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Brain computer interfaces in computer science and engineering areas: a systematic study

Jozsef Katona[1,2,4], Attila Kovari[3,4,5,6], Tibor Guzsvinecz[7], Judit Szűcs[7], Robert Demeter[8], Veronika Szücs[9]

[1]Department of Software Development and Application and CogInfoCom based LearnAbility Research Team, Institute of Computer Engineering, University of Dunaujvaros, Dunaujvaros, Hungary
[2]Department of Instrumentation and Automation, Institute of Electronics and Communication Systems, Kandó Kálmán Faculty of Electrical Engineering, Obuda University, Budapest, Hungary
[3]Institute of Digital Technology, Faculty of Computer Science, Eszterházy Károly Catholic University, Eger, Hungary
[4]GAMF Faculty of Engineering and Computer Science, John Von Neumann University, Kecskemét, Hungary
[5]Kandó Kálmán Faculty of Electrical Engineering, Óbuda University, Budapest, Hungary
[6]Department of Natural Sciences, Institute of Engineering, University of Dunaújváros, Dunaujvaros, Hungary
[7]Department of Information Technology and its Applications, University of Pannonia, Zalaegerszeg, Hungary
[8]Departament of Automation and Information Technology, Transilvania University of Brasov, Brasov, Romania
[9]Department of Electrical Engineering and Information Systems, University of Pannonia, Veszprém, Hungary

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ABSTRACT

Brain-computer interfaces (BCI) are a channel that implements direct communication between the brain and some external unit. Developments of BCIs can provide new application opportunities in a large number of fields of use. In the development of BCI devices, the development of technology and digital technology represented a big change, as it provided the necessary computing power to implement and run the continuously developing signal processing algorithms that ensure processing and evaluation. The aim of this paper is to provide an overview of BCI research results which were published in the engineering field. In the present study, articles that had a greater impact, where the annual average number of citations is greater than 30, in the BCI field were reviewed and processed in a systematic way, in order to make individual research more comparable. The systematic processing was focused on the aims of application, used device/dataset, applied data process and achieved best accuracy. This systematic study summarizes the most effective methods used in the BCI processing and highlights the future trends. The results showed an accuracy of 85% thanks to increasingly reliable, accurate and cost-effective signal detection and processing devices, as well as algorithms.

Corresponding Author:

Attila Kovari
Institute of Digital Technology, Faculty of Computer Science, Eszterházy Károly Catholic University
3300 Eger, Hungary
Email: kovari.attila@uni-eszterhazy.hu

1. INTRODUCTION

Brain-computer interfaces (BCI) are a channel that implements direct communication between the brain and some external unit. The history of BCI can be followed back to the 60s [1]. Even the initial research related to brain waves attracted attention, when the German Hans Berger researcher was able to record brain activity through the human scalp in 1929 [2]. The technology available at that time was even less suitable for processing and evaluating these brain electrical signals. As a result of this problem, Hans Berger did not was able to prove beyond a doubt the importance of brain signals. The devices that measure, record and process brain signals, as well as the signal processing algorithms - which perform the determination of brain signals- have developed significantly as a result of research [3], [4]. In the last 20 years, the number of research based on brain-computer interface technology, which processes and transmits measurable signals of the brain, has increased considerably. While at the beginning of the nineties we could only find a few publications about brain-computer interfaces, today the number of articles, publications and research dealing with this technology has increased significantly [5]. Figure 1 shows the quantitative development of BCI-based articles in the field of computer science and engineering from 2000 to 2020. A significant increase even more in the number of publications in 2010s as compared to 2000s implicates the growing importance of BCI technology.

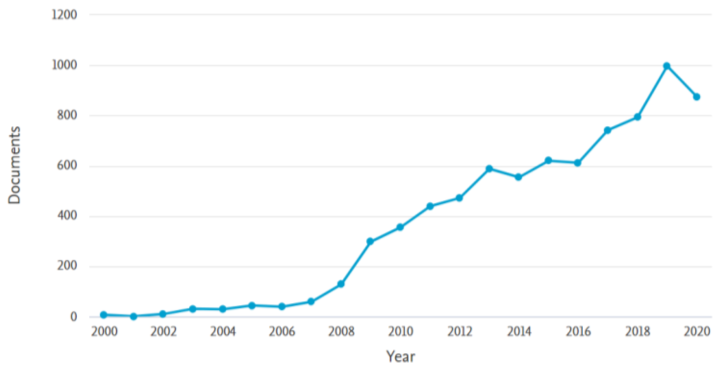

Figure 1. The number of BCI publications in computer science and engineering fields over 20 years: the statistics was based on a search on Scopus

As a result of research in recent years, the reliability of the technology has improved significantly. The implemented brain-computer interface provides an alternative communication channel between the BCI unit wearing and a program running on a computer. In the 2000s, the primary goal of the technology was to help patients with severe neuromuscular disabilities [6]. Cognitive neuroscience-multidisciplinary research and developments-have encouraged researchers to set novel goals for the BCI field. Brain-computer-based interfaces and their current and future developments can provide new application opportunities in a large number of fields of use. They can also play a significant role in studies based on human attention and alert states, such as sleep detection, which can be used to detect waning attention or a state close to falling asleep [7], [8]. In addition to all of this, applications where the reduction of the reaction time is the main goal, as well as the intervention in the shortest possible time in the event of an unexpected emergency, which can occur in the event of sudden braking of a passenger car in an emergency situation, also have great research potential too [9]. Electroencephalogram (EEG)-based BCI systems can be portable in terms of their design, with the development of technology they are becoming more and more compact, and their use has also become relatively simple. In the development of BCI devices, the development of technology and digital technology represented a substantial change, as it provided the necessary computing power to implement and run the continuously developing signal processing algorithms that ensure processing and evaluation. Nowadays, portable BCI systems with a simpler design do not require expensive equipment that requires serious expertise in its application. After measuring, digitizing, pre-processing, normalizing and filtering the bioelectrical signals generated during brain activity, the characteristics of the EEG signals primarily in the time domain and/or frequency domain are determined. Based on the characteristics of the EEG signal, the signals are classified and, as a result, brain activity is identified, which information can be displayed, or even additional functions can be implemented with their use as shown in Figure 2.

In the present study, articles that had a greater impact in the BCI field were reviewed and processed in a systematic way, in order to make individual research more comparable. The aim of this paper is to provide an overview of BCI research results which were published in engineering field. The systematic processing was focused on the aims of application, used device/dataset, applied data process, investigated EEG feature and achieved best accuracy, which make the main contribution to the reviewed papers and highlight the importance of the methods used. The paper presents the reviewed papers selection methodology, summarizes the most important parameters of the articles in a table form and summarizes the essential contributions of the papers, supplemented by an overview of other relevant articles in the results and discussion section. Finally summarize the results of the systematic review. The authors included the papers in the study from 2015, since from this period, in addition to clinical devices, more and more commercially available BCI devices appeared on the market, which expanded the possibilities of research.

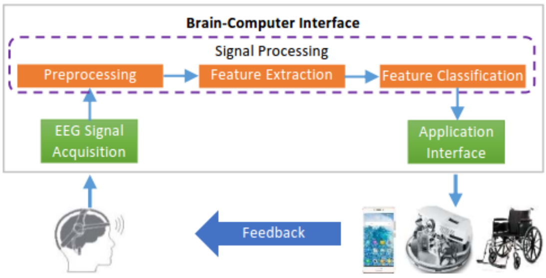

Figure 2. A functional model of the BCI system

2. PAPER SELECTION METHOD

In this paper, it was investigated only BCI applications in engineering field since we consider these applications relevant to possible industrial use in the future. The publication selection process includes a designated set of papers from important Scopus indexed journals and conferences within the field. Preferred reporting items for systematic reviews and meta-analyses (PRISMA) method was used in the selection and analysis process of the papers included in this review.

The manuscript collection process involved four steps: i) the identification of papers using to the search arguments; ii) the application of the eligibility criteria; iii) the screening to select the manuscripts which are not relevant; and iv) the selection of most cited papers to be presented in this review.

The most cited papers were selected based on the annual citation (AC) number calculated using (1) (the result was rounded to the nearest whole number);

$$AC = \frac{Total\ citation\ number}{Number\ of\ years\ since\ publication} \tag{1}$$

Section 1 explained the relevant selected papers are those which describe BCI research in the field of different engineering applications. The main eligibility criteria were: i) papers in English language; ii) papers in computer science and engineering fields; and iii) from year 2015.

A search was carried out on the 23rd of September 2022, using the Scopus database. The Boolean string query applied in the search were achieved based on these inclusion criteria:

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(TITLE-ABS-KEY (brain?computer) OR TITLE-ABS-KEY (BCI)) AND PUBYEAR>2014 AND (LIMIT-TO(SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE,"ch") OR LIMIT-TO (DOCTYPE, "bk" )) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD, "Brain Computer Interface") OR LIMIT-TO (EXACTKEYWORD, "Brain-Computer Interfaces") OR LIMIT-TO (EXACTKEYWORD, "Brain-computer Interface")).
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The OR operator was used for terms considered synonyms and the AND operator to separate criteria. The selection criteria summarized in Table 1. The total number of papers were 2020 and based on the AC values and selection criteria 23 were finally added in this study. This method does not include any subjective criteria the result is based on the query criteria, AC value, and year.

Table 1. Summary of the paper selection criteria

Inclusion	Exclusion
Topic is BCI research	Articles are review articles
BCI application in engineering and computer science fields	BCI application in medicine, social science, and neuroscience
Fit the query criteria	Not fit the query criteria
Paper in English	Paper not in English
Year≥2015	Year<2015
AC≥30	AC<30

3. PAPER PROCESSING RESULTS AND DISCUSSION

The data collection process to extract relevant information from the articles was based on an information summarization matrix. For each inserted article, key characteristics were extracted as data summary matrix shown in Table 2 in *appendix* [10]–[31]. The main findings of the papers are summarized below.

We have summarized some of the abbreviations in the table: convolutional neural network (CNN), P300 visual-evoked potential (P300), movement-related cortical potential (MRCP), error-related negativity (ERN), sensory motor rhythm (SMR), deep learning (DL), motor imagery (MI), stacked autoencoder (SAE), short time fourier transform (STFT), steady-state visual evoked potentials (SSVEP), task-related component analysis (TRCA), infinite impulse response (IIR), filter-bank common spatial patterns (FBCSP), machine learning (ML), signal processing (SP), channel mixing convolutional neural network (CM-CNN), channel-wise convolutional neural network (CW-CNN), channel-wise convolution with channel mixing (C2CM), support vector machine (SVM), empirical mode decomposition (EMD), discrete wavelet transform (DWT), wavelet packet decomposition (WPD), higher order statistics (HOS), multiscale principal component analysis (MSPCA), restricted Boltzman machine (RBM), frequential deep belief network (FDBN), extreme learning machine (ELM), multi-kernel learning (MKL), common spatial pattern (CSP), constrained sparse group spatial pattern (TSGSP), continuous wavelet transform (CWT), bispectrum (BiS), multi-layer perceptron (MLP), autoencoder (AE), logistic regression (LR), sparse group representation model (SGRM), canonical correlation analysis (CCA), filter bank canonical correlation analysis (FBCCA), amplitude and signal to noise ratio (SNR), auto regression (AR), dataset for emotion analysis using EEG, physiological and video signals (DEAP), genetic algorithms and a support vector machines (GA-SVM), minimum-redundancy-maximum-relevance (mRMR), Hjorth parameters (HP), fractal dimension (FD), band power (BP), radial basis function (RBF), radial basis function (SP), sparse Bayesian learning (SBL), Bayesian learning of frequency bands (SBLFB), sparse discriminant analysis (SDA), event-related potentials (ERP), Bayesian linear discriminant analysis (BLDA), region of interest (RoI), event related desynchronization (ERD), time–frequency representation (TFR), cortical current density estimation (CCDE), variational autoencoder (VAE), common spatiospectral pattern (CSSP), linear discriminant analysis (LDA), Bayesian spatiospectral filter optimization (BSSFO), multivariate empirical mode decomposition (MEMD), and multivariate intrinsic mode function (MIMF).

The researches shown in the overview table have the following important characteristics: i) BCI methods: most used methods the EEG, CNN, P300, SSVEP, DL and ML; ii) Device/ dataset: most used BCI Competition datasets and different EEG devices; iii) Data process: spatial filtering, CNN based classification and interpretation, CSP and SVM are the most used data processing methods; iv) investigated EEG feature: MI; and v) best accuracy: 80-90%.

The following sections briefly summarise the research analysed, highlighting the main points of the research. Lawhern *et al*. [10] studied four BCI data processing methods-P300 visually evoked potentials, ERN, MRCP and SM-using CNNs. Their goal was to find out whether there exists a CNN architecture that can classify EEG signals generated by different BCI test methods. The EEGNet system they have created is widely applicable and shows stable performance. Tabar and Halici [11] applied DL methods, including CNNs and SAEs, to improve the classification of EEG motor image signals. A new input shape and deep network were introduced, which achieved better results compared to previous approaches. Nakanishi *et al*. [12] proposed a novel data-driven spatial filtering approach to improve the detection of SSVEPs. TRCA component analysis helped to improve the reproducibility of SSVEPs and resulted in SSVEP signals with improved signal strength (SNR). Their results show that the TRCA-based method yields significant improvements over the CCA-based method. Sakhavi *et al*. [13] proposed a classification framework for MI data. They introduced a new temporal representation and a CNN architecture for classification, which yielded very good results. Kevric and Subasi [14] investigated three feature extraction methods for decomposing EEG signals: empirical mode decomposition, discrete wavelet transforms and wavelet packet decomposition. The researchers pointed out the importance of higher frequency bands in improving the classification of EEG signals. Lu *et al*. [15] proposed a DL scheme based on RBM for MI classification of EEG features. They trained three RBMs using FFT representations and WPD, and then applied an extra output layer named FDBN. Their results showed that FDBN improved significantly over previous methods.

Zhang *et al*. [16] proposed an multi-kernel ELM (MKELM)-based method for MI electroencephalograph classification. The integration of gaussian and polynomial kernel functions with a multikernel learning strategy enabled a more robust EEG classification with higher classification accuracy. Zhang's [17] further improved the classification accuracy of MI EEG using the TSGSP algorithm, which simultaneously optimizes filter bands and time windows. A linear SVM was trained on the optimized EEG features, which accurately identified AI tasks. Ieracitano *et al*. [18] proposed a multimodal ML-based new approach for automatic EEG classification for screening neurological patients with mild cognitive impairment or Alzheimer's disease. EEG signals were processed using continuous wavelet transform and BiS representation based on higher order statistics. Their method proved to be effective in classification based on CWT and BiS features. Jin *et al*. [19] applied an ELM method for classification of MI EEG signals using the Bayesian ELM-based algorithm, achieving high classification accuracy. Jiao *et al*. [20] proposed a new SGRM method to improve the efficiency of AI-based BCI, which reduces the number of training samples required from the target, resulting in excellent classification performance. Chen *et al*. [21] proposed the application of

FBCCA method in the integration of fundamental and harmonic frequency components to improve the detection of SSVEPs, which enhanced the performance and usability of SSVEP-based BCI systems. Tang *et al*. [22] developed a new CNN-based method for a single-trial MI EEG-based BCI system, which improved feature extraction and classification. The applied 5-layer CNN model showed better average performance than conventional classification methods.

Atkinson and Campos [23] investigated the automatic recognition of emotions using an EEG-based BCI system and presented a new feature-based model that can identify multiple emotions. To improve the emotion classification efficiency of SVM, the mRMR feature selection method was used for preprocessing. The method resulted in significant improvements for SVM classifiers using the RFB kernel. Jin *et al*. [24] applied the CSS algorithm to improve the classification performance of MI-based BCI systems. The method used higher correlation channel selection and efficient feature extraction using the RCSP method. The results were tested on EEG datasets and it was shown that the CSS algorithm and RCSP further improve the classification accuracy. Edelman *et al*. [25] developed a non-invasive EEG-based BCI system for controlling robotic devices to efficiently support the performance of everyday tasks. The implemented framework significantly improved the quality of neural decoding and non-invasive based control. Jiao *et al*. [20] presented a new method for classifying EEG signals of motor imagery based on the SBLFB method. Their test results showed that the SBLFB method improves AI classification. Zhang *et al*. [27] used a rarely used Bayesian method, SBLaplace, for EEG classification. Their results show that the SBLaplace algorithm outperforms other EEG classification algorithms. Edelman *et al*. [28] presented a method for classifying four complex motor images of the right hand: flexion, extension, supination and pronation. Their results showed that they performed 18.6% better in classification than the traditional sensor-based method. Dai *et al*. [29] proposed a classification framework for EEG signal processing that combines a CNN architecture with a VAE. Their method outperformed other classification methods studied by 3%.

Kwon *et al*. [30] created an EEG database based on MI, in which 54 subjects performed two different MI tasks for right and left hands on two different days. By analyzing the resulting 21,600 MI trials, they created a person-independent model. In the feature representation, spectral-spatial inputs were individually trained on a CNN and then coupled using a concatenation fusion technique. The classification accuracy of their model outperforms CSP, CSSP, FBCSP and Bayesian spatial-spectral filter optimization. Gaur *et al*. [31] presented a new personalized multivariate empirical mode decomposition method. This decomposition allows to extract multichannel information and localize specific frequency information. The classification after statistical preprocessing was performed using Riemann geometry, which achieved better results than the other algorithms investigated.

The quality of processing is greatly influenced by external noise and other factors affecting the information quality, such as changes in the position of the electrodes. BCI systems record the signals from several channels in order to spatially identify the signals and increase accuracy, but this in-creases the amount of data required for the proper description of the signals processed by each characteristic extraction method exponentially. However, the algorithms presented in the article may not necessarily be applicable only in the BCI field but may also provide models that can be adapted to other general human computer interface (HCI) implementations. Many HCIs use methods that use multiple sensors [32], the determination of certain characteristics are their processing models [33], and with regard to the methods used therein, the use of methods that have already been proven in BCI systems may also arise. The development of HCI systems can contribute to a more accurate understanding of human factors [34] and, through this, even to their development, such as the analysis and improvement of learning abilities [35]. In addition to the above new approaches have been appeared that shows improvement in the field of classification [36], [37]. Sánchez-Reyes *et al*. [38] reviewed the available literature and performed an analysis of the effectiveness of EEG parameters in detecting dementia. The results of the review showed that EEG parameters can help in the early detection and differentiation of dementia from other cognitive disorders [38]. Using brain imaging procedures, the activity of the cerebral cortex of strabismus and amblyopia patients can be examined. Ibrahimi *et al*. [39] showed that these patients experienced changes in the activity of the cerebral cortex both in the baseline state and in response to light stimulation.

3.1. Summary of other most cited papers

In the previous chapter, it is reviewed in detail the BCI-related articles that had high annual citations. However, in this section it is briefly summarized further publications that are also highly cited and relevant to the topic of this paper. Khan and Hong [40] present a BCI capable of decoding eight active commands from frontal areas of the brain using a combination of EEG and functional near-infrared spectroscopy (fNIRS). The fNIRS is located in the prefrontal cortex, while the EEG operates around the frontal, parietal and visual cortex. Four commands are decoded by the fNIRS using mathematical reasoning, counting, mental rotation and word formation tasks. EEG is generated by two, three eye movements and up/down and left/right eye movements. The commands were tested in free space on a quadcopter and achieved an average accuracy of 75.6% with fNIRS and 86% with EEG in decoding the four commands. The results show that the proposed hybrid EEG-fNIRS interface can be used to control a quadcopter in real time and online. Wang *et al*. [41] investigate a BCI system focusing on decoding EEG features prior to finger movements. The research analyzed EEG features elicited by intentional movements of the left and right fingers, highlighting MRCP and ERD features. These features were evaluated using DCPM and CSP and classified using fisher discriminant analysis (FDA). The results showed that the combination of DCPM and CSP achieved an average accuracy of 80.96%, which is significantly higher than the results obtained using DCPM or CSP methods alone. The highest accuracy of the combined method was 91.5%.

Jin *et al*. [42] investigated P300-based BCI systems that provide an additional communication channel for people with communication difficulties. Their generated set includes ten models trained by weighted linear discriminant analysis (WLDA). Their results show that all new participants found the most appropriate generic model. The average classification accuracy after online training is 80%, which is roughly equivalent to the accuracy achieved with the typical training model method. In addition, the calibration time was 70.7% shorter compared to the typical model method. Amin *et al*. [43] concluded that the new CNN methods show better results in EEG classification than any previous ML and DL techniques. The results show that using different architectures, depths and filter sizes, CNN models are able to extract and represent different types of features from EEG data. The proposed CNN method achieves an accuracy of 75.7% and 95.4% on the BCI Competition IV-2a dataset, respectively, and autoencoder cross-routing achieves more than 10% improvement in cross-sub-EEG classification.

Xu *et al*. [44] developed a novel mini asymmetric visually evoked potential (aVEP)-based BCI interpreter that encodes 32 characters using space-coded multiple access (SCDMA) and decodes EEG features using the discriminative canonical pattern matching (DCPM) algorithm. Their results show that online tests can achieve data rates of up to 63.33 bits/minute. The experimental results show that even for very small and undetectable visual stimuli, an efficient BCI system can be implemented, even if the induced EEG features are very weak. Liu *et al.* [45] present a new BN3 CNN developed to detect P300 signals from EEG data. These signals are fundamental to the creation of P300 character recognition systems that allow users to write messages simply by controlling eye movements. The new BN3 model introduces batch normalization in the input and convolutional layers to alleviate the problem of over-learning, while ReLU in the convolutional layers speeds up learning. Results on the P300 datasets of the previous BCI competition show that BN3 provides state-of-the-art character recognition performance and outperforms existing detection approaches.

Lin *et al*. [46] developed the AgPMS EEG electrode, which is easy to fabricate, cost-effective, flexible, robust and gel-free, and can solve hair-related problems. Compared to conventional gel-based electrodes, the efficiency of the new electrode was 86% on hairless skin and similar efficiency on hairy skin. Tang *et al.* [47] proposed a new method for detecting MI EEG signals. The method was successfully applied on different datasets and achieved higher accuracy than previous works. Katona and Kovari [48] tested the BCI system with the Corsi block test and the Ebbinghaus procedure, which showed a moderate-strong correlation with the average attention of BCI. Zanini *et al*. [49] investigated the problem of transfer learning in BCIs. They represented the data using spatial covariance matrices of EEG signals and obtained significant improvements in classification performance. Ang and Guan [50] presented the results of their previous work in six stroke patients who participated in a BCI rehabilitation clinical trial and showed significant improvement.

Foong *et al*. [51] investigated the effectiveness of the nBETTER system in upper limb stroke rehabilitation. Xu *et al*. [52] developed a high-speed hybrid BCI system that can encode up to 108 instructions simultaneously. Fahimi *et al*. [53] proposed a framework for detecting attentional mental state from single-channel EEG data. Tayeb *et al*. [54] presented three DL-based models for online decoding of imagined hand movements from EEG signals. Wang *et al.* [55] presented a SSVEP dataset collected for 40 target BCI spellings. Chiarelli *et al*. [56] investigated the capabilities of combining EEG and fNIRS recordings with recent DL techniques. Lee *et al.* [57] presented a BCI dataset that included three main BCI paradigms-MI, ERP and SSVEP-across multiple samples and sessions. Dose *et al.* [58] developed a CNN for generalized feature learning and dimension reduction, while using the traditional fully connected (FC) layer for classification. Wang *et al*. [59] proposed a classification framework based on LSTM networks, which achieved almost 80% classification accuracy.

4. CONCLUSION

The article provides an overview of the results of the most influential, i.e. the most cited, BCI research in the fields of computer science and engineering over 20 years. The research field of BCI systems is quite diverse, researchers have used it in several areas of application and use, such as robotics, control, sensing and processing of medical signals, neurophysiology, rehabilitation, and education, thus achieving significant and for-ward-looking results. In most cases, the studies aimed to improve the quality of life of persons with disabilities using the non-invasive EEG device and different signal processing and classification algorithms such as: CSP and SVM. In this way, near-real-time communication between the human brain and the computer has been created for patients who, for some reason, can only communicate in this alternative way. Overall, BCI research is a very active area of research and many other signal processing, and classification algorithms are being explored in this field. The results of the examined research typically showed an efficiency of 85%, and a continuous improvement of this value is expected thanks to increasingly reliable, accurate and cost-effective signal detection and processing devices, as well as algorithms support-ed by AI, ML, and neural decoding techniques. Another major goal in BCI research is to make these systems more accessible and easier to use for a wider range of individuals, including those with disabilities. Advances in hardware and software design, as well as advances in user training and interface design, are likely to make BCI systems more user-friendly and intuitive. BCI research is increasingly being combined with other technologies, such as augmented and virtual reality, haptic feedback, and wearable devices. These combinations have the potential to create even more powerful and versatile interfaces between the brain and external devices. In spite of the fact that BCI systems hide many possibilities, the human brain is an extremely complex, non-linear and non-stationary system, in which the detection and processing of neural activity is a great challenge. That is why the processing of BCI signals, and the implementation of communication interfaces pose many challenges, which is why they are trying to implement the related processing methods with a wide variety of methods in order to create the most efficient systems possible.

APPENDIX

Table 2. Systematic overview of the main aims, investigation methods and accuracy of the BCI papers

Ref	Year	Authors	BCI methods	Device/ dataset	Data process	Investigated EEG feature	Best accuracy (%)
[10]	2018	Lawhern *et al.*	BCI, EEG, CNN, P300, ERN, SMR, DL	BCI Challenge @ NER 2015 dataset	EEGNet-8,2 optimal spatial filtering and filter-bank construction, CNN based classification and interpretation, depthwise and separable convolutions	Within-subject P300 MRCP ERN SMR Cross subject P300 MRCP ERN SMR	 92 81 83 68 90 81 75 40
[11]	2017	Tabar and Halici	EEG, BCI, CNN, DL, SAE	BCI Competition IV dataset 2b, BCI Competition II dataset III	Combined CNN-SAE based classification and interpretation, STFT	MI	90
[12]	2018	Nakanishi *et al.*	BCI, EEG, SSVEP, TRCA	Synamp2 system (Neuroscan, Inc.)	TRCA-based target identification algorithm, IIR filter, zero-phase forward and reverse filtering	SSVEP	89.83
[13]	2018	Sakhavi *et al.*	BCI, CNN, DL, ML, SP	BCI competition IV-2a EEG dataset	FBCSP, CM-CNN, CW-CNN, C2CM, DL,	MI	SVM 71.18 CW-CNN 73.07 C2CM 74.46
[14]	2017	Kevric and Subasi	BCI, EMD, DWT	BCI competition III dataset IVa	WPD, HOS, MSPCA	MI	92.8
[15]	2017	Lu *et al.*	BCI, EEG, DL, WPD	BCI competition IV dataset 2b	RBM, FDBM	MI	84
[16]	2018	Zhang *et al.*	BCI, EEG, ELM, MKL	BCI Competition III dataset Iva, BCI Competition IV dataset IIb	CSP, SVM, multi-kernel ELM	MI	BCI Competition III dataset Iva 87.5 BCI Competition IV dataset IIb 78.9
[17]	2019	Zhang *et al.*	BCI, EEG, sparse group spatial pattern, temporal constraint	BCI Competition III dataset IIIa, BCI Competition IV datasets IIa, BCI Competition IV dataset IIb	Sparse filter bank, TSGSP, sliding window	MI	BCI Competition III dataset IIIa 88.5 BCI Competition IV datasets IIa 83.3 BCI Competition IV dataset IIb 84.3

Table 2. Systematic overview of the main aims, investigation methods and accuracy of the BCI papers (*continue*)

Ref	Year	Authors	BCI methods	Device/ dataset	Data process	Investigated EEG feature	Best accuracy (%)
[18]	2020	Ieracitano *et al.*	ML, Alzheimer's disease, Mild Cognitive Impairment	19 channel general EEG	CWT, BiS, MLP, AE, LR	MI	96.5
[19]	2020	Jin *et al.*	BCI, EEG, ML	BCI Competition IV dataset IIb	SVM, ELM, sparse Bayesian ELM	MI	78.5
[20]	2019	Jiao *et al.*	BCI, EEG, ML	BCI Competition IV dataset IIb, BCI Competition III dataset IVa	SGRM, CSP	MI	BCI Competition IV dataset IIb 78.2 BCI Competition III dataset IVa 77.7
[21]	2015	Chen *et al.*	BCI speller, filter bank	Synamps2 system (Neuroscan, Inc.)	CCA, FBCCA, SNR	SSVEP	91.95
[22]	2017	Tang *et al.*	BCI, EEG, CNN, deep CNN	ActiveTwo 64-channel EEG system (BioSemi B.V., Amsterdam, Netherlands)	SVM, CSP, AR	MI	86.41
[23]	2016	Atkinson and Campos	BCI, EEG, emotion recognition, feature selection, emotion classification	DEAP dataset	GA-SVM, mRMR	HP, FD, BP	Arousal 60.72 Valence 62.4
[24]	2019	Jin *et al.*	BCI, EEG, SP, correlation-based channel selection	BCI competition IV dataset 1, BCI competition III dataset Iva, BCI competition III dataset IIIa	regularized CSP, SVM, RBF	MI	BCI competition IV dataset 1 81.6 BCI competition III dataset Iva 87.4 BCI competition III dataset IIIa 91.9
[25]	2019	Edelman *et al.*	high-dimensional robotic device control, neural control of a robotic device, target tracking, control of virtual cursor to the real-time control of a robotic arm	BCI2000, 128-channel Biosemi EEG headcap	filtering, EEG bands, EEG alpha power	MI	Center-out tasks 50 Realistic continuous pursuit task 500
[26]	2017	Zhang *et al.*	BCI; EEG; frequency band	BCI Competition IV dataset IIb	CSP, SBL, SBLFB, SDA	MI	81.7
[27]	2016	Zhang *et al.*	BCI, EEG, ERP	unique EEG cap, g.USBamp amplifier 256-Hz sampling rate with a 64-channel	sparse Bayesian method by exploiting a Laplace prior, SBL, BLDA	ERP	95
[28]	2016	Edelman *et al.*	BCI, brain mapping, EEG source imaging, neuroimaging	64 channels, 1Khz, 17 electrodes, SynAmpsRT amplifier	ROI, ERD, TFR, CCDE, Wavelet transform, Mahalanobis distance-based classifier, Cortical Mapping	MI	82.2
[29]	2019	Dai *et al.*	EEG, DL	BCI Competition IV dataset 2b, EEG recording 250Hz, 10-20 system	STFT, CNN, VAE	MI	-
[30]	2020	Kwon *et al.*	BCI, EEG, DL	dataset, 62 EEG and 4 EMG electrodes, 1Khz, BrainAmp amplifier	CNN, CSP, CSSP, filter bank, LDA, BSSFO	MI	Subject-dependent 71.32 Subject-independent 74.15
[31]	2018	P. Gaur *et al.*	EEG, motor imagery related brainwave modulations over μ and β rhythms	BCI competition IV dataset 2A	MEMD based filtering, mean frequency, MIMF decomposition, sample covariance matrix, Riemannian geometry classification	MI	Kappa value 0.60

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BIOGRAPHIES OF AUTHORS

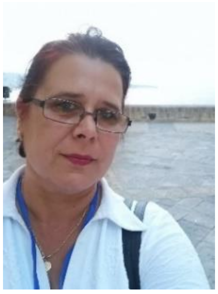
Jozsef Katona is Associate Professor at University of Dunaujvaros, Obuda University and John von Neumann University, Hungary. He holds a Ph.D. degree in Computer Engineering. His research areas are human-computer interfaces, brain-computer-interfaces, programming, software development, eye-tracking analysis. He can be contacted at email: katonaj@uniduna.hu.

Prof. Attila Kovari is Professor at Eszterhazy Karoly Catholic University, University of Dunaujvaros, Obuda University and John von Neumann University, Hungary. He holds a Ph.D. degree in Engineering and Habilitation in Computer Engineering and Education. His research areas are human-computer interaction, brain-computer-interfaces, eye-tracking analysis, IT in industrial applications. He can be contacted at email: kovari.attila@uni-eszterhazy.hu.

Tibor Guzsvinecz is an Assistant Professor at the University of Pannonia, Hungary. He obtained his Ph.D. degree in the field of Information Science in 2021. His research areas are data science, gamification, human-computer interaction, spatial ability, and virtual reality. He can be contacted at email: guzsvinecz.tibor@zek.uni-pannon.hu.

Judit Szűcs is an Associate Professor at at Department of Automation and Computer Science, Faculty of Electrical Engineering and Computer Science (UTBV), Brasov. She is involved in a number of international interdisciplinary research projects in which she contributes to the IT side. Her main research interests are ICT-supported education, classification of big data, planning and implementation of communication applications. She can be contacted at email: rdemeter@unitbv.ro.

Robert Demeter is an Associate Professor at at Department of Automation and Computer Science, Faculty of Electrical Engineering and Computer Science (UTBV), Brasov. He is involved in a number of international interdisciplinary research projects in which he contributes to the IT side. His main research interests are ICT-supported education, classification of big data, planning and implementation of communication applications. He can be contacted at email: rdemeter@unitbv.ro.



Veronika Szücs is an Assistant Professor at the Faculty of Information Technology of the University of Pannonia, Hungary. She obtained her Ph.D. degree in the field of Information Science in 2019. Her research areas are human-computer interaction, information systems, virtual environments, IT and information systems' security. She can be contacted at email: szucs.veronika@mik.uni-pannon.hu.