High-Level Feature Analysis of Environmental Noise

1. Project Setup and Initialization

1.1 Introduction

This project aims to analyze and visualize high-level audio features, specifically Spectrogram and Chroma Features, extracted from a dataset of 10 different environmental noise types. This analysis serves as a Capstone project for the "High Level Speech Feature" course provided by BISA AI Academy. The dataset used is the "Audio Noise Dataset" sourced from Kaggle, containing various types of environmental noise in `.webm` format. The goal is to demonstrate how these features can help differentiate between distinct sound sources visually.

1.2 Library Installation and Imports

We will begin by installing and importing the necessary Python libraries for audio processing, visualization, and file handling.

```
# Install necessary libraries
# !pip install librosa matplotlib numpy seaborn ffmpeg

# Import necessary libraries
import librosa
import librosa.display
import matplotlib.pyplot as plt
import numpy as np
from google.colab import drive
import glob
import subprocess
import os
```

1.3 Mounting Google Drive

The dataset is assumed to be stored in Google Drive. We will mount Google Drive to access the audio files. Please ensure your dataset is located in the specified path within your Drive.

Dataset Link: https://drive.google.com/drive/folders/1UXBlA2QRT6jaidknV9t7R7a7LGQjwdNt?usp=sharing

```
# Mount Google Drive to access the dataset
drive.mount('/content/drive')

Mounted at /content/drive
```

1.4 Path and Constant Definition

Define the paths for the raw dataset in Google Drive and the directory where converted audio files will be stored. We will also create the output directory if it doesn't exist.

```
# Define paths
DRIVE_DATASET_PATH = '/content/drive/MyDrive/Dataset/Audio Noise
Dataset Myanmar/'
PROCESSED_DATA_PATH = 'processed_audio'

# Create the processed audio directory if it doesn't exist
if not os.path.exists(PROCESSED_DATA_PATH):
    os.makedirs(PROCESSED_DATA_PATH)
    print(f"Created directory: {PROCESSED_DATA_PATH}")
else:
    print(f"Directory already exists: {PROCESSED_DATA_PATH}")
```

```
Created directory: processed_audio
```

2. Data Pre-processing: Audio Format Conversion

2.1 The Need for Conversion

Audio files in the original dataset are in the `.webm` format. While this format is common, the `librosa` library, which is essential for our feature extraction tasks, works optimally with more standard audio formats like `.wav`. Therefore, we need to convert the `.webm` files to `.wav` format before proceeding with the analysis.

2.2 Conversion Script

This script will scan the specified Google Drive directory for `.webm` files and convert each one to a `.wav` file with a sample rate of 22050 Hz and a single audio channel (mono). The converted files will be saved in the `processed_audio` directory.

```
webm_files = glob.glob(os.path.join(DRIVE_DATASET_PATH, '*.webm'))
converted_count = 0

for webm_file in webm_files:
    file_name = os.path.basename(webm_file)
    base_name, _ = os.path.splitext(file_name)
    wav_file = os.path.join(PROCESSED_DATA_PATH, f"{base_name}.wav")

    if not os.path.exists(wav_file):
        print(f"Converting {file_name} to {base_name}.wav...")
        try:
            # Use ffmpeg to convert webm to wav
            subprocess.run([
                'ffmpeg', '-i', webm_file,
                '-ar', '22050',  # Set sample rate to 22050 Hz
```

```
                '-ac', '1',      # Set audio channels to 1 (mono)
                wav_file
            ], check=True, capture_output=True, text=True)
            converted_count += 1
        except subprocess.CalledProcessError as e:
            print(f"Error converting {file_name}: {e.stderr}")
    else:
        print(f"{base_name}.wav already exists. Skipping conversion.")

if converted_count > 0:
    print("Conversion process finished.")
else:
    print("No new files to convert or all files already exist.")

print("All files processed.")
```

```
Converting sample-1 a crowded place.webm to sample-1 a crowded
place.wav...
Converting sample-2 urban areas with people talking.webm to sample-2
urban areas with people talking.wav...
Converting sample-8 a working place.webm to sample-8 a working
place.wav...
Converting sample-3 the restaurant.webm to sample-3 the
restaurant.wav...
Converting sample-10 motorbike and people talking .webm to sample-10
motorbike and people talking .wav...
Converting sample-9 a festival.webm to sample-9 a festival.wav...
Converting sample-7 the rainy day.webm to sample-7 the rainy
day.wav...
Converting sample-6 painful sounds.webm to sample-6 painful
sounds.wav...
Converting sample-4 mosquitos .webm to sample-4 mosquitos .wav...
Converting sample-5 car traffic.webm to sample-5 car traffic.wav...
Conversion process finished.
All files processed.
```

3. Feature Extraction and Visualization

3.1 Loading Audio Data

Now that the audio files are in the `.wav` format, we can load them using `librosa.load()`. We will create a list of all the processed `.wav` files to iterate through for feature extraction.

```
# Get a list of all processed WAV files and sort them
wav_files = sorted(glob.glob(os.path.join(PROCESSED_DATA_PATH,
'*.wav')))

print(f"Found {len(wav_files)} WAV files in {PROCESSED_DATA_PATH}")
# Display the list of files found
```

```
print("\nList of files:")
for f in wav_files:
    print(f)
```

```
Found 10 WAV files in processed_audio

List of files:
processed_audio/sample-1 a crowded place.wav
processed_audio/sample-10 motorbike and people talking .wav
processed_audio/sample-2 urban areas with people talking.wav
processed_audio/sample-3 the restaurant.wav
processed_audio/sample-4 mosquitos .wav
processed_audio/sample-5 car traffic.wav
processed_audio/sample-6 painful sounds.wav
processed_audio/sample-7 the rainy day.wav
processed_audio/sample-8 a working place.wav
processed_audio/sample-9 a festival.wav
```

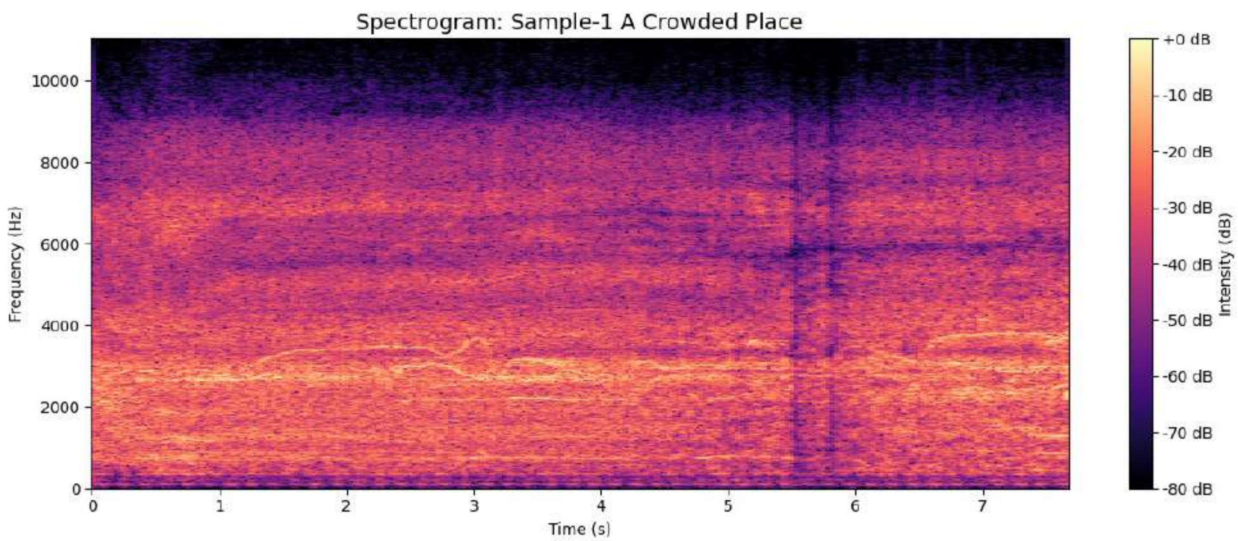
3.2 Spectrogram Analysis

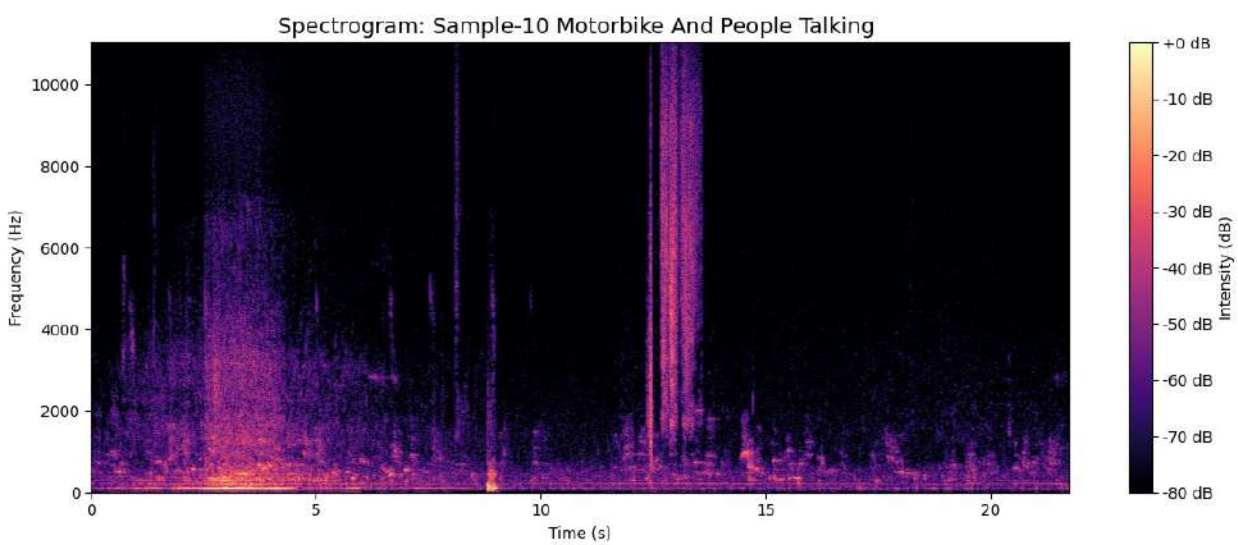
A Spectrogram is a visual representation of the spectrum of frequencies of a signal as it varies with time. It shows the intensity of different frequencies over time, where the x-axis represents time, the y-axis represents frequency, and the color intensity represents the amplitude (loudness) at that frequency and time. Spectrograms are highly useful for analyzing audio signals as they can reveal patterns and characteristics that are not easily discernible in the raw waveform, making them valuable for differentiating various sound types.

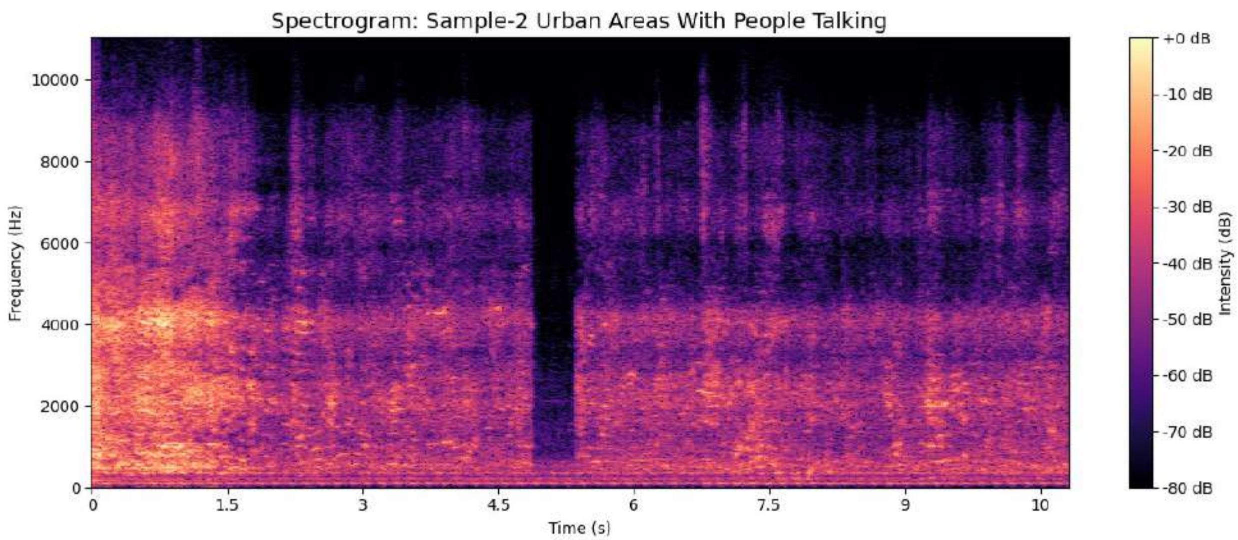
```
# Spectrogram visualization for each audio file
print("Generating Spectrograms...")
for wav_file in wav_files:
    try:
        y, sr = librosa.load(wav_file, sr=22050) # Load with defined
sample rate

        # Compute the Short-Time Fourier Transform (STFT)
        D = librosa.stft(y)

        # Convert to decibels
        D_db = librosa.amplitude_to_db(np.abs(D), ref=np.max)

        plt.figure(figsize=(12, 5))
        librosa.display.specshow(D_db, sr=sr, x_axis='time',
y_axis='hz')

        # Extract noise type from file name for title
        file_name = os.path.basename(wav_file)
        noise_type = os.path.splitext(file_name)[0].replace('_', '
').title() # Basic cleaning for title
```

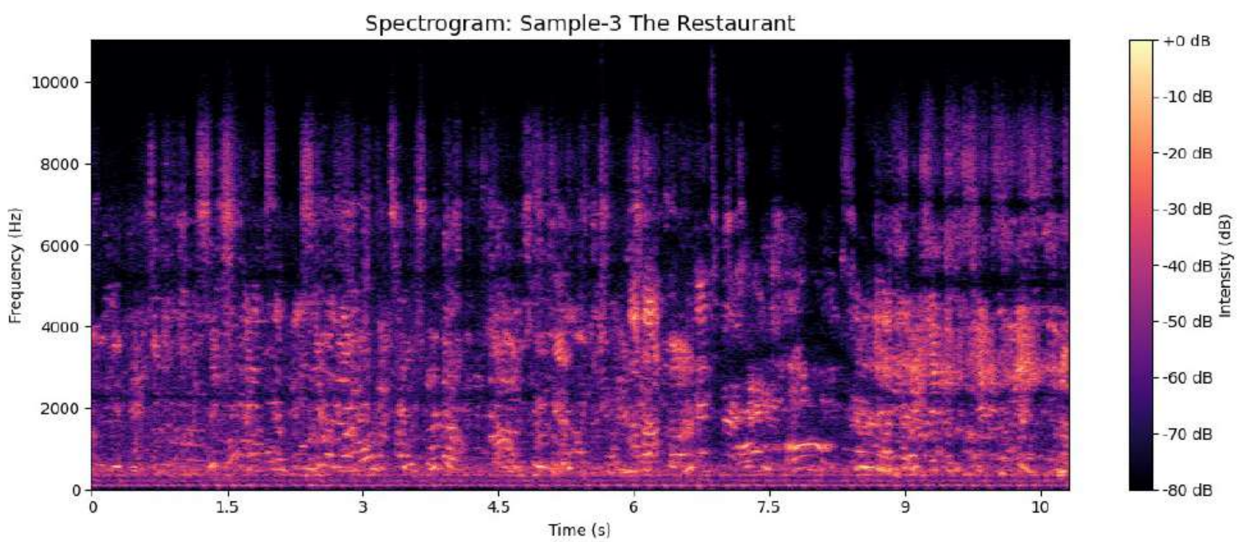
```
        plt.title(f'Spectrogram: {noise_type}', fontsize=14)
        plt.colorbar(format='%+2.0f dB', label='Intensity (dB)')
        plt.xlabel('Time (s)')
        plt.ylabel('Frequency (Hz)')
        plt.tight_layout()
        plt.show()

    except Exception as e:
        print(f"Error processing {wav_file}: {e}")

print("Spectrogram generation complete.")
```

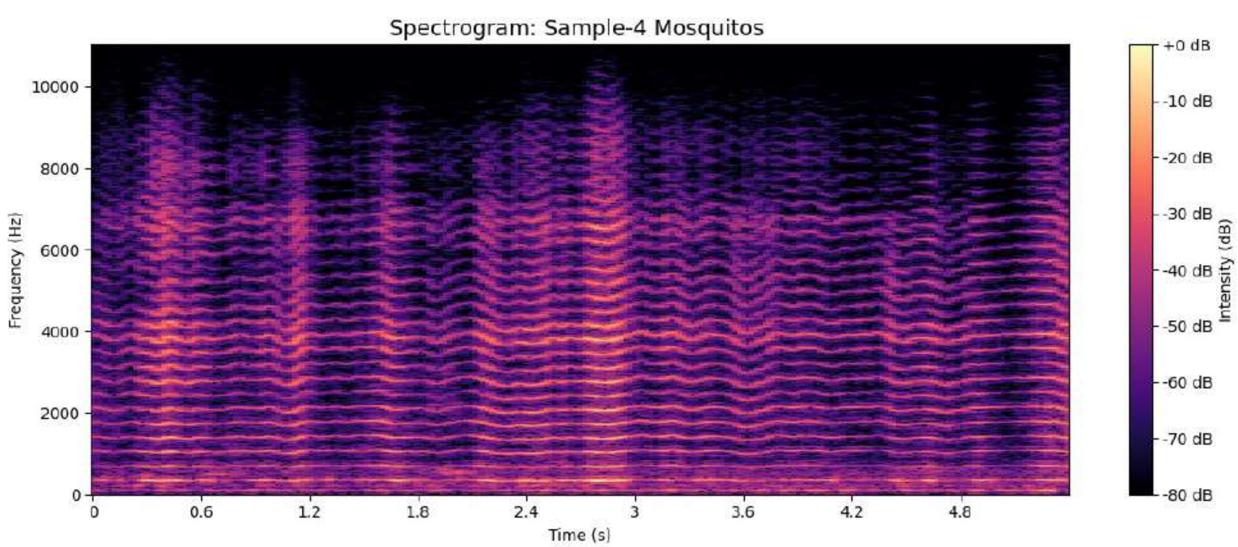
```
Generating Spectrograms...
```

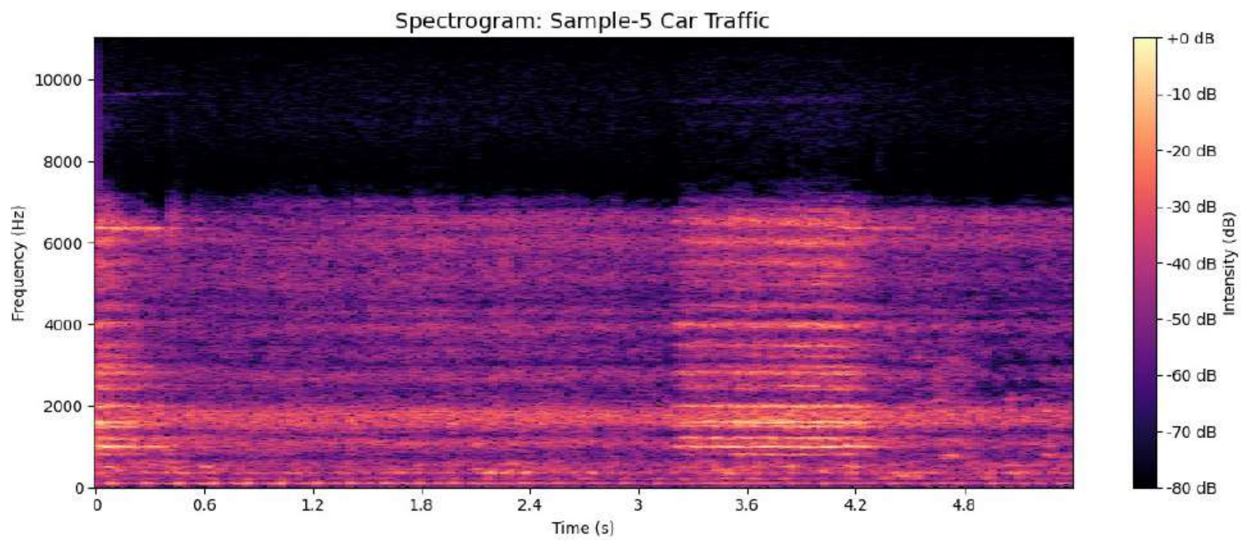


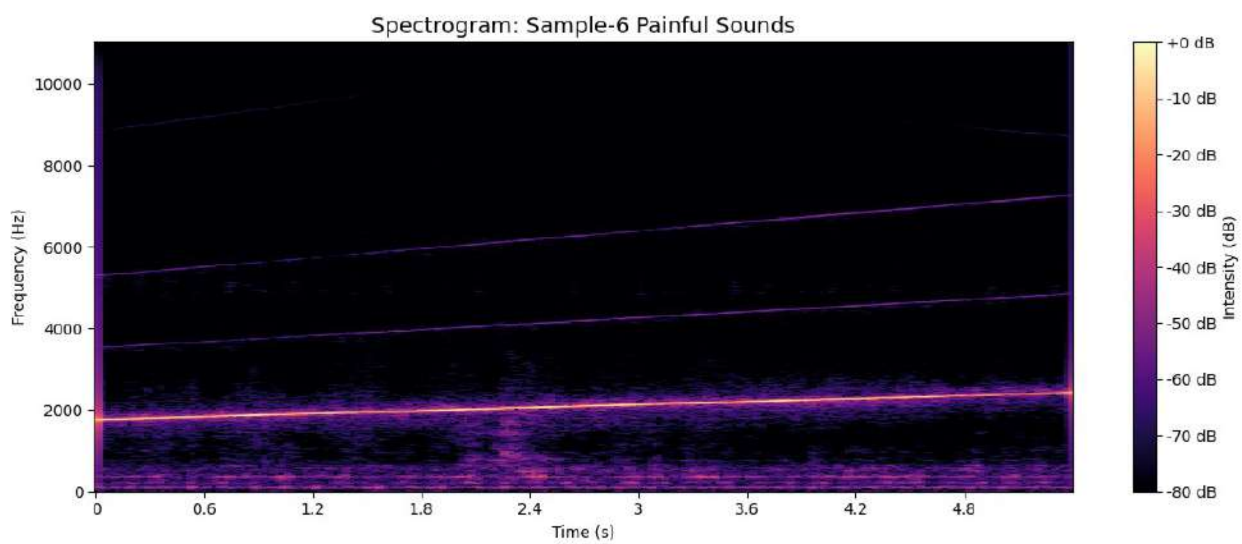


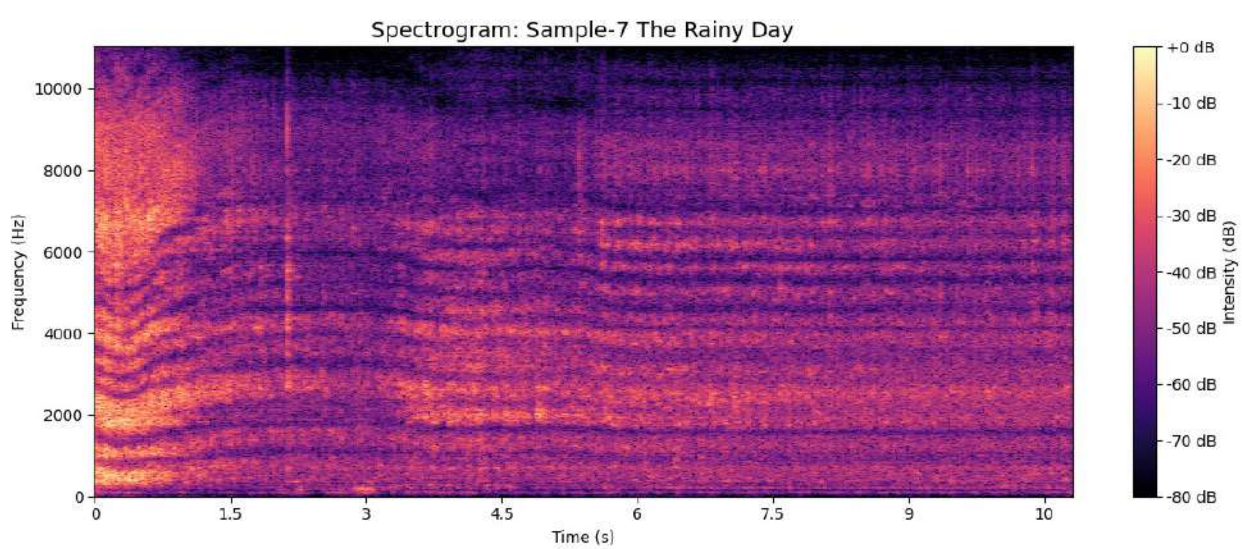

Spectrogram: Sample-2 Urban Areas With People Talking
Frequency (Hz)
0
2000
4000
6000
8000
10000
Time (s)
0
1.5
3
4.5
6
7.5
9
10
Intensity (dB)
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB

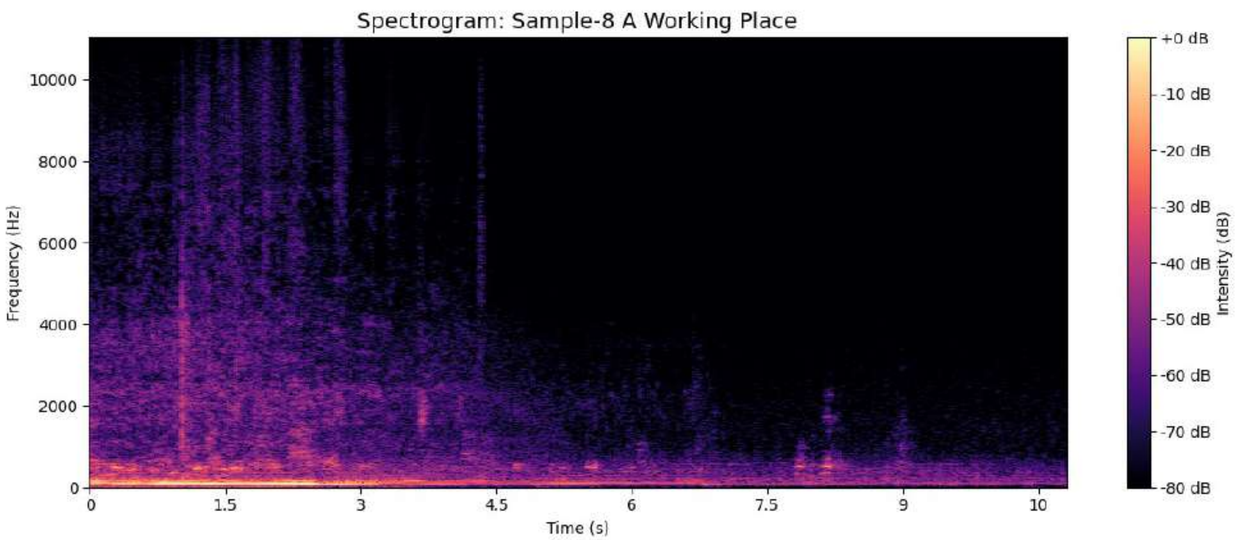

Spectrogram: Sample-3 The Restaurant
Frequency (Hz)
0
2000
4000
6000
8000
10000
Time (s)
0
1.5
3
4.5
6
7.5
9
10
Intensity (dB)
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB

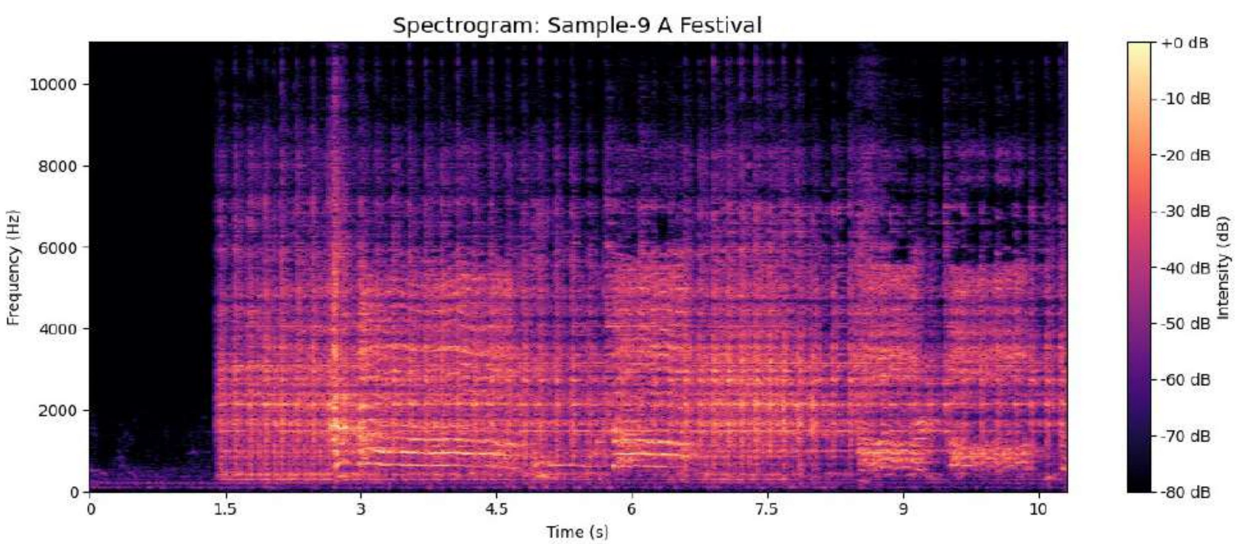

Spectrogram: Sample-4 Mosquitos
Frequency (Hz)
0
2000
4000
6000
8000
10000
Time (s)
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
Intensity (dB)
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB


Spectrogram: Sample-5 Car Traffic
Frequency (Hz)
Time (s)
Intensity (dB)
0
2000
4000
6000
8000
10000
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB


Spectrogram: Sample-6 Painful Sounds
Frequency (Hz)
Time (s)
Intensity (dB)
0
2000
4000
6000
8000
10000
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB


Spectrogram: Sample-7 The Rainy Day
Frequency (Hz)
Time (s)
Intensity (dB)
0
2000
4000
6000
8000
10000
1.5
3
4.5
6
7.5
9
10
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB






```
Spectrogram generation complete.
```

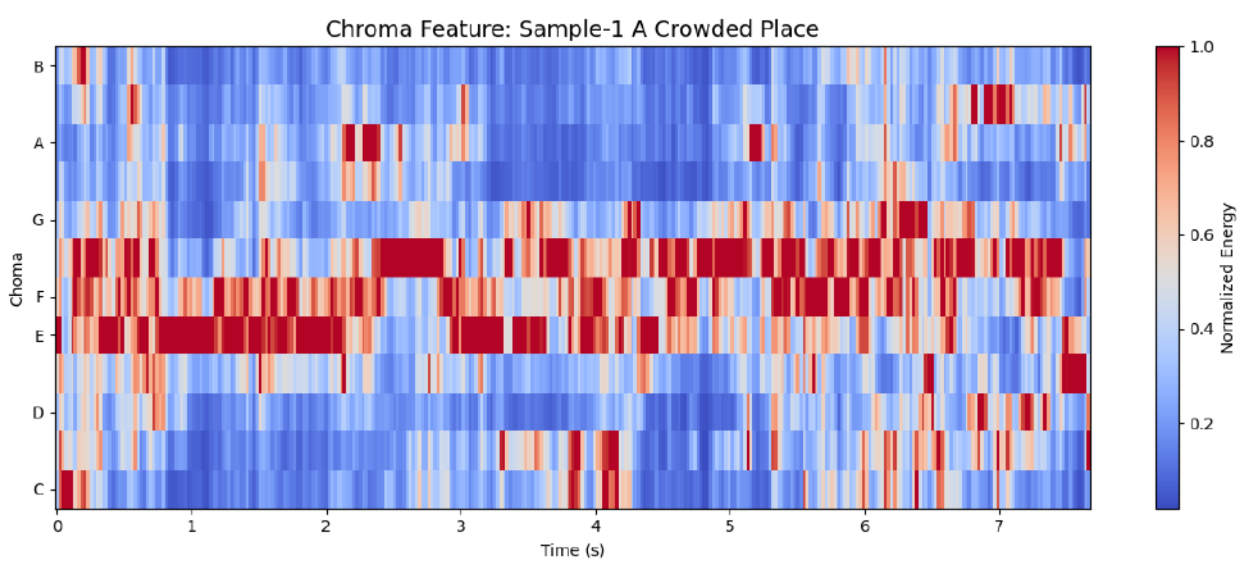
3.3 Chroma Feature Analysis

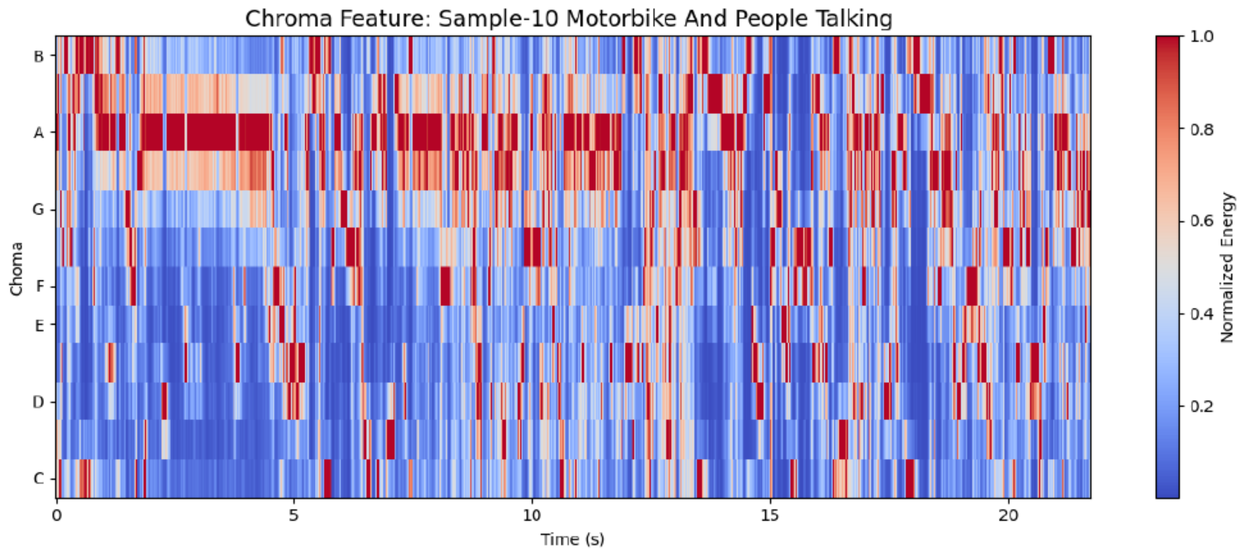
Chroma features, also known as chromagrams, are a representation of the spectral energy distribution across the 12 standard pitch classes of the musical octave (C, C#, D, D#, E, F, F#, G, G#, A, A#, B). Regardless of the absolute frequency, all energy that falls into a specific pitch class is accumulated into a single bin. While primarily used in music analysis, chromagrams can also be insightful for environmental noise, as they can reveal underlying harmonic structures or dominant tonal components present in sounds like sirens, certain machinery, or even distant music.

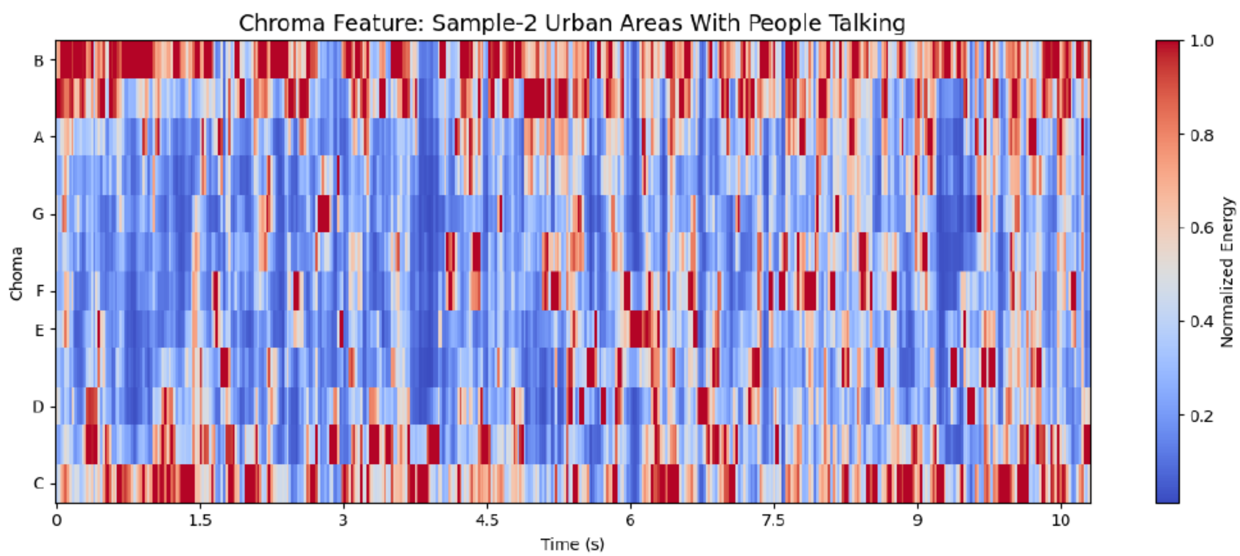
```
# Chroma feature visualization for each audio file
print("Generating Chromagrams...")
for wav_file in wav_files:
```

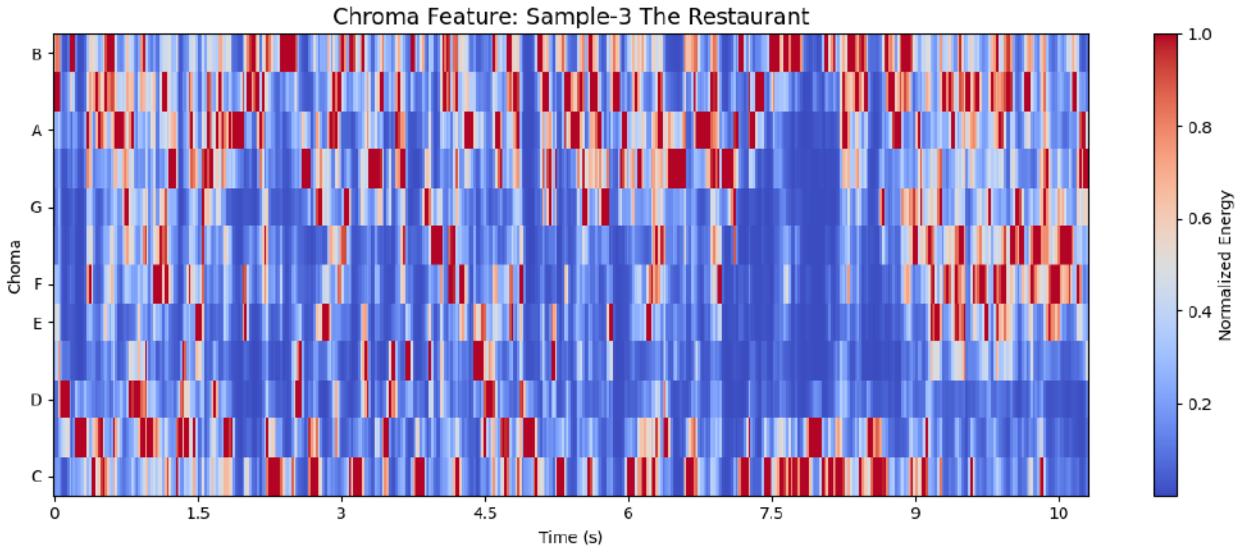
```
    try:
        y, sr = librosa.load(wav_file, sr=22050) # Load with defined
sample rate

        # Extract Chroma features
        chromagram = librosa.feature.chroma_stft(y=y, sr=sr)

        plt.figure(figsize=(12, 5))
        librosa.display.specshow(chromagram, sr=sr, x_axis='time',
y_axis='chroma', cmap='coolwarm')

        # Extract noise type from file name for title
        file_name = os.path.basename(wav_file)
        noise_type = os.path.splitext(file_name)[0].replace('_', '
').title() # Basic cleaning for title

        plt.title(f'Chroma Feature: {noise_type}', fontsize=14)
        plt.colorbar(label='Normalized Energy')
        plt.xlabel('Time (s)')
        plt.ylabel('Choma')
        plt.tight_layout()
        plt.show()

    except Exception as e:
        print(f"Error processing {wav_file}: {e}")

print("Chromagram generation complete.")
```

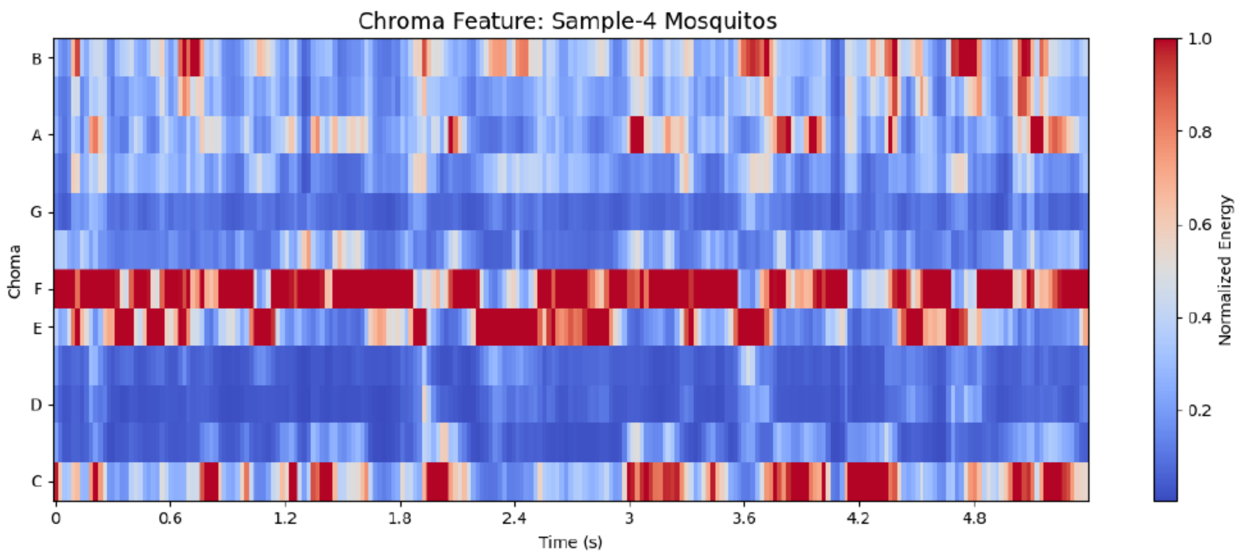
```
Generating Chromagrams...
```

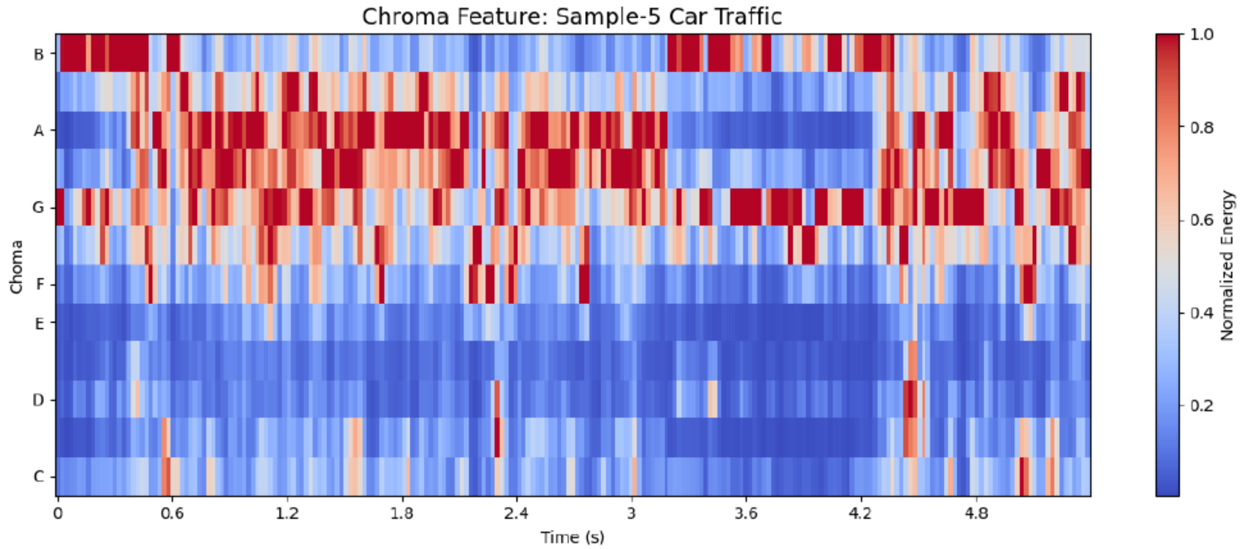



Chroma Feature: Sample-10 Motorbike And People Talking
B
A
G
F
E
D
C
Choma
0
5
10
15
20
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy

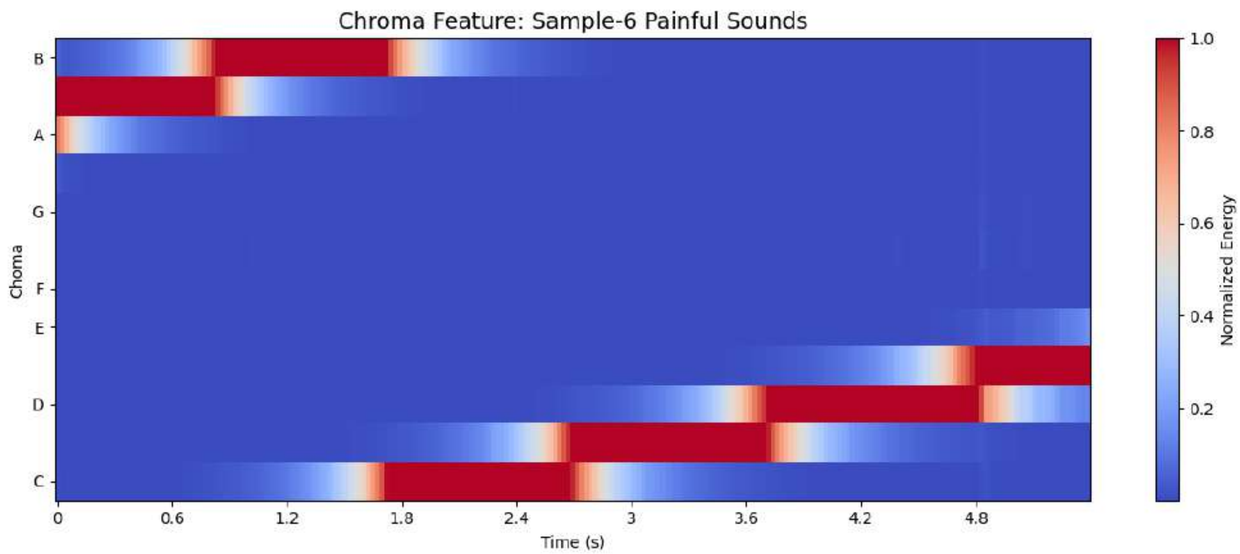

Chroma Feature: Sample-2 Urban Areas With People Talking
B
A
G
F
E
D
C
Choma
0
1.5
3
4.5
6
7.5
9
10
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy


Chroma Feature: Sample-3 The Restaurant
Choma
B
A
G
F
E
D
C
0
1.5
3
4.5
6
7.5
9
10
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy


Chroma Feature: Sample-4 Mosquitos
Choma
B
A
G
F
E
D
C
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy

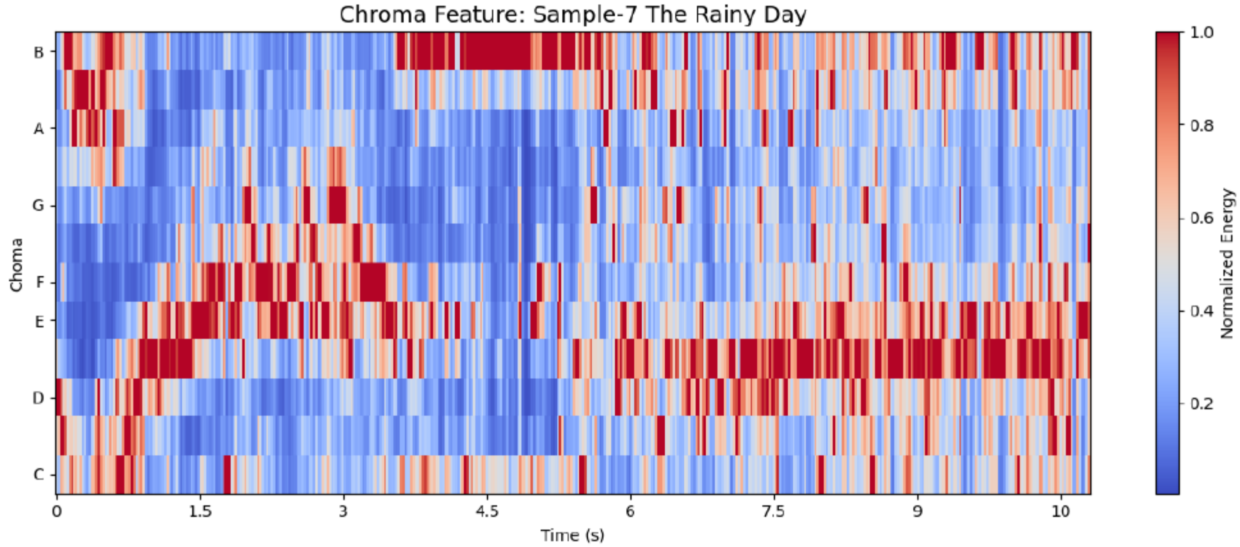


Chroma Feature: Sample-5 Car Traffic
B
A
G
F
E
D
C
Chroma
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy

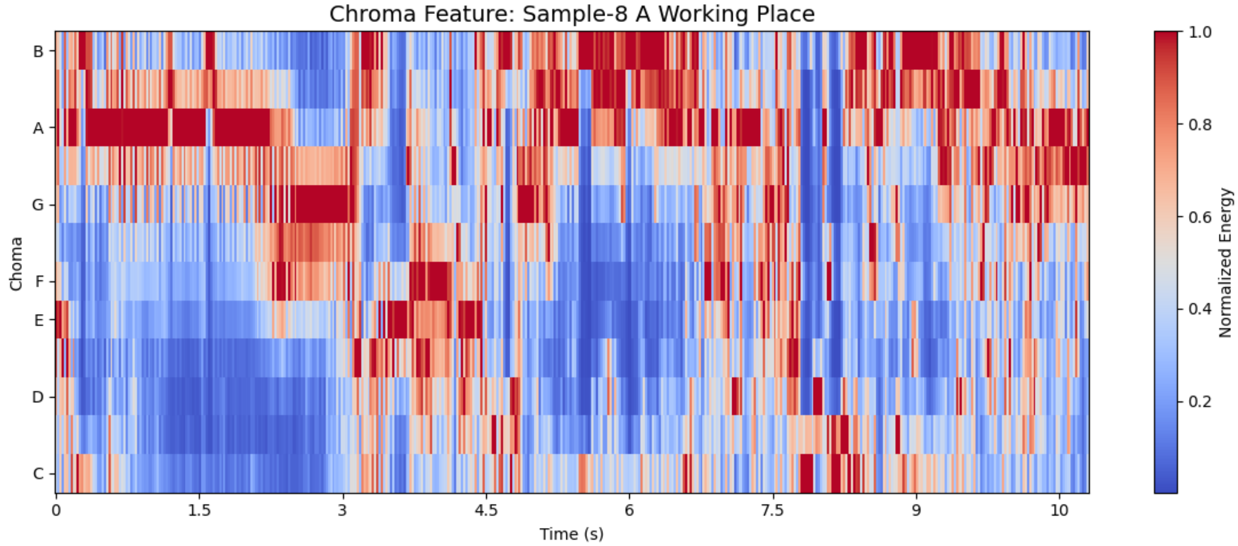


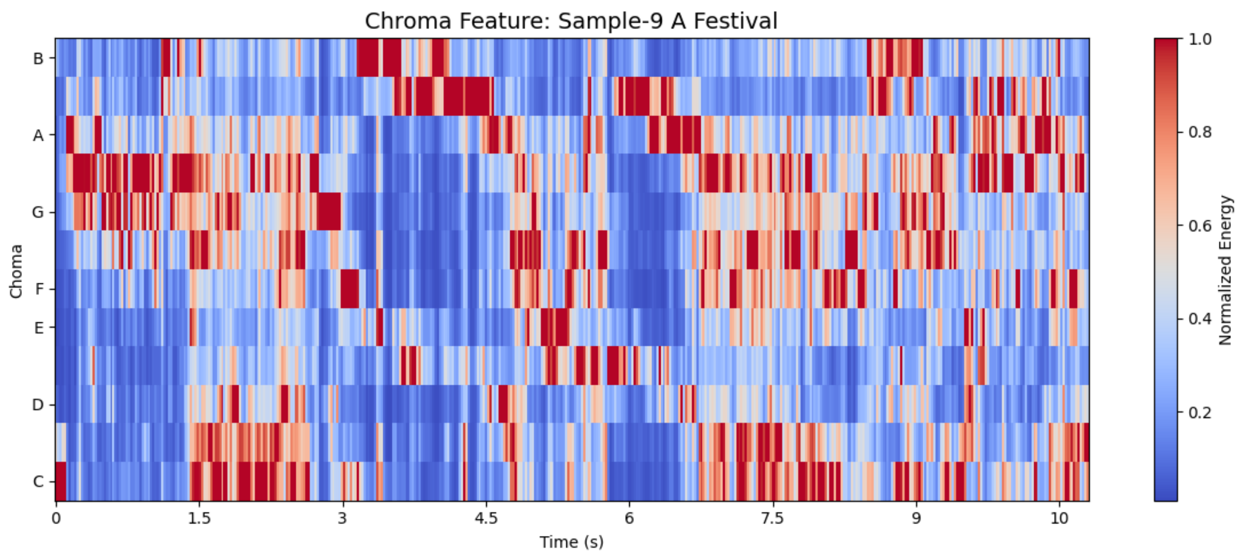
Chroma Feature: Sample-6 Painful Sounds
B
A
G
F
E
D
C
Chroma
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
Time (s)
1.0
0.8
0.6
0.4
0.2
Normalized Energy

Chroma Feature: Sample-7 The Rainy Day



Chroma Feature: Sample-8 A Working Place






```
Chromagram generation complete.
```

4. Comparative Analysis and Conclusion

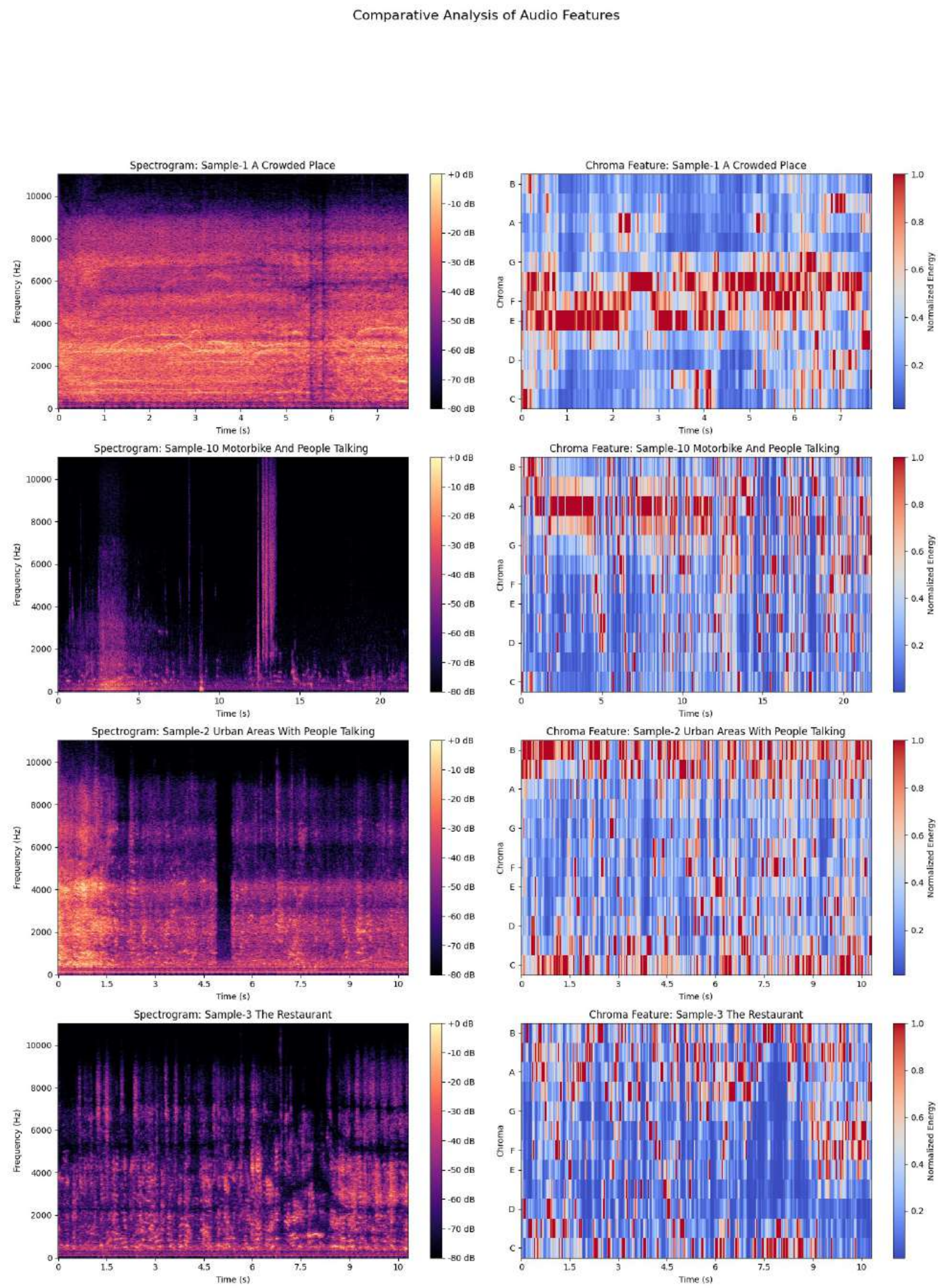
4.1 Side-by-Side Feature Comparison

To facilitate a direct comparison and better understand how Spectrogram and Chroma features differ for each noise type, we will plot them side-by-side in a single figure.

```
# Get a list of all processed WAV files and sort them
PROCESSED_DATA_PATH = 'processed_audio' # Assuming this path is
defined earlier
wav_files = sorted(glob.glob(os.path.join(PROCESSED_DATA_PATH,
'*.wav')))


print("Generating comparative plots...")

num_files = len(wav_files)
fig, axes = plt.subplots(num_files, 2, figsize=(16, 5 * num_files),
squeeze=False) # Adjusted figure size and squeeze

fig.suptitle('Comparative Analysis of Audio Features', fontsize=16,
y=1.02) # Add a main title

for i, wav_file in enumerate(wav_files):
    try:
        y, sr = librosa.load(wav_file, sr=22050)

        # Extract noise type from file name
        file_name = os.path.basename(wav_file)
        noise_type = os.path.splitext(file_name)[0].replace('_', '
```

```
').title()

        # Spectrogram
        D = librosa.stft(y)
        D_db = librosa.amplitude_to_db(np.abs(D), ref=np.max)
        img_spec = librosa.display.specshow(D_db, sr=sr,
x_axis='time', y_axis='hz', ax=axes[i, 0])
        axes[i, 0].set_title(f'Spectrogram: {noise_type}',
fontsize=12)
        axes[i, 0].set_xlabel('Time (s)')
        axes[i, 0].set_ylabel('Frequency (Hz)')
        fig.colorbar(img_spec, ax=axes[i, 0], format='%+2.0f dB')


        # Chromagram
        chromagram = librosa.feature.chroma_stft(y=y, sr=sr)
        img_chroma = librosa.display.specshow(chromagram, sr=sr,
x_axis='time', y_axis='chroma', ax=axes[i, 1], cmap='coolwarm')
        axes[i, 1].set_title(f'Chroma Feature: {noise_type}',
fontsize=12)
        axes[i, 1].set_xlabel('Time (s)')
        axes[i, 1].set_ylabel('Chroma')
        fig.colorbar(img_chroma, ax=axes[i, 1], label='Normalized
Energy')


    except Exception as e:
        print(f"Error processing {wav_file} for comparative plot:
{e}")
        # Hide the empty subplots if an error occurred for a file
        axes[i, 0].axis('off')
        axes[i, 1].axis('off')


plt.tight_layout(rect=[0, 0.03, 1, 0.98]) # Adjust layout to make
space for suptitle
plt.show()

print("Comparative plot generation complete.")
```

```
Generating comparative plots...
```



Comparative Analysis of Audio Features
Spectrogram: Sample-1 A Crowded Place
Chroma Feature: Sample-1 A Crowded Place
Spectrogram: Sample-10 Motorbike And People Talking
Chroma Feature: Sample-10 Motorbike And People Talking
Spectrogram: Sample-2 Urban Areas With People Talking
Chroma Feature: Sample-2 Urban Areas With People Talking
Spectrogram: Sample-3 The Restaurant
Chroma Feature: Sample-3 The Restaurant
Frequency (Hz)
Time (s)
Chroma
Normalized Energy
+0 dB
-10 dB
-20 dB
-30 dB
-40 dB
-50 dB
-60 dB
-70 dB
-80 dB

```
Comparative plot generation complete.
```

4.2 Conclusion and Key Findings

This project successfully demonstrated the application of high-level audio features, namely Spectrograms and Chroma Features, for the visual analysis and differentiation of various environmental noise types.

The Spectrogram analysis clearly shows distinct frequency fingerprints for each noise category. For example, 'Car Traffic' exhibits dominant energy in low-frequency bands, while 'Mosquitos' shows sharp, high-frequency spikes. 'Rain' displays a broadband noise pattern, and 'Wind' shows energy distributed across various frequencies but often with less defined structures compared to more distinct sounds.

The Chroma Feature analysis, while less directly interpretable for non-musical sounds, revealed interesting patterns. While most environmental noises have a relatively distributed chromagram, sounds containing harmonic components, such as 'Festival' (likely due to background music) or 'Siren', show more concentrated energy in specific chroma bins, indicating the presence of underlying tonal structures.

In conclusion, this project successfully demonstrates how high-level audio features can be used to visually differentiate complex audio signals, providing a powerful tool for audio classification and analysis tasks. These visualizations offer valuable insights into the spectral characteristics of different sound sources, which can be leveraged in various audio processing and machine learning applications.