Speech and Image Analysis

Course Project

Submitted by

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3

1. Implementation

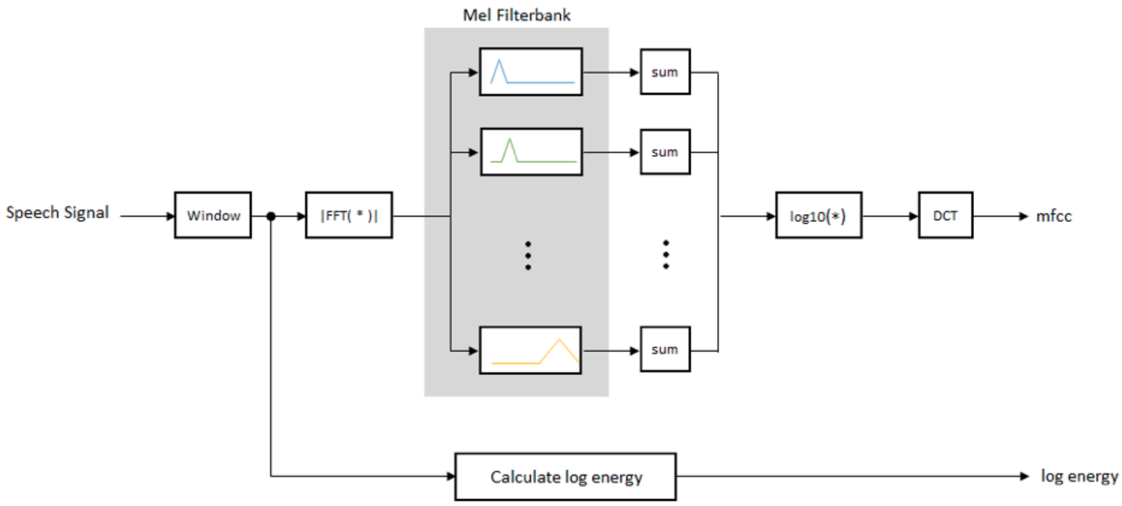
Programming language used: Python,

In this project we utilize the Audio MNIST dataset to build a model for speaker identification. The Audio MNIST dataset contains 30,000 audio samples of 60 speakers (each speaker has 500 audio samples).

The process is as follows:

a) Feature extraction

While speaker identification can use features like pitch and energy, this project focuses on Mel-Frequency Cepstral Coefficients (MFCC). MFCCs represent the vocal tract characteristics by analyzing speech spectral patterns. This approach efficiently compresses the unique aspects of a person's speech into a small set of meaningful coefficients by examining the spectral envelope, making it highly effective for speaker recognition tasks.



(Source:https://www.mathworks.com/help/audio/ug/speaker-identification-using-pitch-and-mfcc.html#SpeakerIdentificationUsingPitchAndMFCCExample-3)

Installing and loading the Audio MNIST dataset

```
#Install kaggle
!pip install -q kaggle
```

Installing kaggle

```
[ ]
    from google.colab import files
    files.upload()

Choose Files no files selected    Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
    Saving kaggle.json to kaggle (1).json
    {'kaggle (1).json': b'{"username":"gayanthikashankar","key":"5b9c41bbeec3ed9536d9e2eb3ff1e91e"}'}
```

```
#Create a kaggle folder
! mkdir ~/.kaggle
```

```
#Copy the kaggle.json to created folder
! cp kaggle.json ~/.kaggle/
```

```
#Permission for the json to act
! chmod 600 ~/.kaggle/kaggle.json
```

```
#Download Audio MNIST dataset
!kaggle datasets download sripaadsrinivasan/audio-mnist

Dataset URL: https://www.kaggle.com/datasets/sripaadsrinivasan/audio-mnist
License(s): CC0-1.0
audio-mnist.zip: Skipping, found more recently modified local copy (use --force to force download)
```

Downloading and extracting .wav files using Kaggle API

```
#Unzip to access audio files
!unzip audio-mnist.zip
```

```
Streaming output truncated to the last 5000 lines.
  inflating: data/51/0_51_1.wav
  inflating: data/51/0_51_10.wav
  inflating: data/51/0_51_11.wav
  inflating: data/51/0_51_12.wav
  inflating: data/51/0_51_13.wav
  inflating: data/51/0_51_14.wav
  inflating: data/51/0_51_15.wav
  inflating: data/51/0_51_16.wav
  inflating: data/51/0_51_17.wav
  inflating: data/51/0_51_18.wav
  inflating: data/51/0_51_19.wav
  inflating: data/51/0_51_2.wav
  inflating: data/51/0_51_20.wav
  inflating: data/51/0_51_21.wav
  inflating: data/51/0_51_22.wav
  inflating: data/51/0_51_23.wav
  inflating: data/51/0_51_24.wav
  inflating: data/51/0_51_25.wav
```

Unzip files to utilize in the notebook

Play and visualize a chosen audio file

```
import numpy as np
import librosa
import librosa.display as dsp
import matplotlib.pyplot as plt
from IPython.display import Audio, display, clear_output
import os
import ipywidgets as widgets

class SequentialAudioPlayer:
    def __init__(self, base_path="data"):
        #Initialize player with file paths and UI controls
        self.base_path = base_path
        self.current_speaker = None
        self.current_digit = 0
        #Define navigation order for recordings
        self.recording_order = ['0','1','10','11','12','13','14','15','16','17','18','19','2',
                              '20','21','22','23','24','25','26','27','28','29','3','30','31',
                              '32','33','34','35','36','37','38','39','4','40','41','42','43',
                              '44','45','46','47','48','49','5','6','7','8','9']
        self.current_index = 0
        self.total_recordings = 50  #Recordings per speaker

        #Initialize UI input widgets and controls
        self.speaker_input = widgets.IntText(
            value = 1,
            description = 'Speaker:',
            min = 1,
            max = 60
        )

        self.digit_input = widgets.IntText(
            value = 0,
            description = 'Digit:',
```

```python
        self.digit_input = widgets.IntText(
            value = 0,
            description = 'Digit:',
            min = 0,
            max = 9
        )

        self.play_button = widgets.Button(description="Play")
        self.next_button = widgets.Button(description="Next")
        self.prev_button = widgets.Button(description="Previous")
        self.jump_input = widgets.IntText(
            value = 1,
            description = 'Jump to:',
            min = 1,
            max = 500
        )
        self.jump_button = widgets.Button(description = "Jump")

        #Labels to track position and the current file
        self.position_label = widgets.Label()
        self.filename_label = widgets.Label()

        #Connect button click handlers
        self.play_button.on_click(self.play_current)
        self.next_button.on_click(self.next_audio)
        self.prev_button.on_click(self.prev_audio)
        self.speaker_input.observe(self.speaker_changed, names = 'value')
        self.digit_input.observe(self.digit_changed, names = 'value')
        self.jump_button.on_click(self.jump_to_recording)

        #Building the player
        self.controls = widgets.VBox([
            widgets.HBox([
```

```python
        #Building the player
        self.controls = widgets.VBox([
            widgets.HBox([
                self.speaker_input,
                self.digit_input,
                self.prev_button,
                self.play_button,
                self.next_button
            ]),
            widgets.HBox([
                self.jump_input,
                self.jump_button
            ]),
            self.position_label,
            self.filename_label
        ])

    def get_current_recording_number(self):
        #Convert position to recording number (1-500)
        return self.current_digit * 50 + self.current_index + 1

    def get_file_path(self):
        #File path from current position
        speaker = self.current_speaker
        digit = self.current_digit
        index = self.recording_order[self.current_index]
        speaker_str = f"0{speaker}" if speaker < 10 else str(speaker)
        filename = f"{digit}_{speaker_str}_{index}.wav"
        return os.path.join(self.base_path, speaker_str, filename), filename
```

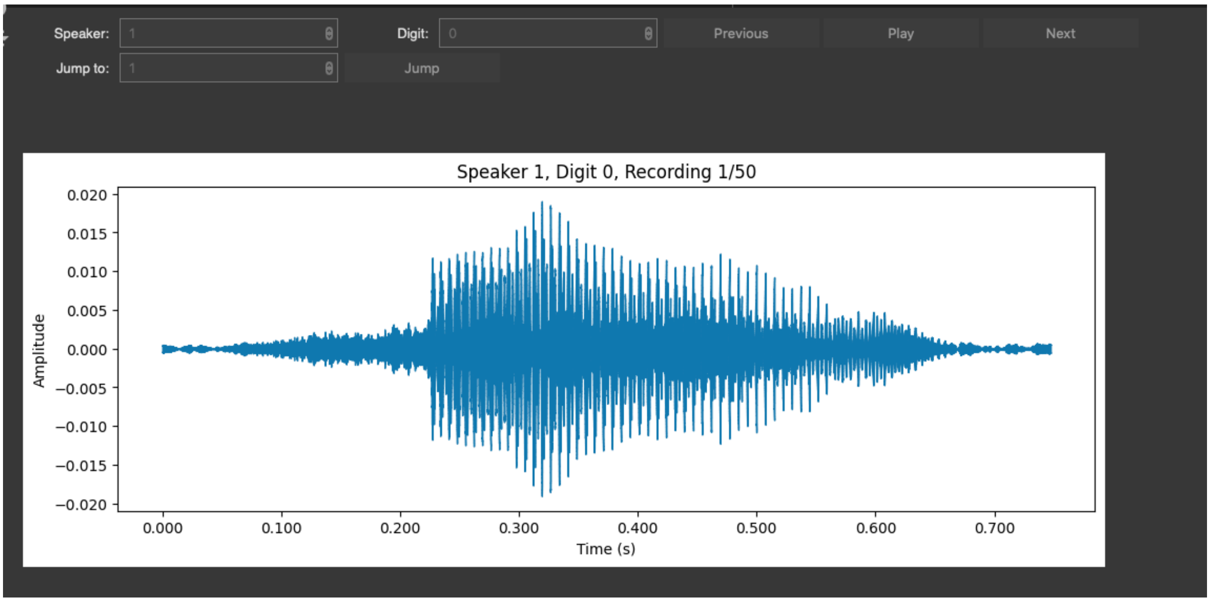
- Initialize Player with base path to audio files
- Navigation variables are set up: current_speaker/digit, recording_order
- Uses ipywidgets to create widgets such as buttons for jumping and playback control
- These functionalities are used to build a UI layout
- Add functions to get the current recording number, the file path (file name)
- Format: "data/01/0_01_0.wav" (data/speaker/digit_speaker_index)

```python
def update_labels(self):
    #Current position label
    file_path, filename = self.get_file_path()
    current_recording = self.get_current_recording_number()
    self.position_label.value = f"Recording {current_recording}/500"
    self.filename_label.value = f"Current file: {filename}"

def speaker_changed(self, change):
    #Reset position when speaker changes
    self.current_speaker = change.new
    self.current_digit = self.digit_input.value
    self.current_index = 0
    self.update_labels()
    self.display_current()

def digit_changed(self, change):
    #Reset position when digit changes
    self.current_digit = change.new
    self.current_index = 0
    self.update_labels()
    self.display_current()

def jump_to_recording(self, b=None):
    #Navigate to chosen recording number
    target = self.jump_input.value
    if 1 <= target <= 500:
        self.current_digit = (target - 1) // 50
        self.current_index = (target - 1) % 50
        self.digit_input.value = self.current_digit
        self.update_labels()
        self.display_current()
```

- After navigation changed by user, the UI is updated to show current waveform, audio recording, filename etc
- A direct navigation is also added to jump to a specific recording number instead of clicking next or rewind, saving time

```
def play_current(self, b=None):
    #Play current audio file
    file_path, _ = self.get_file_path()
    if os.path.exists(file_path):
        data, sr = librosa.load(file_path)
        display(Audio(data=data, rate=sr, autoplay=True))

def next_audio(self, b=None):
    #Next recording
    self.current_index += 1
    if self.current_index >= 50:
        self.current_index = 0
        self.current_digit += 1
        if self.current_digit > 9:
            self.current_digit = 0
            new_speaker = self.current_speaker + 1
            if new_speaker <= 60:
                self.speaker_input.value = new_speaker
    self.digit_input.value = self.current_digit
    self.update_labels()
    self.display_current()

def prev_audio(self, b=None):
    #Previous recording
    self.current_index -= 1
    if self.current_index < 0:
        self.current_index = 49
        self.current_digit -= 1
        if self.current_digit < 0:
            self.current_digit = 9
            new_speaker = self.current_speaker - 1
            if new_speaker >= 1:
                self.speaker_input.value = new_speaker
```

```python
        self.digit_input.value = self.current_digit
        self.update_labels()
        self.display_current()

    def display_current(self):
        #Visualize audio
        clear_output(wait=True)
        display(self.controls)

        file_path, _ = self.get_file_path()
        if os.path.exists(file_path):
            data, sr = librosa.load(file_path)
            plt.figure(figsize=(12, 4))
            dsp.waveshow(data, sr=sr)
            plt.title(f"Speaker {self.current_speaker}, Digit {self.current_digit}, Recording {self.current_index + 1}/50")
            plt.xlabel("Time (s)")
            plt.ylabel("Amplitude")
            plt.show()
        else:
            print(f"File not found: {file_path}")

def create_player():
    #Display interface
    player = SequentialAudioPlayer()
    player.current_speaker = player.speaker_input.value
    player.display_current()
    return player

if __name__ == "__main__":
    player = create_player()
```



Here, we see the initial speaker interface and display. Speaker one (01) speaks the digit 0 (zero). This is the first out of fifty recordings of speaker one speaking the digit 0. We also have a visual of the audio recording as a graph of time vs amplitude.

Extracting the MFCC coefficients from the audio files

```
import numpy as np
import librosa
import librosa.display
import matplotlib.pyplot as plt
%matplotlib inline
import os
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import torch
from torch.utils.data import Dataset, DataLoader
import IPython.display as ipd

def extract_mfcc(audio_path, sample_rate=16000, window_length=0.03, hop_length=0.025, n_mfcc=13):
    #Extract MFCC features from audio file
    try:
        audio, sr = librosa.load(audio_path, sr=sample_rate)
        #Calculate FFT parameters
        n_fft = int(window_length * sample_rate)
        hop_length_samples = int(hop_length * sample_rate)

        #Compute MFCC features
        mfcc = librosa.feature.mfcc(
            y = audio,
            sr = sample_rate,
            n_mfcc = n_mfcc,
            n_fft = n_fft,
            hop_length = hop_length_samples
        )
        return mfcc.T
    except Exception as e:
        print(f"Error processing {audio_path}: {str(e)}")
        return None
```

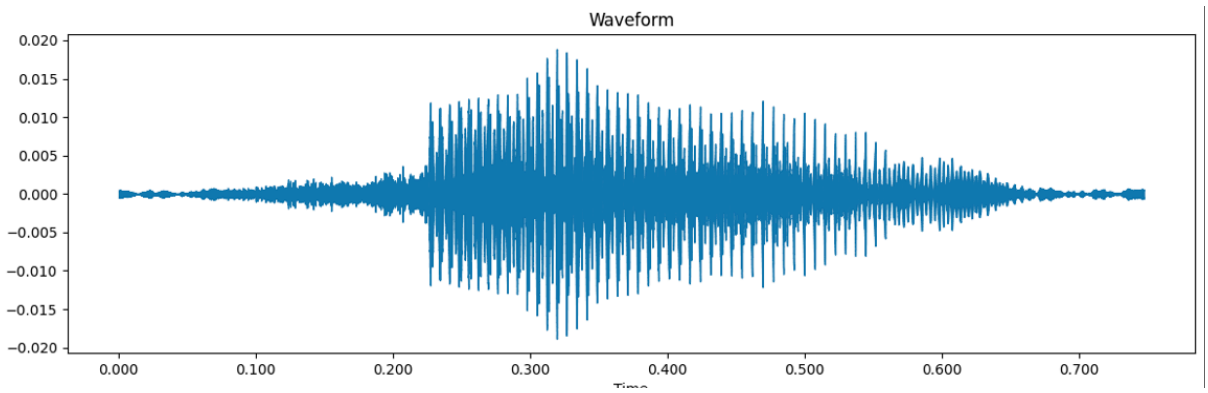
We extract the MFCC coefficients from the audio files by:

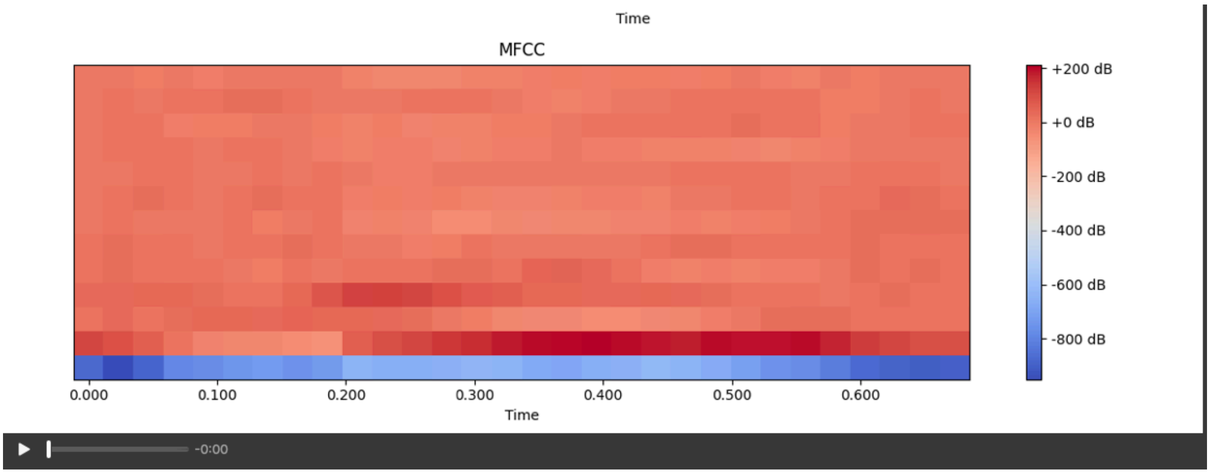
- Loading the audio file using librosa
- Calculating the FFT (Fast fourier transforms) parameters from window/hop lengths
- Use the built in function to compute the MFCCs
- Return the transposed MFCC as we want (time_frames, coefficient) as this is easier to feed into our CNN
- A sampling rate of 16000 Hz is standard for speech processing and captures frequencies up to the Nyquist frequency
- To balance time and frequency resolution we use 30 ms window length for FFT analysis
- For feature transition we use a window hop length of 25ms overlap between each window

- The standard number of MFCC coefficients for each audio frame ranges between 12-13. To minimize underfitting we use 13 coefficients.

```
def visualize_mfcc(audio_path, sample_rate=16000):
    #Visualize audio and extracted MFCC Features
    plt.clf()

    #Load and process audio
    audio, sr = librosa.load(audio_path, sr=sample_rate)
    mfcc = extract_mfcc(audio_path, sample_rate)

    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))

    #Plot waveform and MFCC
    librosa.display.waveshow(y=audio, sr=sr, ax=ax1)
    ax1.set_title('Waveform')
    img = librosa.display.specshow(mfcc.T, x_axis='time', ax=ax2)
    fig.colorbar(img, ax=ax2, format='%+2.0f dB')
    ax2.set_title('MFCC')

    plt.tight_layout()
    plt.show()
    return ipd.Audio(audio, rate=sr)

#Test visualization on sample file
sample_file = "data/01/0_01_0.wav"
visualize_mfcc(sample_file)
```

Visualizes audio waveform and MFCC features. We use the sample file to test these functions.





We see the 13 coefficients horizontally. The x-axis shows time (0-0.6 seconds) and the y-axis represents different frequency bands. The colors indicate intensity: red shows high energy regions and blue shows low energy regions. This particular speech segment has strong frequency components concentrated in the middle-to-upper frequency ranges.

Preparing the dataset

```
#Import required libraries
import numpy as np
import librosa
import os
from sklearn.model_selection import train_test_split
from torch.utils.data import Dataset, DataLoader
from concurrent.futures import ThreadPoolExecutor
from tqdm import tqdm

def process_file(args):
    #Pad/truncate MFCC features to fixed length
    file_path, speaker = args
    mfcc = extract_mfcc(file_path)
    if mfcc is not None:
        #Standardize MFCC length to 40 frames (explained why in report)
        if mfcc.shape[0] < 40:
            pad_width = ((0, 40 - mfcc.shape[0]), (0, 0))
            mfcc = np.pad(mfcc, pad_width, mode='constant')
        else:
            mfcc = mfcc[:40, :]
        return mfcc, speaker - 1
    return None

def prepare_dataset(base_path="data", test_size=0.2, verbose=True):
    if verbose:
        print("Preparing dataset...")

    #Collect all audio files
    file_list = []
    for speaker in range(1, 61):
        speaker_dir = f"{base_path}/{'0' + str(speaker) if speaker < 10 else str(speaker)}"
        if not os.path.exists(speaker_dir):
            continue
```

We process each individual file and calculate their MFCC coefficients and then standardize these coefficients to 40 frames as neural networks requires fixed-size inputs. 40 frames typically captures enough of the speech information (and since our audio files tend to be less than 2 seconds this would be ideal) to identify the characteristic of the speaker while still balancing the computational efficiency, memory usage, and recognition accuracy. The shorter segments are padded with zeros while the longer segments are truncated, maintaining 13 MFCC coefficients per frame.

The dataset is prepared by collecting these audio files, processing them parallelly, then splitting them into 80% training and 20% testing. The features are then normalized per dimension and returned.

```python
        for file in os.listdir(speaker_dir):
            if file.endswith('.wav'):
                file_list.append((os.path.join(speaker_dir, file), speaker))

    #Extract features
    features = []
    labels = []
    with ThreadPoolExecutor(max_workers=8) as executor:
        results = list(tqdm(executor.map(process_file, file_list),
                           total=len(file_list),
                           desc="Processing audio files"))

    #Collect successful results
    for result in results:
        if result is not None:
            features.append(result[0])
            labels.append(result[1])

    #Convert to numpy arrays and split dataset
    X = np.array(features)
    y = np.array(labels)
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=test_size, random_state=42, stratify=y
    )

    #Normalize features
    for i in range(X_train.shape[2]):
        mean = X_train[:, :, i].mean()
        std = X_train[:, :, i].std()
        X_train[:, :, i] = (X_train[:, :, i] - mean) / std
        X_test[:, :, i] = (X_test[:, :, i] - mean) / std
```

Normalizing general formula: X_std = X - mean/ std

Std = standard deviation

The SpeakerDataset function is a custom pytorch dataset which converts the features and labels into pytorch tensors. Tensors track gradients automatically during the training stage, this being essential in our neural networks optimization. This also makes the dataset compatible with our CNN.

```python
    if verbose:
        print("\nDataset Info:")
        print(f"Total samples: {len(features)}")
        print(f"Training samples: {len(X_train)}")
        print(f"Test samples: {len(X_test)}")
        print(f"Feature dimensions: {X_train.shape}")
        print(f"Number of speakers: {len(np.unique(y_train))}")
        print(f"Files processed: {len(results)}")

    return X_train, X_test, y_train, y_test

class SpeakerDataset(Dataset):
    #PyTorch dataset for speaker recognition
    def __init__(self, features, labels):
        self.features = torch.FloatTensor(features)
        self.labels = torch.LongTensor(labels)

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        return self.features[idx], self.labels[idx]

#Create and load datasets
if __name__ == "__main__":
    X_train, X_test, y_train, y_test = prepare_dataset()
    train_dataset = SpeakerDataset(X_train, y_train)
    test_dataset = SpeakerDataset(X_test, y_test)
    train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
    test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

```
Preparing dataset...
Processing audio files: 100%|██████████| 30000/30000 [03:53<00:00, 128.52it/s]

Dataset Info:
Total samples: 30000
Training samples: 24000
Test samples: 6000
Feature dimensions: (24000, 40, 13)
Number of speakers: 60
Files processed: 30000
```

- 30,000 audio files
- 24,000 samples for training
- 6000 samples for testing
- 13 MFCC coefficients
- Dataset has 60 unique speakers

b) Training a classifier

Based on the extracted MFCC features we train a CNN model to differentiate between speakers. CNNs analyze spectral-temporal patterns in speech features to identify unique speaker characteristics. By processing MFCCs and spectrograms, CNNs detect distinctive vocal traits like formants, harmonics, and phoneme structures that help differentiate speakers. Their parallel processing architecture enables faster computation compared to sequential RNN models, making them well-suited for speaker recognition tasks. The network learns hierarchical representations from low-level acoustic features to high-level speaker-specific patterns, allowing effective speaker classification.

Advantages include:

- Efficient pattern recognition in time-frequency domain
- Parallel data processing for faster computation
- Automatic learning of relevant acoustic features

Creating and training the CNN model

```
#Import PyTorch modules
import torch
import torch.nn as nn
from torch.optim import Adam
from torch.optim.lr_scheduler import ReduceLROnPlateau
from tqdm import tqdm

class SpeakerCNN(nn.Module):
    def __init__(self):
        super().__init__()
        #CNN architecture => 3 convolutional blocks
        self.conv = nn.Sequential(
            #First convolutional block: 32 filters
            nn.Conv2d(1, 32, 3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(2),

            #Second
            nn.Conv2d(32, 64, 3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(2),

            #Third
            nn.Conv2d(64, 128, 3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
```

For the CNN, we implement the convolutional neural network consisting of three blocks with increasing filters. Increasing the filters helps capture hierarchical features, each layer builds upon the features learned in the previous layer. This progression allows the network to learn increasingly sophisticated representations of vocal characteristics while keeping computational costs manageable.

Each convolutional block consists of Conv2D => BatchNorm => ReLU => MaxPool.

- Conv2D: Extracts spatial features from input data using learned filters

- BatchNorm: Normalizes layer outputs to stabilize training and reduce internal covariate shift
- ReLU: Adds non-linearity to allow learning of complex patterns while preventing the vanishing/exploding gradient problem
- MaxPool: Reduces spatial dimensions while preserving important features, making computation more efficient

```
        #Classifier => 2-layer fully connected with dropout
        self.fc = nn.Sequential(
            nn.Linear(128 * 5 * 1, 256),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(256, 60)
        )

    def forward(self, x):
        x = x.unsqueeze(1)  #Add channel dimension
        x = self.conv(x)
        x = x.view(-1, 128 * 5 * 1)
        return self.fc(x)

def train(model, train_loader, test_loader, epochs=20):
    #Setup training
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    print(f"Using device: {device}")
    model = model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = Adam(model.parameters(), lr=0.001)
    scheduler = ReduceLROnPlateau(optimizer, mode='min', patience=3, factor=0.5)
    best_accuracy = 0
    best_model_state = None
```

The classifier uses two fully connected layers (128*5*1 => 256 => 60) to transform CNN features into speaker predictions. The first layer processes the flattened CNN output of 640 features and expands it to 256 neurons, enabling the network to learn complex speaker-specific patterns. This expansion allows the model to capture subtle variations in voice characteristics. The second layer then maps these learned features to 60 output neurons, corresponding to each unique speaker in the dataset. A dropout rate of 0.5 prevents overfitting by randomly disabling half the neurons during training, forcing the network to learn redundant features for better generalization.

```python
    #Training
    for epoch in range(epochs):
        model.train()
        train_loss = 0
        for features, labels in tqdm(train_loader, desc=f'Epoch {epoch+1}/{epochs}'):
            features, labels = features.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(features)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

        print(f"\nEpoch {epoch+1} - Average Loss: {train_loss/len(train_loader):.4f}")

        #Validation
        model.eval()
        correct = total = 0
        val_loss = 0
        with torch.no_grad():
            for features, labels in test_loader:
                features, labels = features.to(device), labels.to(device)
                outputs = model(features)
                val_loss += criterion(outputs, labels).item()
                predictions = outputs.argmax(1)
                correct += (predictions == labels).sum().item()
                total += len(labels)

        accuracy = 100 * correct / total
        print(f"Validation Accuracy: {accuracy:.2f}%")
        scheduler.step(val_loss/len(test_loader))
```

```python
        #Save best model
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model_state = model.state_dict().copy()
            print(f"New best accuracy: {best_accuracy:.2f}%")

    print(f"\nSaving best model with accuracy: {best_accuracy:.2f}%")
    torch.save(best_model_state, 'best_speaker_model.pth')
    return model

#Initialize and train model
model = SpeakerCNN()
trained_model = train(model, train_loader, test_loader)
```

The training function uses two key components for optimization:

CrossEntropyLoss:

- Ideal for multi-class classification

- Measures difference between predicted and actual speaker probabilities
- Provides useful gradients for backpropagation

Adam optimizer + ReduceLROnPlateau:

- Adam adaptively adjusts learning rates per parameter
- ReduceLROnPlateau decreases learning rate when validation metrics plateau
- Prevents getting stuck in local minima and helps fine-tune model convergence

This combination enables efficient training while avoiding optimization pitfalls. After running each epoch (total of 20), we save the model with the best validation accuracy to continue with our project.

```
Using device: cpu
Epoch 1/20: 100%|██████████| 750/750 [00:40<00:00, 18.65it/s]

Epoch 1 - Average Loss: 2.4339
Validation Accuracy: 68.67%
New best accuracy: 68.67%
Epoch 2/20: 100%|██████████| 750/750 [00:41<00:00, 18.28it/s]

Epoch 2 - Average Loss: 0.9985
Validation Accuracy: 85.68%
New best accuracy: 85.68%
Epoch 3/20: 100%|██████████| 750/750 [00:41<00:00, 17.96it/s]

Epoch 3 - Average Loss: 0.6550
Validation Accuracy: 84.67%
Epoch 4/20: 100%|██████████| 750/750 [00:40<00:00, 18.45it/s]

Epoch 4 - Average Loss: 0.4988
Validation Accuracy: 92.40%
New best accuracy: 92.40%
Epoch 5/20: 100%|██████████| 750/750 [00:40<00:00, 18.49it/s]

Epoch 5 - Average Loss: 0.4120
Validation Accuracy: 93.77%
New best accuracy: 93.77%
Epoch 6/20: 100%|██████████| 750/750 [00:41<00:00, 18.23it/s]

Epoch 6 - Average Loss: 0.3475
Validation Accuracy: 96.10%
New best accuracy: 96.10%
Epoch 7/20: 100%|██████████| 750/750 [00:40<00:00, 18.36it/s]

Epoch 7 - Average Loss: 0.3131
Validation Accuracy: 95.00%
Epoch 8/20: 100%|██████████| 750/750 [00:40<00:00, 18.51it/s]
```

```
Epoch 8 - Average Loss: 0.2601
Validation Accuracy: 97.02%
New best accuracy: 97.02%
Epoch 9/20: 100%|██████████| 750/750 [00:39<00:00, 18.88it/s]

Epoch 9 - Average Loss: 0.2236
Validation Accuracy: 95.83%
Epoch 10/20: 100%|██████████| 750/750 [00:41<00:00, 18.18it/s]

Epoch 10 - Average Loss: 0.2037
Validation Accuracy: 96.38%
Epoch 11/20: 100%|██████████| 750/750 [00:40<00:00, 18.58it/s]

Epoch 11 - Average Loss: 0.1924
Validation Accuracy: 97.28%
New best accuracy: 97.28%
Epoch 12/20: 100%|██████████| 750/750 [00:40<00:00, 18.55it/s]

Epoch 12 - Average Loss: 0.1670
Validation Accuracy: 96.78%
Epoch 13/20: 100%|██████████| 750/750 [00:40<00:00, 18.39it/s]

Epoch 13 - Average Loss: 0.1654
Validation Accuracy: 97.82%
New best accuracy: 97.82%
Epoch 14/20: 100%|██████████| 750/750 [00:44<00:00, 17.00it/s]

Epoch 14 - Average Loss: 0.1498
Validation Accuracy: 97.62%
Epoch 15/20: 100%|██████████| 750/750 [00:39<00:00, 18.99it/s]

Epoch 15 - Average Loss: 0.1409
Validation Accuracy: 96.77%
Epoch 16/20: 100%|██████████| 750/750 [00:40<00:00, 18.70it/s]
```

```
Epoch 16 - Average Loss: 0.1351
Validation Accuracy: 97.82%
Epoch 17/20: 100%|██████████| 750/750 [00:40<00:00, 18.74it/s]

Epoch 17 - Average Loss: 0.1250
Validation Accuracy: 97.48%
Epoch 18/20: 100%|██████████| 750/750 [00:40<00:00, 18.46it/s]

Epoch 18 - Average Loss: 0.0718
Validation Accuracy: 98.77%
New best accuracy: 98.77%
Epoch 19/20: 100%|██████████| 750/750 [00:40<00:00, 18.41it/s]

Epoch 19 - Average Loss: 0.0599
Validation Accuracy: 98.38%
Epoch 20/20: 100%|██████████| 750/750 [00:40<00:00, 18.31it/s]

Epoch 20 - Average Loss: 0.0604
Validation Accuracy: 98.68%

Saving best model with accuracy: 98.77%
```

The model shows strong performance:

- Starting accuracy: 68.67% (Epoch 1)
- Best accuracy: 98.77% (Epoch 18)
- Final accuracy: 98.68% (Epoch 20)
- Training loss decreased from 2.43 to 0.06
- Steady improvement in validation accuracy indicates good generalization
- Model saved with 98.77% accuracy suggests reliable speaker identification

These results demonstrate effective speaker recognition capabilities with minimal overfitting.

Testing the CNN Model

```
import torch
import numpy as np
from sklearn.metrics import precision_recall_fscore_support, classification_report
import random
import os

def test_model(model, test_loader, device):
    #Evaluate model performance on test set
    model.eval()
    all_predictions = []
    all_labels = []
    correct = total = 0

    with torch.no_grad():
        for features, labels in test_loader:
            features, labels = features.to(device), labels.to(device)
            outputs = model(features)
            predictions = outputs.argmax(1)

            correct += (predictions == labels).sum().item()
            total += len(labels)
            all_predictions.extend(predictions.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    #Calculate and print performance metrics
    accuracy = 100 * correct / total
    precision, recall, f1, _ = precision_recall_fscore_support(
        all_labels, all_predictions, average = 'weighted'
    )
```

We evaluate the model on the entire test set (6000 samples) and compute the following metrics: accuracy, precision, recall, and F1-score.

- Precision: out of all the times the model predicted speaker X, how often was it correct?
- Recall: Out of all actual samples of speaker X, how many did the model correctly identify?
- F1-Score: The harmonic mean of precision and recall
- Support: The number of test samples for each speaker

```
print("\nModel Performance Metrics:")
print(f"Test Accuracy: {accuracy:.2f}%")
print(f"Weighted Precision: {precision:.4f}")
print(f"Weighted Recall: {recall:.4f}")
print(f"Weighted F1-Score: {f1:.4f}")
print("\nDetailed Classification Report:")
print(classification_report(all_labels, all_predictions))

return all_predictions, all_labels
```

```python
def predict_speaker(model, audio_file, device):
    #Predict speaker identity from audio file
    mfcc = extract_mfcc(audio_file)

    #Standardize input length
    if mfcc.shape[0] < 40:
        pad_width = ((0, 40 - mfcc.shape[0]), (0, 0))
        mfcc = np.pad(mfcc, pad_width, mode='constant')
    else:
        mfcc = mfcc[:40, :]

    #Normalize features (X-mean/s.d)
    mfcc = (mfcc - mfcc.mean(axis=0)) / (mfcc.std(axis=0) + 1e-8)
    mfcc_tensor = torch.FloatTensor(mfcc).unsqueeze(0).to(device)

    model.eval()
    with torch.no_grad():
        output = model(mfcc_tensor)
        temperature = 1.5  #Calibration parameter
        scaled_output = output / temperature
        probabilities = torch.nn.functional.softmax(scaled_output, dim=1)
        predicted_speaker = probabilities.argmax(1).item() + 1
        confidence = probabilities.max().item() * 100

    return predicted_speaker, confidence, probabilities.cpu().numpy()[0]
```

For an audio file, we make a prediction and process the MFCC features. We utilize a temperature scaling of 1.5 for confidence calibration.

```python
def get_audio_file_path(speaker_id, base_path="data"):
    #Get random audio sample from speaker
    speaker_str = f"{'0' + str(speaker_id) if speaker_id < 10 else str(speaker_id)}"
    speaker_dir = os.path.join(base_path, speaker_str)

    if os.path.exists(speaker_dir):
        audio_files = [f for f in os.listdir(speaker_dir) if f.endswith('.wav')]
        if audio_files:
            return os.path.join(speaker_dir, random.choice(audio_files))
    return None
```

An extra function to test our models accuracy, we retrieve a random audio sample for the given speaker and returns the file path (or None if not found)

```python
def test_random_sample(model, test_loader, device, base_path="data"):
    #Test model on random sample
    batch_idx = random.randint(0, len(test_loader) - 1)
    for i, (features, labels) in enumerate(test_loader):
        if i == batch_idx:
            sample_idx = random.randint(0, len(features) - 1)
            test_feature = features[sample_idx:sample_idx+1]
            true_speaker = labels[sample_idx].item() + 1
            audio_file = get_audio_file_path(true_speaker, base_path)

            #Predict
            test_feature = test_feature.to(device)
            model.eval()
            with torch.no_grad():
                output = model(test_feature)
                predicted_speaker = output.argmax(1).item() + 1
                probabilities = torch.nn.functional.softmax(output, dim=1)
                confidence = probabilities.max().item() * 100

            print("\nSingle Sample Test Results:")
            print(f"Audio File: {audio_file}")
            print(f"True Speaker ID: {true_speaker}")
            print(f"Predicted Speaker ID: {predicted_speaker}")
            print(f"Confidence: {confidence:.2f}%")
            print(f"Prediction {'Correct' if predicted_speaker == true_speaker else 'Incorrect'}")
            break
```

An extra function to test our models accuracy. Tests the model on a random sample from the test set and calculates the prediction details and the accuracy.

```python
if __name__ == "__main__":
    #Run evaluation suite
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    model = SpeakerCNN().to(device)
    model.load_state_dict(torch.load('best_speaker_model.pth'))

    predictions, true_labels = test_model(model, test_loader, device)
    test_random_sample(model, test_loader, device)

    specific_speaker = 17  #Test specific speaker (can be changed)
    test_file = get_audio_file_path(specific_speaker)
    if test_file:
        predicted_speaker, confidence, probabilities = predict_speaker(model, test_file, device)
        print(f"\nSpecific File Test Results:")
        print(f"Test File: {test_file}")
        print(f"Predicted Speaker: {predicted_speaker}")
        print(f"Confidence: {confidence:.2f}%")
```

2. Results

< Here, you present and discuss the results (Screenshots) >

c) Evaluating the classifiers performance

```
Model Performance Metrics:
Test Accuracy: 98.68%
Weighted Precision: 0.9870
Weighted Recall: 0.9868
Weighted F1-Score: 0.9869
```

```
Detailed Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       100
           1       0.96      1.00      0.98       100
           2       1.00      1.00      1.00       100
           3       0.99      0.99      0.99       100
           4       1.00      0.99      0.99       100
           5       0.97      0.99      0.98       100
           6       0.98      0.96      0.97       100
           7       0.98      1.00      0.99       100
           8       0.99      1.00      1.00       100
           9       0.99      1.00      1.00       100
          10       1.00      1.00      1.00       100
          11       1.00      1.00      1.00       100
          12       1.00      1.00      1.00       100
          13       0.99      0.99      0.99       100
          14       1.00      0.98      0.99       100
          15       1.00      0.98      0.99       100
          16       1.00      0.98      0.99       100
          17       1.00      0.97      0.98       100
          18       0.97      1.00      0.99       100
          19       0.99      0.98      0.98       100
          20       0.99      0.98      0.98       100
          21       1.00      0.98      0.99       100
          22       0.93      0.97      0.95       100
          23       0.98      0.98      0.98       100
          24       1.00      0.98      0.99       100
          25       0.98      1.00      0.99       100
          26       0.99      0.98      0.98       100
          27       1.00      1.00      1.00       100
          28       0.97      1.00      0.99       100
          29       1.00      1.00      1.00       100
          30       0.99      0.99      0.99       100
          31       0.99      0.97      0.98       100
```

```
          31       0.99      0.97      0.98       100
          32       1.00      0.98      0.99       100
          33       0.99      0.97      0.98       100
          34       0.99      0.98      0.98       100
          35       0.98      0.99      0.99       100
          36       0.99      1.00      1.00       100
          37       0.98      1.00      0.99       100
          38       0.93      0.95      0.94       100
          39       1.00      0.99      0.99       100
          40       1.00      0.96      0.98       100
          41       0.99      0.99      0.99       100
          42       1.00      1.00      1.00       100
          43       0.99      0.98      0.98       100
          44       1.00      0.99      0.99       100
          45       0.98      0.99      0.99       100
          46       1.00      1.00      1.00       100
          47       1.00      0.99      0.99       100
          48       1.00      0.97      0.98       100
          49       0.96      0.98      0.97       100
          50       0.95      0.99      0.97       100
          51       1.00      0.97      0.98       100
          52       0.99      0.98      0.98       100
          53       0.99      1.00      1.00       100
          54       0.98      0.97      0.97       100
          55       0.98      0.97      0.97       100
          56       0.97      0.99      0.98       100
          57       0.97      1.00      0.99       100
          58       1.00      1.00      1.00       100
          59       0.99      1.00      1.00       100

    accuracy                           0.99      6000
   macro avg       0.99      0.99      0.99      6000
weighted avg       0.99      0.99      0.99      6000
```

```
Single Sample Test Results:
Audio File: data/54/4_54_46.wav
True Speaker ID: 54
Predicted Speaker ID: 54
Confidence: 99.53%
Prediction Correct

Specific File Test Results:
Test File: data/17/1_17_41.wav
Predicted Speaker: 17
Confidence: 96.45%
```

The model shows the following performance:

- Overall accuracy: 98.68%, therefore the model generalizes well on unseen data
- **Weighted**[1] precision/recall/F1-score: ~0.99.
- Per-class metrics show consistent performance across all speakers (60 total)
- Single sample test correctly identified Speaker 54 with 99.53% confidence

Specific file test correctly identified Speaker 17 with 96.45% confidence

The results indicate a highly accurate speaker identification system with balanced performance across all classes and high confidence in predictions (very few false positives and false negatives).

To improve this project, we could utilize attention mechanisms, residual connections for the model. Under data augmentation (eg: noise, varied MFCC parameters), we can consider robustness testing.

3. Complete working code as text

```
#Importing the dataset
"""
#Install kaggle
!pip install -q kaggle

from google.colab import files
files.upload()

#Create a kaggle folder
! mkdir ~/.kaggle

#Copy the kaggle.json to created folder
! cp kaggle.json ~/.kaggle/
```

[1] **Weighted** accounts for potential class imbalance by taking the average across all speakers for that particular metric

```
#Permission for the json to act
! chmod 600 ~/.kaggle/kaggle.json

#Download Audio MNIST dataset
!kaggle datasets download sripaadsrinivasan/audio-mnist

#Unzip to access audio files
!unzip audio-mnist.zip

"""#Play and visualize the chosen audio file"""

import numpy as np
import librosa
import librosa.display as dsp
import matplotlib.pyplot as plt
from IPython.display import Audio, display, clear_output
import os
import ipywidgets as widgets

class SequentialAudioPlayer:
    def __init__(self, base_path="data"):
        #Initialize player with file paths and UI controls
        self.base_path = base_path
        self.current_speaker = None
        self.current_digit = 0
        #Define navigation order for recordings
        self.recording_order = ['0','1','10','11','12','13','14','15','16','17','18','19','2',
                      '20','21','22','23','24','25','26','27','28','29','3','30','31',
                      '32','33','34','35','36','37','38','39','4','40','41','42','43',
                      '44','45','46','47','48','49','5','6','7','8','9']
        self.current_index = 0
        self.total_recordings = 50  #Recordings per speaker
```

```
#Initialize UI input widgets and controls
self.speaker_input = widgets.IntText(
    value = 1,
    description = 'Speaker:',
    min = 1,
    max = 60
)

self.digit_input = widgets.IntText(
    value = 0,
    description = 'Digit:',
    min = 0,
    max = 9
)

self.play_button = widgets.Button(description="Play")
self.next_button = widgets.Button(description="Next")
self.prev_button = widgets.Button(description="Previous")
self.jump_input = widgets.IntText(
    value = 1,
    description = 'Jump to:',
    min = 1,
    max = 500
)
self.jump_button = widgets.Button(description = "Jump")

#Labels to track position and the current file
self.position_label = widgets.Label()
self.filename_label = widgets.Label()

#Connect button click handlers
self.play_button.on_click(self.play_current)
self.next_button.on_click(self.next_audio)
```

```
        self.prev_button.on_click(self.prev_audio)
        self.speaker_input.observe(self.speaker_changed, names = 'value')
        self.digit_input.observe(self.digit_changed, names = 'value')
        self.jump_button.on_click(self.jump_to_recording)

        #Building the player
        self.controls = widgets.VBox([
            widgets.HBox([
                self.speaker_input,
                self.digit_input,
                self.prev_button,
                self.play_button,
                self.next_button
            ]),
            widgets.HBox([
                self.jump_input,
                self.jump_button
            ]),
            self.position_label,
            self.filename_label
        ])

    def get_current_recording_number(self):
        #Convert position to recording number (1-500)
        return self.current_digit * 50 + self.current_index + 1

    def get_file_path(self):
        #File path from current position
        speaker = self.current_speaker
        digit = self.current_digit
        index = self.recording_order[self.current_index]
        speaker_str = f"0{speaker}" if speaker < 10 else str(speaker)
        filename = f"{digit}_{speaker_str}_{index}.wav"
```

```
        return os.path.join(self.base_path, speaker_str, filename), filename

    def update_labels(self):
        #Current position label
        file_path, filename = self.get_file_path()
        current_recording = self.get_current_recording_number()
        self.position_label.value = f"Recording {current_recording}/500"
        self.filename_label.value = f"Current file: {filename}"

    def speaker_changed(self, change):
        #Reset position when speaker changes
        self.current_speaker = change.new
        self.current_digit = self.digit_input.value
        self.current_index = 0
        self.update_labels()
        self.display_current()

    def digit_changed(self, change):
        #Reset position when digit changes
        self.current_digit = change.new
        self.current_index = 0
        self.update_labels()
        self.display_current()

    def jump_to_recording(self, b=None):
        #Navigate to chosen recording number
        target = self.jump_input.value
        if 1 <= target <= 500:
            self.current_digit = (target - 1) // 50
            self.current_index = (target - 1) % 50
            self.digit_input.value = self.current_digit
            self.update_labels()
            self.display_current()
```

```
def play_current(self, b=None):
    #Play current audio file
    file_path, _ = self.get_file_path()
    if os.path.exists(file_path):
        data, sr = librosa.load(file_path)
        display(Audio(data=data, rate=sr, autoplay=True))

def next_audio(self, b=None):
    #Next recording
    self.current_index += 1
    if self.current_index >= 50:
        self.current_index = 0
        self.current_digit += 1
        if self.current_digit > 9:
            self.current_digit = 0
            new_speaker = self.current_speaker + 1
            if new_speaker <= 60:
                self.speaker_input.value = new_speaker
    self.digit_input.value = self.current_digit
    self.update_labels()
    self.display_current()

def prev_audio(self, b=None):
    #Previous recording
    self.current_index -= 1
    if self.current_index < 0:
        self.current_index = 49
        self.current_digit -= 1
        if self.current_digit < 0:
            self.current_digit = 9
            new_speaker = self.current_speaker - 1
            if new_speaker >= 1:
```

```
            self.speaker_input.value = new_speaker
        self.digit_input.value = self.current_digit
        self.update_labels()
        self.display_current()

    def display_current(self):
        #Visualize audio
        clear_output(wait=True)
        display(self.controls)

        file_path, _ = self.get_file_path()
        if os.path.exists(file_path):
            data, sr = librosa.load(file_path)
            plt.figure(figsize=(12, 4))
            dsp.waveshow(data, sr=sr)
            plt.title(f"Speaker {self.current_speaker}, Digit {self.current_digit}, Recording
{self.current_index + 1}/50")
            plt.xlabel("Time (s)")
            plt.ylabel("Amplitude")
            plt.show()
        else:
            print(f"File not found: {file_path}")

def create_player():
    #Display interface
    player = SequentialAudioPlayer()
    player.current_speaker = player.speaker_input.value
    player.display_current()
    return player

if __name__ == "__main__":
    player = create_player()
```

```
"""#Extracting MFCC Coefficients from the audio files"""

# Commented out IPython magic to ensure Python compatibility.
import numpy as np
import librosa
import librosa.display
import matplotlib.pyplot as plt
# %matplotlib inline
import os
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import torch
from torch.utils.data import Dataset, DataLoader
import IPython.display as ipd

def extract_mfcc(audio_path, sample_rate=16000, window_length=0.03,
hop_length=0.025, n_mfcc=13):
  #Extract MFCC features from audio file
  try:
    audio, sr = librosa.load(audio_path, sr=sample_rate)
    #Calculate FFT parameters
    n_fft = int(window_length * sample_rate)
    hop_length_samples = int(hop_length * sample_rate)

    #Compute MFCC features
    mfcc = librosa.feature.mfcc(
      y = audio,
      sr = sample_rate,
      n_mfcc = n_mfcc,
      n_fft = n_fft,
      hop_length = hop_length_samples
    )
    return mfcc.T
```

```
    except Exception as e:
        print(f"Error processing {audio_path}: {str(e)}")
        return None

def visualize_mfcc(audio_path, sample_rate=16000):
    #Visualize audio and extracted MFCC Features
    plt.clf()

    #Load and process audio
    audio, sr = librosa.load(audio_path, sr=sample_rate)
    mfcc = extract_mfcc(audio_path, sample_rate)

    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))

    #Plot waveform and MFCC
    librosa.display.waveshow(y=audio, sr=sr, ax=ax1)
    ax1.set_title('Waveform')
    img = librosa.display.specshow(mfcc.T, x_axis='time', ax=ax2)
    fig.colorbar(img, ax=ax2, format='%+2.0f dB')
    ax2.set_title('MFCC')

    plt.tight_layout()
    plt.show()
    return ipd.Audio(audio, rate=sr)

#Test visualization on sample file
sample_file = "data/01/0_01_0.wav"
visualize_mfcc(sample_file)

"""#Prepare the dataset"""

#Import required libraries
import numpy as np
```

```
import librosa
import os
from sklearn.model_selection import train_test_split
from torch.utils.data import Dataset, DataLoader
from concurrent.futures import ThreadPoolExecutor
from tqdm import tqdm

def process_file(args):
    #Pad/truncate MFCC features to fixed length
    file_path, speaker = args
    mfcc = extract_mfcc(file_path)
    if mfcc is not None:
        #Standardize MFCC length to 40 frames (explained why in report)
        if mfcc.shape[0] < 40:
            pad_width = ((0, 40 - mfcc.shape[0]), (0, 0))
            mfcc = np.pad(mfcc, pad_width, mode='constant')
        else:
            mfcc = mfcc[:40, :]
        return mfcc, speaker - 1
    return None

def prepare_dataset(base_path="data", test_size=0.2, verbose=True):
    if verbose:
        print("Preparing dataset...")

    #Collect all audio files
    file_list = []
    for speaker in range(1, 61):
        speaker_dir = f"{base_path}/{'0' + str(speaker) if speaker < 10 else str(speaker)}"
        if not os.path.exists(speaker_dir):
            continue
        for file in os.listdir(speaker_dir):
            if file.endswith('.wav'):
```

```
        file_list.append((os.path.join(speaker_dir, file), speaker))

#Extract features
features = []
labels = []
with ThreadPoolExecutor(max_workers=8) as executor:
    results = list(tqdm(executor.map(process_file, file_list),
                  total=len(file_list),
                  desc="Processing audio files"))

#Collect successful results
for result in results:
    if result is not None:
        features.append(result[0])
        labels.append(result[1])

#Convert to numpy arrays and split dataset
X = np.array(features)
y = np.array(labels)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=test_size, random_state=42, stratify=y
)

#Normalize features
for i in range(X_train.shape[2]):
    mean = X_train[:, :, i].mean()
    std = X_train[:, :, i].std()
    X_train[:, :, i] = (X_train[:, :, i] - mean) / std
    X_test[:, :, i] = (X_test[:, :, i] - mean) / std

if verbose:
    print("\nDataset Info:")
    print(f"Total samples: {len(features)}")
```

```
        print(f"Training samples: {len(X_train)}")
        print(f"Test samples: {len(X_test)}")
        print(f"Feature dimensions: {X_train.shape}")
        print(f"Number of speakers: {len(np.unique(y_train))}")
        print(f"Files processed: {len(results)}")

    return X_train, X_test, y_train, y_test

class SpeakerDataset(Dataset):
    #PyTorch dataset for speaker recognition
    def __init__(self, features, labels):
        self.features = torch.FloatTensor(features)
        self.labels = torch.LongTensor(labels)

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        return self.features[idx], self.labels[idx]

#Create and load datasets
if __name__ == "__main__":
    X_train, X_test, y_train, y_test = prepare_dataset()
    train_dataset = SpeakerDataset(X_train, y_train)
    test_dataset = SpeakerDataset(X_test, y_test)
    train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
    test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

"""#Creating and Training the CNN Model"""

#Import PyTorch modules
import torch
import torch.nn as nn
```

```
from torch.optim import Adam
from torch.optim.lr_scheduler import ReduceLROnPlateau
from tqdm import tqdm

class SpeakerCNN(nn.Module):
    def __init__(self):
        super().__init__()
        #CNN architecture => 3 convolutional blocks
        self.conv = nn.Sequential(
            #First convolutional block: 32 filters
            nn.Conv2d(1, 32, 3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(2),

            #Second
            nn.Conv2d(32, 64, 3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(2),

            #Third
            nn.Conv2d(64, 128, 3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )

        #Classifier => 2-layer fully connected with dropout
        self.fc = nn.Sequential(
            nn.Linear(128 * 5 * 1, 256),
            nn.ReLU(),
            nn.Dropout(0.5),
```

```
            nn.Linear(256, 60)
        )

    def forward(self, x):
        x = x.unsqueeze(1)  #Add channel dimension
        x = self.conv(x)
        x = x.view(-1, 128 * 5 * 1)
        return self.fc(x)

def train(model, train_loader, test_loader, epochs=20):
    #Setup training
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    print(f"Using device: {device}")
    model = model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = Adam(model.parameters(), lr=0.001)
    scheduler = ReduceLROnPlateau(optimizer, mode='min', patience=3, factor=0.5)
    best_accuracy = 0
    best_model_state = None

    #Training
    for epoch in range(epochs):
        model.train()
        train_loss = 0
        for features, labels in tqdm(train_loader, desc=f'Epoch {epoch+1}/{epochs}'):
            features, labels = features.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(features)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()
```

```
        print(f"\nEpoch {epoch+1} - Average Loss: {train_loss/len(train_loader):.4f}")

        #Validation
        model.eval()
        correct = total = 0
        val_loss = 0
        with torch.no_grad():
            for features, labels in test_loader:
                features, labels = features.to(device), labels.to(device)
                outputs = model(features)
                val_loss += criterion(outputs, labels).item()
                predictions = outputs.argmax(1)
                correct += (predictions == labels).sum().item()
                total += len(labels)

        accuracy = 100 * correct / total
        print(f"Validation Accuracy: {accuracy:.2f}%")
        scheduler.step(val_loss/len(test_loader))

        #Save best model
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model_state = model.state_dict().copy()
            print(f"New best accuracy: {best_accuracy:.2f}%")

    print(f"\nSaving best model with accuracy: {best_accuracy:.2f}%")
    torch.save(best_model_state, 'best_speaker_model.pth')
    return model

#Initialize and train model
model = SpeakerCNN()
trained_model = train(model, train_loader, test_loader)
```

```
"""#Test the CNN Model"""

import torch
import numpy as np
from sklearn.metrics import precision_recall_fscore_support, classification_report
import random
import os

def test_model(model, test_loader, device):
    #Evaluate model performance on test set
    model.eval()
    all_predictions = []
    all_labels = []
    correct = total = 0

    with torch.no_grad():
        for features, labels in test_loader:
            features, labels = features.to(device), labels.to(device)
            outputs = model(features)
            predictions = outputs.argmax(1)

            correct += (predictions == labels).sum().item()
            total += len(labels)
            all_predictions.extend(predictions.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    #Calculate and print performance metrics
    accuracy = 100 * correct / total
    precision, recall, f1, _ = precision_recall_fscore_support(
        all_labels, all_predictions, average = 'weighted'
    )

    print("\nModel Performance Metrics:")
```

```
    print(f"Test Accuracy: {accuracy:.2f}%")
    print(f"Weighted Precision: {precision:.4f}")
    print(f"Weighted Recall: {recall:.4f}")
    print(f"Weighted F1-Score: {f1:.4f}")
    print("\nDetailed Classification Report:")
    print(classification_report(all_labels, all_predictions))

    return all_predictions, all_labels

def predict_speaker(model, audio_file, device):
    #Predict speaker identity from audio file
    mfcc = extract_mfcc(audio_file)

    #Standardize input length
    if mfcc.shape[0] < 40:
        pad_width = ((0, 40 - mfcc.shape[0]), (0, 0))
        mfcc = np.pad(mfcc, pad_width, mode='constant')
    else:
        mfcc = mfcc[:40, :]

    #Normalize features (X-mean/s.d)
    mfcc = (mfcc - mfcc.mean(axis=0)) / (mfcc.std(axis=0) + 1e-8)
    mfcc_tensor = torch.FloatTensor(mfcc).unsqueeze(0).to(device)

    model.eval()
    with torch.no_grad():
        output = model(mfcc_tensor)
        temperature = 1.5  #Calibration parameter
        scaled_output = output / temperature
        probabilities = torch.nn.functional.softmax(scaled_output, dim=1)
        predicted_speaker = probabilities.argmax(1).item() + 1
        confidence = probabilities.max().item() * 100
```

```
    return predicted_speaker, confidence, probabilities.cpu().numpy()[0]

def get_audio_file_path(speaker_id, base_path="data"):
    #Get random audio sample from speaker
    speaker_str = f"{'0' + str(speaker_id) if speaker_id < 10 else str(speaker_id)}"
    speaker_dir = os.path.join(base_path, speaker_str)

    if os.path.exists(speaker_dir):
        audio_files = [f for f in os.listdir(speaker_dir) if f.endswith('.wav')]
        if audio_files:
            return os.path.join(speaker_dir, random.choice(audio_files))
    return None

def test_random_sample(model, test_loader, device, base_path="data"):
    #Test model on random sample
    batch_idx = random.randint(0, len(test_loader) - 1)
    for i, (features, labels) in enumerate(test_loader):
        if i == batch_idx:
            sample_idx = random.randint(0, len(features) - 1)
            test_feature = features[sample_idx:sample_idx+1]
            true_speaker = labels[sample_idx].item() + 1
            audio_file = get_audio_file_path(true_speaker, base_path)

            #Predict
            test_feature = test_feature.to(device)
            model.eval()
            with torch.no_grad():
                output = model(test_feature)
                predicted_speaker = output.argmax(1).item() + 1
                probabilities = torch.nn.functional.softmax(output, dim=1)
                confidence = probabilities.max().item() * 100

            print("\nSingle Sample Test Results:")
```

```
        print(f"Audio File: {audio_file}")
        print(f"True Speaker ID: {true_speaker}")
        print(f"Predicted Speaker ID: {predicted_speaker}")
        print(f"Confidence: {confidence:.2f}%")
        print(f"Prediction {'Correct' if predicted_speaker == true_speaker else 'Incorrect'}")
        break

if __name__ == "__main__":
   #Run evaluation suite
   device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
   model = SpeakerCNN().to(device)
   model.load_state_dict(torch.load('best_speaker_model.pth'))

   predictions, true_labels = test_model(model, test_loader, device)
   test_random_sample(model, test_loader, device)

   specific_speaker = 17  #Test specific speaker (can be changed)
   test_file = get_audio_file_path(specific_speaker)
   if test_file:
      predicted_speaker, confidence, probabilities = predict_speaker(model, test_file, device)
      print(f"\nSpecific File Test Results:")
      print(f"Test File: {test_file}")
      print(f"Predicted Speaker: {predicted_speaker}")
      print(f"Confidence: {confidence:.2f}%")
```

4. References (IEEE Format)

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