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A convolutional deep learning framework for classification of EEG signals

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Abstract

A brain-computer interface (BCI) is a form of assistive technology that facilitates communication between users and machines by interpreting brain signals. The P300 wave, an event-related potential (ERP) in oddball paradigms, is generated approximately 300 milliseconds after the presentation of the target stimulus selected by the user in the brain. Accurate recognition of these waves in a P300 spelling system enables the user to write letters. Classification of P300 waves in an EEG-based spelling system faces several challenges, including accurate detection of P300 waves and handling the high dimensionality of these signals. This study presents a Convolutional Deep Learning Framework (CDLF) for character recognition using EEG signals. The proposed model uses CNN with a one-dimensional kernel to extract features over time. The proposed model was applied to two public datasets: BCI Competition III dataset II and BCI Competition II dataset IIb. The proposed model showed an average character recognition rate of 95% at epoch 15 for BCI Competition III dataset II and 100% at epoch 15 for BCI Competition II dataset IIb, without using any feature and channel selection methods before classification. The proposed model is promising for brain-computer interface classification applications in the spelling domain.

Keywords: Brain-Compute Interface (BCI), Electroencephalogram (EEG), Spelling, Classification, Convolutional Neural Network (CNN)

1. Introduction

A brain-computer interface (BCI) serves as a communication and control link between the human brain and machines. These systems enable people to operate devices without relying on motor skills. BCI works by measuring brain activity [1-3]. These systems are used in both healthy and sick people and are proving to be particularly beneficial for people who are limited in their mobility, such as people with amyotrophic lateral sclerosis (ALS) [2,3]. For such patients who have difficulties with conventional communication methods, BCI offers an alternative means of interaction [1,3]. In this context, EEG signals are used for non-invasive and cost-effective measurement of brain activity [2-4]. Recently, BCI systems based on EEG signals have been used in various fields of medicine and robotics [1].

The electroencephalogram can be used to record P300 ERP in brain-computer interface systems in various domains, e.g. motor imagery [1], drowsy driving [5] and especially in spelling tasks [2-4], [6-9]. These P300 waves are positive spikes that manifest approximately 300 milliseconds after the presentation of an odd-ball paradigm, such as rows or columns of a character matrix displayed to individuals for character recognition [2,3]. Accurate estimation of P300 is critical for effective character recognition [3]. Repetition of signal recording for each stimulus is becoming increasingly important to aim for a low signal-to-noise ratio to produce reliable responses [2].

BCI systems operate through the steps of signal recording via the amplifier and storage in the

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computer, signal processing, signal classification based on different stimuli, and transmission of the classification results to the output device. During the signal processing and classification phases, various operations such as feature or channel extraction and selection can be performed [3].

BCI systems function through the steps of signal recording via the amplifier and storage in the computer, signal processing, signal classification based on various stimuli, and transmission of the classification results to the output device. During the signal processing and classification phases, various operations, such as feature or channel extraction and selection, can be performed [3].

In the following, some work done by others in the field of character recognition with similar datasets is described. They were applied to the Competition III dataset II and the Competition II dataset IIb with the spelling task. Some of the studies were presented by focusing on the goal of EEG signal classification in BCI systems. Many of them were based on the traditional machine learning methods or used pre-selected/hand-crafted features and channels [10]. A modified genetic algorithm known as Dual-Front Genetic Algorithm (DFGA), which focuses on selecting the optimal channel for each individual, was presented in the study [2]. Several experiments were conducted using different evolutionary and meta-heuristic algorithms in both single and multi-objective forms. DFGA, applied to the Competition III dataset II, achieved an average accuracy of 94.5% in character recognition at epoch 15, even after using 20 optimal channels determined by the algorithm.

Research [11] presented an integrated probabilistic model for spelling ERP. In this study, the introduced probabilistic classifier inherently incorporates a Dynamic Stopping (DS) strategy. This method uses identical parameters for three individuals from two different datasets. The results of the classifier show an improvement in spelling speed and accuracy, especially when augmented with language models (LM) and dynamic stopping. However, it achieved an accuracy of about 96% for Competition III-Dataset II and 92% at epoch 15 for Competition II-Dataset IIb.

In the study [12], another classification method for character recognition was presented, which includes discrete wavelet transform (DWT) preprocessing and a set of linear Fisher classifiers. The performance of the proposed method achieved 100% accuracy in BCI Competition II and 95% accuracy in BCI Competition III at epoch 15. The classifier achieved approximately 90% accuracy in Competition II at epoch 3 using selected channels determined by the model. The study [13] presented BN3, a convolutional neural network developed for P300 signal detection. In BN3, batch normalization was applied to the input and convolutional layers to prevent overfitting. Although the model showed an impressive accuracy of about 96% for Competition III and 100% for Competition II at epoch 15, it achieved an accuracy of about 96% for Competition II at epoch 8. Additional CNN models, as presented in studies [3] and [14], achieved an average accuracy of approximately 94% and 91% at epoch 15 for Competition III. Table 1 provides a comparison of relevant studies conducted on similar datasets with spelling tasks.

Table 1
Summary Of The Related Works On BCI With Spelling Task On The Similar Databases (Percentage)

Method	Channel Selection	Dataset/ Subject Number	Mean Accuracy ($\approx 15^{th}$ Epoch)
DFGA [2]	Yes	Comp. III / 2	94
CNN [3]	No	Comp. III / 2	94
BPSO [9]	Yes	Comp. III / 2	89.9
LM + DS [11]	No	Comp. III + Comp. II / 3	95
Ensemble Fisher's LD (EFLD) [12]	Yes	Comp. III + Comp. II / 3	96
CNN (BN^3) [13]	No	Comp. III + Comp. II / 3	97
CNN [14]	No	Comp. III + Comp. II / 3	94
CNN-RG-MINMAX (CNN)/ CNN-RG-MINMAX (MDRM) [14]	No	Comp. III + Comp. II / 3	98/ 96
CNN-LSTM/CLSTM-AE [15]	Yes	Comp III / 2	90/94
SVM [16]	Yes	Comp. III /2	94
Deep Neural Network [17]	Yes	Comp. III /2	93
CDLF [This study]	No	Comp. III + Comp. II / 3	96
CDLF [This study]	No	Comp. III / 2	95
CDLF [This study]	No	Comp. II / 1	100

Traditional machine learning methods have produced satisfactory results in EEG classification, but they often struggle to capture the nonlinearities inherent in high-dimensional, multi-channel EEG data. Compared to the models based on convolutional neural networks introduced by others, the proposed model has a simpler structure and consists of simpler layers. However, it has shown better performance in character recognition. Unlike the works of others, such as model [3], in the proposed model, batch normalization layers are used to accelerate convergence, which leads to reducing the time complexity of model training. In addition, unlike some works based on optimization algorithms of others, such as models [2,9], by using the information from all the channels of each subject, the desired performance has been achieved, and no information from the proposed model has been added or removed in a tasteful or manual manner. The proposed model is less complicated than some other works, such as [2,9,14]. More complex models require more time and computing resources to train and run.

The proposed model has high potential to improve its performance by combining the concept of convolution with other powerful concepts compared to previous works, such as [14,15], which did not achieve impressive performance even by combining many concepts. Extracting features from the data and developing an accurate brain-computer interface system remain challenging tasks that open up opportunities for further research in this area, particularly through the use of advanced deep learning techniques.

The rest of the article unfolds as follows: Section 2 outlines the proposed methodology. The experimental results and the corresponding discussions are detailed in Section 3 and the conclusions are presented in Section 4.

2. Methodology

2.1. Pre-Processing

The EEG signals were subjected to an initial segmentation in which a 650-millisecond segment was extracted from the onset of each gain. Given the sampling rate of 240 Hz for the BCI Competition datasets, the extracted segment for each channel comprised 156 points for both datasets. The data were then downsampled to a sampling rate of 120 Hz. The EEG samples were then band-pass filtered from 0.1 to 20 Hz using an eighth-order Butterworth band-pass filter. Finally, the signals were normalized by subtracting the time feature of each channel from the average time value across all channels for each sample. The mean was then divided by the standard deviation of the time value across all channels for each sample. The mean and standard deviation were calculated for each individual sample and electrode. Each signal segment consisted of 78 data points.

2.2. Proposed Deep Learning Model

The obtained EEG signal samples from the preprocessing section were used as input in the input layer of the proposed CDLF model. Figure 1 gives an overview of the block diagram of the proposed CDLF.

This novel Convolutional Deep Learning Network uses three convolutional layers to extract the spatial features of the EEG signal data over time in the CDLF classifier. Two dense layers (100/2 dense nodes) were involved in the fusion part of the model. In this context, a standard convolutional layer, more precisely a two-dimensional convolution (2D), whose kernels are structured in a one-dimensional (1D) format was used. This means that the organization of the sensor data within the split input window had no influence on the extracted features in the final convolutional layer. This property resulted from the use of a [number of channels×1] kernel in the first layer of the convolution, in which the values of the EEG channels were merged using 10 filters and a linear activation function. Consequently, the spatial and temporal features were not combined in a single kernel.

In the second convolutional layer, a 2D convolution with a linear activation function and a [1×26] kernel five times the size of the first layer was implemented for signal sampling. The third layer of convolution for sampling in the CNN used 2 filters with a [1×1] kernel. In addition, a batch normalization (BN) layer was applied after each convolution operation to accelerate the convergence of the CNN. Furthermore, steps of size [1×1], [26×1] and [1×1] were used in the first, second and third layers of the convolution, respectively. Then, the output of the last layer was flattened, resulting in a vector with six features, which was then passed to the fusion layer of the proposed model for classification. The classification architectures of the proposed CDLF are shown in Figure 2.

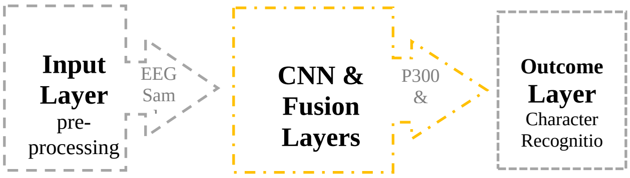


Fig. 1. Overview block diagram of the proposed CDLF

3. Result and Discussion

In this section, the BCI Competition datasets were subjected to the application of the proposed method, where feature extraction was performed automatically using convolutional layers and classification was performed using the CDLF classifier. The results of the proposed method were then compared with those of other studies for both competitions.

3.1. BCI Competition Dataset

The proposed method was applied to dataset II of BCI Competition III [18] and dataset IIb of BCI Competition II [19].

BCI Competition III dataset II: This dataset contains P300 evoked potentials from subjects A and B following a 6 × 6 matrix paradigm described in [20] and originally introduced by Farwell and Donchin [21]. During the five-session experiments, the 36-character paradigm was presented, as shown in Figure 3, and participants were instructed to focus on the characters forming a given word. The six rows and columns of the matrix were randomly alternated at a frequency of 5.7 Hz, with each row or column being emphasized for 100 milliseconds, followed by a 75 millisecond blank period. Two out of 12 reinforcements showed the target character (a specific row and a specific column). This set of 12 flashes formed an epoch that took a total of (100 + 75) × 12 = 2.1 seconds for each character recognition. The repetition of each epoch for individual characters occurred 15 times, resulting in a total of 180 intensifications per character. A 2.5-second interval with an empty spelling matrix was inserted between successive spellings of two characters. For signal acquisition, a 64-channel data acquisition system was used, band-pass filtered in the range of 0.1 to 60 Hz and digitized at a frequency of 240 Hz.

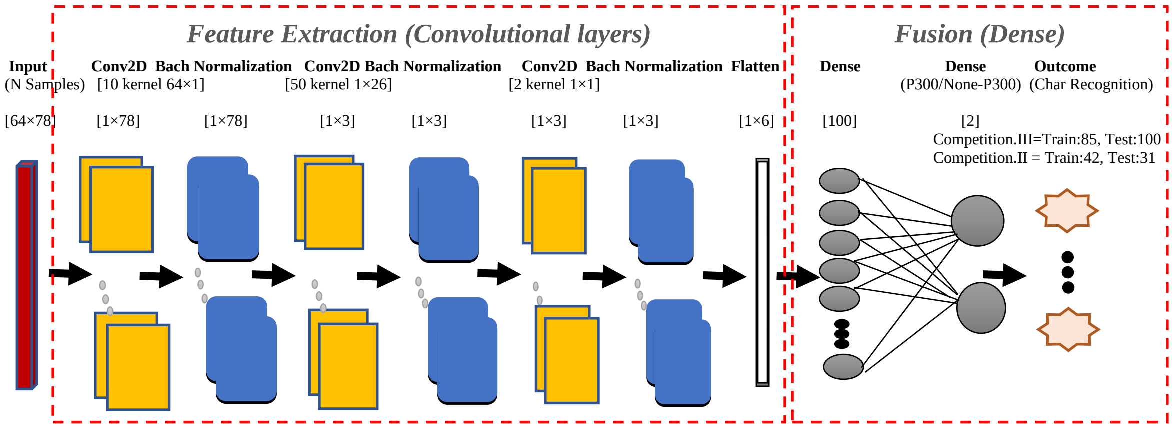


Fig. 2. The proposed CDLF model architecture

For each A and B subjects of Competition III, the training and test databases comprise 85 and 100 characters respectively. Consequently, for each character, there are 30 (2 × 15) samples for the P300 response and 150 (10 × 15) samples for the non-P300 response. In the offline step, where 85 characters were used, there were 2550 samples representing the target and 12750 samples (85 × 150) representing the non-target.

BCI Competition II dataset IIb: This dataset is very similar to BCI Competition III dataset II, with the only difference being that 42 characters were used for training and 31 characters for testing. In the offline sessions (42-character spelling), a total of 7560 trials (42 × 12 × 15) were performed. Similarly, during the online sessions (31 characters), a total of 5580 trials (31 × 12 × 15) were recorded for subject C [11-14].

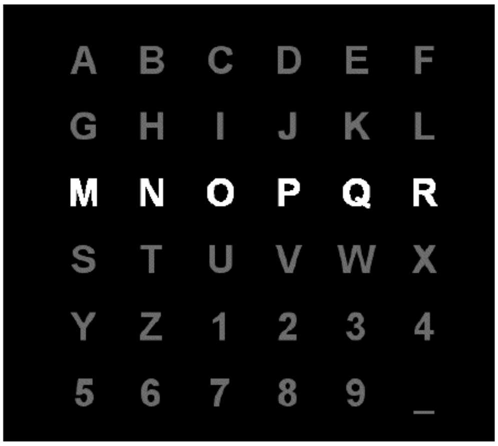


Fig. 3. The P300 speller paradigm

3.2. Evaluation Criteria

The proposed CDLF model utilized the area under the curve (AUC) and Equations (1)-(4) to evaluate performance. The performance evaluation results of the proposed CDLF classifier are shown in Tables 2 and 3. The performance evaluation criteria are as follows [9,22,23].

$$\text{Recall} = \frac{TP}{TP+FN} \tag{1}$$

$$\text{Recognition Rate} = \frac{TP+TN}{NP} \times 100 \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{F\_Measure} = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{4}$$

Where True Positive (TP) refers to the number of correctly identified P300 samples. True Negative (TN) indicates the number of non-P300 samples correctly identified as such. False Positive (FP) is the number of non-P300 samples incorrectly identified as P300. False Negative (FN) is the number of P300 samples incorrectly identified as non-P300. The total number of samples that include both P300 and non-P300 samples is referred to as NP. In addition, the recognition rate refers to the recognition of P300 from non-P300 and the character recognition rate refers to the correct recognition of characters.

3.3. Evaluation Results

To better assess the performance of the proposed model, it was tested on two databases and compared with models used in previous studies for the same databases (see Section 1). The results showed that the novel CDLF model has significant potential for recognizing characters in various subjects (A, B and C).

Table 2
P300 Detection Results For Subjects A & B (Competition III) & C (Competition II) (Percentage)

Method	Subject	TP	TN	FP	FN	Recognition rate	Recall	Precision	F_Measure	AUC
CDLF	A	1995	10766	4234	1005	70.89	0.665	0.320	0.432	0.761
[This Study]	B	2141	11197	3803	859	74.10	0.713	0.360	0.478	0.802
	C	798	3861	789	132	83.49	0.858	0.502	0.634	0.920
	Mean	-	-	-	-	.	0.745	0.394	0.515	0.828

Table 3
Character Recognition Rate (Percentage) For Different Proposed Classifiers (Competition III & Competition II & EEG Dataset)

Method	Subject	Epochs														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CDLF	A	21	36	51	55	57	62	77	78	85	88	88	90	92	94	94
[This Study]	B	37	54	54	67	75	78	80	84	87	93	94	95	95	96	96
	C	70	70	90	100	100	100	100	100	100	100	100	100	100	100	100
	Mean														96.6	96.6

In this study, an innovative deep learning convolutional architecture was introduced to address uncertainties in character recognition by EEG signals. To address the prevalence of noise, a batch normalization layer was incorporated into the model after the convolutional layers. This layer makes the network less susceptible to significant variations in spatial features by adjusting the inputs. The proposed CDLF model has shown almost better performance. In particular, the proposed CDLF model achieved an average test value accuracy (character recognition rate) of 96.6% in all three subjects in epoch 15, outperforming most other models [2,3,9,11,12,14-17] in character recognition for these subjects.

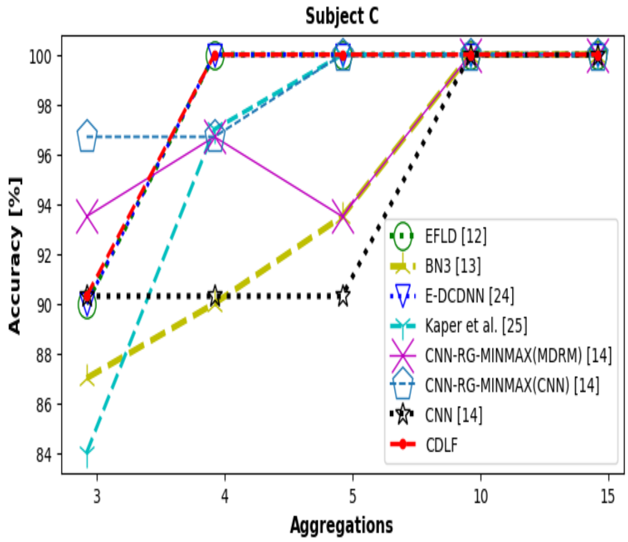
The data presented in Tables 2 and 3 show that subject C achieved more favourable evaluation results in Competition II compared to all other subjects in both data sets. In addition, this subject achieved an accuracy of 100% after the third epoch and showed an accuracy of approximately 90% after the third epoch, outperforming other work [11-14]. In addition, subject B showed better results compared to subject A, with an accuracy of over 93% after the tenth epoch. Figure 4(a) shows the average character recognition rate (accuracy) of the proposed CDLF classifier compared to other studies for Subject C. Figure 4(b) also shows the average accuracy of the proposed novel CDLF classifier for all subjects during epochs 1 through 15. Table 4 shows the average accuracy values in percentages for epochs 3, 4, 5, 10, and 15 in Competition II.

Table 4
The Character Predicted And Accuracy (In %) Of The Proposed T2TFCRNN (GRU) On BCI Competition II

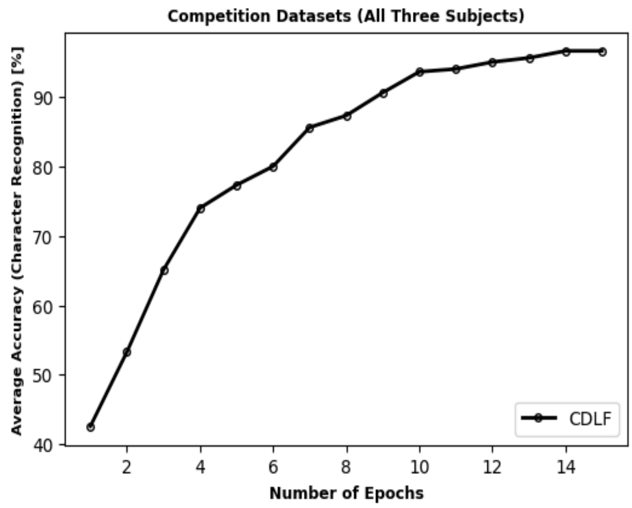
Ref.	Epochs				
	3	4	5	10	15
E-DCDNN [24]	90.	100	100	100	100
Kaper et al. [25]	83.	96.	100	100	100
EFLD [12]	90.	100	100	100	100
BN[3] [13]	87.	90.	93.	100	100
CNN-RG-MINMAX MDRM [14]	93.	96.	93.	100	100
CNN-RG-MINMAX CNN [14]	96.	96.	100	100	100
CNN [14]	90.	90.	90.	100	100
CDLF [This study]	90.	100	100	100	100

Furthermore, it is important to note that all channels and features are used without selecting the most appropriate ones. This approach aims to provide a fair basis for comparing classifiers. The accuracy figures in both datasets show that the novel classifier performs commendably in character classification, especially after 15 epochs for all datasets and especially after 3 epochs for Competition II. The results show that the proposed CDLF classifier effectively classifies the majority of the 100/31 characters in each subject's test dataset (subject A: 94%, subject B: 96%, subject C: 100%, and mean: 96.6%).

These results are significant in that the proposed approach uses all data in an unrefined manner and outperforms other studies with multiple subjects. Some studies, such as [2, 9, 12-17], either selectively manipulated the training dataset or excluded the last three sign-related EEG signals of subject C in Competition II by not including them in the training of the model. Despite these challenges, the proposed CDLF model achieved comparable results.



(a)



(b)

Fig. 4. The 3th, 4th, 5th, 10th and 15th epochs accuracy of the proposed classifiers (CDLF) are shown in (a) for Competition II. The average accuracy of the proposed novel CDLF classifier for all subjects during the 1st to 15th epochs are shown in (b).

4. Conclusion

In this study, a novel convolutional deep learning framework called CDLF is presented. CDLF was developed for the effective classification of characters based on EEG signals. Its accuracy is comparable to and in some cases exceeds that of previous studies in Competition III. In addition, CDLF outperforms the results of previous studies in Competition II. The results of the proposed classifier show superiority over other studies, especially in epoch 3 of Competition II and in many studies in epoch 15 in both contests with three subjects. The convolutional layers in the CDLF model automatically extract features without the need for channel selection. In addition, a BN layer was applied after each convolutional operation to accelerate the convergence of the CNN.

Future research efforts could explore the use of deeper models by integrating uncertainty management methods, such as type 2 fuzzy set theory, with deep neural networks. The reason for this is the robustness of these models in solving real-world problems, as demonstrated by recent applications of deep learning models [26,27], especially when dealing with high levels of uncertainty associated with unstable and time-dependent data [26]. Consequently, the proposed framework provides ample opportunities for improvement and fine-tuning. The identified limitations can be considered as challenges for future research initiatives

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