Abstract

Dementia, particularly Alzheimer's Disease (AD), is a progressive neurological disorder with increasing global prevalence and no known cure. Early detection is crucial but remains challenging, as current diagnostic methods such as neuroimaging, cognitive assessments, and Cerebrospinal Fluid (CSF) analysis are often expensive, time-consuming, invasive, or impractical for routine clinical use. Diagnosis is further complicated by overlapping symptoms across dementia subtypes, frequently leading to misclassification. Importantly, neuropathological changes, such as tau tangles and amyloid plaques, begin in subcortical regions like the hippocampus nearly a decade before the onset of clinical symptoms. This early "clinically silent" stage underscores the urgent need for non-invasive, affordable, and portable tools that can enable routine brain health assessment and early-stage intervention.

To address these challenges, the thesis work proposes a multi-faceted ElectroEncephalography (EEG)-based framework for early diagnosis, dementia subtype classification, disease severity estimation, and treatment response monitoring. The framework leverages both source-domain and sensor-domain EEG analysis during resting-state and Working Memory (WM) tasks to capture functional brain dynamics across cortical and subcortical regions. The feasibility of using moderate-density EEG systems (31-channel) in clinical practice is demonstrated with validation, confirming the reliable detection of memory-related hippocampus activity. Building on this, a subcortical image-based deep learning framework is developed to classify dementia subtypes and progression stages with high accuracy across varying EEG channel densities using a Conventional Convolutional Neural Network (CNN) and novel fusion strategies.

For objective clinical interpretation, a threshold-based biomarker, the Dementia Severity Index (DSI), is introduced using interpretable EEG spectral information. A key strength of the framework lies in its threshold-based formulation, whereby specific feature ranges directly indicate the presence of dementia or its subtype, thus offering clinicians a straightforward diagnostic aid. DSI shows a strong correlation with cognitive assessments such as the Mini-Mental State Examination (MMSE), offering a scalable, quantitative alternative for evaluating cognitive decline. Furthermore, sensor-based computational markers are formulated to sensitively capture dementia-related signal disruptions.

At the sensor-network level, Cross-Plot Transition Entropy (CPTE), a robust and noise-tolerant synchronization measure, is employed that demonstrates superior classification performance in both resting-state and WM tasks compared to existing network methods. In addition, the functional Excitation-to-Inhibition (fE/I) ratio is proposed to quantify temporal complexity differences across dementia stages. The results reveal characteristic disruptions in neural dynamics. The translational potential of the framework is further validated in a pilot intervention study. The EEG-derived fE/I biomarker captures treatment-related improvement through before and after intervention assessments conducted over a three-month course of Ayurvedic (Saraswata Ghrita) therapy. These findings establish EEG as a clinically viable, non-invasive,

and sensitive modality for disease staging and for monitoring therapeutic efficacy across diverse medical contexts.

In summary, the thesis establishes EEG source localization–based analysis as a clinically feasible framework for dementia diagnosis, staging, and therapy monitoring. By integrating source imaging, deep learning, graph networks, and interpretable biomarkers, the work demonstrates the potential of EEG to evolve into a reliable, scalable, and non-invasive tool for clinical dementia research and patient care.