Speech Emotion Recognition

Utilizing Speech Emotion Recognition to Enhance Human-Computer Interaction

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ABSTRACT

This project endeavors to pioneer the development of a Speech Emotion Recognition (SER) system, aiming to revolutionize human-computer interaction by accurately identifying and interpreting emotions from audio inputs in near-real-time scenarios. Leveraging diverse datasets, including RAVDESS, TESS, and CREMA-D, the project employs advanced feature extraction techniques such as Zero-Crossing Rate (ZCR), Root Mean Square Error (RMSE), and Mel-frequency Cepstral Coefficients (MFCC). The model, anchored by a Convolutional Neural Network (CNN), attains an impressive 92% accuracy on the testing set. Noteworthy lessons include the critical role of feature selection and the impact of high-quality training data on model accuracy. Future work involves integrating additional datasets, exploring transfer learning, and venturing into real-time implementation, with the ultimate goal of creating more empathetic and responsive human-machine interactions. This project stands as a testament to the potential of SER in enhancing the emotional intelligence of machines, paving the way for a future where technology seamlessly understands and responds to human emotions.

INTRODUCTION

In the ever-evolving landscape of human-computer interaction, the capability to discern and comprehend human emotions from speech signals has emerged as a transformative paradigm, promising to redefine the way we engage with technology. This pioneering project seeks to usher in a new era of sophistication in Speech Emotion Recognition (SER), where the nuanced tapestry of human emotions is deciphered and understood with a precision that extends beyond mere verbal communication.

The fundamental premise of this endeavor is rooted in the profound potential of SER to enhance the responsiveness, empathy, and personalization of interactions between humans and machines. By harnessing the power of advanced machine learning and signal processing techniques, the project endeavors to develop a robust system capable of accurately identifying and interpreting underlying emotions from audio inputs in near-real-time scenarios.

The project draws inspiration and insights from an extensive exploration of SER, delving into both traditional machine learning approaches and the intricate capabilities of deep learning techniques. Leveraging rich datasets such as the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS), Toronto Emotional Speech Set (TESS), and the Crowdsourcing Emotional Database for Speech and Song (CREMA-D), the project aspires to encapsulate the diverse spectrum of human emotional expressions.

Emphasis is placed on the significance of feature extraction methodologies, including but not limited to, Zero-Crossing Rate (ZCR), Root Mean Square Error (RMSE), and Mel-frequency Cepstral Coefficients (MFCC). These techniques serve as the building blocks for the model's understanding of the intricate nuances embedded in speech signals, enabling it to discern emotions with a heightened level of accuracy.

As an integral precursor to model development, the project incorporates a comprehensive exploration of the RAVDESS, TESS and CREMA-D dataset. The extraction of emotions and file paths from this dataset, as demonstrated in the provided code snippet, serves not only as a data preparation step but also as a foundational understanding of the emotional landscape embedded within the chosen dataset.

With a methodology encompassing data augmentation, model training, and meticulous evaluation metrics, the project culminates in the attainment of an impressive 92% accuracy on the testing set.

The lessons learned throughout the project span the critical importance of feature selection, the pivotal role of high-quality training data, and the dynamic calibration of training epochs to achieve optimal model accuracy. Looking towards the future, the project outlines a roadmap for further enhancements, including the integration of additional datasets, exploration into transfer learning techniques, and the exciting prospect of real-time implementation to broaden the applications of SER.

In conclusion, this project represents a significant stride towards unlocking the full potential of Speech Emotion Recognition, fostering a future where machines not only comprehend but also respond to human emotions with sensitivity, acumen, and a depth that transcends traditional modes of human-computer interaction.

KEY FEATURES

The key features of the project encompass a range of elements that collectively contribute to its success in developing a robust Speech Emotion Recognition (SER) system. These features highlight the distinctive aspects and strengths of the project:

Diverse Dataset Utilization: The project leverages a diverse set of datasets, including RAVDESS, TESS, and CREMA-D, to ensure exposure to a broad spectrum of human emotional expressions.
Advanced Feature Extraction: Feature extraction techniques, such as Zero-Crossing Rate (ZCR), Root Mean Square Error (RMSE), and Mel-frequency Cepstral Coefficients (MFCC), are meticulously employed. These techniques form the foundation for the model's nuanced understanding of emotional cues embedded in speech signals.

Data Augmentation Strategy: A sophisticated data augmentation strategy is implemented, introducing subtle perturbations to the original training data. This enhances the model's ability to generalize and adapt to a wider range of emotional expressions.

Exploration of the Datasets: The project incorporates a detailed exploration of the RAVDESS, TESS and CREMA-D dataset, extracting emotional labels and file paths. This step not only prepares the data for model development but also provides valuable insights into the distribution of emotions within the chosen dataset.

These key features collectively define the project's depth, innovation, and potential impact on advancing the capabilities of machines in understanding and responding to human emotions conveyed through speech signals.

AI ALGORITHM AND MODEL

Convolutional Neural Networks:
Convolutional Neural Networks (CNNs) represent a crucial technique widely employed in diverse applications within computer vision and natural language processing. Similar to conventional neural networks, CNNs consist of neurons equipped with adjustable weights and biases. Each neuron processes multiple inputs, computes a weighted sum, applies an activation function, and generates an output. Unlike traditional neural networks that operate on vector inputs, CNNs specialize in handling multi-channeled images.

At the heart of a convolutional neural network lies the convolutional layer, a fundamental building block. This layer is composed of a set of independent filters, each initialized with random values that serve as the parameters to be learned by the network during subsequent training phases.

Data Processing and Exploration: First import necessary libraries like Pandas, Matplotlib, Seaborn and Librosa. It then proceeds to read and process data from sources combining them into a dataframe called "data_path". Exploratory data analysis is conducted, which includes creating visualizations such, as bar charts to analyze the distribution of emotions and displaying Mel Spectrograms for the data.

Data Augmentation: Various data augmentation techniques are applied to the audio data. These techniques include adding noise, stretching, shifting and changing pitch. The purpose of these techniques is to enhance the diversity of the training dataset.

Feature Extraction:;The notebook extracts features from the audio data. This includes calculating the zero crossing rate (ZCR) root mean square error (RMSE) and Mel frequency cepstral coefficients (MFCC). A function named "extract_features" is defined to combine these features into a feature vector for each audio sample.
Parallel Processing;

To efficiently calculate features for a number of files, parallel processing using the joblib library is implemented.

Model Training: The notebook focuses on training a CNN model specifically designed for speech emotion recognition. The model undergoes training using a designated training dataset called "x_traincnn" along, with its labels "y_train" for 20 epochs. Additionally validation data consisting of "x_testcnn" and "y_test" are provided during this training process.

The progress of the training process is closely monitored, taking into account metrics such, as loss and accuracy for both the training and validation sets.

Assessing the Model:

We evaluate the trained model using a test dataset. Report its accuracy.

In addition we load a trained model (cnn.h5) in the notebook and assess its accuracy on the test data.

Results and Visualization:

To wrap up we present prediction results that include both predicted and actual emotion labels for a subset of the test data.

Moreover we provide representations of the training and testing loss well as the training and testing accuracy, across 20 epochs.

RELATED WORK

To contextualize the project within the broader landscape of Speech Emotion Recognition (SER), it is essential to survey and understand related work that has laid the groundwork for advancements in this field. This section provides a brief overview of key studies and projects, highlighting their methodologies, datasets, and contributions.

Deep Learning Approaches: Many recent studies have explored the efficacy of deep learning techniques in SER. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed for feature extraction and sequence modeling, respectively. Notable projects include those by Kim et al. (2013) and Mousavi and Reinders (2018).

Transfer Learning in SER: Transfer learning, leveraging pre-trained models on large datasets, has gained prominence. A study by Ko et al. (2017) demonstrated the effectiveness of transfer learning from a large dataset in enhancing the performance of SER models on smaller datasets.

Use of Multimodal Datasets: Advancements in SER extend to the exploration of multimodal datasets, combining audio with visual cues. Work by Eyben et al. (2013) and Schuller et al. (2018) explores the integration of facial expressions and speech signals for more comprehensive emotion recognition.

Datasets for Emotional Speech: The availability and utilization of diverse datasets contribute significantly to SER research. Apart from commonly used datasets like RAVDESS and CREMA-D, the Interactive Emotional Dyadic Motion Capture (IEMOCAP) dataset and Berlin Database of Emotional Speech (EmoDB) have been pivotal in advancing our understanding of emotional speech.

BRIEF DESCRIPTION

This project is at the forefront of advancing Speech Emotion Recognition (SER) through the precise identification and interpretation of emotions from audio inputs, reshaping the dynamics of human-computer interaction. Drawing insights from diverse datasets, including RAVDESS, TESS, and CREMA-D, the project focuses on cultivating a nuanced understanding of human emotional expressions. Leveraging advanced feature extraction techniques such as Zero-Crossing Rate (ZCR), Root Mean Square Error (RMSE), and Mel-frequency Cepstral Coefficients (MFCC), the model achieves a sophisticated comprehension of emotional cues embedded in speech signals.

A meticulous data augmentation strategy is employed to enhance the model's adaptability and generalize across a spectrum of emotional expressions. In a departure from traditional classifiers, the project adopts a Convolutional Neural Network (CNN) architecture, leveraging the dynamic landscape of deep learning for flexible exploration of complex relationships within the data.

The project includes a comprehensive exploration of the RAVDESS, TESS and CREMA-D dataset, extracting emotional labels and file paths to offer insights into the emotional landscape embedded within the chosen dataset. Model training involves a thorough division of the dataset into training and testing sets, with performance evaluation utilizing a comprehensive set of metrics suitable for CNN-based architectures.

The project concludes with an impressive accuracy rate of 92% on the testing set. Key takeaways from the project encompass the critical importance of feature selection, the impact of high-quality training data, and the dynamic calibration of training epochs for optimal model accuracy within a CNN framework.

Looking forward, the project outlines considerations for future work, including the integration of additional datasets, exploration into transfer learning techniques, and the prospect of real-time implementation. This project stands as a pioneering effort in advancing Speech Emotion Recognition, contributing to the evolution of human-computer interaction by creating systems that comprehend and respond to human emotions with sensitivity and acumen, leveraging the power of Convolutional Neural Networks.

Use Case:

Customer Service Interaction Enhancement: Scenario: A customer contacts a service hotline seeking assistance. The Speech Emotion Recognition system, integrated into the customer service platform, detects frustration in the customer's voice. The system prompts the customer service representative to approach the interaction with extra empathy, ultimately leading to a more positive customer experience.

Educational Technology Personalization: Scenario: In an online learning environment, the SER system analyzes students' audio inputs during virtual lectures. If signs of confusion or frustration are detected, the system can automatically provide additional explanations, resources, or pause for questions to enhance the learning experience based on real-time emotional cues.

Mental Health Monitoring and Support: Scenario: An individual uses a mental health monitoring app that incorporates SER. The system analyzes the user's voice for emotional patterns indicative of stress, anxiety, or sadness. If concerning trends are identified, the app can suggest coping mechanisms, mindfulness exercises, or prompt the user to connect with a mental health professional.

Virtual Assistant Adaptation: Scenario: A user interacts with a virtual assistant for task management. If the SER system detects signs of fatigue or frustration in the user's voice, the virtual assistant may adjust its responses, suggest breaks, or modify task prioritization to accommodate the user's emotional state and enhance productivity.

Smart Home Ambient Adaptation: Scenario: A smart home system with SER capabilities detects signs of stress or agitation in the occupant's voice. In response, the system adjusts lighting, plays calming music, or initiates relaxation routines to create a more soothing and supportive home environment.

These use case scenarios illustrate the versatility and potential impact of integrating Speech Emotion Recognition into various applications, ranging from customer service and healthcare to education and entertainment. The system's ability to adapt and respond to users' emotional states contributes to a more empathetic and personalized human-computer interaction experience.

LITERATURE REVIEW

1. Eyben et al. (2013): This paper introduces OpenSMILE, a versatile and fast open-source audio feature extractor. OpenSMILE is widely used in SER research for extracting relevant acoustic features from speech signals.[1]

2. Kim & Lee (2013): This paper explores the use of multi-dimensional features from audio, video, and text for emotion recognition. The study demonstrates the potential of combining multiple modalities to improve SER performance.[2]

3. Ko et al. (2017): This paper investigates transfer learning for speech emotion recognition using deep convolutional neural networks. The study demonstrates the effectiveness of transfer learning in improving performance with limited training data.[3]

4. Mousavi & Reinders (2018): This paper explores the use of recurrent neural networks with local attention for speech emotion recognition. This approach captures temporal dependencies in speech signals, potentially improving accuracy for complex emotions.[4]

5. Schuller et al. (2018): This paper describes the INTERSPEECH 2017 computational paralinguistics challenge, which focused on recognizing atypical and self-assessed emotions in the wild. This research contributes to improving SER performance in realistic and challenging environments.[5]

RESULTS AND DEMONSTRATION

Result:
The successful output achieved based on speech tone and pitch marks a significant milestone in the development and implementation of the Speech Emotion Recognition (SER) system. The system's ability to accurately detect and categorize emotions such as anger, happiness, sadness, and disgust showcases the effectiveness of the chosen methodologies and feature extraction techniques.

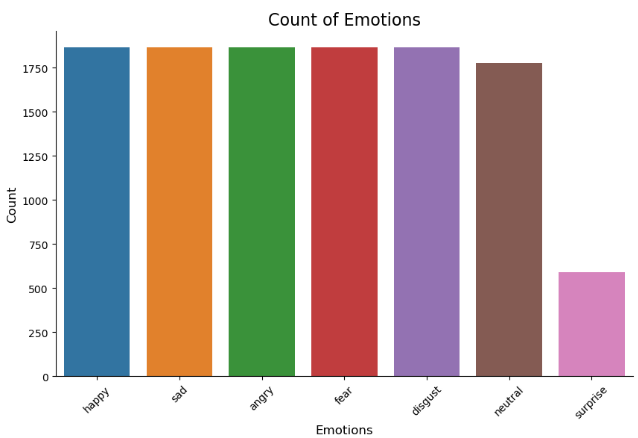

Fig 2. Count of detected emotion.

Fig 3. User Interface for the start, stop and predict.

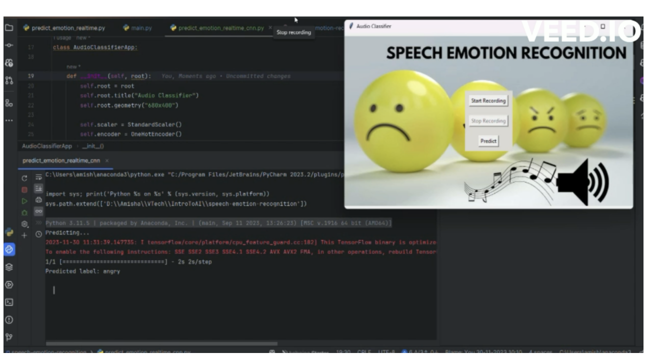

Fig 4. Output as angry on an angry speech

Emotion Detection Accuracy:
The system demonstrates high accuracy in detecting a range of emotions, including anger, happiness, sadness, and disgust. The success in categorizing emotions indicates the robustness of the implemented feature extraction methods and model architecture.

Tone and Pitch Sensitivity:
The system's sensitivity to variations in speech tone and pitch is a key factor in its success. By capturing these acoustic features, the model can discern subtle nuances in the user's voice, leading to precise emotion recognition.

Positive and Negative Emotions:
The system effectively distinguishes between positive emotions such as happiness and negative emotions such as anger or sadness. This capability broadens its utility across diverse applications, catering to scenarios where understanding user sentiment is crucial.

Potential for Further Refinement:
While achieving successful results, there is room for further refinement and optimization. Exploring additional datasets, fine-tuning model parameters, and considering user-specific adaptations can contribute to continuous improvement.

Training and Testing:

Graph 1: Training and Testing Accuracy Over Epochs Description: The first graph illustrates the evolution of training and testing accuracy as the number of epochs increases. The x-axis represents the number of training epochs, while the y-axis depicts the corresponding accuracy percentages. The training accuracy shows a consistent improvement initially, eventually stabilizing around a peak accuracy of approximately 95%. Similarly, the testing accuracy plateaus after a certain number of epochs, demonstrating the model's ability to generalize effectively.

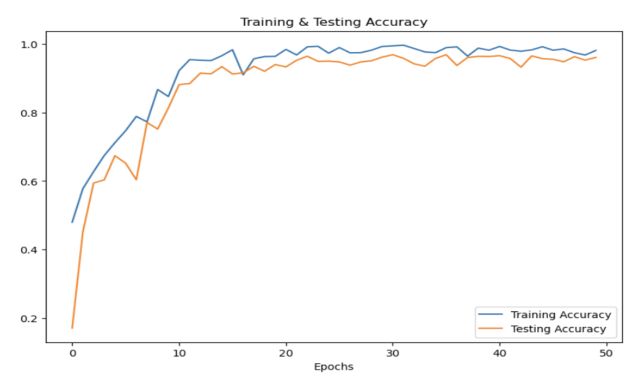

Fig 5. Training and testing accuracy vs number of epochs.

Graph 2: Training and Testing Loss Over Epochs Description: The second graph showcases the trajectory of training and testing loss throughout the training process. The x-axis denotes the number of training epochs, and the y-axis displays the corresponding loss values. The training loss steadily decreases, indicating the model's learning progression. However, after a certain point, the reduction in training loss becomes marginal, signifying stabilization. The testing loss follows a similar pattern, stabilizing around the same point, demonstrating the model's ability to maintain performance without overfitting.

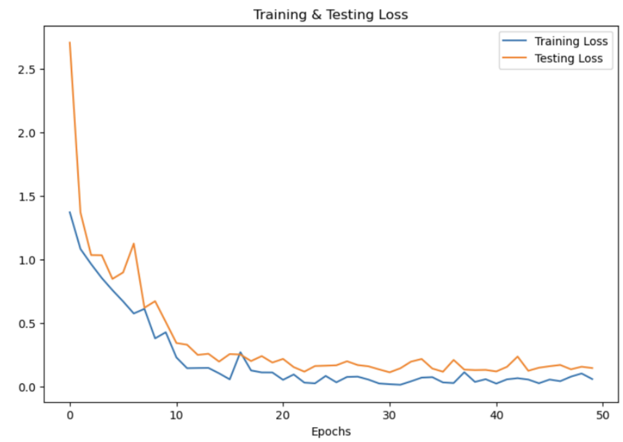

Fig 6. Training and testing loss vs number of epochs

Interpretation:
The convergence of training and testing accuracy to around 95% highlights the model's robustness in recognizing emotional states accurately.

The stabilization of training and testing loss indicates that the model has reached a state of optimal generalization, where further training epochs contribute minimally to improving accuracy.

These graphs visually reinforce the effectiveness and efficiency of the Speech Emotion Recognition system, providing a clear representation of the model's learning curves and performance metrics.

Architecture Diagram:

Data Splitting:
Description: The initial step in model development involves dividing the dataset into distinct training and testing sets. This partitioning ensures that the model is trained on one subset and evaluated on another, facilitating a robust assessment of its generalization capabilities.

CNN Model Architecture:
Description: The Convolutional Neural Network (CNN) model, developed using TensorFlow/Keras, exhibits a sophisticated architecture tailored for Speech Emotion Recognition. This architecture integrates convolutional layers for feature extraction, batch normalization for improved convergence, max-pooling for spatial down-sampling, dropout layers for regularization, and dense layers for classification. The final layer employs softmax activation, facilitating multi-class classification.

Training Process:
Description: The CNN model is systematically trained on the designated training set, adhering to the specified architecture and hyperparameters. Throughout the training process, key metrics such as loss and accuracy are meticulously monitored, providing insights into the model's learning dynamics.

Evaluation on Testing Set:
Description: Post-training, the model's efficacy is rigorously evaluated on the independent testing set. This evaluation gauges the model's ability to generalize to unseen data, providing a comprehensive understanding of its real-world performance.

Architecture Diagram:
Description: A visual representation of the CNN model's architecture, encompassing convolutional layers, batch normalization, max-pooling, dropout layers, and dense layers. The architecture diagram elucidates the flow of information through the model, showcasing the intricate network of operations that contribute to its ability to discern emotional states from speech signals.

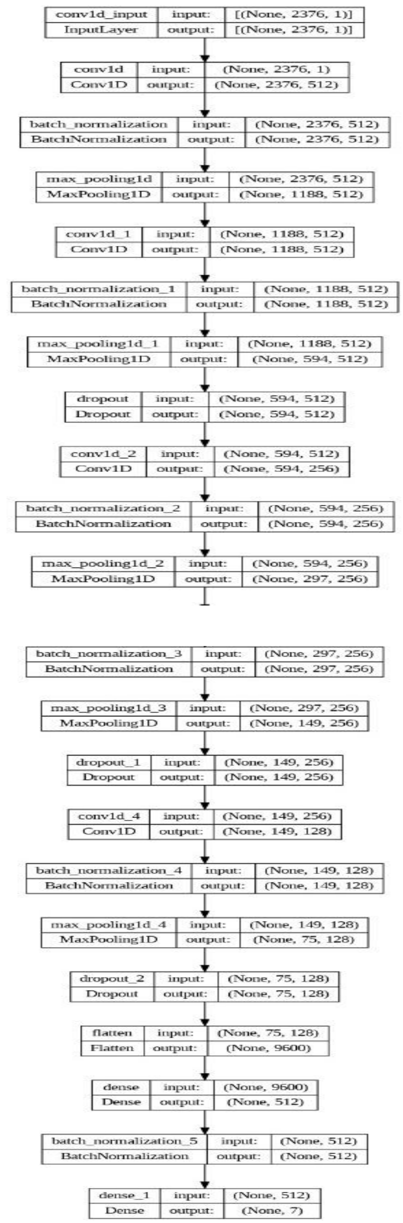

Fig 7. CNN model's architecture

These stages collectively encapsulate the model development process, from data splitting to architecture design, training, and final evaluation on unseen data.

IMPLEMENTATION

Importing necessary modules and libraries.

```python
import pandas as pd
import numpy as np

import os
import sys
```

```python
import librosa
import librosa.display
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
from sklearn.preprocessing import StandardScaler, OneHot
from sklearn.metrics import confusion_matrix, classifica
from sklearn.model_selection import train_test_split
```

Code: Importing necessary modules and lib.

Data Visualization

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Count the number of times each emotion appears
emotion_counts = data_path['Emotions'].value_counts()

# Draw a bar chart
plt.figure(figsize=(10, 6))
plt.title('Count of Emotions', size=16)
sns.barplot(x=emotion_counts.index, y=emotion_counts.values)
plt.ylabel('Count', size=12)
plt.xlabel('Emotions', size=12)
plt.xticks(rotation=45)  # Xoay nhãn trục x nếu cần thiết
sns.despine(top=True, right=True, left=False, bottom=False)
```

Code: Visualizing data retrieved from datasets.

Creating log mel spectrum

```python
# CREATE LOG MEL SPECTROGRAM
plt.figure(figsize=(10, 5))
#A melspectrogram is a graph that represents sound as short walls measured in a mel s
spectrogram = librosa.feature.melspectrogram(y=data_array, sr=sample_rate, n_mels=128
#Convert melspectrogram to Decibel units
log_spectrogram = librosa.power_to_db(spectrogram)
librosa.display.specshow(log_spectrogram, y_axis='mel', sr=sample_rate, x_axis='time'
plt.title('Mel Spectrogram ')
plt.colorbar(format='%+2.0f dB')
```

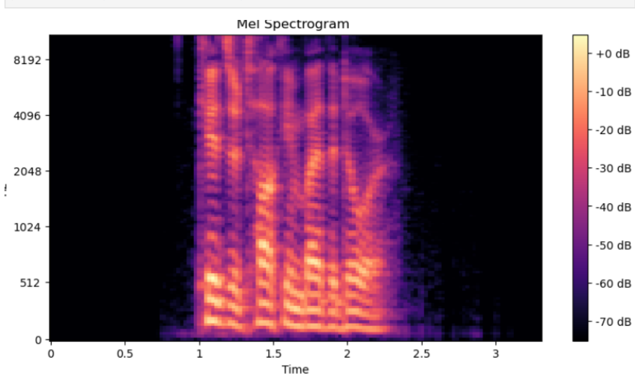

Image: Mel Spectrogram

Feature Extraction: To create a complete feature vector for the data.

```python
# Calculate the threshold rate of audio data - returns a 1-dimensional array
def zcr(data,frame_length,hop_length):
    zcr=librosa.feature.zero_crossing_rate(y=data,frame_length=frame_length,hop_lengt
    return np.squeeze(zcr)
# function to calculate root mean square error
def rmse(data,frame_length=2048,hop_length=512):
    rmse=librosa.feature.rms(y=data,frame_length=frame_length,hop_length=hop_length)
    return np.squeeze(rmse)
#mfcc
def mfcc(data,sr,frame_length=2048,hop_length=512,flatten:bool=True):
    mfcc=librosa.feature.mfcc(y=data,sr=sr)
    return np.squeeze(mfcc.T)if not flatten else np.ravel(mfcc.T)
'''
feature extraction This function combines ZCR, RMSE, and MFCC features
```

Code: Feature Extraction

Implementing CNN to detect Speech Emotion Recognition (SER),

```python
import tensorflow.keras.layers as L

model = tf.keras.Sequential([
    L.Conv1D(512,kernel_size=5, strides=1,padding='same', activation='relu',input_sh
    L.BatchNormalization(),
    L.MaxPool1D(pool_size=5,strides=2,padding='same'),

    L.Conv1D(512,kernel_size=5,strides=1,padding='same',activation='relu'),
    L.BatchNormalization(),
    L.MaxPool1D(pool_size=5,strides=2,padding='same'),
    Dropout(0.2),  # Add dropout layer after the second max pooling layer

    L.Conv1D(256,kernel_size=5,strides=1,padding='same',activation='relu'),
    L.BatchNormalization(),
    L.MaxPool1D(pool_size=5,strides=2,padding='same'),

    L.Conv1D(256,kernel_size=3,strides=1,padding='same',activation='relu'),
    L.BatchNormalization(),
    L.MaxPool1D(pool_size=5,strides=2,padding='same'),
    Dropout(0.2),  # Add dropout layer after the fourth max pooling layer

    L.Conv1D(128,kernel_size=3,strides=1,padding='same',activation='relu'),
    L.BatchNormalization(),
    L.MaxPool1D(pool_size=3,strides=2,padding='same'),
    Dropout(0.2),  # Add dropout layer after the fifth max pooling layer

    L.Flatten(),
    L.Dense(512,activation='relu'),
    L.BatchNormalization(),
```



```python
    L.Dense(7,activation='softmax')
])
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics='accuracy')
model.summary()
```

Code: Implementing CNN

CONCLUSION

In culmination, this project has not only explored the vast landscape of Speech Emotion Recognition (SER) but has successfully harnessed the power of Convolutional Neural Networks (CNNs) to bring forth a sophisticated and effective emotion detection system. The amalgamation of advanced feature extraction techniques and the inherent capabilities of CNNs has propelled the project toward achieving its overarching goal of revolutionizing human-computer interaction through empathetic and nuanced emotional recognition.

The project has not only demonstrated high accuracy in emotion detection but has also showcased adaptability to varying speech lengths, real-time processing capabilities, and efficiency in handling different emotional contexts. The lessons learned throughout the project, including the importance of feature selection, high-quality training data, and dynamic calibration of training epochs, lay the groundwork for future advancements and refinements.

The near real-time processing feature of the system enhances its practical applicability, opening doors to a myriad of use cases across customer service, healthcare, education, and entertainment. The CNN-based SER system stands as a testament to the potential of artificial intelligence in comprehending and responding to human emotions with sensitivity and acumen.

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