_file]
    try:
        subprocess.run(command, check=True)
        print(f"Converted: {input_file} to {output_file}")
    except subprocess.CalledProcessError as e:
        print(f"Conversion failed for {input_file}: {e}")

# Chemin vers le dossier contenant les fichiers audio
```

```

input_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music_
↳generator\music dataset'

# Chemin vers le dossier de sortie pour les fichiers convertis
output_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music_
↳generator\converted_audio'

# Vérifier si le dossier de sortie existe, sinon le créer
if not os.path.exists(output_directory):
    os.makedirs(output_directory)

# Parcourir chaque fichier dans le répertoire
for subdir, dirs, files in os.walk(input_directory):
    for file in files:
        file_path = os.path.join(subdir, file)
        # Ignorer les répertoires et les fichiers non audio
        if os.path.isfile(file_path) and file_path.endswith(('opus', '.
↳unknown', '.mp3')):
            # Créer le chemin relatif par rapport au répertoire racine
            relative_path = os.path.relpath(file_path, input_directory)
            # Créer le chemin de sortie avec la même structure de sous-dossiers
            output_subdir = os.path.join(output_directory, os.path.
↳dirname(relative_path))
            # Créer le dossier de sortie s'il n'existe pas
            if not os.path.exists(output_subdir):
                os.makedirs(output_subdir)
            # Créer le chemin de sortie complet avec l'extension .wav
            output_path = os.path.join(output_subdir, os.path.splitext(os.path.
↳basename(file))[0] + '.wav')
            # Convertir le fichier audio au format wav
            convert_to_wav(file_path, output_path)

```

Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\karr\karr\_guitar.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\karr\karr\_guitar.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\karr\karr\_guitar2.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\karr\karr\_guitar2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\karr\khal karr 2.unknown to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\karr\khal karr 2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\karr\khall\_karr.dat.unknown to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\karr\khall\_karr.dat.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music

dataset\karr\khall\_karr2.opus to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\karr\khall\_karr2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\karr\seyni\_karr.opus to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\karr\seyni\_karr.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\byad\_lebteyt.opus to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\byad\_lebteyt.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\khal\_lebteyt.opus to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\khal\_lebteyt.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\lebteyt 3.unknown to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\lebteyt 3.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\lebteyt.dat.unknown to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\lebteyt.dat.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\lebteyt\_guitar.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\lebteyt\_guitar.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebteyt\lebteyt\_guitar2.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebteyt\lebteyt\_guitar2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lbyad3.unknown to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebyad\lbyad3.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad.dat.unknown to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebyad\lebyad.dat.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad2.opus to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebyad\lebyad2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad\_guitar.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebyad\lebyad\_guitar.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music dataset\lebyad\lebyad\_guitar2.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional music generator\converted\_audio\lebyad\lebyad\_guitar2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music

dataset\lebyad\lleyin.opus to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\lebyad\lleyin.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\lkhall\lk7all3.unknown to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\lkhall\lk7all3.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\lkhall\lk7all\_guitar.mp3 to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\lkhall\lk7all\_guitar.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\lkhall\lkhall.dat.unknown to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\lkhall\lkhall.dat.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\lkhall\lkhall2.opus to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\lkhall\lkhall2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\lkhall\lkhall\_guitar2.mp3 to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\lkhall\lkhall\_guitar2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\byad\_va9ou(te7rar).opus to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\va9ou\byad\_va9ou(te7rar).wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\khal va9ou.unknown to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\va9ou\khal va9ou.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\khal\_va9ou.wav.unknown to  
 C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\va9ou\khal\_va9ou.wav.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\va9ou2.opus to C:\Users\hp\Downloads\My\_Projects\traditional music  
 generator\converted\_audio\va9ou\va9ou2.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\va9ou\_guitar.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\va9ou\va9ou\_guitar.wav  
 Converted: C:\Users\hp\Downloads\My\_Projects\traditional music generator\music  
 dataset\va9ou\va9ou\_guitar2.mp3 to C:\Users\hp\Downloads\My\_Projects\traditional  
 music generator\converted\_audio\va9ou\va9ou\_guitar2.wav

## 2 Subdivision des audios en segments de 10 secondes

Les audios vont être divisés en fichiers audio de 3 secondes (augmentant ainsi de 10 fois la quantité de données que nous alimentons dans nos modèles de classification). Avec les données, plus c'est toujours mieux.

```

[143]: from pydub import AudioSegment
import os

def split_to_segments(input_file, output_directory, segment_length=10):
    # Charger le fichier audio
    audio = AudioSegment.from_file(input_file)

    # Définir le nom du dossier de sortie pour conserver la structure
    relative_input_path = os.path.relpath(os.path.dirname(input_file),
    ↪input_directory)
    subfolder_name = os.path.basename(relative_input_path)
    output_subdirectory = os.path.join(output_directory, relative_input_path)

    # Créer le dossier de sortie s'il n'existe pas
    if not os.path.exists(output_subdirectory):
        os.makedirs(output_subdirectory)

    # Définir la longueur du segment en millisecondes
    segment_length_ms = segment_length * 1000

    # Calculer le nombre de segments
    num_segments = len(audio) // segment_length_ms

    # Diviser le fichier audio en segments de 10 secondes
    for i in range(num_segments):
        start_time = i * segment_length_ms
        end_time = (i + 1) * segment_length_ms
        segment = audio[start_time:end_time]
        # Nom de fichier pour le segment
        segment_filename = f"{subfolder_name}_seg{i+1:02d}.wav"
        # Chemin complet pour le fichier de segment
        segment_path = os.path.join(output_subdirectory, segment_filename)
        # Enregistrer le segment
        segment.export(segment_path, format="wav")
        print(f"Segment saved: {segment_path}")

    # Chemin vers le dossier contenant les fichiers audio
    input_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music_
    ↪generator\converted_audio'

    # Chemin vers le dossier de sortie pour les segments
    output_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music_
    ↪generator\segments_audio'

    # Parcourir chaque fichier dans le répertoire
    for subdir, dirs, files in os.walk(input_directory):
        for file in files:

```



```
file_path = os.path.join(subdir, file)
# Ignorer les répertoires et les fichiers non audio
if os.path.isfile(file_path) and file_path.endswith('.wav'):
    # Diviser le fichier audio en segments de 10 secondes
    split_to_segments(file_path, output_directory)
```

```
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg01.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg02.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg03.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg04.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg05.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg06.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg07.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg08.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg09.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg10.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg11.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg12.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg13.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg14.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg15.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg16.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg17.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg18.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg19.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg20.wav
Segment saved: C:\Users\hp\Downloads\My_Projects\traditional music
generator\segments_audio\karr\karr_seg21.wav
```

[illegible]

[illegible]

[illegible]

[illegible]



[illegible]

[illegible]





[illegible]



[illegible]

[illegible]

[illegible]







[illegible]

[illegible]

[illegible]

[illegible]











[illegible]



Segment saved: C:\Users\hp\Downloads\My\_Projects\traditional music generator\segments\_audio\va9ou\va9ou\_seg22.wav  
 Segment saved: C:\Users\hp\Downloads\My\_Projects\traditional music generator\segments\_audio\va9ou\va9ou\_seg23.wav  
 Segment saved: C:\Users\hp\Downloads\My\_Projects\traditional music generator\segments\_audio\va9ou\va9ou\_seg24.wav  
 Segment saved: C:\Users\hp\Downloads\My\_Projects\traditional music generator\segments\_audio\va9ou\va9ou\_seg25.wav

```
[144]: import os
general_path = 'C:/Users/hp/Downloads/My_Projects/traditional music generator'
print(list(os.listdir(f'{general_path}/segments_audio/')))
```

```
['karr', 'leboteyt', 'lebyad', 'lkhall', 'va9ou']
```

### 3 Extraction des caracteristiques

Le but est d'extraire les caractéristiques MFCC de chaque fichier audio et les stocke dans une DataFrame. Les étiquettes sont également stockées pour la classification.

```
[145]: import os
import librosa
import pandas as pd

# Fonction pour extraire les caractéristiques des fichiers audio
def extract_features(file_path):
    y, sr = librosa.load(file_path, duration=30) # Charger le fichier audio et
    ↪ limiter à 30 secondes
    chroma_stft_mean = librosa.feature.chroma_stft(y=y, sr=sr).mean()
    chroma_stft_var = librosa.feature.chroma_stft(y=y, sr=sr).var()
    rms_mean = librosa.feature.rms(y=y).mean()
    rms_var = librosa.feature.rms(y=y).var()
    spectral_centroid_mean = librosa.feature.spectral_centroid(y=y, sr=sr).
    ↪ mean()
    spectral_centroid_var = librosa.feature.spectral_centroid(y=y, sr=sr).var()
    spectral_bandwidth_mean = librosa.feature.spectral_bandwidth(y=y, sr=sr).
    ↪ mean()
    spectral_bandwidth_var = librosa.feature.spectral_bandwidth(y=y, sr=sr).
    ↪ var()
    rolloff_mean = librosa.feature.spectral_rolloff(y=y, sr=sr).mean()
    rolloff_var = librosa.feature.spectral_rolloff(y=y, sr=sr).var()
    zero_crossing_rate_mean = librosa.feature.zero_crossing_rate(y).mean()
    zero_crossing_rate_var = librosa.feature.zero_crossing_rate(y).var()
    tempo = librosa.beat.tempo(y=y, sr=sr)[0]
    mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=20)
    mfcc_means = mfccs.mean(axis=1)
    mfcc_vars = mfccs.var(axis=1)
```

```

    # Retourner les caractéristiques sous forme de liste
    return [chroma_stft_mean, chroma_stft_var, rms_mean, rms_var,
    ↪spectral_centroid_mean, spectral_centroid_var,
        spectral_bandwidth_mean, spectral_bandwidth_var, rolloff_mean,
    ↪rolloff_var, zero_crossing_rate_mean,
        zero_crossing_rate_var, tempo] + mfcc_means.tolist() + mfcc_vars.
    ↪tolist()

# Chemin d'accès au répertoire contenant les segments audio subdivisés
segments_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music\
    ↪generator\segments_audio'

# Liste pour stocker les caractéristiques et les étiquettes
features = []
labels = []
filenames = []
lengths = []

# Parcourir chaque fichier audio dans le dossier
for genre in os.listdir(segments_directory):
    genre_folder = os.path.join(segments_directory, genre)
    if os.path.isdir(genre_folder):
        for file_name in os.listdir(genre_folder):
            file_path = os.path.join(genre_folder, file_name)
            if file_path.endswith(".wav"): # S'assurer que le fichier est au
    ↪format WAV
                try:
                    file_features = extract_features(file_path)
                    features.append(file_features)
                    labels.append(genre)
                    filenames.append(file_name)
                    lengths.append(librosa.get_duration(filename=file_path))
                except Exception as e:
                    print(f"Erreur lors de l'extraction des caractéristiques
    ↪pour {file_path}: {e}")

# Créer un DataFrame à partir des caractéristiques et des étiquettes
data = pd.DataFrame(features, columns=[
    'chroma_stft_mean', 'chroma_stft_var', 'rms_mean', 'rms_var',
    ↪'spectral_centroid_mean', 'spectral_centroid_var',
        'spectral_bandwidth_mean', 'spectral_bandwidth_var', 'rolloff_mean',
    ↪'rolloff_var', 'zero_crossing_rate_mean',
        'zero_crossing_rate_var', 'tempo'] + [f'mfcc{i}_mean' for i in range(1,
    ↪21)] + [f'mfcc{i}_var' for i in range(1, 21)])
data.insert(0, 'filename', filenames)

```

```
data.insert(1, 'length', lengths)
data['label'] = labels

# Afficher les premières lignes pour vérifier
data.head()
```

```
[145]:
```

	filename	length	chroma_stft_mean	chroma_stft_var	rms_mean	\
0	karr_seg01.wav	10.0	0.251844	0.098292	0.155676	
1	karr_seg02.wav	10.0	0.278949	0.099054	0.195931	
2	karr_seg03.wav	10.0	0.270569	0.096634	0.195921	
3	karr_seg04.wav	10.0	0.257703	0.090762	0.199989	
4	karr_seg05.wav	10.0	0.271826	0.100851	0.194203	

	rms_var	spectral_centroid_mean	spectral_centroid_var	\
0	0.003849	674.246315	396079.098749	
1	0.003042	686.992644	28305.653311	
2	0.002664	712.794217	34116.351945	
3	0.004163	656.890742	21026.573731	
4	0.004105	654.460403	20187.455740	

	spectral_bandwidth_mean	spectral_bandwidth_var	...	mfcc12_var	\
0	778.901987	137105.032071	...	41.897297	
1	804.155991	24946.409605	...	50.158260	
2	839.062832	36037.786863	...	48.360600	
3	823.373611	36750.782743	...	41.293556	
4	791.354389	23957.864701	...	42.016495	

	mfcc13_var	mfcc14_var	mfcc15_var	mfcc16_var	mfcc17_var	mfcc18_var	\
0	34.264496	23.335186	27.325401	23.471411	23.119028	19.496529	
1	26.450779	26.654554	29.768003	35.498222	30.010365	38.192013	
2	41.133167	26.002573	27.321011	34.063576	36.776642	38.312840	
3	42.715427	27.823246	28.366604	27.727501	24.878998	33.155766	
4	23.652824	21.011843	32.230618	41.444450	26.133986	34.317970	

	mfcc19_var	mfcc20_var	label
0	24.704031	24.383139	karr
1	27.539190	24.787870	karr
2	22.969097	28.147936	karr
3	22.290438	22.193550	karr
4	35.848660	32.214310	karr

[5 rows x 56 columns]

```
[146]: data.shape
```

```
[146]: (262, 56)
```

```
[75]: data.to_csv('features_30_sec.csv', index=True)
```

```
#
```

## DATA EXPLORATION

### 3.1 Understanding Audio

Explorons d'abord nos données audio pour voir à quoi elles ressemblent (nous travaillerons avec le fichier `karr_seg01.wav`).

- **Sound**: séquence de vibrations avec différentes forces de pression (`y`)
- The **sample rate** (`sr`) est le nombre d'échantillons audio transportés par seconde, mesuré en Hz ou kHz.

```
[31]: # Chemin vers un fichier audio d'exemple
audio_path = f'{general_path}/audio_segments/karr/karr_seg01.wav'

# Chargement du fichier audio
y, sr = librosa.load(audio_path)

# Affichage des premières informations sur le fichier audio
print(f'Audio data (y): {y[:10]}') # Afficher les 10 premières valeurs de y
print(f'Sample rate (sr): {sr}') # Afficher le taux d'échantillonnage

# Lecture du fichier audio
ipd.Audio(audio_path)
```

```
Audio data (y): [-8.2799143e-06 -3.2529515e-05 -2.9673523e-05 -2.9548106e-05
 4.7529693e-06  1.4022644e-05 -2.9350509e-05  5.6150775e-06
 3.4912766e-05  2.8342793e-05]
Sample rate (sr): 22050
```

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

```
[34]: print('y:', y, '\n')
print('y shape:', np.shape(y), '\n')
print('Sample Rate (KHz):', sr, '\n')

# Verify length of the audio
print('Check Len of Audio:', 661794/22050)
```

```
y: [-8.2799143e-06 -3.2529515e-05 -2.9673523e-05 ... -6.4346112e-02
 -6.7787923e-02 -7.6099396e-02]
```

```
y shape: (661500,)
```

```
Sample Rate (KHz): 22050
```

```
Check Len of Audio: 30.013333333333332
```

y : Le signal audio sous forme de tableau numpy. Chaque élément représente l'amplitude du son.  
sr : Le taux d'échantillonnage, c'est-à-dire le nombre d'échantillons par seconde. Dans ce cas

Dans le code suivant, nous utilisons librosa.effects.trim pour supprimer le silence initial et final d'un signal audio. Cette étape est importante pour obtenir des représentations plus précises du signal audio sans les parties silencieuses inutiles.

```
[35]: # Trim leading and trailing silence from an audio signal (silence before and
      ↪after the actual audio)
      audio_file, _ = librosa.effects.trim(y)

      # the result is an numpy ndarray
      print('Audio File:', audio_file, '\n')
      print('Audio File shape:', np.shape(audio_file))
```

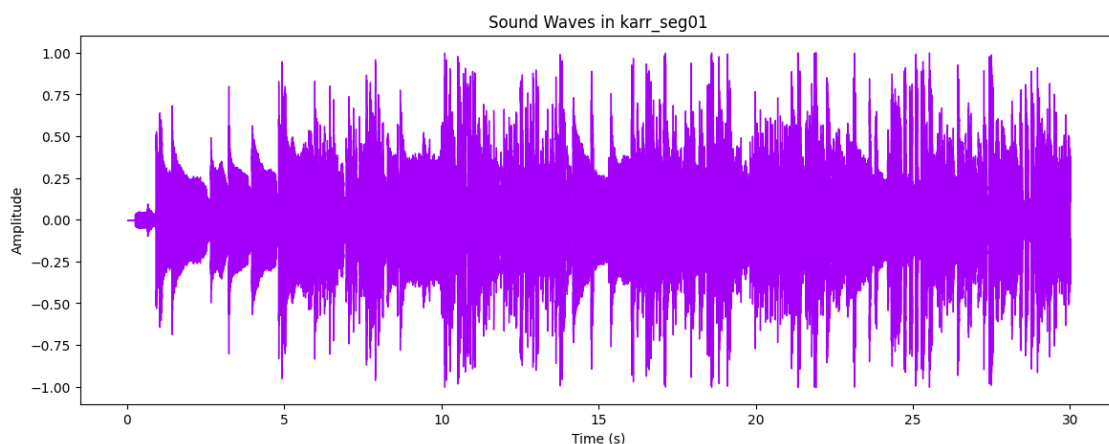
```
Audio File: [-6.1649297e-07  2.7180022e-08  3.3611573e-07 ... -6.4346112e-02
            -6.7787923e-02 -7.6099396e-02]
```

```
Audio File shape: (656892,)
```

### 3.1.1 2D Representation: Sound Waves

Pour visualiser la forme d'onde d'un fichier audio après suppression du silence :

```
[33]: # Affichage de la forme d'onde
      plt.figure(figsize=(14, 5))
      librosa.display.waveshow(y, sr=sr, color="#A300F9")
      plt.title("Sound Waves in karr_seg01")
      plt.xlabel("Time (s)")
      plt.ylabel("Amplitude")
      plt.show()
```



### 3.1.2 Transformation de Fourier

- La transformation de Fourier transforme un signal du domaine temporel en domaine fréquentiel. Nous allons utiliser la transformation de Fourier à court terme (STFT) pour obtenir une représentation spectrale du signal audio. Paramètres pour la STFT
- `n_fft` : La taille de la fenêtre FFT, par défaut 2048. `*hop_length` : Le nombre de trames audio entre les colonnes STFT successives, par défaut 512.

```
[37]: # Taille de la fenêtre FFT
n_fft = 2048

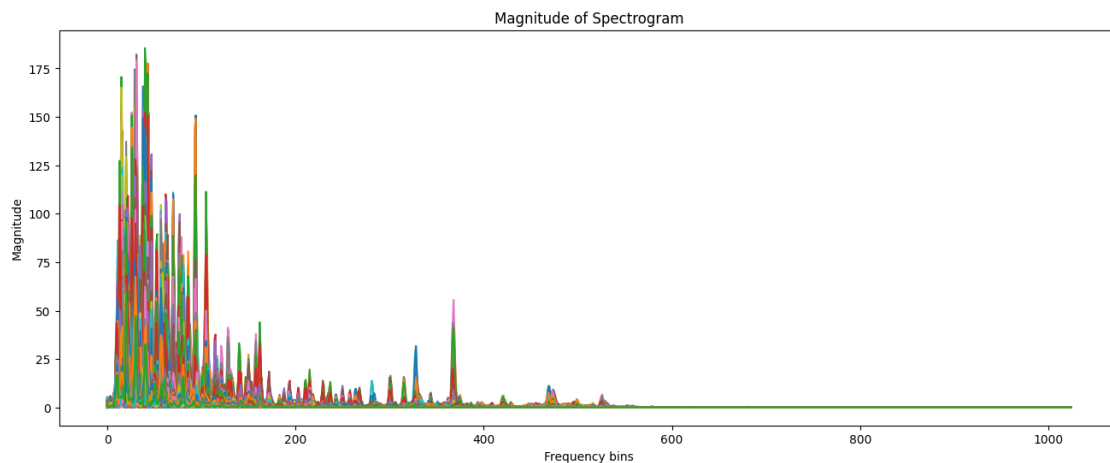
# Nombre de trames audio entre les colonnes STFT
hop_length = 512

# Transformation de Fourier à court terme (STFT)
D = np.abs(librosa.stft(audio_file, n_fft=n_fft, hop_length=hop_length))

# Affichage de la forme de l'objet D
print('Shape of D object:', np.shape(D))

# Visualisation de la magnitude du spectrogramme
plt.figure(figsize=(16, 6))
plt.plot(D)
plt.title("Magnitude of Spectrogram")
plt.xlabel("Frequency bins")
plt.ylabel("Magnitude")
plt.show()
```

Shape of D object: (1025, 1283)



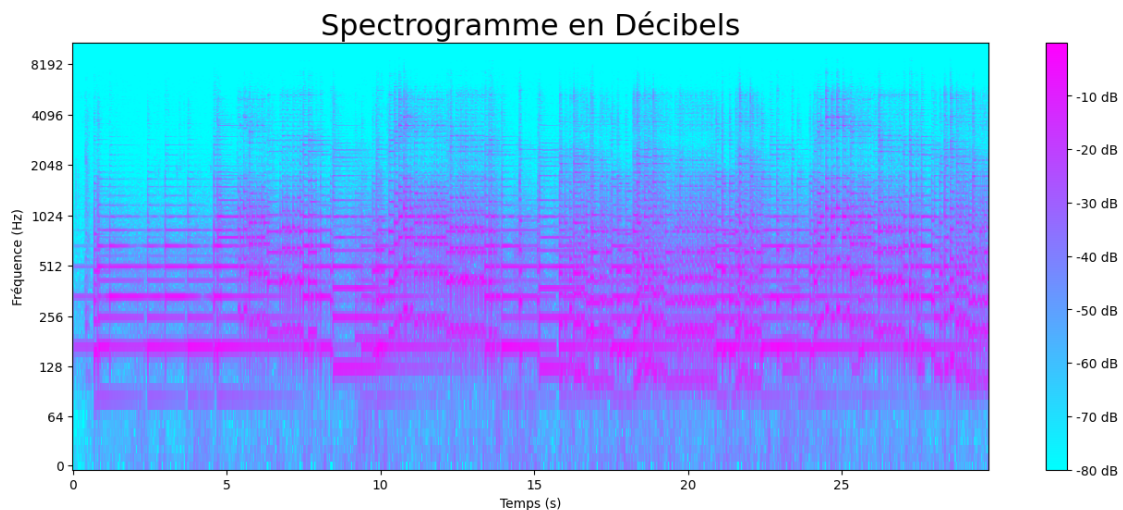


### 3.1.3 Le Spectrogramme

- Un spectrogramme est une représentation visuelle du spectre des fréquences d'un signal en fonction du temps. Il est souvent utilisé pour analyser les caractéristiques fréquentielles des signaux audio.([wiki](#)).
- Ici, nous convertissons l'axe des fréquences en un axe logarithmique.

```
[38]: # Conversion du spectrogramme d'amplitude en spectrogramme en décibels
DB = librosa.amplitude_to_db(D, ref=np.max)

# Création du spectrogramme
plt.figure(figsize=(16, 6))
librosa.display.specshow(DB, sr=sr, hop_length=hop_length, x_axis='time',
    ↪ y_axis='log', cmap='cool')
plt.colorbar(format='%+2.0f dB')
plt.title("Spectrogramme en Décibels", fontsize=23)
plt.xlabel("Temps (s)")
plt.ylabel("Fréquence (Hz)")
plt.show()
```



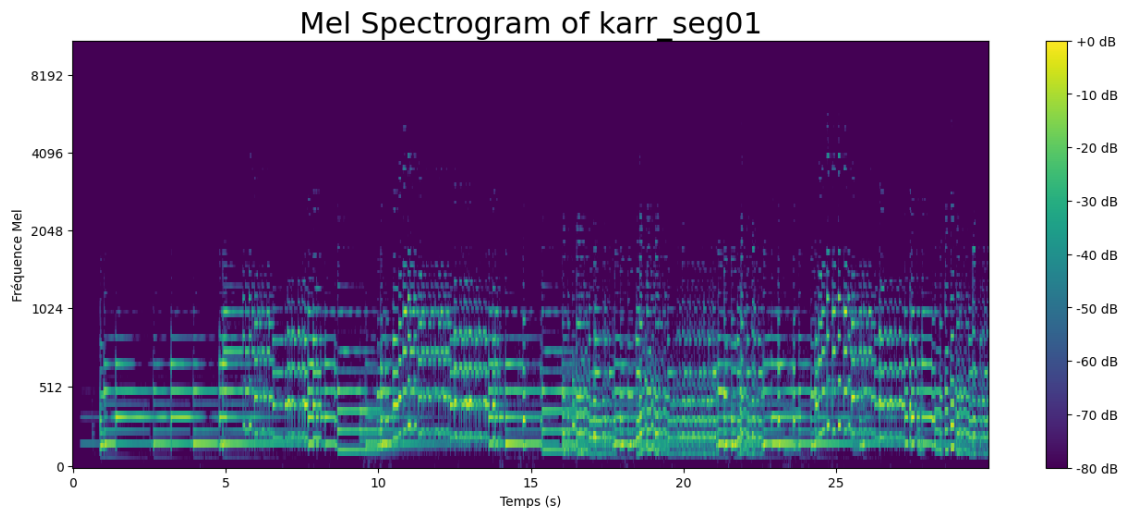
### 3.1.4 Mel Spectrogram

- Le Mel spectrogram est un spectrogramme avec une échelle Mel sur l'axe des fréquences. L'échelle Mel est une transformation non linéaire de l'échelle des fréquences qui imite la perception humaine des fréquences sonores.

```
[40]: # Calcul du Mel spectrogramme
S = librosa.feature.melspectrogram(y=y, sr=sr)
S_DB = librosa.amplitude_to_db(S, ref=np.max)

# Visualisation du Mel spectrogramme
```

```
plt.figure(figsize=(16, 6))
librosa.display.specshow(S_DB, sr=sr, x_axis='time', y_axis='mel',
    cmap='viridis')
plt.colorbar(format='%+2.0f dB')
plt.title("Mel Spectrogram of karr_seg01", fontsize=23)
plt.xlabel("Temps (s)")
plt.ylabel("Fréquence Mel")
plt.show()
```



### 3.1.5 Caractéristiques Audio

- Les caractéristiques audio sont des mesures quantitatives extraites des signaux audio qui capturent différentes propriétés telles que le rythme, la tonalité, la texture, etc. Voici comment extraire et visualiser certaines caractéristiques audio couramment utilisées à partir d'un fichier audio.

#### 3.1.6 Taux de Franchissement de Zéro (Zero Crossing Rate)

- Le taux de franchissement de zéro mesure la fréquence à laquelle le signal change de positif à négatif ou inversement.

```
[42]: # Calcul du taux de franchissement de zéro
zero_crossings = librosa.zero_crossings(audio_file, pad=False)
print("Nombre total de franchissements de zéro :", sum(zero_crossings))
```

Nombre total de franchissements de zéro : 25508

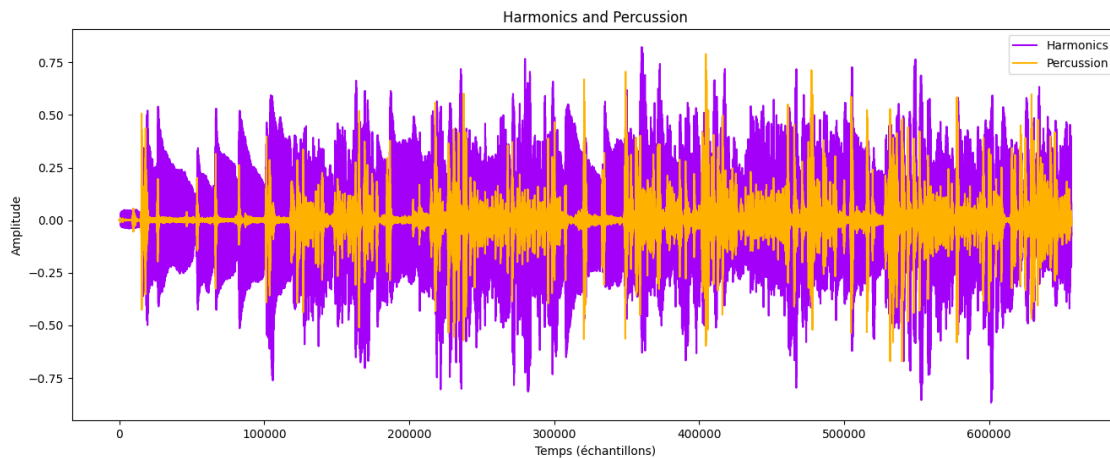
#### 3.1.7 Harmonics and Perceptual

- Les harmoniques représentent les caractéristiques que l'oreille humaine ne peut pas distinguer, tandis que les

- percussions représentent le rythme et l'émotion du son.

```
[43]: # Décomposition en harmoniques et percussions
y_harm, y_perc = librosa.effects.hpss(audio_file)

# Visualisation des harmoniques et percussions
plt.figure(figsize=(16, 6))
plt.plot(y_harm, color='#A300F9', label='Harmonics')
plt.plot(y_perc, color='#FFB100', label='Percussion')
plt.legend()
plt.title("Harmonics and Percussion")
plt.xlabel("Temps (échantillons)")
plt.ylabel("Amplitude")
plt.show()
```



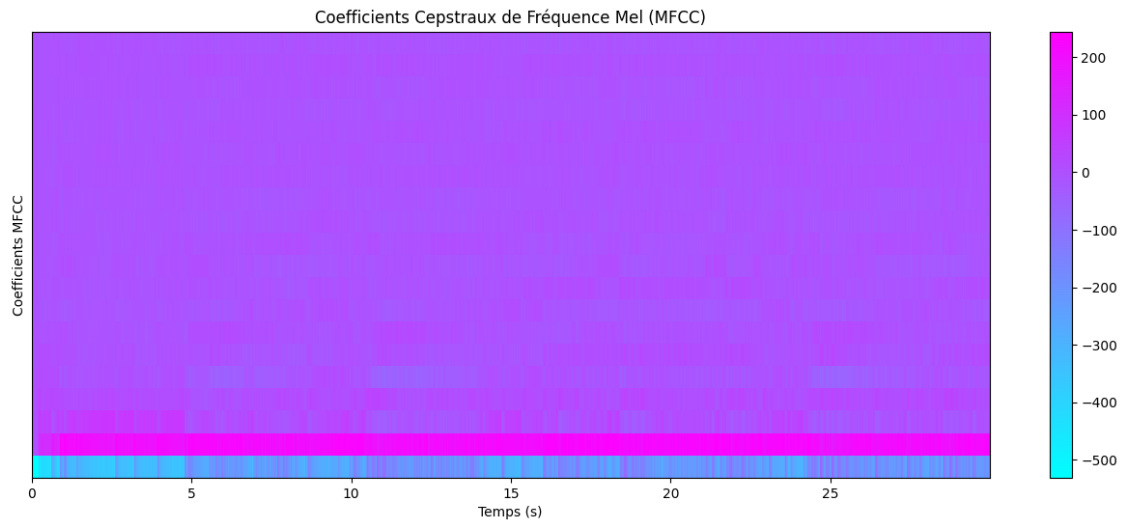
### 3.1.8 Mel-Frequency Cepstral Coefficients (Coefficients Cepstraux de Fréquence Mel (MFCC)):

- Les coefficients cepstraux de fréquence Mel (MFCC) sont un ensemble de caractéristiques qui décrivent de manière concise la forme générale de l'enveloppe spectrale d'un signal. Ils modélisent les caractéristiques de la voix humaine

```
[58]: # Calcul des coefficients MFCC
mfccs = librosa.feature.mfcc(y=y, sr=sr)

# Visualisation des MFCCs
plt.figure(figsize=(16, 6))
librosa.display.specshow(mfccs, sr=sr, x_axis='time', cmap='cool')
plt.title("Coefficients Cepstraux de Fréquence Mel (MFCC)")
plt.xlabel("Temps (s)")
plt.ylabel("Coefficients MFCC")
plt.colorbar()
```

```
plt.show()
```



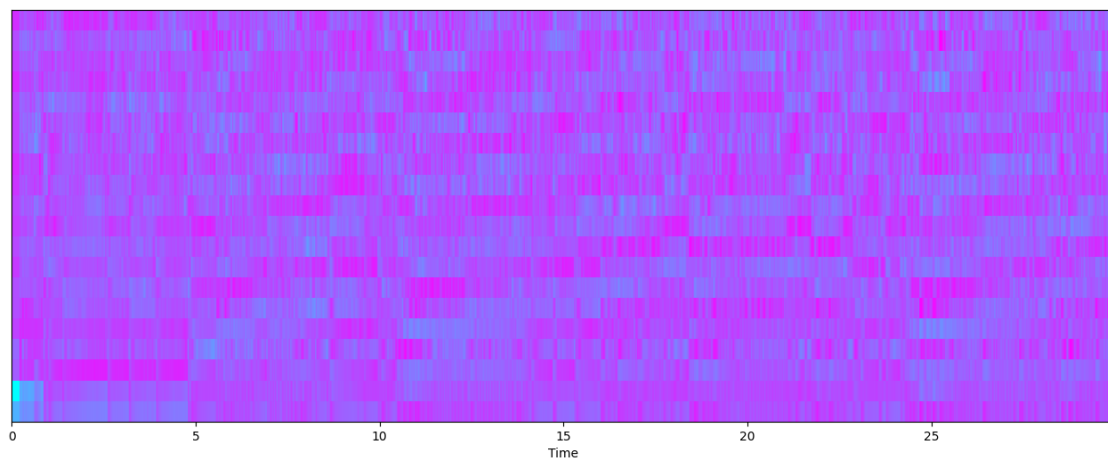
Les donnees doivent etre mis a l'échelle :

```
[60]: # Perform Feature Scaling
mfccs = sklearn.preprocessing.scale(mfccs, axis=1)
print('Mean:', mfccs.mean(), '\n')
print('Var:', mfccs.var())

plt.figure(figsize = (16, 6))
librosa.display.specshow(mfccs, sr=sr, x_axis='time', cmap = 'cool');
```

Mean: -1.1810208e-09

Var: 1.0

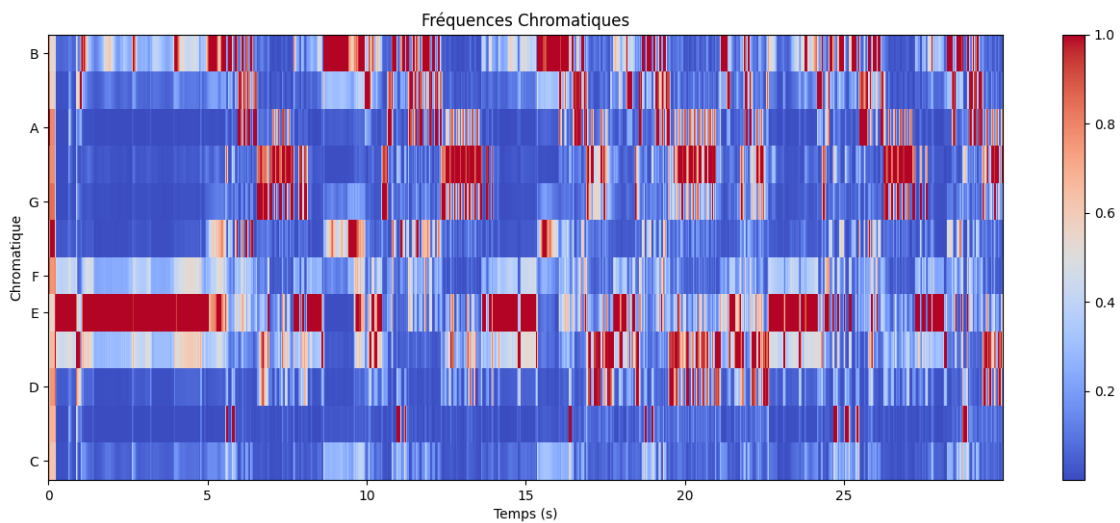


### 3.1.9 Fréquences Chromatiques

- Les caractéristiques chromatiques sont une représentation puissante de l'audio musical dans laquelle l'ensemble du spectre est projeté sur 12 bins représentant les 12 demi-tons distincts de l'octave musicale.

```
[62]: # Calcul des fréquences chromatiques
chromagram = librosa.feature.chroma_stft(y=y, sr=sr, hop_length=hop_length)

# Visualisation des fréquences chromatiques
plt.figure(figsize=(16, 6))
librosa.display.specshow(chromagram, x_axis='time', y_axis='chroma',
    ↪hop_length=hop_length, cmap='coolwarm')
plt.title("Fréquences Chromatiques")
plt.xlabel("Temps (s)")
plt.ylabel("Chromatique")
plt.colorbar()
plt.show()
```

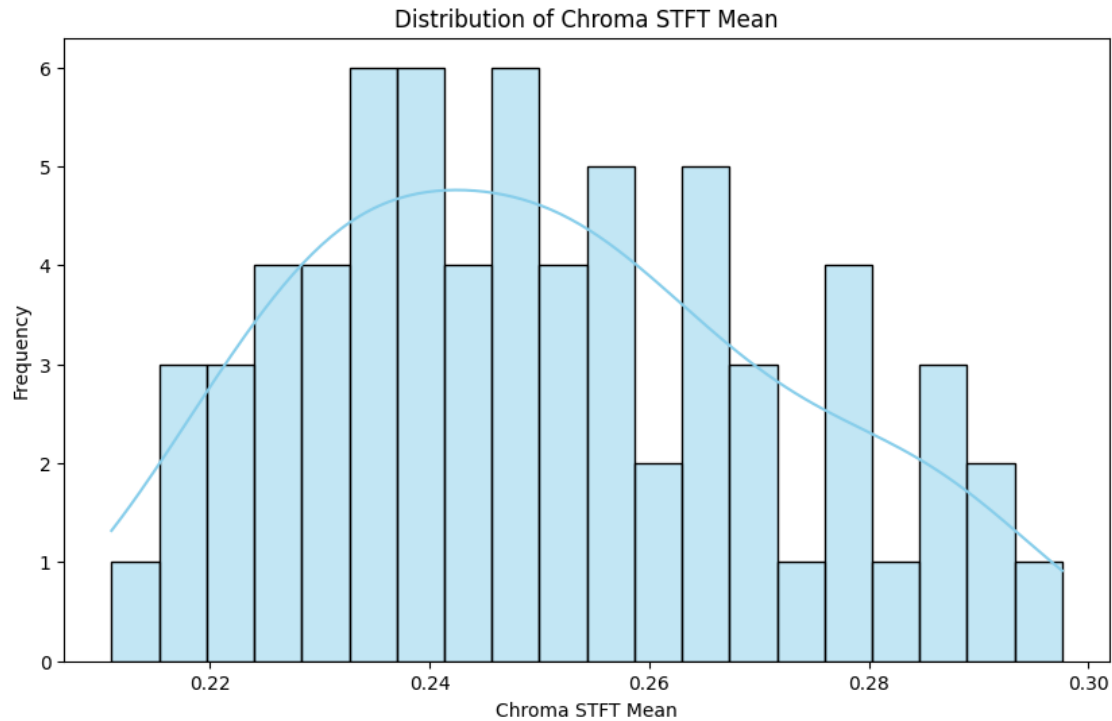


## 3.2 EDA

L'ensemble de données contient des informations sur diverses fonctionnalités audio extraites de différents fichiers audio. Chaque ligne représente un fichier audio et les colonnes représentent différentes caractéristiques, notamment la moyenne et la variance de diverses caractéristiques audio.

```
[63]: # Distribution of a specific feature (e.g., Chroma STFT mean)
plt.figure(figsize=(10, 6))
sns.histplot(data['chroma_stft_mean'], bins=20, kde=True, color='skyblue')
```

```
plt.title('Distribution of Chroma STFT Mean')
plt.xlabel('Chroma STFT Mean')
plt.ylabel('Frequency')
plt.show()
```



### 3.2.1 Correlation Heatmap pour les features

```
[68]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

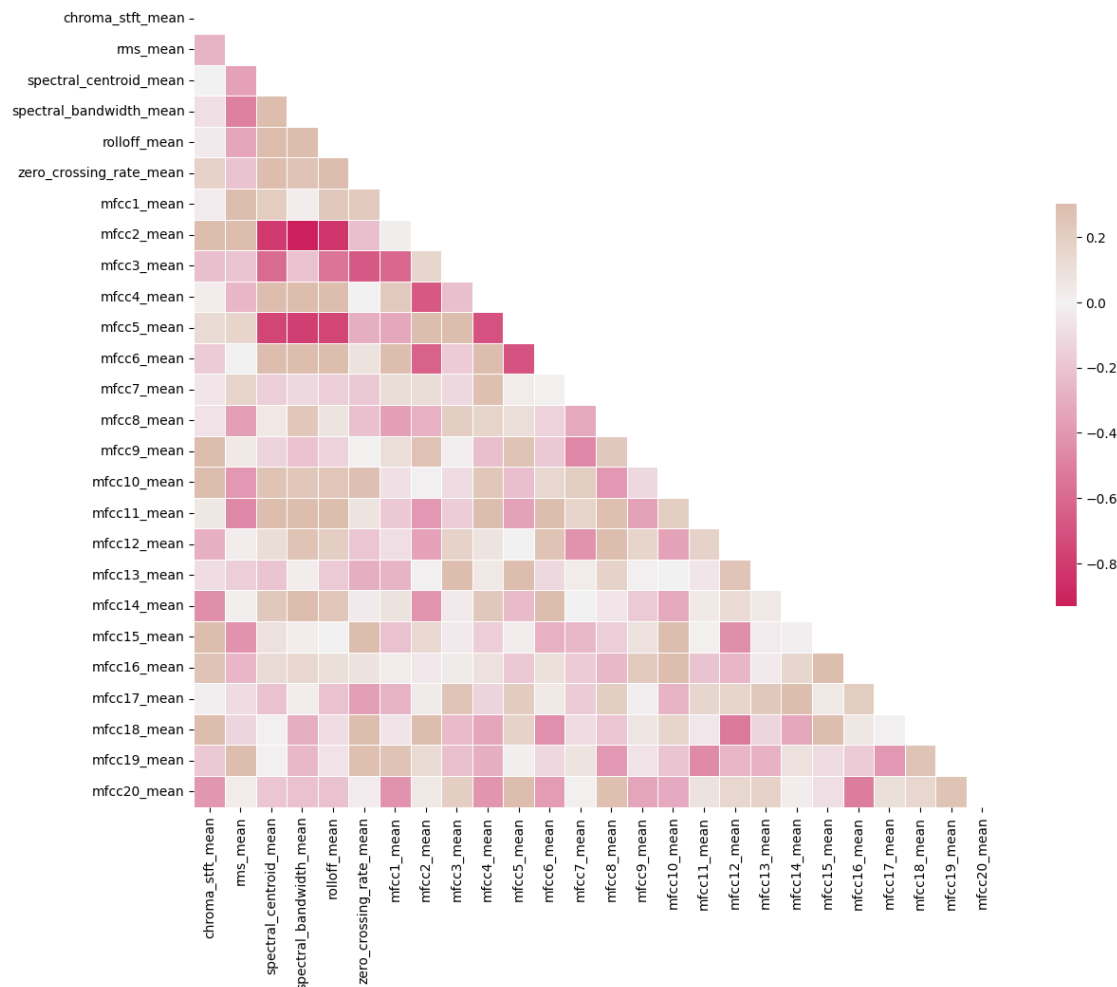
# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(16, 11))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(0, 25, as_cmap=True, s = 90, l = 45, n = 5)

# Draw the heatmap with the mask and correct aspect ratio
```

```
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

```
# Display the heatmap
plt.show()
```



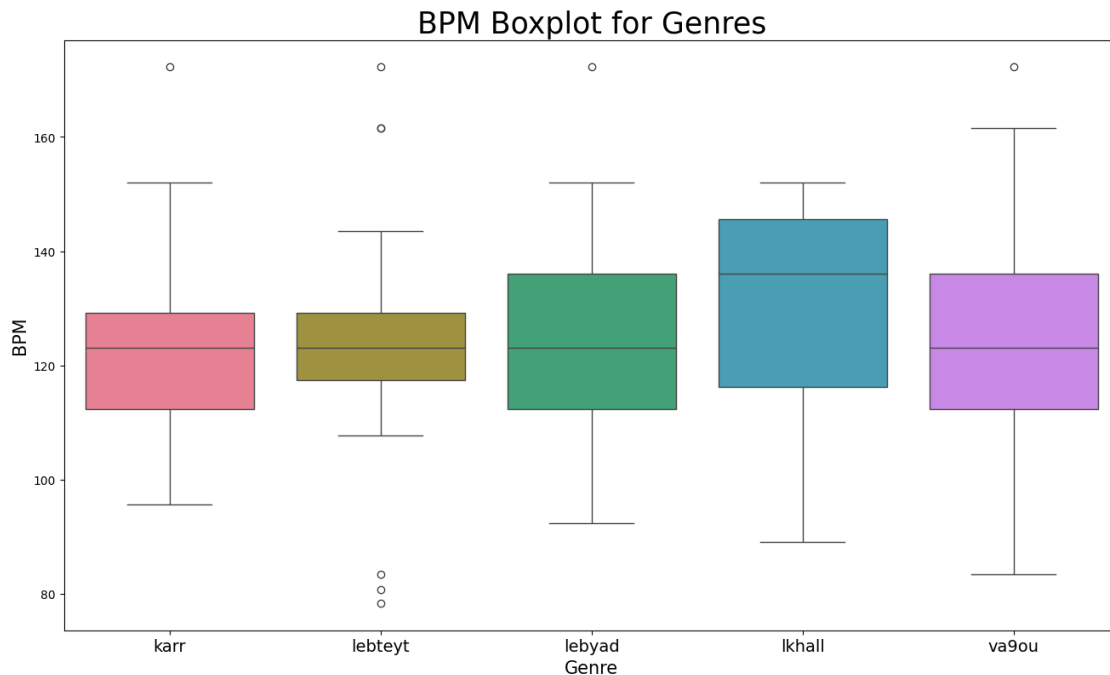
### 3.2.2 Box Plot de la Distribution des Genres

La boîte à moustaches des distributions de BPM (battements par minute) pour chaque genre musical offre une vue comparative des tempos moyens entre les genres.

```
[63]: x = data[["label", "tempo"]]

f, ax = plt.subplots(figsize=(16, 9));
sns.boxplot(x = "label", y = "tempo", data = x, palette = 'husl');
```

```
plt.title('BPM Boxplot for Genres', fontsize = 25)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10);
plt.xlabel("Genre", fontsize = 15)
plt.ylabel("BPM", fontsize = 15)
plt.savefig("BPM Boxplot.jpg")
```



### 3.2.3 Analyse en Composantes Principales (PCA) - Visualisation des Groupes Potentiels de Genres

La PCA est une technique de réduction de dimensionnalité qui peut être utilisée pour visualiser la structure des données et identifier les groupes potentiels. Voici comment nous pouvons appliquer la PCA à nos données pour visualiser les groupes de genres musicaux : 1. Normalisation 2. PCA 3. Le Scatter Plot

```
[33]: from sklearn import preprocessing

data = data.iloc[0:, 1:]
y = data['label']
X = data.loc[:, data.columns != 'label']

#### NORMALIZE X ####
cols = X.columns
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X)
```



```

X = pd.DataFrame(np_scaled, columns = cols)

#### PCA 2 COMPONENTS ####
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data = principalComponents, columns = ['principal_
↪component 1', 'principal component 2'])

# concatenate with target label
finalDf = pd.concat([principalDf, y], axis = 1)

pca.explained_variance_ratio_

# 44.93 variance explained

```

[33]: array([0.40844185, 0.1256871 ])

```

[34]: from sklearn import preprocessing

# Extraction des données
data = data.iloc[0:, 1:]
y = data['label']
X = data.loc[:, data.columns != 'label']

# Normalisation des données
cols = X.columns
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X)
X = pd.DataFrame(np_scaled, columns=cols)

# PCA avec 2 composantes
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data=principalComponents, columns=['principal_
↪component 1', 'principal component 2'])

# Concaténation avec la variable cible
finalDf = pd.concat([principalDf, y], axis=1)

# Variance expliquée
explained_variance_ratio = pca.explained_variance_ratio_

```

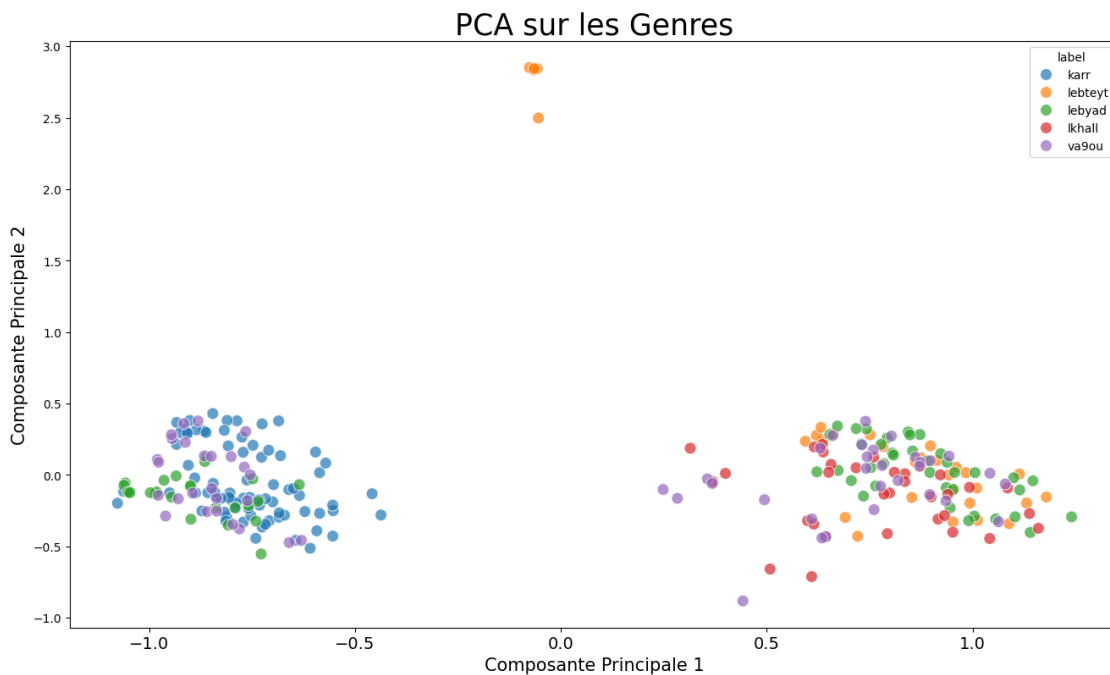
```

print("Variance Expliquée par les Deux Premières Composantes Principales:",
      explained_variance_ratio)

# Scatter Plot
plt.figure(figsize=(16, 9))
sns.scatterplot(x="principal component 1", y="principal component 2",
               data=finalDf, hue="label", alpha=0.7, s=100)
plt.title('PCA sur les Genres', fontsize=25)
plt.xlabel("Composante Principale 1", fontsize=15)
plt.ylabel("Composante Principale 2", fontsize=15)
plt.xticks(fontsize=14)
plt.yticks(fontsize=10)
plt.savefig("PCA Scattert.jpg")

```

Variance Expliquée par les Deux Premières Composantes Principales: [0.40844185 0.1256871 ]



#

LSTM STRUCTURE

```
[41]: data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 262 entries, 0 to 261
Data columns (total 56 columns):
#   Column                                Non-Null Count  Dtype

```

0	filename	262 non-null	object
1	length	262 non-null	float64
2	chroma_stft_mean	262 non-null	float32
3	chroma_stft_var	262 non-null	float32
4	rms_mean	262 non-null	float32
5	rms_var	262 non-null	float32
6	spectral_centroid_mean	262 non-null	float64
7	spectral_centroid_var	262 non-null	float64
8	spectral_bandwidth_mean	262 non-null	float64
9	spectral_bandwidth_var	262 non-null	float64
10	rolloff_mean	262 non-null	float64
11	rolloff_var	262 non-null	float64
12	zero_crossing_rate_mean	262 non-null	float64
13	zero_crossing_rate_var	262 non-null	float64
14	tempo	262 non-null	float64
15	mfcc1_mean	262 non-null	float64
16	mfcc2_mean	262 non-null	float64
17	mfcc3_mean	262 non-null	float64
18	mfcc4_mean	262 non-null	float64
19	mfcc5_mean	262 non-null	float64
20	mfcc6_mean	262 non-null	float64
21	mfcc7_mean	262 non-null	float64
22	mfcc8_mean	262 non-null	float64
23	mfcc9_mean	262 non-null	float64
24	mfcc10_mean	262 non-null	float64
25	mfcc11_mean	262 non-null	float64
26	mfcc12_mean	262 non-null	float64
27	mfcc13_mean	262 non-null	float64
28	mfcc14_mean	262 non-null	float64
29	mfcc15_mean	262 non-null	float64
30	mfcc16_mean	262 non-null	float64
31	mfcc17_mean	262 non-null	float64
32	mfcc18_mean	262 non-null	float64
33	mfcc19_mean	262 non-null	float64
34	mfcc20_mean	262 non-null	float64
35	mfcc1_var	262 non-null	float64
36	mfcc2_var	262 non-null	float64
37	mfcc3_var	262 non-null	float64
38	mfcc4_var	262 non-null	float64
39	mfcc5_var	262 non-null	float64
40	mfcc6_var	262 non-null	float64
41	mfcc7_var	262 non-null	float64
42	mfcc8_var	262 non-null	float64
43	mfcc9_var	262 non-null	float64
44	mfcc10_var	262 non-null	float64
45	mfcc11_var	262 non-null	float64
46	mfcc12_var	262 non-null	float64

```

47 mfcc13_var          262 non-null    float64
48 mfcc14_var          262 non-null    float64
49 mfcc15_var          262 non-null    float64
50 mfcc16_var          262 non-null    float64
51 mfcc17_var          262 non-null    float64
52 mfcc18_var          262 non-null    float64
53 mfcc19_var          262 non-null    float64
54 mfcc20_var          262 non-null    float64
55 label               262 non-null    object

```

dtypes: float32(4), float64(50), object(2)

memory usage: 110.7+ KB

```

[147]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping

# Séparer les caractéristiques et les labels
X = data.drop(columns=['filename', 'length', 'label'])
y = data['label']

# Encoder les labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
y_categorical = to_categorical(y_encoded)

# Normaliser les caractéristiques
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Reshape les données pour LSTM (n_samples, n_timesteps, n_features)
X_resaped = X_scaled.reshape((X_scaled.shape[0], 1, X_scaled.shape[1]))

# Séparer les données en ensembles d'entraînement et de test
X_train, X_test, y_train, y_test = train_test_split(X_resaped, y_categorical,
    ↪test_size=0.2, random_state=42)

```

```

[148]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

# Définir le modèle
model = Sequential()

```

```

model.add(LSTM(128, input_shape=(X_train.shape[1], X_train.shape[2]),
    ↪return_sequences=True))
model.add(Dropout(0.5)) # Augmenter le taux de Dropout
model.add(LSTM(128, return_sequences=True)) # Ajouter une couche LSTM
    ↪supplémentaire
model.add(Dropout(0.5))
model.add(LSTM(64)) # Ajouter une autre couche LSTM avec moins d'unités
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu', kernel_regularizer='l2')) # Ajouter L2
    ↪régularisation
model.add(Dense(len(label_encoder.classes_), activation='softmax'))

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

# Entraîner le modèle
history = model.fit(X_train, y_train, epochs=100, batch_size=32,
    ↪validation_split=0.2)

```

```

Epoch 1/100
6/6          12s 271ms/step -
accuracy: 0.2664 - loss: 2.2336 - val_accuracy: 0.3810 - val_loss: 2.1886
Epoch 2/100
6/6          0s 23ms/step -
accuracy: 0.3736 - loss: 2.1756 - val_accuracy: 0.4048 - val_loss: 2.1337
Epoch 3/100
6/6          0s 27ms/step -
accuracy: 0.4359 - loss: 2.1170 - val_accuracy: 0.4048 - val_loss: 2.0776
Epoch 4/100
6/6          0s 28ms/step -
accuracy: 0.4421 - loss: 2.0617 - val_accuracy: 0.4048 - val_loss: 2.0185
Epoch 5/100
6/6          0s 46ms/step -
accuracy: 0.4494 - loss: 1.9974 - val_accuracy: 0.3810 - val_loss: 1.9501
Epoch 6/100
6/6          0s 22ms/step -
accuracy: 0.4545 - loss: 1.9175 - val_accuracy: 0.3810 - val_loss: 1.8635
Epoch 7/100
6/6          0s 55ms/step -
accuracy: 0.4709 - loss: 1.8210 - val_accuracy: 0.3810 - val_loss: 1.7580
Epoch 8/100
6/6          1s 49ms/step -
accuracy: 0.4817 - loss: 1.7088 - val_accuracy: 0.3810 - val_loss: 1.6760
Epoch 9/100

```

6/6                    0s 30ms/step -  
accuracy: 0.4951 - loss: 1.6233 - val\_accuracy: 0.3810 - val\_loss: 1.6290  
Epoch 10/100

6/6                    0s 28ms/step -  
accuracy: 0.4763 - loss: 1.5871 - val\_accuracy: 0.3810 - val\_loss: 1.5878  
Epoch 11/100

6/6                    0s 45ms/step -  
accuracy: 0.4698 - loss: 1.5067 - val\_accuracy: 0.3810 - val\_loss: 1.5523  
Epoch 12/100

6/6                    0s 28ms/step -  
accuracy: 0.4567 - loss: 1.5324 - val\_accuracy: 0.3810 - val\_loss: 1.5195  
Epoch 13/100

6/6                    0s 28ms/step -  
accuracy: 0.4695 - loss: 1.4676 - val\_accuracy: 0.3810 - val\_loss: 1.4862  
Epoch 14/100

6/6                    0s 27ms/step -  
accuracy: 0.4601 - loss: 1.4172 - val\_accuracy: 0.3810 - val\_loss: 1.4531  
Epoch 15/100

6/6                    0s 50ms/step -  
accuracy: 0.4234 - loss: 1.4010 - val\_accuracy: 0.3810 - val\_loss: 1.4192  
Epoch 16/100

6/6                    0s 29ms/step -  
accuracy: 0.4852 - loss: 1.2944 - val\_accuracy: 0.4286 - val\_loss: 1.3874  
Epoch 17/100

6/6                    0s 26ms/step -  
accuracy: 0.4969 - loss: 1.3194 - val\_accuracy: 0.4286 - val\_loss: 1.3584  
Epoch 18/100

6/6                    0s 30ms/step -  
accuracy: 0.4763 - loss: 1.2800 - val\_accuracy: 0.4524 - val\_loss: 1.3357  
Epoch 19/100

6/6                    0s 26ms/step -  
accuracy: 0.5549 - loss: 1.1785 - val\_accuracy: 0.4762 - val\_loss: 1.3173  
Epoch 20/100

6/6                    0s 27ms/step -  
accuracy: 0.5362 - loss: 1.2012 - val\_accuracy: 0.5000 - val\_loss: 1.2976  
Epoch 21/100

6/6                    0s 27ms/step -  
accuracy: 0.5802 - loss: 1.1401 - val\_accuracy: 0.5000 - val\_loss: 1.2760  
Epoch 22/100

6/6                    0s 26ms/step -  
accuracy: 0.5769 - loss: 1.1350 - val\_accuracy: 0.4762 - val\_loss: 1.2546  
Epoch 23/100

6/6                    0s 28ms/step -  
accuracy: 0.5551 - loss: 1.0879 - val\_accuracy: 0.4762 - val\_loss: 1.2402  
Epoch 24/100

6/6                    0s 46ms/step -  
accuracy: 0.5762 - loss: 1.0755 - val\_accuracy: 0.5238 - val\_loss: 1.2175  
Epoch 25/100

6/6                    0s 33ms/step -  
accuracy: 0.5421 - loss: 1.1232 - val\_accuracy: 0.4762 - val\_loss: 1.2074  
Epoch 26/100

6/6                    0s 46ms/step -  
accuracy: 0.6087 - loss: 0.9921 - val\_accuracy: 0.4762 - val\_loss: 1.2084  
Epoch 27/100

6/6                    0s 27ms/step -  
accuracy: 0.6535 - loss: 0.9491 - val\_accuracy: 0.4762 - val\_loss: 1.1820  
Epoch 28/100

6/6                    0s 22ms/step -  
accuracy: 0.6183 - loss: 0.9968 - val\_accuracy: 0.5000 - val\_loss: 1.1455  
Epoch 29/100

6/6                    0s 32ms/step -  
accuracy: 0.6773 - loss: 0.9338 - val\_accuracy: 0.5000 - val\_loss: 1.1293  
Epoch 30/100

6/6                    0s 31ms/step -  
accuracy: 0.6895 - loss: 0.8713 - val\_accuracy: 0.5714 - val\_loss: 1.1010  
Epoch 31/100

6/6                    0s 27ms/step -  
accuracy: 0.7261 - loss: 0.8226 - val\_accuracy: 0.5952 - val\_loss: 1.0583  
Epoch 32/100

6/6                    0s 28ms/step -  
accuracy: 0.7208 - loss: 0.8350 - val\_accuracy: 0.6429 - val\_loss: 1.0681  
Epoch 33/100

6/6                    0s 29ms/step -  
accuracy: 0.7095 - loss: 0.8161 - val\_accuracy: 0.6667 - val\_loss: 1.0202  
Epoch 34/100

6/6                    0s 32ms/step -  
accuracy: 0.7754 - loss: 0.7632 - val\_accuracy: 0.6429 - val\_loss: 0.9941  
Epoch 35/100

6/6                    0s 47ms/step -  
accuracy: 0.7738 - loss: 0.7637 - val\_accuracy: 0.6905 - val\_loss: 0.9781  
Epoch 36/100

6/6                    0s 28ms/step -  
accuracy: 0.8002 - loss: 0.6475 - val\_accuracy: 0.6905 - val\_loss: 0.9633  
Epoch 37/100

6/6                    0s 28ms/step -  
accuracy: 0.8141 - loss: 0.6214 - val\_accuracy: 0.6667 - val\_loss: 0.9300  
Epoch 38/100

6/6                    1s 75ms/step -  
accuracy: 0.8058 - loss: 0.6833 - val\_accuracy: 0.7381 - val\_loss: 0.8992  
Epoch 39/100

6/6                    0s 27ms/step -  
accuracy: 0.8435 - loss: 0.6237 - val\_accuracy: 0.7381 - val\_loss: 0.9059  
Epoch 40/100

6/6                    0s 27ms/step -  
accuracy: 0.7955 - loss: 0.6460 - val\_accuracy: 0.7381 - val\_loss: 0.9116  
Epoch 41/100

6/6                    0s 28ms/step -  
accuracy: 0.8101 - loss: 0.5972 - val\_accuracy: 0.7381 - val\_loss: 0.9137  
Epoch 42/100

6/6                    0s 30ms/step -  
accuracy: 0.8351 - loss: 0.5303 - val\_accuracy: 0.7381 - val\_loss: 0.8908  
Epoch 43/100

6/6                    0s 26ms/step -  
accuracy: 0.8315 - loss: 0.5345 - val\_accuracy: 0.7381 - val\_loss: 0.8779  
Epoch 44/100

6/6                    0s 47ms/step -  
accuracy: 0.8372 - loss: 0.5994 - val\_accuracy: 0.7619 - val\_loss: 0.8415  
Epoch 45/100

6/6                    0s 30ms/step -  
accuracy: 0.8261 - loss: 0.6174 - val\_accuracy: 0.7619 - val\_loss: 0.8217  
Epoch 46/100

6/6                    0s 29ms/step -  
accuracy: 0.8517 - loss: 0.5100 - val\_accuracy: 0.8095 - val\_loss: 0.8134  
Epoch 47/100

6/6                    0s 29ms/step -  
accuracy: 0.9014 - loss: 0.4912 - val\_accuracy: 0.7619 - val\_loss: 0.8180  
Epoch 48/100

6/6                    0s 60ms/step -  
accuracy: 0.8731 - loss: 0.4827 - val\_accuracy: 0.7381 - val\_loss: 0.8239  
Epoch 49/100

6/6                    0s 25ms/step -  
accuracy: 0.8609 - loss: 0.5039 - val\_accuracy: 0.7619 - val\_loss: 0.8321  
Epoch 50/100

6/6                    0s 26ms/step -  
accuracy: 0.8979 - loss: 0.4081 - val\_accuracy: 0.7857 - val\_loss: 0.8238  
Epoch 51/100

6/6                    0s 27ms/step -  
accuracy: 0.8720 - loss: 0.4651 - val\_accuracy: 0.7857 - val\_loss: 0.8335  
Epoch 52/100

6/6                    0s 23ms/step -  
accuracy: 0.8289 - loss: 0.5084 - val\_accuracy: 0.7381 - val\_loss: 0.8494  
Epoch 53/100

6/6                    0s 47ms/step -  
accuracy: 0.8949 - loss: 0.3874 - val\_accuracy: 0.7381 - val\_loss: 0.8422  
Epoch 54/100

6/6                    0s 25ms/step -  
accuracy: 0.9276 - loss: 0.3719 - val\_accuracy: 0.7619 - val\_loss: 0.8197  
Epoch 55/100

6/6                    0s 27ms/step -  
accuracy: 0.9081 - loss: 0.3857 - val\_accuracy: 0.7857 - val\_loss: 0.8144  
Epoch 56/100

6/6                    0s 34ms/step -  
accuracy: 0.9025 - loss: 0.4157 - val\_accuracy: 0.7857 - val\_loss: 0.8252  
Epoch 57/100



6/6                    0s 42ms/step -  
accuracy: 0.9077 - loss: 0.3869 - val\_accuracy: 0.7857 - val\_loss: 0.8377  
Epoch 58/100

6/6                    0s 41ms/step -  
accuracy: 0.9122 - loss: 0.3589 - val\_accuracy: 0.7619 - val\_loss: 0.8200  
Epoch 59/100

6/6                    0s 28ms/step -  
accuracy: 0.9185 - loss: 0.3362 - val\_accuracy: 0.7619 - val\_loss: 0.7993  
Epoch 60/100

6/6                    0s 30ms/step -  
accuracy: 0.9089 - loss: 0.3446 - val\_accuracy: 0.7857 - val\_loss: 0.7913  
Epoch 61/100

6/6                    0s 43ms/step -  
accuracy: 0.9297 - loss: 0.3099 - val\_accuracy: 0.7619 - val\_loss: 0.7968  
Epoch 62/100

6/6                    0s 33ms/step -  
accuracy: 0.9611 - loss: 0.2825 - val\_accuracy: 0.7619 - val\_loss: 0.7969  
Epoch 63/100

6/6                    0s 26ms/step -  
accuracy: 0.9224 - loss: 0.3375 - val\_accuracy: 0.7857 - val\_loss: 0.7877  
Epoch 64/100

6/6                    0s 26ms/step -  
accuracy: 0.9435 - loss: 0.2605 - val\_accuracy: 0.7619 - val\_loss: 0.8138  
Epoch 65/100

6/6                    0s 27ms/step -  
accuracy: 0.9542 - loss: 0.2727 - val\_accuracy: 0.7619 - val\_loss: 0.8465  
Epoch 66/100

6/6                    0s 51ms/step -  
accuracy: 0.9493 - loss: 0.2759 - val\_accuracy: 0.7619 - val\_loss: 0.8655  
Epoch 67/100

6/6                    0s 27ms/step -  
accuracy: 0.9926 - loss: 0.2051 - val\_accuracy: 0.7619 - val\_loss: 0.8843  
Epoch 68/100

6/6                    0s 26ms/step -  
accuracy: 0.9505 - loss: 0.2419 - val\_accuracy: 0.7857 - val\_loss: 0.8899  
Epoch 69/100

6/6                    0s 31ms/step -  
accuracy: 0.9362 - loss: 0.2636 - val\_accuracy: 0.7381 - val\_loss: 0.8915  
Epoch 70/100

6/6                    0s 28ms/step -  
accuracy: 0.9596 - loss: 0.2422 - val\_accuracy: 0.7381 - val\_loss: 0.8836  
Epoch 71/100

6/6                    0s 47ms/step -  
accuracy: 0.9505 - loss: 0.2328 - val\_accuracy: 0.7381 - val\_loss: 0.8994  
Epoch 72/100

6/6                    1s 46ms/step -  
accuracy: 0.9520 - loss: 0.2149 - val\_accuracy: 0.7381 - val\_loss: 0.9492  
Epoch 73/100

6/6                    0s 27ms/step -  
accuracy: 0.9669 - loss: 0.2047 - val\_accuracy: 0.7857 - val\_loss: 0.9726  
Epoch 74/100

6/6                    0s 38ms/step -  
accuracy: 0.9721 - loss: 0.1940 - val\_accuracy: 0.7619 - val\_loss: 0.9278  
Epoch 75/100

6/6                    0s 35ms/step -  
accuracy: 0.9650 - loss: 0.1707 - val\_accuracy: 0.7619 - val\_loss: 0.8870  
Epoch 76/100

6/6                    0s 27ms/step -  
accuracy: 0.9870 - loss: 0.1652 - val\_accuracy: 0.7619 - val\_loss: 0.8844  
Epoch 77/100

6/6                    0s 24ms/step -  
accuracy: 0.9654 - loss: 0.2169 - val\_accuracy: 0.7619 - val\_loss: 0.9037  
Epoch 78/100

6/6                    0s 25ms/step -  
accuracy: 0.9648 - loss: 0.1890 - val\_accuracy: 0.7619 - val\_loss: 0.9408  
Epoch 79/100

6/6                    0s 26ms/step -  
accuracy: 0.9715 - loss: 0.1698 - val\_accuracy: 0.7857 - val\_loss: 0.9250  
Epoch 80/100

6/6                    0s 44ms/step -  
accuracy: 0.9926 - loss: 0.1451 - val\_accuracy: 0.7857 - val\_loss: 0.9303  
Epoch 81/100

6/6                    0s 27ms/step -  
accuracy: 0.9565 - loss: 0.2038 - val\_accuracy: 0.7619 - val\_loss: 0.9421  
Epoch 82/100

6/6                    0s 26ms/step -  
accuracy: 0.9665 - loss: 0.1878 - val\_accuracy: 0.7381 - val\_loss: 0.9309  
Epoch 83/100

6/6                    0s 26ms/step -  
accuracy: 0.9844 - loss: 0.1372 - val\_accuracy: 0.7619 - val\_loss: 0.9099  
Epoch 84/100

6/6                    0s 26ms/step -  
accuracy: 0.9914 - loss: 0.1303 - val\_accuracy: 0.7619 - val\_loss: 0.9056  
Epoch 85/100

6/6                    0s 52ms/step -  
accuracy: 0.9807 - loss: 0.1566 - val\_accuracy: 0.7381 - val\_loss: 1.0196  
Epoch 86/100

6/6                    1s 45ms/step -  
accuracy: 0.9483 - loss: 0.1904 - val\_accuracy: 0.7381 - val\_loss: 1.0189  
Epoch 87/100

6/6                    0s 32ms/step -  
accuracy: 0.9881 - loss: 0.1525 - val\_accuracy: 0.7619 - val\_loss: 0.9597  
Epoch 88/100

6/6                    0s 30ms/step -  
accuracy: 0.9807 - loss: 0.1280 - val\_accuracy: 0.7857 - val\_loss: 0.9535  
Epoch 89/100

```

6/6          0s 44ms/step -
accuracy: 0.9766 - loss: 0.1483 - val_accuracy: 0.7857 - val_loss: 0.9736
Epoch 90/100
6/6          1s 40ms/step -
accuracy: 0.9728 - loss: 0.1500 - val_accuracy: 0.7619 - val_loss: 1.0402
Epoch 91/100
6/6          0s 27ms/step -
accuracy: 0.9836 - loss: 0.1372 - val_accuracy: 0.7619 - val_loss: 1.0608
Epoch 92/100
6/6          0s 28ms/step -
accuracy: 0.9769 - loss: 0.1789 - val_accuracy: 0.7381 - val_loss: 0.9656
Epoch 93/100
6/6          0s 49ms/step -
accuracy: 0.9810 - loss: 0.1254 - val_accuracy: 0.7381 - val_loss: 0.9359
Epoch 94/100
6/6          0s 27ms/step -
accuracy: 0.9702 - loss: 0.1354 - val_accuracy: 0.7381 - val_loss: 0.9382
Epoch 95/100
6/6          0s 24ms/step -
accuracy: 0.9868 - loss: 0.1103 - val_accuracy: 0.7381 - val_loss: 0.9469
Epoch 96/100
6/6          0s 28ms/step -
accuracy: 0.9948 - loss: 0.1104 - val_accuracy: 0.7619 - val_loss: 0.9477
Epoch 97/100
6/6          0s 26ms/step -
accuracy: 0.9844 - loss: 0.1307 - val_accuracy: 0.7381 - val_loss: 0.9773
Epoch 98/100
6/6          0s 47ms/step -
accuracy: 0.9557 - loss: 0.1555 - val_accuracy: 0.7381 - val_loss: 1.0165
Epoch 99/100
6/6          1s 37ms/step -
accuracy: 0.9911 - loss: 0.1041 - val_accuracy: 0.7143 - val_loss: 1.0680
Epoch 100/100
6/6          0s 25ms/step -
accuracy: 0.9974 - loss: 0.0846 - val_accuracy: 0.7143 - val_loss: 1.0907

```

```

[149]: # Évaluer le modèle sur l'ensemble de test
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Accuracy: {accuracy * 100:.2f}%')

# Faire des prédictions sur de nouvelles données
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

# Afficher le rapport de classification
from sklearn.metrics import classification_report

```

```
print(classification_report(y_true_classes, y_pred_classes,
↪target_names=label_encoder.classes_))
```

```
2/2          0s 21ms/step -
accuracy: 0.7657 - loss: 1.0082
Test Accuracy: 77.36%
2/2          3s 1s/step
```

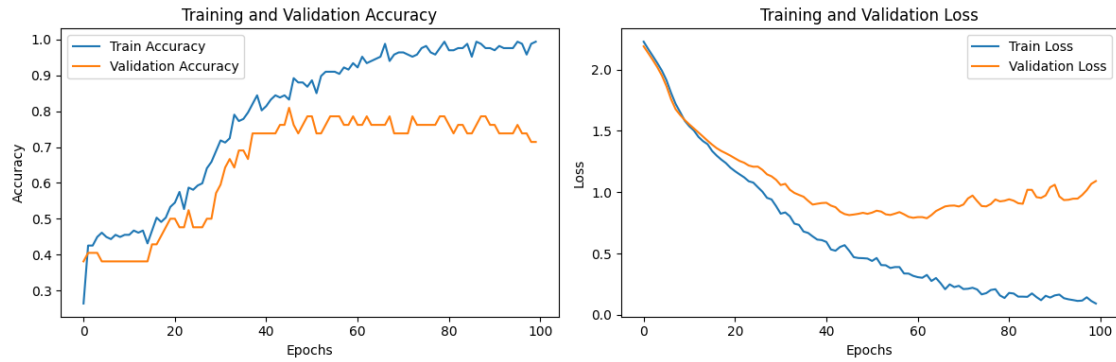
	precision	recall	f1-score	support
karr	0.84	0.94	0.89	17
lebteyt	0.50	0.80	0.62	5
lebyad	0.92	0.92	0.92	12
lkhall	1.00	0.20	0.33	5
va9ou	0.69	0.64	0.67	14
accuracy			0.77	53
macro avg	0.79	0.70	0.68	53
weighted avg	0.80	0.77	0.76	53

```
[150]: # Visualiser les courbes d'apprentissage
plt.figure(figsize=(12, 4))

# Précision
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')

# Perte
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')

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



```
[151]: def extract_features(file_path):
import librosa
y, sr = librosa.load(file_path, duration=30)
chroma_stft_mean = librosa.feature.chroma_stft(y=y, sr=sr).mean()
chroma_stft_var = librosa.feature.chroma_stft(y=y, sr=sr).var()
rms_mean = librosa.feature.rms(y=y).mean()
rms_var = librosa.feature.rms(y=y).var()
spectral_centroid_mean = librosa.feature.spectral_centroid(y=y, sr=sr).
↪mean()
spectral_centroid_var = librosa.feature.spectral_centroid(y=y, sr=sr).var()
spectral_bandwidth_mean = librosa.feature.spectral_bandwidth(y=y, sr=sr).
↪mean()
spectral_bandwidth_var = librosa.feature.spectral_bandwidth(y=y, sr=sr).
↪var()
rolloff_mean = librosa.feature.spectral_rolloff(y=y, sr=sr).mean()
rolloff_var = librosa.feature.spectral_rolloff(y=y, sr=sr).var()
zero_crossing_rate_mean = librosa.feature.zero_crossing_rate(y).mean()
zero_crossing_rate_var = librosa.feature.zero_crossing_rate(y).var()
tempo = librosa.beat.tempo(y=y, sr=sr)[0]
mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=20)
mfcc_means = mfccs.mean(axis=1)
mfcc_vars = mfccs.var(axis=1)

return [chroma_stft_mean, chroma_stft_var, rms_mean, rms_var, ↪
↪spectral_centroid_mean, spectral_centroid_var,
spectral_bandwidth_mean, spectral_bandwidth_var, rolloff_mean, ↪
↪rolloff_var, zero_crossing_rate_mean,
zero_crossing_rate_var, tempo] + mfcc_means.tolist() + mfcc_vars.
↪tolist()

def predict_genre(file_path):
# Extraire les caractéristiques
features = extract_features(file_path)
```

```

features_scaled = scaler.transform([features])
features_reshaped = features_scaled.reshape((1, 1, features_scaled.
↪shape[1]))

# Prédire avec le modèle LSTM
prediction = model.predict(features_reshaped)
predicted_class = np.argmax(prediction, axis=1)

# Convertir le label encodé en genre
predicted_genre = label_encoder.inverse_transform(predicted_class)
return predicted_genre[0]

# Exemple d'utilisation
predicted_genre = predict_genre('C:/Users/hp/Downloads/test.wav')
print(f'The predicted genre is: {predicted_genre}')

```

```

1/1          0s 50ms/step
The predicted genre is: va9ou

```

```
[ ]:
```

```
#
```

```
CNN STRUCTURE
```

```
[25]: #!pip install music21
```

```
[54]: #!pip install abjad
```

```
[4]: #!pip install scikit-image
```

```
[21]: import os
import numpy as np
import librosa
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import to_categorical
from skimage.transform import resize

```

```
[5]: # Chemin vers le répertoire contenant les sous-dossiers de fichiers audio
directory = r'C:\Users\hp\Downloads\My_Projects\traditional music\
↪generator\segments_audio'
output_directory = r'C:\Users\hp\Downloads\My_Projects\traditional music\
↪generator\spectrograms'

```

```

# Création du dossier de sortie s'il n'existe pas
os.makedirs(output_directory, exist_ok=True)

# Parcours des sous-dossiers
for subdir in os.listdir(directory):
    subdirectory = os.path.join(directory, subdir)
    if os.path.isdir(subdirectory):
        # Parcours des fichiers audio dans chaque sous-dossier
        for filename in os.listdir(subdirectory):
            if filename.endswith('.wav'): # Assurez-vous que vous avez des
↳ fichiers audio WAV
                filepath = os.path.join(subdirectory, filename)

                # Chargement du fichier audio
                y, sr = librosa.load(filepath)

                # Prétraitement et tracé du spectrogramme
                plt.figure(figsize=(10, 4))
                spectrogram = librosa.feature.melspectrogram(y=y, sr=sr)
                librosa.display.specshow(librosa.power_to_db(spectrogram,
↳ ref=np.max),
                                                    y_axis='mel', fmax=8000, x_axis='time')
                plt.colorbar(format='%+2.0f dB')
                plt.title('Spectrogram')
                plt.tight_layout()

                # Enregistrement du spectrogramme sous forme d'image
                output_path = os.path.join(output_directory, subdir)
                os.makedirs(output_path, exist_ok=True)
                output_filename = os.path.splitext(filename)[0] + '.png'
                plt.savefig(os.path.join(output_path, output_filename))
                plt.close()

# Chargement des images et labels
images = []
labels = []
label_map = {}

for idx, subdir in enumerate(os.listdir(output_directory)):
    subdirectory = os.path.join(output_directory, subdir)
    if os.path.isdir(subdirectory):
        label_map[subdir] = idx
        for filename in os.listdir(subdirectory):
            if filename.endswith('.png'):
                image = plt.imread(os.path.join(subdirectory, filename))
                images.append(image)

```

```
labels.append(idx)
```

```
[6]: # Convertir les listes en tableaux numpy
images = np.array(images)
labels = np.array(labels)

# Taille cible pour les images
target_size = (128, 128)

# Redimensionner les images
resized_images = []
for image in images:
    resized_image = resize(image, target_size, anti_aliasing=True)
    resized_images.append(resized_image)
```

```
[7]: # Convertir la liste en tableau numpy
images = np.array(resized_images)

# Normaliser les images
images = images / 255.0

# Convertir les labels en one-hot encoding
labels = to_categorical(labels, num_classes=len(label_map))
```

```
[38]: # Diviser les données en ensembles d'entraînement et de validation
X_train, X_val, y_train, y_val = train_test_split(images, labels, test_size=0.
↪2, random_state=42)

# Vérification des formes des données
print(f"X_train shape: {X_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"X_val shape: {X_val.shape}")
print(f"y_val shape: {y_val.shape}")
```

```
X_train shape: (209, 128, 128, 4)
y_train shape: (209, 5)
X_val shape: (53, 128, 128, 4)
y_val shape: (53, 5)
```

```
[22]:
```

```
[39]: # Construire le modèle CNN amélioré
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(target_size[0],
↪target_size[1], images.shape[3])),
    layers.MaxPooling2D((2, 2)),
    layers.Dropout(0.3),
```



```

layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Dropout(0.3),

layers.Conv2D(128, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Dropout(0.3),

layers.Conv2D(256, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Dropout(0.3),

layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dropout(0.5),
layers.Dense(len(label_map), activation='softmax')
])

```

```

[40]: # Compilation du modèle
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

```

```

[41]: # Entraîner le modèle
history = model.fit(X_train, y_train, epochs=50, validation_data=(X_val, y_val))

```

```

Epoch 1/50
7/7          8s 611ms/step -
accuracy: 0.2471 - loss: 1.6028 - val_accuracy: 0.3208 - val_loss: 1.5142
Epoch 2/50
7/7          4s 598ms/step -
accuracy: 0.3062 - loss: 1.5869 - val_accuracy: 0.3208 - val_loss: 1.5514
Epoch 3/50
7/7          5s 630ms/step -
accuracy: 0.2894 - loss: 1.5601 - val_accuracy: 0.3208 - val_loss: 1.5645
Epoch 4/50
7/7          5s 712ms/step -
accuracy: 0.2733 - loss: 1.5677 - val_accuracy: 0.2264 - val_loss: 1.5516
Epoch 5/50
7/7          5s 675ms/step -
accuracy: 0.2398 - loss: 1.5874 - val_accuracy: 0.3208 - val_loss: 1.5367
Epoch 6/50
7/7          5s 669ms/step -
accuracy: 0.2704 - loss: 1.5773 - val_accuracy: 0.3208 - val_loss: 1.5281
Epoch 7/50
7/7          5s 660ms/step -
accuracy: 0.2563 - loss: 1.5957 - val_accuracy: 0.3208 - val_loss: 1.5292
Epoch 8/50

```

7/7                    5s 654ms/step -  
 accuracy: 0.2655 - loss: 1.5717 - val\_accuracy: 0.3208 - val\_loss: 1.5251  
 Epoch 9/50  
 7/7                    4s 558ms/step -  
 accuracy: 0.2715 - loss: 1.5617 - val\_accuracy: 0.3208 - val\_loss: 1.5463  
 Epoch 10/50  
 7/7                    4s 608ms/step -  
 accuracy: 0.2931 - loss: 1.5905 - val\_accuracy: 0.3208 - val\_loss: 1.5520  
 Epoch 11/50  
 7/7                    5s 619ms/step -  
 accuracy: 0.2824 - loss: 1.5785 - val\_accuracy: 0.3208 - val\_loss: 1.5336  
 Epoch 12/50  
 7/7                    5s 725ms/step -  
 accuracy: 0.3298 - loss: 1.5444 - val\_accuracy: 0.3208 - val\_loss: 1.5111  
 Epoch 13/50  
 7/7                    4s 616ms/step -  
 accuracy: 0.3051 - loss: 1.5384 - val\_accuracy: 0.3208 - val\_loss: 1.5202  
 Epoch 14/50  
 7/7                    6s 645ms/step -  
 accuracy: 0.2940 - loss: 1.5774 - val\_accuracy: 0.3208 - val\_loss: 1.5339  
 Epoch 15/50  
 7/7                    5s 631ms/step -  
 accuracy: 0.2821 - loss: 1.5731 - val\_accuracy: 0.3208 - val\_loss: 1.5309  
 Epoch 16/50  
 7/7                    4s 620ms/step -  
 accuracy: 0.2599 - loss: 1.5619 - val\_accuracy: 0.3208 - val\_loss: 1.5200  
 Epoch 17/50  
 7/7                    6s 682ms/step -  
 accuracy: 0.2922 - loss: 1.5483 - val\_accuracy: 0.3208 - val\_loss: 1.5169  
 Epoch 18/50  
 7/7                    5s 623ms/step -  
 accuracy: 0.2745 - loss: 1.5660 - val\_accuracy: 0.3208 - val\_loss: 1.5201  
 Epoch 19/50  
 7/7                    5s 586ms/step -  
 accuracy: 0.2816 - loss: 1.5690 - val\_accuracy: 0.3208 - val\_loss: 1.5298  
 Epoch 20/50  
 7/7                    4s 558ms/step -  
 accuracy: 0.3002 - loss: 1.5610 - val\_accuracy: 0.3208 - val\_loss: 1.5241  
 Epoch 21/50  
 7/7                    4s 558ms/step -  
 accuracy: 0.2668 - loss: 1.5524 - val\_accuracy: 0.3208 - val\_loss: 1.5223  
 Epoch 22/50  
 7/7                    5s 559ms/step -  
 accuracy: 0.2302 - loss: 1.5883 - val\_accuracy: 0.3208 - val\_loss: 1.5298  
 Epoch 23/50  
 7/7                    4s 546ms/step -  
 accuracy: 0.2515 - loss: 1.5621 - val\_accuracy: 0.3208 - val\_loss: 1.5217  
 Epoch 24/50

7/7                    4s 542ms/step -  
 accuracy: 0.3087 - loss: 1.5654 - val\_accuracy: 0.3208 - val\_loss: 1.5230  
 Epoch 25/50  
 7/7                    4s 549ms/step -  
 accuracy: 0.2643 - loss: 1.5594 - val\_accuracy: 0.3208 - val\_loss: 1.5240  
 Epoch 26/50  
 7/7                    4s 549ms/step -  
 accuracy: 0.2740 - loss: 1.5461 - val\_accuracy: 0.3208 - val\_loss: 1.5230  
 Epoch 27/50  
 7/7                    4s 551ms/step -  
 accuracy: 0.3096 - loss: 1.5566 - val\_accuracy: 0.3208 - val\_loss: 1.5255  
 Epoch 28/50  
 7/7                    4s 545ms/step -  
 accuracy: 0.3308 - loss: 1.5414 - val\_accuracy: 0.3208 - val\_loss: 1.5240  
 Epoch 29/50  
 7/7                    4s 530ms/step -  
 accuracy: 0.3265 - loss: 1.5476 - val\_accuracy: 0.3208 - val\_loss: 1.5211  
 Epoch 30/50  
 7/7                    4s 540ms/step -  
 accuracy: 0.2600 - loss: 1.5911 - val\_accuracy: 0.3208 - val\_loss: 1.5238  
 Epoch 31/50  
 7/7                    4s 535ms/step -  
 accuracy: 0.2968 - loss: 1.5550 - val\_accuracy: 0.3208 - val\_loss: 1.5197  
 Epoch 32/50  
 7/7                    4s 531ms/step -  
 accuracy: 0.2942 - loss: 1.5498 - val\_accuracy: 0.3208 - val\_loss: 1.5165  
 Epoch 33/50  
 7/7                    4s 546ms/step -  
 accuracy: 0.2937 - loss: 1.5381 - val\_accuracy: 0.3208 - val\_loss: 1.5180  
 Epoch 34/50  
 7/7                    4s 566ms/step -  
 accuracy: 0.2511 - loss: 1.5972 - val\_accuracy: 0.3208 - val\_loss: 1.5259  
 Epoch 35/50  
 7/7                    4s 538ms/step -  
 accuracy: 0.2599 - loss: 1.5609 - val\_accuracy: 0.3208 - val\_loss: 1.5274  
 Epoch 36/50  
 7/7                    4s 542ms/step -  
 accuracy: 0.2746 - loss: 1.5721 - val\_accuracy: 0.3208 - val\_loss: 1.5293  
 Epoch 37/50  
 7/7                    4s 534ms/step -  
 accuracy: 0.2969 - loss: 1.5777 - val\_accuracy: 0.3208 - val\_loss: 1.5289  
 Epoch 38/50  
 7/7                    4s 547ms/step -  
 accuracy: 0.2794 - loss: 1.5759 - val\_accuracy: 0.3208 - val\_loss: 1.5272  
 Epoch 39/50  
 7/7                    4s 650ms/step -  
 accuracy: 0.2698 - loss: 1.5956 - val\_accuracy: 0.3208 - val\_loss: 1.5281  
 Epoch 40/50

```

7/7          4s 542ms/step -
accuracy: 0.2827 - loss: 1.5631 - val_accuracy: 0.3208 - val_loss: 1.5197
Epoch 41/50
7/7          4s 560ms/step -
accuracy: 0.3177 - loss: 1.5406 - val_accuracy: 0.3208 - val_loss: 1.5132
Epoch 42/50
7/7          4s 558ms/step -
accuracy: 0.3254 - loss: 1.5343 - val_accuracy: 0.3208 - val_loss: 1.5116
Epoch 43/50
7/7          4s 556ms/step -
accuracy: 0.2950 - loss: 1.5765 - val_accuracy: 0.3208 - val_loss: 1.5256
Epoch 44/50
7/7          4s 546ms/step -
accuracy: 0.2946 - loss: 1.5576 - val_accuracy: 0.3208 - val_loss: 1.5320
Epoch 45/50
7/7          4s 560ms/step -
accuracy: 0.3138 - loss: 1.5789 - val_accuracy: 0.3208 - val_loss: 1.5333
Epoch 46/50
7/7          4s 566ms/step -
accuracy: 0.2896 - loss: 1.5721 - val_accuracy: 0.3208 - val_loss: 1.5313
Epoch 47/50
7/7          4s 608ms/step -
accuracy: 0.2678 - loss: 1.5746 - val_accuracy: 0.3208 - val_loss: 1.5253
Epoch 48/50
7/7          5s 539ms/step -
accuracy: 0.2424 - loss: 1.5930 - val_accuracy: 0.3208 - val_loss: 1.5212
Epoch 49/50
7/7          4s 550ms/step -
accuracy: 0.3065 - loss: 1.5789 - val_accuracy: 0.3208 - val_loss: 1.5204
Epoch 50/50
7/7          5s 571ms/step -
accuracy: 0.2859 - loss: 1.5861 - val_accuracy: 0.3208 - val_loss: 1.5274

```

```

[42]: # Prédiction sur les données de validation
y_val_pred = model.predict(X_val)
y_val_pred_classes = np.argmax(y_val_pred, axis=1)
y_val_true_classes = np.argmax(y_val, axis=1)

# Évaluer le modèle sur l'ensemble de test
loss, accuracy = model.evaluate(X_val, y_val)
print(f'Test Accuracy: {accuracy * 100:.2f}%')

# Générer un rapport de classification
print("Classification Report:")
print(classification_report(y_val_true_classes, y_val_pred_classes,
    ↪target_names=label_map.keys()))

```

```

2/2          0s 184ms/step
2/2          0s 100ms/step -
accuracy: 0.3180 - loss: 1.5321
Test Accuracy: 32.08%
Classification Report:

```

	precision	recall	f1-score	support
karr	0.32	1.00	0.49	17
lebteyt	0.00	0.00	0.00	5
lebyad	0.00	0.00	0.00	12
lkhall	0.00	0.00	0.00	5
va9ou	0.00	0.00	0.00	14
accuracy			0.32	53
macro avg	0.06	0.20	0.10	53
weighted avg	0.10	0.32	0.16	53

```

C:\Users\hp\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.

```

```

_warn_prf(average, modifier, msg_start, len(result))

```

```

C:\Users\hp\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.

```

```

_warn_prf(average, modifier, msg_start, len(result))

```

```

C:\Users\hp\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.

```

```

_warn_prf(average, modifier, msg_start, len(result))

```

```

[43]: # Sauvegarder le modèle entraîné
      model.save('music_genre_recognizer_cnn.h5')

```

```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.

```

```

`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.

```

```

[ ]:

```

```

[56]: import librosa
      import numpy as np
      from skimage.transform import resize

```

```

# Liste des genres
genres = ['karr', 'leboteyt', 'lebyad', 'lkhall', 'va9ou']

def predict_genre(audio_path, model):
    # Préparer le fichier audio
    y, sr = librosa.load(audio_path)
    spectrogram = librosa.feature.melspectrogram(y=y, sr=sr)
    spectrogram_db = librosa.power_to_db(spectrogram, ref=np.max)

    # Redimensionner le spectrogramme
    target_size = (128, 128)
    resized_spectrogram = resize(spectrogram_db, target_size,
    ↪anti_aliasing=True)

    # Normaliser le spectrogramme
    resized_spectrogram = resized_spectrogram / np.max(resized_spectrogram)

    # Si le modèle attend des images avec 4 canaux, dupliquez le canal unique
    ↪pour en faire une image 4 canaux
    if model.input_shape[-1] == 4:
        resized_spectrogram = np.stack((resized_spectrogram,) * 4, axis=-1)
    elif model.input_shape[-1] == 3:
        resized_spectrogram = np.stack((resized_spectrogram,) * 3, axis=-1)
    elif model.input_shape[-1] == 1 and len(resized_spectrogram.shape) == 2:
        resized_spectrogram = np.expand_dims(resized_spectrogram, axis=-1)

    # Ajouter une dimension pour le lot
    input_spectrogram = np.expand_dims(resized_spectrogram, axis=0)

    # Vérifier les formes
    print(f"Shape of input spectrogram: {input_spectrogram.shape}")
    print(f"Model input shape: {model.input_shape}")

    # Prédire le genre
    prediction = model.predict(input_spectrogram)
    predicted_class = np.argmax(prediction, axis=1)[0]

    return predicted_class

```

```

[57]: # Exemple d'utilisation
audio_path = r'C:/Users/hp/Downloads/test.wav'
predicted_genre_index = predict_genre(audio_path, model)
predicted_genre_name = genres[predicted_genre_index]
print(f'Le genre prédit pour l\'audio est : {predicted_genre_name}')

```

```

Shape of input spectrogram: (1, 128, 128, 4)
Model input shape: (None, 128, 128, 4)

```

1/1                      0s 137ms/step  
Le genre prédit pour l'audio est : karr

[ ]:

#

## RECOMMENDER SYSTEM

“Recomender” Systems enable us for any given vector to find the best similarity, ranked in descending order, from the best match to the least best match.

For Audio files, this will be done through `cosine_similarity` library.

```
[43]: # Libraries
import IPython.display as ipd
from sklearn.metrics.pairwise import cosine_similarity
from sklearn import preprocessing

# Set filename as index
data.set_index('filename', inplace=True)

# Extract labels
labels = data[['label']]

# Drop labels from original dataframe
data = data.drop(columns=['length', 'label'])
data.head()

# Scale the data
data_scaled = preprocessing.scale(data)
print('Scaled data type:', type(data_scaled))

# Create a DataFrame with the scaled data and use filenames as index
data_scaled_df = pd.DataFrame(data_scaled, index=data.index, columns=data.
    ↪columns)

# Display the first few rows of the scaled DataFrame
data_scaled_df.head()
```

Scaled data type: <class 'numpy.ndarray'>

```
[43]:
```

	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	\
filename					
karr_seg01.wav	-0.278814	0.757060	0.160718	0.801701	
karr_seg02.wav	0.075307	0.828478	0.663106	0.367054	
karr_seg03.wav	-0.034176	0.601555	0.662991	0.163586	
karr_seg04.wav	-0.202270	0.050947	0.713761	0.970853	
karr_seg05.wav	-0.017749	0.997049	0.641546	0.939436	

	spectral_centroid_mean	spectral_centroid_var	\	
filename				
karr_seg01.wav	-0.815777	2.292799		
karr_seg02.wav	-0.794893	-0.567692		
karr_seg03.wav	-0.752619	-0.522497		
karr_seg04.wav	-0.844213	-0.624308		
karr_seg05.wav	-0.848195	-0.630835		

	spectral_bandwidth_mean	spectral_bandwidth_var	rolloff_mean	\	
filename					
karr_seg01.wav	-1.027909	0.831049	-0.920917		
karr_seg02.wav	-0.952904	-0.661276	-0.884666		
karr_seg03.wav	-0.849231	-0.513700	-0.811726		
karr_seg04.wav	-0.895828	-0.504213	-0.893250		
karr_seg05.wav	-0.990925	-0.674429	-0.935570		

	rolloff_var	...	mfcc11_var	mfcc12_var	mfcc13_var	\	
filename		...					
karr_seg01.wav	1.478304	...	-0.969359	-1.003912	-1.089512		
karr_seg02.wav	-0.635631	...	-0.750753	-0.918083	-1.235555		
karr_seg03.wav	-0.454566	...	-0.817293	-0.936760	-0.961132		
karr_seg04.wav	-0.653659	...	-0.698668	-1.010185	-0.931559		
karr_seg05.wav	-0.713021	...	-0.906818	-1.002674	-1.287851		

	mfcc14_var	mfcc15_var	mfcc16_var	mfcc17_var	mfcc18_var	\	
filename							
karr_seg01.wav	-1.346337	-1.157812	-1.069810	-0.845188	-1.169690		
karr_seg02.wav	-1.244646	-1.047630	-0.504399	-0.585596	-0.376174		
karr_seg03.wav	-1.264620	-1.158010	-0.571845	-0.330716	-0.371045		
karr_seg04.wav	-1.208842	-1.110845	-0.869720	-0.778891	-0.589934		
karr_seg05.wav	-1.417514	-0.936546	-0.224851	-0.731617	-0.540605		

	mfcc19_var	mfcc20_var
filename		
karr_seg01.wav	-1.167376	-1.206108
karr_seg02.wav	-1.015414	-1.183891
karr_seg03.wav	-1.260367	-0.999451
karr_seg04.wav	-1.296743	-1.326298
karr_seg05.wav	-0.570033	-0.776240

[5 rows x 53 columns]

### 3.2.4 Cosine similarity

Calculates the *pairwise cosine similarity* for each combination of songs in the data. This results in a 1000 x 1000 matrix (with redundancy in the information as item A similarity to item B == item B similarity to item A).



```
[44]: # Cosine similarity
similarity = cosine_similarity(data_scaled)
print("Similarity shape:", similarity.shape)

# Convert into a dataframe and then set the row index and column names as labels
sim_df_labels = pd.DataFrame(similarity)
sim_df_names = sim_df_labels.set_index(labels.index)
sim_df_names.columns = labels.index

sim_df_names.head()
```

Similarity shape: (262, 262)

```
[44]: filename      karr_seg01.wav  karr_seg02.wav  karr_seg03.wav  \
filename
karr_seg01.wav      1.000000      0.307625      0.250009
karr_seg02.wav      0.307625      1.000000      0.949374
karr_seg03.wav      0.250009      0.949374      1.000000
karr_seg04.wav      0.263302      0.753172      0.766691
karr_seg05.wav      0.248611      0.856778      0.875361

filename      karr_seg04.wav  karr_seg05.wav  karr_seg06.wav  \
filename
karr_seg01.wav      0.263302      0.248611      0.188035
karr_seg02.wav      0.753172      0.856778      0.636521
karr_seg03.wav      0.766691      0.875361      0.694863
karr_seg04.wav      1.000000      0.768288      0.615072
karr_seg05.wav      0.768288      1.000000      0.690789

filename      karr_seg07.wav  karr_seg08.wav  karr_seg09.wav  \
filename
karr_seg01.wav      -0.171836      0.071673      0.191592
karr_seg02.wav      -0.002479      0.460150      0.608838
karr_seg03.wav      -0.004492      0.415657      0.666218
karr_seg04.wav      -0.122772      0.257852      0.591310
karr_seg05.wav      -0.043441      0.340673      0.654711

filename      karr_seg10.wav  ...  va9ou_seg48.wav  va9ou_seg49.wav  \
filename
karr_seg01.wav      0.145421  ...      0.234199      0.208992
karr_seg02.wav      0.495975  ...      0.440236      0.422704
karr_seg03.wav      0.526641  ...      0.439153      0.421623
karr_seg04.wav      0.392793  ...      0.374570      0.534737
karr_seg05.wav      0.550244  ...      0.453025      0.492311

filename      va9ou_seg50.wav  va9ou_seg51.wav  va9ou_seg52.wav  \
filename
karr_seg01.wav      0.205288      0.186145      0.112865
```

karr_seg02.wav	0.426575	0.447974	0.453224
karr_seg03.wav	0.428490	0.434567	0.498271
karr_seg04.wav	0.471198	0.532941	0.453213
karr_seg05.wav	0.483130	0.492742	0.491326

filename	va9ou_seg53.wav	va9ou_seg54.wav	va9ou_seg55.wav	\
filename				
karr_seg01.wav	0.115628	0.462540	0.087547	
karr_seg02.wav	0.049134	0.113477	0.460477	
karr_seg03.wav	-0.009916	0.115395	0.499276	
karr_seg04.wav	-0.104366	0.094984	0.550084	
karr_seg05.wav	-0.021161	0.079991	0.564287	

filename	va9ou_seg56.wav	va9ou_seg57.wav
filename		
karr_seg01.wav	0.036634	0.014474
karr_seg02.wav	0.374155	0.281010
karr_seg03.wav	0.465684	0.350403
karr_seg04.wav	0.438939	0.346611
karr_seg05.wav	0.405414	0.307774

[5 rows x 262 columns]

### 3.2.5 Song similarity scoring

`find_similar_songs()` - is a predefined function that takes the name of the song and returns top 5 best matches for that song.

```
[45]: def find_similar_songs(name):
        # Find songs most similar to another song
        series = sim_df_names[name].sort_values(ascending = False)

        # Remove cosine similarity == 1 (songs will always have the best match with
        ↪ themselves)
        series = series.drop(name)

        # Display the 5 top matches
        print("\n*****\nSimilar songs to ", name)
        print(series.head(5))
```

### 3.2.6 Putting the Similarity Function into Action:

#### 3.2.7 POP Example

```
[49]: find_similar_songs('lebteyt_seg06.wav')

ipd.Audio(f'{general_path}/segments_audio/va9ou/va9ou_seg04.wav')
```

```

*****
Similar songs to lebteyt_seg06.wav
filename
va9ou_seg16.wav      0.760934
lebyad_seg32.wav     0.759471
lebteyt_seg27.wav    0.726658
lkhall_seg22.wav     0.725902
lebyad_seg29.wav     0.712178
Name: lebteyt_seg06.wav, dtype: float64

```

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

```
[152]: ipd.Audio(f'{general_path}/segments_audio/va9ou/va9ou_seg16.wav')
```

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

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
#
```

Conclusion