High Dimensional Convolutional Neural Network for EEG Connectivity-Based Diagnosis of ADHD

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ABSTRACT

Background: Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental disorder in children and adults and its early detection is effective in the successful treatment of children. Electroencephalography (EEG) has been widely used for classifying ADHD and normal children. In recent years, deep learning leads to more accurate classification.

Objective: This study aims to adapt convolutional neural networks (CNNs) for classifying ADHD and normal children based on the connectivity measure of their EEG signals.

Material and Methods: In this experimental study, the dataset consisted of 61 ADHD and 60 normal children from which 13021 epochs were extracted as input for model training and evaluation. Synchronization likelihood (SL) and wavelet coherence (WC) were considered connectivity measures. The neighborhood between EEG channels was arranged in a two-dimensional matrix for better representation. Four-dimensional (4D) and six-dimensional (6D) connectivity tensors were composed as model inputs. Two architectures were developed, one 4D and 6D CNN for SL and WC-based diagnosis of ADHD, respectively.

Results: A 5-fold cross-validation was utilized to assess developed models. The average accuracy of 98.56% for 4D CNN and 98.85% for 6D CNN in epoch-based classification were obtained. In the case of subject-based classification, the accuracy was 99.17% for both models.

Conclusion: Based on the evaluation metrics of the proposed models, ADHD children can be diagnosed and ADHD and normal children can be successfully distinguished.

Citation: Mafi M, Radfar Sh. High Dimensional Convolutional Neural Network for EEG Connectivity-Based Diagnosis of ADHD. *J Biomed Phys Eng*. 2022;12(6):645-654. doi: 10.31661/jbpe.v0i0.2108-1380.

Keywords

Attention-Deficit/Hyperactivity Disorder (ADHD); Functional Connectivity; Electroencephalography; Neural Networks; Deep Learning; Artificial Intelligence

Introduction

Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental disorder in children and adults characterized by inattention, excess activity, and impulsive behavior.

Electroencephalography (EEG) is widely used for diagnosing ADHD since 1938 [1]. The features extracted from EEG for ADHD classification or markers are as follows: absolute and relative power [2], theta/beta ratio [3-9], nonlinear features such as fractal dimension, Lyapunov exponent, entropy [10-13], event-related potentials features [14, 15], and connectivity features [16, 17].

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Received: 10 August 2021
Accepted: 20 February 2022

EEG connectivity is a highly effective method to investigate synchronization between EEG channels, categorized into functional, nonlinear, effective, and information-based methods. Functional connectivity applies cross-correlation and coherence while effective connectivity uses Granger causality and partial directed coherence. Nonlinear connectivity measures are phase synchronization and generalized synchronization [18]. EEG functional connectivity has been a marker in developmental brain disorders, such as ADHD [19-22], and EEG coherence and weighted phase lag index are two examples of connectivity measures applied for separating ADHD and normal patients [23-26]. Ahmadlou et al. [27] used synchronization likelihood as a connectivity measure in combination with wavelet decomposition. EEG connectivity is also used for investigating and diagnosing other neurological disorders, such as Alzheimer's disease [28, 29], epilepsy [30, 31], Parkinson's disease [32], and autism [33-35].

Machine learning approaches have been widely applied in classifying medical diseases and disorders such as ADHD in the last two decades such as multilayer perceptron [12] and support vector machines [13].

Chen et al. [36] used convolutional neural networks (CNNs) in combination with a visualization technique to indicate personalized spatial-frequency differences between EEG signals of ADHD and normal children with an accuracy of 90.29%. In the other work, Chen et al. [17] used mutual information as a synchronization measure and rearranged it in a connectivity matrix in which some channels were repeated to ensure that adjacent channels were correctly stored in the matrix using a convolutional neural network with an accuracy of 94.67% on the test data as well. Moghaddari et al. [37] also used convolutional neural networks to classify ADHD and normal children. Considering multichannel EEG as an image, Moghaddari et al. decomposed EEG signals to its frequency sub-bands to make an RGB image and used it as CNN input. They also achieved an average accuracy of 98.48%. Ahmadi et al. [38] used a convolutional neural network with different bands and spatial filtering kernels and reported 99.46% accuracy for classifying ADHD and normal children.

This study aims to introduce CNN models with connectivity features extracted from EEG signals for classifying ADHD and normal children.

Material and Methods

In this experimental study, EEG data were used for ADHD/control children, which is available online [39].

Data Acquisition

The data was collected from 121 healthy and ADHD subjects (males and females) aged 7-12 years old. The experienced psychiatrist confirmed the disorder of the ADHD group, including 61 children by a diagnostic and statistical manual of mental disorders, fourth edition (DSM-IV) criteria. The control group consisted of 60 healthy children without any history of psychiatric disorders.

EEG signals were recorded based on 10-20 standards using 19 channels (Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, O2) with a sampling rate of 128 Hz. The reference electrodes were located on earlobes.

Based on the protocol description, participants were asked to count a set of comic strip pictures shown on a screen during EEG recording. The number of pictures in each image was randomly selected between 5 and 16. After child response, the next image was displayed immediately with a variety of the time duration of EEG recordings based on the average response speed [39].

The proposed method

The proposed method is described as follows: 1) data were preprocessed to remove noise and artifacts from EEG signals. Since deep CNNs usually use big data to train models, they were augmented to make big data and split it into train and test sets; in addition, the functional connectivity measure was calculated for all data epochs. The functional connectivity measures were arranged in four-dimensional (4D) and six-dimensional (6D) tensors according to their scalar or image nature. 4D connectivity and 6D scalogram tensors were given to the convolutional neural network as input.

Two different CNN architectures were used for 4D and 6D connectivity tensors; the train and validation sets were used for training the model and checking the model performance. 5-fold cross-validation was used to report the evaluation metrics of the model.

Data preprocessing and augmentation

EEG signals were bandpass filtered between 1 and 40 Hz using a 6th order Butterworth filter. Then EEG signals were segmented into 2-second epochs with an overlap of 1s and those with amplitude exceeding 150 mv were removed due to motion artifacts. Independent component analysis (ICA) was used to minimize eye-blink artifacts [40]. Further, each epoch was considered as a sample to make big data; 7460 and 5561epochs of ADHD children and normal children were extracted.

A 5×5 channel location matrix was defined with all 19 channels to consider adjacent channels in a convolutional scheme. Figure 1 shows how the channels are located in the matrix; for example, the elements located at positions (3,4) and (4,5) represent C4 and P8 channels, respectively.

Connectivity Measures and Tensors

In this study, two methods were used for measuring functional connectivity between EEG signals: synchronization likelihood (SL) and wavelet coherence (WC). SL is a nonlinear method between two signals calculated based on the distance of each point of the first signal from its nearest neighbors and the replacement of nearest neighbors by the equal time closest neighbors of the second signal.

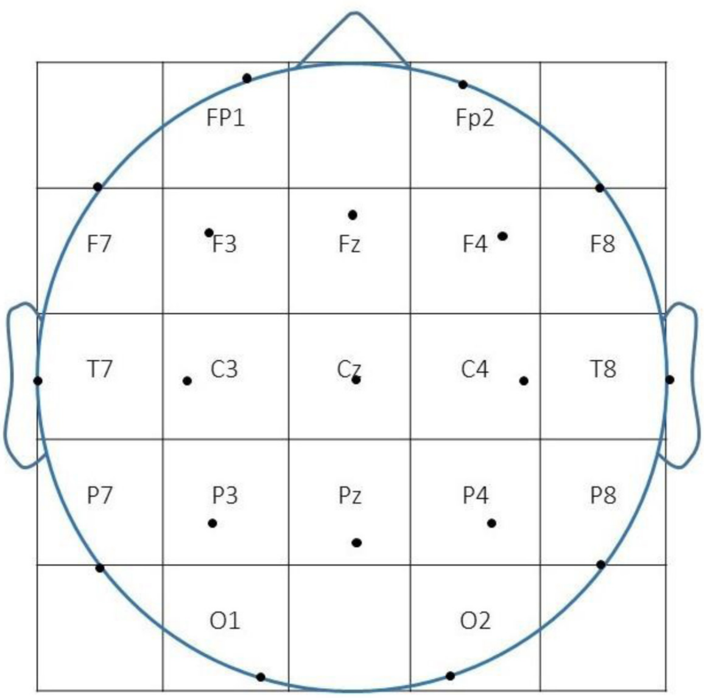

Figure 1: The proposed two-dimensional channel location matrixes.

Based on chaos theory two signals are represented in embedding space [41].

Wavelet coherence is a linear method for coherence estimation between two signals considering non-stationarity by using wavelet transform, known as scalogram [42]. WC represents a two-dimensional (2D) map as a function of time and frequency as shown in Figure 2.

Functional connectivity should be measured between each two EEG channels, represented as a 2D matrix. In this work, the connectivity values were rearranged in a 4D tensor based on the described 2D channel location matrix. Hence a 2D by 2D (5×5×5×5) tensor is composed to represent the functional connectivity as a connectivity tensor. For example, the element located at the position (3,4,5) of the 4D connectivity tensor represents the functional connectivity value between C4 and P8 channels. A schematic stacked view of the 4D connectivity tensor is shown in Figure 3.

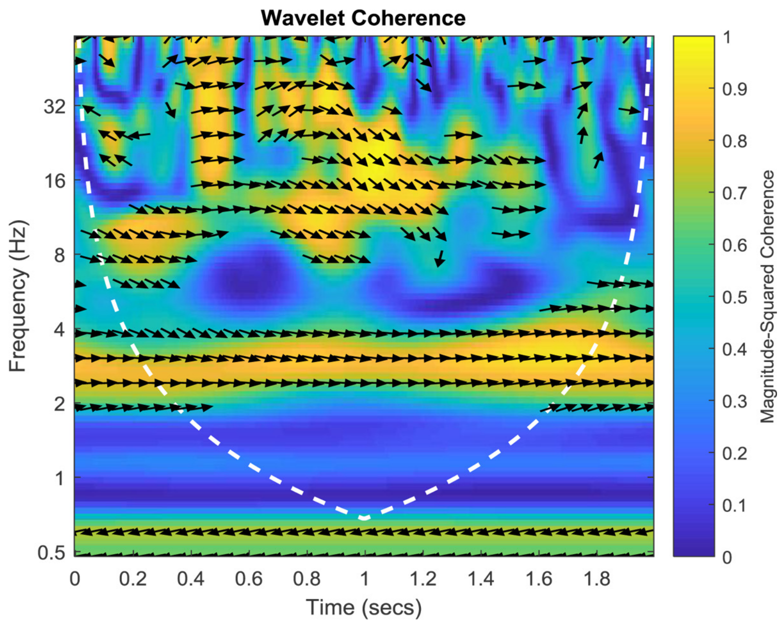

Figure 2: A sample of wavelet coherence between two electroencephalography channels

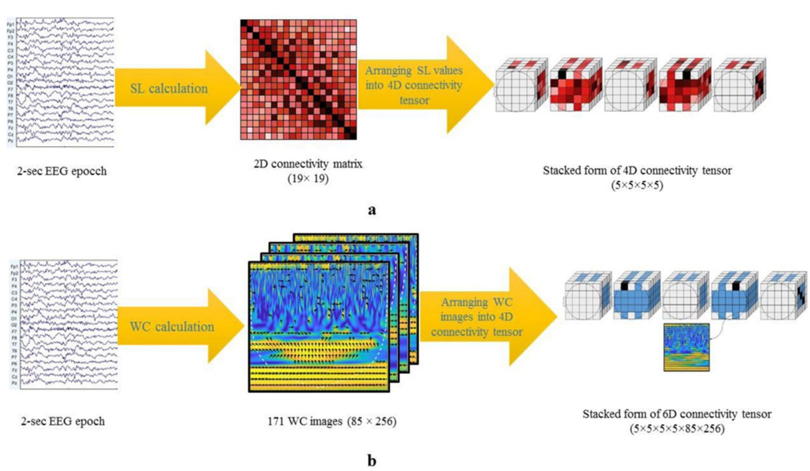

Figure 3: Block diagram of connectivity tensors construction; a) 4D connectivity tensor for synchronization likelihood (SL) and b) 6D connectivity tensor for wavelet coherence (WC).

Wavelet coherence represents functional connectivity between two channels as a 2D image with the connectivity matrix 6D for WC. To understand better this 6D tensor, the 4D connectivity tensor whose elements are 2D WC images individually was considered.

CNN Architecture

The convolutional neural network is a powerful tool for image classification with the main layers of a CNN, including convolutional, pooling, fully connected, and softmax layers. The convolutional layer extracts features from its input by using a kernel. During CNN training, the kernel coefficients are adjusted in a way to yield the minimum error and the pooling layer commonly comes after the convolutional layer(s) to reduce dimensionality and keep the best features. The fully connected layer flattens the output of its previous layer and feeds it to a common neural layer for predicting the classification output. Finally, the softmax layer generates the predicted class. In this study, for better representation of connectivity between nearby channels, CNNs were used, i.e. the inputs come in 4D and 6D for SL and WC connectivity measures, respectively. An architecture of 4D and 6D was used for the architecture of the CNNs. Tables 1 and 2 show the architecture of the proposed 4D and 6D CNNs, respectively. The input, convolutional, and pooling layers are 4D or 6D, while the fully connected layer flattens its input as common and processes in 1D.

Results

The proposed high dimensional convolutional neural networks were evaluated using 5-fold cross-validation. For this purpose, epochs were split into 5 subsets that in each fold, 4 subsets were used to train the model and the remaining subset was used for evaluation. Moreover, 20% of training data was kept for evaluation during training to prevent overfitting. The confusion matrix of 5 folds and the average for the proposed 4D and 6D CNNs are

Table 1: Architecture of the proposed four-dimensional convolutional neural network

Layer Type	Input Dimensions	Kernel Size	Padding	Output Dimensions	Parameters
Input				5×5×5×5	
Convolution	5×5×5×5	3×3×3×3	1×1×1×1	5×5×5×5	82
Max Pooling	5×5×5×5	3×3×3×3		3×3×3×3	
Fully Connected	81			5	410
Softmax	5			1	6

Table 2: Architecture of the proposed six-dimensional convolutional neural network

Layer Type	Input Dimensions	Kernel Dimensions	Padding	Stride	Output Dimensions	Parameters
Input					5×5×5×5×85×256	
Convolution	5×5×5×5×85×256	1×1×1×1×7×7			5×5×5×5×79×250	50
Max Pooling	5×5×5×5×79×250	1×1×1×1×5×5		1×1×1×1×5×5	5×5×5×5×15×50	
Convolution	5×5×5×5×15×50	3×3×3×3×3×3	1×1×1×1×0×0		3×3×3×3×13×48	730
Max Pooling	3×3×3×3×13×48	3 3 3 3 3 3		1×1×1×1×1×1	1×1×1×1×11×46	
Fully Connected	506				8	4049
Softmax	8				1	9

shown in Figures 4 and 5, respectively. On average, 4D CNN could truly predict 98.81% of ADHD epochs and 98.24% of normal epochs, while 6D CNN can truly predict 99.25% of ADHD epochs and 98.31% of normal epochs.

In supervised learning, accuracy is a fine metric to evaluate the model. Since the number of epochs in ADHD and control classes was not the same, F1_score, recall, and precision metrics were also used and defined according to the number of true positives (TP), i.e. the number of epochs associated truly with the ADHD group by the model, true negatives (TN), i.e. the number of epoch associated truly

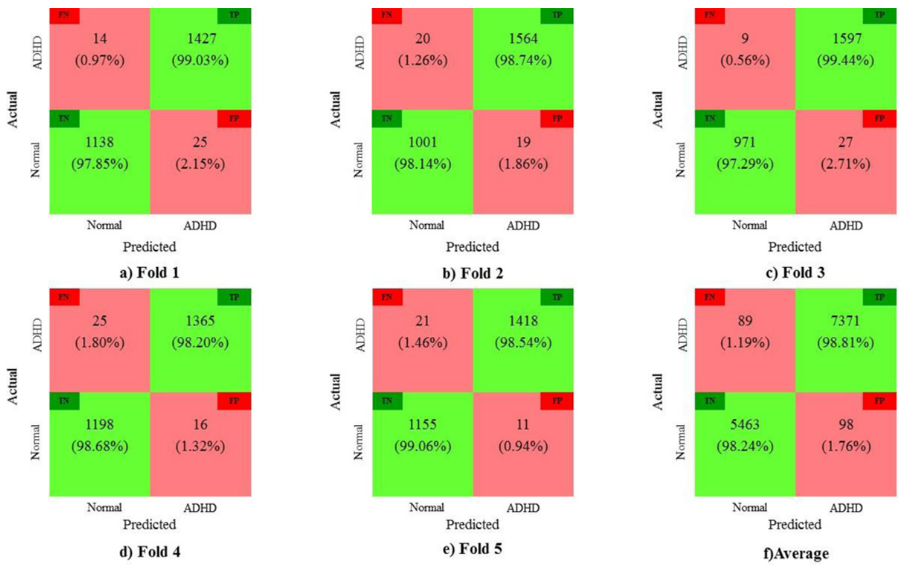

Figure 4: Confusion matrices for 5-fold cross-validation of four-dimensional convolutional neural network classifier. Each confusion matrix shows true positive, true negative, false positive, and false negative of each fold with an average of 5 folds.

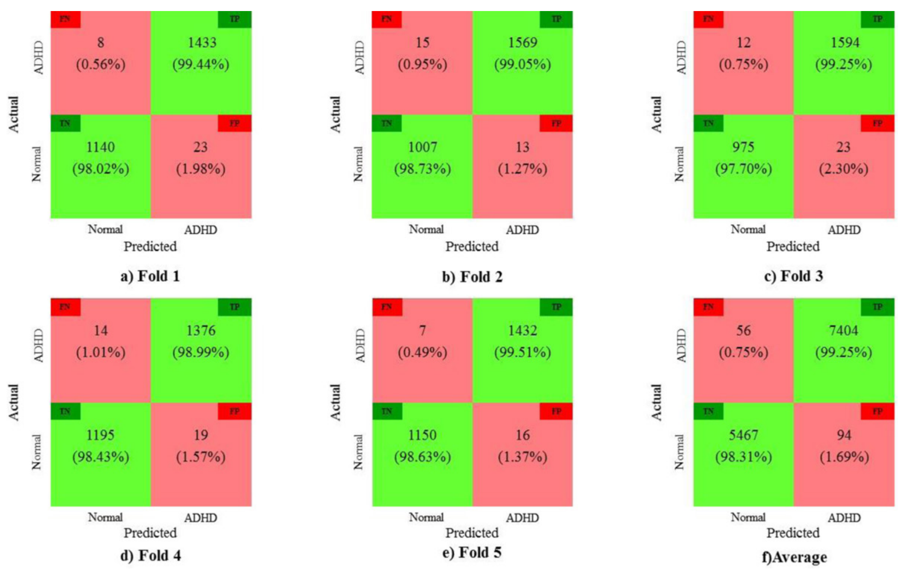

Figure 5: Confusion matrices for evaluation of six-dimensional convolutional neural network classifier. Each confusion matrix shows true positive, true negative, false positive, and false negative of each fold and the average of 5 folds.

to the control group by the model, false positives (FP), i.e. the number of epochs associated wrongly to the ADHD group by the model, and false negatives (FN), i.e. the number of epochs associated wrongly to the control group by the model as below:

$$Accuracy = (TP + TN)/(TP + FP + TN + FN)$$

$$Precision = TP/(TP + FP)$$

$$Recall = TP/(TP + FN)$$

$$F1\_\text{score} = \frac{(2 \times recall \times precision)}{(recall + precision)}$$

Table 3 shows the described metrics for epoch-based classification.

Subject-based classification

The high-dimensional neural network was evaluated to classify each subject. For this purpose, all 2-second epochs of each subject were considered and the class of each subject for each of 5 trained models was determined by the most repetitive class. The final class for each subject was determined by the most voted class by the 5 trained models. Table 4 represents the results for subject-based classification.

Discussion

In this study, a novel CNN approach was proposed for classifying ADHD and normal children. Based on the importance of nearby channels in functional connectivity measures, a channel location matrix was designed and functional connectivity measures were arranged in 4D and 6D tensors, depending on their scalar or 2D image nature. The architectures designed for convolutional neural networks are capable of getting 4D or 6D tensors as input and setting the weights in the kernel of convolutional layers and fully connected layers to achieve minimum error. 13021 2-second epochs of EEG signals were extracted to make connectivity tensors and feed them to the proposed models. 5-fold cross-validation was utilized to assess the proposed models.

Kernels in convolutional layers of CNNs consider adjacent elements for processing. Moreover, adjacency among EEG channels plays an important role in connectivity analysis. Thus, considering adjacency among EEG channels is important before feeding connectivity measures to CNN. Since EEG electrodes are placed on the surface head, adjacency among EEG channels can be better represented in 2D (the described channel location matrix) rather than 1D. Hence, the connectivity measures could have higher dimensions, i.e. four-dimensional for scalar connectivity measures and six-dimensional for 2D connectivity measures. In comparison with arranging EEG channels in 1D and making a 2D connectivity matrix [17], connectivity tensors with higher dimensions to feed CNN can reach higher accuracy.

Table 3: Results of epoch-based classification

Method	Precision (%)	Recall (%)	F1_score (%)	Accuracy (%)
Four-dimensional convolutional neural network	98.69	98.81	98.75	98.56
Six-dimensional convolutional neural network	98.75	99.25	99	98.85

Table 4: Results of subject-based classification

Method	Precision (%)	Recall (%)	F1_score (%)	Accuracy (%)
Four-dimensional convolutional neural network	98.39	100	99.19	99.17
Six-dimensional convolutional neural network	98.39	100	99.19	99.17

Table 5 shows comparing the proposed methods with similar previous works using EEG to diagnose ADHD. Moreover, in the current study, the dataset consists of 121 subjects, including 60 healthy and 61 ADHD children, which is significantly larger than mostly those used in other works. The accuracy of subject-based classification in the proposed method is 99.17%, comparable with other works.

Conclusion

In this paper, two architectures are presented for high dimensional convolutional networks to classify ADHD and normal children using EEG connectivity. The proposed methods use 4D and 6D connectivity tensors as convolutional neural network input, with a CNN architecture designed for better adjacent channels connectivity. Both of the proposed 4D and 6D CNNs could classify ADHD and normal children with 100% recall, 98.39% precision, and 99.17% accuracy, i.e. the proposed classifiers can successfully diagnose ADHD, and discriminate the ADHD and normal children significantly. In the future, we would study neural source-space methods in combination with the proposed method.

Authors' Contribution

All authors contributed to this paper: M. Mafi wrote the article, gathered the images and the related literature, and analyzed the results. Also, M. Mafi and Shokoufeh Radfar supervised his research. Sh. Radfar clinically contributed to this study. All the authors read, modified, and approved the final version of the manuscript.

Ethical Approval

The Ethics Committee of Baqiyatallah University of Medical Sciences approved the protocol of the study (Ethic cod: IR.BMSU.REC.1399.458).

Informed consent

We have the consent of participants in preparing our article.

Conflict of Interest

None

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Table 5: Comparison of accuracy of the proposed methods with other studies.

Study	Year	Dataset	Method	Accuracy (%)
The current study	2021	60 healthy, 61 attention-deficit/ hyperactivity disorder	Wavelet coherence, six-dimensional convolutional neural network	99.17
The current study	2021	60 healthy, 61 attention-deficit/ hyperactivity disorder	Synchronization likelihood, four-dimensional convolutional neural network	99.17
Moghaddari et al. [37]	2020	30 healthy, 31 attention-deficit/ hyperactivity disorder	Color images by decomposing multichannel electroencephalography into 3 sub-bands, deep convolutional neural network	98.48
Ahmadi et al. [38]	2021	14 healthy, 26 attention-deficit/ hyperactivity disorder	Different band and spatial filtering kernels, deep convolutional neural network	99.46
Mohammadi et al. [12]	2016	30 healthy, 31 attention deficit/ hyperactivity disorder	Nonlinear features, multilayer perceptron neural network	93.65
Chen et al. [17]	2019	51 healthy, 50 attention-deficit/ hyperactivity disorder	Mutual information, deep convolutional neural network	94.67
Chen et al. [36]	2019	57 healthy, 50 attention deficit/ hyperactivity disorder	Visualization technique, deep convolutional neural network	90.29

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