A Deep Learning Approach for Automatic Classification of Cognitive Task Using the Scalp Electroencephalogram Signals

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Abstract Cognitive abilities are the vital skills that the human brain requires to perform any type of task, from simple to complex. These skills have a huge impact on the day-to-day lives of people. The electroencephalogram (EEG) is an efficacious technique to study the brain activity while it executes these different cognitive tasks. With low-cost EEG hardware available these days, measuring accurate EEG data has become an effortless task, thereby leading to new innovations like the brain–computer interfaces. In this study, four cognitive tests: Hopkins verbal learning test, Stroop test, Symbol digit modality test, and Benton's visual retention test were considered to stimulate the cognitive abilities. After performing the frequency domain analysis on the EEG signals from a predefined dataset, we obtain the spectral topographical images as classification data, and a deep learning model with convolutional neural network was used to classify these images based on the cognitive tasks. We have obtained a classification accuracy of 84% using our proposed model.

Keywords Electroencephalography · Cognitive tasks · Fast Fourier transform · Deep learning

1 Introduction

Cognitive abilities are a set of natural skills that the brain uses to carry out any task. It has been used to measure the productivity of human brain. They are based on the thinking mechanism of the brain, information processing and learning ability rather than the actual knowledge. They are a collection of skills such as attention, memory, reason, auditory and visual processing. Incompetence in any of these abilities will give rise to difficulties in comprehending a subject, solving problems, brain

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A. Sivasubramanian et al. (eds.), *Futuristic Communication and Network Technologies*,
Lecture Notes in Electrical Engineering 792,
https://doi.org/10.1007/978-981-16-4625-6_37

storming, analyzing and focusing. Hence, identifying these short comings becomes very important in developing efficient methods to cope with such problems. The idea of humans interacting with computers has gained importance recently. The brain–computer interface (BCI) is being seen as the future solution to cognitive impairment. Not only do BCIs have their applications in medicine, for instance, brain tumor diagnosis and neuronal rehabilitation, they are also being used for entertainment, neuromarketing and advertising [1].

Electroencephalography (EEG) is a convenient non-destructive instrument for examining brain activities with extraordinary temporal resolution that is on the scale of milliseconds. There has been a drastic improvement in the size and expense of EEG devices, which has made the process of procuring EEG signals much easier. EEG is effective in recording and analyzing brain functions for a plethora of that encompasses gaming, dealing with traumatic and sleep disorders, cognitive impairment, etc. The use of EEG has expanded from its conventional applications like neurological diagnosis [2] to neurotherapy and brain–computer interfacing [3]. With low-cost EEG hardware available these days, measuring accurate EEG data has become an effortless task. EEG records data from the scalp when electrical variations are detected due to synchronized activity of millions of neurons. BCI is a device that interprets the EEG signals and further translates it for communication purposes or for controlling appliances without manual commands.

Deep learning has caused radical breakthroughs in the field of data science. Convolutional neural networks (CNNs) are considered as the building blocks of deep learning architectures. They are incredible at capturing and learning the right set of features from any kind of input data at different levels similar to a human brain. The main task of BCI is to recognize brain signals. Since brain signals are prone to corruption by various biological artifacts and concentration levels, deep learning models with CNN are best suited for classifying such signals. In [4], the authors have used several complex CNN architectures like CifarNet, AlexNet and VGGNet to segregate the levels of consciousness of patients who have been under anesthetics. The capsule network [5] has been designed for the classification of motor imagery signals.

Although numerous types of EEG signals are used in the study of BCI, the signals of interest depend upon the brain states that generate the distinct cognitive abilities [6]. The various brain states are responsible for producing different brain waves at different frequency ranges. The classic names of these EEG bands are delta, theta, alpha, beta, and gamma. For our research, we have considered the three most predominant brain waves, i.e., theta, alpha, and beta bands.

EEG classification has been performed using many feature extraction techniques and with both deep and machine learning algorithms. Neural synchrony measures such as power analysis, phase amplitude coupling, and phase locking have been applied to EEG signals to assess which mathematical method provides the best discrimination between cognitive tasks using Support Vector Machines (SVM) for classification [6]. For classifying the Raven's advance progressive metric test and a baseline task, wavelet-based feature extraction was proposed by Amin et al. [7] along with the use K-nearest neighbors, SVM and naive Bayes classifiers. Radial basis function SVM has been suggested by Hosni et al. [8] for the classification of mental tasks, by using a new independent component analysis technique for EEG pre-processing. Letter composition and visual counting tasks can be distinguished using empirical wavelet transform [9].

The BCI dealing with EEG signals associated with cognitive tasks has features obtained from wavelet transform, fast Fourier transform, and other methods, with multilayer perceptron and SVM being used for classification [10]. An automated computer platform has been proposed for clustering EEG signals corresponding with left-hand and right-hand gestures, with the independent component analysis being applied on associated channels for noise alleviation of generated EEG sources. The independent components of the feature datasets were given as input to multilayer perceptron and SVM. This research shows that the categorization of diverse pairs of motor cognitive tasks can be utilized in a BCI to manage plethora of instruments [11]. Application of neural networks for identifying and grouping EEG patterns related to motor imagery, i.e., real and imaginary movement of left/right leg in untrained subjects is discussed [12]. CNN with stacked autoencoders, which are dense feed forward connections, has been utilized by Tabar and Halici [13] for the segregation of EEG-based motor imagery signals.

In this paper, we have used fast Fourier transform (FFT) for feature extraction and have transformed the intermediate results into three-channel images before applying deep learning CNN model for classification.

2 Data Acquisition

2.1 Subjects and Experimental Design

The EEG was recorded, while the test subjects performed different neurophysiological tests. The four cognitive tasks conducted were Hopkins Verbal Learning Test (HVLT), Stroop Test (ST), Symbol Digit Modality Test (SDMT), and Benton's Visual Retention Test (MODBENT). The tests were performed by each subject in the same order. The cognitive tests chosen focused on a variety of skill set like memory, attention, processing speed, visual retention, etc.

EEG was recorded from 14 electrodes placed in a standard 10–20 electrode system. The International 10–20 electrode placement system is recognized as a standard procedure for describing the location of electrodes on top of the human scalp. The system is based on the position of an electrode and the underlying area of the cerebral cortex. Each region in the cerebral cortex has a letter corresponding to the lobe and a number which identifies the segment of hemisphere. Frontal (F), Temporal (T), Central (C), Parietal (P), and Occipital (O) are the letters designated for the lobes [14].

EEG readings for the four cognitive tests along with the baseline readings were obtained from the dataset collected by Dvorak et al. [6] and were sampled at 250 Hz.

The main presumption is that, as the dissimilar cognitive tasks require distinct brain functions and different regions of brain to activate, the EEG characteristics during the variety of tasks would diverge. The extent to which attributes in the EEG can be used for mapping EEG signal analogous to its task provides insight into feature extraction for task discrimination.

2.2 Neuropsychological Tests

HVLT has been corroborated within brain disordered populations (e.g., Alzheimer's disease, amnesic disorders) as an estimate of verbal learning and memory. In this test, a list of words was read out to the subjects and they were asked to recall after a short period of time. ST is considered to measure selective attention and processing speed. Subjects had to skim through three different lists of words. The three lists contained names of colors printed in black ink, same colored ink, jumbled color ink (e.g., "red" printed in "blue" ink), respectively [6]. In SDMT, to assess the divided visual attention, the subjects had to promptly comprehend and coincide symbols with corresponding numbers. MODBENT assesses visual perception and memory. The subjects were given four figure designs and had to select the best match from the previously seen figures [9]. The tests were conducted in the same duration of time for each test (HVLT: 149 $\pm$ 96 s, ST: 207 $\pm$ 93 s, SDMT: 167 $\pm$ 85 s, MODBENT 950 $\pm$ 108 s) with baseline being conducted for 660 $\pm$ 350 s. Fifty-four subjects who participated in four cognitive activities and a baseline recording contributed to a total of 270 samples of data.

3 Design Methodology

3.1 Proposed Classification Model

The EEG time series data were down sampled from 250 to 125 Hz. From the down-sampled signals, 15,000 data points were extracted. This was done to exclude segments of the signal with extremely low relevance. The data points were converted into csv files with EEG signals from the 14 electrodes placed around the scalp. This marks the end of the preprocessing stage.

The spectral topography maps were generated with the preprocessed data. These maps are the three-channel 2D images [15]. These images were then classified using our CNN model. The process of generating the images and the CNN architecture are explained in the following sections. Figure 1 shows the classification model.

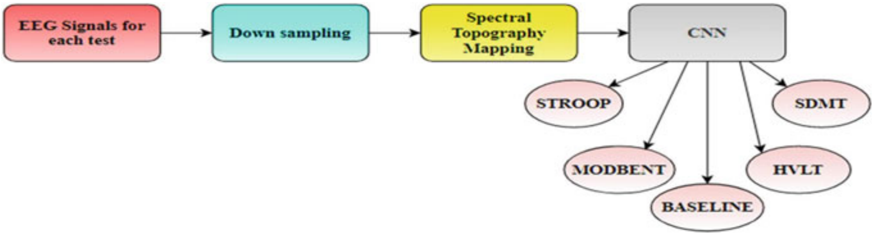


Fig. 1 Proposed classification model

Fig. 2 Spectral topography mapping block

3.2 Spectral Topography Mapping

The EEG data were chopped into overlapping discrete one second "snippets". Hanning window was applied to each of these snippets. In order to obtain mean FFT amplitude, which is required for the succeeding steps, we must calculate the total number of intervals per electrode. The following specifications were considered to estimate the number of intervals. The sampling frequency is 125 Hz, and the frame duration is one second. The overlap percentage between snippets is taken as 75% with 15,000 data points. As a result, for one electrode we get 464 intervals. Since there are 14 electrodes, there are 6496 intervals for each subject.

Fast Fourier transform was applied for each interval and converted from time to frequency domain. The mean of the FFT amplitudes is calculated for each frequency band: beta (12–40 Hz), theta (4–8 Hz), alpha (8–12 Hz) for all intervals, giving three scalar values for each interval. This process is called as frequency binning, and it yields a three-dimensional array of size ($464 \times 14 \times 3$). These values were deciphered as RGB color channels and extrapolated onto a 2D map of the head [16]. This process of projecting theta, alpha, and beta values onto the map of electrode locations is known as Azimuthal projection. Thus, the entire procedure of spectral topography mapping results in three-channel 2D images of size $28 \times 28 \times 3$ which are sent to the CNN network. Figure 2 shows the spectral mapping procedure.

3.3 Convolutional Neural Network

In the last decade, the CNN has become a very popular deep learning algorithm and has been applied to a variety of pattern recognition problems. In terms of accuracy and speed, it has been proven over time that CNNs outperform other classification

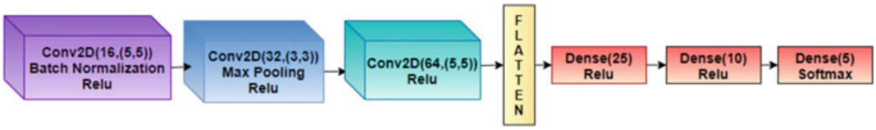


Fig. 3 CNN architecture model

algorithms. The hidden layers of a CNN typically consist of convolution and max pooling layers, fully connected layers, and activation function applied in the end [17]. For a completely new task/problem, CNNs prove to be very good feature extractors. Depth-wise and separable convolutions are used to extract EEG features in a CNN called EEGNet devised by Lawhern et al. [18]. The five-layer CNN model has been designed for automatic motor imagery classification. The first convolution layer in the five layer model aims at filtering EEG in the space domain, whereas the second convolution layer does subsampling on the EEG signal and transforms it into the time domain [19]. Baseline architecture was designed in [20] with the convolution block containing one-dimensional convolution layer, batch normalization layer [21], and ReLU activation. Three such blocks are stacked with global average pooling and softmax activation applied in the end.

The CNN architecture illustrated in Fig. 3 is used to classify the previously obtained EEG images. The first block consists of 16 two-dimensional convolution filters each of 5×5 kernel size, batch normalization layer and ReLU activation. The second block is constructed with a convolution layer having 32 filters each with 3×3 kernel size, followed by maxpooling operation and ReLU activation. The third block is made only with convolution layer (64 filters with 5×5 kernel size) and ReLU function. The resulting feature maps are flattened and given as input to the dense layers. Softmax activation is applied to the final dense layer. Scores for each data are then obtained from the network's output based on the interpolated images.

4 Results and Discussion

We obtained a training accuracy of 87.15% and testing accuracy of 84.33% on our proposed CNN. Figure 4 shows the accuracy plot. The number of EEG images generated from 270 data samples and 464 frames generated per data sample was 125,280. Training and testing data are split according to the ratio of 3:1. The model was trained for 30 epochs with a learning rate of 0.01 and a batch size of 256. Adadelta optimizer along with categorical cross entropy loss function was used to train the networks. The training was done on a Windows machine with 4 GB RAM. The preprocessing was done using MATLAB and Python with Keras API used to construct the CNN.

Figure 5 shows the testing accuracy along with a set of predicated and actual values for few images. Figure 6 shows the heat map obtained with the testing images, for the

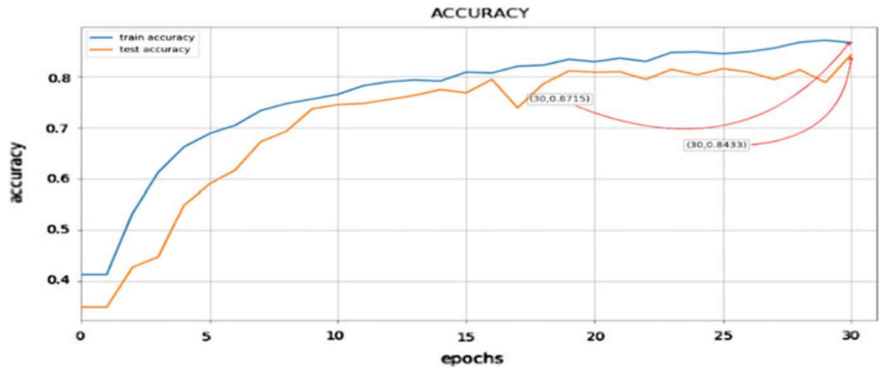
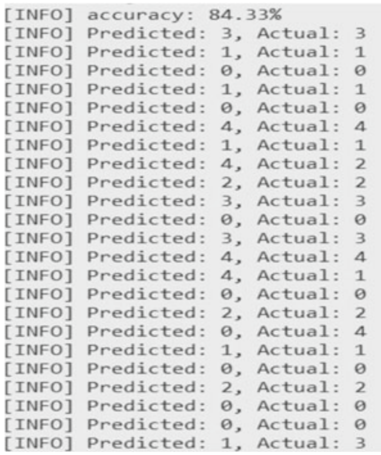


Fig. 4 Accuracy plot for the proposed CNN

Fig. 5 Predicted and actual values



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[INFO] accuracy: 84.33%
[INFO] Predicted: 3, Actual: 3
[INFO] Predicted: 1, Actual: 1
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 1, Actual: 1
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 4, Actual: 4
[INFO] Predicted: 1, Actual: 1
[INFO] Predicted: 4, Actual: 2
[INFO] Predicted: 2, Actual: 2
[INFO] Predicted: 3, Actual: 3
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 3, Actual: 3
[INFO] Predicted: 4, Actual: 4
[INFO] Predicted: 4, Actual: 1
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 2, Actual: 2
[INFO] Predicted: 0, Actual: 4
[INFO] Predicted: 1, Actual: 1
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 2, Actual: 2
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 0, Actual: 0
[INFO] Predicted: 1, Actual: 3
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Fig. 6 Heat map for cognitive task classification

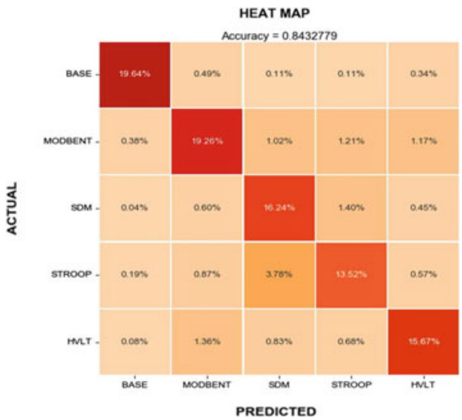

Table 1 Comparing accuracies with other methods

Architectures	Classification methods	Accuracy (%)
Machine learning	Radial basis function SVM [8]	70.00
	SVM [6]	78.80
Deep learning	CNN with autoencoders [13]	75.10
	CNN [15]	79.56
	Proposed CNN	84.33

CNN. We infer that the prediction percent is the highest for baseline task, followed by MODBENT, HVLT, SDMT and ST.

Radial basis function SVM was used as the classifier in [8], for distinguishing three cognitive tasks, and they obtained an accuracy of 70.00%. SVM was used by [6] for the classification of cognitive tasks, and the accuracy score was 78.80%. CNN perform better than machine learning methods since they deal with end-to-end classification. The deep learning model proposed by [13] has an accuracy of 75.10%, for classifying motor imagery signals. The CNN model designed by [15] consists of four convolution layers followed by three dense layers, and it classifies known skills from unknown skills. The accuracy obtained is 79.56%. Our CNN architecture can segregate more than two classes and achieves a higher accuracy score of 84.33%, performing better than all other methods listed in Table 1.

5 Conclusion

We transform EEG data into spectral 2D images that are topologically preserved, as opposed to traditional EEG analysis techniques that ignore vital spatial information. Consequently, the proposed approach is designed to conserve the spectral, spatial and temporal framework of EEG which aids in finding properties that are less susceptible to irregularities within each dimension. The process of spectral topographical mapping takes a long time; hence, it increases the computational time. The unique combination of EEG frequency band (alpha, beta and theta) components in the projected spectral topographical maps proved to be the distinguishing feature between the tasks. The CNN takes the spectral topography maps as features for classification. Cognitive classification can be used to facilitate interactions between a computer and a human, such as the brain–computer interface. The number of tests can be increased so that we can classify other cognitive behaviors.

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