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So First importing the libraries

Importing Libraries

```python
import zipfile
import os
import librosa
import numpy as np
import matplotlib.pyplot as plt
import librosa.display
import soundfile as sf
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

Extracting the zip fille

```python
[9] zip_file_path = '/content/data.zip'
    extract_dir = '/content/extracted_data'
    with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
        zip_ref.extractall(extract_dir)
```

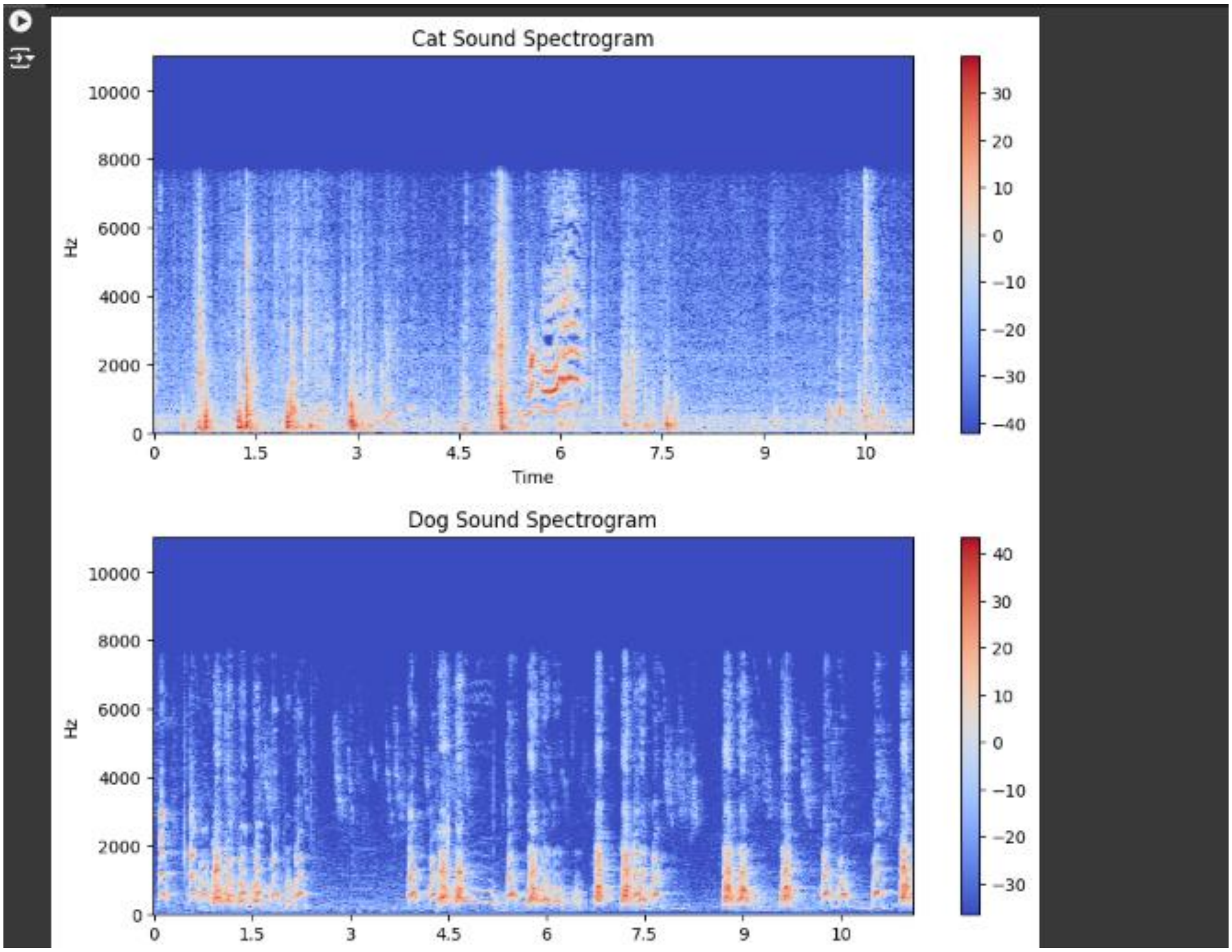
Afterwards we will load and display a sample audio, the code loads two audio files and creates visualizations of their waveforms, which helps in understanding the audio signal characteristics for both the cat and dog sounds.

```python
audio_dir = '/content/extracted_data/cats_dogs'
#loding the cat sound
cat_sound_path = os.path.join(audio_dir, 'cat_1.wav')
cat_audio, sr = librosa.load(cat_sound_path)

#Plotting the Cat Sound Waveform
plt.figure(figsize=(10, 4))
librosa.display.waveshow(cat_audio, sr=sr)
plt.title('Cat Sound Waveform')
plt.show()

dog_sound_path = os.path.join(audio_dir, 'dog_barking_1.wav')
dog_audio, sr = librosa.load(dog_sound_path)
#dog sound waveform
plt.figure(figsize=(10, 4))
librosa.display.waveshow(dog_audio, sr=sr)
plt.title('Dog Sound Waveform')
plt.show()
```

This code generates and visualizes the spectrograms of the cat and dog sound recordings. A spectrogram provides a visual representation of the frequency content of an audio signal over time, which can reveal more detailed information about the sound than a waveform alone.



This extracts MFCC features from audio files, assigns labels based on the file names, and prepares the data for training and testing a machine learning model.

```python
cats_dogs_dir = '/content/extracted_data/cats_dogs'
labels = []
features = []


for file_name in os.listdir(cats_dogs_dir):
    if file_name.endswith('.wav'):
        file_path = os.path.join(cats_dogs_dir, file_name)
        audio_data, sample_rate = librosa.load(file_path, sr=None)

        # Extract MFCC
        mfccs = librosa.feature.mfcc(y=audio_data, sr=sample_rate, n_mfcc=13)
        mfccs = np.mean(mfccs.T, axis=0)


        features.append(mfccs)
        if 'cat' in file_name:
            labels.append(0)  # 0 for cat
        elif 'dog' in file_name:
            labels.append(1)  # 1 for dog

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Audio augmentation, here the augments the audio dataset by applying time stretching, pitch shifting, noise addition, time shifting, and volume changes. This can help improve the robustness of machine learning models by providing a more varied training set.

Process and Augment Data

```python
def augment_audio(audio_data, sample_rate):
    # Time Stretching
    stretch_rate = np.random.uniform(0.8, 1.2)
    audio_stretched = librosa.effects.time_stretch(audio_data, rate=stretch_rate)


    # Pitch Shifting
    pitch_shift = np.random.randint(-2, 3)
    audio_shifted = librosa.effects.pitch_shift(audio_stretched, sr=sample_rate, n_steps=pitch_shift)

    # Adding Noise
    noise = np.random.randn(len(audio_shifted))
    audio_noisy = audio_shifted + 0.005 * noise

    # Shifting
    shift_max = np.random.randint(1, sample_rate)
    audio_shifted_time = np.roll(audio_noisy, shift_max)

    # Changing Volume
    audio_augmented = audio_shifted_time * np.random.uniform(0.8, 1.2)

    return audio_augmented


for file_name in os.listdir(cats_dogs_dir):
    if file_name.endswith('.wav'):
        file_path = os.path.join(cats_dogs_dir, file_name)
        audio_data, sample_rate = librosa.load(file_path, sr=None)

        audio_augmented = augment_audio(audio_data, sample_rate)

        augmented_file_path = os.path.join(cats_dogs_dir, 'aug_' + file_name)
        sf.write(augmented_file_path, audio_augmented, sample_rate)
```

Here I trained an MLP classifier on the audio features, evaluates its accuracy, and provides a detailed classification report to assess the model's performance in distinguishing between cat and dog sounds. Relu and adam were used.

Model Building and Evaluation

```
mlp = MLPClassifier(hidden_layer_sizes=(128, 64), activation='relu', solver='adam', max_iter=500)
mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')
print(classification_report(y_test, y_pred, target_names=['Cat', 'Dog']))
```

```
Accuracy: 78.38%
              precision    recall  f1-score   support

         Cat       0.94      0.69      0.80        68
         Dog       0.66      0.93      0.77        43

    accuracy                           0.78       111
   macro avg       0.80      0.81      0.78       111
weighted avg       0.83      0.78      0.79       111
```

Here we compared the accuracy after tuning

Model Building and Hyperparameter Tuning

```
mlp = MLPClassifier(hidden_layer_sizes=(256, 128, 64),
                    activation='relu',
                    solver='adam',
                    max_iter=1000,
                    alpha=0.0001,
                    learning_rate='adaptive')

mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy after tuning: {accuracy * 100:.2f}%')
```

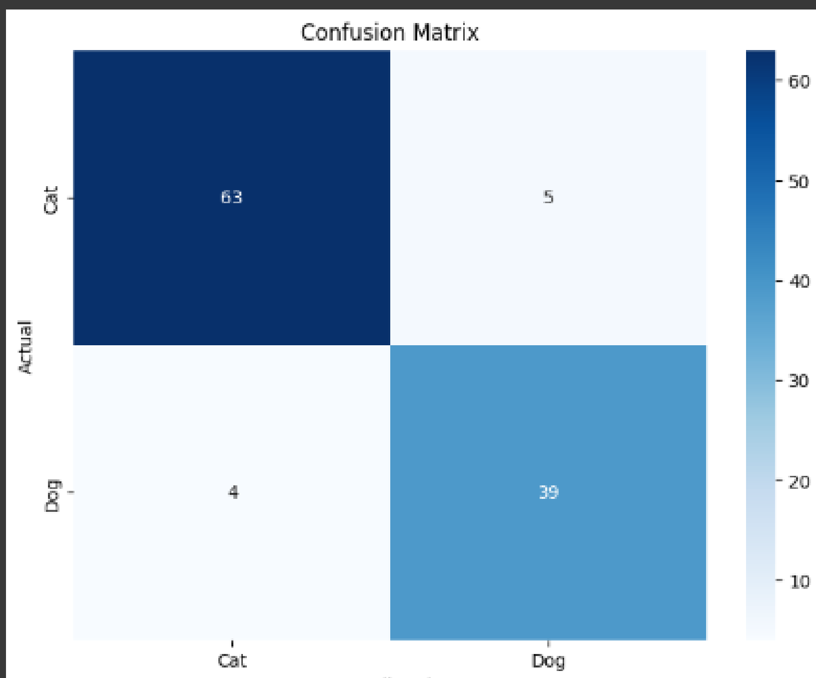
```
Accuracy after tuning: 91.89%
```

Model evaluation, visualizing the confusion matrix as a heatmap to help understand the classifier's performance by showing where the predictions match or differ from the actual class labels.

Model Evaluation (Confusion Matrix Visualization)

```
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Cat', 'Dog'], yticklabels=['Cat', 'Dog'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Finally, adding a test audio to classify if the audio is for a cat or a dog

Finally Classifying Multiple Audios

```python
def preprocess_audio(file_path):
    audio_data, sample_rate = librosa.load(file_path, sr=None)

    mfccs = librosa.feature.mfcc(y=audio_data, sr=sample_rate, n_mfcc=13)
    mfccs = np.mean(mfccs.T, axis=0)
    return mfccs.reshape(1, -1)

new_audio_file = '/content/extracted_data/cats_dogs/aug_aug_cat_121.wav'
X_new = preprocess_audio(new_audio_file)
```

```python
prediction = mlp.predict(X_new)

if prediction[0] == 0:
    print("The sound is from a Cat.")
else:
    print("The sound is from a Dog.")
```

```
The sound is from a Cat.
```