Response to examiner queries.

Examiner 1

Query 1: Are all data recorded locally found suitable, or were some discarded?

Response 1: The data used for EMG and EEG studies was recorded locally at the School of Biomedical Engineering, IIT (BHU), Sir Sunderlal Hospital (BHU), and affiliated local clinics. Only those recordings that met the required signal quality standards and aligned with the study objectives were retained. Data exhibiting excessive noise, motion artifacts, or incomplete recordings were excluded to maintain the integrity and accuracy of the analysis.

Response to Additional Recommendations:

a) The differences in vertical scale observed in the graphs are due to variations in signal amplitude across different clinical cases. These variations are the result of differences in muscle activation and neuronal response associated with underlying medical conditions. For instance, in hemiplegic patients, signal magnitudes tend to be lower due to partial neuronal loss. In contrast, other pathological conditions may exhibit elevated signal amplitudes due to compensatory muscle activity required for movement maintenance.
b) The suggested graphical improvements will be incorporated into the viva voce presentation as per the recommendation.
c) EEG signals are inherently susceptible to noise, commonly originating from motion artifacts, signal crosstalk, and other disturbances. Wavelet transform has been employed to reduce such noise, resulting in enhanced signal clarity. It should be noted that the current study utilized EEG data captured during simple hand opening and closing tasks, and did not include forward or backward hand movement.
d) Confusion matrices illustrating classification performance will be presented during the viva voce.
e) The detailed architecture, including layer sizes of the deep learning models used, will be provided during the viva voce.
f) The configuration and parameters of the attention block, along with the corresponding attention maps, will be discussed and demonstrated during the viva voce.

Examiner 2

Recommendation 1: Language and grammatical inconsistencies.

Response 1: The thesis has undergone a thorough revision to correct grammatical errors and ensure consistency in language. Improvements have been made throughout the document to enhance clarity and readability.

Recommendation 2: Clear distinction between contributions and existing literature in some sections.

Response 2: Extensive research has been conducted in the domain of gait classification, as highlighted in Chapter 2. However, there is a notable gap in the literature regarding the integration of attention-based deep learning techniques with EMG scalogram analysis for this purpose. Only a limited number of studies have explored this specific combination. This thesis addresses that gap by proposing a novel framework that utilizes attention-based neural networks in conjunction with EMG scalograms for improved gait classification performance. A similar research gap exists in the domain of hand movement classification using combined EEG-EMG scalograms, which is also explored in this work. The specific contributions related to these underexplored areas are detailed in Chapters 4 and 5. Additionally, the broader research challenges and existing limitations are thoroughly discussed in the Introduction and elaborated upon throughout the subsequent chapters.

Recommendation 3: Stronger discussion of limitations and comparative benchmarking.

Response 3: The discussion on limitations has been expanded in the revised thesis in section 7.2 of chapter 7. It now includes considerations such as sample size, variability across subjects, generalizability of models, and signal acquisition constraints.

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 applica-bility 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.

Recommendation 4: A note on ethical considerations in the deployment of BCIs and assistive devices.

Response: A dedicated section (Section 7.3) on ethical considerations has been incorporated in Chapter 7. This section discusses key issues surrounding the responsible development and deployment of brain-computer interfaces (BCIs) and assistive technologies. Topics include informed patient consent, data privacy, potential misuse, equitable accessibility, and adherence to biomedical ethics standards.

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 popula-

tions 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.