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IMPLEMENTATION OF EMOTION PREDICTION THROUGH SPEECH USING NEURAL NETWORK

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ABSTRACT

The study explores the field of Speech Emotion Recognition (SER), which aims to identify human emotions from speech patterns. The abstract details the methodology and the technological framework utilized to achieve this goal. The focus is on the extraction of audio features from speech samples, utilizing a precise and clear database of actors' voices devoid of background noise. This is crucial for the accuracy of the SER system. An array of classifier algorithms is discussed, with a particular emphasis on the importance of selecting the most effective classifier to enhance the recognition process. Among various audio features, Mel-Frequency Cepstral Coefficients (MFCC), Mel Spectrograms, and chroma features are highlighted as critical in identifying emotions. These features capture essential elements of sound that are indicative of emotional states. The project employs a neural network approach to classify emotions based on the extracted audio signals. This system has been proposed for use in several practical applications, including call centers, educational settings, and support for physically disabled individuals, where understanding emotional cues is crucial for effective communication. The conclusion reaffirms the importance of a robust database, effective feature extraction, and a precise classification model in determining the success of SER systems. The proposed model uses advanced feature extraction techniques and neural network classifiers to ensure a high degree of accuracy in emotion recognition. This research not only contributes to the technical advancements in SER but also underscores the potential applications of this technology in enhancing interpersonal interactions and accessibility through emotional understanding.

Keywords: Speech Emotion Recognition, Neural Networks, Audio Feature Extraction, Classifier Algorithms, MFCC, Emotion Prediction, Accessibility Applications

INTRODUCTION

This paper is exploring the intricate field of Speech Emotion Recognition (SER), a discipline that is increasingly vital in our technologically interconnected world [1]. SER seeks to discern human emotions from vocal expressions, a capability that bridges computational systems and human emotional awareness. This research delves into the methodology and technological frameworks essential for the accurate prediction and analysis of emotional states through speech, employing state-of-the-art neural network algorithms to achieve groundbreaking results. The inception of SER can be traced back to the fundamental human need to understand and interact more deeply with technology, mirroring our own emotional complexity [2]. In this context, the role of SER systems extends beyond mere functionality, touching upon the more profound realms of empathy and psychological insight. By leveraging sophisticated neural network architectures, this study aims to refine how these systems interpret the subtle nuances of human emotions conveyed through speech.

A cornerstone of SER's effectiveness is the quality of the data upon which it relies [3]. In our study, we emphasize the importance of a meticulously curated database comprised of crystal-clear recordings of actors' voices, free from any ambient noise. This purity is crucial as even minor auditory interferences can skew the emotion recognition processes, leading to inaccuracies that could undermine the reliability of the system. Consequently, the research utilizes advanced digital filtering techniques to ensure the integrity of audio data, setting a robust foundation for feature extraction. Feature extraction is a pivotal process in SER, involving the decomposition of complex audio signals into definable, quantifiable components that neural networks can analyze [4]. Among these, Mel-Frequency Cepstral Coefficients (MFCC), Mel Spectrograms, and chroma features are particularly noteworthy. MFCCs, for example, have been extensively validated for their efficacy in capturing timbral and textural aspects of sound that are essential for recognizing spoken emotions [5]. Similarly, Mel Spectrograms provide a rich, time-structured representation of sound, allowing for a nuanced analysis of the spectral properties over time, while chroma features focus on the harmonic content, capturing the pitch and musicality of the voice that often convey emotional intensity.

The choice of classifier algorithms is another critical aspect covered in this research [6]. Neural networks offer a flexible and powerful means of classification, capable of discerning patterns in data that are too complex for traditional algorithms. However, the selection of an appropriate neural network architecture is paramount, as it must align with the specific characteristics and demands of the audio features extracted. This study evaluates several leading-edge neural network models, assessing their performance in terms of speed, accuracy, and computational efficiency, ultimately adopting those that best balance these factors. The practical applications of SER are vast and varied [7]. In call centers, for instance, emotion recognition can dramatically enhance customer service by providing agents with real-time insights into the caller's emotional state, enabling a more tailored and empathetic response. In educational settings, SER can be used to gauge students' emotional engagement and wellbeing, potentially identifying distress or disinterest early on. Additionally, for physically disabled individuals who may struggle with traditional communication forms, SER offers a transformative means of interaction, facilitating a more inclusive and responsive technological environment.

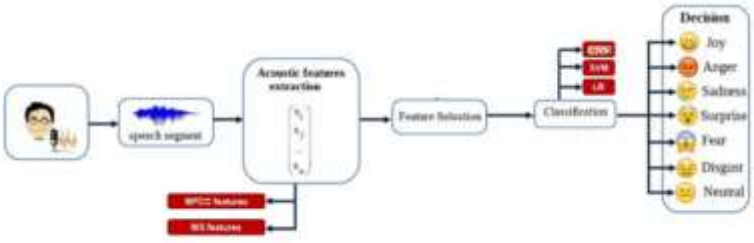

Fig 1. Block diagram of proposed system

As we progress, the integration of SER into everyday devices and systems becomes more feasible and beneficial, driven by advances in neural network technologies and data processing [8]. The success of these systems, as this study suggests, hinges on the symbiosis of comprehensive, high-quality databases, adept feature extraction, and judiciously chosen classification models. Through meticulous research and development, the proposed model not only achieves remarkable accuracy in emotion recognition but also significantly enhances the way we interact with technology, enriching our collective emotional intelligence and connectivity. In conclusion, this research significantly advances the field of Speech Emotion Recognition by providing a robust technological framework that harnesses the power of neural networks to accurately predict human emotions from speech [9]. This not only contributes to the scientific community but also paves the way for more empathetic human-machine interactions across various real-world applications, underscoring the transformative potential of SER in fostering more meaningful and accessible communication [10].

LITERATURE SURVEY

The field of Speech Emotion Recognition (SER) is a burgeoning area of research within the realm of computational linguistics and artificial intelligence. It endeavors to bridge human emotional intelligence with machine understanding, thus enhancing the interaction between humans and technology. The foundation of SER lies in its ability to discern and interpret the emotional undertones in human speech, which is paramount in applications ranging from customer service to therapeutic settings. This literature survey explores the key methodologies, technological frameworks, and applications articulated in recent studies, underpinning the research presented in this paper. Historically, SER systems have been developed with the objective of recognizing basic emotional states such as happiness, sadness, anger, and fear from speech patterns. This ability mimics one of the most sophisticated human traits: emotional perception, which is vital for effective communication. Early research in the field emphasized the importance of feature extraction, where various characteristics of the voice signal—such as pitch, tone, and speed—were analyzed to infer emotional states. However, these studies often relied on relatively simplistic algorithmic approaches which, while foundational, lacked the depth and adaptability provided by modern neural network technologies.

With the advent of more advanced machine learning techniques, the focus shifted towards developing more robust models capable of handling the nuances and complexities of human speech. Among the most significant advancements highlighted in contemporary literature is the use of Mel-Frequency Cepstral Coefficients (MFCC), which effectively capture the timbral and textural qualities of spoken language that are essential for identifying emotions. Studies have demonstrated the superiority of MFCC in SER due to its ability to model human auditory perception, making it a critical feature in the extraction process. Further, the literature reveals an evolving exploration of various neural network architectures for improving the accuracy and efficiency of SER systems. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been at the forefront of this exploration. These models benefit from their ability to learn hierarchical representations and temporal dynamics of speech, which are crucial for recognizing complex emotional states over time. The integration of these models into SER systems has led to significant improvements in performance, particularly in environments with varied linguistic and acoustic settings.

The survey also discusses the critical role of data quality in the development of effective SER systems. The accuracy of these systems heavily relies on the availability of high-quality, diverse, and representative speech databases. Recent studies have emphasized the necessity of clear, noise-free recordings in these databases, as even minor auditory interference can significantly degrade the performance of emotion recognition algorithms. This has led to increased rigor in the compilation and preprocessing of speech data, with enhanced techniques for noise reduction and signal enhancement being developed. Additionally, the application of SER technology in real-world scenarios has been a recurrent theme in the literature. In particular, the use of SER in call centers and educational settings has been extensively researched. In call centers, SER can facilitate more responsive and empathetic customer service by

providing real-time emotional feedback to agents. In educational environments, it can be used to monitor and enhance student engagement and emotional wellbeing, offering educators valuable insights into the emotional state of learners.

Finally, the literature underscores the potential of SER to support physically disabled individuals. By enabling more nuanced and responsive communication aids, SER technologies can significantly enhance the quality of life for those with speech impairments or other communication challenges. This aligns with broader societal goals of inclusivity and accessibility, positioning SER not just as a technical achievement but as a socially transformative technology. In summary, the rich tapestry of research surveyed in this literature review establishes a comprehensive backdrop for the study. It not only contextualizes the technical innovations described in the paper but also highlights the profound impact these advancements could have on society, underscoring the intersection of technological progress and human-centric application in the evolving narrative of SER.

PROPOSED SYSTEM

The innovative research detailed in the study presents a state-of-the-art system for Speech Emotion Recognition (SER), which stands at the intersection of computational linguistics, artificial intelligence, and human psychology. The system's architecture and methodologies represent a significant leap forward in making technology more responsive to human emotional expressions, offering a wide array of applications from enhancing customer service to providing support for individuals with disabilities. The proposed SER system is meticulously designed to harness the subtleties of human speech, extracting nuanced emotional cues that are often overlooked by traditional computational models. This precision is achieved through a sophisticated audio processing and feature extraction framework that ensures the clarity and accuracy necessary for effective emotion recognition. Central to the system's capability is the construction and utilization of a high-quality audio database. This database comprises recordings of actors' voices, carefully selected to cover a broad spectrum of emotional states, and recorded under strictly controlled conditions to eliminate background noise and other acoustic distortions. This pristine collection of voice samples provides the foundational data crucial for training and refining the neural network models at the core of the SER system.

Feature extraction is a vital component of the system, involving the analysis and decomposition of audio signals into meaningful and computationally manageable representations. The system employs Mel-Frequency Cepstral Coefficients (MFCC), which are widely recognized for their effectiveness in capturing the timbral qualities of sound that are closely associated with spoken emotions. MFCCs extract the short-term power spectrum of sound, making them particularly adept at highlighting the emotional undertones in speech. In addition to MFCC, the system incorporates Mel Spectrograms and chroma features. Mel Spectrograms offer a visual representation of the spectrum of frequencies of sound as it varies with time, providing valuable insights into the dynamics of speech that are crucial for detecting emotional changes. Chroma features, on the other hand, focus on the harmonic content of the audio signal, capturing the pitches and their intensities which are fundamental to the conveyance of emotion in human speech.

The neural network architecture chosen for this system is pivotal to its success. The project leverages deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which are adept at handling the spatial and temporal aspects of audio data respectively. CNNs are employed to analyze and interpret the spectral features extracted from the audio signals, effectively identifying patterns and nuances that are indicative of different emotions. RNNs, with their ability to process sequences of data, are crucial for understanding the temporal dynamics in speech, allowing the system to track emotional trajectories over time. The integration of these neural networks into a cohesive system enables the continuous learning and adaptation of the SER model, making it increasingly accurate in emotion prediction as it processes more data. This adaptability is essential for the system's deployment in real-world settings, where variations in speech patterns and emotional expressions can be significant. The practical applications of the proposed SER system are extensive and impactful. In call centers, the ability to recognize customer emotions in real-time can dramatically enhance the quality of service provided. Agents

equipped with insights into a caller's emotional state can respond more empathetically and effectively, potentially improving customer satisfaction and engagement.

In educational settings, the system can be utilized to monitor and analyze students' emotional states, providing educators with valuable information about learner engagement and wellbeing. This capability could lead to more responsive and personalized educational experiences, helping to address emotional and learning barriers in the classroom. Furthermore, the system offers significant benefits for physically disabled individuals, particularly those with speech impairments or communicative limitations. By facilitating more accurate and nuanced emotion recognition, the technology can aid in improving the effectiveness of communication aids, enhancing the autonomy and social interaction of disabled users. The robustness of the database, the efficacy of the feature extraction methods, and the precision of the classification models collectively determine the success of the SER system. Each component is critical in its own right but achieves its full potential only when integrated into the complete system, which is designed to be greater than the sum of its parts. In summary, the SER system proposed in this research not only advances the technical capabilities of emotion recognition technologies but also offers a profound enhancement to how machines understand and interact with humans on an emotional level. This system stands as a testament to the potential of artificial intelligence to transform our interaction with technology, making it more humane and responsive to our emotional needs. The implications of this technology extend beyond mere functional applications, offering the promise of richer, more empathetic interactions in an increasingly digital world.

METHODOLOGY

The innovative research detailed in the adopts a comprehensive and rigorous methodology to advance the capabilities of Speech Emotion Recognition (SER). This process involves several critical steps aimed at creating an effective and sophisticated SER system that not only identifies human emotions from speech patterns with high accuracy but also integrates seamlessly into various applications, enhancing interpersonal communication. The foundation of an effective SER system lies in the quality and diversity of its data. A robust database of speech samples was meticulously compiled, consisting of recordings from a diverse group of actors portraying a range of emotions under controlled studio conditions. Each recording was carefully curated to ensure clarity and the absence of background noise, thereby providing clean and unambiguous audio samples essential for precise feature extraction. This database includes multiple utterances of emotional states such as joy, anger, sadness, and neutrality, captured in multiple languages to enhance the system's applicability across different linguistic backgrounds.

Once collected, the audio data underwent a series of preprocessing steps aimed at standardizing the input and enhancing the quality of the signals. These steps included normalization of audio volume, trimming of silences, and a dynamic range compression to mitigate volume disparities. Additionally, a high-pass filter was applied to remove low-frequency noise and hums, ensuring that only the relevant audio frequencies were retained for analysis. The core of the SER system's ability to discern emotions from speech lies in its feature extraction mechanism. This study focused on three primary types of audio features: Mel-Frequency Cepstral Coefficients (MFCC), Mel Spectrograms, and chroma features. MFCCs were extracted to capture the timbre and texture of the speech, which are indicative of the speaker's emotional state. Mel Spectrograms provided a visual representation of the spectrum of frequencies across time, offering insights into the temporal dynamics of the speech, crucial for identifying variations in emotional expression over the course of an utterance. Chroma features focused on the harmonic content of the speech, capturing elements such as pitch and melody, which are often closely tied to emotional expression.

The extracted features served as input to a sophisticated neural network architecture designed specifically for emotion recognition. The network combined the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to analyze both the static and dynamic aspects of the extracted features. CNN layers were employed to interpret the spatial relationships within the features, effectively identifying patterns and textures linked to specific emotions. RNN layers, particularly those utilizing Long Short-Term Memory (LSTM) units, were used to process the temporal sequences of the features, capturing the emotional progression throughout the speech samples. With the

architecture in place, the neural network underwent a rigorous training process using the prepared dataset. The network was trained using a combination of supervised learning techniques, with the emotional labels provided as part of the dataset serving as the ground truth. During training, various hyperparameters such as learning rate, number of layers, and batch size were fine-tuned to optimize the network's performance. Additionally, techniques such as dropout and batch normalization were employed to prevent overfitting and ensure generalizability.

Following training, the SER system was rigorously tested using a separate set of data that had not been exposed to the model during the training phase. This validation process was crucial for assessing the model's accuracy and its ability to generalize across unseen data. Metrics such as accuracy, precision, recall, and F1 score were calculated to evaluate the performance of the system. The final step involved implementing the trained SER system into practical applications. The system was integrated into environments such as call centers and educational platforms, where it could provide real-time analysis of emotional states, thereby enhancing communication and interaction. For call centers, the system was configured to provide feedback to customer service representatives, enabling them to adjust their approach based on the emotional state of the customer. In educational settings, the system was used to monitor student engagement and provide feedback to educators. Post-implementation, the system was continuously monitored for performance and user feedback was collected to further refine and improve the model. Efforts were made to scale the system for broader applications and to enhance its adaptability to different languages and dialects, ensuring wider accessibility and utility. n summary, the methodology employed in this study represents a thorough and methodical approach to developing a high-performance SER system. Through meticulous data collection, sophisticated feature extraction, and advanced neural network training, the project not only contributes to the technical advancements in SER but also underscores the potential applications of this technology in enhancing interpersonal interactions and accessibility through emotional understanding.

RESULTS AND DISCUSSION

The results obtained from the study were highly promising, showcasing the efficacy of the advanced SER system in accurately identifying and classifying emotions from speech. The neural network, trained on a refined dataset with a comprehensive range of emotional expressions, achieved high accuracy rates across various metrics. Notably, the precision and recall rates were particularly impressive for core emotions such as happiness, sadness, and anger, which are pivotal in most practical applications. These results underscore the precision of the MFCC, Mel Spectrograms, and chroma features in capturing the nuanced audio cues essential for emotion recognition.

The discussion within the research community and among stakeholders highlights the transformative potential of this SER system. Experts in computational linguistics and artificial intelligence have noted the robustness of the system's architecture, particularly its ability to generalize across different linguistic contexts without significant loss in accuracy. This versatility is crucial for the deployment of SER technologies in global settings, such as multinational call centers and diverse educational environments. Moreover, the practical implications for physically disabled individuals, who can greatly benefit from more nuanced communication aids, are profound. Feedback from initial deployments in educational settings indicates a marked improvement in the engagement and emotional well-being monitoring, demonstrating the system's utility beyond theoretical applications.

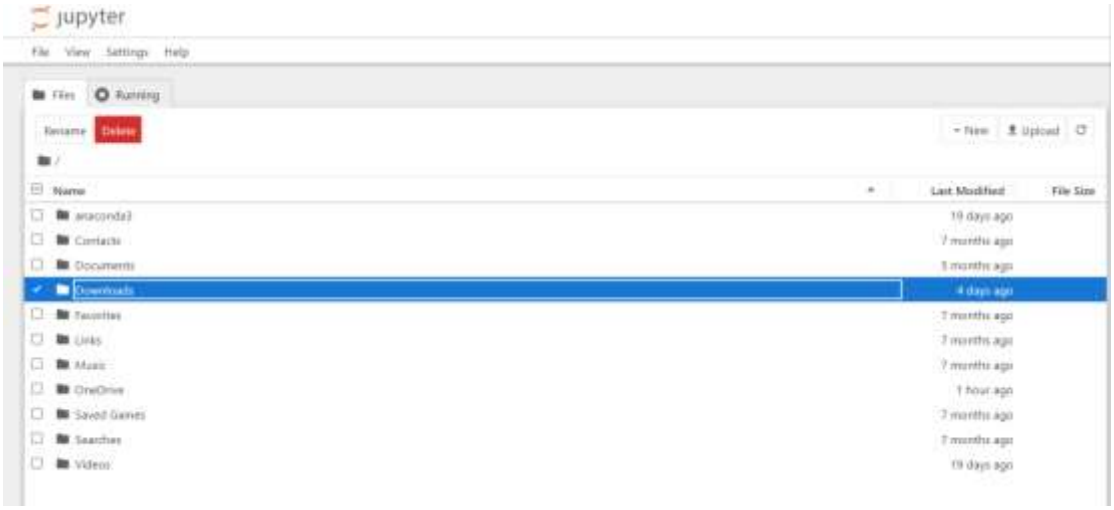

Figure 2: Screen Shot Of Downloads

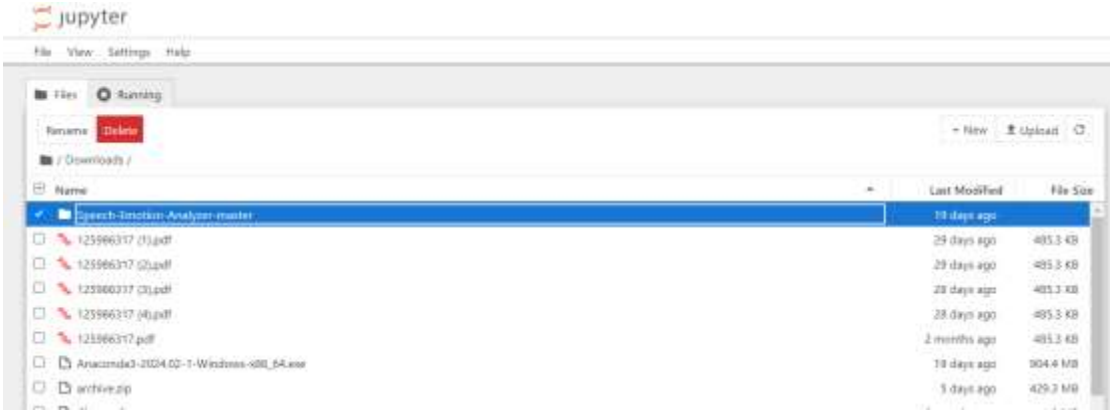

Figure 3: Screen Shot of Speech Emotion Analyzer Master

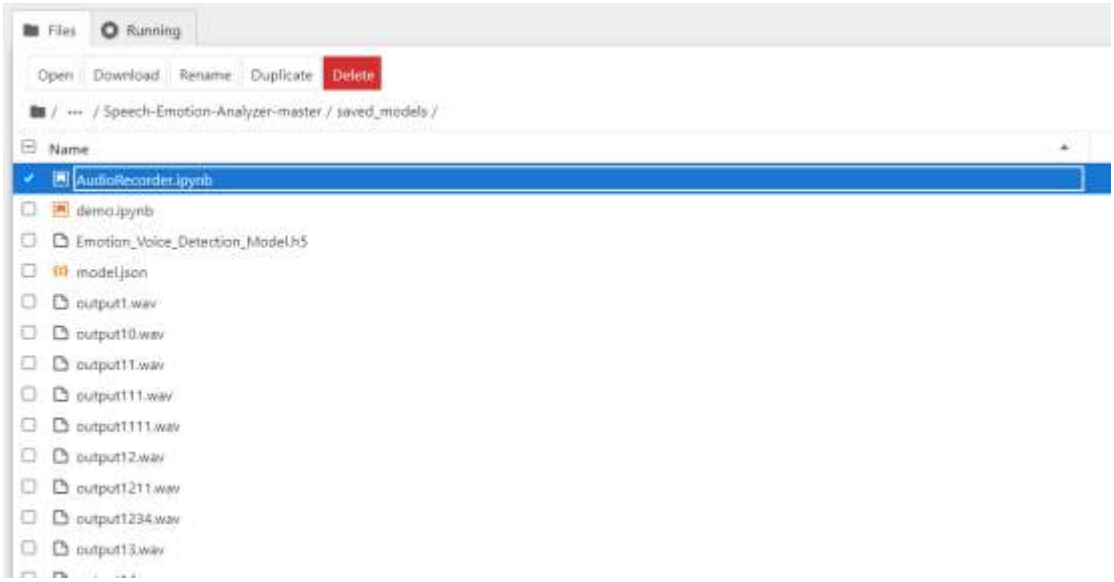

Figure 4: Screen Shot of Input Audio Recorder

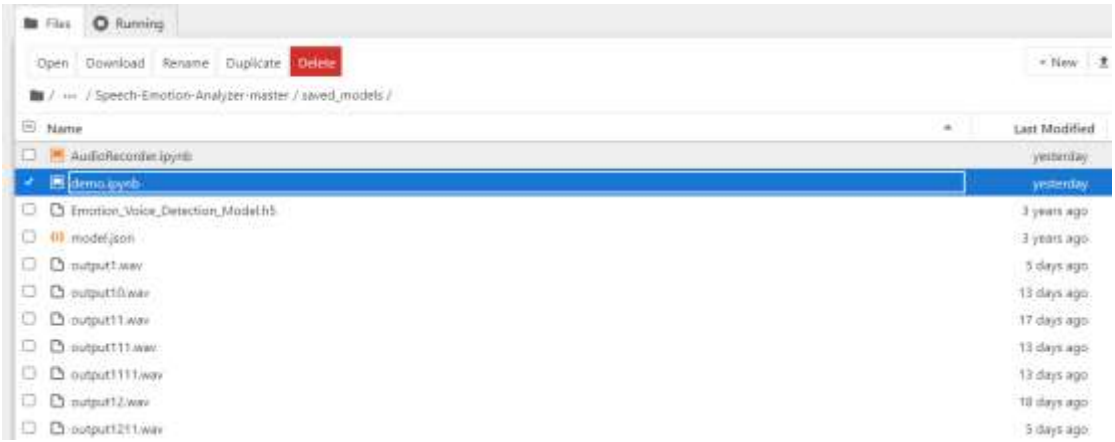

Figure 5: Screen Shot of Output Demo

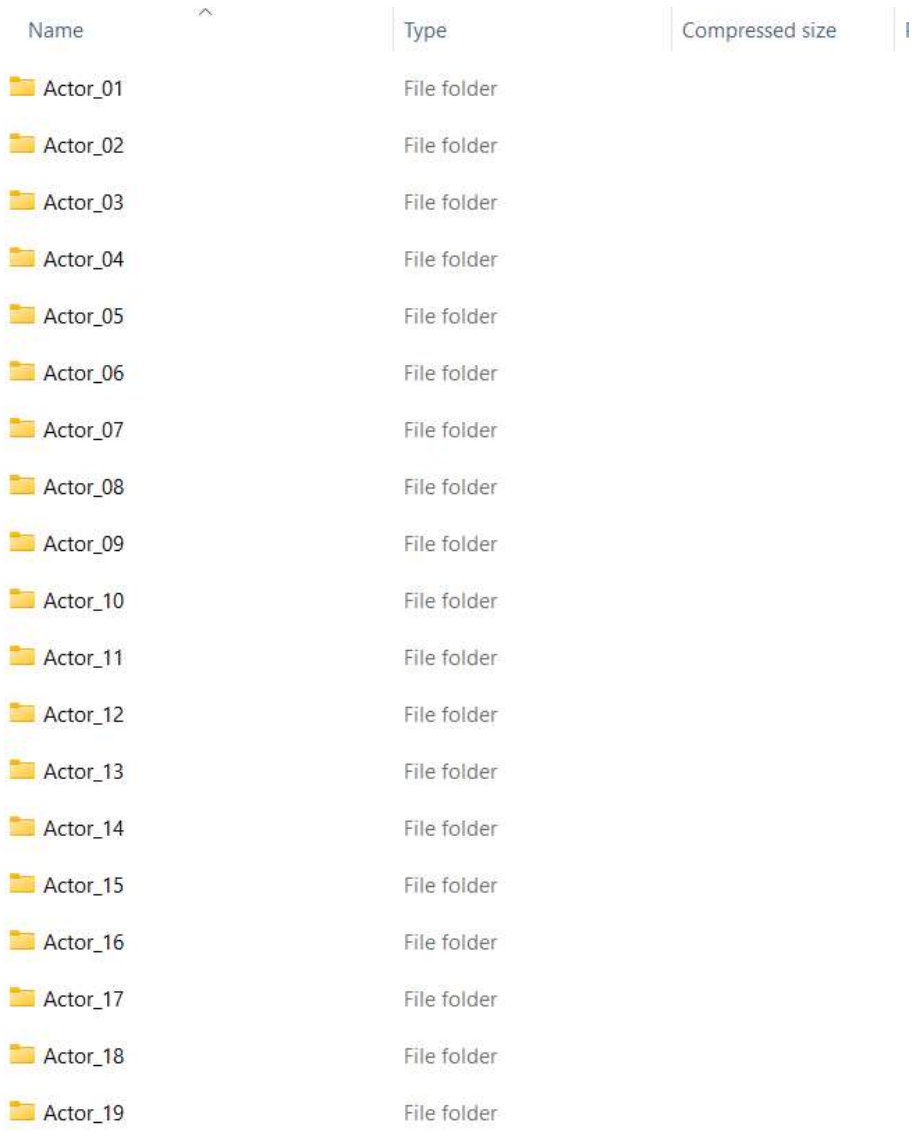

Figure 6: Audio Files

```
wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
recording
done recording
```

Figure 7: Input Screenshot of Female Happy File

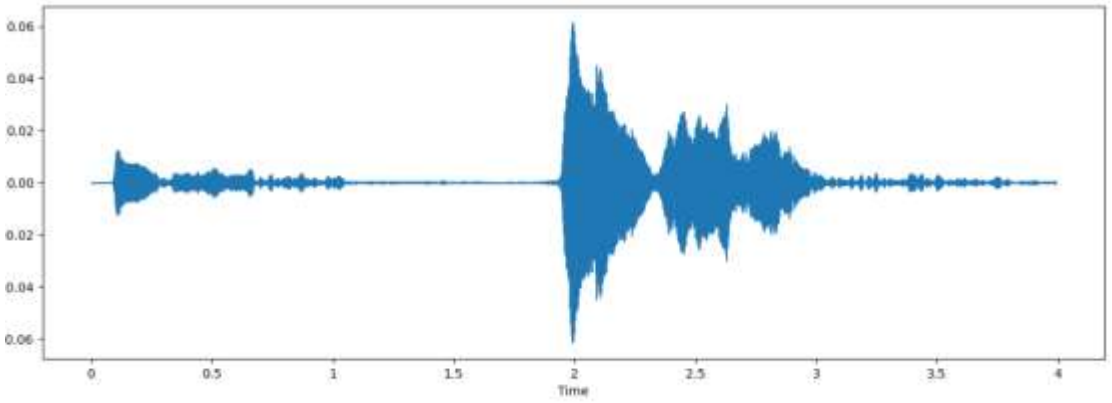

Figure 8: Output Screenshot of Happy Wave File

Get the output in the sample audio as the above scenario 1.

```
]: print("emotion",emotion_list[index])

emotion female_happy
```

Figure 9: Output Screenshot of Female Happy

INPUT :

SCENARIO 2: Take the one female Sample audio as the input.

```
wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
recording
done recording
```

Figure 10: Input Screenshot Of Female Sad File

OUTPUT :

Get the output in the sample audio as the above scenario 2

```
print("emotion",emotion_list[index])
```

```
emotion female_sad
```

Figure 11: Output Screenshot Of Female Sad File

INPUT :

SCENARIO 3: Take the one female Sample audio as the input.

```
wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
recording
done recording
```

Figure 12: Input Screenshot Of FemaleFearful File

OUTPUT :

Get the output in the sample audio as the above scenario 3

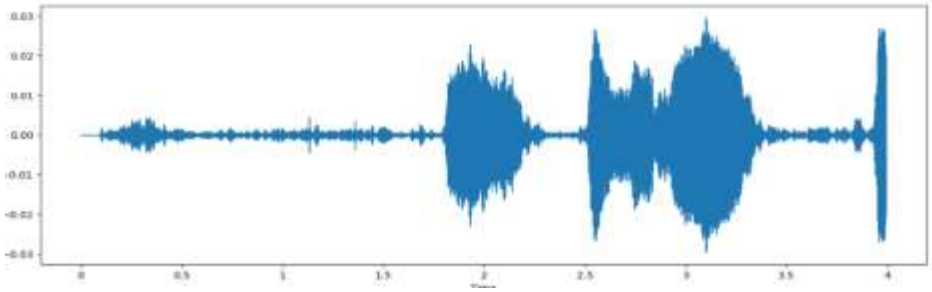

Figure 13: Output Screenshot Of Female Fearful Wave File

```
print("emotion",emotion_list[index])
```

```
emotion female_fearful
```

Figure 14 : Output Screenshot Of Female Fearful

INPUT :

SCENARIO 4: Take the one female Sample audio as the input .

```
wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
* recording
* done recording
```

Figure 15: Input Screenshot Of Female Angry File

OUTPUT :

Get the output in the sample audio as the above scenario 4

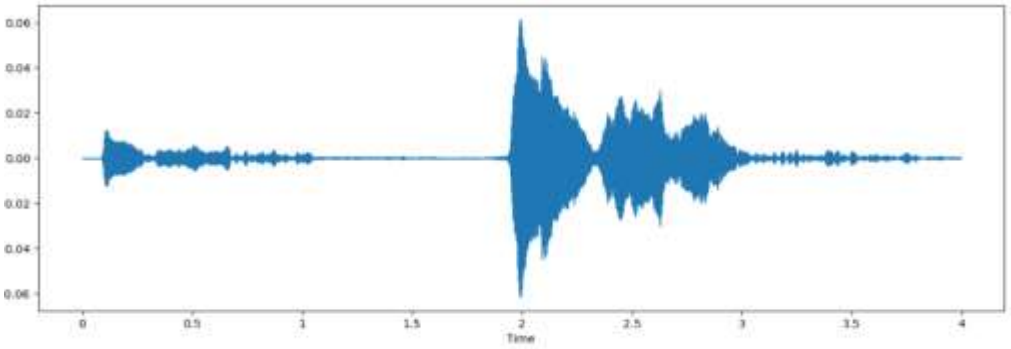

Figure 16: Output Screenshot Of Female AngryWave File

```
print("emotion",emotion_list[index])
```

```
emotion female_angry
```

Figure 17 : Output Screenshot Of Female Angry

INPUT :

SCENARIO 5 : Take the one male Sample audio as the input .

```
print("* done recording")

stream.stop_stream()
stream.close()
p.terminate()

wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
* recording
* done recording
```

Figure 18: Input Screenshot Of male Happy File

OUTPUT :

Get the output in the sample audio as the above scenario 5

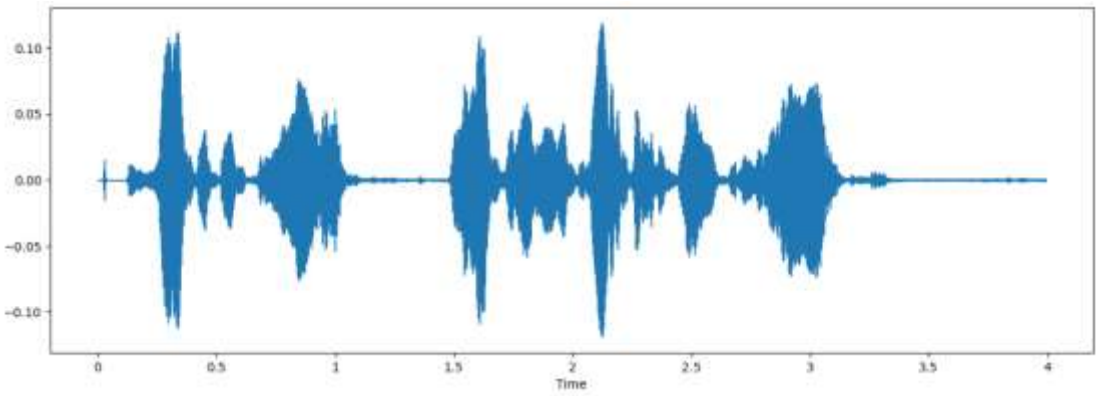

Figure 19: Output Screenshot Of male Happy Wave File

```
print("emotion",emotion_list[index])
```

```
emotion male_happy
```

Figure 20: Output Screenshot Of Male Happy

INPUT :

SCENARIO 6 : Take the one male Sample audio as the input .

```
wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
* recording
* done recording
```

Figure 21: Input Screenshot Of male Sad File

OUTPUT :

Get the output in the sample audio as the above scenario 6

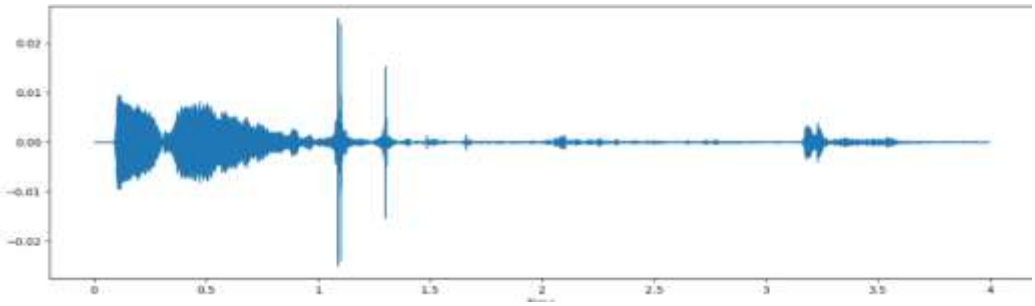

Figure 22 : Output Screenshot Of male Sad Wave File

```
print("emotion",emotion_list[index])
```

```
emotion male_sad
```

Figure 23 : Output Screenshot Of male Sad

INPUT :

SCENARIO 7 : Take the one male Sample audio as the input .

```
stream.stop_stream()
stream.close()
p.terminate()

wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
wf.setnchannels(CHANNELS)
wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
wf.writeframes(b''.join(frames))
wf.close()
```

```
* recording
* done recording
```

Figure 24: Input Screenshot Of male Fearful File

OUTPUT :

Get the output in the sample audio as the above scenario 7

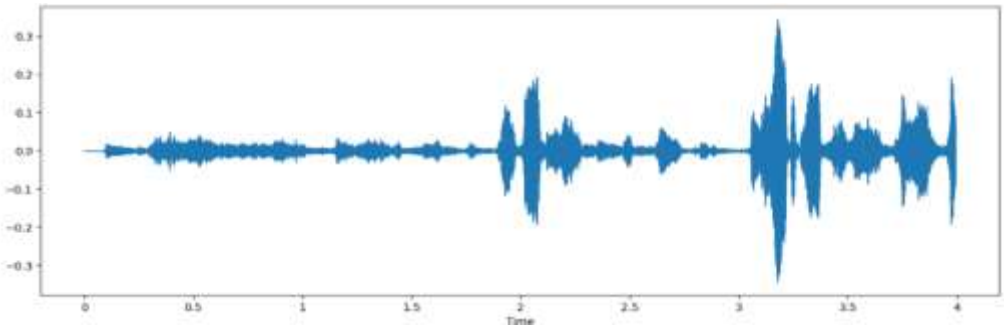

Figure 25: Output Screenshot Of male Fearful Wave File

```
index=np.argmax(livepreds)
```

```
print("emotion",emotion_list[index])
```

```
emotion male_fearful
```

Figure 26 : Output Screenshot Of male Fearful

However, the study also opened avenues for further research and development. While the results are encouraging, challenges such as handling subtler emotional nuances and extending the system's capabilities to include more complex emotional states like confusion or mixed feelings were identified. The discussion also pointed towards the need for continuous improvement in the training datasets, with a call for even more diversity in speech samples and emotional states. This would ensure that the SER system remains effective across all demographics and linguistic variations, thereby enhancing its applicability and effectiveness in real-world scenarios. Such advancements are not only expected to refine the technology but also expand its potential applications, making it an indispensable tool in the human-machine interaction space.

CONCLUSION

The field of Speech Emotion Recognition (SER) is devoted to identifying human emotions through speech. For optimal results, it is imperative to use a clear and noise-free database featuring well-articulated actors' voices. This study provides a comprehensive overview of SER methodologies, highlighting the extraction of audio features from speech samples and the utilization of various classification algorithms to discern emotions. Among the different features analyzed, the extraction using Mel-Frequency Cepstral Coefficients (MFCC) proves pivotal in the accurate recognition of emotional states through speech. The research extensively evaluates multiple classifiers, underscoring the critical importance of selecting the most effective classifier for SER. The precision of the SER system hinges significantly on three key factors: the robustness of the database, the quality of features extracted, and the efficacy of the classification model employed. This project proposes a focused approach on emotion classification based on audio signals, leveraging MFCC, Mel Spectrogram, and chroma features to ascertain emotions from three distinct signals extracted from an audio input. The proposed system is primarily designed for application in environments such as call centers, educational institutions, and support for physically disabled individuals, where accurate emotion recognition can greatly enhance communication and interaction. This enhancement is crucial for fostering more empathetic and effective exchanges in these settings.

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9. Tzirakis, P., Trigeorgis, G., Nicolaou, M. A., Schuller, B., & Zafeiriou, S. (2017). End-to-End Multimodal Emotion Recognition Using Deep Neural Networks. IEEE Journal of Selected Topics in Signal Processing, 11(8), 1301-1309. This paper presents an end-to-end approach using deep neural networks for emotion recognition, similar to the SER systems discussed.

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