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Mild Cognitive Impairment detection based on EEG and HRV data

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ABSTRACT

Brain volume decrease is usually connected to neurodegeneration and aging. In this environment, an important percentage of elderly persons suffer from mild cognitive impairment (MCI), a kind of dementia that can lead to Alzheimer's disease (AD). Since the symptoms of cognitive impairment are scarcely discernible, developing a safe and effective method for early MCI detection has emerged as an important challenge. According to this regard, numerous cognitive training tests can be targeted to help aging people retain a good quality of life, especially in the case of fragility disorders. A Consortium to Establish a Registry for Alzheimer's Disease (CERAD) task was initially created to detect the early stages of AD. This task specifically targets various tests related to specific cognitive domains. However, it has since developed into a popular diagnostic tool for many kinds of dementia, such as MCI. Several low-cost equipment, such as electroencephalography (EEG) and heart rate variability (HRV), may be useful for predicting MCI. On the other side, various machine learning (ML) models can be employed to extract/analyse relevant features from biomedical and physiological signals, especially in the context of anomaly detection and classification. To this regard, we developed a new method based on ML models to categorize MCI and healthy control (HC) patients during the CERAD task using EEG and HRV multimodal data. Our dataset includes 15 subjects who were randomly assigned to training and testing groups of 7 HC and 8 MCI, respectively. Our raw EEG and HRV data are analyzed to extract time, frequency, and non-linear features. A scaling step is employed to reduce the significant disparity between features. For the classification task, five ML models are evaluated, including support vector machine (SVM), k-nearest neighbors (KNN), decision tree (DT), random forest (RF), and gradient boosting (GB). To enhance accuracy, a hybrid ML model with a voting system is developed, combining the top ML models with the highest accuracy rates. A comparison step is performed between the use of ML and hybrid ML models. The experimental findings demonstrated the efficacy of our proposed technique, which included a hybrid ML model. An average accuracy of 93.86%, a sensitivity of 93.87%, and a specificity of 93.53% are achieved. The obtained results allow one to conclude that the first CERAD test plays a prominent role as a novel biomarker with an ultra-short duration for early MCI identification through the combination of EEG and HRV signals.

1. Introduction

Memory loss is a common result of aging [1], and if the impairment level rises above what is expected with normal aging [2], it may lead to mild cognitive impairment (MCI). MCI is a condition that occurs between normal aging and dementia [3] and is often associated with Alzheimer's disease (AD), which is the most typical factor in dementia [4, 5]. Approximately 50 million people worldwide are affected by AD, and there is a 54% risk that MCI may progress to AD or other related dementias [6, 7]. However, MCI is not easily detected, and AD can result in billions of dollars in annual costs and a loss of brain health [8]. Early detection of MCI is therefore crucial for improving the treatment of AD and dementia. There are two primary forms of MCI [9]: amnesic MCI (aMCI) and non-amnesic MCI (naMCI). aMCI is characterized by memory loss and is linked to a high probability of progression to AD [10, 11], while naMCI

affects other thinking abilities, such as decision-making and visual perception [12]. Functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and positron emission tomography (PET) are among the main diagnosis tools for MCI [13]. Various studies have proposed multiple learning views and deep learning (DL) techniques for early MCI detection using brain imaging, achieving high classification rates between MCI and healthy control (HC) groups. However, these diagnostic techniques are expensive and not portable.

MCI patients have a greater likelihood of developing non-AD dementias, such as frontotemporal dementia and Lewy body dementia [14]. Thus, distinguishing between these two forms of MCI is critical for accurate diagnosis and appropriate treatment. There have been various attempts to detect and diagnose MCI, including cognitive assessments, imaging techniques, and biomarker tests. However, none of these methods alone can provide a definitive diagnosis of MCI or predict its progression to AD or other dementias. Therefore, researchers are exploring the potential of combining different methods and developing new approaches, such as machine learning (ML) algorithms, to improve the accuracy of MCI detection and diagnosis [15, 16]. In [15], the authors

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propose multiple learning views based on numerous models for MCI diagnosis using MRI images. An accuracy of 87.50% was achieved for MCI and HC classification. A DL technique is presented in [17] for early MCI detection using MRI. For the classification of early MCI and HC, the best classifier has an accuracy of 94.2%. In [18], a transfer learning strategy is suggested for early AD diagnosis using brain imaging. The highest classification rate between AD and HC is 98.73%. Despite the fact that these types of equipment give us multidimensional data about the brain, there are also expensive and not portable techniques. Recently, researchers employed low-cost wearable devices or sensors [19] to detect MCI. Among them, electroencephalography (EEG), a relatively inexpensive method, is being explored to detect various neurological disorders such as epilepsy [20], hypovigilance [21], drowsiness [22], MCI [19], dementia [23], and AD [24]. Furthermore, heart rate variability (HRV) signals can be investigated to detect this cognitive disease [25]. In parallel, there are multiple kinds of AD biomarkers, including those based on blood [26], cerebrospinal fluid (CSF) [27], and neuroimaging [28]. The main drawback of using such biomarkers lies mainly in their cost and invasivity. Physiological data-based biomarkers may hence be very helpful [29, 30]. A variety of EEG biomarkers could therefore be useful in the development of innovative therapies. According to [31], researchers looked into a new EEG biomarker linked to slowing down EEG and decreasing EEG complexity and connectivity based on brainwaves and selected channels. In [32], the authors proposed to use eight selected biomarkers including power spectral density, kurtosis, spectral kurtosis, skewness, spectral skewness, spectral entropy, spectral crest factor, and fractal dimension to classify MCI, dementia, and healthy subjects using a support vector machine (SVM) model. The best achieved accuracy is from 73.4% to 89.8%. A technique for differentiating between subjects with subjective cognitive impairment (SCI), AD, MCI, and additional diseases has been proposed in [33] where accuracy rates of 91.6% are reached. In [34], the authors choose the best configuration of channels using a wearable EEG device for MCI detection based on the ML technique. In [19], only one EEG electrode was used in MCI identification with voice brain reactions. As published in [35], a method based on five EEG electrodes was suggested to classify MCI and HC patients. A novel kernel eigen-relative-power (KERP) feature was extracted from the EEG signals. In [36], a method based on EEG signals during sleep is developed to classify MCI and HC. Spindle features and sleep slow waves are extracted and mixed with spectral and complexity features. Using a SVM model associated with a gated recurrent unit (GRU) network the greatest accuracy reached 93.46%. As developed in [37], nineteen spectral features are generated from each EEG electrode. Using a correlation-based approach, these characteristics are analyzed. K-nearest neighbor (KNN) classifier and the neuro-fuzzy algorithm are used in combination to classify the selected features. In order to identify aMCI using EEG signals, a novel technique is proposed [38] based on spectral

entropy images and convolutional neural networks (CNNs). During rest state, an innovative method [39] was developed to automatically identify MCI patients using EEG data. To efficiently separate MCI patients from HC, three ML techniques including Extreme Learning Machine (ELM), SVM, and KNN were used. In [40], the authors proposed to use a spectral-temporal analysis algorithm to extract features in order to identify MCI patients. An ideal feature subset can be produced using a three-dimensional method. As designed in [41], time and frequency features are extracted from EEG signals using Fourier and wavelet transforms to recognize AD, MCI, and HC classes. Using tree-based supervised methods, the achieved accuracy of MCI vs HC is equal to 92%. In [25], physiological functions such as oxygen saturation, respiratory rate, heart rate (HR), and HRV were collected to classify MCI and HC patients. Using two ML algorithms, gradient boosting decision tree (GBDT) and eXtreme gradient boosting (XGBoost) the highest accuracy was achieved at 84.04%. In [42], a non-invasive solution is proposed based on HRV signals using a wearable CorSense sensor to differentiate between MCI and HC patients. Using a 10-fold cross-validation technique with the logistic regression (LR) model the best accuracy is equal to 76.5%. Recently, the multimodal concept has been used in a number of anomaly detection investigations. In [43, 44, 45], the authors suggested using multimodal DL and ML for early AD detection. Consequently, different types of data can be analyzed based on a multimodality system, providing a good interpretation of each participant's neurological disorders. On the other hand, numerous cognitive tests [46, 47, 48] have been made to help clinicians in making an early MCI diagnosis. According to [49, 50, 51, 52], the most correlated attributes which impacts neuropsychological tests are age, gender, and educational level. These measurements aid neurologists and researchers in keeping track of each patient's mental state. Therefore, we can focus on different cognitive examinations like Neurotrack [53, 54], Consortium to Establish a Registry for Alzheimer's Disease (CERAD) [55, 56], Mini-Mental State Examination (MMSE) [57, 58], Montreal Cognitive Assessment (MoCA) [48, 59], Stroop [60, 61], etc. These measures may be useful in assisting clinicians in identifying MCI early on. To this regard, simple tests and questions are addressed for the participant during the exam to focus on a variety of mental processes. Each test verifies one or more of the requirements, such as the comprehension of place, time, and people. Additionally, each senior participant's speed of concentration, attention, and memory can be evaluated by these tests.

In this study, a data acquisition protocol is made using EEG and HRV signals during the CERAD task. An *Emotiv EPOC X* and *polar H10* devices are used during this experiment to collect both EEG and HRV signals. Time, frequency, and non-linear features are extracted from raw EEG and HRV signals. After that, various ML models are targeted in this work as SVM with a Gaussian kernel, decision tree (DT), random forest (RF), gradient boosting (GR), and KNN algorithms. To improve the accuracy of the used models, we

propose to use a hybrid ML algorithm. Our key contribution in this work is the development of a method for early MCI detection using ML, and this is by jointly analysing EEG and HRV data acquired during CERAD cognitive task. As we can deduce from the results, the first CERAD test is a special biomarker with an ultra-short duration for the early MCI identification via the combination of EEG and HRV signals based on ML techniques.

The rest of this paper is organized as follows. The data acquisition protocol is described in Section 2, while the proposed method is developed in Section 3. Our experimental validation which presents both ML and hybrid ML results is detailed in Section 4. Discussion which include advantages, limitations, and future direction is developed in Section 5. Finally, the conclusion are drawn in Section 6 with some perspectives.

2. Data acquisition protocol

During the data acquisition protocol, a questionnaire of 10 min is done in order to evaluate the general health of each individual. Then, a participant feels more relaxed during 5 min rest period. After that, the record of EEG and HRV signals starts during the CERAD task. The third CERAD test has been ignored due to the difficulty in identifying MCI [62]. Specialists in neurodegenerative diseases have proposed our procedure, which combines cognitive and physiological tests to determine MCI at an initial stage. To simultaneously record EEG and HRV data, the patient is equipped with the *Emotiv EPOC X* and *Polar H10*. Figure 1 illustrates our data acquisition protocol.

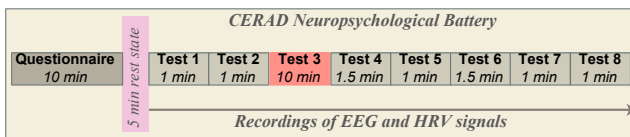


Figure 1: Data acquisition protocol.

2.1. Participants description

This clinical study is approved by a diverse researchers team from Department of Sport Science, German Center for Neurodegenerative Diseases, and Medical Faculty of Otto von Guericke University of Magdeburg. Before starting the experimentation, a questionnaire of 10 min is performed to assess general patient health. In this sense, we can define this assessment as a collection of queries with associated response options. The participant's general health state is therefore established. Sleep quality and physical activity are the most evaluated criteria for each participant. Age, height, weight, education, drinking habits, employment position, body mass index (BMI), smoking (number of cigarettes smoked), and chronic diseases are all included in this questionnaire. Additionally, numerous exclusion and inclusion criteria should be checked for each participant. In this sense, to meet the inclusion criteria, a patient must be between the

Table 1

General description of each participant.

ID	M/F	Age	Group	MCI	Sleep (H)	BMI (kg/m ²)	Education
P3	F	72	HC	--	7	24.1	PT
P5	M	65	MCI	aMCI	8.5	25.2	PT
P7	F	63	HC	--	8	22.9	University
P9	F	65	HC	--	7	24.4	PT
P11	M	79	MCI	naMCI	8	26.4	PS
P12	M	70	MCI	naMCI	8	29.3	University
P14	F	72	MCI	naMCI	9	25.4	TS
P15	M	78	MCI	naMCI	7.5	25.3	University
P19	M	80	MCI	aMCI	8	25.7	TS
P20	F	79	HC	--	8	30.8	University
P22	F	83	HC	naMCI	5	24.7	TS
P23	F	78	MCI	aMCI	8	29.7	University
P24	F	69	HC	--	6	31.2	University
P25	F	64	HC	--	7	25.9	PT
P26	M	70	MCI	aMCI	8	27.1	PS

* M/F = Male/Female, H = hour, PT= Professional Training, PS= Primary School, TS= Technical School.

ages of 50 and 85 and have an MCI diagnosis. Among the exclusion criteria, the participant must not suffer from eye disorders, psychiatric illnesses, orthopedic diseases, muscular disorders, and other neurological diseases. Furthermore, patients must also refrain from consuming caffeine for the preceding 24 hours.

During this study, our data was gathered from 24 participants including 13 MCI (6 aMCI and 7 naMCI) and 11 HC aged from 63 to 83. Based on the collected raw data and the calculated score of the CERAD task 9 participants are excluded. Therefore, this work is limited on only 15 patients. Various other factors should be taken into consideration as BMI, sleep duration, and education level. A general description of each patient is provided in Table 1.

2.2. Neurophysiological modalities

In this study, both EEG and HRV measurements were collected during the CERAD task. Synchronization between these two modalities is ensured for each patient. The EEG and HRV signal data export is not available in an open version. We made the software payment. The following sections detail each of these modalities.

2.2.1. Electroencephalogram

The Emotiv EPOC X EEG headset (by Emotive) is designed to record and analyze brain activity for various applications, including neurofeedback and brain-computer interface, in addition to specific studies. This headset uses several electrodes placed on the scalp, following the international 10-20 system. During this study, we have used this device which involves 14 EEG electrodes including AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, O1, O2, P7, and P8, as well as two references electrodes. The sampling rate of this device is equal to 128 Hz. The software *EmotivPRO* was used for the collection, examination, and storage of brain activity measures (visualization, export raw EEG data,

Table 2

Correlation between brain lobes and specific CERAD test and EEG electrodes.

Brain lobes	CERAD test	EEG channels
Frontal	Test 1	AF3, AF4, F3, F4, F7, and F8
Temporal	Tests 4, 6, 7, 8	T7 and T8
Parietal	Test 3	P7 and P8
Occipital	Test 2 and Test 5	O1 and O2

evaluation metrics, motion sensor data). Yet, particular lobes and brain areas are frequently related to particular cognitive tasks, and anomalies in these regions may help in identifying cognitive impairment [63]. Thus, the frontal lobe controls executive functions like working memory, decision-making, and problem-solving. In this sense, challenges with organizing, planning, and finishing work may be caused by abnormalities in the frontal lobe. Consequently, the first CERAD test which refers to the executive function domain can help in MCI detection based on the frontal lobes with his associated EEG channels (AF3, AF4, F3, F4, F7, and F8). The temporal lobe, on the other hand, is involved in language and memory. Therefore, abnormalities in the temporal lobe may have an impact on episodic memory and can be a factor in language-related problems. With the use of T4, T6, T7, and T8 CERAD tests based on the temporal lobes and specific EEG channels (T7 and T8) can be an efficient marker for MCI prediction. The parietal lobe also plays a role in attention and spatial cognition. Attentional functions and spatial orientation may be impacted by parietal lobe disorders the third CERAD test can be used to identify AD at his early stage using P7 and P8 EEG electrodes. While visual processing is mainly handled by the occipital lobe. Accordingly, abnormalities in the occipital lobe might be a factor in visual-spatial impairments. In this way, MCI can be identified by integrating both T2 and T5 tests of the CERAD task based on the occipital area using O1 and O2 EEG electrodes. The correlation between brain lobes, specific CERAD tests and EEG electrodes is shown in Table 2. We can infer from the previous findings that all brain lobes may be involved in the identification of MCI. In spite of the limited number of EEG channels (14 channels) to collect comprehensive data from deep brain structures, this number of electrodes can yet provide important insights into neural functions related to cognitive activities, including MCI. Depending on the MCI types, we can restrict the area of the brain and the number of EEG channels. Accordingly, MCI may appear in different kinds [64], with the differentiation made between them according to the type of cognitive impairment. Two main types of MCI include amnesic MCI (aMCI) and Non-Amnesic MCI (naMCI). In this sense, the main symptom of aMCI, is memory impairment, while aMCI patients may exhibit obvious memory issues, particularly when trying to remember details or events from the recent past. AD has been shown its antecedent in aMCI. On the other hand, cognitive impairment occurs in naMCI, however, it does not

primarily affect memory. As an alternative, people might have difficulty with cognitive abilities related to language, executive function, attention, and visuospatial skills.

2.2.2. Heart rate variability

During this research, a Polar H10 device is used in order to measure the electrical signals of the HR with a sampling frequency of 10 Hz. This device (by Polar) is commonly used for sports training and fitness technology, to measure heart rate effectively, and to track and analyze HRV. To this regard, HR refers to the amount of time that the heart is pumping per minute. HRV is a term used to describe the variation of the interval between successive HR. The fluctuation in beat-to-beat duration, which is measured in milliseconds, can change depending on a number of circumstances. Additionally, HRV may be used as a non-invasive indicator to monitor a person's physiological status. Therefore, using an HRV device allows us to monitor the HR, HRV, sleep quality as well as stress levels and environmental factors. A number of neurological disorders can therefore be characterized. To keep track of the recorded data, a Polar Flow application is used for HRV data visualization. As collected data correspond to aged subjects, heart rates typically range from 60 to 100 beats per minute [65]. Moreover, the HRV range is lower for aged MCI patients [66]. As presented in Figure 2, the used devices during this experiment include Emotiv EPOC X and polar H10. It is worth noting that a software license was necessary to export raw data.



Figure 2: (a) Emotiv EPOC X, and (b) Polar H10.

2.3. CERAD task

In combination with neurophysiological modalities, several cognitive tests can be helpful in MCI detection. To this regard, individuals who practice a variety of cognitive activities are more determined to keep their cognitive functioning at a higher level and develop less neurocognitive disorders. In this sense, we have used a cognitive CERAD task which is established by the National Institute on Aging in 1986 in order to create standard and validated measures for evaluating AD [67]. The several CERAD tests related to its cognitive domains and duration are presented in Table 3. The CERAD task is a short and comprehensive battery of standardized exams used to assess basically cognitive impairments in AD [68]. It may be a useful technique to distinguish between MCI, dementia, and normal cognitive aging [69]. A maximum total score of 100 points [70] was obtained by adding the results of all CERAD subscores, excluding the third test.

Table 3
Description of each CERAD tests.

Test	Cognitive domains	Duration
T1: Verbal fluency	Executive function	1 min
T2: Boston naming test	Visual perception	1 min
T3: Mini-Mental Status (MMS)	Orientation, repetition, attention	5-10 min
T4: Word list learning	Short and long-term memory	4.5 min
T5: Sign-off figures	Visuo-construction	1 min
T6: Retrieve Word List	Verbal episodic memory	1.5 min
T7: Word List Recognition	Verbal episodic memory	1 min
T8: Retrieve Figures	Non-verbal episodic memory (recall)	1 min

In this sense, this excluding test (i.e., T3: MMSE) is effective for AD detection [30, 71]. According to [55], the authors combined all CERAD tests while ignoring the MMSE test, as it is not particularly successful in detecting MCI. Each test targets a distinct cognitive domain. For instance, the verbal fluency test (T1) focuses on evaluating episodic memory by giving the subject a list of 10 common words and asking them to recall the words. Furthermore, evaluating constructional and visuospatial skills is the aim of boston naming test (T2). The procedure of this test is to involve copying geometric designs. Moreover, word list learning test (T4) is used to gauge how long it takes for participants to recall words from the word list memory test. However, this method is based on asking the person to repeat the words after a delay. In addition to that, the purpose of sign-off figures test (T5) is to assess language and identification skills by involving naming objects depicted in pictures. Retrieve word test (T6) ensures the assessment of processing speed, visual attention, and executive function. Likewise, the goal of word list recognition test (T7) is to assess semantic or category fluency by the production of words that fall into a particular category in a predetermined amount of time. The goal of the last CERAD test is to evaluate if the candidate recognise words that have already been given. The methodology of this test is to give the subject a list of words, some of which are from the original word list memory test. After that, subjects are asked to mark the words they can still recall.

3. Proposed method for physiological data analysis

Based on our data acquisition protocol, we focus on EEG and HRV data analysis during CERAD task. Figure 3 presents the pipeline of the proposed method. The input signals are both EEG and HRV which are divided into segments. A panel of temporal, frequency and non-linear features are extracted. A features fusion step is then applied. The next phase is the preprocessing process which involves

feature scaling and reduction. The process ends with a classification of MCI and HC using both five ML and hybrid ML models. Accordingly, the first CERAD test is considered as our novel biomarker with a relatively short duration for the early diagnosis of MCI using the combination of EEG and HRV data.

3.1. Feature extraction

Feature extraction attempts to summarize the main information in the raw data. The following sections present a detailed description of the used features for EEG and HRV signals.

3.1.1. EEG features

Features in time and frequency domains are extracted for EEG data.

1. **Time domain:** Statistical features like *mean*, *median*, *variance*, *skewness*, *kurtosis* are extracted. Additionally, we use Hjorth parameters that provide a simple and computationally efficient way to extract key characteristics of EEG signals. Mobility, activity, and complexity [72] are the first three derivatives of the signal and the most-used Hjorth parameters.

- *Coefficient of variation (CV)*: helps to measure the degree of consistency and uniformity in the distribution of a data sets. It is also called the relative standard deviation (RSD). It helps determining if the data standard deviation (SD) is small or large with respect to the mean.

$$CV = (SD/Mean) * 100, \quad (1)$$

with

$$SD = \sqrt{\frac{\sum_{i=1}^n (x - \bar{x})^2}{N - 1}}, \quad (2)$$

where $x \in \mathbb{R}^N$ is the input signal and \bar{x} is the empirical mean.

- *Hjorth* parameters are indicators of statistical properties, introduced by Bo Hjorth in 1970 [73]. The parameters are activity, mobility, and complexity [74]. They are commonly used in the analysis of EEG signals [75]. One of the advantages of using Hjorth parameters is that their calculation involves variance, making the cost of their computation very low. These parameters are therefore mainly useful for real-time tasks. The different Hjorth activity, mobility and complexity equations are developed below.
 - *Hjorth activity (H activity)* is the total power of the signal. It represents the variance of a time function:

$$H\ activity = var(x(t)). \quad (3)$$

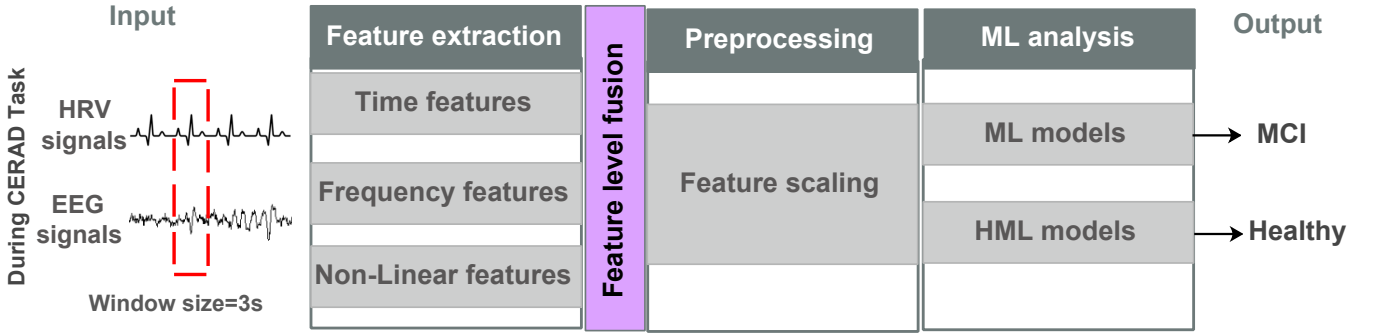


Figure 3: Pipeline of the proposed method.

- *Hjorth mobility (H mobility)* is proportional to the SD of the power spectrum:

$$Hmobility = \sqrt{\frac{Hactivity(x'(t))}{Hactivity(x(t))}}. \quad (4)$$

- *Hjorth complexity (H complexity)* gives an estimate of the bandwidth of the signal:

$$Hcomplexity = \frac{Hmobility(x'(t))}{Hmobility(x(t))}. \quad (5)$$

where $x(t)$ is the input signal and $x'(t)$ is the first derivative of $x(t)$.

- *Skewness* is the characteristic parameter to attribute asymmetry degree of probability density curve with respect to the mean. Positive skewness indicates that an EEG signal data set is distributed more to the left of the mean point:

$$Skewness = \frac{1}{n} \frac{\sum_{i=1}^n (x - \bar{x})^3}{SD^3}. \quad (6)$$

- *Kurtosis* is a statistical metric used to characterize the form of a probability distribution, especially its tailedness. This feature can be used to describe the distribution of the EEG amplitudes, providing information about the peakedness of the amplitude distribution.

$$Kurtosis = \frac{1}{n} \frac{\sum_{i=1}^n (x - \bar{x})^4}{SD^4}. \quad (7)$$

2. **Frequency domain:** The power spectral density (PSD) of the signal is used as the basis for calculating the frequency domain features. It can be calculated with several parametric and nonparametric methods [76]. Non-parametric methods are used more often and include methods like *Fourier transform* and *Welch's* method. Autoregressive (AR), multivariate autoregressive models or autoregressive-moving average models are a few examples of parametric techniques for PSD estimation [77].

- *Brain waves* are often linked to specific states of the brain. Various features such as *delta*, *theta*, *alpha*, *beta*, *delta/theta*, *delta/alpha*, *theta/alpha*, and *(delta+ theta)/alpha* are extracted from our EEG signals [78].
- *Autoregression* estimates the PSD of an input window. This method fits an AR model to the signal by minimizing the forward and backward prediction errors. The order of this algorithm is calculated as the half number of the input data.

3.1.2. HRV features

In this work, both temporal and non-linear features have been used for HRV signals. A description of the different used features is developed in the following.

1) Time domain:

- *Mean Normal to Normal (NN) intervals* presents the interval between two heartbeats.
- *SDNN* is the standard deviation between successive normal heartbeats of the time interval.
- *SDDSD* is the standard deviation of differences between adjacent NN intervals.
- *MSSD* presents the mean squared successive difference.
- *MEDIAN NN* presents the median absolute values of the successive differences between the NN intervals.
- *CVSD* is the coefficient of variation of successive differences equal to the Root Mean Square of the Successive Differences (RMSSD) divided by the mean NN intervals.
- *CVNNI* is a statistical metric used to evaluate the variability of normal to normal intervals (nni). It is determined as the ratio of the standard deviation divided by the mean_nni and multiplied by 100, where mean_nni stands for the average of normal-to-normal characteristic of HRV signals, which describes the time intervals between consecutive normal heartbeats.

- *Mean HR* presents the mean of HR.
- *STD HR* presents the standard deviation of HR.

2) Non-linear domain: Poincaré plot features are the most used non-linear features [79, 80]. This geometrical and non-linear method assesses the dynamics of HRV. It presents a diagram in which each R-R interval is plotted as a function of the previous R-R interval. The values of each pair of successive R-R intervals define a point in the plot. On the Poincaré plot, SD1 is the width, and SD2 is the length of the ellipse:

- *SD1* is the means of the standard deviation of the Poincaré plot perpendicular to the line of identity.
- *SD2* represents the standard deviation of the Poincaré plot along the line of identity.

3.2. Features preprocessing

To reduce the possible influence of significantly different feature ranges on the learning process, a preprocessing step is essential. Features having larger numerical ranges may significantly affect the learning process in lack of normalization or scaling, affecting the model results. We guarantee that every feature contributes equally to the learning algorithm by standardizing the features. Regardless of the original numerical ranges of each feature, the scaling step promotes a more equitable and efficient learning process, improving the capacity of the model to identify patterns and generate precise predictions. In this sense, a standardization phase is applied to the input features. A Z-score method was used, allowing to center the values around the mean:

$$Z_{score} = \frac{v - \mu}{\sigma}, \quad (8)$$

where v presents the input value, μ the mean of features, and σ is the features standard deviation.

3.3. Proposed classification model

In this work, various ML models [81, 82] including SVM with Gaussian kernel, DT, RF, GB, and KNN are used to classify MCI and HC participants. These supervised models have been employed in a number of similar anomaly detection and classification tasks as AD [83] and MCI [84]. SVM with a Gaussian kernel is commonly used for non-linear problems [85]. The kernel has two configurable parameters: γ , which determines the kernel width, and C , which controls the model's tolerance for learning misclassification. When a DT model is used, the classification between MCI and HC participants is done based on each leaf node [86]. As regards KNN, one first needs to fix the number of neighbors to consider, and then classification can be performed. For RF and GB classifiers [87, 88] an ensemble learning approach is employed [89] using our input features based on the average prediction of numerous DT algorithms to classify MCI and HC patients. Ensemble and hybrid models have garnered significant interest from researchers as they have been shown

to outperform single-weak learners in classification problems. Ensemble models combine several algorithms to produce more accurate predictions [90], while hybrid models integrate two or more ML methods [91]. In this regard, numerous ML hybridized classification algorithms that employ optimization methodologies have been proposed to improve and enhance the classification process [92]. In this paper, we propose to use both EEG and HRV modalities to extract significant time, frequency, and non-linear features in order to detect MCI. After that, a preprocessing step is done based on feature scaling. A hybrid ML model is then used to classify MCI and HC elderly participants. In this sense, the used hybrid ML model includes the following classifiers: SVM with a Gaussian kernel ($\gamma = 0.01$ and $C = 10$), GB, and RF. Initially, classifiers are created to append these three models. The prediction of MCI and HC individuals is then performed for each estimation using a hard voting (majority voting) step. The used features, based on EEG and HRV fusion, in relation to the first CERAD test, is claimed as a new biomarker for MCI detection. Figure 4 illustrates the main steps of the proposed model, where the training data go through the three classifiers during the training phase. The individual predictions are then used as input to the voting system, which provides the final classification.

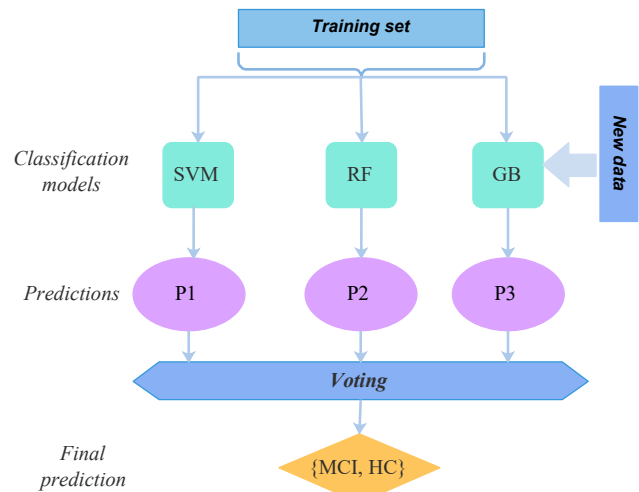


Figure 4: Flowchart of the proposed hybrid ML method for MCI classification.

4. Experimental validation

This section includes three experiments: two of them focus on unimodal classification with EEG and HRV respectively, while the third one proceeds by features fusion to investigate the effectiveness of bimodal classification.

4.1. Setup

Our purpose is to extract a new marker and ultra-short (3, 6, and 9s) duration based on the use of each CERAD task. For each test, we separated our data into 75% for the training set and 25% for the testing set. To boost the

effectiveness of ML model accuracy and to reduce the rate of overfitting, we applied the shuffling strategy throughout the data partitioning process. Various metrics such as accuracy (Acc), precision (Pre), sensitivity (Sen), specificity (Spec), and F1-score (F1-S) are used for numerical validation:

$$Acc = (TP + TN)/(TP + TN + FP + FN), \quad (9)$$

$$Pre = TP/(TP + FP), \quad (10)$$

$$Sen = TP/(TP + FN), \quad (11)$$

$$Spec = TN/(TN + FP), \quad (12)$$

$$F1 - S = (2 * Pre * Sen)/(Pre + Sen), \quad (13)$$

where TP, TN, FP, and FN stand respectively for true positive, true negative, false positive, and false negative values. Furthermore, we used the receiver operating characteristic (ROC) curve as a criteria for evaluation metrics. Two parameters are plotted on this curve: the True Positive Rate (TPR) which presents the sensitivity, and the False Positives rate (FPR) which presents the specificity. The Area Under the ROC Curve (AUC) is an indicator of classification performance presented at different threshold levels. In this sense, higher AUC values indicate more accurate model predictions, while lower AUC values indicate inaccurate model predictions.

4.2. Unimodal classification

To determine the best window duration, various time intervals such as 3s, 6s, and 9s are tested using EEG and HRV signals. In this context, the above-mentioned ML algorithms are compared: SVM, DT, RF, GB, and KNN. Table 4 presents the comparison of the average classification accuracy using data acquired for all CERAD tests using static time segment without overlap. According to the findings, the best time window corresponds to the lowest duration (i.e., 3s) for both EEG and HRV signals. The highest accuracy obtained for the EEG signals is 91.05%, while the highest result for the HRV is 74.10%. These best performances are obtained with the KNN algorithm with $k = 5$ neighbors. At this level, one can conclude that EEG data is more informative for MCI detection than HRV. However, our goal is to make both modalities collaborate to reach better classification performance. The detailed results of each test with a 3s time interval using the EEG and HRV signals are presented in Table 5. This table provides accuracy scores for all tests, using the same ML classifiers for independent EEG and HRV data analysis. The best average (over all tests) results are obtained by the KNN algorithm with $k=$

Table 4

Comparison of the average accuracy for all CERAD tests based on ML models during different window durations using EEG and HRV signals.

Mod.	Time	SVM	DT	RF	GB	KNN		
						k=1	k=3	k=5
Accuracy (%)								
EEG	3s	89.36	75.45	87.06	84.79	89.55	90.91	91.05
	6s	80.53	68.93	83.88	82.37	77.90	79.34	77.83
	9s	85.15	73.44	85.07	78.25	85.64	82.91	81.31
HRV	3s	73.11	72.43	72.51	73.55	70.05	72.30	74.10
	6s	64.49	70.22	73.33	69.57	66.42	65.18	63.91
	9s	66.73	62.63	65.00	67.17	67.17	63.34	63.07

Mod.= Modality.

5 for both EEG and HRV signals. To increase classification accuracy, a multimodal technique is proposed. To this regard, we suggest a features-level fusion method for these modalities. The outcomes of this experiment are described in the following subsection.

4.3. Multimodal classification

Multimodal classification is a promising strategy that uses several and complementary sources of data with ML techniques to enhance the precision and reliability of the target task (e.g. classification). In the same line, hybrid ML systems can leverage the advantages of using conventional ML techniques. The outcomes of applying both ML and hybrid ML classifiers are shown in the sections below.

4.3.1. ML classifiers results

By combining the EEG and HRV features, fusion was accomplished as follows. Table 6 presents the experimental results obtained for the different CERAD tests. For each test, accuracy scores are provided for the 5 used classifiers. The best average accuracy results are taken by the GB algorithm with **92.15%** followed by respectively SVM with **91.43%** and RF with **90.93%**. These findings lead to different conclusions in Section 4.2 where the two modalities were analysed separately, and where the KNN model outperformed the others. In this sense, using EEG and HRV fusion together yields better results than using each modality alone as presented respectively in Table 5 and Table 6. As a result, KNN scored better for unimodal classification than the other employed algorithms, demonstrating its ability to find specific local patterns in the features that were used. It was more advantageous to adapt to the complexity of the data for our specific dataset and problem attributes. Indeed, individual ML classifiers may lead to slightly different results for such a specific dataset due to the properties of the classifier and its ability to learn local/global patterns, as well as its vulnerability to overfit. Based on the previous results, we propose a hybrid ML approach to enhance the efficiency and precision of the suggested methods with stable performance.

Table 5
ML algorithms results using EEG and HRV signals for 3s duration.

Test	Mod.	SVM	DT	RF	GB	KNN		
						k=1	k=3	k=5
T1	EEG	85.33%	73.33%	84.00%	89.33%	90.66%	94.66%	90.66%
	HRV	68.42%	69.73%	73.68%	72.36%	69.73%	65.78%	65.78%
T2	EEG	91.13%	86.07%	91.13%	87.34%	91.13%	88.60%	94.93%
	HRV	79.01%	77.77%	77.77%	83.95%	72.84%	80.24%	80.24%
T4	EEG	90.66%	65.33%	81.33%	82.66%	89.33%	90.66%	90.66%
	HRV	78.16%	78.16%	77.58%	75.86%	75.86%	79.31%	77.58%
T5	EEG	90.66%	72.00%	92.00%	81.33%	90.66%	86.66%	89.33%
	HRV	61.53%	62.50%	58.65%	62.50%	59.61%	59.61%	61.53%
T6	EEG	94.59%	82.43%	90.54%	86.48%	93.24%	94.59%	94.59%
	HRV	76.13%	72.72%	72.72%	75.36%	70.45%	73.86%	79.54%
T7	EEG	90.54%	75.67%	86.48%	83.78%	89.18%	90.54%	90.54%
	HRV	76.13%	72.72%	72.72%	69.31%	70.45%	73.86%	79.54%
T8	EEG	82.66%	73.33%	84.00%	82.66%	82.66%	90.66%	86.66%
	HRV	72.44%	73.47%	74.49%	75.51%	71.42%	73.47%	74.49%
Avg	EEG	89.36%	75.45%	87.06%	84.79%	89.55%	90.91%	91.05%
	HRV	73.11%	72.43%	72.51%	73.55%	70.05%	72.30%	74.10%

Avg= Average.

Table 6
ML algorithms results based on EEG and HRV fusion.

Test	SVM	DT	RF	GB	KNN		
					k=1	k=3	k=5
Accuracy (%)							
T1	96.05	78.94	89.47	93.42	90.78	88.15	84.21
T2	87.34	87.34	89.87	92.40	83.54	82.27	79.74
T4	95.29	90.58	95.29	95.29	94.11	94.11	92.94
T5	92.94	83.52	91.76	92.94	80.00	85.88	84.70
T6	91.30	92.75	91.30	95.65	78.26	84.05	82.60
T7	90.47	88.09	91.66	91.66	84.52	86.90	88.09
T8	86.04	76.74	87.20	83.72	79.06	83.72	84.88
Average	91.34	85.42	90.93	92.15	84.32	86.44	85.30

Table 7
Hybrid ML algorithm results based on EEG and HRV fusion.

Test	Acc.	F1-S	Sens.	Spec.	Pre.
T1	97.43%	97.74%	97.71%	97.77%	97.72%
T2	95.88%	95.80%	97.14%	94.63%	93.95%
T4	96.20%	96.65%	95.42%	95.42%	97.92%
T5	95.10%	95.76%	95.67%	95.67%	95.86%
T6	95.59%	95.59%	97.05%	97.08%	94.18%
T7	90.63%	91.45%	91.53%	91.54%	91.36%
T8	86.19%	87.64%	82.60%	82.60%	93.35%
AVG	93.86%	94.37%	93.87%	93.53%	94.90%

AVG= Average

4.3.2. Hybrid ML results

Our hybrid ML model combines the best findings of these three models: SVM, GB, and RF. To identify MCI and HC participants, a voting step is performed after training all models on the same data. Evaluation metrics as accuracy, F1 score, sensitivity, specificity, and precision, are summarized in Table 7. Notably, an impressive enhancement in average accuracy of all tests, reaching 93.86%, is observed. This confirms the usefulness of the performed data fusion at the features level. In light of the previous findings, the first test called "Verbal fluency" related to the executive function had the highest accuracy (97.43%). However, this test is not the most sensitive and specific one. Indeed, an excellent F1-score is obtained for T4 (i.e: word list learning related to short and long-term memory) which demonstrates a good ability to identify MCI patients as positive. On the other hand, a high specificity is noted for T6 (i.e: retrieve word list related to verbal episodic memory) which refers to the true capacity to label HC patients. In this way, we can conclude that MCI can be identified based on the integration of

verbal episodic memory, executive function, and short-long-term memory. Based on the first test, Figure 5 presents the confusion matrix results using the hybrid ML model. where the corresponding TP and TN classified sets are 34 and 39. While the ROC curve is shown in Figure 6, displaying

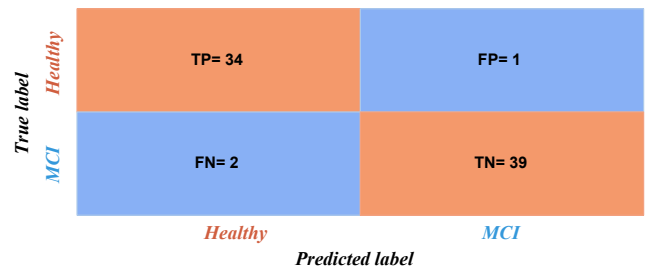


Figure 5: Confusion matrix of Test 1 using a hybrid ML model.

a higher AUC value of 94.91%. It illustrates the capacity for discrimination of the architecture. The results show that our model can effectively distinguish between MCI and HC

classes with a high degree of predictive accuracy, making it suitable for classification tasks. To further investigate

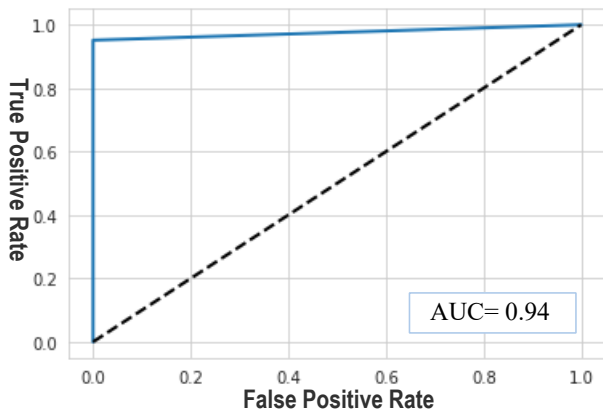


Figure 6: ROC curves of the hybrid ML model.

the performance reproducibility of our model, two cross-validation methods are used, including k-fold and leave-one-out over 100 runs. K-fold cross-validation proceeds by splitting the dataset into k smaller folds. In this work, we fixed the k to 10. Using distinct folds for testing and training, the model is trained and evaluated k times. The average of the measurements from each iteration generates the final performance metric. As regards leave-one-out cross-validation (LOOCV) method, the model is evaluated on an instance that was left out following the training on all other instances. This process is repeated for each instance achieving n iterations for a dataset with n samples. Despite being computationally costly, this method is generally used for small datasets. Table 8 reports the average and the standard deviation (STD) accuracy values obtained using k-fold and LOOCV over 100 runs. We can infer from these outcomes that the reported STDs indicate moderate variability across runs. As a result, the performance of our model appears to be consistent and stable according to the close values between k-fold and LOOCV. Additionally, T1 demonstrates the best test results for both k-fold and LOOCV with respectively 95.23% and 96.14% compared to the other tests. With an extremely short processing time, our model performs successfully, making it possible to identify MCI using the CERAD test quickly and accurately. As a result, k-fold cross-validation executes faster than LOOCV, which usually takes a few minutes compared to a few seconds. The performance of our used approach guarantees the diagnostic process for early detection of cognitive decline for elderly peoples.

4.4. Comparison

To evaluate the efficiency of our method, we compare it with some existing close methods in the literature. In [93], the authors developed an novel ML algorithm using EEG, eye tracking, and neuropsychological evaluations to distinguish MCI from HC. To remove external noises, two filters were applied to raw EEG data. Frequency domain features are extracted from EEG signals. The feature selection step

Table 8
k-fold and leave-one-out cross-validation accuracy values.

Test	k-fold	Leave-one-out
T1	95.23% \pm 0.034	96.14% \pm 0.166
T2	93.40% \pm 0.046	94.40% \pm 0.229
T4	94.60% \pm 0.026	95.76% \pm 0.176
T5	93.01% \pm 0.047	93.52% \pm 0.246
T6	94.60% \pm 0.039	94.35% \pm 0.187
T7	90.37% \pm 0.052	90.34% \pm 0.281
T8	86.03% \pm 0.052	86.02% \pm 0.250

was done using a Minimum Redundancy-Maximum Relevance (MRMR) algorithm. Using the SVM model and various kernel functions, a classification step is carried out. The best accuracy of $84.5 \pm 4.34\%$ is achieved by using the SVM with a Gaussian kernel with $C=1.1$ and $\gamma=0.001$. Other related work [94], presents multi-modal features based on ML models for categorizing EEG records for dementia. This study aims to distinguish HC from MCI and AD patients. Time-frequency and non-linear features are extracted from EEG signals. In this sense, a Continuous Wavelet Transform (CWT) is used to calculate the extracted time-frequency features. Non-linear features are extracted from the bispectrum (BiS) representation. The greatest accuracy of $91.80 \pm 0.9\%$ is delivered for MCI and HC classification using the Multilayer Perceptron (MLP) algorithm. According to [32], the authors proposed to extract eight EEG biomarkers recorded from 44 participants. Continuous performance test (CPT) and finger tapping test (FTT) were involved to assess sustained attention and motor speed. To select the best markers, a feature selection step is done. The classifier output contains three states, including dementia, MCI, and HC, based on the SVM classifier. The achieved accuracy ranges from 73.4% to 89.8%. Using data collected from 169 patients under clinical conditions, an automated EEG diagnosis is carried out [33]. To distinguish between individuals with SCI, MCI, AD, and patients with other pathologies, a polynomial SVM classifier is employed. A pair of EEG features are employed to effectively differentiate between these categories. A classification accuracy of 91.6% was obtained while distinguishing between these different groups. With our dataset, we put these methods into practice. For each CERAD test, the comparison between our suggested method and these works is shown in Table 9. The best average accuracy of 93.86% was obtained using our suggested method. The comparison findings obtained with the first CERAD test are presented in Table 10. Based on the above results, we can assume that our proposed approach gives us the best results with the highest accuracy of 97.43% given by the first CERAD test. As a result, a new marker for early MCI identification could be a verbal fluency test related to executive function.

Table 9

Performance comparison for each CERAD test using state of the art methods.

Test	C. Ieracitano et al. [94]	J. Jiang et al. [93]	N. Sharma et al. [32]	N. Houmani et al. [33]	Proposed method
T1	96.47%	89.41%	84.21%	92.10%	97.43%
T2	86.27%	80.95%	79.74%	75.94%	95.88%
T4	90.19%	85.88%	87.05%	85.88%	96.20%
T5	84.31%	91.66%	84.70%	78.82%	95.10%
T6	94.11%	91.76%	85.50%	82.60%	95.59%
T7	90.19%	89.28%	90.47%	90.47%	90.63%
T8	69.23%	84.88%	77.90%	84.88%	86.19%
Avg	87.25%	87.68%	84.22%	84.38%	93.86%

Table 10

Comparison with existing works for the best accuracy test.

Proposed approach	Best ACC	Classification method
C. Ieracitano et al. [94]	96.47%	MLP
J. Jiang et al. [93]	91.76%	SVM RBF
Sharma et al. [32]	89.8%	Gaussian SVM
N. Houmani et al. [33]	91.6%	Polynomial SVM
Proposed method	97.43%	Hybrid ML

5. Discussion

The present section includes three main parts: advantages, limitations, and future directions.

5.1. Advantages

Despite some limitations, EEG is still a useful and efficient tool in clinical research and cognitive neuroscience. The importance of EEG in early MCI identification is also being confirmed. The sensitivity and specificity of EEG-based techniques for the early diagnosis of cognitive impairment continues to be investigated by researchers as an inexpensive and non-invasive neuroimaging modality. Thanks to its high temporal resolution, researchers can monitor brain activity with millisecond precision. In light of this, it is an ideal tool to record rapid alterations in brain activity connected with cognitive functions. Furthermore, brain activity monitoring is offered in real-time, allowing the observation of dynamic shifts in cognitive processes. Investigating cognitive processes and identifying early indicators of impairment can benefit from this. Moreover, alteration in neural oscillations (alpha, beta, theta, and delta) rhythms is associated with cognitive impairment. On the other hand, HRV signals is responsible for the autonomic nervous system based on the balance between sympathetic and parasympathetic branches. HRV is a possible diagnostic for early-stage detection since alterations in autonomic control may occur before cognitive decline. To prevent MCI at its earliest stage, the previously mentioned benefits are combined to create an effective solution based on EEG and HRV fusion during the CERAD cognitive test employing a variety of ML techniques. A robust, stable and efficient hybrid ML model is proposed and validated.

5.2. Limitations

The primary constraint of our work is the usage of a limited database. On the other hand, using a limited number of electrodes for EEG data recording may be considered as a limitation, even if using more sophisticated headsets may interfere with patients comfort and concentration. On the other hand, despite EEG signals can offer significant details about brain activity, its poor spatial resolution may be raised as a limitation. It may ignore important crucial information from the deepest brain regions like the hippocampus, which is relevant in MCI and AD identification. As regards the ML model, and since it is relying on a voting system, a lack of consensus between weak classifiers may lead to performance decrease. Even if this effect has not been observed in our experimental setting, testing on larger databases may be helpful to better characterize the proposed model.

5.3. Future directions

Future research will focus on using additional cognitive tasks and integrating other physiological, postural, and video data to identify MCI. Additionally, a deeper knowledge of brain anatomy and activity can be obtained by combining EEG with other neuroimaging modalities, such as structural Magnetic Resonance Imaging (MRI). Also we can integrate postural stability in our upcoming projects using smart balance master system. To this respect, multimodal approaches are frequently required for a more precise assessment of MCI. Furthermore, various DL techniques can be targeted in our future work in order to increase the accuracy findings, although explainability of such models is more difficult to assess.

Finally, as stated hereabove, validations on larger datasets with additional experimentation on volunteers will be considered.

6. Conclusion

Assuming that the symptoms of cognitive deterioration are hardly perceptible, developing a reliable approach for identifying MCI earlier has become a major issue. Therefore, early recognition of this neurodegenerative disease can help clinicians better understand the patient's situation. In this work, a CERAD task is used to evaluate the general mental health of each participant. This task includes 8 tests that are

related to specific cognitive domains. This study's objective was to create a multimodal approach that utilizes both EEG and HRV signals to identify MCI during this cognitive task. The approach consisted of several steps, including extracting significant features from the signals and standardizing them, followed a dimension reduction step. Different ML models were then utilized to classify patients as either HC or MCI. Finally, the best-performing models were combined into a hybrid ML model. The results were highly effective, achieving a maximum accuracy of 97.43% during the first CERAD task, which indicates that this method can be used as an early indicator of MCI. The results demonstrate a correlation between three tests related to executive function (T1), short and long-term memory (T4), and verbal episodic memory (T6). The highest accuracy is achieved by the use of an ultra-short duration based on the first CERAD test, which can be a new marker for MCI identification.

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