Chapter 6

Limitations and Future Directions

The use of the CASE dataset provides a solid foundation for this study, allowing for delving into emotional classification. However, it's crucial to acknowledge the potential constraints associated with relying exclusively on this dataset. While it offers valuable insights, its limited scope might not fully represent the diverse range of emotions present in other datasets. This limitation could affect the generalizability of the research findings, as emotions are complex and multifaceted phenomena that can vary across different contexts and populations.

The current analysis focuses primarily on categorizing emotions, which provides a structured framework for understanding emotional responses. However, the importance of incorporating dimensional emotional analysis is well understood and can be incorporated in future research to gain a more nuanced understanding. Dimensional analysis allows for exploring emotions using two dimensions, such as valence and arousal, providing a more comprehensive view of emotional experiences.

EDA signals serve as valuable indicators of emotional arousal, offering insights into physiological responses associated with emotional experiences. However, it's essential to acknowledge that EDA signals may not capture the full complexity of emotional responses. Factors such as individual differences and contextual influences can contribute to variability in EDA signals, highlighting the need for a more holistic approach to understanding emotions. To address the limitations of relying solely on EDA signals, studies need to integrate multiple datasets encompassing a diverse range of emotional experiences. This approach allows for leveraging complementary sources of data, such as EEG, ECG, EMG, BVP, SKT, and others, to gain a more comprehensive understanding of emotions. By combining different modalities, a broader range of physiological and behavioral emotional responses can be captured, enhancing the analysis's richness and depth.

In addition, various decomposition methods for EDA signals can be explored. Techniques such as Leda lab: CDA, DDA, SCRalyze, and SparsEDA offer insights into the underlying components of EDA signals, such as tonic and phasic activity. By decomposing EDA signals into their constituent parts, the dynamics of emotional arousal can be better understood, improving the accuracy of the analysis.

The study employed STFT and MFC spectrogram techniques to optimize the analysis of phasicEDA segments. STFT allows for the examination of signal variations over time and frequency, while MFC captures the spectral characteristics of the signal. However, it's noteworthy that other transformative techniques such as CWT, DWT, CWD, and SP-WVD were not explored for generating spectrograms. These alternative methods offer unique advantages in capturing both temporal and frequency features of EDA signals, and their exploration in future research could provide additional insights into the dynamics of emotional arousal.

Additionally, in the study, GASF, GADF, MTF, and RP methods were utilized to convert the time series phasic EDA signals into images, thus optimizing the windowing approach for analysis. While these techniques offer effective visualization of temporal patterns in EDA data, there is potential for further enhancement by incorporating advanced image processing techniques. Future research endeavors will explore advanced image processing methods to improve the representation and analysis of EDA signals. By leveraging these advanced techniques, the aim is to enhance the granularity and interpretability of the study's findings, thereby advancing the field of emotional classification and analysis.

The study primarily focuses on machine learning algorithms for emotion classification, as they have demonstrated superior performance compared to deep learning methods in the pipeline. However, remaining open to exploring more sophisticated ML algorithms, deep learning techniques, and hybrid models in future research is important. By combining traditional ML approaches with deep learning and hybrid models, the potential for improving the robustness and accuracy of emotion recognition systems exists.

Finally, the approach holds promise for real-time applications in domains such as wearable devices and virtual reality environments. By developing personalized and adaptive interventions for emotion regulation, overall well-being can be enhanced, and positive emotional experiences can be promoted in real-world settings. This highlights the research's practical relevance and potential impact on improving human-computer interaction and emotional well-being.