MILD cognitive impairment (MCI) is broadly defined as an intermediate stage of cognitive decline between normal aging and dementia. MCI patients are at higher risk of developing dementia [1, 2]. Nevertheless, not all individuals with MCI will transition to Alzheimer’s disease (AD) and dementia [3, 4]. Identifying biological markers that differentiate MCI from healthy aging is essential for developing preventative interventions, which can enhance quality of life, reduce caregiver burden, and lower the cost of dementia care [5, 6].

To better understand and monitor these cognitive changes, electroencephalogram (EEG) and event-related potential (ERP) have shown significant potential [7, 8]. Compared to the diagnostic biomarkers of AD, like magnetic resonance imaging (MRI) scans, cerebrospinal fluid (CSF), and positron emission tomography (PET) scans, EEG offers several advantages [8, 9]:

1. Cost-Effectiveness: EEG is relatively inexpensive and more accessible than MRI, CSF analysis, or PET scans, making it a practical option for widespread screening.
2. Real-Time Monitoring and Portability: Unlike MRI and PET scans, which provide static images, EEG, specifically using portable EEG devices, with high temporal resolution offers real-time data on brain activity, allowing for dynamic observation of neural processes and changes over time.
3. Non-Invasiveness: EEG, unlike CSF, is a non-invasive technique and does not imply any injections or complex procedures analysis
4. Complementary Insights: EEG can complement MRI, CSF, and PET scans by providing additional information on brain function and connectivity, enhancing the overall diagnostic accuracy for MCI and AD.

This review aims to provide a comprehensive synthesis of recent advancements in the use of EEG and ERP technologies for the detection and classification of MCI. By critically examining signal processing techniques, feature extraction methods, and applications of machine learning and deep learning, this paper aims to highlight the strengths, limitations, and emerging trends in the field. Furthermore, the review seeks to identify gaps in current research and propose future directions, including the integration of EEG and ERP with other neuroimaging modalities and the development of explainable AI approaches to improve the diagnostic accuracy and clinical utility of these non-invasive tools.

In this paper, Section II explores the existing methods and challenges in diagnosing MCI, offering insights into contemporary clinical practices. Section III includes the method part of the paper. Section IV examines the comparative effectiveness of resting-state and task-state EEG approaches in identifying MCI, highlighting their respective advantages and limitations. Section V delves into the advanced signal processing techniques and neural markers derived from EEG data that are instrumental in detecting and understanding MCI. Section VI focuses on the application of machine learning algorithms to classify MCI and validate the effectiveness of these models in distinguishing between different cognitive states. Section VII investigates the role of deep learning (techniques in enhancing the accuracy and depth of MCI detection, presenting novel approaches and future directions for research. Finally, Section VIII focuses on future research directions, including multivariate multiscale entropy analysis, component differentiation, higher-order interactions, causal and explainable deep learning, and multimodal integration of EEG with MRI, functional MRI (fMRI), or functional near-infrared spectroscopy (fNIRS) for MCI.