Comparison of Deep Learning and Traditional Machine Learning Classification Performance in a SSVEP Based Brain Computer Interface

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Abstract—**Brain-computer interfaces (BCIs) offer a very high potential to help those who cannot use their organs properly. In the literature, many electroencephalogram (EEG) based BCIs exist. Steady state visual evoked potential (SSVEP) based BCIs provide relatively higher accuracy values which make them very popular in BCI research. Recently, deep learning (DL) based methods have been used in EEG classification problems and they had superior performance over traditional machine learning (ML) methods, which require a feature extraction step. This study aimed at comparing the performance of DL and traditional ML-based classification performance in terms of stimuli duration, number of channels, and number of trials in an SSVEP based BCI experiment. In the traditional approach, canonical correlation analysis method was used for the feature extraction and then three well-known classifiers were used for classification. In DL-based classification, spatio-spectral decomposition (SSD) method was integrated as a preprocessing step to extract oscillatory signals in the frequency band of interest with a convolutional neural network structure. Obtained offline classification results show that proposed DL approach could generate better accuracy values than traditional ML-based methods for short time segments (< 1 s). Besides, use of SSD as a preprocessing step increased the accuracy of DL classification. Superior performance of proposed SSD based DL approach over the traditional ML methods in short trials shows the feasibility of this approach in future BCI designs. A similar approach can be used in other fields where there are oscillatory activities in the recorded signals.**

Index Terms—**Brain computer interface, classification, convolutional neural network, deep learning, spatio-spectral decomposition, steady state visual evoked potential.**

I. Introduction

BRAIN COMPUTER INTERFACES (BCIs) have the potential to improve the quality of disabled people's lives by providing an additional communication channel [1].

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Therefore, people who lost their ability to use their organs can still benefit from their neuronal signals in the brain to execute the desired action.

Steady state visual evoked potential (SSVEP) is one of the most popular evoked potentials due to its robustness and high signal-to-noise ratio (SNR) [2]. SSVEP based BCIs offer high information transfer rate (ITR) - a common measure to calculate the performance of a BCI [3].

In the SSVEP based BCIs, one common feature extraction method is the canonical correlation analysis (CCA) that has been shown to be superior to the other existing methods like the power spectral density [4] and minimum energy combination [5]. In the problems where two sets of data are expected to have some correlations CCA method can be preferred.

Deep learning (DL) is a relatively new approach in neuroscience. However, it has already shown its superiority over traditional feature based classification algorithms in several electroencephalogram (EEG) classification problems [6]–[8]. Convolutional neural network (CNN) is a class of deep neural network (DNN), which is commonly used in DL based approaches. Kwak et al. [9] proposed a CNN for classifying SSVEP under a static and an ambulatory environment. The proposed CNN generated better classification rates than the standard neural network, CCA classifier, CCA combined with k-nearest neighbor (KNN), and a multivariate synchronization index. Ravi et al. [10] compared user-dependent and user-independent training of CNN for SSVEP based BCI classification in two datasets using magnitude and complex spectrum features. They used the CCA method as the baseline method and applied task-related component analysis and filter-bank CCA. Their results suggested that user-independent complex CNN method provides a good trade-off between performance and training cost. Ikeda and Washizawa [11] proposed a complex valued CNN to overcome the limitation of available frequencies in the SSVEP based BCIs. Their method outperformed the CCA based classification methods. Guney et al. [12] proposed a new CNN based DNN and reached an ITR of 265.23 bits/min and 196.59 bits/min on two different SSVEP datasets for a very short (0.4 s) stimuli duration. By the time of the publication, these ITR rates were reported to be the highest performance results obtained on these datasets. Recently, Zhao et al. [13] verified the feasibility of using CNN for augmented reality based SSVEP classification.

Although many studies run the DL algorithms on the raw data, DL based classification algorithms were shown to be sensitive to the preprocessing [14]. In EEG classification problems, SNR is a critical value. It is important to obtain the oscillatory sources reliably for an accurate classification. Spatio-spectral decomposition (SSD) is a method to find linear filters that maximizes the power in the frequency band of studied neuronal oscillations while minimizing the power at the neighboring frequencies [15]. In this study, SSD method was used to reliably extract oscillatory signals in the frequency band of interest in the DL-based classification.

Channel selection is an important step in finding the relevant EEG channels that are used in feature extraction process [16]. Therefore, this step is directly affecting the accuracy of the classification. Several channel selection methods have been proposed in the literature. For example, common spatial pattern (CSP) is one of the popular methods in motor imagery based BCIs [17]. Arvaneh et al. [18] proposed a decision tree based channel selection method in a motor imagery based BCI dataset and showed that this method outperformed the other methods based on Fisher Criterion, Mutual Information, Support Vector Machine and CSP coefficients especially when there are few channels. They later proposed a sparse CSP algorithm for channel selection in two motor imagery based BCI datasets and showed its superiority over the regularized CSP in addition to the other methods [19]. Recently Feng et al. [20] proposed a multi frequency CSP-Rank method for channel selection in a motor imagery-based BCI dataset and showed that it improved the classification accuracy compared with the CSP-rank channel selection method.

In SSVEP based BCIs there are other approaches for channel selection. For example, Zhang et al. proposed spatial temporal correlation method to select the best channels and showed that it increased the average accuracy [21]. In another SSVEP based BCI, Meng et al. used sequential floating forward selection, discrete particle swarm optimization and F-score to select the optimal EEG channels and showed that this generates higher classification accuracies than using traditional O1, O2 and Oz channels [22]. Webster et al. used an unsupervised channel selection method in an SSVEP based BCI with the majority voting of classification outputs obtained from each subset of channels and showed that this method could be better from a priori channel selection method when CCA is used in feature extraction [23]. Carvalho et al. compared many methods for feature extraction and classification in an SSVEP-based two-class BCI, and noticed that the best feature selection method was incremental wrapper method that performed feature selection using the performance of the classifier as in the case of genetic algorithms (GAs) [24]. In fact, GAs have been used in many EEG classification problems. Yang et al. applied the genetic neural mathematic method to two EEG channel selection and classification problems, and showed that it improved the generalization ability [25]. In a slow cortical potential based BCI task, Schroder et al. used a GA for feature selection and showed an increase in classification accuracy [26]. Peterson et al. also used GA for feature selection in a two-class visual BCI task and showed that this method found better features than using all features or random feature subsets [27].

Stimuli duration is another important factor for SSVEP based BCIs which directly influences the ITR. Although the accuracy of the SSVEP increases with the increasing duration of the stimuli, ITR starts to decay after some time [28].

In the study, DL and traditional ML-based classification accuracies were compared in an SSVEP based BCI experiment in terms of stimuli length, number of channels, and number of trials. Furthermore, SSD method was incorporated in DL based approach as a preprocessing step to increase the classification accuracy.

II. MATERIALS AND METHODS

A. *Participants*

Seven right-handed healthy subjects (four males) between 17 and 24 years with an average age of 21 years voluntarily participated in the study and gave their written informed consent. Ethical approval was obtained from the Local Ethics Committee of National Research University Higher School of Economics, Moscow.

B. *Experiment setup*

The experiments were performed by the author in a shielded dark room at the EEG laboratory of the Center for Cognition and Decision Making of National Research University Higher School of Economics, Moscow. The setup used in the study was same as a previous study [29]. During the experiments, subjects were sitting on a chair and looking at an LED monitor in front of them. EEG were recorded simultaneously with the electrodes attached to the scalp while the subjects were following the visual stimuli. Electrode cables were attached to the EEG amplifier and the amplifier was connected to the recording computer. Visual stimuli presented to the subjects were four circles on the LED monitor (Resolution: 1920 × 1080 pixels, refresh rate: 60 Hz). Each of the circles had a different flickering frequency: 5.45 Hz for upper circle, 8.57 Hz for lower circle, 12 Hz for the right circle, and 15 Hz for the left circle. These frequencies depend on the refresh rate of the monitor and were selected in a way that the first and second harmonics of the stimuli will not coincide. In Fig. 1, the locations of the circles on the LED monitor are presented.

The visual stimuli interface was prepared on Matlab software (https://www.mathworks.com/products/matlab.htm) with the help of Psychophysics Toolbox (http://psychtoolbox.org/).

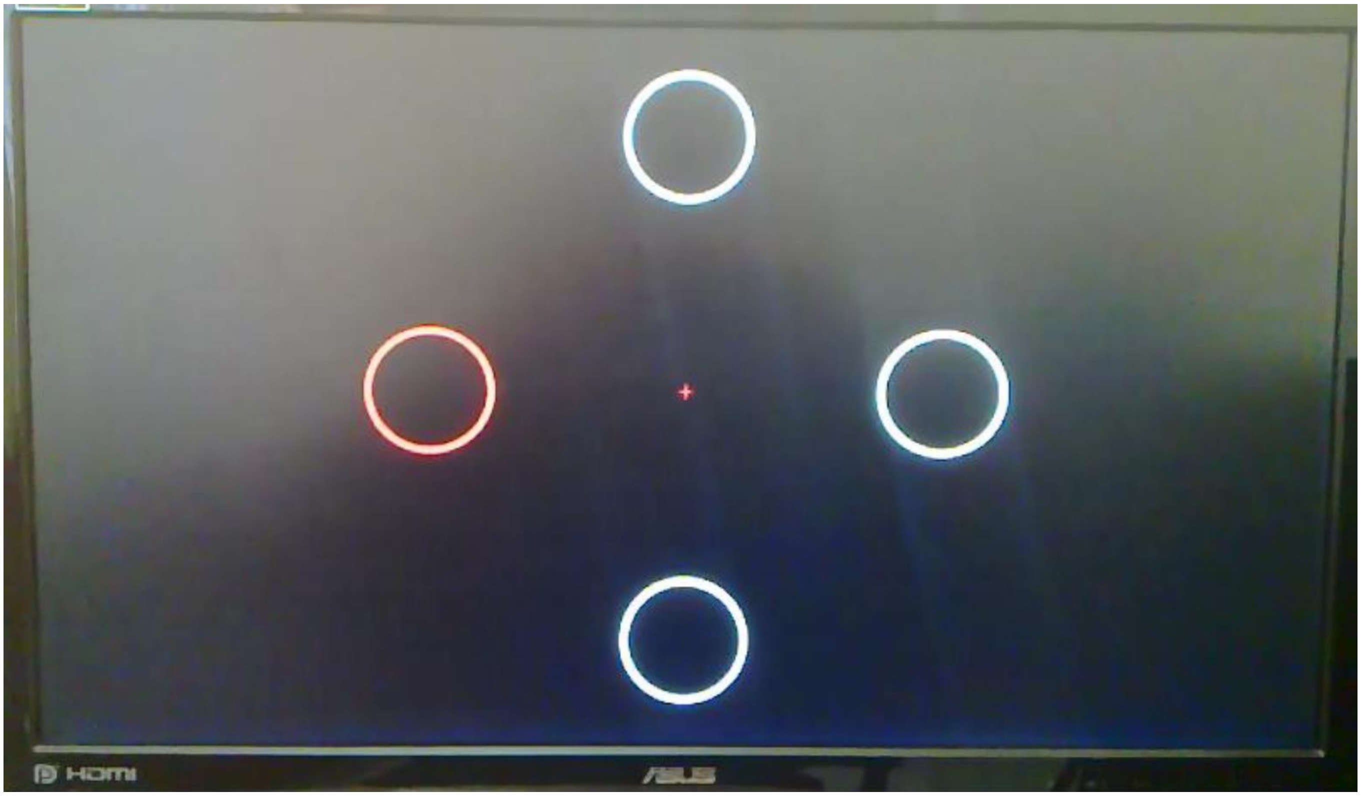

Fig.1. Locations of flickering circles: Up: 5.45 Hz, Down: 8.57 Hz, Right: 12 Hz, and Left: 15 Hz

Further details about the setup can be seen in [29].

Subjects focused their eyes on one of the four flickering circles that are specified with a visual cue (red frame) for three seconds. The order of the cues was permuted randomly. During one trial, subjects focused on each circle once.

There were 30 trials. Therefore, each subject had 120 (30 trials × 4 classes) SSVEP responses. During the experiment, there was no feedback for the participants about the classification result (i.e. decision of the classifier). In Fig. 2, experiment blocks were presented with their timing. As it can be seen in Fig. 2, there are six different blocks in the experiment.

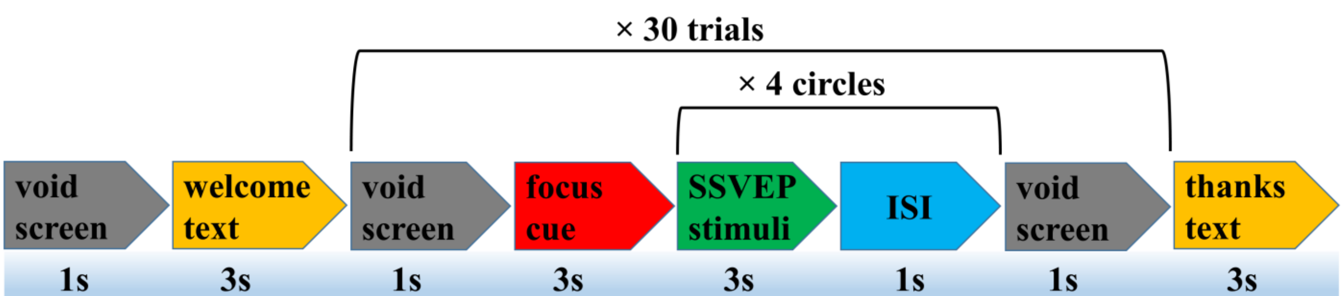

Fig.2. Blocks and timing of the experiment.

During the **void screen** block, the screen is blank (i.e. totally black). In the **welcome text** block, there is a welcome message for the participants. During the **focus cue** block, a message is displayed for the subject to focus on the presented circle. The **SSVEP stimuli** block is where four circles are displayed on the screen simultaneously with their corresponding flickering frequencies. Subjects fixate their eyes and give their attention to the specified flickering circle. After this block, there is an inter-stimulus interval (**ISI**) block which is another void screen between the consecutive **SSVEP stimuli** blocks. The **SSVEP stimuli** and the **ISI** blocks are repeated four times (once for each circle). After all circles are presented once in a trial, this step is repeated 30 times. Hence, there are 120 SSVEP responses (each response lasts 3 s) in total. Finally, experiment thanks the participant in the **thanks text** block.

C. Data recording

Data were recorded from 60 EEG channels using active electrodes with ActiCHamp system and a Python based software (PyCorder) of Brain Products, Germany. In Fig. 3, electrode locations in the experiments were presented.

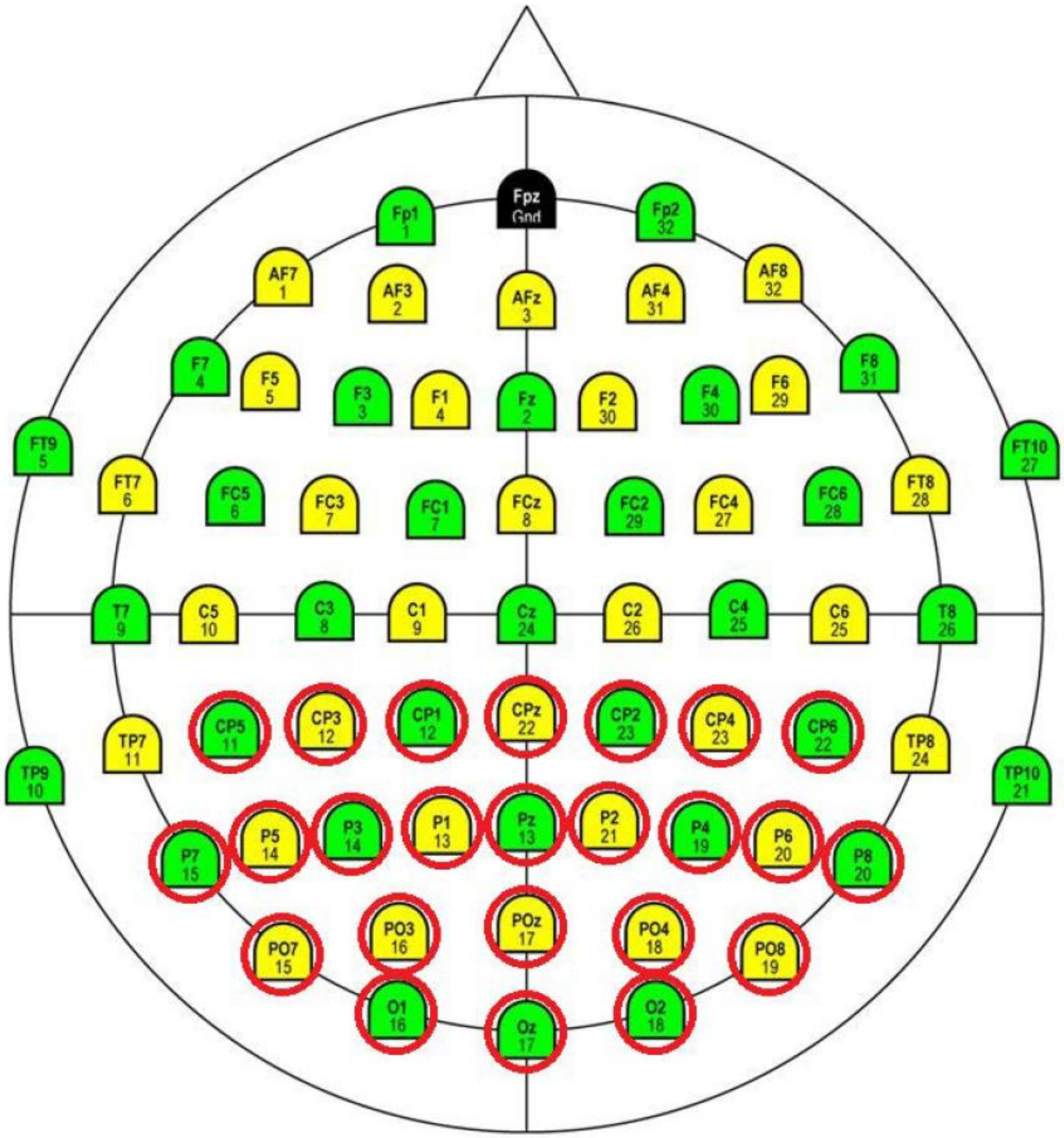

Fig. 3. Standard electrode locations (Addendum actiCHamp Version 002 05/2012) for 64 channel EEG recording system and selected 24 channels (in red circles) for smaller channel set.

Three electrodes (TP9, TP10, and FT10) were used as electrooculogram (EOG) electrodes and FT9 electrode was used for reference. Placement of three EOG electrodes were according to [30]. Reference electrode was attached to the left mastoid. Other 60 electrodes were placed on their standard locations. Impedance values between scalp and electrodes were less than 20 kΩ and sampling frequency was set to 1 kHz. Data were analyzed offline.

D. *Classification*

Data were resampled to 100 Hz and split into a training (2/3 of the samples) and a test set (1/3 of the samples) similar to [31]. A defected electrode channel (F5) was removed from the analyses. The classifications were done using all (59) vs. selected (24) channels. These channels were selected from the scalp areas where the SSVEP responses are known to be stronger (See Fig. 3). Trial numbers per class were kept constant (20 train / 10 test) or increased (up to 240 train / 120 test) for shorter stimuli lengths. Before starting feature extraction process, trends in the segmented EEG were removed. A traditional machine learning approach and a deep learning approach were used for classification. The details of these approaches are given below.

E. *Traditional machine learning approach*

Traditional machine learning (ML) based approach needs a feature extraction step to obtain critical features and then these features are classified with classification algorithms. In Fig. 4, traditional ML approach used in the study was presented with the CCA as the feature extracting method.

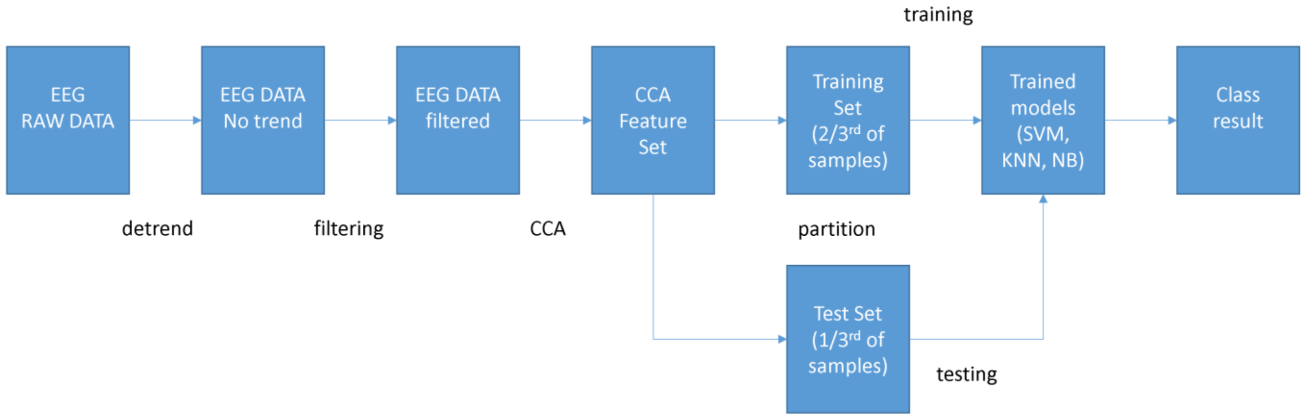

Fig.4. Blocks of traditional machine learning approach using SVM, KNN, and NB classifiers with features obtained from canonical correlation analysis.

First of all, trends in the EEG data were removed. Using a band-pass filter (0.53 - 40 Hz) very slow signal variations and high frequency artifacts including power line noise (50 Hz) were eliminated. Other artifact removal methods were not used as SSVEPs are not very sensitive to eye movements or other physiological artifacts [32].

Canonical correlation analysis (CCA) based feature extraction method was used for all EEG channels. These features were extracted from the segmented EEG records corresponding to the **SSVEP stimuli** blocks (3 seconds each).

CCA method tries to maximize the correlation between linear combinations (canonical variables) of two given data sets [33]. In order to use the method, one set of the data was taken from the recorded EEG segment, and the other set of the data was artificially generated using sine and cosine functions at the stimulation frequencies and their second harmonics. In the end, 16 canonical correlation features were generated. Details on how to implement the method were given in a former study [34].

Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree classifiers were used to determine the class of the featurevectors obtained from SSVEP responses. These classifiers have been used in literature for SSVEP-based BCIs [35]–[37].

Naïve Bayes is a probabilistic classifier that assigns the new sample to the most likely class. In this study, Naïve Bayes classifier was used with kernel density estimation for all features. KNN is a non-parametric instance based classifier where the new sample is assigned by calculating the distance from the existing K neighboring samples. In the study, K = 5 and the distance metric was euclidean. Decision Tree classifiers build a tree structure by checking the values of features at each node and generating new branches until arriving a leaf corresponding to the class label. Here, a decision tree with binary split was used for classification. All these three classifiers were provided in Matlab R2020b.

F. *Deep learning approach*

In Fig. 5, proposed DL based approach was presented. Here the DL block is based on a convolutional neural network (CNN) architecture.

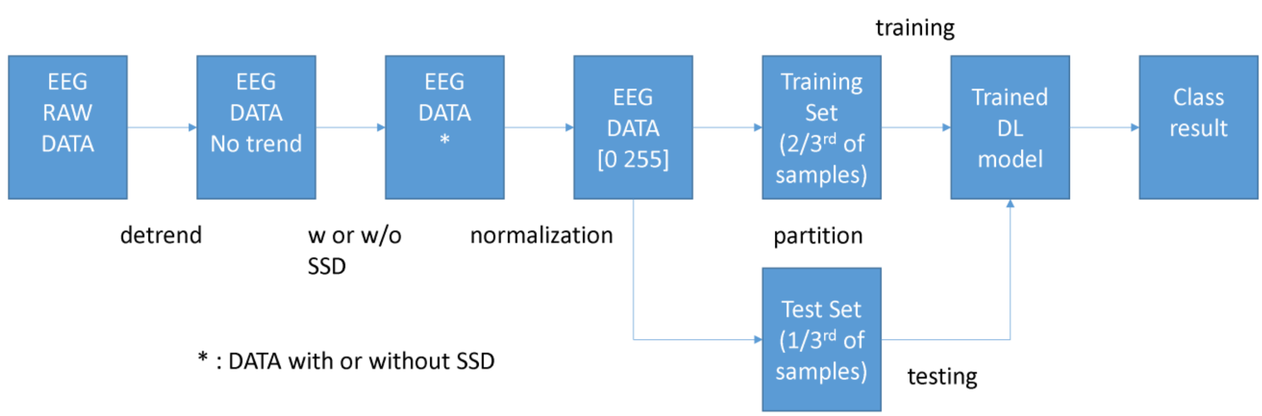

Fig.5. Blocks of deep learning approach with or without SSD

After detrending the data, there were two cases: In the first one, SSD method was applied to extract the oscillatory signals due to the visual stimuli. In Table 1, the cut-off frequencies of the extracted oscillations, flanking intervals, and the band-stop intervals are given for the presented stimuli frequencies.

TABLE I
THE SELECTED CUT-OFF FREQUENCIES OF THE EXTRACTED OSCILLATIONS, FLANKING INTERVALS, AND THE BAND-STOP INTERVALS (IN HZ) FOR THE STIMULI FREQUENCIES IN THE SSD METHOD

Stimulus frequency (Hz)	Frequency of interest	Flanking interval	Band-stop interval
15	[14 - 16]	[12 - 18]	[13 - 17]
12	[11 - 13]	[9 - 15]	[10 - 14]
8.57	[7.5 - 9.5]	[5.5 - 11.5]	[6.5 - 10.5]
5.45	[4.5 - 6.5]	[2.5 - 8.5]	[3.5 - 7.5]

As there are four stimuli frequencies, SSD method generated four different data from the original data. Therefore, the method increased the data size by four. In the second case, SSD method was not applied.

After this block, the data were normalized between 0 and 255 in order to save them as 8 bit images. In the proposed approach, the EEG Data were considered as gray level images (channels × samples).

CNN based DL architecture can be summarized as follows:

There is an input layer with the same size as the images (i.e. normalized EEG data). Then there is a convolution layer with a filter size 4, and a filter number 20. This layer is convolving the input by moving the filters along the input vertically and horizontally and computing the dot product of the weights and the input, and then adding a bias term. Next, there is a batch normalization layer that normalizes the activations and gradients propagating through the neural network, making network training an easier optimization problem. This layer is followed by a rectified linear unit which basically sets each negative element of its input to zero. This layer is followed by a pooling layer with a size (2 x 2) and a stride value of 1. After this layer, there is a fully connected layer with an output size 4. This layer is followed by a softmax layer that transformed the values into probability values. Last layer is the classification layer that calculates the cross entropy loss. In Fig. 6, all layers of the proposed CNN structure was given.

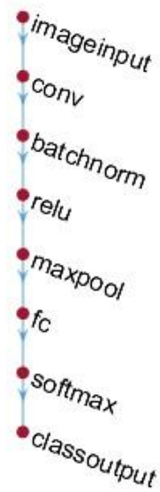

Fig.6. Layers of the proposed CNN

In the training of CNN, stochastic gradient descent with momentum (SGDM) optimizer was used. Initial learning rate was set to 0.0001. Maximum number of epochs was 50. Factor for L2 regularization was 0.0001.

III. RESULTS

Accuracy of the traditional ML and proposed DL approaches with (w) and without (w/o) SSD were compared in terms of number of channels (i.e. all (59) vs selected 24) and stimuli length for constant (20 Train / 10 Test trials per class) and increasing (240 Train / 120 Test trials per class) number of trials in Tables 2 and 3, respectively. These results were visualized in Fig. 7.

TABLE II
CLASSIFICATION ACCURACIES (%) FOR TRADITIONAL ML VS. DL APPROACHES (CONSTANT NUMBER OF TRIALS)

			Traditional ML algorithm			Deep learning algorithm	
# of channels	Train / Test trials per class	Length (s)	Decision Tree	Naïve Bayes	KNN	DL w/o SSD	DL with SSD
24	20 / 10	0.25	20.36	26.07	23.93	29.64	35.71
		0.5	30.36	36.43	31.43	61.43	62.50
		0.75	59.64	68.57	60.00	68.93	80.00
		1	72.14	81.79	80.36	72.14	84.64
		1.5	88.21	92.86	90.36	76.79	86.07
		2	92.86	94.64	95.36	77.86	89.29
		3	93.93	97.50	97.14	82.14	91.07
59	20 / 10	0.25	31.43	27.86	26.43	31.43	27.14
		0.5	25.71	22.50	23.93	54.64	53.21
		0.75	33.93	36.43	27.86	65.71	66.43
		1	55.00	56.07	47.50	64.29	76.79
		1.5	77.86	80.00	81.07	72.14	79.29
		2	88.57	91.07	95.00	72.14	82.50
		3	94.64	95.71	96.07	75.36	83.93

TABLE III
CLASSIFICATION ACCURACIES (%) FOR TRADITIONAL ML VS. DL APPROACHES (VARYING NUMBER OF TRIALS)

			Traditional ML algorithm			Deep learning algorithm	
# of channels	Train / Test trials per class	Length (s)	Decision Tree	Naïve Bayes	KNN	DL w/o SSD	DL with SSD
24	240 / 120	0.25	25.42	23.99	24.64	48.24	**59.14**
	120 / 60	0.5	59.11	68.04	53.51	53.10	74.40
	80 / 40	0.75	76.07	83.30	77.95	61.61	80.27
	60 / 30	1	82.26	88.57	87.62	65.83	81.79
	40 / 20	1.5	91.07	93.57	92.32	64.46	83.04
	20 / 10	2	92.86	94.64	95.36	77.86	89.29
	20 / 10	3	93.93	97.50	97.14	82.14	91.07
59	240 / 120	0.25	25.00	25.09	24.61	46.10	55.15
	120 / 60	0.5	25.36	25.06	25.12	49.05	66.25
	80 / 40	0.75	42.14	50.54	37.14	55.45	74.91
	60 / 30	1	65.60	75.00	61.79	60.71	71.90
	40 / 20	1.5	80.71	86.43	86.07	64.29	74.82
	20 / 10	2	88.57	91.07	95.00	72.14	82.50
	20 / 10	3	94.64	95.71	96.07	75.36	83.93

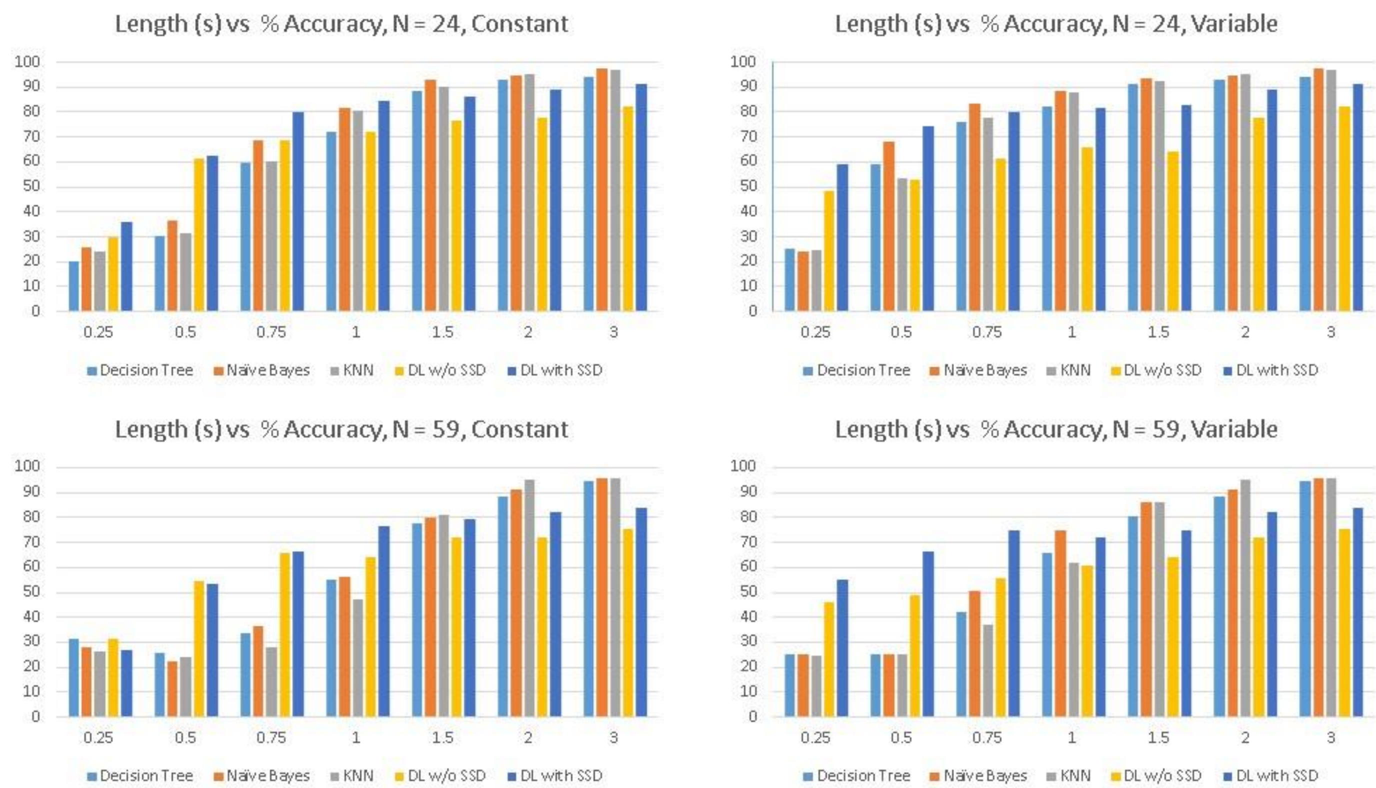

Fig.7. Stimuli length vs. (%) accuracies for constant (left) and variable (right) number of trials using 24 (top) and 59 (bottom) channels.

IV. Discussion

In Tables 2 and 3, very high (>90%) accuracy values were obtained by traditional machine learning algorithms when the stimuli length were long enough >1.5 s. These results were expected as SSVEP based BCIs that use CCA features can generate very high performance in overt attention [38]. In fact, traditional ML algorithms generated higher accuracies than the proposed DL approach for stimuli length >1 s. The advantage of the DL approach over the traditional ML algorithms was pronounced for shorter stimuli length. For the shortest stimuli length (i.e. 0.25 s), traditional methods performed around chance level (25%) whereas the proposed DL method reached to 59.14% for the varying number of trials using 24 channels. The confusion matrix related to this case was given in Fig. 8. The results emphasize the advantage of DL methods when including more trials in the classification.

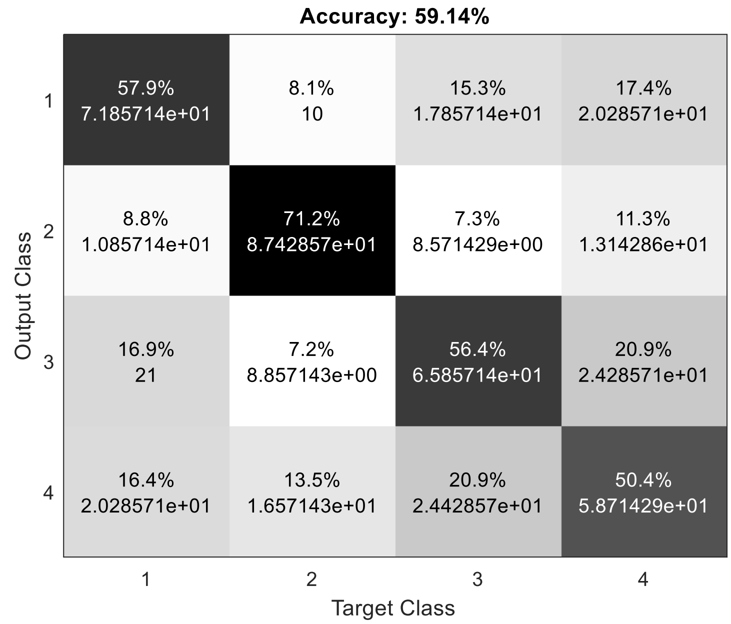

Fig. 8. Confusion matrix for DL with SSD, N = 24, length 0.25 s, varying number of trials

Accuracies for the DL approach that used the SSD as a preprocessing step were in general higher than those that belong to the DL without SSD. There were only two exceptions of this statement for the constant trial case, for a stilmuli length ≤0.5 s, and 59 channels. This proves that the SSD is a proper preprocessing step in DL approaches for SSVEP based BCIs.

Another result of the study is that selected 24 channels gave higher accuracies than all channels for both ML and DL based approaches. This is a promising result, as using higher number of channels is not desired for BCIs due to practical reasons.

One limitation of the study is that there were few participants in the study. In the future, this approach should be tested on a bigger dataset to validate the generalization capability of the presented results. This will also help in evaluation of the results using statistical analyses. Moreover, by integrating an optimization method for channel selection (e.g. genetic algorithm), upper limit of the classification accuracies can be enhanced. Besides, DL performance presented here could be suboptimal due to the selection of the parameters. Determination of the optimal parameter values can boost the classification accuracies.

This study shows a systematic comparison of traditional ML approaches and DL approaches in an SSVEP based BCI experiment in terms of stimuli length, number of channels, and number of trials. This is the first study that incorporates SSD with a CNN based classification. The results of this study pave the way for combining DL with SSD in different fields where there are expected oscillatory activities in the recorded signal.

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