



Analysis of Dementia EEG Signals Using Empirical Mode Decomposition Variants and Deep Learning

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Abstract— Dementia is among the most frequent neurological diseases that result in worsening cognitive functions and damaging consequences on quality of life. In this study, a novel method is proposed by using electroencephalogram (EEG) signals and signal decomposition methods to detect Alzheimer's disease (AD). Intrinsic Mode Functions (IMFs) are obtained by utilizing Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) methods. Five time-domain and five spectral-domain features are extracted from one-minute and five-second EEG segments, as well as from the corresponding IMF segments, using EEG recording. Topographic heat maps are generated for each feature. These feature maps give temporal and spatial information simultaneously on a single image. Feature map images are classified with two-dimensional convolutional neural network (2D-CNN). Three CNN architectures are used for classification and comparison between networks. The proposed method achieves promising results, with accuracy up to 96%.

Keywords—Alzheimer's Dementia (AD); topographic heat map; 2D-CNN; EMD; EEMD

I. INTRODUCTION

Dementia refers to the loss of brain functions. AD is the most common type of dementia. AD accounts for 65% to 80% of all dementia cases and is known as one of the leading causes of death in adults over the age of 65 [1]. AD is an advancing neurological illness and widespread public health issue. Its effects include cognitive decline, memory loss, and behavioral abnormalities [2]. A patient's response to treatment and the diagnosis of AD can be made using a variety of medical methods. Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) are performed to detect symptoms associated with AD [3]. Also, EEG is another technique that uses electrodes applied to the scalp to record electrical impulses from the brain [4]. While techniques like MRI and PET offer high spatial resolution, they may miss certain abnormalities due to their limited temporal resolution. In contrast, EEG is superior in terms of temporal resolution, cost-effectiveness, and availability [5].

There are many studies to analyze EEG signals. In some of them, features from EEG signals like tsallis entropy [6],

multivariate multiscale weighted permutation entropy [7], permutation Jaccard distance [8], and Fuzzy Entropy (FuzzyEn) [9] are used to distinguish patient and control group. Each of these studies emphasized how the brain complexity of AD patients was lower compared to the control group. Apart from calculating many features from EEG signals, signal decomposition approaches with the help of machine learning are also used for AD classification. Some of these approaches are EMD, and EEMD. EMD, and EEMD are used especially to analyze nonlinear and non-stationary signals like EEG. EMD decomposes signal into intrinsic mode functions (IMFs). Each IMF represents the part of the signal that contains a certain oscillation. When the IMFs are added together, the original signal is reconstructed. Sometimes, similar oscillations can be found in different IMFs, and different oscillations can be found in the same IMF. To prevent this issue, the EEMD method is utilized. In a study, segmented EEG signals were decomposed into the first seven IMFs with EMD and EEMD methods. Then, spectral and time-domain features were extracted from these IMFs and used to classify AD patients and healthy control subjects using machine learning methods such as Decision Tree (DT), k-Nearest Neighbors (kNN), Support Vector Machine (SVM), and Random Forest (RF) [10]. In that study, 91.8% classification accuracy was obtained using EMD, and 94.1% classification accuracy was obtained using EEMD. Another study benefited from discrete wavelet transform (DWT) and EMD for decomposing the signal, and SVM, k-NN, and Linear Discriminant Analysis (LDA) for classification [11]. Their study achieved 97.64% accuracy using k fold cross-validation and 81.08% accuracy using leave-one-subject-out (LOSO) validation. Even though these manual feature extraction and machine learning-based techniques have produced good classification results, they are still computationally demanding and challenging for doctors to understand. These issues can be resolved by the suggested mixed deep learning (DL) approaches, which are used with EEG time-series data and frequency domain representations, also known as time-frequency representations (TFRs) [12].

In this study, the classification of patients and healthy control subjects is performed using EEG signals. The first three

IMFs are extracted from the EEG signals using EMD and EEMD. Spectral and time-domain features are then derived from both the IMFs which are extracted with EMD and the original EEG signals. Only spectral features are derived from the IMFs which are obtained with EEMD. Topographic heat maps in RGB format are generated based on these features. Later, these RGB images are classified using 2D CNN architectures, including ResNet50, EfficientNet-b0, and ResNet-18. The classification process is implemented in the MATLAB environment.

II. MATERIALS AND METHODS

A. Dataset

EEG data used in this study were obtained from patients evaluated at the dementia clinic of the Neurology Department, Izmir Katip Celebi University Faculty of Medicine. These patients were diagnosed with early-stage Alzheimer's disease by diagnostic tests and neuroimaging. EEG signals were recorded for 15 AD patients (30 minutes for each patient). Their average age is 64. 7 of them are males, and 8 of them are females. EEG recording was done for each patient from 19 channels at 200 Hz sampling frequency in the resting state with the eyes closed. EEG signals were recorded only, and different biological signals like ECG and EOG were not collected during the recording process. Recordings were obtained from 19 scalp electrodes placed according to the International 10–20 system at the following positions: Fp1, F7, T3, T5, O1, O2, T6, T4, F8, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4. For comparison, EEG data were also collected from 11 cognitively healthy, age-matched control subjects (CS) using the same recording system and electrode placement. 6 of them are males, and 5 of them are females. Their average age is 57. To collect these EEG signals for use in this study, ethical approval numbered **83** and dated **22.10.2020** is obtained from the Clinical Research Ethics Committee of Izmir Katip Celebi University.

B. Preprocessing and Feature Extraction

Firstly, at the preprocessing stage, a Butterworth band pass filter was used to all channels of patients and controls. Pass band of 0.5 - 40 Hz is applied to all channels to eliminate unwanted electrical noise, and some artifacts such as eye-blinking and muscle activity of individuals. Filtered EEG signals were divided into nonoverlapping 5 seconds and 1 minute segment durations separately. For each segment of 1 min, EMD and EEMD are applied. For each segment of 5s, only EMD is applied. 5 spectral-domain and 5 time-domain features are extracted from segments of EEG and IMFs, which are first three IMFs obtained using EMD and EEMD, for AD patients and CS. Spectral features are total power, higher order spectral (HOS) moments of order 1, 2, and 3, and spectral entropy. Time domain features are activity, mobility, complexity, skewness, and kurtosis.

C. Topographic Heat Map Generation

After the feature extraction process, topographic heat maps were generated for time and spectral features of 1 min and 5 s segments of EEG signals and IMFs. Matlab's eeglab toolbox was used for it. Topoplot function, defined in EEGLAB was used to plot topo maps. In order to get visually distinctive images, appropriate transformations are made on time-domain

and spectral features. Log 10 transformation is applied for total power, activity, complexity, kurtosis, HOS moments of order 1, 2, and 3. Min-max normalization is applied for skewness. No transformation is applied for mobility and spectral entropy. Transformations are done per-image. Topographic heat maps give information about the spatial resolution of brain activity across EEG channels for a given feature. They allow for the visualization of which features are more dominant in specific channels for the corresponding signal (such as EEG or IMFs). Examples of topographic heat maps of spectral entropy of the first IMF obtained with EMD, extracted from 1 min segments of a control subject and an AD patient are given in Fig. 1.

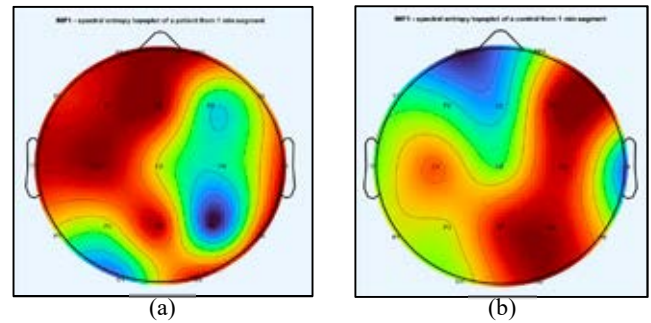


Figure 1: Examples topographic heat maps of spectral entropy for control and patient groups. a) AD patient b) CS

It can be observed that left temporal region is more active for a patient whereas right temporal region is more active for a control subject.

D. CNN Architectures for Classification

Topographic heat maps for spectral and time features from IMFs and EEG signals were used to classify patient and control with deep learning. 2D CNN was used for classification of images. ResNet-50, ResNet-18, and EfficientNet-b0 are the CNN architectures used in this study. These architectures are designed for classifying 1000 classes. In our study, suitable changes are made in layers, because there are two classes which are patient and control. Also, images are resized to 224 x 224 x 3, because these architectures expect 224 x 224 x 3 as an input image.

III. RESULTS AND DISCUSSION

In this study, there are a total of 9 cases for 1-minute segment duration of spectral features topographic heat maps. Each CNN architecture has 3 cases. On the other hand, there are a total of 6 cases for 1-minute segment duration of time features topographic heat maps, and each CNN architecture has 2 cases. In addition, for the 5-second segment duration, there are a total of 6 cases for the time-domain features and another six cases for the spectral-domain features' topographic heat maps. For each case, data was split into 80% for training and 20% for validation. Data split was done using all patients and control subjects for each case. Training options are adjusted for all three CNN architectures. Maximum epoch is set to 10, and learning rate is set to 0.0001. Performance metrics which are validation accuracy (ACC), sensitivity (SEN), specificity (SPE), precision (PRE), and F1 score are examined. Classification results for the 1-minute segment duration and the 5-second segment duration are given in Table 1 and Table 2, respectively.

TABLE I: Performance evaluation results of CS and AD EEG classification obtained using spectral and temporal features topographic heat maps for 1min segment duration.

Spectral Features						
CNN Architectures	Method	Validation ACC	SEN	SPE	PRE	F1-Score
ResNet-50	EEG	0.9474	0.9606	0.9292	0.9491	0.9548
	EMD	0.9271	0.9535	0.8910	0.9228	0.9379
	EEMD	0.9560	0.9569	0.9551	0.9550	0.9559
ResNet-18	EEG	0.9234	0.8967	0.9595	0.9676	0.9308
	EMD	0.9166	0.9303	0.8979	0.9255	0.9279
	EEMD	0.9228	0.9138	0.9316	0.9301	0.9219
EfficientNet-b0	EEG	0.9598	0.9800	0.9324	0.9515	0.9655
	EMD	0.9154	0.9210	0.9077	0.9315	0.9263
	EEMD	0.9366	0.9497	0.9235	0.9251	0.9372
Temporal Features						
CNN Architectures	Method	Validation ACC	SEN	SPE	PRE	F1-Score
ResNet-50	EEG	0.8336	0.8967	0.7754	0.7866	0.8380
	EMD	0.8	0.8185	0.7816	0.7885	0.8032
ResNet-18	EEG	0.8352	0.7900	0.8769	0.8556	0.8215
	EMD	0.7215	0.6182	0.8245	0.7784	0.6891
EfficientNet-b0	EEG	0.8240	0.8400	0.8092	0.8029	0.8208
	EMD	0.7494	0.7528	0.7459	0.7467	0.7497

TABLE II: Performance evaluation results of CS and AD EEG classification obtained using spectral and temporal features topographic heat maps for 5s segment duration.

Spectral Features						
CNN Architectures	Method	Validation ACC	SEN	SPE	PRE	F1-Score
ResNet-50	EEG	0.9150	0.9344	0.8960	0.8984	0.9160
	EMD	0.8402	0.8524	0.8273	0.8396	0.8459
ResNet-18	EEG	0.8687	0.9046	0.8333	0.8474	0.8724
	EMD	0.8002	0.8184	0.7808	0.7987	0.8085
EfficientNet-b0	EEG	0.8891	0.8790	0.8990	0.8955	0.8872
	EMD	0.7870	0.8432	0.7273	0.7666	0.8031
Temporal Features						
CNN Architectures	Method	Validation ACC	SEN	SPE	PRE	F1-Score
ResNet-50	EEG	0.7817	0.7764	0.7869	0.7820	0.7792
	EMD	0.6775	0.6943	0.6590	0.6923	0.6933
ResNet-18	EEG	0.7389	0.7713	0.7071	0.7217	0.7457
	EMD	0.5990	0.6781	0.5116	0.6054	0.6397
EfficientNet-b0	EEG	0.7013	0.5836	0.8172	0.7587	0.6597
	EMD	0.5960	0.4038	0.8084	0.6997	0.5121

From these tables, it can be observed that classification results of 1 min cases is better than 5 s cases. Also, spectral features topographic heat maps give better results than time features topographic heat maps. In addition, spectral features topographic heat maps for 1 min segment duration is best when we compare with other cases. Because of that, EEMD method is benefited for only spectral features topographic heat maps for 1 min segment duration to save computation time. The best accuracy value 95.98% is achieved with EEG from Efficient-b0 architecture. Although EEG gives higher performance from EMD and EEMD, we can observe that accuracy of EEMD is very close to EEG even EEMD accuracy (% 95.60) is higher than EEG for ResNet-50 network. So, performance of EMD is increased with EEMD which is a variant of EMD method. If we compare CNN architectures, Efficient-b0 and ResNet-50

architectures give better results than ResNet-18. This can be expected, as ResNet-18 is a more basic architecture compared to the others.

IV. CONCLUSION

Detection of AD is important in terms of starting treatment as soon as possible and raising an individual's awareness. In this study, detection of AD was done with signal decomposition methods which are EMD and its variant EEMD, and deep learning. It is aimed to help doctors' judgment as fast as possible. In this study, 2D CNN was used to classify control subjects and patients. Topographic heat maps were used as input images to CNN. EMD and EEMD were used to decompose EEG signals into IMFs. Spectral and temporal features were extracted from IMFs (obtained with EMD) and

original EEG signal for 1 min and 5 s cases. Only spectral features were extracted from IMFs (obtained with EEMD) for 1 min cases. These features were transformed into topographic heat maps. Topographic heat maps give information about the spatial resolution of brain activity across EEG channels for a given feature. They allow for the visualization of which features are more dominant in specific channels for the corresponding signal (such as EEG or IMFs). This spatial perspective adds interpretability to machine learning models by linking features to specific brain regions. These maps help show which brain areas work differently in different groups. Furthermore, researchers can learn more about how brain disorders work by looking at differences in heat maps for different features or conditions. In neurological conditions like AD, these visual comparisons are extremely helpful.

After generating topographic heat maps, classification of these topo maps was done with ResNet-50, ResNet-18 and EfficientNet-b0 architectures. Spectral features topo maps were classified better than time-domain features topo maps for 1 min and 5 s cases. In addition, EEG spectral topo maps were classified better than IMFs spectral topo maps. Classification performance of 1 min IMFs spectral topo maps was increased using EEMD. For all architectures, classification performance of EEMD is higher than EMD for 1 min IMFs spectral. For ResNet-50 architecture, performance of EEMD is also higher than EEG for 1 min spectral case. These results highlight the potential of EEMD as a robust decomposition method for increasing classification accuracy. 96% accuracy was achieved with 1 min EEG spectral topo maps as the highest accuracy rate in this study. This high accuracy demonstrates the reliability of spectral features and the effectiveness of the 2D CNN approach in EEG based AD detection.

In this study, because of large data, computation time is a constraint. It takes hours to do classification process with 2D CNN architectures. Later, to decrease computation time, another computer with powerful GPU and CPU can be used. Implementing parallel computing or using cloud-based platforms could also be considered to overcome these computational challenges.

For future work, feature selection can be done to improve classification performance of IMFs. Other signal decomposition methods like ITD, Multivariate Empirical Mode Decomposition (MEMD) can be obtained to compare with EMD and EEMD. Also, different features like Logarithmic band power (LBP), Approximate entropy (ApEn), Zero-crossing rate (ZCR), Norm (Norm) can be extracted from signal. These features can be compared with the features of the proposed study. In addition, the first three IMFs were used in this study. Different combinations of IMFs can be used to find out which IMFs are more successful in classification. As a result, IMF selection can be made to increase classification performance. After all comparisons between signal decomposition methods, extracted features, and IMFs selection processes the most effective approach can be learned to classify AD patients.

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