A Convolutional Neural Network based self-learning approach for classifying neurodegenerative states from EEG signals in dementia

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***Abstract*—In this paper, a novel deep learning based approach is proposed for the automatic classification of Electroencephalographic (EEG) signals of subjects diagnosed with the dementia of Alzheimer's disease (AD), Mild Cognitive Impairment (MCI) and Healthy Control (HC). Specifically, a custom Convolutional Neural Network (CNN) is designed to receive as input AD/MCI/HC EEG segments (epochs) of the same temporal width, and perform 2-way classification tasks: AD vs. HC, AD vs. MCI, MCI vs. HC. Our proposed architecture, termed *EEG-CNN*, is shown to exhibit remarkable abilities to *self-learn* relevant features directly from the EEG traces, avoiding the need for hand-crafted feature extraction engineering. Comparative experimental results demonstrate the promising performance of *EEG-CNN*, which is based on an analysis of the EEG time series only, reporting accuracies of 85.78 $\pm$ 2.18%, 69.03 $\pm$ 1.33%, 85.34 $\pm$ 1.86% in AD vs. HC, AD vs. MCI and MCI vs. HC classifications, respectively.**

***Index Terms*—Deep Learning, Convolutional Neural Network, Self-learning, EEG signal, Alzheimer's disease, Mild Cognitive Impairment.**

I. Introduction

Alzheimer's disease (AD) is the most common form of neural degenerative disorder among dementia cases in the elderly [1] that causes a progressive decline of cognitive functions (such as language, memory, reasoning), deterioration of behavior and also of visuospatial abilities and skills [2]. AD is preceded by a prodromal stage referred as Mild Cognitive Impairment (MCI) which often goes unnoticed. MCI is not considered a disease on its own, it is a condition characterized by mild neural deficits that does not heavily affect the patient's ability to live and act independently [3]. MCI condition may worsen with time, remain stable or even go back to normal, depending on its inherent etiology [4]. When the cognitively impaired subject is no longer able to carry out her/his daily life independently, a diagnosis of dementia may be issued on the basis of a full neurological, clinical and cognitive evaluation. Dementia due to Alzheimer's Disease (AD) is the most common form of dementia [5]. The number of MCI subjects degenerating into AD is estimated to be nearly 10%-15% per year and it is constantly growing, due to people ageing [6], [7]. Once the diagnosis of dementia due to AD is issued, it is a common practice to make the subject undertake medical therapy, which is not however expected to stop or revert the disease but only to help managing and controlling symptoms. By that time, unfortunately, atrophy would have indeed involved most of brain tissues. Whether the ineffectiveness of medical drugs is due to a late intervention is still an open question [8]. In order to reply to this question it is necessary to develop tools than can help to diagnose AD as early as possible. To this end, the development of objective and reliable biomarkers of AD are necessary, possibly based on non-invasive, well tolerated and widely spread medical examinations. In this context, Electroencephalography (EEG) would be a technology of choice. EEG can indeed be found in all the neurological clinics, it is relatively affordable, non-invasive, easy and fast to use. It consists in recording scalp potentials produced by the bio-electromagnetic fields generated by neurons within the brain. Communication between neurons results impaired in MCI and AD subjects, which shows up as an abnormal behaviour of EEG signals. The quantification of such abnormalities may provide diagnostic information and has been widely investigated in the literature [9], [10]. Machine learning has extensively been applied to the classification of MCI/AD signals [11]. Trambaiolli et al. [12] used SVM to classify healthy people and probable AD patients, exploiting EEG signals, with 79.9% accuracy.

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Ahmadlou et al. [13] introduced a chaos-wavelet methodology for EEG-based diagnosis of AD employing the concept of Visibility Graph (VG) from the graph theory. They report an accuracy of 97.7% in the discrimination between AD and healthy controls (HC). Ahmadlou et al. [14] used two different fractal dimensions (FD), Katz's FD (KFD) and Higuchi's FD (HFD), for evaluation of the dynamical changes in the AD brain. They report a high accuracy of 99.3% for diagnosis of the AD based on the global KFD in the beta band of the eyes-closed condition. The aforementioned studies lack a validation on a large dataset or a comparison between AD vs. MCI, which is of paramount importance in the early diagnosis of AD. Ieracitano et al. [15] recently successfully classified EEG signals from 63 healthy controls (HC), 63 MCI and 63 AD subjects through a novel multimodal approach based on Continuous Wavelet Transform (CWT) and Bispectral features extracted from the main EEG rhythms: delta (0-4Hz), theta (4-8Hz), alpha1 (8-10.5Hz), alpha2 (10.5-13Hz) and beta (13-30Hz). Multi-Layer Perceptron (MLP) outperformed Autoencoder (AE), Logistic Regression (LR) and Support Vector Machine (SVM) classifiers. The application of Deep Learning (DL, [16]) to MCI/AD EEG is still in its infancy. Ieracitano et. [17] proposed a Convolutional Neural Network (CNN) to classify EEGs through their power spectral density representations, achieving an accuracy of 93.11% in AD vs HC classification. Bi et al. proposed a Discriminative Contractive Slab and Spike Convolutional Deep Boltzmann Machine (CssCDBM) to carry out EEG spectral image classification. Their algorithm applied to a small dataset of 4 HC, 4 MCI patients and 4 mild-to-severe AD patients [18]. Kim et al. introduced a Deep Neural Network to discriminate 10 HC from 10 MCI subjects by means of relative power features extracted from their EEG signals [19]. The present paper aims at giving a contribution in assessing the potential of deep learning approaches to the EEG-based classification of AD, MCI and HC subjects. Specifically, we developed a custom CNN able to *self-learn* relavant features directly from the analysis of EEG recordings only, without applying any hand-crafted feature extraction technique. Such network is here referred as *EEG-CNN* and is employed to perform the following binaries classification tasks: (i) AD vs. HC, (ii) AD vs. MCI, (iii) MCI vs. HC.

This work is organized as follows. Section II introduces the proposed methodology. Section III describes the EEG dataset used and the EEG pre-processing operations. Section IV reports the proposed classification system, including the developed *EEG-CNN*. Section V reports the experimental results. Finally, discussion and conclusions are addressed in Section VI.

II. Methodology

Figure 1 depicts the proposed CNN based framework. EEG signals are recorded and stored on a computer. Given a EEG time series, first, it is cleaned from residual artifacts, then, splitted into N non-overlapped 5s windows (i.e., epochs). A dataset of EEG epochs is generated and used to train the proposed DL-based classifier. Specifically, a CNN is developed to discriminate epochs belonging to AD, MCI and HC subjects and perform 2-way classifications (AD vs. HC, AD vs. MCI, MCI vs. HC).

Futher deails are described in the following Sections.

III. EEG dataset description and EEG signal preprocessing

EEG dataset description. Three groups of subjects, 63 with AD, 63 with MCI and 63 HC were recruited at I.R.C.C.S. (*Istituto di Ricovero e Cura a Carattere Scientifico*) Centro Neurolesi Bonino-Pulejo of Messina (Italy), where the local Ethical Committee approved the medical protocol used to carry out this research. In particular, the diagnosis of AD and MCI was established by following both the practical recommendations of the Diagnostic and Statistical Manual of Mental Disorders (fifth edition, DSM-5) [20] and the definition of some exclusion criteria as: the presence of neurological diseases (comprising possible psychiatric disorders) that could cause mental impairments, traumatic brain injuries (TBI), moderate or severe systemic diseases or the existence of forms of epilepsy. Before undertaking any examination, each person involved (i.e., patients and caregivers) signed a formal consent agreement that reported purposes, advantages and disadvantages of the present study. Moreover, all the individuals underwent to neuroradiological evaluations, in order to exclude the presence of other cerebral disorders that may have similar symptoms to Alzheimer's disease (such as TBI or tumors). It is to be noted that MCI patients were not subjected to any medical therapy; whereas, AD patients were under clinical treatments such as anti-epileptic drugs, anti-psychotics, Memantine, cholinesterase inhibitors (ChEis) and anti-depressants, to study the possible effects.

The recording of the EEG signal was carried out during the morning. All the patients and their caregivers were asked about the last meal and quality and length of the last rest. The EEG recordings were acquired according with the standard 10-20 International System, consisted of the conventional 19-electrodes (i.e., channels) montage (Figure 2) that allowed the recording of EEGs simultaneously. The sampling rate was of 1024 Hz and a 50 Hz notch filtering was also applied. Finally, linked ears reference (A1-A2) were used. During the EEG recording, AD/MCI/HC individuals were sitting in a resting condition with eyes closed. Note that an expert neurophysiologist technician monitored the EEG acquisition in order to immediately detect and label possible sleep activities. Next, the EEG signals were examined one by one in order to remove potential artifactual components.

EEG pre-processing. First, a band pass filter ranged between 0.5 and 32 Hz was applied to each EEG recording. Notably, the *eegfiltfft* Matlab function of *EEGLab* toolobox [21] was used. Then, given an EEG under analysis, it was downsampled to 256 Hz and divided into N non-overlapping temporal segments (i.e., EEG epochs) of the same duration, that is 5s. Therefore, each EEG epoch was sized n x S, where n is the number of channels (n=19) and S is the number of samples in a 5s window (S= 256 x 5= 1280).

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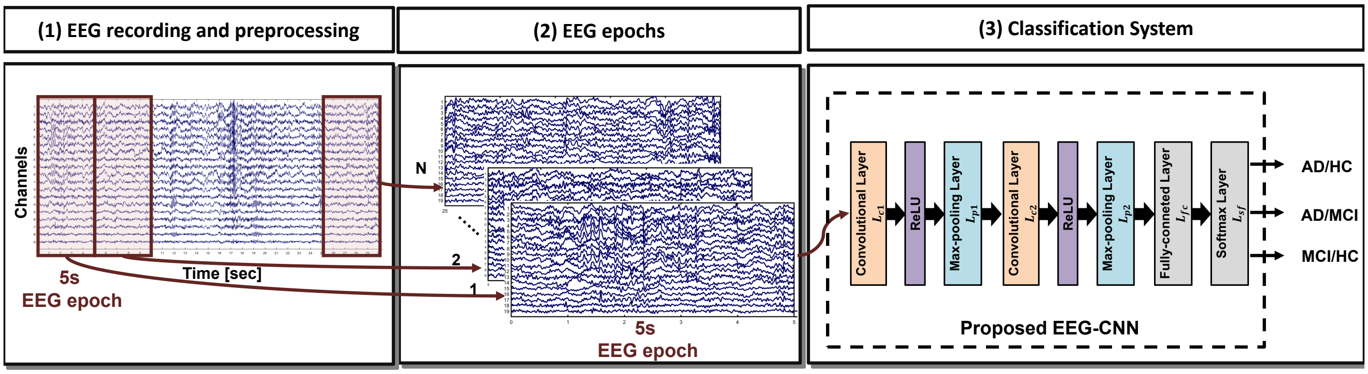

Fig. 1. Procedure of the proposed methodology. (1) 19-channels EEG signals are recorded and stored on a computer. (2) Each EEG is divided into N 5s temporal windows and a dataset of EEG epochs is created. (3) The EEG epoch of AD/MCI/HC subject is the input of the proposed Convolutional Neural Networks (i.e. *EEG-CNN*) for performing binaries discriminations: AD vs. HC; AD vs. MCI; MCI vs.HC.

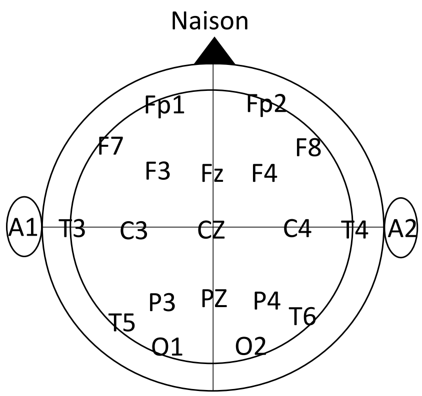

Fig. 2. 10-20 International System of the 19-channels EEG recording, where electrodes with odd numbers refer to the left hemisphere and electrodes with even numbers refer to the right hemisphere.

IV. Classification System

A Convolutional Neural Network is developed to discriminate AD/MCI/HC subjects directly from EEG time series. After a brief introduction of CNN (Section IV-A), the proposed architecture (i.e., *EEG-CNN*), employed to perform binaries classifications tasks (AD vs. HC, AD vs. MCI, MCI vs. HC), is presented (Section IV-B).

A. Convolutional Neural Network

A CNN is a common DL architecture typically used in computer vision [22]. It is composed of four main types of layers (L): convolutional (L_c), activation (L_a), pooling (L_p) and fully connected (L_{fc}). In a convolutional layer, the input pattern (X_j) convolves with a set of learnable filters (F_i). In particular, each filter (usually small-size) scans the input data with a stride (s) and computes the dot product between the filter's weights and the corresponding sub-region of the input under analysis. The result of this operation is the so called *feature or activation map* (FM_i):

$$FM_i = \sum X_j * F_i + B_i \tag{1}$$

where, * represents the convolution operator and B_i denotes the bias. The estimated feature map FM_i is sized fm_1 x fm_2:

$$fm_1 = \frac{x_1 - f_1 + 2p}{s} + 1 \tag{2}$$

and

$$fm_2 = \frac{x_2 - f_2 + 2p}{s} + 1 \tag{3}$$

where (x_1, x_2) and (f_1, f_2) are the corresponding dimension (height, width) of the input X and filter F, respectively; p is the zero-padding parameter (generally used to output the same size of the original input). It is be noted that, in a L_c layer, the number of feature maps is the same of the number of filters. The activation layer consists of a nonlinear transfer function that allows to learn nonlinear properties. The "*Rectified Linear Units*" (ReLu, $z(x) = max(0, x)$) is the most widely used as provides faster learning and better generalization performance as compared to conventional *sigmoid* or *hyperbolic tangent* functions [23] [24]. In a pooling layer, the estimated feature maps (FM_i) are downsampled through max or average operations. Specifically, filters sized $\tilde{f}_1$ x $\tilde{f}_2$ slides over the features map of the previous layer with step-size s and estimates the mean or maximum value of the sub-region selected by the filter. The result is a reduced representation of FM_j of dimension $\tilde{fm}_1$ x $\tilde{fm}_2$, where:

$$\tilde{fm}_1 = \frac{fm_1 - \tilde{f}_1}{\tilde{s}} + 1 \tag{4}$$

and

$$\tilde{fm}_2 = \frac{fm_2 - \tilde{f}_2}{\tilde{s}} + 1 \tag{5}$$

Here, the max pooling is used as allows to extracts invariant features more efficiently and provides better generalization [25]. The CNN ends with one or multiple fully connected layers (where all neural units are connected with those of the previous layer as a typical NN) for classification purpose.

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B. Proposed architecture: EEG-CNN

In this study, EEG epochs (5s width) are used as input to the proposed CNN, denoted as *EEG-CNN* (Figure 3). It includes 2 convolutional layers (each followed by a ReLU activation function), 2 max pooling and 1 fully connected layers. Specifically, the first convolutional layer (L_{c1}) has: 4 filters sized 3 x 3 that convolve with the input X (i.e., EEG epoch); stride s=1 and zero-padding parameter p=1. Four features maps of the same input size (19 x 1280) are generated. Next, the ReLU is applied for non-linearity (L_{ReLU}). L_{c1} is followed by a max pooling layer (L_{p1}) composed of a filter sized 3 x 6 that sweeps over each FM (achieved from the previous layer) with stride $\tilde{s}$=2, reducing the original FM dimension from 19 x 1280 to 9 x 638. Similarly, the second convolutional layer (L_{c2}) has 8 filters sized 3 x 3, s=1 and p=1. After applying ReLU, the max operation of the second max pooling layer (L_{p2}) dowsamples the spatial resolution and generates 8 FM sized 4 x 317. Finally, the resulting feature maps are reshaped as a d-dimensional vector (with d= 8 x 4 x 317=10144), subsequently used as input to a 1-fully connected layer (L_{fc_1}) comprising 5000 hidden units. EEG-CNN ends with a softmax layer (L_{sf}) that performs binaries classifications: (i) AD vs. HC, (ii) AD vs. MCI, (iii) MCI vs. HC.

The EEG-CNN was designed with MATLAB R2018b (The MathWorks, Inc., Natick, MA, USA) and trained using the Adaptive Moment (ADAM) optimization algorithm [26] on two NVIDIA GeForce RTX 2080 Ti for 600 iterations until the convergence of the cross entropy loss function. After several simulation tests (trial and error strategy), the default ADAM setting with learning rate α= 0.001, exponential decay rates β_1=0.9 and β_2=0.999, has been chosen. The training time was roughly 300s for each of the 2-way classification scenario.

V. Results

The dataset used in the present research included 189 EEG traces recorded from: 63 subjects diagnosed with AD, 63 subjects diagnosed with MCI and 63 healthy individuals. Each EEG signal under analysis, was divided into temporal windows of the same duration (i.e., EEG epochs) and used as input to the proposed CNN classifier (denoted as *EEG-CNN*) able to perform the 2-way EEG epoch-based classifications tasks: AD vs. HC, AD vs. MCI, MCI vs. HC. Precision, recall, F1-score and accuracy were the metrics employed to estimate the effectiveness of *EEG-CNN*:

$$precision = \frac{tp}{tp + fp} \tag{6}$$

$$recall = \frac{tp}{tp + fn} \tag{7}$$

$$F1 - score = 2 * \frac{precision * recall}{precision + recall} \tag{8}$$

$$accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{9}$$

where tp, fp represent the true positive and false positive; whereas tn, fn are the true negative and false negative, respectively [27]. For example, in AD vs. HC discrimination: tp and fp correspond to the number of EEG epochs correctly and erroneously detected as epochs belonging to AD patients, respectively; while, tn, fn correspond to the number of EEG epochs correctly and erroneously classified as epochs of HC, respectively. In order to assess the robustness of the proposed model the k- fold cross validation technique (with k=8) was applied as validation criterion. Specifically, for every iteration, 70% of instances (i.e. EEG epochs) represented the train test and 30% the test set. The overall results are quantified by estimating the *average value* $\pm$ *standard deviation*. It is to be noted that the best CNN topology was determined by experimentally estimating the performance of configurations with different processing layers (Table I). The proposed *EEG-CNN* described in Section IV-B and referred in Table I as *EEG-CNN*$_2$, was firstly trained and tested with only L_{c_1}, L_{ReLU}, L_{p_1}, L_{fc_1} (*EEG-CNN*$_1$); then, additional fully connected layers were used. In particular, the developed *EEG-CNN* was also studied with 2-fully connected layers (L_{fc_1} of 5000 and L_{fc_2} 2000 units, respectively - *EEG-CNN*$_3$) and with 3-fully connected layers (L_{fc_1} of 5000, L_{fc_2} of 2000, L_{fc_3} of 500 units, respectively - *EEG-CNN*$_4$). All the networks end with a softmax output layer for binaries classification. As can be seen from Table I, *EEG-CNN*$_2$ (in this study referred simply as *EEG-CNN*) achieved the maximum accuracy performance in all the scenarios (AD vs. HC, AD vs. MCI, MCI vs. HC). However, It is worth mentioning that higher F1-scores of 76.03 $\pm$ 4.72 %, 55.66 $\pm$ 5.57 %, 83.56 $\pm$ 1.23 % were achieved by *EEG-CNN*$_3$ (in AD vs. HC comparison), *EEG-CNN*$_1$ (in AD vs. MCI comparison), *EEG-CNN*$_4$ (in the MCI vs. HC comparison), respectively. Table II shows the EEG epoch classification performance of the proposed *EEG-CNN* in terms of precision, recall, F1-score and accuracy. Notably, the *EEG-CNN* achieved the highest accuracy in the AD vs. HC scenario with a value of 85.78 $\pm$ 2.18% and reported precision of 80.92 $\pm$ 5.58%, recall of 69.67 $\pm$ 11.27% and consequently F1-score of 74.17 $\pm$ 6.07 %. Very good results were observed also in the MCI vs. HC classification task, where *EEG-CNN* achieved accuracy rate up to 85.34 $\pm$ 1.86% and F1-score up to 83.02 $\pm$ 1.55 %. Lower discrimination performance were achieved in the AD vs. MCI, reporting an accuracy of 69.03 $\pm$ 1.33% and F1-score of 50.10 $\pm$ 4.48%.

VI. Discussion and Conclusion

This ambitious study aims at exploring the potential of deep learning to discriminate AD/MCI/HC subjects directly from EEG signals. In particular, our developed innovative approach is designed to *self-learn* and extract discriminating features directly from EEG time series, without the need for an engineering feature extraction stage. Specifically, a custom Convolutional Neural Network (denoted as *EEG-CNN*, comprising 2 convolutional layers, 2 pooling layers and 1 fully connected followed by a softmax output layer), was developed to perform the following 2-way classification tasks: AD vs.

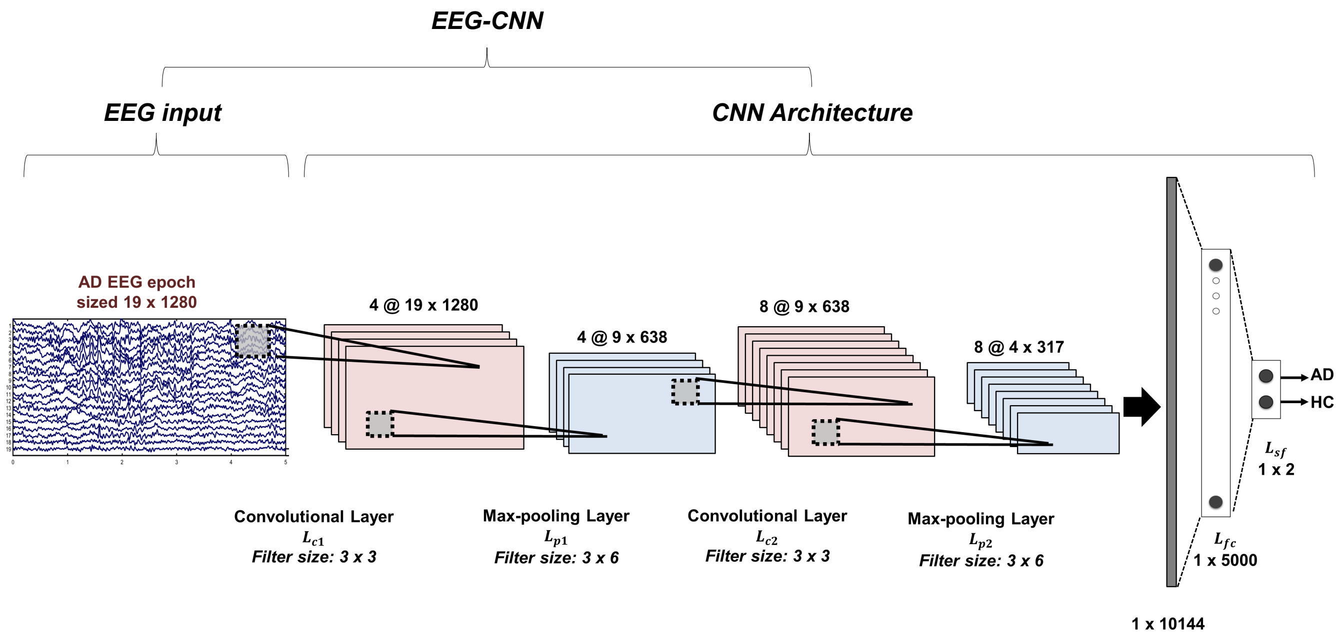

Fig. 3. Proposed *EEG-CNN* architecture. It is designed to receive the temporal EEG epoch (sized 19 x 1280) and comprises 2 convolutional layers (L_{c1}, L_{c2}), 2 max pooling layers (L_{p1}, L_{p2}), 1 fully connected layer (L_{fc}) followed by a softmax (L_{sf}) for classification purpose. Note that after each convolutional layer a ReLU activation function is applied. As an example, the figure shows the AD vs. HC classification task.

HC, AD vs. MCI, MCI vs. HC. To this end, EEG segments were extracted from a dataset of 189 EEG recordings (63 of AD, 63 of MCI, 63 of HC) and used directly as input to the *EEG-CNN*. Comparative test results showed accuracies of 85.78 $\pm$ 2.18%, 69.03 $\pm$ 1.33%, 85.34 $\pm$ 1.86% in AD vs. HC, AD vs. MCI, MCI vs HC, respectively (Table II). In order to assess the validity of the proposed EEG-CNN, the overfitting was also analyzed by comparing the accuracy of train and test. Indeed, experimental results showed that the performance achieved in training and testing stage do not diverge, reporting an average accuracy gap of about 15%. It is worth mentioning that, although the proposed network achieved very good results (especially in AD vs. HC and MCI vs. HC discrimination tasks), higher performances are reported in the literature. Specifically, for a fair comparison, we referred to recent studies that employed the AD/MCI/HC EEG database used here and performed EEG epoch-based 2-way classifications. Table III reports positive and negative aspects of each work. In particular, in [17], a CNN with only 1 layer of convolutional, ReLu and max pooling, was developed, achieving accuracy rate up to 92.95%, 84.62% and 91.88% in AD vs. HC, AD vs. MCI, MCI vs. HC, respectively. However, the proposed methodology comprised a complex feature-engineering step to estimate the Power Spectral Density (PSD). Spectrum profiles were then mapped into 2-d gray scale images (PSD-images) used as input to the developed CNN. Furthermore, the proposed PSD-based approach was deeply influenced by the position of the dominant power peak in the α band. In [28], each EEG signal was projected into the time-frequency (TF) domain via Continuous Wavelet Transform (CWT) and five statistical parameters (mean, standard deviation, skewness, kurtosis entropy) were evaluated from TF maps within every EEG sub-band δ, θ, α_1, α_2, β. The resulting CWT feature vector was fed into different machine learning based classifiers: Autoeconder (AE), Multi-Layer Perceptron (MLP), Logistic Regression (LR) and Support Vector Machine (SVM). Experimental results reported accuracy values of 95.76 $\pm$ 0.45% and 86.84 $\pm$ 0.98% in AD vs. HC and AD vs. MCI classification task, respectively, with 1-hidden layer MLP. In [15], a set of higher order statistics features is extracted from the bispectrum (BiS) representation (denoted as BiS features) and fused together with the CWT feature vector proposed in [28]. The multi-modal (CWT+BiS) features vector was used as input to AE, MLP, LR and SVM architectures, achieving accuracy rates up to: 96.95 $\pm$ 0.5% in AD vs. HC, 90.24 $\pm$ 0.7% in AD vs. MCI; 96.24 $\pm$ 0.5% in MCI vs. HC. Although the methodologies discussed above reported better discrimination results as compared to the approach proposed in the present work, it is to be noted that [17], [28], [15] are based on handcrafted feature-extraction methods, specifically for extraction of power spectral density, time-frequency or high order statistic features. In contrast, our proposed *EEG-CNN* was able to *self-learn* and extract discriminating features directly from the EEG time series without any engineering feature extraction stage, with promising outcomes. Nonetheless, the current methodology also has some drawbacks. First, the

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TABLE I
EPOCH-CLASSIFICATION PERFORMANCES EVALUATED ON THE TEST SETS OF DIFFERENT CNN CONFIGURATIONS. NOTE THAT *EEG-CNN*$_2$ ACHIEVED THE HIGHEST ACCURACY AND IN THIS STUDY, IT IS SIMPLY REFERRED AS *EEG-CNN*. ALL THE RESULTS (PRECISION, RECALL, F1-SCORE, ACCURACY) ARE REPORTED AS MEAN VALUE ± STANDARD DEVIATION.

AD vs. HC				
Model	**Precision**	**Recall**	**F1-score**	**Accuracy**
EEG-CNN$_1$	77.29 ± 3.77%	67.04 ± 12.12%	71.16 ± 6.42%	84.10 ± 2.20%
EEG-CNN$_2$	80.92 ± 5.58%	69.67 ± 11.27%	74.17 ± 6.07%	85.78 ± 2.18%
EEG-CNN$_3$	72.88 ± 2.64%	80.68 ± 12.61%	76.03 ± 4.72%	85.08 ± 1.53%
EEG-CNN$_4$	80.32 ± 4.36%	65.59 ± 17.26%	70.76 ± 11.25%	84.66 ± 3.39%
AD vs. MCI				
Model	**Precision**	**Recall**	**F1-score**	**Accuracy**
EEG-CNN$_1$	54.67 ± 7.27%	61.04 ± 17.08%	55.66 ± 5.572	65.40 ± 3.47%
EEG-CNN$_2$	61.95 ± 4.33%	42.71 ± 6.97%	50.10 ± 4.48%	69.03 ± 1.33%
EEG-CNN$_3$	56.35 ± 6.22%	41.35 ± 3.92%	47.34 ± 1.72%	66.14 ± 3.18%
EEG-CNN$_4$	56.02 ± 5.44%	47.26 ± 10.09%	50.40 ± 4.78%	66.36 ± 2.07%
MCI vs. HC				
Model	**Precision**	**Recall**	**F1-score**	**Accuracy**
EEG-CNN$_1$	77.30 ± 5.00%	89.51 ± 8.32%	82.60 ± 2.73%	84.12 ± 2.32%
EEG-CNN$_2$	82.23 ± 6.64%	84.87 ± 8.16%	83.02 ± 1.55%	85.34 ± 1.86%
EEG-CNN$_3$	81.95 ± 7.25%	83.66 ± 9.76%	82.14 ± 2.59%	84.69 ± 2.31%
EEG-CNN$_4$	82.55 ± 3.41%	84.61 ± 5.04%	83.56 ± 1.23%	84.33 ± 0.94%

TABLE II
EPOCH-CLASSIFICATION PERFORMANCES EVALUATED ON THE TEST SETS OF THE PROPOSED *EEG-CNN*. ALL THE RESULTS (PRECISION, RECALL, F1-SCORE, ACCURACY) ARE REPORTED AS MEAN VALUE ± STANDARD DEVIATION.

Classification task	Precision	Recall	F1-score	Accuracy
AD vs. HC	80.92 ± 5.58%	69.67 ± 11.27%	74.17 ± 6.07%	85.78 ± 2.18%
AD vs. MCI	61.95 ± 4.33%	42.71 ± 6.97%	50.10 ± 4.48%	69.03 ± 1.33%
MCI vs. HC	82.23 ± 6.64%	84.87 ± 8.16%	83.02 ± 1.55%	85.34 ± 1.86%

EEG dataset is composed of MCI and AD patients at different stages of the disorder. This means that EEG epochs of mild-AD could have comparable properties to severe-MCI (and vice versa), possibly causing misclassification. In the future, the classification will be carried out taking into account the stage of the disease. Second, different epochs of the same patients can occur in train and test set. In the future, a larger cohort of AD/MCI/HC subjects will be enrolled in order to avoid that EEG segments of a AD/MCH/HC subject are included in the test stage. Furthermore, in this work, low-density EEG with 19 electrodes (i.e., channels) was used. We believe that a higher number of EEG channels may allow for the extraction of more discriminating features and consequently improve the classification performance. To this end, in the future, high-density EEG recordings will be collected.

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TABLE III
COMPARISON WITH RECENT WORKS THAT EMPLOYED THE AD/MCI/HC EEG DATABASE USED HERE AND PERFORMED THE EEG EPOCH-BASED 2-WAY CLASSIFICATION.

Reference	Methodology	Positive and negative aspects
[17]	Power Spectral Density (PSD) estimation; Mapping of the spectrum profiles into 2-d gray scale images (PSD-images) used as input to the developed CNN	pro: very good performance with accuracy rate up to 92.95%, 84.62% and 91.88% in AD vs. HC, AD vs. MCI, MCI vs. HC, respectively. $cons$: complex feature-engineering step to estimate the PSD; the proposed approach was deeply Influenced by the position of the dominant power peakin the α band
[28]	Continuous Wavelet Transform (CWT) estimation; Evaluation of five statistical parameters from TF maps used as input to the developed AE, MLP, LR and SVM.	pro: very good performance with accuracy rate up to 95.76 ± 0.45% and 86.84 ± 0.98% in AD vs. HC and AD vs. MCI classification task, respectively, with 1-hidden layer MLP. $cons$: complex feature-engineering step to estimate the TF features vector; developing of only the binaries AD vs. HC, AD vs. MCI classifications
[15]	Higher order statistics features estimation from the bispectrum (BiS) and fused together with the CWT feature vector of [28]. The multi-modal (CWT+BiS) features vector was used as input to AE, MLP, LR and SVM architectures.	pro: very good performance with accuracy rate up to 96.95 ± 0.5% in AD vs. HC, 90.24 ± 0.7% in AD vs. MCI; 96.24 ± 0.5% in MCI vs. HC, respectively. $cons$: complex feature-engineering step to estimate the BiS and TF features vectors
Proposed $self\text{-}learning$ approach	Custom CNN able to self-learn relavant features directly from the analysis of EEGs only, avoiding any hand-crafted feature extraction .	pro: extract discriminating features directly from the EEG without any engineering feature extraction stage. $cons$: low-density EEG with 19 electrodes was used. A higher number of EEG channels may allow for the extraction of more discriminating features and consequently improve the classification performance

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