Deep Learning for Electroencephalography (EEG) classification in Virtual Reality (VR)

Thomas Weikert

Tutor: Matti Siekkinen

Keywords: Deep Learning, Electroencephalography, Virtual Reality

Abstract

Electroencephalography (EEG) classification became important in commercial applications, such as virtual reality (VR). In practice, Machine Learning algorithms have been commonly deployed, but given the enhanced accessibility of large EEG datasets and the current trend in Deep Learning, attention starts to shift towards the applicability of Deep Learning algorithms. To pave the way for commercialisation of EEG analysis in VR, a robust and fully automatized approach that is independent from domain experts is required. This paper provides an analysis of EEG classification tasks with Deep Learning algorithms, its underlying architecture, and specific input formulations for training purpose. Reviewed paper used Deep Learning methods for EEG classification in motor imagery, mental workload, cyber sickness and emotional responses. Regardless of the underlying task type, Convolutional Neural Networks (CNN) has been the most popular design choice among reviewed papers, followed by Multilayer Perceptrons (MLP). For both design choices, a description of each specific input formulation, major characteristics, and end classifier has been performed.

1 Introduction

In recent years, virtual reality (VR) has been declared as a mainstream technology [1], and public interest has been increasing as VR technology offers opportunities for various commercial, research and industrial applications. Current VR headsets provide the incorporation of electroencephalography (EEG) sensors. Towards the use of EEG signals within applications, an automatic classification is required without dependence on domain experts.

In the last decade, classic Machine Learning algorithms have been adopted for EEG analysis. Such procedure contains artefact removal, feature engineering and classification for task solving. As Subasi, Abdulhamit and Gursoy and Ismail [2] stated, independent component analysis (ICA) is a popular method for artifact removal. A common method for feature extraction is the use of time-frequency transformation, such as wavelet transformation. Following extraction, features can be passed as input for classic Machine Learning algorithms, such as a Support Vector Machine (SVM). Nevertheless, these methods come with certain disadvantages as stated by Yue and Wang [3]. First, the accuracy mainly relies on the choice of feature extraction methods. Second, the process of feature engineering requires the knowledge of domain experts. Third, the overall performance of classic Machine Learning algorithm is not satisfying, although features were correctly identified. As large EEG datasets became more accessible and high performance graphic processing units were developed, attention has been drawn towards Deep Learning. The performance achieved with Deep Learning exceeded those achieved with Machine Learning algorithms.

As such, this paper endeavoured to investigate how Deep Learning may be used for EEG classification in a VR domain, and provide examples how these signals can be used to model VR user experience. Therefore, this paper investigates which EEG classification tasks with Deep Learning has been explored in VR and reviewed their EEG pre-processing methods, architecture and performance. The organization of this paper is as follows. The background section introduces the use of EEG in VR, reviews classic Machine Learning approaches and recent Deep Learning methods for EEG classification. The following section outlines signal-acquisition and data pre-processing. Next, the research highlights will be laid out dealing with Deep Learning architecture trends, followed by a discussion on design choices and its usage in VR. The conclusion is provided in the last section.

2 Background

This section reviews the use of EEG in VR and earlier work in machine and Deep Learning in terms of EEG classification.

2.1 Use of EEG in VR

The application of EEG in VR devices has been examined over a couple of years within research related to brain computer interfaces (BCI). Focus has been on interaction monitoring, user behaviour and learning environment. Using EEG, the hope was to design a VR experience in which the environment adapts to the user workload. For example, the use of BCIs in VR has been investigated to achieve avatar control with EEG or to transform the shape of the Avatar [4, 5]. Also, NASA scientists used EEG to enhance users vigilance and composure during gameplay [6]. Other research has been carried out to adapt games level of difficulty based on changes in EEG signals [7] or to use EEG signals to keep track of items that were detected by the user [8]. Nevertheless, major challenges must be addressed for BCIs in order to grow into an established technology for VR applications as stated by Lecuyer et al. [9]. Nowadays, companies such as Neureble and Looxid are developing VR HMDs that come with integraded EEG electrodes created for BCI, illustrating the successful integration into broader EEG-based devices. Successfull progress has also been made regarding EEG to measure user response. Abdessalem and Frasson developed a VR game for neurological feedback in real-time, classifying player's emotional response to adapt scenarios accordingly [10]. Other researchers have used EEG in a clinical environment using mental workload of users with Autism in a VR driving scenario [11]. To design a training adaptive system, EEG has been used by Gerry et al. [7] to monitor mental load during a visual search task. Although this was an important step forward, there has been little research on the type of tasks and procedures that should be used for EEG classification in a VR scenario.

2.2 Classic Machine Learning

As Karácsony et al. [12] stated, the majority of current BCI-VR systems implement Machine Learning (ML) methods to build classifiers, which involves signal pre-processing, feature extraction and classifiaction steps.

Signal pre-processing helps to reduce noise in EEG data and make the underlying dataset ready for feature engineering. Within this necessary step, various combination of filter technique are being used. To reduce noise coming from differences in electrical activity between electrodes, referencing methods have been applied, such as spatial filter algorithms like the Laplacian-filter or the Common Average Reference (CAR). For illustration purposes, figure 1 shows the principle of several spatial filter algorithm for electrode position C3. On the very left side the C3 electrode is shown with a reference electrode on the earlobe. Next to it, the CAR method is used, which subtracts the mean value of all electrodes from C3. In the middle of the figure the principle of the small Laplacian filter is shown in which the value of C3 is subtracted from the value of the average surrounding electrodes. The principle is repeated with the nearest surrounding electrode in the large Laplacian filter on the right. On the very right side the principle of bipolar derivation is shown, in which the signal from the one electrode is subtracted to the nearest one.

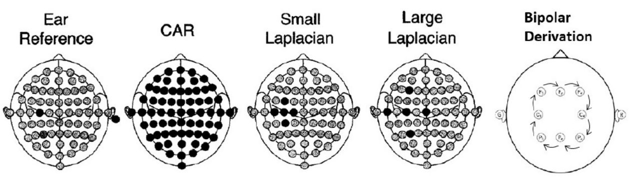

Figure 1: Different approaches of spatial filter algorithm adopted from [13].

As cited by Tremmel [14] most common classification algorithm in BCIs are linear classifiers, such as linear discriminant analysis (LDA) or support vector machines (SVM). Other typical approaches include the use of KNN and tree-based classifiers, achieving results ranging between 65-80% [1].

2.3 Deep Learning

Attention in Deep Learning has not been directly drawn to applications in neural classification given a lack of practicality by a very long computation time and problems with gradient descent algorithms [15]. With recent development in computational resources neural networks became appealing, offering a powerful and inexpensive solution and leading to an enhanced interest and applications of Deep Learning in the past years. [16]. Recently, significant improvements in performance by using Deep Learning techniques can be observed in areas, such as images, videos, speech, and text. As Deep Learning techniques require less domain knowledge on the data due to its automatic optimization of it parameters [16], applications in medical imaging were adopted, requiring traditionally expert knowledge for interpretation [17]. With the appearance of accessible EEG data sets online, Deep Learning techniques started to get applied to decoding and classification of EEG signals that is conventionally correlated to a low signal to noise ratios and high dimensional data. Regardless of recent developments current research on BCI systems applying Deep Learning is very limited and mostly involves non-VR settings, thus further exploration of this particular field is required, including optimal pre-processing methods and architecture design.

2.4 Summary

This section shows that EEG has been successfully used as a tool in adaptive scenarios for VR. Current research in EEG classification shifts from classic Machine Learning methods towards Deep Learning. However, there is limited research available using EEG in VR settings with Deep Learning.

3 Measuring EEG

EEG signals contain several overlapping frequencies that can be separated by signal processing techniques. The frequencies can be separated into different bands, these are usually the bands of delta (2-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (15-30Hz), lower gamma (30-80Hz) and upper gamma (80-150Hz) [18]. This section describes the overall approach adopted in conducting EEG analysis consisting of signal acquisition and pre-processing steps, each of will be explained in the following sections below.

3.1 Signal Acquisition

As stated by Tremmel [14], electrodes EEG signal tracking record usually in a bandwidth of 128-512 Hz, measuring the voltage between scalp and electrode, which are systematically placed in the target region of the scalp. In order to compensate for interfering signals, such as those caused by the heartbeat, reference electrodes are placed on the head, which are normally placed in expected inactive places, such as the earlobe of the forehead. It is necessary to fulfill the Nyquist frequency criterion when recording EEG signals, which requires a sampling rate twice as high as the expected frequency of the observed signal [14].

The most popular approach to place electrodes on the scalp is the international standard 10-20 system [19, 20]. The name of the system refers to the space of the adjacent electrodes, where the distance respectively 10% or 20% of the total right-left or front-back distance of the skull is covered [14]. Electrodes for workload estimation are usual placed in the premotor, prefrontal and parietal brain areas, but vary with respect to the underlying task. [21].

3.2 Filtering

A common pre-processing step is filtering, which is necessary, if feature classification is based on time frequency domain. As stated by [22] a widely used filter is a low-pass filter, that passes low frequencies and attenuate high frequencies. The corresponding opposite is a high-pass filter, which passes high frequencies and attenuate low frequencies. In order to pass an intermediate range of frequencies, a band-pass filter is used. Also, a notch filter has been applied in [7], that attenuate only a narrow band of frequencies. In case feature classification is processed in the frequency domain, the undesirable frequency band can be ignored by not considering them as characteristic's for classification. The majority of reviewed studies applies frequency domain filters to process the bandwidth of the aspired EEG signal. A thorough search of the relevant literature yielded no article, which investigates weather the usage of raw EEG signals is able to achieve comparable results.

3.3 Artefact correction

EEG data is naturally noisy and can be caused by unwanted muscle tensions, like eye-blinks or body part movements, which challenges the usability of EEG in the context of VR. Artefact correction remains one of the biggest challenges in the analysis of EEG signals in VR, as it allows users to move freely and interact with their virtual environment [14]. To bridge this problem, VR controllers, with additional tracking sensors to record body movements, offer a pragmatic method that can be used to reduce motion induced contamination in EEG as previously achieved in gait related EEG research [23]. As stated in [22], the most frequent artifact removal algorithms used were independent component analysis (ICA) and discrete wavelet transformation (DWT). Methods for artefact correction has been widely investigated by a number of studies in the past, and will not be repeated in depth within this paper due to the limited scope.

3.4 Feature Extraction

Feature Extraction is the most important prerequisites to build reliable classifiers and requires domain knowledge and the right techniques. In the case of cognitive workload estimation, feature extraction techniques create power band features of the epochs in the desired frequency bands. Reviewed paper used Fast Fourier Transform (FFT) or Welch's method. FFT transforms the data by projecting it onto sinusoidal basis function which shifts the signal from a time domain to a frequency domain. In practice FFT is widely used, but it comes with some disadvantages, as the potential loss of temporal information from data due to stretching into sine waves [24]. Moreover, the same window size is used to calculate power in different frequencies, although higher precision can be achieved by using different windows size for low and high frequencies [25]. The importance of the window size is emphasized by [26], stating that a non-optimal width of the window causes poor frequency if too narrow, or poor time localization that violates the stationary assumption, if too wide. Another very widely used method to gain a spectral estimation of the signal is the Welch method, which is a method that calculates a periodogram for windowed sections of data using FFT and then averaging these windows to reduce the variance of the estimate.

4 Deep Learning algorithms

Craik et al. [22] clusters EEG classification techniques with Deep Learning into the following categories: Convolutional Neural Networks, Deep Belief Networks, Recurrent Neural Networks, Stacked Auto-Encoders, Multi-layer Perceptron Neural Network and hybrid architectures. For the understanding of the reviewed articles, this sections briefly introduces two techniques used for EEG classification with Deep Learning.

4.1 Multilayer Perceptrons (MLP)

Multilayer Perceptrons, also called Feed Forward Neural Networks, is a subclass of Artificial Neural Networks (ANN). The neurons within an ANN can be interconnected arbitrarily in principle. MLPs are ANNs where the neurons are grouped into consecutive groups or 'layers' and only connections between neurons in consecutive layers are allowed (with some exceptions such as 'skip connections') [27]. They are called feedforward as an information passes through the function being assessed from x, through the intermediate computations used to define f, and at last to the output y [27]. Each MLP is a network of interconnected units, which are defined as neurons. The input of a neuron is a weighted sum, which gets activated through a non-linear activation function. Each layer consists of several individual neurons, whose input is taken from the output of the previous layer. The layers are piled up on each other to embrace a more complex MLP. Figure 2 illustrates a MLP with two hidden layers enclosed by an input and output layer. The word 'hidden' refers to the fact that neurons in hidden layers are not directly accessible. The input layer takes input features, which gets activated by using an activation function. In contrast to the other layers, it does not contain a non-linear activation function. The illustrated example has three feature values. The following two hidden layers are called fully connected, densely connected layer or dense layer. Finally, the output layer consists of three neurons, which are representative for three class classification. Its value represent its confidence in assigning this data point to its label.

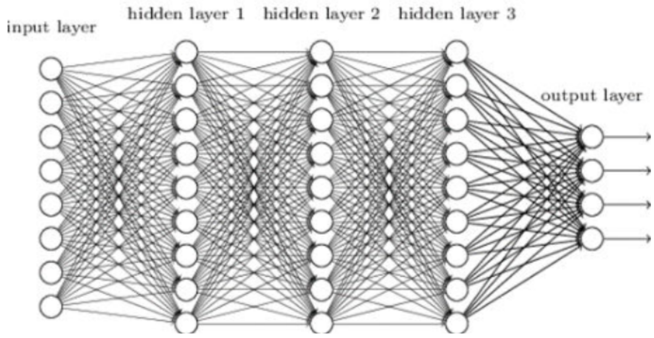

Figure 2: Illustration of a Deep Neural Network [?]

4.2 Convolutional Neural Networks (CNN)

CNNs is a specialized kind of neural network for processing data inspired by the human visual cortex [28]. Consisting of several layers, a CNN is characterized by a varying number of convolutional and pooling layers, with a fully connected layer placed at the output. In general, Convolution can be done in two or three dimensions, e.g. for images and video, however to analyse raw EEG data, a one-dimensional Convolution is needed. One refers to raw EEG data as the time domain. The most important building block is the Convolutional Layer, that performes covolutional operations among the image and the kernels, computing the weighted sum of the patch of the image. Pooling layers aim to down sample feature maps [27]. Another layer is a fully-connected (FC) layer, which gets the feature map from a previous convolutional or pooling layer as an input, flattened as a single vector of values. The FC layer has the same mathematical operations as an ANN [27]. An exemplary CNN architecture is illustrated in Figure 3. CNN framework choices contains kernels regulated using back-propagation algorithm. Due to a multi folded feature extraction of different layers and filters, CNN features are robust to spatial translation [29] and make analysis for task solving possible, such as the correct representation of cognitive states over different brain zones.

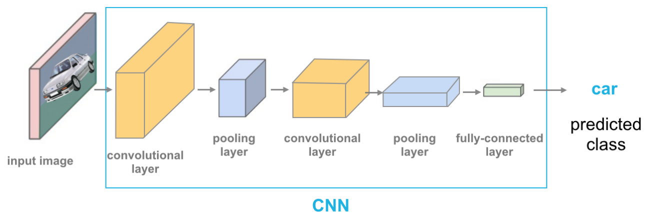

Figure 3: Illustration of a Convolutional Neural Network [30].

5 Research Highlights

This section first details the EEG classification tasks with Deep Learning found within reviewed papers. Then, the input formulations, and architecture trends are analyzed.

5.1 EEG classification tasks

EEG classification tasks that have been examined with Deep Learning can be distinguished in three categories. The classification of emotion recognition, motor imagery, and mental workload. Emotion recognition tasks requires subjects to watch video clips, which have been labeled with a particular emotion by an expert prior to the experiment. Meanwhile EEG signals were recorded, which allows an assessment on emotion recognition. In virtual reality, a better understanding of the user's emotion will help to determine, if a particular movement was the intended movement and help computers to enhance their understanding of the user's emotional status, which enables further applications.Motor imagery tasks are related to intended user's movements, such as the limb or the tongue, and are often in the context of stroke treatment. Mental workload classification involves EEG analysis while the subject is in the process of task solving with variant level of difficulty. Many studies aim to perform mental workload classification in the context of driving simulation studies [31], live pilot studies [32], and responsibility tasks [33]. Based on statistical behaviour of pilots and drivers, such as reaction time and path deviation, mental workload has been classified. Conversely, various studies classified mental workload for responsibility tasks, for subjects dealing with an increasing number of actions the subject was responsible for.

5.2 Deep Learning Architecture Trends

This section reviews used EEG classification algorithm with Deep Learning in the context of VR and its most prominent design frameworks, then analyzes its characteristics and compare its results.

Looking at Architecture Design Choices, the center of attention is on outlining the tendency in creation of specific Deep Learning architectures used for VR applications, principally its most important characteristic and end classifier. Among the reviewed papers, the most prominent design framework has been CNNs. Its most important design choice is the amount of different layers and kind of end-classifier. The second identified design framework has been MLPs are composed by a number of layers and a variety of neurons per layer. With regard to Activation Functions, across all studies, rectified linear unit (Relu) has been deployed as an activation function unrelated to the initial architecture design choice. In combination to the Relu activation function the Softmax and Sigmoid activation function has been used, too. Activation functions for fully-connected layers can be assembled in subsections, which are non-classifier fully-connected and fully-connected layers. While the most popular non-classifier fully-connected applied the Sigmoid activation function, the fully-connected layers deployed a Softmax activation function. Looking at the Input formulation by Deep Learning architecture, across all studies the input formulation differ considerably. In general three types of input formulation has been identified: Signal values, calculating features and images. While CNN studies utilized all three types of input formulation, MLP were distributed only among signal values and calculated features. Over all studies and architecture types a preferred choice was towards calculating features. In terms of accuracy, CNN studies which had images as input were not differ from studies that deployed feature calculation as inputs. Both input formulation achieved accuracy over 90% In contrast, raw signals were performing less good and achieving only an accuracy of 74%.

6 Discussion

The following sections derives recommendations for design decisions on Deep Learning architectures for EEG classification tasks and usage in VR. Recommendations are based on the reviewed papers and relate to classification algorithm, its input formulation and practicality for its use in VR. Recommendations are not given by tasks as the number of studies was too low, which is also the main limitation of this paper.

In general a comparison among different architecture design choices, its accuracy's and underlying EEG data sets comes with difficulties. Moreover, most studies were designed for different task solving, which effects the choice of design or input processing. Nevertheless the provided analysis can assist and encourage future research to make use of Deep Learning methods in the context of VR and a variety of tasks. When using CNN for task solving, the use of signal values or images comes with advantages. The majority of the studies used the maximum available channels, supporting the assumption that CNN are capable of handling high dimensional EEG data and size of data sets better compared to other algorithms as stated by Craik et al. [22]. Using images as CNN's input, spectograms were the preferred choice, achieving the highest accuracy. For signal values, the number of convolutional layers vary from three to six layers. When using MLP for task solving, signal values is the preferred choice. Similar to CNN, the channels were not limited. As end classifier, a single dense layer is recommended, which is the most popular choice in most studies. For the final fully-connected layer in all studies, the softmax activation function is the preferred choice, while for fully-connected non classifier layers, the sigmoid activation function is a used.

Despite difficulties of a general comparison, a tendency of a superior performance of Deep Learning strategies compared to classic Machine Learning algorithms has been found. For exemplary illustration of the performance, Table 1 summarizes work on the Physionet EEG Dataset [34]. The created CNN classifiers performance surpassed classic Machine Learning algorithms. Therefore, Deep Learning models should be the prefered choice, when it comes to the highest accuracy. Apart from this, Deep Learning algorithm present an other advantage over classic Machine Learning algorithm as they have the ability to automatically detect features, and thus, do not require cumbersome feature engineering or domain expert.

Table 1: Overview of works performing classification tasks on the Physionet [34] EEG dataset.

Study	#Channels	Max. accuracy	Methods
[35]	16	63.62 %	SVM
[36]	3	68.21 %	Wavelet transform Feed-forward MLP
[37]	9	71.55 %	Phase information
[38]	58	72.55 %	SVM
[39]	14	80.05 %	Random forest
[40]	64	86.13 %	CNN
[40]	14	82.66 %	CNN
[12]	64	88.50 %	CNN
[12]	16	84.13 %	CNN

With regard to the implications for VR technology and EEG classification tasks, reviewed articles illustrated the potential of combining them. This research is representative for the current desire to enhance immersiveness and improve the usability of VR technology. The spectrum of different tasks, setups and experiments is high, which is also reflected in the variety of architectures for Deep Learning classifiers.

7 Conclusion

Researcher in the domain of VR have successfully adopted Deep Learning methods for EEG classification. The implementation ranges over different tasks, including mental workload, motor imagery, emotional responsive and cyber sickness. Among all tasks a popular choice of design framework are CNNs, followed by MLPs. Significant differences occur with respect to input formulization, whereas CNN's performed best when using signal values or spectrogram as inputs. Further research is encouraged on extending the number of studies, the implementation of other methods in the domain of VR, such as hybrid networks, and the assessment of raw EEG signals, as this has not been sufficiently evaluated.

Acknowledgements

I am grateful to Matti Siekkinen, my tutor for the course ELEC-E8127 - Special assignment in automation technologies at Aalto University, for giving me the opportunity to write this paper, and for providing me with feedback throughout the semester.

Table 2: Signal Acquisition and Pre-Processing Methods

Study	Deep Learning Strategy	Signal Acquisition			Pre-Processing	Input formulation	Accuracy
		EEG Device	Channel strategy	Electrode Positions			
[3]	CNN 6 conv 1 FC OUT (3)	Synamps 2 system	Total 34 30xEEG 4xEOG	Reference: A1 Rest: n.a.	Notch filter CAR Raw	19x1200x30x375 (subjects x trials x channels x timing samples)	74.00%
[12]	CNN 4 conv 6 FC OUT (2,3,4)	n.a.	All(64)	n.a.	6th order Butterworth BP Normalization	n.a.	90.14% 89.86% 77.71%
[12]	CNN 4 conv 6 FC OUT (2,3,4)	n.a.	All(16)	FC3, FCz, FC5, C1-C6, Cz, CP3, CPZ, CP4, P3, Pz and P4	6th order Butterworth BP Normalization	n.a.	75.40% 80.81% 61.63%
[41]	CNN 1 FC OUT (2)	Looxidlabs VR	All(6)	n.a.	Notch filter STFT	n.a.	82.00%
[42]	CNN 3 conv 1 FC 0.25, 0.5 DR OUT (2)	Emotiv Epoc+	Total 84 14xRaw EEG 70xBand power data	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6,F4, F8, and AF4	Normalization Filtering	128x84x1	98.82%
[42]	MLP 3 hid. (128,256,128) Um 0,5 DR OUT (2)	Emotiv Epoc+	Total 84 14xRaw EEG 70xBand power data	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6,F4, F8, and AF4	Normalization Filtering	Input Dense layer (84)	98.02%
[1]	MLP 2 hid. 10 Un 0.1 DR	Muse headband	Total 5 4xEEG 1xReference	TP9, AF7, AF8, TP10, Fpz	FFT Butterworth's 4th Order Filter	n.a.	88.07%
[1]	MLP 2 hid. 200 Un 0.1 DR	Muse headband	Total 5 4xEEG 1xReference	TP9, AF7, AF8, TP10, Fpz	FFT Butterworth's 4th Order Filter	n.a.	92.31%
[1]	MLP 2 hid. (2x200) Un 0.7 DR	Muse headband	Total 5 4xEEG 1xReference	TP9, AF7, AF8, TP10, Fpz	FFT Butterworth's 4th Order Filter	n.a.	96.32%

Table 3: Deep Learning Architecture Designs

Study	Deep Learning Strategy	Activation function	Input formation	Frequency range	Artifact strategy	Task information	Accuracy
[3]	CNN 6 conv 1 FC OUT (3)	Relu	Raw All (30)	1 - 100 Hz	AR	ER 20 subj.	74.00%
[12]	CNN 4 conv 6 FC OUT (2,3,4)	Relu (FC) SoftMax (FC)	N All (64)	0.5 - 75 Hz	none	MI 105 subj.	90.14% 89.86% 77.71%
[12]	CNN 4 conv 6 FC OUT (2,3,4)	Relu (FC) SoftMax (FC)	N All (16)	0.5 - 75 Hz	none	MI 105 subj.	75.40% 80.81% 61.63%
[41]	CNN 1 FC OUT (2)	Relu	Spect. All(6)	55 - 65 Hz	AR	ML 9 subj.	82.00%
[42]	CNN 3 conv 1 FC 0.25, 0.5 DR OUT (2)	Relu / Sigmoid	N / All(84)	128 Hz	AR	CS 24 subj.	98.82%
[42]	MLP 3 hid. (128,256,128) Um 0,5 DR OUT (2)	Relu / Sigmoid	N / All(84)	4-45 Hz	AR	CS 24 subj.	98.02%
[1]	MLP 2 hid. 10 Un 0.1 DR	Relu / Softmax	All(4)	N.A.	AR	ER 24 subj.	88.07%
[1]	MLP 2 hid. 200 Un 0.1 DR	Relu / Softmax	All(4)	N.A.	AR	ER 24 subj.	92.31%
[1]	MLP 2 hid. (2x200) Un 0.7 DR	Relu / Softmax	All(4)	N.A.	AR	ER 24 subj.	96.32%

References

[1] Jason Teo and Jia Tian Chia. Deep neural classifiers for eeg-based emotion recognition in immersive environments. In *2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE)*, pages 1–6. IEEE, 2018.

[2] Abdulhamit Subasi and M Ismail Gursoy. Eeg signal classification using pca, ica, lda and support vector machines. *Expert systems with applications*, 37(12):8659–8666, 2010.

[3] Kang Yue and Danli Wang. Eeg-based 3d visual fatigue evaluation using cnn. *Electronics*, 8(11):1208, 2019.

[4] Liu Mingyu, Wang Jue, Yan Nan, and Yang Qin. Development of eeg biofeedback system based on virtual reality environment. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, pages 5362–5364. IEEE, 2006.

[5] Ilkka Kosunen, Mikko Salminen, Simo Järvelä, Antti Ruonala, Niklas Ravaja, and Giulio Jacucci. Relaworld: neuroadaptive and immersive virtual reality meditation system. In *Proceedings of the 21st International Conference on Intelligent User Interfaces*, pages 208–217, 2016.

[6] Game and simulation control - control modification through user physiological state. https://ntts-prod.s3.amazonaws.com/t2p/prod/t2media/tops/pdf/LAR-TOPS-88.pdf. Accessed: 2020-10-27.

[7] Lynda Gerry, Barrett Ens, Adam Drogemuller, Bruce Thomas, and Mark Billinghurst. Levity: A virtual reality system that responds to cognitive load. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–6, 2018.

[8] Thorsten O Zander, Matti Gaertner, Christian Kothe, and Roman Vilimek. Combining eye gaze input with a brain–computer interface for touchless human–computer interaction. *Intl. Journal of Human–Computer Interaction*, 27(1):38–51, 2010.

[9] Anatole Lécuyer, Fabien Lotte, Richard B Reilly, Robert Leeb, Michitaka Hirose, and Mel Slater. Brain-computer interfaces, virtual reality, and videogames. *Computer*, 41(10):66–72, 2008.

[10] Hamdi Ben Abdessalem and Claude Frasson. Real-time brain assessment for adaptive virtual reality game: A neurofeedback approach. In *international conference on brain function assessment in learning*, pages 133–143. Springer, 2017.

[11] Lian Zhang, Joshua Wade, Dayi Bian, Jing Fan, Amy Swanson, Amy Weitlauf, Zachary Warren, and Nilanjan Sarkar. Cognitive load measurement in a virtual reality-based driving system for autism intervention. *IEEE transactions on affective computing*, 8(2):176–189, 2017.

[12] Tamás Karácsony, John Paulin Hansen, Helle Klingenberg Iversen, and Sadasivan Puthusserypady. Brain computer interface for neuro-rehabilitation with deep learning classification and virtual reality feedback. In *Proceedings of the 10th Augmented Human International Conference 2019*, pages 1–8, 2019.

[13] Dennis J McFarland, Lynn M McCane, Stephen V David, and Jonathan R Wolpaw. Spatial filter selection for eeg-based communication. *Electroencephalography and clinical Neurophysiology*, 103(3):386–394, 1997.

[14] Christoph Tremmel. Estimating cognitive workload in an interactive virtual reality environment using electrophysiological and kinematic activity. 2019.

[15] Yoshua Bengio, Patrice Simard, and Paolo Frasconi. Learning long-term dependencies with gradient descent is difficult. *IEEE transactions on neural networks*, 5(2):157–166, 1994.

[16] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436–444, 2015.

[17] Hayit Greenspan, Bram Van Ginneken, and Ronald M Summers. Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique. *IEEE Transactions on Medical Imaging*, 35(5):1153–1159, 2016.

[18] Jean Gotman. A few thoughts on "what is a seizure?". *Epilepsy & Behavior*, 22:S2–S3, 2011.

[19] Herbert H Jasper. The ten-twenty electrode system of the international federation. *Electroencephalogr. Clin. Neurophysiol.*, 10:370–375, 1958.

[20] Frank Sharbrough. American electroencephalographic society guidelines for standard electrode position nomenclature. *J clin Neurophysiol*, 8:200–202, 1991.

[21] Adrian M Owen, Kathryn M McMillan, Angela R Laird, and Ed Bullmore. N-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. *Human brain mapping*, 25(1):46–59, 2005.

[22] Alexander Craik, Yongtian He, and Jose L Contreras-Vidal. Deep learning for electroencephalogram (eeg) classification tasks: a review. *Journal of neural engineering*, 16(3):031001, 2019.

[23] Kristine L Snyder, Julia E Kline, Helen J Huang, and Daniel P Ferris. Independent component analysis of gait-related movement artifact recorded using eeg electrodes during treadmill walking. *Frontiers in human neuroscience*, 9:639, 2015.

[24] Luck SJ. Setting up and running an erp lab. *An introduction to the event-related potential technique*, pages 16–1, 2014.

[25] Steven J Luck. *An introduction to the event-related potential technique*. MIT press, 2014.

[26] Andrea Varsavsky, Iven Mareels, and Mark Cook. *Epileptic seizures and the EEG: measurement, models, detection and prediction*. Taylor & Francis, 2011.

[27] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016. http://www.deeplearningbook.org.

[28] Yann LeCun, Koray Kavukcuoglu, and Clément Farabet. Convolutional networks and applications in vision. In *Proceedings of 2010 IEEE international symposium on circuits and systems*, pages 253–256. IEEE, 2010.

[29] Kai Kang and Xiaogang Wang. Fully convolutional neural networks for crowd segmentation. *arXiv preprint arXiv:1411.4464*, 2014.

[30] Cezanne Camacho. Convolutional neural networks, June 2018. [Online; posted 03-June-2018].

[31] Mohammad A Almogbel, Anh H Dang, and Wataru Kameyama. Cognitive workload detection from raw eeg-signals of vehicle driver using deep learning. In *2019 21st International Conference on Advanced Communication Technology (ICACT)*, pages 1–6. IEEE, 2019.

[32] Feng Li, Guangfan Zhang, Wei Wang, Roger Xu, Tom Schnell, Jonathan Wen, Frederic McKenzie, and Jiang Li. Deep models for engagement assessment with scarce label information. *IEEE Transactions on Human-Machine Systems*, 47(4):598–605, 2016.

[33] Zhong Yin and Jianhua Zhang. Cross-session classification of mental workload levels using eeg and an adaptive deep learning model. *Biomedical Signal Processing and Control*, 33:30–47, 2017.

[34] Ary L Goldberger, Luis AN Amaral, Leon Glass, Jeffrey M Hausdorff, Plamen Ch Ivanov, Roger G Mark, Joseph E Mietus, George B Moody, Chung-Kang Peng, and H Eugene Stanley. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. *circulation*, 101(23):e215–e220, 2000.

[35] Vikram Shenoy Handiru and Vinod A Prasad. Optimized bi-objective eeg channel selection and cross-subject generalization with brain–computer interfaces. *IEEE Transactions on Human-Machine Systems*, 46(6):777–786, 2016.

[36] Martina Tolić and Franjo Jović. Classification of wavelet transformed eeg signals with neural network for imagined mental and motor tasks. *Kinesiology: International journal of fundamental and applied kinesiology*, 45(1):130–138, 2013.

[37] Ana Loboda, Alexandra Margineanu, Gabriela Rotariu, and Anca Mihaela Lazar. Discrimination of eeg-based motor imagery tasks by means of a simple phase information method. *International Journal of Advanced Research in Artificial Intelligence*, 3(10), 2014.

[38] Cheolsoo Park, Clive Cheong Took, and Danilo P Mandic. Augmented complex common spatial patterns for classification of noncircular eeg from motor imagery tasks. *IEEE Transactions on neural systems and rehabilitation engineering*, 22(1):1–10, 2013.

[39] Youngjoo Kim, Jiwoo Ryu, Ko Keun Kim, Clive C Took, Danilo P Mandic, and Cheolsoo Park. Motor imagery classification using mu and beta rhythms of eeg with strong uncorrelating transform based complex common spatial patterns. *Computational intelligence and neuroscience*, 2016, 2016.

[40] Jingnian Chen, Houkuan Huang, Shengfeng Tian, and Youli Qu. Feature selection for text classification with naïve bayes. *Expert Systems with Applications*, 36(3):5432–5435, 2009.

[41] Dongjae Kim, Jiseong Park, Jeongseok Hwang, Wan Hee Cho, and Sang Wan Lee. Decoding prefrontal cognitive states from electroencephalography in virtual reality environment. *2020 8th International Winter Conference on Brain Computer Interface (BCI)*, pages 1–3, 2020.

[42] Daekyo Jeong, Sangbong Yoo, and Jang Yun. Cybersickness analysis with eeg using deep learning algorithms. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 827–835. IEEE, 2019.