Chapter 7

Conclusion and Future Scope

Abstract

This concluding chapter presents the study's main findings, limitations, and proposed directions for future research. This thesis thoroughly outlined the methodologies for classifying gait abnormalities using EMG signals and scalograms and demonstrated the effectiveness of attention networks and transfer learning in improving classification accuracy for conditions such as hemiplegia, Parkinson's, and ALS. Integrating EEG and EMG signals, primarily through CNNs and transfer learning, enhanced classification accuracy, which is crucial for brain-computer interfaces and neuroprosthesis applications.

7.1 Conclusions

This chapter summarizes the thesis's critical findings on gait analysis and signal processing while acknowledging study limitations and suggesting future research directions. It discusses methodologies for gait abnormality classification using EMG signals, scalograms, and machine learning techniques, showcasing the effectiveness of attention networks and transfer learning. Integrating EEG and EMG signals, mainly through CNNs and transfer learning, holds promise for improving classification reliability.

Chapter 2 provided a comprehensive review of the existing literature on gait abnormalities and gait analysis, covering methodologies and technologies used in gait analysis, including signal processing techniques and feature extraction methods. The chapter also introduced the applications of EEG and EMG across various domains and briefly touched upon machine learning and deep learning concepts, emphasizing their relevance to the study.

Chapter 3 focused on classifying hemiplegic gait abnormalities using EMG signals. The study employed machine learning algorithms to successfully classify hemiplegic gait abnormalities using EMG signals, achieving an impressive 98% accuracy with an ensemble approach. These findings hold significant promise for applications in neuroprosthesis, brain-computer interfaces, and motor rehabilitation.

Chapter 4 discussed the use of EMG scalograms to classify gait abnormalities such as Hemiplegia, Rheumatoid Arthritis, Osteoarthritis, and PIVD and extended the classification to other neurological disorders, including Parkinson's, ALS, and Huntington's, using scalograms of foot insole data. The study demonstrates that scalogram-based analysis, coupled with CNN classification, provides a robust framework for accurate and reliable diagnosis of gait abnormalities. The methodology shows significant promise in differentiating between different types of gait disorders, offering potential applications in clinical settings for reliable and accurate diagnosis of gait abnormalities.

Chapter 5 explored attention networks for classifying EMG scalograms related to various gait abnormalities, emphasizing the impact of combining different wavelet family scalograms on classification accuracy. This chapter provided a comprehensive overview of the network architecture, training methodology, and performance assessment, highlighting the advancements facilitated by attention mechanisms in EMG signal classification. Gait analysis provides a valuable window into the effects of various conditions on an individual's gait patterns. By identifying these patterns, clinicians can better evaluate the impact of a given condition and develop targeted interventions to improve function and mobility. With this study, we aim to highlight the viability of scalogram-based classification and the advantages of using attention-based networks. By incorporating the scalograms generated from multiple wavelet families, the proposed approach seeks to leverage the strengths of each wavelet while mitigating the loss of signal features in each wavelet type. This study used the CBAM architecture combined with CNN to classify individual and combined scalograms generated from different wavelet functions. The CBAM + CNN model achieved a decent accuracy on all wavelet types. Combining the scalograms results in an accuracy of 99%, precision of 99%, recall of 100%, area under ROC curve of 1.0, and PRC of 1.0. This technique holds significant promise for improving the accuracy and precision of medical diagnoses and rehabilitation plans.

Chapter 6 focused on the classification of hand movements based on EEG and EMG scalograms using transfer learning. This highlighted the potential of combining EEG and EMG signals to improve classification performance. The research showcased the possibility of increasing accuracy, reducing noise, and minimizing variability in EEG signals. The combination of EEG and EMG signals consistently outperformed EEG-only methods. Integrating transfer learning allowed models to capitalize on insights from one problem to tackle related challenges. Overall, this approach holds significant promise for healthcare and assistive technology.

7.2 Limitations

While this study demonstrates the potential of scalogram-based techniques combined with attention-based deep learning networks for the classification of gait abnormalities and brain-computer interface (BCI) applications, several limitations must be acknowledged that may affect the generalizability and robustness of the findings.

1. **Sample Size and Diversity:** One of the primary limitations of the study is the relatively small sample size. A limited cohort may not adequately capture the full variability present in real-world neuromuscular and neurodegenerative disorders. Small sample sizes can lead to model overfitting, reduced statistical power, and compromised ability to generalize findings to broader populations.

2. **Scope of Medical Conditions:** The current study focuses on a selected subset of neuromuscular conditions, including hemiplegia and related gait-affecting disorders. While this targeted approach provides valuable insights, it may restrict the applicability of the proposed methodology across other gait disorders such as Parkinson's disease, multiple sclerosis, or orthopedic impairments.

3. **Lack of Age-Related Gait Profiles:** The dataset does not include aged individuals with standard (i.e., non-pathological) gait patterns, which limits the assessment of the model's ability to distinguish between age-related physiological changes and pathological gait abnormalities.

4. **Simplicity of Task Design in BCI Application:** In the BCI component of the study, EEG and EMG signals were recorded during basic motor tasks, such as simple hand

opening and closing. While this provided a controlled and noise-minimized dataset, it does not reflect the complexity of real-world motor intention scenarios.

5. **Technical and Hardware Constraints:** The study was conducted using a specific set of hardware and recording environments, which may influence the signal quality and system performance. Differences in electrode placement, sensor quality, and environmental noise can affect the reproducibility of results.

6. **Absence of Longitudinal Data:** All recordings in this study were cross-sectional, representing a single time-point observation per participant. As a result, the ability of the model to track disease progression or adapt to temporal changes in patient condition could not be evaluated. Incorporating longitudinal data will be essential for assessing the stability of the method over time and for developing systems capable of monitoring treatment outcomes or disease evolution.

Despite these limitations, the outcomes of this pilot study present a strong case for the utility of scalograms in multimodal biomedical signal classification. The integration of attention mechanisms with time-frequency representations offers a promising direction for improving classification accuracy and interpretability. These preliminary findings provide a foundational framework for future investigations.

7.3 Ethical Considerations in the Deployment of BCIs and Assistive Devices

The ethical deployment of Brain-Computer Interfaces (BCIs) and assistive technologies necessitates a comprehensive, multidisciplinary approach encompassing bioethics, data privacy, psychology, engineering, and policy-making. As these technologies directly interact with neural systems, they raise significant ethical concerns that require thorough scrutiny.

Below are key ethical domains that are essential for the responsible implementation of BCI-based systems:

1. **Informed Consent:** A fundamental principle of biomedical ethics is the assurance of informed and voluntary participation in research and the use of technology. This is especially challenging in brain-computer interfaces (BCIs), where end users may experience cognitive, communicative, or psychological impairments. In such cases, it is essential to ensure that participants possess the capacity to provide meaningful consent. Enhanced consent procedures should be implemented to address this, such as using simplified language, providing assisted decision-making tools, and conducting repeated assessments to confirm understanding over time.

2. **Data Privacy, Confidentiality, and Security:** BCIs collect and process neurophysiological signals that can provide insights into a person's thoughts, intentions, and mental health status. The potential for this neural data to be accessed, shared, or misused—intentionally or through data breaches—raises concerns regarding cognitive privacy. Therefore, ethical BCI design must integrate secure data acquisition protocols, end-to-end encryption, anonymization techniques, and stringent access controls.

3. **Equity and Inclusivity:** The progress and implementation of BCIs and assistive technologies predominantly benefit well-funded research environments and populations with access to advanced healthcare systems. This creates disparities in access and equity. Ethical frameworks must promote equitable access, affordability, and inclusive design to ensure these technologies are available to all who may benefit from them.

4. **Safety, Reliability, and Long-Term Impacts:** While generally safer, non-invasive systems also present risks linked to electromagnetic exposure, long-term wearability,

and signal fatigue. Thorough preclinical and clinical testing is crucial to assess these systems' immediate and long-term physiological effects. Furthermore, users should be made aware of uncertainties regarding device longevity, maintenance requirements, and the potential psychological implications of extended BCI use.

5. **User Training, Support, and Post-Deployment Care:** The ethical deployment of assistive devices and BCIs extends beyond their technical design to encompass responsibilities after use. Users often need training to operate these systems effectively, ongoing technical support, and healthcare follow-up. Ethical frameworks should promote a continuum of care that includes maintenance, troubleshooting, device upgrades, and user re-education as interfaces develop.

7.4 Future Work

In the future, the sample size will be expanded; the classification framework will be refined to encompass complex motor tasks and multimodal data will be incorporated to enhance the accuracy and comprehension of neurological and muscular disorders. Furthermore, examining adaptability across various conditions could allow the development of more personalized diagnostic tools, thus advancing neuroprosthetics and motor rehabilitation. The workplan is summarized as follows:

1. To strengthen the validity of the results, future studies will involve larger and more demographically diverse populations, encompassing a wider range of age groups, disease severities, and physiological variations. Expanding the range of conditions studied will help determine the adaptability and scalability of the developed framework.

2. Since aging significantly affects gait dynamics, incorporating elderly participants with normal gait in future research is essential. This would allow the model to learn

the nuances between age-related variations and clinically significant gait deviations, thereby enhancing diagnostic precision.

3. More complex and varied motor tasks—including multi-directional movements and fine motor activities will be explored in subsequent studies to enhance the application scope of the system.

4. Transition from offline classification to real-time applications in clinical settings. Develop and optimize algorithms for real-time processing in assistive technologies, neuroprosthetics, and brain-computer interfaces.

5. Exploring advanced deep learning architectures, such as transformers, and unsupervised or semi-supervised learning to reduce reliance on labeled data.

6. Incorporate additional physiological signals to enhance classification accuracy and develop fusion algorithms to integrate data from multiple sources for a more comprehensive understanding of disorders.