Enhanced Alzheimer's disease and Frontotemporal Dementia EEG Detection: Combining lightGBM Gradient Boosting with Complexity Features

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***Abstract*—Alzheimer's disease and Frontotemporal dementia are the two most reported dementia cases. They both are neurodegenerative disorders without cure while existing treatments only halt their progress. Thus, early detection is of crucial importance. In this work, we utilize electroencephalographic signals of AD and FTD patients and propose a classification pipeline to distinguish them from healthy signals. This pipeline consists of Independent Component Analysis as a preprocessing stage, the extraction of time, frequency and complexity features, feature elimination through importance ranking and finally classification through utilizing Gradient Boosting Decision Trees. The proposed methodology achieved 92.27% F1 score in the Dementia versus Control problem, 83.06% in the AD versus Control and 80.67% in the FTD versus Control.**

Keywords*—EEG, Alzheimer's Disease, Frontotemporal dementia, lightGBM, Classification

I. Introduction

Dementia is a wide group of neurodegenerative brain disorders that leads to cognitive impairment and interferes with social and occupational functioning [1]. The occurrence of dementia increases in frequency with age and its treatment is based on therapies that slow the progress of the illness or manage symptoms. Alzheimer's disease (AD) is the most common type of dementia and it involves severe memory loss, cognitive impairment and changes in behavioral changes [2]. Another common type of dementia is the Frontotemporal (FTD), which causes focal degeneration in the frontal lobe, anterior temporal lobe and islet.

Despite Alzheimer's disease severity of impact, its diagnosis typically occurs after the patient has already started developing symptoms. Brooker et al. report that memory clinic facilities availability covers only 50% of the EU population, while only 43% of countries reported having specific policies to accommodate the diagnosis at an earlier stage [3]. Usually, dementia diagnosis procedures involve the detection of multiple concurrent symptoms along with cognitive ability assessment of patients through questionnaires and tests. Other methods of detecting AD and cases of dementia involve the employment of neurophysiological data and neuroimaging techniques. The most common imaging methods utilized are the Magnetic Resonance Imaging (MRI) and single-photon emission tomography (SPET). Although such methods are not commonly employed by clinics, there is strong evidence that they can contribute significantly for accurate and early diagnosis as well as prediction of dementia onset.

EEG is yet another tool that is utilized for the discrimination of dementia. Automated EEG diagnosis is under scientific exploration over the past 2 decades with increasing interest mainly because it is a non-invasive tool that has good temporal resolution and is sensitive enough for the classification of dementia severity [4]. Additionally, its low cost, consumer availability and the fact that it is faster than other neuroimaging techniques makes its use especially desirable in the medical field.

Many Alzheimer studies through EEG focus on the frequency changes of signals. Power increase in low frequency bands delta and theta along with decrease in alpha and beta -EEG slowing- is considered an Alzheimer or other dementia indicator [5]. Additionally, in the recent years complexity features such as entropy and fractal dimensions have gained interest as they reflect and incorporate better the high complex dynamics of the brain while being greatly influenced by functional changes in the brain of dementia patients [5].

Moreover, a wide variety of supervised machine learning algorithms have been employed [6] for the detection of AD and FTD, as well as their discrimination. Most methodologies use ensemble methods like Random Forest [7] or Support Vector Machines (SVM) [8]. Recently, deep learning methods such as Recursive Neural Networks and Transformers Neural Networks [9] or Gradient Boosting methods such as XGBoost [10] and lightGBM [11] have gained popularity due to the increase of the computational power of current processing units.

This paper proposes a methodology that utilizes the Independent Component Analysis (ICA) for the signal clearing and combines the reliability of time and frequency domain features with the capabilities of the complexity features. Also, the lightGBM is hired, which is a Gradient Boosting Decision Tree (GBDT) algorithm. The hyperparameters of this algorithm are optimized via a

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Bayesian optimization with Gaussian processes. The feature vector of this classification pipeline is reduced using a feature importance ranking acquired from a non-optimized lightGBM classifier. The performance of this analysis is evaluated through the Leave One Patient Out (LOPO) validation method that ensures that there is no bias towards the classification results that could occur due to the simultaneous existence of the same participant data time windows in both the training and the test set.

II. Materials and Methods

The proposed methodology is described in this section. This methodology is consisted of the data acquisition procedure, the preprocessing routine, the feature extraction process, and the machine learning stage. A summary of the whole methodology can be found in Fig 1.

A. Database Description and Data Acquisition

The participant's pool for this study consisted of 32 subjects: 14 patients that were affected by Alzheimer's disease (8 male and 6 female), 10 patients that were affected by Frontotemporal dementia (6 male and 4 female) as well as 8 healthy subjects that comprised the Control group (CN) (4 male and 4 female). The patients were classified as Alzheimer (AD) or Frontotemporal (FTD) according to the World Health Organization Standard. The Mini Mental State Examination (MMSE) score has been used as a descriptor for the evaluation of the cognitive decline and the functional performance of the patients [12]. Also, the Clinical Dementia Rating [13] is provided for AD and FTD patients. The statistical details of the participants are presented in Table 1. The EEG recordings were obtained from the 2nd Department of Neurology of AHEPA General University Hospital of Thessaloniki. The EEG device used was the Nihon Kohden EEG 2100 that provides 19 scalp electrodes and 2 reference electrodes placed on the mastoids. The electrode locations are (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2). An impendence value below 5kΩ was ensured throughout the duration of the recordings. Participants were placed in a sitting relaxed position, with their eyes closed. The sampling rate was 500 Hz. The duration of the recordings was 11-17 minutes (mean 13) for the dementia groups and 20-23 (mean 21) for the control group.

Table 1. Demographics of the Participants

	Gender (Male/Female)	Age	MMSE	CDR	Disease Duration in Months
AD	8/6	70.5 (7.1)	19.7 (2.76)	1 (0.54)	24 (9.88)
FTD	6/4	67.5 (4.5)	21.5 (1.83)	0.75 (0.26)	26 (9.24)
CN	4/4	68.5 (7.2)	30 (0)	-	-

B. Preprocessing

This section describes the preprocessing protocol that was implemented for every EEG recording. First, the EEG signal was re-referenced to the reference electrodes A1, A2 that were placed on left and right earlobe, respectively. Then, a 4th order Butterworth FIR filter was applied at 0.4-47 Hz, so that power line noise interference could be removed (line noise in Europe is at 50 Hz). Furthermore, an ICA decomposition was performed using the runICA algorithm in the EEGLAB, Matlab environment [14]. ICA is a well-established method for artifact rejection in neurophysiological datasets [15]. ICA functionality is based on the assumption that the electric dipoles in the cortex can be modelled as independent sources [16]. Thus, artifacts can be independent components based on their special properties and can be rejected. So, after the ICA decomposition has taken place, the components get labeled via a pretrained classifier, namely ICLabel [17], included in the EEGLAB platform, and are classified as eye, muscle or line artifacts and brain components. The components that are classified as artifacts with a probability >0.9 are automatically rejected. It should be noted that, even in a resting state eyes closed recording, eye artifacts can exist due to eye movement. Especially patients with severe cognitive impairment are having a hard time keeping their eye movement minimal, as observed during the recording stage, so the ICA preprocessing stage is important to ensure that the high classification accuracy is not achieved due to the eye artifacts but rather due to the brain components.

C. Feature Extraction

Useful classification features were extracted from the preprocessed EEG signals in this stage. Every part of this methodology was implemented with the Python library MNE [18]. First, the signals were divided in 4 second time windows with 2 second overlap. This time windows are also called epochs. Given that the lower useful frequency is 0.5 Hz, it is essential that the minimum duration of an epoch is 4 second.

Then, frequency domain, time domain, entropy and fractal dimension features were calculated for each epoch. For the frequency domain characteristics, the Power Spectral Density (PSD) was estimated using the Welch method that segments the signal in non-rectangular Hamming windows. For L time windows a periodogram of the mth time window is defined by the equation 1.

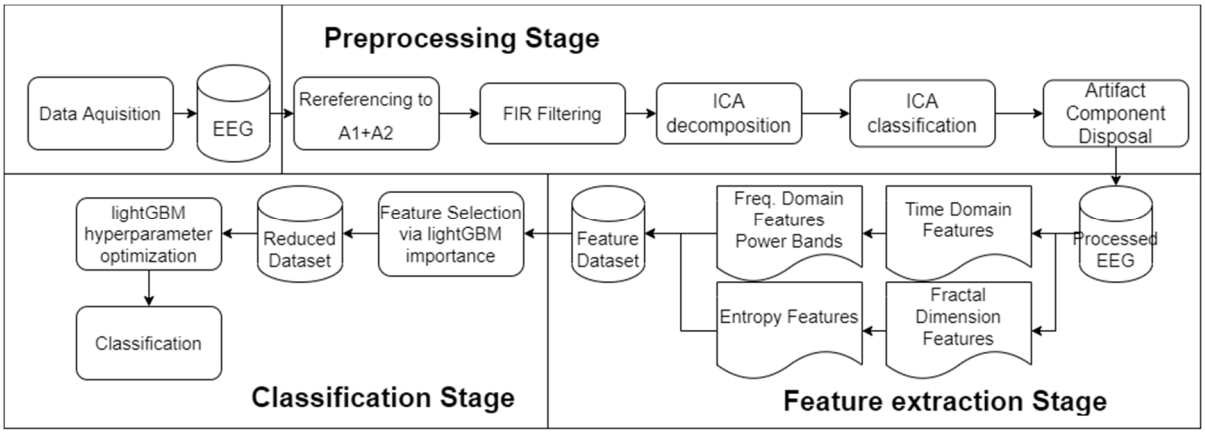
$$P_{x_m,M}(\omega_k) = \frac{1}{M}\left|FFT_{N,k}(x_m)\right|^2 \triangleq \frac{1}{M}\left|\sum_{n=0}^{N-1} x_m(n)e^{-j2\pi nk/N}\right|^2 \quad (1)$$

Then, for the frequency domain features, the relative power of each of the main 5 frequency bands was calculated for each electrode. The brain rhythms were defined as:

- Delta: 0.5 – 4 Hz
- Theta: 4 – 8 Hz
- Alpha: 8 – 13 Hz
- Beta: 13-25 Hz
- Gamma: 25-45 Hz

The time domain characteristics that were extracted for each epoch were: mean, standard deviation, skewness and kurtosis. The entropy characteristics were Permutation, Spectral, Singular Value Decomposition (SVD), approximate and sample entropy and the Hjorth features namely Mobility and Complexity. Finally, the fractal dimension features were

Fig 1. Flowchart of the Proposed Methodology



Petrosyan, Katz, Higuchi fractal dimension and Detrended Fluctuation. In total 20 (5 frequency domain + 4 time domain + 7 entropy + 4 fractal dimension) * 19 electrodes = 380 features were extracted. The entropy and fractal dimension characteristics were extracted using the AntroPy Python library. Spectral and time characteristics are vastly used in the EEG research for neurodegenerative diseases [19], [20] and cognitive disorders [21]. Entropy [22] and fractal dimensions [23] have also had significant importance in the field. Nevertheless, their combined use is not common.

D. Classification

The classification pipeline is described in this section. It is comprised of the feature selection step, the hyperparameter optimization step and the classification step. The three classification problems that were explored are: Alzheimer's group versus control group (AD/CN), Frontotemporal Dementia group versus control group (FTD/CN) and Dementia group versus control group (AD+FTD/CN).

1) Classification Algorithm

The classification algorithm that has been used in this experiment is a GBDT ensemble model that has been proposed and implemented from Microsoft Research team [24]. In a GBDT model, the decision trees are trained in sequence based on their residual errors (negative gradients) from the original value (for regression) or from the log (class probability) plus the pseudo residual from all the decision trees created in the previous steps. Considering a regression problem, and F(x) the target approximation function for the F*(x), where $D = \{x_i, y_i\}_1^N$ the training dataset, gradient boosting tries to minimize a loss function L(y, F(x)). F(x) is an iterative weighted sum [25]

$$F_m(\boldsymbol{x}) = F_{m-1}(\boldsymbol{x}) + \rho_m h_m(\boldsymbol{x}) \qquad (2)$$

and ρ_m is the weight of the m^{th} h(x). The approximation of the first function is normally the average of the training classes values. Each next approximation is trained on a new dataset $D = \{x_i, r_{mi}\}_{i=1}^N$ where r_{mi} are the pseudo residuals for the step m and calculated as:

$$r_{mi} = \left[\frac{\partial L(y_i, F(x))}{\partial F(x)}\right]_{F(x)=F_{m-1}(x)} \qquad (3)$$

The lightGBM implementation proposes a novel method to rank the absolute values of the training instances residual errors and discard the least informative one called Gradient-based One-Side Sampling (GOSS). It also introduces a method to effectively reduce the number of features called Exclusive Feature Bundling. The documentation of these methodologies can be found in the work of Guolin et al. [24].

2) Feature Selection

To perform feature reduction a simple SelectFromModel wrapper method from the scikit-learn python package was implemented. A lightGBM classifier with the default configuration was selected. The default configuration leaves aside the GOSS technique and produces a traditional GBDT. After the feature importance is calculated, we discarded every feature that does not exceed 1,5* mean feature importance.

3) Hyperparameter Optimization

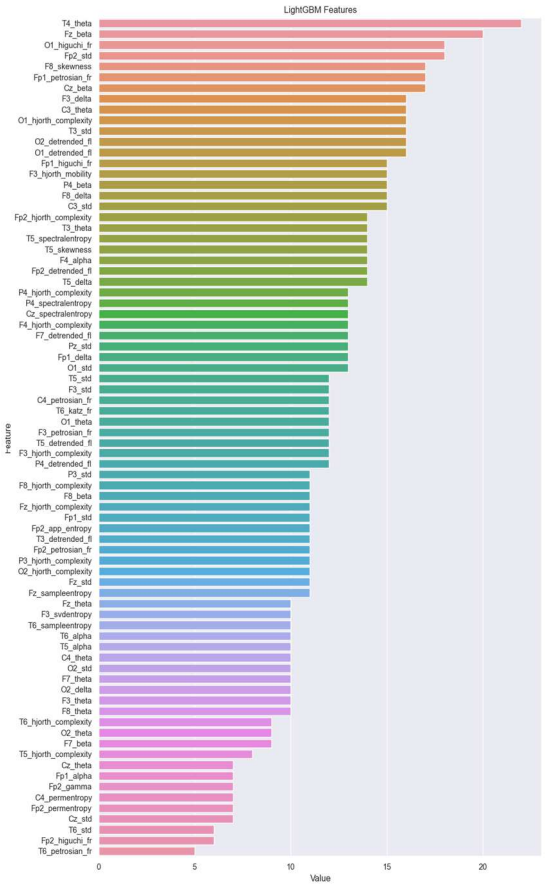
For the optimization of the classification algorithm's hyperparameters, a Bayesian optimization with Gaussian processes was used by the scikit optimize library (gp_minimize). The default settings were used which include a Matern kernel with automatically tuned hyperparameters and the acquisition function gp_hedge. The hyperparameter space of which the optimal values obtained were:

- learning_rate : 0.01 – 1.0
- num_leaves: 2 – 500
- max_depth: 1 – 500
- min_child_samples: 0 - 200
- max_bin: 100 - 100000
- subsample: 0.01 – 1.0
- subsample_freq: 0 – 10
- colsample_bytree: 0.01 – 1.0
- subsample_for_bin : 0.01 – 1.0
- reg_lambda: 1e-9 – 1000
- reg_alpha: 1e-9 – 1.0
- n_estimators: 10 - 10000

Table 2. Classification results

Problem	ACC	SENS	SPEC	F1	AOC
AD / CN	79.64%	83.52%	73.88%	83.06%	0.863
FTD / CN	82.67%	75.23%	89.56%	80.67%	0.925
AD+FTD/CN	89.72%	95.34%	72.75%	92.27%	0.941

Fig 2. Feature Importance's



The following parameters were set as constants: min_child_weight = 2 (for stability issues) and boosting_type = "goss".

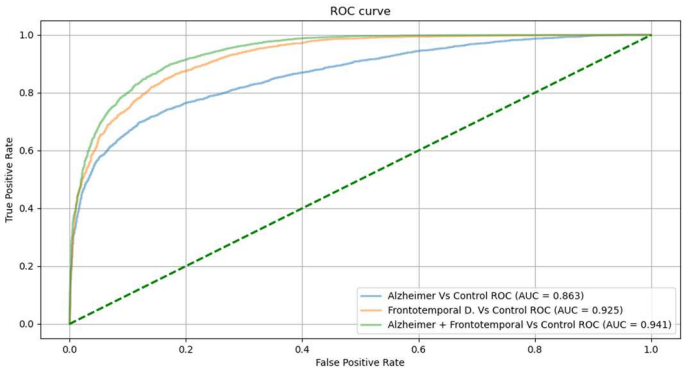
4) Validation Method and Performance Metrics

To measure the performance of the methodology, the LOPO validation method was implemented. For each participant X, test set $= t_x \, \forall \, t \in X, training\ set = t_y \, \forall \, t \notin X$, where t a time window. The performance metrics used were : Accuracy (ACC), Sensitivity (SENS), Specificity (SPEC), F1 score (F1) and Area Under Curve (AOC).

III. Results

In this section, the results of the classification pipeline are presented. Firstly, the feature selection step reduced the number of features from 380 to 78 for the AD/CN problem, 50 for the FTD/CN and 56 for the AD+FTD/CN. Figure 2 provides an indicative rating for the 78 AD/CN features as selected by the feature selection step. Table 2 presents the classification results for every problem. The F1 score achieved for the AD/CN was 83.06%, for the FTD/CN was 80.67% while for the AD+FTD/CN the F1 score was significantly higher at 92.67%, outperforming the other two problems. Furthermore, the AD/CN achieved 79.64% ACC (83.52 SENS, 73.88% SPEC), the FTD/CN achieved 82.67 % ACC (75.23% SENS, 89.56% SPEC) and the AD+FTD/CN achieved 89.72% ACC (95.34% SENS, 72.75% SPEC). Figure 3 presents the Receiver Operating Characteristic (ROC) curve for the three problems.

Fig 3. ROC curves of all three problems



IV. Discussion

A robust methodology for Alzheimer's disease and Frontotemporal dementia recognition through EEG signal was presented in this paper that achieves high performance results (92.27% F1 score) at the dementia detection problem. Although there are multiple neuroimaging techniques that can be employed to aid the diagnosis of dementia utilizing quantitative data such as Magnetic Resonance Imaging [26] and Positron Emission Tomography [27], EEG has the advantage of being cheaper and easier to perform while making use of its better temporal resolution compared to the other methods. In this context, automated EEG analysis is deemed to play a crucial role in neurodegenerative diseases diagnosis. Also, the employment of Machine Learning algorithms can perform recognition of the disease severity.

There are multiple studies that explore the distinguishability of EEG signals recorded from Alzheimer patients or other dementias against healthy subjects. The novelty of these studies can be at the classification methodology [28] i.e., using modern neural network implementations and novel gradient boosting algorithms like lightGBM [29] or at the signal analysis procedure by using novel combinations of methodologies of signal analysis like Time-Frequency decompositions such as Discrete Wavelet Transform [30] and Empirical Mode Decomposition [31] and extracted features. However, a limitation of multiple methodologies is the use of k-fold cross validation for the calculation of the performance metrics when using time windows [32]. Moreover, studies focus on extracting specific features such as permutation entropy [33] or a certain fractal dimension characteristic [34]. However, the computational cost of extracting multiple (as many as possible) characteristics and performing an automatic feature selection procedure in a modern computer is minimal and should not be considered a limitation. In this study, we employed one of the most innovative tree ensemble algorithms, lightGBM. We also capitalized on a wide range of characteristics such as spectral, time, entropy and fractal dimension features while performing dimensionality reduction through the algorithm's build in feature importance ranking.

The performance metrics of the classification for all the classification problems were comparable with other similar works that use LOPO as their validation method [19], [35]. The best classification F1 score was acquired for the AD+FTD/CN problem (92.27%) followed by AD/CN (83.06%) and FTD/CN (80.67%). On the contrary, even

though AD+FTD/CN achieved the higher accuracy (89.72%), the FTD/CN achieved higher accuracy (82.67%) than the AD/CN (79.64%), something that could be a warning that the dataset should be better balanced. Finally, the FTD/CN problem outperformed the AD/CN problem in terms of AUC score (0.925 vs 0.863) indicating that the Frontotemporal dementia is overall easier to detect through EEG than the Alzheimer's disease.

The selection of the lightGBM algorithm was not made arbitrarily. Multiple studies have highlighted the effectiveness of ensemble tree-based algorithms like Random Forest, on Alzheimer's recognition [19], [20] (along with Support Vector Machines). Comparative analysis shows that light GBM is the fastest gradient boosting algorithm. [36]. Therefore, this algorithm was the best fit amongst all other tree ensemble classifiers for this preliminary study. However, a more thorough comparative study using multiple tree-based algorithms should be performed to accurately evaluate the best suitability for these classification problems.

Another limitation of this study that should be addressed is the limited size of the dataset. The number of participants used in this study is small and bias towards the performance metrics might occur. Hence, our following work will utilize a much larger dataset. Furthermore, the time window sizing was set at 4 second in an arbitrary manner. Despite the fact that there is no commonly accepted duration size window proposed and accepted, most studies set a time window size around 4 seconds. The exact size of the time window for maximizing the classification performance should be explored in future studies.

V. Conclusions

In this study, we presented a comprehensive methodology for distinguishing EEG signals between 2 conditions; AD/CN, FTD/CN and AD+FTD/CN. An ICA decomposition was employed for the artifact rejection procedure while multiple features from time and frequency domain, such as entropy and fractal dimensions were used to create the classification dataset. After a feature reduction step, a lightGBM implementation achieved high classification performance for each one of the three problems, namely 83.06% for AD/CN, 80.67% for FTD/CN and 92.27% for AD+FTD/CN.

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