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A Survey on Deep Learning based Brain Computer Interface: Recent Advances and New Frontiers

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Brain-Computer Interface (BCI) bridges human's neural world and the outer physical world by decoding individuals' brain signals into commands recognizable by computer devices. Deep learning has enhanced the performance of brain-computer interface systems significantly in recent years. In this article, we systematically investigate brain signal types for BCI and related deep learning concepts for brain signal analysis. We then present a comprehensive survey of deep learning techniques used for BCI, by summarizing over 230 contributions, most published in the past five years. Finally, we discuss the applied areas, emerging challenges, and future directions for deep learning-based BCI.

Additional Key Words and Phrases: Brain-Computer Interface, deep learning, survey

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1 INTRODUCTION

Brain-Computer Interface (BCI)¹ is a system that translates activity patterns of the human brain into messages or commands to communicate with the outer world [119]. BCI underpins many novel applications that are important to people's daily life, especially to people with psychological/physical diseases or disabilities. For example, ordinary individuals can enjoy enhanced entertainment and security when brain waves-based techniques are applied for high fake-resistant user identification [249]. Another example is that BCI can assist the disabled, elders and people with limited motion ability (e.g., people with muscle diseases) in controlling wheelchairs, home appliances, and robots. The key challenge of BCI is to recognize human intents accurately given the meager Signal-to-Noise Ratio (SNR) of brain signals. Both low classification accuracy and poor generalization ability limit the real-world application of BCI.

¹There are several terms similar to BCI, e.g., Brain Machine Interface (BMI), Brain Interface (BI), Direct Brain Interface (DBI), and Adaptive Brain Interface (ABI). They all describe machines that are directly controlled by human brain signals.

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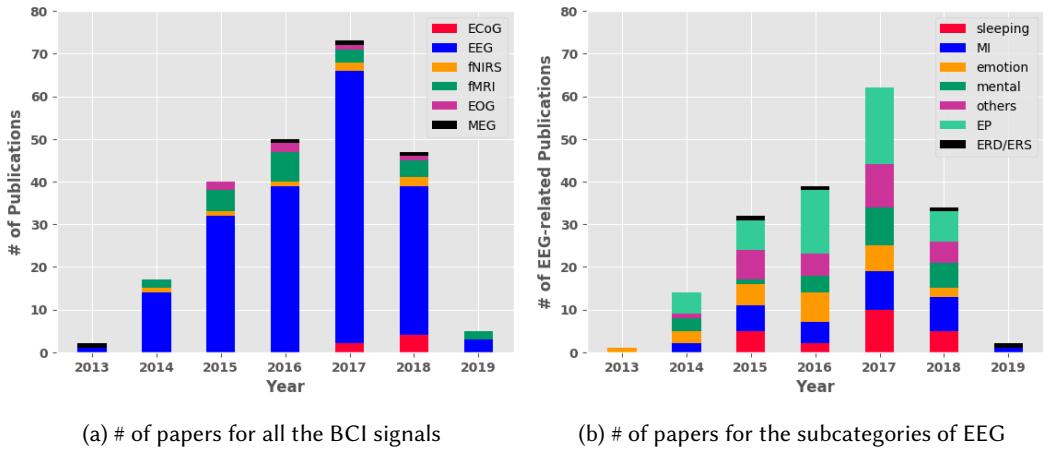


Fig. 1. Breakdown of the papers included in this survey in year of publication and BCI signals. Not all papers are counted for the years 2018 and 2019 due to limited availability of the related data.

To overcome the above challenges, deep learning techniques, i.e., deep neural networks, have been investigated to deal with the brain information in the past few years. Deep Learning is a sub-field of machine learning inspired by the structure and function of the brain. It has shown excellent representation learning ability since 2006 [42] and therefore been impacting a wide range of information-processing domains such as computer vision, natural language processing, activity recognition, and logic reasoning [217]. Differing from traditional machine learning algorithms, deep learning can learn distinct high-level features from raw brain signals without manual feature selection, and its accuracy scales well with the size of the training set.

1.1 Why Deep Learning?

Although traditional BCI systems have made tremendous progress [2, 20] in the past decades, the research in BCI still faces significant challenges. First, brain signals are easily corrupted by various biological (e.g., eye blinks, muscle artifacts, fatigue and concentration level) and environmental artifacts (e.g., environmental noise) [2]. Therefore, it is crucial to distill informative data from corrupted brain signals and build a robust BCI system that works under different situations.

Second, BCI has a low SNR due to the non-stationary nature of electrophysiological brain signals [168]. Although several preprocessing and feature engineering methods have been developed to decrease the noise level, such methods (e.g., feature selection and extraction both in the time domain and frequency domain) are time-consuming and may cause information loss in the extracted features [250].

Third, feature engineering highly depends on human expertise in the specific domain. For example, it requires basic knowledge of biology to investigate the sleep state through EEG signals. Human experience may help capture features on some particular aspects but prove insufficient in more general conditions. Therefore, an algorithm is required to extract representative features automatically.

Moreover, most existing machine learning research focuses on static data and therefore cannot classify rapidly changing brain signals accurately. For example, the state-of-the-art classification accuracy for motor imagery EEG is merely 60% to 80% [120], which is unfeasible for practical uses. It generally requires novel learning methods to deal with dynamical data streams in BCI systems.

Table 1. The existing survey on BCI in the last decade. The column ‘comprehensive on signals’ indicates whether the survey has summarized all the BCI signals or not.

No.	Reference	Comprehensive on Signals?	Signal	Deep Learning	Publication Time	Area
1	[48]	No	EMG, EOG	No	2007	
2	[222]	No	fMRI	Yes	2018	Mental Disease Diagnosis
3	[120]	Partial	EEG (mainly MI EEG and P300)	No	2007	Classification
4	[119]	Partial	EEG (Mainly MI EEG, P300)	Partial	2018	Classification
5	[134]	Partial	EEG (ERD, P300, SSVEP, VEP, AEP)	No	2007	
6	[113]	No	MRI, CT	Partial	2017	Medical Image Analysis
7	[233]	No	EEG	Yes (but without any model introduction)	2019	
8	[20]	No	EEG	No	2007	Signal Processing
9	[220]	Partial	EEG	No	2016	BCI Applications
10	[2]	Yes		No	2015	
11	[140]	No	EEG	Partial (only DBN)	2018	
12	[184]	No	EEG, fMRI	No	2015	Neurorehabilitation of Stroke
13	[5]	No	MI EEG	No	2015	
14	[165]	No	fMRI	No	2014	
15	[63]	No	ERP (P300)	No	2017	Applications of ERP
16	[114]	No	fMRI	Yes	2018	Applications of fMRI
17	[206]	No	ERP	No	2017	Classification
18	[61]	Partial	EEG	No	2019	Brain Biometrics
19	Ours	yes	Invasive, EEG and the subcategories, fNIRS, fMRI, EOG, MEG	Yes		

Until now, deep learning has been applied extensively in BCI applications and shown success in addressing the above challenges [30, 124]. Deep learning possess two advantages. First, it avoids the time-consuming preprocessing and feature engineering steps by working directly on raw brain signals to learn distinguishable information through back-propagation. Second, deep neural networks can capture both representative high-level features and latent dependencies through deep structures. Our investigation (Figure 1) shows a surge of publications in deep learning based BCI since 2014.

1.2 Why this Survey is Necessary?

We conduct this survey for three reasons. First, there lacks systematic and comprehensive introduction of BCI signals. Table 1 shows a summary of the existing survey on BCI. To the best of our knowledge, the limited existing surveys [2, 20, 48, 114, 119, 120, 134, 222] only focus on partial EEG signals. For example, Lotte et al. [120] and Wang et al. [220] focus on EEG without analyzing EEG signal types; Cecotti et al. [32] focus on Event-Related Potentials (ERP); Haseer et al. [142] focus on functional near-infrared spectroscopy (fNIRS); Fatourechi et al. [48] only focus on EMG and EOG; Wen et al. [222] and Liu et al. [114] only focus on Functional magnetic resonance imaging (fMRI); Mason et al. [134] brief the neurological phenomenons like event-related desynchronization (ERD), P300, SSVEP, Visual Evoked Potentials (VEP), Auditory Evoked Potentials (AEP) but have not organized them systematically; Abdulkader et al. [2] present a topology of brain signals but have not mentioned spontaneous EEG and Rapid Serial Visual Presentation (RSVP); Lotte et al. [119] have not considered ERD and RSVP; Roy et al. [233] list some deep learning based EEG studies but provide little analysis.

Second, although some overviews have conducted in deep learning ([42, 43, 174]) and BCI ([2, 20, 48, 119, 120, 134]), few focus on their combination. To the best of our knowledge, this paper

is the *first comprehensive summary* of the recent advances on deep learning-based BCI. This work also presents the current frontiers and potential directions in research.

Lastly, unlike this survey, all previous BCI surveys focus on specific areas or applications without given an overview of the broad scenarios. For example, Litjens et al. [113] review some leading deep learning concepts pertinent to medical image analysis without covering many other deep learning models; Soekadar et al. [184] review the BCI systems and machine learning methods that help overcome stroke-related motor paralysis and focus on Sensorimotor Rhythms (SMR); Vieira et al. [213] investigate the application of BCI systems on neurological and psychiatric disorders.

1.3 Our Contributions

This survey aims to present a comprehensive and systematic introduction of the recent advances and new frontiers of deep learning based brain-computer interface techniques. We summarize over 240 contributions in this field, most of which were published in the last five years (after 2014). We make several key contributions in this survey:

- We first comprehensively summarized the brain signals used for BCI. Also, this is the first investigation of the biometric signals in deep learning based BCI.
- We summarize deep learning techniques for BCI applications. To our best knowledge, *we are the very first to systematically review Deep learning models for BCI*.
- We provide guidelines for choosing a suitable deep learning model for a specific BCI system and a specific brain signal type.
- We discuss the challenges of deep learning based BCI and highlight the promising topics for the future research.

The rest of this survey is structured as followed. Section 2 briefly introduces the paradigm of BCI systems. Section 3 gives a comprehensively introduction of biometric signals used in BCI. Section 4 overviews the commonly used deep learning models. Section 5 presents the state-of-the-art deep learning techniques for BCI. Section 6 discusses the applications related to brain signals. Section 7 points out the emerging challenges and future directions. Finally, Section 8 gives the concluding remarks.

2 GENERAL BCI SYSTEM

Figure 2 shows the general paradigm of a BCI system, which receives brain signals and converts them into control commands for computers. The system includes several key components: brain signal collection, signal preprocessing, feature engineering, classification, and smart equipment. The brain signals are collected from humans and sent to the preprocessing component for denoising and enhancement. Then, the discriminating features are extracted from the processed signals and sent to the classifier, which recognizes the signals and convert then into external device commands.

The collection methods differ from signal to signal. For example, EEG signals measure the voltage fluctuation resulting from ionic current within the neurons of the brain. Collecting EEG signals requires placing a series of electrodes on the scalp of the human head to record the electrical activity of the brain. Since the ionic current generated within the brain is measured at the scalp, obstacles (e.g., skull) greatly decrease the signal quality—the fidelity of the collected EEG signals, measured as Signal-to-Noise Ratio (SNR), is approximately 5% of that of original brain signals [17]. Therefore, brain signals are usually preprocessed before feature engineering to increase the SNR. The preprocessing component contains multiple steps such as signal cleaning (smoothing the noisy signals or resolving the inconsistencies), signal normalization (normalizing each channel of the signals along time-axis), signal enhancement (removing direct current), and signal reduction (presenting a reduced representation of the signal).

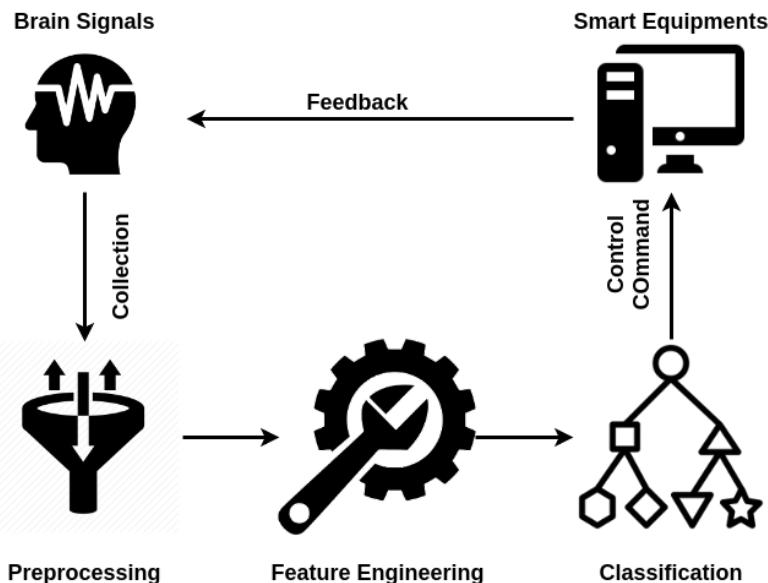


Fig. 2. Generally workflow of BCI system.

Feature engineering refers to the process of extracting discriminating features from the input signals through domain knowledge. Traditional features are extracted from time-domain (e.g., variance, mean value, kurtosis), frequency-domain (e.g., fast Fourier transform), and time-frequency domains (e.g., discrete wavelet transform). They will enrich distinguishable information regarding user intention. Feature engineering is highly dependent on the domain knowledge. For example, biomedical knowledge is required to extract features from brain signals of epileptic seizures. Manual feature extraction is also time-consuming and difficult. Recently, deep learning provides a better option to automatically extract distinguishable features.

The classification component refers to the machine learning algorithms that classify the extracted features into logical control signals recognizable by external devices. Deep learning algorithms are shown to be more powerful than traditional classifiers such as Support Vector Machine (SVM) and Linear discriminant analysis (LDA).

In this survey, we summarize the state-of-the-art studies which adopt deep learning models (will be detailed in Section 5): 1) for feature engineering only; 2) for classification only; 3) for both feature engineering and classification. BCI has vast potential applications for both the disabled and ordinary individuals. For instance, a BCI system can control household appliances through patients' brain signals. Such a system can also serve for entertainment and security purposes. More BCI applications based on deep learning are introduced in Section 6.

3 BCI SIGNAL RECORDING

In this section, we present a comprehensive and systematic introduction of brain signals used in BCI systems. Figure 3 shows a taxonomy of brain signals including invasive and non-invasive signals based on the signal collection method (Section 3.1). Invasive signals are collected from the surface of the cortex or under the cortex surface (Section 3.2); Non-invasive signals are collected by the external sensors. EEG signal plays a dominant role among non-invasive signals. Therefore,

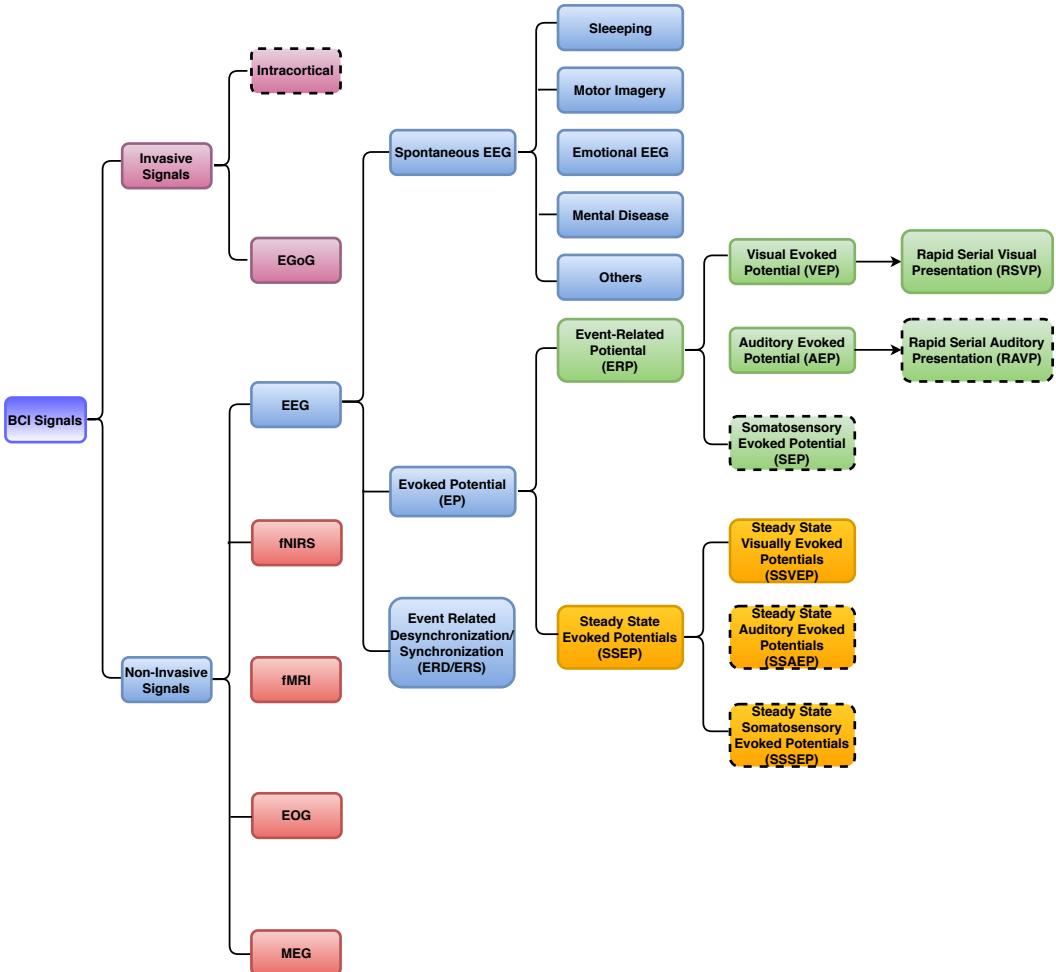


Fig. 3. The biometric signals generally used in BCI system. The dashed quadrilaterals (Intracortical, RAVP, SEP, SSAEP, and SSSEP) are not included in this survey because there is no existing work focussing on them involving deep learning algorithms. P300, which is a positive potential recorded approximately 300 ms after the onset of presented stimuli, is not listed in this signal tree because it is included by ERP (which refers to all the potentials after the presented stimuli).

we introduce the EEG signal and its subordinate categories in particular in Section 3.3. The basic characteristics of various brain signals are summarized in Table 2.

3.1 Invasive Recording

Invasive recordings are acquired by electrodes deployed under the scalp. Figure 4 [102] shows both ‘intraparenchymal signals’ gathered from the cortex and ‘Electrocorticography (ECoG)² gathered from the surface of cortex (dura and arachnoid).

²Some studies name the Intracortical as ‘invasive’ while referring to ECoG as ‘semi-invasive’. In this survey, we combine the so-called ‘invasive’ and ‘semi-invasive’ into ‘invasive’ since they both require surgery.

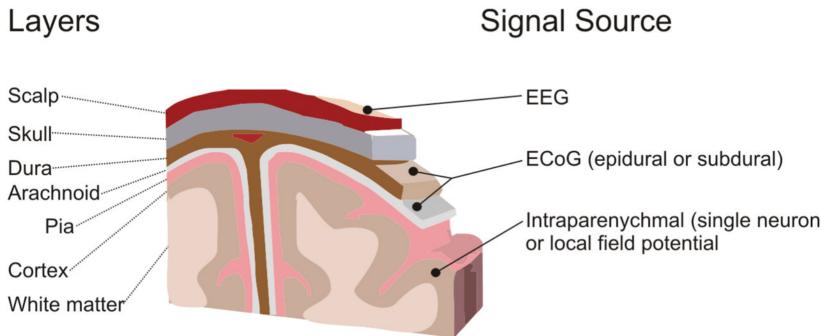


Fig. 4. Signal source locations in the brain

Table 2. Summary of various brain signals' characteristics.

Signals	Invasive		Non-invasive				
	Intracortical	EcoG	EEG	fNIRS	fMRI	EOG	MEG
Risk	High	High	Low	Low	Low	Low	Low
Spatial resolution	Very High	High	Low	Mediate	High	Low	Mediate
Temporal resolution	High	High	Mediate	Low	Low	Mediate	High
Signal-to-Noise Ratio	High	High	Low	Low	Mediate	Mediate	Low
Portability	Mediate	Mediate	High	High	Low	High	Low
Cost	High	High	Low	Low	High	Low	High
Characteristic	Electrical	Electrical	Electrical	Optical	Metabolic	Electrical	Magnetic

Invasive techniques can provide high-quality brain signals as electrodes collect signals directly from locations near the brain neurons. The collected signals have high temporal and spatial resolution³ and high SNR. Nevertheless, invasive methods suffer from two challenges. First, the implantation of electrodes requires a surgical procedure, which is expensive and risky due to the potential medical complications such as transplant rejection. Second, implanted electrodes are fixed and therefore can only measure the brain signals from the same locations. For the above reasons, invasive BCI techniques are mainly used in animals (e.g., monkey and rat) and for people with severe disabilities (e.g., ALS patients) [2] in practice.

3.1.1 Intracortical. The intracortical recording technique involves the insertion of electrodes into the cortex of the subject's brain (Figure 4). The implanted microelectrode can be a single electrode or an array of electrodes. Generally, the intracortical electrodes provide high-resolution motor control brain signals, as movement is the most easily observable phenomenon compared to other phenomena, such as hearing. Under the cortex, the electrodes are sensitive enough to pick up the discrete all-or-none output of single neurons, the action potential, commonly referred to as a “spike”, as well as the summed voltage fluctuations from small to large numbers of neurons, called field potentials. Each electrode provides spiking from up to a few neurons, yielding the population's time evolving output pattern. These represent but a small sample of the entire set of neurons in this limited region, as spiking can only be detected by microelectrodes closely approximated to a neuron [76]. [151] developed a high-performance BCI system for communication of ALS patients. This work implanted a 96-channel silicon microelectrode array in the motor cortex corresponding

³Spatial resolution refers to how well the signal discriminates between nearby locations.

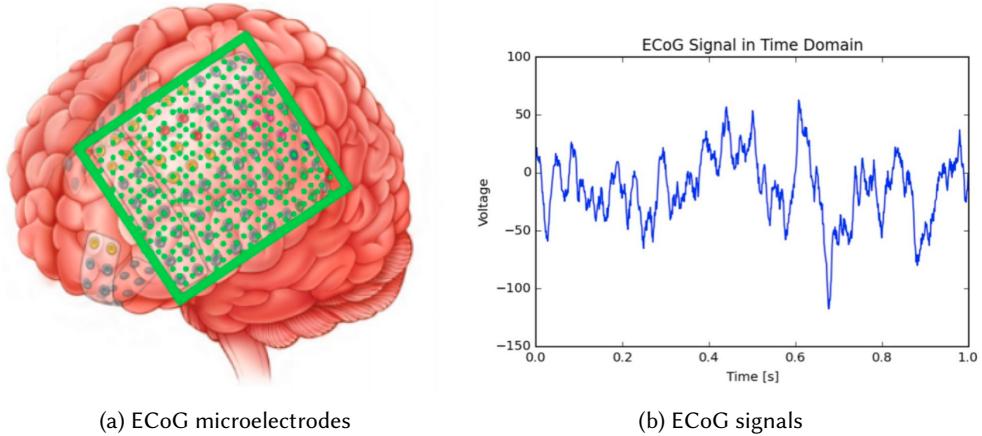


Fig. 5. ECoG grid on cortical surface and ECoG signals.

to hand area and recorded users' motor intention by the microelectrode array. The array was then decoded into point-and-click commands to control a cursor.

3.1.2 Electrocorticography (ECoG). Electrocorticography (ECoG) is an extracortical invasive electrophysiological monitoring method to record brain activity. The electrodes collecting ECoG are attached under the skull, above (epidural) or below (subdural) the dura mater, but not within the brain parenchyma itself (Figure 4) [102]. ECoG provides a trade-off between higher SNR compared to non-invasive recordings and lower risk compared to intracortical recordings. It provides a higher spatial resolution and a rather high SNR with a lower surgical risk. Therefore, ECoG has a better prospect in the medical arena than intracortical recordings.

The ECoG collection approach and the signals are shown in Figure 5 [19]. ECoG signals have a higher amplitude compared to non-invasive brain wave signals. For instance, ECoG has higher than $50 \mu\text{V}$ maximum amplitude while the EEG amplitude is generally lower than $20 \mu\text{V}$. The higher amplitude renders ECoG less vulnerable to artifacts such as eye blink activity. Moreover, ECoG has a bandwidth of 0-500 Hz which is much wider than EEG (0-40Hz), due to the low pass filtering effects of the skull. The wider frequency bands take substantial information from functional areas of a brain (e.g., motor and language) and thus can be used to train a higher-performance BCI system. However, the disadvantages of an invasive methods like ECoG (such as the risky surgery and inconvenience of permanently attached devices) naturally limit its wide deployment in real-world scenarios.

3.2 Noninvasive Recording

Noninvasive recordings can gather user's brain information without electrodes being inserted. Signals can be collected using electrical, magnetic or metabolic methods. Noninvasive signals mainly include Electroencephalogram (EEG), Functional near-infrared spectroscopy (fNIRS), Functional magnetic resonance imaging (fMRI), Electrooculography (EOG), and Magnetoencephalography (MEG). EEG related studies represent the considerable majority of noninvasive signals and have numerous sub-classes. We will introduce more details and sub-classes of EEG in Section 3.3.

3.2.1 Electroencephalography (EEG). Electroencephalography (EEG) is the most commonly used noninvasive technique for measuring brain activities. EEG monitors the voltage fluctuations

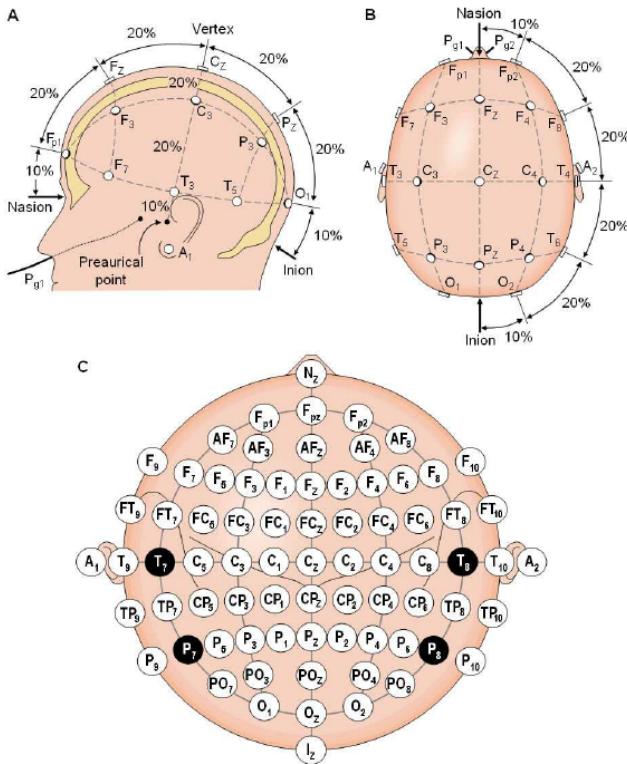


Fig. 6. (A) and (B) are the left and above view of the international 10-20 system. (C) presents the intermediate 10% electrode positions.

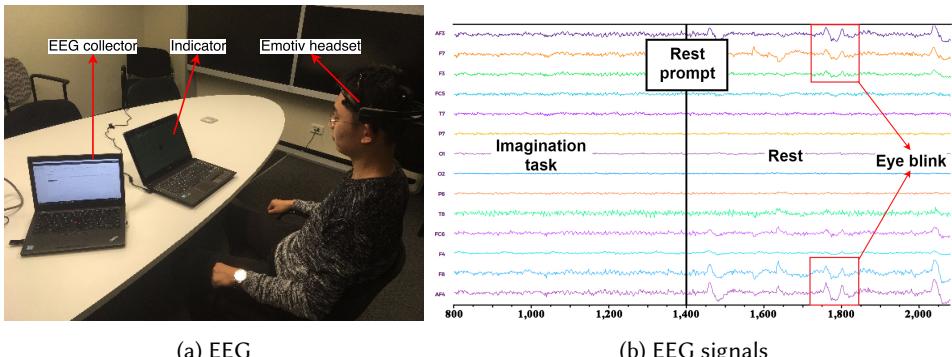


Fig. 7. EEG collection scenario and the gathered signals. The subject is undertaking imagination task.

generated by an electrical current within human neurons. Electrodes placed on the scalp measure the amplitude of EEG signals. EEG signals have a low spatial resolution because the number of electrodes is limited. EEG electrode locations generally follow the international 10-20 system or the intermediate 10% electrode positions [125]. The international 10-20 system divides the scalp

Table 3. EEG patterns and corresponding characters. Awareness Degree denotes the awareness the degree of being aware of an external world.

Patterns	Frequency (Hz)	Amplitude	Brain State	Awareness Degree	Produced Location
Delta	0.5-4	Higher	Deep sleep pattern	Lower	Frontally and posteriorly
Theta	4-8	High	Light sleep pattern	Low	Entorhinal cortex, hippocampus
Alpha	8-12	Medium	Closing the eyes, relax state	Medium	Posterior regions of head
Beta	12-30	Low	Active thinking, focus, high alert, anxious	High	Most evident frontally
Gamma	30-100	Lower	During cross-modal sensory processing	Higher	Somatosensory cortex

in 10% and 20% intervals and totally contains 21 electrode locations (Figure 6). The intermediate 10% electrodeposition is standardized by the American Electroencephalographic Society and split the scalp with 10% intervals, which contains 75 electrodes. The existing EEG collection system is generally less than 75 electrodes, in specific, 64 electrodes (BCI 2000 system), 32 electrodes (openBCI headset), 14 electrodes (Emotiv EPOC+ headset), five electrodes (Emotiv insight headset), and one electrode (Mindware headset).

The temporal resolution of EEG signals is much better than the spatial resolution. The ionic current changes rapidly, which offers a temporal resolution higher than 1000 Hz. The SNR of EEG is generally very poor due to both objective and subjective factors. Objective factors include environmental noises, the obstruction of the skull and other tissues between cortex and scalp, and different stimulations. Subjective factors contain the subject's mental stage, fatigue status, and the variance among different subjects.

EEG recording equipment can be installed in a cap-like headset. As shown in Figure 7 [250], the EEG headset can be mounted on the user's head to gather signals. Compared to other equipment used to measure brain signals, EEG headsets are portable and more accessible for most applications.

The EEG signals collected from any typical EEG hardware have several non-overlapping frequency bands (Delta, Theta, Alpha, Beta, and Gamma) based on the strong intra-band correlation with a distinct behavioral state [250]. Each EEG pattern contains signals associated with particular brain information. Table 3 shows EEG frequency patterns and the corresponding characteristics. In this paper the degree of awareness denotes the perception of individuals when presented with external stimuli. Each frequency band represents a brain state and a qualitative assessment of awareness:

- Delta pattern (0.5 – 4 Hz) corresponds to deep sleep when the subject has lower awareness.
- Theta pattern (4 – 8 Hz) corresponds to light sleep in the realm of low awareness.
- Alpha pattern (8 – 12 Hz) mainly occurs during eyes closed and deeply relaxed state and corresponds to the medium awareness.
- Beta pattern (12 – 30 Hz) is the dominant rhythm while the subject's eyes are open and is associated with high awareness. Beta patterns capture most of our daily activities (such as eating, walking, and talking).
- Gamma pattern (30 – 100 Hz) represents the co-interaction of several brain areas to carry out a specific motor and cognitive function. This pattern is associated with the highest awareness.

3.2.2 Functional Near-infrared Spectroscopy (fNIRS). Functional near-infrared spectroscopy (fNIRS) is a noninvasive functional neuro-imaging technology using near-infrared (NIR) light [143]. In specific, fNIRS employs NIR light to measure the aggregation degree of oxygenated hemoglobin (Hb) and deoxygenated-hemoglobin (deoxy-Hb) because Hb and deoxy-Hb have higher absorbance of light than other head components such as the skull and scalp. fNIRS relies on blood-oxygen-level-dependent (BOLD) response or hemodynamic response to form a functional neuro-image. The BOLD response can detect the oxygenated or deoxygenated blood level in the brain blood. The

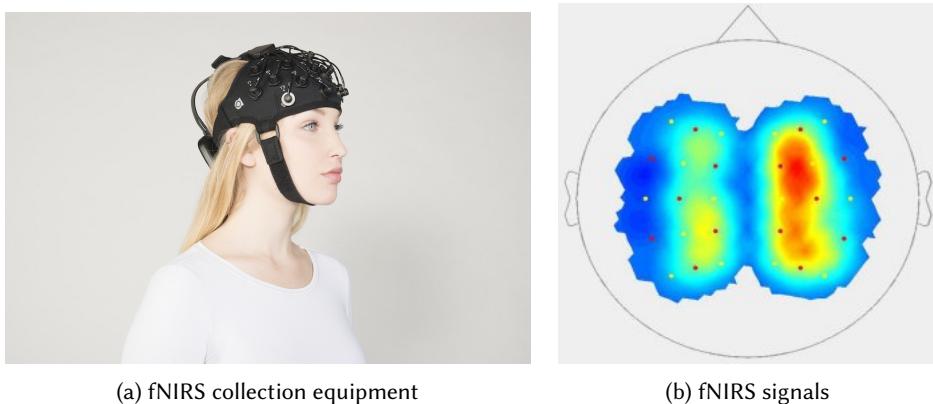


Fig. 8. fNIRS collection equipment and the gathered signals

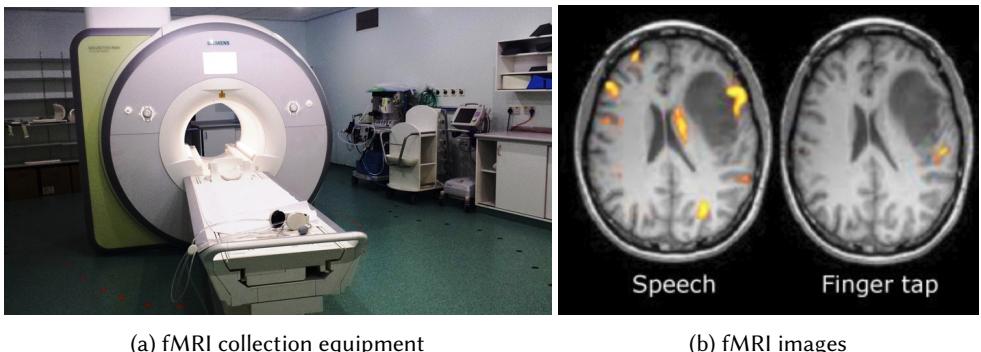
relative levels reflect the blood flow and neural activation, where increased blood flow implies a higher metabolic demand caused by active neurons. For example, when the user is concentrating on a mental task, the prefrontal cortex neurons will be activated, and the BOLD response in the prefrontal cortex area will be stronger [72].

Figure 8⁴ shows the fNIRS collection hardware and the collected signals. Single or multiple emitter-detector pairs measure the Hb and deoxy-Hb: the emitter transmits NIR light through the blood vessels to the detector. Most existing studies use fNIRS technologies to measure the status of prefrontal and motor cortex. The former response to mental tasks and music/image imagery while the latter is a response to motor-related tasks (e.g., motor imagery). The monitored Hb and deoxy-Hb change slowly since the blood speed varies in a relatively slow ratio compared to electrical signals. Therefore, fNIRS signals have lower temporal resolution⁵ compared with electrical or magnetic signals. The spatial resolution depends on the number of emitter-detector pairs. In current studies, three emitters and eight detectors would suffice for adequately acquiring the prefrontal cortex signals; and six emitters and six detectors would suffice for covering the motor cortex area [142]. fNIRS has a drawback in that it cannot be used to measure cortical activity occurring deeper than 4cm in the brain, due to the limitations in light emitter power and spatial resolution.

3.2.3 Functional Magnetic Resonance Imaging (fMRI). Functional magnetic resonance imaging (fMRI) monitors brain activities by detecting changes associated with blood flow in brain areas [222]. Similar to fNIRS, fMRI relies on the BOLD response. The main differences between fNIRS and fMRI are as follows [114]. First, as the name implies, fMRI measures BOLD response through magnetic instead of optical methods. Hemoglobin differs in how it responds to magnetic fields, depending on whether it has a bound oxygen molecule. The magnetic fields are more sensitive to and are more easily distorted by deoxy-Hb than Hb molecules. Second, the magnetic fields have higher penetration than NIR light, which gives fMRI greater ability to capture information from deep parts of the brain than fNIRS. Third, fMRI has a higher spatial resolution than fNIRS since the latter's spatial resolution is limited by the emitter-detector pairs. However, the temporal resolutions of fMRI and fNIRS are at an equal level because they both constrained by the blood flow speed.

⁴<https://www.artinis.com/fnirs>

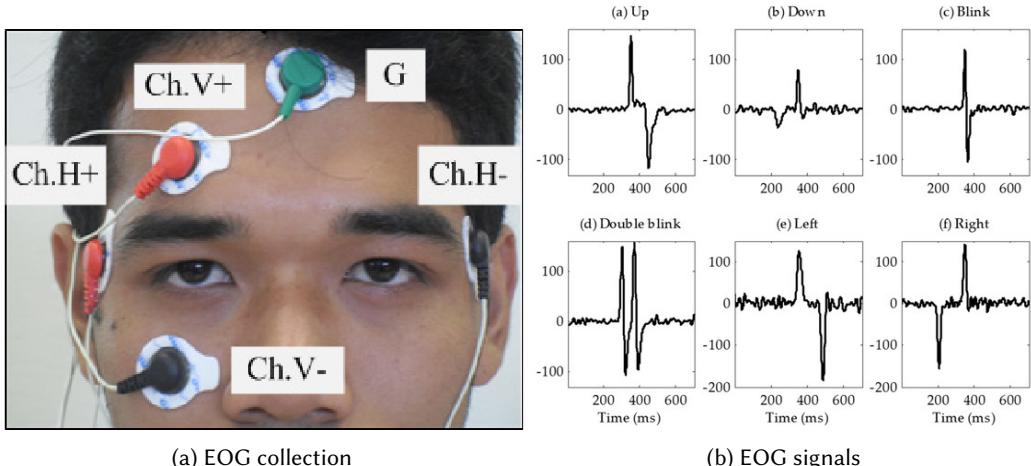
⁵Temporal resolution refers to the smallest time of neural activity reliably separated by the signal.



(a) fMRI collection equipment

(b) fMRI images

Fig. 9. fMRI collection equipment and the gathered fMRI signals while the subject is speaking and finger tapping



(a) EOG collection

(b) EOG signals

Fig. 10. EOG collection equipment and the gathered vertical signals while the subject is looking in different directions and blinking

fMRI has several flaws compared to fNIRS: 1) fMRI requires an expensive scanner to generate magnetic fields; 2) the scanner is heavy and has poor portability. Figure 9⁶ shows the fMRI acquisition machine, and the resulting brain images. fMRI images of speech perception and finger tapping have a significant difference, which indicates that it has high SNR.

3.2.4 Electrooculography (EOG). Electrooculography (EOG) is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eyes. Most patients who have lost voluntary motor movements (e.g., locked-in syndrome patients) remain in partial control of the eyes [231]. The eye movements can be detected by EOG signals to interact with the external devices. Therefore, we regard EOG signals as one class of BCI signals in this survey. EOG can be used to communicate the user and the outer world because different eye movements will cause different electrical potentials. Pairs of electrodes are typically placed above/below the

⁶<https://www.jameco.com/Jameco/workshop/HowItWorks/what-is-an-fmri-scan-and-how-does-it-work.html>

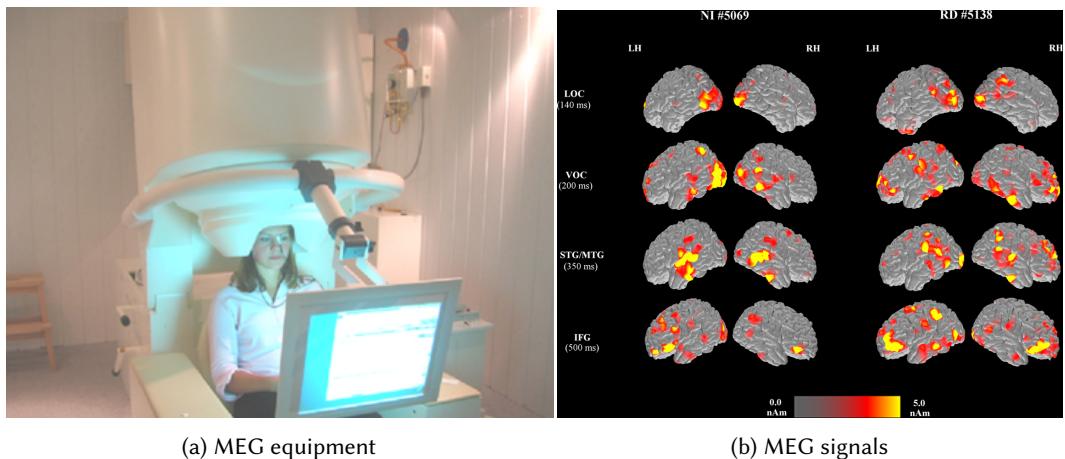


Fig. 11. MEG collection equipment and the gathered signals

eye or to the left/right of the eye to measure EOG signals. The EOG collection equipment [15] and the collected signals [166] can be found in Figure 10. In Figure 10a, EOG electrode placements where electrodes Ch.V+ and Ch.V- measure the vertical movements, and Ch.H+ and Ch.H- measure the horizontal movements. G electrode representing the ground line works as a reference point. Figure 10b shows the vertical EOG in the time domain under six scenarios (looking upward, looking downward, single blink, double blink, looking leftward, and looking rightward). We can observe EOG signals have large variances between different scenarios, indicating they have a relatively high SNR and are easily recognizable by machine learning algorithms. EOG has low spatial resolution compared to other brain signals since we can only detect the vertical and horizontal potentials. The temporal resolution of EOG is higher than neuroimaging techniques because the electrical potentially vary faster than metabolic features (e.g., blood flow).

3.2.5 Magnetoencephalography (MEG). Magnetoencephalography (MEG) is a functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers [39]. The ionic currents of active neurons will create weak magnetic fields. The generated magnetic fields can be measured by magnetometers like SQUIDs (superconducting quantum interference devices). However, producing a detectable magnetic field requires massive (e.g., 50,000) active neurons with similar orientation. The source of the magnetic field measured by MEG is the pyramidal cells which are perpendicular to the cortex surface.

MEG has a relatively low spatial resolution since the signal quality highly depends on the measurement factors (e.g., brain area, neuron orientations, neuron depth). However, MEG can provide very high temporal resolution ($\geq 1000\text{Hz}$) since MEG directly monitors the brain activity from the neuron level, which is in the same level of intracortical signals. The MEG equipment⁷ and the signals collected[163] are shown in Figure 11. MEG equipment is expensive and not portable which limits its real-world deployment for BCI. The brain map snapshots of MEG signals are collected at different times (140, 200, 350, and 500 ms) from two subjects under different mental tasks.

⁷<https://www.biomagcentral.org/biomagnetism/meg>

3.3 EEG Paradigms

Compared to other noninvasive signals (e.g., fMRI, fNIRS, EOG, MEG), EEG has several important advantages: 1) the hardware has higher portability with much lower price; 2) the temporal resolution is very high (milliseconds level)⁸; 3) EEG is relatively tolerant of subject movement and artifacts, which can be minimized by existing signal processing methods; 4) the subject doesn't need to be exposed to high-intensity (>1 Tesla) magnetic fields. Thus, EEG can serve subjects that have metal implants in their body (such as metal-containing pacemakers).

As the most commonly used signals, there are a huge number of sub-classes of EEG signals. In this section, we present a systematic introduction of EEG sub-class signals. As shown in Figure 3, we divided EEG signals into spontaneous EEG, evoked potentials, and event-related desynchronization/synchronization. Evoked potentials can be split into event-related potentials and steady-state evoked potentials based on the frequency of the external stimuli. Each potential contains visual-, auditory-, and somatosensory- potentials based on the external stimuli types. The dashed quadrilaterals in Figure 3, such as Intracortical, SEP, SSAEP, SSSEP, and RSAP, are not included in this survey because there are very few existing studies working on them with deep learning algorithms. We list these signals for systematic completeness.

3.3.1 Spontaneous EEG. Generally, when we talk about the term ‘EEG,’ we refer to *spontaneous* spontaneous EEG which measures the brain signals under a specific state without external stimulation. For example, spontaneous EEG includes the EEG signals while the user is sleeping, undertaking a mental task (e.g., counting), under fatigue stage, suffering brain disorders, undertaking motor imagery tasks, etc.

The EEG signals recorded while a user stares at a color/shape/image belong to this category. While the subject is gazing at a specific image, the visual stimuli are steady without any change. This scenario differs from the visual stimuli in evoked potential, where the visual stimuli are changing at a specific frequency. Thus, we regard the image stimulation as a particular state and categorise it as spontaneous EEG. BCI systems based on spontaneous EEG are challenging to train, due to the lower SNR and the larger variation across subjects [155].

3.3.2 Evoked Potential (EP). Evoked Potentials (EP) or evoked responses refers to the EEG signals which are evoked by a event stimulus instead of spontaneously. An EP is time-locked to the external stimulus while the aforementioned spontaneous EEG is non-time-locked. In contrast to spontaneous EEG, EP generally has higher amplitude and lower frequency. As a result, the EP signals are more robust across subjects. According to the stimulation method, there exist two categories of EP: the Event-Related Potential (ERP) and the Steady State Evoked Potential (SSEP). ERP records the EEG signals in response to an isolated discrete stimulus event. To achieve this isolation, stimuli in an ERP experiment are typically separated from each other by a long inter-stimulus interval, allowing for the estimation of a stimulus-independent baseline reference [144]. The stimuli frequency of ERP is generally lower than 2 Hz. In contrast, SSEP is generated in response to a periodic stimulus at a fixed rate. The stimuli frequency of SSEP generally ranges within 3.5-75 Hz.

Event-related potential (ERP). There are three kinds of evoked potentials in extensive research and clinical use: Visual Evoked Potentials (VEP); Auditory Evoked Potentials (AEP); and Somatosensory Evoked Potentials (SEP) [32]. The VEP signals are mainly on the occipital lobe, and the highest signal amplitudes are collected at the Calcarine sulcus.

1) Visual Evoked Potentials (VEP). Visual Evoked Potentials are a specific category of ERP which is caused by visual stimulus (e.g., an alternating checkerboard pattern on a computer screen).

⁸Among other noninvasive techniques, only MEG has the same level of temporal resolution.

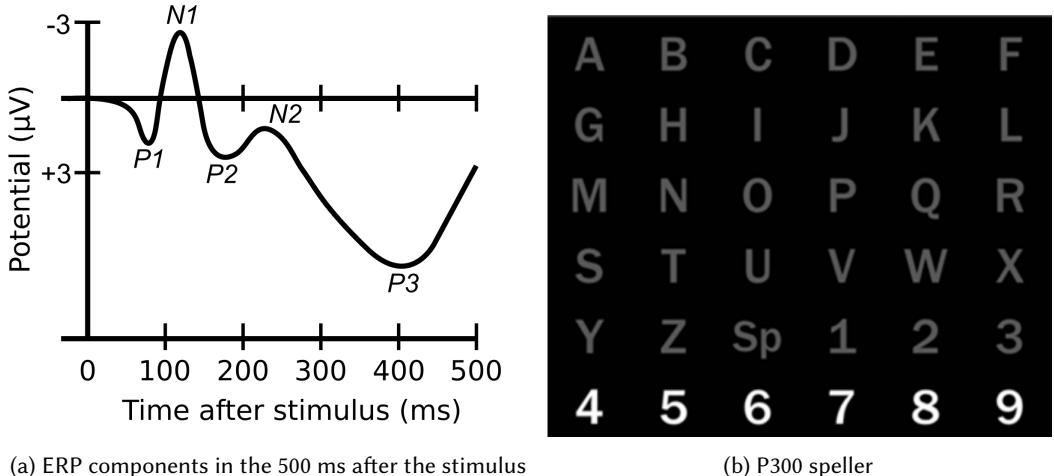


Fig. 12. P300 waves and visual-based P300 speller

VEP signals are hidden within the normal spontaneous EEG. To separate VEP signals from the background EEG readings, repetitive stimulation and time-locked signal-averaging techniques are generally employed.

Rapid Serial Visual Presentation (RSVP) [101] can be regarded as one kind of VEP. An RSVP diagram is commonly used to examine the temporal characteristics of attention. The subject is required to stare at a screen where a series of items (e.g., images) are presented one-by-one. There is a specific item (called the target) separates from the rest of the other items (called distractors). The subject knows which is the target before the RSVP experiment. Generally, the distractors can either be a color change or letters among numbers. RSVP contains a static mode (the items appear on the screen and then disappear without moving) and a moving mode (the items appear on the screen, move to another place, and finally disappear). Nowadays, BCI research mainly focuses on the static mode RSVP. Usually, the frequency of RSVP is 10Hz which means that each item will stay on the screen for 0.1 seconds.

2) Auditory Evoked Potentials (AEP). Auditory Evoked Potentials are a specific subclass of ERP in which responses to auditory (sound) stimuli are recorded. AEP is mainly recorded from the scalp but originates at the brainstem or cortex. The most common AEP measured is the auditory brainstem response (ABR) which is generally employed to test the hearing ability of newborns and infants. In the BCI area, AEP is mainly used in clinical tests for its accuracy and reliability in detecting unilateral loss [36]. Similar to RSVP, Rapid Serial Auditory Presentation (RSAP) refers to experiments with rapid serial presentation of sound stimuli. The task for the subject is to recognize the target audio among the distractors.

3) Somatosensory Evoked Potentials (SEP).⁹ Somatosensory Evoked Potentials are another commonly used subcategory of ERP which is elicited by electrical stimulation of the peripheral nerves. SEP signals conclude a series of amplitude deflection that can be elicited by virtually any sensory stimuli.

⁹Generally, Somatosensory Evoked Potentials is abbreviated as SSEP or SEP. In this paper, we choose SEP as the abbreviation in case of the conflict with Steady-State Evoked Potentials (SSEP).

P300. P300 (also called P3) is an important component in ERP [60]. Here we introduce P300 signal separately since it is widely-used for BCI. Figure 12a shows the ERP signal fluctuation in the 500 ms after the stimuli onset¹⁰. The waveform mainly concludes five components, P1, N1, P2, N2, and P3. The capital character P/N represents positive/negative electrical potentials. The following number refers to the occurrence time of the specific potential. Thus, P300 denotes the positive potential of ERP waveform at approximately 300 ms after the presented stimuli. Compared to other components, P300 has the highest amplitude and is easiest to detect. Thus, a large number of BCI studies focus on P300 analysis. P300 is more of an informative feature instead of a type of brain signal (e.g., VEP). Therefore, we do no list P300 in Figure 3. P300 can be analyzed in most of ERP signals such as VEP, AEP, SEP.

In practice, P300 can be elicited by rare, task-relevant events in an ‘oddball’ paradigm (e.g., P300 speaker). In the oddball paradigm, the subject receives a series of stimuli where low-probability target items are mixed with high-probability non-target items. Visual and auditory stimuli are the most commonly used in the oddball paradigm. Figure 12b shows an example of visual-based P300 speller which enables the subject the spell letters/numbers directly through brain signals [47]. The 26 letters of the alphabet and the Arabic numbers are displayed on a computer screen which serves as the keyboard. The subject focuses attention successively on the characters they wish to spell. The computer detects the chosen character online in real time. This detection is achieved by repeatedly flashing rows and columns of the matrix. When the elements containing the selected characters are flashing, a P300 fluctuation is elicited. In the 6×6 matrix screen, the rows and columns flash in mixed random order. The flash duration and interval among adjacent flashes are generally set as 100 ms [25]. The columns and rows flash separately. First, the columns flash six times with each column flashing one time. Second, the rows will flash for six times. After that, this paradigm repeats for several times (e.g., N times). The P300 signals of the total $12N$ flash will be analyzed to output a single outcome (i.e., one letter/number).

Steady State Evoked Potentials (SSEP). Steady State Evoked Potentials is another subcategory of evoked potentials, which are periodic cortical responses evoked by certain repetitive stimuli with a constant frequency. It has been demonstrated that the brain oscillations generally maintain a steady level over time while the potentials are evoked by steady state stimuli (e.g., a flickering light with fixed frequency). Technically, SSEP is defined as a form of response to repetitive sensory stimulation in which the constituent frequency components of the response remain constant over time in both amplitude and phase [161]. Depending on the type of stimuli, SSEP can be divided into three subcategories: Steady-State Visually Evoked Potentials (SSVEP), Steady-State Auditory Evoked Potentials (SSAEP), and Steady-State Somatosensory Evoked Potentials (SSSEP). In the BCI area, most studies are focused on visual evoked steady potentials, and only rarely do papers focus on auditory and somatosensory stimuli. Therefore, in this survey, we mainly introduce SSVEP rather than SSAEP and SSSEP.

Difference Among various visual evoked potentials paradigms. Visual evoked potentials are the most common used potentials. Therefore, it is essential to distinguish the three different visual evoked potential paradigms: VEP, RSVP, SSVEP. Here, we theoretically introduce the characteristics of each paradigm and then give three demonstration videos to provide a better understanding. First, the frequencies are different: the frequency of VEP is less than 2Hz while the frequency of RSVP is around 10Hz, and the frequency of SSVEP ranges from 3.5 to 75Hz. Second, they have various presentation protocols. In the VEP paradigm, different visual patterns will be presented on the screen to check the user’s brain signals changes. For instance, in this video¹¹, the image pattern is

¹⁰Note that the negative voltage of ERP is plotted upward, which is common in ERP research.

¹¹https://www.youtube.com/watch?v=iUW_l5YAEEM

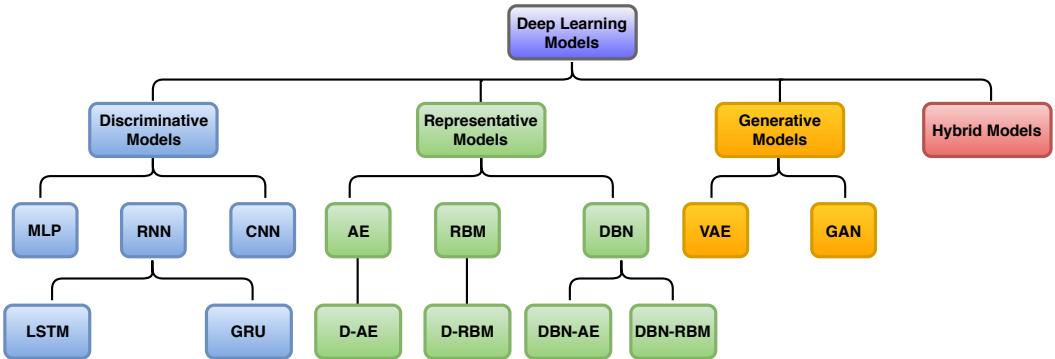


Fig. 13. Deep learning models. They can be divided into discriminative, representative, generative and hybrid models based on the algorithm function. D-AE denotes Stacked-Autoencoder which refers to the autoencoder with multiple hidden layers. Deep Belief Network can be composed of AE or RBM, therefore, we divided DBN into DBN-AE (stacked AE) and DBN-RBM (stacked RBM).

full of the screen and changes dramatically. In RSVP diagram, several items will be presented on a screen one-by-one. All the items are shown in the same place and share the same frequency. For example, the video¹² shows an RSVP scenario which is called speed reading. In SSVEP paradigm, several items will be presented on a screen at the same time while the items are shown at *variant positions* with different frequencies. For example, in this demonstration video¹³, there are four circles distributed on the up, down, left, and right sides of a screen and the frequency of each item differs from each other.

3.3.3 Event-related Desynchronization/Synchronization (ERD/ERS). Event-related desynchronization/synchronization (ERD/ERS) refers to the phenomena that the magnitude and frequency distribution of the EEG signal power changes during a specific brain state [81]. In particular, ERD denotes the power decrease of ongoing EEG signals while ERS represents the power increase of EEG signals. This characteristic of ERD/ERS of brain signals can be used to detect the event which caused the EEG fluctuation. For example, [154] presents the ERD/ERS phenomena in motor cortex recorded during a motor-imagery task. The task causes an ERD in the mu band (8-13 Hz) of EEG and an ERS in the beta band (13-30 Hz).

Compared to spontaneous EEG signals, ERD/ERS is not only a kind of spontaneous brain signal but also a decreasing/increasing phenomena. Differing from other spontaneous EEG, ERD/ERS analysis exploits power fluctuations. Compared to evoked potentials, ERD/ERS does not require external stimuli. ERD/ERS can be collected by performing mental tasks, such as motor imagery, mental arithmetic, or mental rotation. However, to collect the high-quality ERD/ERS signals, the subjects are required to take extensive training which may take several weeks. Moreover, the performance of ERD/ERS among users is quite variable, and the accuracy is not very high [2]. Thus, this paradigm is not one of the most dominant BCI approaches.

4 DEEP LEARNING MODELS

In this section, we formally introduce the deep learning models including concepts, architectures, and techniques commonly used in the BCI field. Deep learning is a class of machine learning

¹²<https://www.youtube.com/watch?v=5ydddeRrd0hA&t=36s>

¹³<https://www.youtube.com/watch?v=t96rl1SFHII>

techniques that uses many layers of information-processing stages in hierarchical architectures for pattern classification and feature/representation learning [42]. The standard neural network (Figure 14a) contains three neuron layers including an input layer, a hidden layer, and an output layer. Any neural network with more than four layers (one input layer, ≥ 2 hidden layers, and one output layer) can be called deep neural network for the reason that it is ‘deeper’ than the standard/shallow neural networks (3 layers).

In this survey, we will give relative detail introduction of various deep learning models for the reason that a part of the potential readers who are from non-computer area (e.g., biomedical) are not familiar to deep learning.

Deep learning algorithms divide into several subcategories based on the aim of the techniques (as shown in Figure 13):

- Discriminative deep learning models, which classify the input data into a pre-known label based on the adaptively learned discriminative features. Discriminative algorithms are able to learn distinctive features by non-linear transformation, and classification through probabilistic prediction¹⁴. Thus these algorithms can play the role of both feature engineering and classification (corresponding to Figure 2). Discriminative architectures mainly include Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), along with their variations.
- Representative deep learning models, which learn the pure and representative features from the input data. These algorithms only have the function of feature engineering (corresponding to Figure 2) but fail to classify. Commonly used deep learning algorithms for representation are Autoencoder (AE), Restricted Boltzmann Machine (RBM), Deep Belief networks (DBN), along with their variations.
- Generative deep learning models, which learn the joint probability distribution of the input data and the target label. In the BCI scope, generative algorithms are mostly used in reconstruction or to generate a batch of brain signals samples to enhance the training set. Generative models commonly used in BCI include variational Autoencoder (VAE)¹⁵, Generative Adversarial Networks (GANs), etc.
- Hybrid deep learning models, which combine more than two deep learning models. For example, the typical hybrid deep learning model employs a representation algorithm for feature extraction and discriminative algorithms for classification.

The summary of the characteristics of each deep learning subcategories are listed in Table 4. Almost all the classification functions in neural networks are implemented by a softmax layer, which will not be regarded as an algorithmic component in this survey. For instance, a model combining a DBN, and a softmax layer will still be regarded as a representative model instead of a hybrid model.

4.1 Discriminative Deep Learning Models

Since the main task of BCI is brain signal recognition, the discriminative deep learning models are the most popular and powerful algorithms. Suppose we have a dataset of brain signal samples $\{\mathbb{X}, \mathbb{Y}\}$ where \mathbb{X} denotes the set of brain signal observations and \mathbb{Y} denotes the set of sample ground truth (i.e., labels). Suppose an specific sample-label pair $\{\mathbf{x} \in \mathbb{R}^N, \mathbf{y} \in \mathbb{R}^M\}$ where N and M denote the dimension of observations and the number of sample categories, respectively. The aim

¹⁴The classification function is achieved by the combination of a softmax layer and one-hot label encoding. The one-hot label encoding refers to encoding the label by the one-hot method, which is a group of bits among which the only valid combinations of values are those with a single high (1) bit and all the others low (0) bits. For instance, a set of labels 0, 1, 2, 3 can be encoded as (1, 0, 0, 0), (0, 1, 0, 0), (0, 0, 1, 0), (0, 0, 0, 1).

¹⁵VAE is a variation of AE. However, they are working on different aspects. Therefore, we separately introduce AE and VAE.

Table 4. Summary of deep learning model types

Deep Learning	Input	Output	Function	Training method
Discriminative	Input data	Label	Feature extraction, Classification	Supervised
Representative	Input data	Representation	Feature extraction	Unsupervised
Generative	Input data	New Sample	Generation, Reconstruction	Unsupervised
Hybrid	Input data	-	-	-

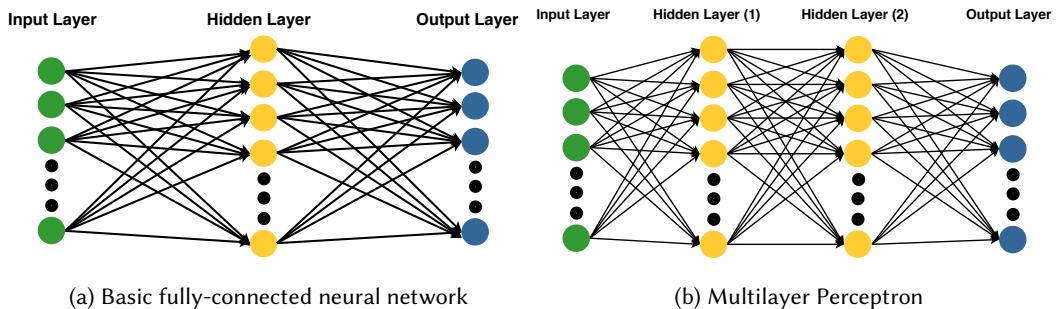


Fig. 14. Illustration of standard neural network and multilayer perceptron. (a) The basic structure of the fully-connected neural network. The input layer receives the raw data or extracted features of brain signals while the output layer shows the classification results. The term ‘fully-connected’ denotes each node in a specific layer is connected with all the nodes in the previous and next layer. (b) MLP could have multiple hidden layers, the more, the deeper. This is an example of MLP with two hidden layers, which is the simplest MLP model.

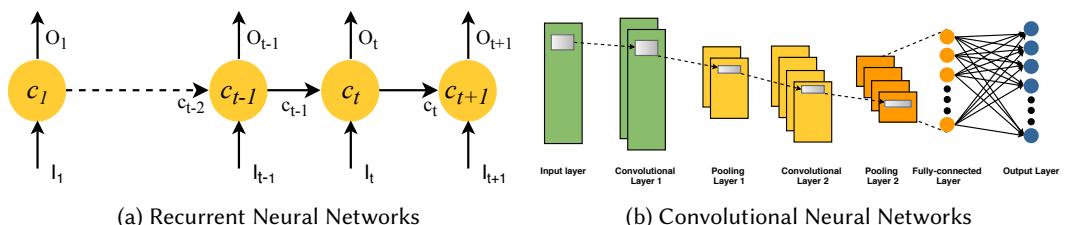


Fig. 15. Illustration of RNN and CNN models. (a) The recurrent procedure of the RNN model. This procedure describes the recurrent procedure of a specific node in time range $[1, t + 1]$. The node at time t receives two inputs variables (I_t denotes the input at time t and c_{t-1} denotes the hidden state at time $t - 1$) and exports two variables (the output O_t and the hidden state c_t at time t). (b) The paradigm of CNN model which includes two convolutional layers, two pooling layers, and one fully-connected layer.

of discriminative deep learning models is to learn a function with the mapping: $\mathbf{x} \rightarrow \mathbf{y}$. In short, the discriminative models receive the input data and output the corresponding category or label. All the discriminative models introduced in this section are supervised learning techniques which require the information of both the observations and the ground truth.

4.1.1 Multi-Layer Perceptron (MLP). Multilayer Perceptron is the simplest and the most basic deep learning model. The key difference between MLP and the shallow neural network is that MLP has more than one hidden layers. All the nodes are fully-connected with the nodes of the adjacent layers but without connection with the other nodes of the same layer. MLP includes multiple

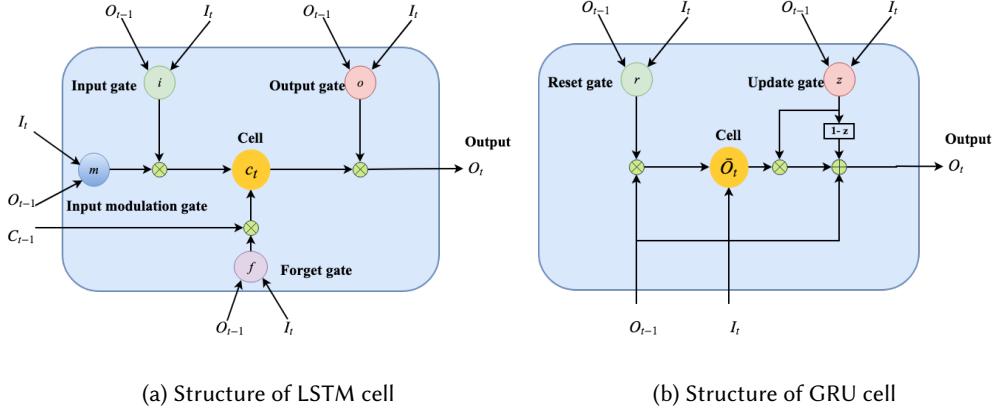


Fig. 16. Illustration of detailed LSTM and GRU cell structures. (a) LSTM cell receives three inputs (I_t denotes the input at time t , O_{t-1} denotes the output of previous time, and c_{t-1} denotes the hidden state of the previous time) and exports two outputs (the output of this time O_t and the hidden state of this time c_t). LSTM cell contains four gates in order to control the data flow, which are the input gate, output gate, forget gate, and input modulation gate. (b) GRU cell receives two inputs (the input of this time I_t and the output of the previous time O_{t-1}) and exports its output O_t . GRU cell only contains two gates which are the reset gate and the update gate. Unlike the hidden state c_t in LSTM cell, there is no transmittable hidden state in GRU cell except one intermediate variable \bar{O}_t .

hidden layers. As shown in Figure 14b, we take a structure with two hidden layers as an example to describe the data flow in MLP. First, we define an operation $\mathcal{T}(\cdot)$ as

$$\begin{aligned}\mathcal{T}(\mathbf{x}) &= \mathbf{w} * \mathbf{x} + \mathbf{b} \\ \mathcal{T}(\mathbf{x}, \mathbf{x}') &= \mathbf{w} * \mathbf{x} + \mathbf{b} + \mathbf{w}' * \mathbf{x}' + \mathbf{b}'\end{aligned}$$

where \mathbf{x} and \mathbf{x}' denote two variables while \mathbf{w} , \mathbf{w}' , \mathbf{b} , and \mathbf{b}' denote the corresponding weights and basis.

The input layer receives the observation \mathbf{x} and feeds forward to the first hidden layer,

$$\mathbf{x}^{h1} = \sigma(\mathcal{T}(\mathbf{x}))$$

where \mathbf{x}^{h1} denotes the data flow in the first hidden layer and σ represents the non-linear activation function. There several commonly used activation function such as sigmoid/Logistic, Tanh, ReLU, we choose sigmoid activation function as an example in this section. Then, the data flow to the second hidden layer and the output layer,

$$\begin{aligned}\mathbf{x}^{h2} &= \sigma(\mathcal{T}(\mathbf{x}^{h1})) \\ \mathbf{y}' &= \sigma(\mathcal{T}(\mathbf{x}^{h2}))\end{aligned}$$

where \mathbf{y}' denotes the predict results in one-hot format. The error (i.e., loss) could be calculated based on the distance between \mathbf{y}' and the ground truth \mathbf{y} . For instance, the Euclidean-distance based error can be calculated by

$$\text{error} = \|\mathbf{y}' - \mathbf{y}\|_2 \quad (1)$$

where $\|\cdot\|_2$ denotes the Euclidean norm. Afterward, the error will be back-propagated and optimized by a suitable optimiser. The optimizer will adjust all the weights and basis in the model until the error converges. The most widely used loss functions includes cross-entropy, negative log likelihood,

mean square estimation, etc. The most widely used optimizers include Adaptive moment estimation (Adam), Stochastic Gradient Descent (SGD), Adagrad (Adaptive subgradient method), etc.

Several terms may be easily confused with each other: Artificial Neural Network (ANN), Deep Neural Network (DNN), and MLP. These terms have no strict difference and often mixed in literature. Generally, ANN represents neural networks with fewer hidden layers (shallow) while DNN have more (in this case, DNN is equivalent to MLP). Additionally, DNN can be used to describe deep learning models overall, including not only fully-connected networks but also other networks (e.g., recurrent, convolutional networks).

4.1.2 Recurrent Neural Networks (RNN). Recurrent Neural Network is a specific subclass of discriminative deep learning model which are designed to capture temporal dependencies among input data. Figure 15a describes the activity of a specific RNN node in the time domain. At each time ranges from $[1, t + 1]$, the node receives an input I ¹⁶ and a hidden state c from the previous time (except the first time). For instance, at time t it receives not only the input I_t but also the hidden state of the previous node c_{t-1} . The hidden state can be regarded as the ‘memory’ of the nodes which can help the RNN ‘remember’ the historical input.

Next, we will report two typical RNN architectures which have attracted much attention and achieved great success: long short-term memory and gated recurrent units. They both follow the basic principles of RNN, and we will pay our attention to the complicated internal structures in each node. Since the structure is much more complicated than general neural nodes, we call it a ‘cell.’ Cells in RNN are equivalent to nodes in MLP.

Long Short-Term Memory (LSTM). Figure 16a shows the structure of a single LSTM cell at time t . The LSTM cell has three inputs (I_t , O_{t-1} , and c_{t-1}) and two outputs (c_t and O_t). The operation is as follows:

$$I_t, O_{t-1}, c_{t-1} \rightarrow c_t, O_t$$

I_t denotes the input value at time t , O_{t-1} denotes the output at the previous time (i.e., time $t - 1$), and c_{t-1} denotes the hidden state at the previous time. c_t and O_t separately denote the hidden state and the output at time t . Therefore, we can observe that the output O_t at time t not only related to the input I_t but also related to the information at the previous time. In this way, LSTM is empowered to remember the important information in the time domain. Moreover, the essential idea of LSTM is to control the memory of specific information. For this aim, LSTM cell adopts four gates: the input gate, forget gate, output gate, and input modulation gate. Each gate is a weight to control how much information can flow through this gate. For example, if the weight of the forget gate is zero, the LSTM cell would remember all the information passed from the previous time $t - 1$; if the weight is one, the LSTM cell would remember nothing. The corresponding activation function determines the weight. The detailed data flow as follows:

$$\begin{aligned} f &= \sigma(\mathcal{T}(I_t, O_{t-1})) \\ i &= \sigma(\mathcal{T}(I_t, O_{t-1})) \\ o &= \sigma(\mathcal{T}(I_t, O_{t-1})) \\ m &= \tanh(\mathcal{T}(I_t, O_{t-1})) \\ c_t &= f * c_{t-1} + i * m \\ h_t &= o * \tanh(c_t) \end{aligned}$$

where i , f , o and m represent the input gate, forget gate, output gate and input modulation gate, respectively.

¹⁶The subscript represents the specific time.

Gated Recurrent Units (GRU). Another widely used RNN architecture is GRU. Similar to LSTM, GRU attempts to exploit the information from the past. GRU does not require hidden states, however, it receives temporal information only from the output of time $t - 1$. Thus, as shown in Figure 16b, GRU has two inputs (I_t and O_{t-1}) and one output (O_t). The mapping can be described as:

$$I_t, O_{t-1} \rightarrow O_t$$

GRU contains two gates: reset gate r and update gate z . The former decides how to combine the input with previous memory. The latter decides how much of previous memory to keep around, which is similar to the forget gate of LSTM. The data flow as follows:

$$z = \sigma(\mathcal{T}(I_t, O_{t-1}))$$

$$r = \sigma(\mathcal{T}(I_t, O_{t-1}))$$

$$\bar{O}_t = \tanh(\mathcal{T}(I_t, r * O_{t-1}))$$

$$O_t = (1 - z) * O_{t-1} + z * \bar{O}_t$$

It can be observed that there's a intermediate variable \bar{O}_t which is similar to the hidden state of LSTM. However, \bar{O}_t only works on this time point and unable to pass to the next time point.

We here give a brief comparison between LSTM and GRU since they are very similar. First, LSTM and GRU have comparable performance as studied by literature. For any specific task, it is recommended to try both of them to determine which provides better performance. Second, GRU is lightweight since it only has two gates and without the hidden state. Therefore, GRU is faster to train and requires few data for generalization. Third, in contrast, LSTM generally works better if the training dataset is big enough.

4.1.3 Convolutional Neural Networks (CNN). Convolutional Neural Networks is one of the most popular deep learning models specialized in spatial information exploration. This section will briefly introduce the working mechanism of CNN. CNN is widely used to discover the latent spatial information in applications such as image recognition, ubiquitous, and object searching due to their salient features such as regularized structure, good spatial locality, and translation invariance. In BCI, specifically, CNN is supposed to capture the distinctive dependencies among the patterns associated with different brain signals.

We present a standard CNN architecture as shown in Figure 15b. The CNN contains one input layer, two convolutional layers with each followed by a pooling layer, one fully-connected layer, and one output layer. The square patch in each layer shows the processing progress of a specific batch of input values. The key to the CNN is to reduce the input data into a form which is easier to recognize, with as little information loss as possible. CNN has three stacked layers: the convolutional Layer, pooling Layer, and fully-connected Layer.

The convolutional layer is the core block of CNN, which contains a set of filters to convolve the input data followed by a nonlinear transformation to extract the geographical features. In the deep learning implementation, there are several key hyper-parameters should be set in the convolutional layer, like the number of filters, the size of each filter, etc. The pooling layer generally follows the convolutional layer. The pooling layer aims to reduce the spatial size of the features progressively. In this way, it can help to decrease the number of parameters (e.g., weights and basis) and the computing burden. There are three kinds of pooling operation: max, min, average. Take max pooling for example. The pooling operation outputs the maximum value of the pooling area as a result. The hyper-parameters in the pooling layer includes the pooling operation, the size of the pooling area, the strides, etc. In the fully-connected layer, as in the basic neural network, the nodes have full connections to all activations in the previous layer.

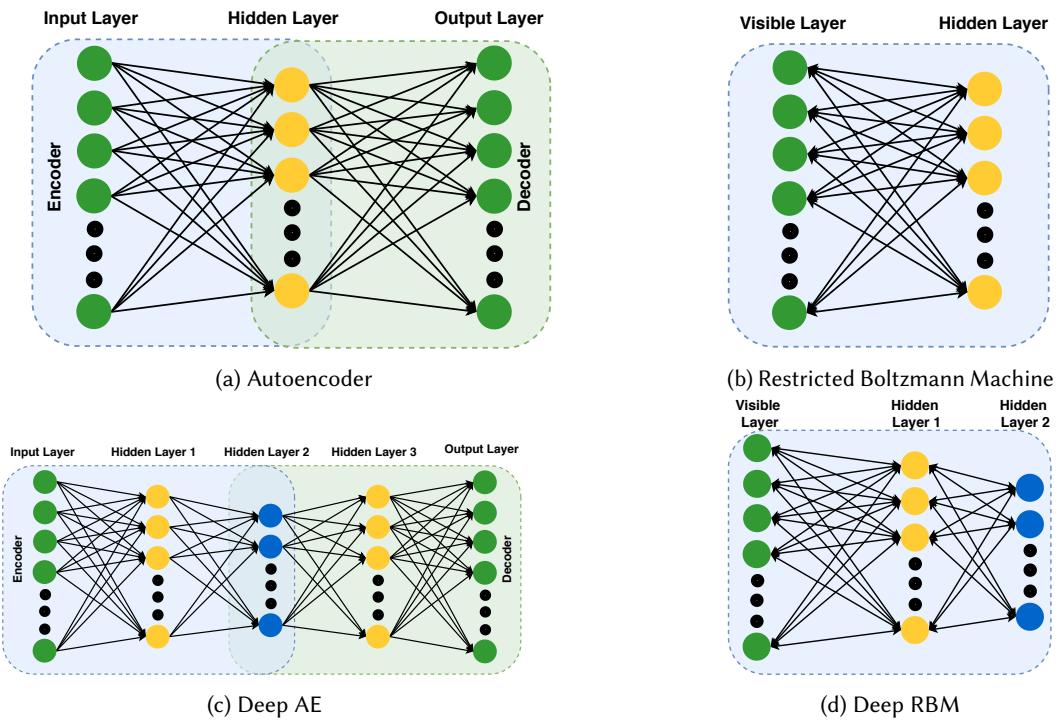


Fig. 17. Illustration of several standard representative deep learning models. (a) A basic autoencoder contains three layers where the input layer and the output layer are supposed to have the same values. The process from the input layer to the hidden layer is an encoder while the process from the hidden layer to the output layer is a decoder. (b) In the Restricted Boltzmann Machine, the encoder and the decoder share the same transformation weights. The input layer and the output layer are merged into the visible layer. (c) The stacked autoencoder has more than one hidden layer. Generally, the number of hidden layers is odd, and the middle layer is the learned representative features. (d) The deep RBM has one visible layer and multiple hidden layers, the last layer is the encoded representation.

The CNN is the most popular deep learning model in BCI research, which can be used to exploit the latent spatial dependencies among the input brain signals like fMRI image, spontaneous EEG, and so on. More details will be reported in Section 5.

4.2 Representative Deep Learning Models

The essential blocks of representative deep learning models are autoencoders, and restricted Boltzmann machines¹⁷. Deep Belief Networks are composed of AE or RBM. The representative models including AE, RBM¹⁸, and DBN, are unsupervised learning methods. Thus, they can learn the representative features from only the input observations \mathbf{x} without the ground truth \mathbf{y} . In short, representative models receive the input data and output a dense representation of the data. There are various definitions in different studies for several models (such as DBN, Deep RBM, and Deep AE), in this survey, we choose the most understandable definitions and will present them in detail in this section.

¹⁷ AE and RBM are generally regarded as kind of deep learning although they only have three and two layers, respectively.

¹⁸ We regard AE, and RBMs as most researches in BCI adopt them for feature representation.

4.2.1 Autoencoder (AE). As shown in Figure 17a, A autoencoder is a neural network that has three layers: the input layer, the hidden layer, and the output layer. It differs from the standard neural network, in that the AE is trained to reconstruct its inputs, which forces the hidden layer to try to learn good representations of the inputs.

The structure of AE contains two blocks. The first block is called the encoder, which embeds the observation to a latent representation (also called ‘code’),

$$\mathbf{x}^h = \sigma(\mathcal{T}(\mathbf{x}))$$

where \mathbf{x}^h represents the hidden layer. The second block is called the decoder, which decodes the representation into the original space,

$$\mathbf{y}' = \sigma(\mathcal{T}(\mathbf{x}^h))$$

where \mathbf{y}' represents the output.

AE forces \mathbf{y}' to be equal to the input \mathbf{x} and calculates the error based on the distance between them. Thus, AE can compute the loss function only by \mathbf{x} without the ground truth \mathbf{y}

$$\text{error} = \|\mathbf{y}' - \mathbf{x}\|_2 \quad (2)$$

Compared to Equation 1, this equation does not involve the variable \mathbf{y} because it takes the input \mathbf{x} as the ground truth. This is the reason why AE is able to perform unsupervised learning.

Naturally, one variant of AE is Deep-AE (D-AE) which has more than one hidden layer. We present the structure of D-AE with three hidden layers in Figure 17c. From the figure, we can observe that there is one more hidden layer in both the encoder and the decoder. The symmetrical structure ensures the smoothness of encoding and decoding procedure. Thus, D-AE generally has an odd number of hidden layers (e.g., $2n + 1$) where the first n layers belong to the encoder, the $(n + 1)$ -th layer works as the code which belongs to both encoder and decoder, and the last n layers belong to the decoder. The data flow of D-AE (Figure 17c) can be represented as

$$\mathbf{x}^{h1} = \sigma(\mathcal{T}(\mathbf{x}))$$

$$\mathbf{x}^{h2} = \sigma(\mathcal{T}(\mathbf{x}^{h1}))$$

where \mathbf{x}^{h2} denotes the median hidden layer (the code). Then decode the hidden layer, we can get

$$\mathbf{x}^{h3} = \sigma(\mathcal{T}(\mathbf{x}^{h2}))$$

$$\mathbf{y}' = \sigma(\mathcal{T}(\mathbf{x}^{h3}))$$

It is almost the same as AE except that D-AE has more hidden layers. Apart from D-AE, AE has many other variants like denoising autoencoder, sparse autoencoder, contractive AE, etc. Here we only introduce the D-AE because it is easily confused with the AE-based deep belief network. The key difference between them will be provided in Section 4.2.3.

The core idea of AE and its variants is simple, which is that condensing the input data \mathbf{x} into a code \mathbf{x}^h (generally the code layer has lower dimension) and then reconstructing the data based on the code. If the reconstructed \mathbf{y}' can approximate to the input data \mathbf{x} , it can be demonstrated that the condensed code \mathbf{x}^h carries enough information about \mathbf{x} , thus, we can regard \mathbf{x}^h as a representation of the input data for future operation (e.g., classification).

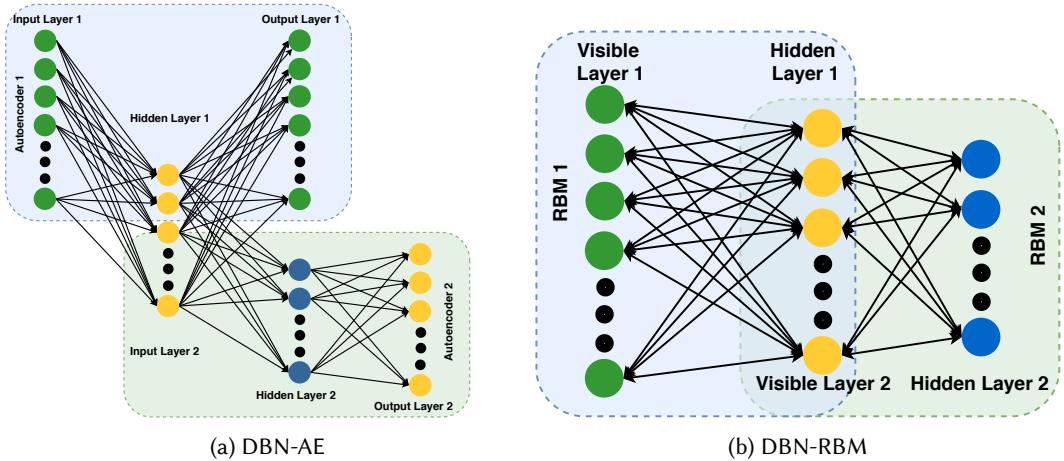


Fig. 18. Illustration of deep belief networks. (a) DBN composed of autoencoders. DBN-AE contains multiple AE components (in this case, two AE), with the hidden layer of the previous AE working as the input layer of the next AE. The hidden layer of the last AE is the learned representation. (b) DBN composed of RBM. In this illustration, there are two RBM components with the hidden layer of the first RBM working as the visible layer of the second RBM. The last hidden layer is the encoded representation. While DBN-RBM and D-RBM (Figure 17d) have similar architecture, the former is trained greedily while the latter is trained jointly.

4.2.2 Restricted Boltzmann Machine (RBM). Restricted Boltzmann Machine is a stochastic artificial neural network that can learn a probability distribution over its set of inputs. It contains two layers including one visible layer (input layer) and one hidden layer, as shown in Figure 17b. From the figure, we can see that the connection lines between the two layers are bidirectional. RBM is a variant of Boltzmann Machine with stronger restriction of being without intra-layer connections¹⁹. Similar to AE, the procedure of RBM also includes two steps. The first step condenses the input data from the original space to the hidden layer in a latent space. After that, the hidden layer is used to reconstruct the input data in an identical way. Compared to AE, RBM has a stronger constraint which is that the encoder weights and the decoder weights should be equal. We have

$$\begin{aligned} \mathbf{x}^h &= \sigma(\mathcal{T}(\mathbf{x})) \\ \mathbf{x}' &= \sigma(\mathcal{T}(\mathbf{x}^h)) \end{aligned}$$

In the above two equations, the weights of $\mathcal{T}(\cdot)$ are the same. Then, the error for training can be calculated by

$$\text{error} = \|\mathbf{x}' - \mathbf{x}\|_2$$

We can observe from the Figure 17d that the Deep-RBM (D-RBM) is an RBM with multiple hidden layers. The input data from the visible layer firstly flow to the first hidden layer and then the second hidden layer. Then, the code will flow backward into the visible layer for reconstruction.

4.2.3 Deep Belief Networks (DBN). A Deep Belief Network (DBN) is a stack of simple networks, such as AEs or RBMs [55]. Thus, we divided DBN into DBN-AE (also called stacked AE) which is composed of AE and DBN-RBM (also called stacked RBM) which is composed of RBM.

As shown in Figure 18a, the DBN-AE contains two AE structures while the hidden layer of the first AE works as the input layer of the second AE. This diagram has two stages. In the first stage,

¹⁹In a general Boltzmann machine, the nodes in the same hidden layer will connect.

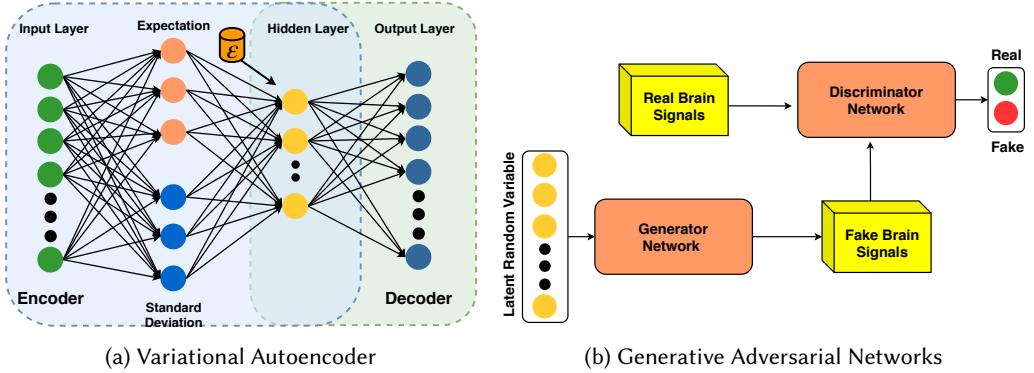


Fig. 19. Illustration of generative deep learning models. (a) VAE contains two hidden layers. The first hidden layer is composed of two components: the expectation and the standard deviation, which are learned separately from the input layer. The second hidden layer represents the encoded information. ϵ denotes the standard normal distribution. (b) GAN mainly contain two crucial components: the generator and the discriminator network. The former receives a latent random variable to generate a fake brain signal while the latter receives both the real and the generated brain signals and attempts to determine if its generated or not. In BCI, GAN reconstructs or augments data instead of classification.

the input data feed into the first AE follows the rules introduced in Section 4.2.1. The reconstruction error is calculated and back propagated to adjust the corresponding weights and basis. This iteration continues until the AE converges. We get the mapping,

$$\mathbf{x}^1 \rightarrow \mathbf{x}^{h1}$$

Then, we move on to the second stage where the learned representative code in the hidden layer \mathbf{x}^{h1} will be used as the input layer of the second AE, which is

$$\mathbf{x}^2 = \mathbf{x}^{h1}$$

and then, after the second AE converges, we have

$$\mathbf{x}^2 \rightarrow \mathbf{x}^{h2}$$

where \mathbf{x}^{h2} denotes the hidden layer of the second AE, meanwhile, it is the final outcome of the DBN-AE.

The core idea of AE is that of learning a representative code with lower dimensionality but containing most information of the input data. The idea behind DBN-AE is to learn a more representative and purer code.

Similarly, the DBN-RBM is composed of several single RBM structures. Figure 18b shows a DBN with two RBMs where the hidden layer of the first RBM is used as the visible layer of the second RBM.

Compare the DBN-RBM (Figure 18b) and D-RBM (Figure 17d). They almost have the same architecture. Moreover, DBN-AE (Figure 18a) and D-AE (Figure 17c) have similar architecture. The most important difference between the DBN and the deep AE/RBM is that the former is trained greedily while the latter is trained jointly. In particular, for the DBN, the first AE/RBM is trained first, after it converges, the second AE/RBM is trained[74]. For the deep AE/RBM, jointly training means that the whole structure is trained together, no matter how layers it has.

4.3 Generative Deep Learning Models

Generative deep learning models are mainly used to generate training samples or data augmentation. In other words, generative deep learning models play a supporting role in the BCI field to enhance the training data quality and quantity. After the data augmentation, the discriminative models will be employed for the classification. This procedure is created to improve the robustness and effectiveness of the trained deep learning networks, especially when the training data is limited. In short, the generative models receive the input data and output a batch of similar data. In this section, we will introduce two typical generative deep learning models: variational Autoencoder (VAE) and Generative Adversarial Networks (GAN).

4.3.1 Variational Autoencoder (VAE)). Variational Autoencoder, proposed in 2013 [92], is an important variant of AE, and one of the most powerful generative algorithms. The standard AE and its other variants can be used for representation but fail in generation for the reason that the learned code (or representation) may not be continuous. Therefore, we cannot generate a random sample which is similar to the input sample. In other words, the standard AE does not allow interpolation. Thus, we can replicate the input sample but cannot generate a similar one. VAE has one fundamentally unique property that separates it from other AEs, and it is this property that makes VAE so useful for generative modeling: the latent spaces are designed to be continuous which allows easy random sampling and interpolation. Next, we will introduce how VAE works.

Similar to the standard AE, VAE can be divided into an encoder and decoder where the former embeds the input data to a latent space and the latter transfers the data from the latent space to the original space. However, the learned representation in the latent space is forced to approximate a prior distribution $p(\bar{z})$ which is generally set as Standard Gaussian distribution. Based on the reparameterization trick [92], the first hidden layer of VAE is designed to have two parts where one denotes the expectation μ and another denotes the standard deviation σ , thus we have

$$\mu = \sigma(\mathcal{T}(x))$$

$$\sigma = \sigma(\mathcal{T}(x))$$

Then, the latent code in the hidden layer is not directly calculated but sampled from a Gaussian distribution $\mathcal{N}(\mu, \sigma^2)$. The statistic code

$$z = \mu + \sigma * \epsilon \quad (3)$$

where $\epsilon \sim \mathcal{N}(0, I)$. The representation z is forced to a prior distribution, and the distance $error_{KL}$ is measured by Kullback-Leibler divergence,

$$error_{KL} = D_{KL}(z, p(\bar{z}))$$

where $p(\bar{z})$ denotes the prior distribution. In the decoder, z is decoded into the output y' ,

$$y' = \sigma(\mathcal{T}(z))$$

and the reconstruction error is

$$error_{recon} = \|y' - x\|_2$$

The overall error for VAE is combined by the DL divergence and the reconstruction error,

$$error = error_{KL} + error_{recon}$$

The key point of VAE is that all the latent representations z are forced to obey the normal distribution. Thus, we can randomly sample a representation $z' \in p(\bar{z})$ from the prior distribution and then reconstruct a sample based on z' . This is why VAE is so powerful in generation.

4.3.2 Generative Adversarial Networks (GAN). Generative Adversarial Networks [57] is proposed in 2014 and achieved great success in a wide range of research areas (e.g., computer vision and natural language processing). GAN is composed of two simultaneously trained neural networks with a generator and a discriminator. The generator captures the distribution of the input data, and the discriminator is used to estimate the probability that a sample came from the training data. The generator aims to generate fake samples while the discriminator aims to distinguish whether the sample is genuine. The functions of the generator and the discriminator are opposite; that's why GAN is called 'adversarial.' After the convergence of both the generator and the discriminator, the discriminator ought to be unable to recognize the generated samples. Thus, the pre-trained generator can be used to create a batch of samples and use them for further operations such as as classification.

Figure 19b shows the procedure of a standard GAN. The generator receives a noise signal s which is randomly sampled from a multimodal Gaussian distribution and outputs the fake brain signals x_F . The distributor receives the real brain signals x_R and the generated fake sample x_F , and then it predicts whether the received sample is real or fake. The internal architecture of the generator and discriminator are designed depending on the data types and scenarios. For instance, we can build the GAN by convolutional layers on fMRI images since CNN has an excellent ability to extract spatial features. The discriminator and the generator are trained jointly. After the convergence, numerous brain signals x_G can be created by the generator. Thus, the training set is enlarged from x_R to $\{x_R, x_G\}$ to train a more effective and robust classifier.

4.4 Hybrid Model

Hybrid deep learning models refers to models which are composed of at least two deep basic learning models where the basic model is a discriminative, representative, or generative deep learning model. Hybrid models comprise two subcategories based on their targets: classification-aimed (CA) hybrid models and the non-classification-aimed (NCA) hybrid models.

Most of the deep learning related studies in BCI are focussed on the first category. Based on the existing literature, the representative and generative models are employed to enhance the discriminative models. The representative models can provide more informative and low dimensional features for the discrimination while the generative models can help to augment the training data quality and quantity which supply more information for the classification. The CA hybrid models can be further subdivided into²⁰: 1) several discriminative models combined to extract more distinctive and robust features (e.g., CNN+RNN); 2) representative model followed by a discriminative model (e.g., DBN+MLP); 3) generative + representative model followed by a discriminative model; 4) generative + representative model followed by a non-deep learning classifier.

A few NCA hybrid models aim for brain signal reconstruction. For example, St-yves et al. [188] adopted GAN to reconstruct visual stimuli based on fMRI images.

5 STATE-OF-THE-ART DL TECHNIQUES FOR BCI

In this section, we will systematically summarize the existing state-of-the-art studies for BCI based on deep learning. Some literature combined deep learning and traditional machine learning methods are also listed.

²⁰The representative model followed by a non-deep learning classifier is regarded as a representative deep learning model.

5.1 Intracortical and ECoG

As a highly invasive method, intracortical brain signals are mainly investigated by researchers in medical or biological fields who may not pay much attention to deep learning techniques. Thus, few publications work on intracortical brain signal and ECoG using deep learning algorithms.

Antoniades et al. [12] employed CNN to automatically extract features from epileptic intracortical data in the field of interictal epileptic discharge (IED) detection. IEDs are transients of electrical activities that appear in brainwaves of patients with epilepsy. Their accurate detection and localization are vital to the diagnosis and treatment of epilepsy. This paper designed a CNN model with two convolutional layers to automatically explore the latent features from the raw input signals. The input data are sliced into many 80 ms segments with 40 ms overlapping, and the designed model achieved an epilepsy state recognition accuracy of 87.51%. To solve the problem that the intracortical signals are expensive to collect, the authors also proposed a deep neural architecture aimed at mapping scalp signals to pseudo-intracranial brain signals [11].

Most ECoG related studies focus on medical healthcare, especially epileptic seizure diagnosis. For example, Hosseini et al. [77] worked on seizure prediction and localization based on scalp EEG and ECoG. The ECoG signals were filtered by a fourth-order Butterworth Bandpass filter (0.5 ~ 150 Hz). After that, the authors manually extracted features through Principal Component Analysis (PCA), ICA, and Differential Search Algorithm (DSA). Then they compared two deep learning structures. The first structure is composed of three convolutional layers followed by a softmax layer, which achieved the binary recognition accuracy of 96%. The second structure adopted a DBN-AE model with two AE components, and the learned representations were fed into a softmax layer for classification, which obtained an accuracy of around 93%. This work demonstrated that CNN is more powerful than DBN in feature engineering of seizure signals. Kiral-Kornek et al. [93] attempted to develop an epileptic seizure prediction system operable on a wearable device for ultra-low power applications. They proposed an MLP algorithm for the prediction and achieved a mean sensitivity of 69% and a mean time in warning of 27%. Apart from seizure diagnosis, Xie et al. [225, 226] focused on finger trajectory tracking from ECoG signals. They developed a hybrid deep learning model based on convolutional layer and LSTM cells. The main contribution of this paper is that they employed CNN for not only spatial convolution but also temporal convolution. The motivation of temporal convolutional layer was to make the model learn the optimal band partition in a data-driven way. The convolution operation produced fixed-length vector representations to send to the LSTM cell for trajectory tracking. Each ECoG segment lasts for 1 second with 40 ms overlapping. Thus, the model was enabled to receive a stream of ECoG and form a complete finger trajectory.

5.2 EEG

More than half of the recent publications are related to EEG signals because this approach is non-invasive, high-portable and low-cost. In this section, we will summarize the state-of-the-art research based on three aspects: EEG oscillations, evoked potentials, and ERD/ERS.

5.2.1 EEG Oscillatory. Spontaneous EEG has a vast range of applications since it is well suited to a range of different scenarios. In particular, spontaneous EEG includes sleeping EEG, motor imagery EEG, emotional EEG, mental disease EEG, and others. Next, we will present the studies in each scenario and the deep learning models used.

(1) **Sleeping EEG.** Sleep quality is significant for diagnosing sleep disorders and cultivating healthy habits. Sleep EEG is mainly used to recognize sleep stages (or sleep score/state) [35]. In Rechtschaffen and Kales (R&K) rules, the sleep stages include wakefulness, non-REM (rapid eye movement) 1, non-REM 2, non-REM 3, non-REM 4, and REM. However, there is no clear distinction

between non-REM 3 and non-REM 4. Therefore, they are combined into slow wave sleep (SWS) [241]. The American Academy of Sleep Medicine (AASM) recommends segmentation of sleep in five stages: wakefulness, non-REM (rapid eye movement) 1, non-REM 2, SWS, and REM. Generally, in sleep stage analysis, the EEG signals are preprocessed by a filter which has various passband in different papers, but most of the studies notched at 50 Hz to remove powerline noise. The EEG signals are usually segmented into 30s windows.

(i) *Discriminative models.* Many publications have adopted CNN for sleep-stage classification on single-channel EEG [186, 206]. Viamala et al. [214] manually extracted time-frequency features from sleeping EEG signals and adopted a CNN algorithm to analyze them. The EEG signal collected from $Fpz - Cz$ and $Pz - Oz$ channels, was sliced into 30 s segments. The employed CNN achieved an accuracy of 86% in five-class classification. Shahin et al. [177] manually extract 57 features in the frequency domain and fed them into an MLP for classification, which obtained an accuracy of 90% in insomnia detection. Fernande et al. [49] adopted CNN to analyze physiological signals including EEG, EOG, and EMG. The model was evaluated over the Sleep Heart Health Scoring dataset and achieved a precision of 91%, recall of 90%, and F-1 score of 90%.

RNN is also often used in sleep disorder detection. Biswal et al. [27] demonstrated that RNN performed better than MLP, and CNN for sleep stage prediction. Tsioris et al. [207] extracted many features from the time domain, frequency domain, correlation, and graph theoretical features. An LSTM was employed to discover the latent dependencies of the features for seizure detection.

(ii) *Representative models.* Zhang et al. [241] combined a DBN-RBM with three RBMs for sleep feature extraction and traditional machine learning classifiers (e.g., SVM) for classification. Tan et al. [201] adopted a DBN-RBM algorithm to detect sleep spindles from the extracted PSD features of the sleeping EEG signals. They finally reached an F-1 measure of 92.78% in a local dataset.

(iii) *Hybrid models.* Manzano et al. [128, 129] proposed a multi-view model to predict sleep stage by combining CNN and MLP. The CNN was employed to receive the raw EEG data in the time domain while the MLP received the spectrum obtained by a Short-Time Fourier Transform (STFT) between 0.5–32 Hz. Supratak et al. [197] proposed a model by combining a multi-view CNN and LSTM for automatic sleep-stage scoring based on raw single-channel EEG. The proposed method utilized convolutional neural networks to extract time-invariant features, and bidirectional-long short-term memory to learn transition rules among sleep stages. Dong et al. [44] proposed a hybrid deep learning model aimed at temporal sleep stage classification. They have taken advantage of MLP for detecting hierarchical features and LSTM for sequential data learning to optimize classification performance with single-channel recordings.

(2) **MI EEG.** Extreme Learning Machine (ELM) [46] Deep learning models have shown the superior on the classification of MI EEG and real-motor EEG [69, 145].

(i) *Discriminative models.* CNN is widely used for the recognition of MI EEG [245]. On the one hand, some studies CNN is only used as a classifier to recognize manually extracted features [86, 232]. Uktveris et al. [210] extracted a large number of EEG features including Mean channel energy (MCE), Mean window energy (MWE), Channel variance (CV), Mean band power (BP), etc. All the extracted features were sent into a 2-D CNN for classification. Lee et al. [100] first processed the MI EEG signals through wavelet transformation and then manually extracted PSD from mu and beta bands. Finally, they employed a CNN model for recognition and achieved an accuracy of 78.93%. Apart from CNN, Zhang et al. [247] used a modified LSTM structure to learn affective information from EEG signals to control smart home appliances.

On the other hand, CNN deals with the raw EEG data based on feature engineering and classification results [202]. Wang et al. [219] designed a fast convolutional feature extraction approach based on CNN to learn the latent features from MI-EEG signals. Several weak classifiers are applied

to choose important features for the final classification. Hartmann et al. [69] worked on the EEG signals corresponding to real motor action. They investigated how the CNN represented spectral features through the sequence of intermediate stages of the network, which showed higher sensitivity to EEG phase features at earlier stages and higher sensitivity to EEG amplitude features at later stages. Moreover, MLP is also applied for MI EEG recognition [193].

(ii) *Representative models.* DBN is widely employed for MI EEG classification because of its high representative ability [97, 121]. Ren et al. [162] applied a convolutional DBN based on RBM components. They claimed that the DBN worked better in feature representation than traditional hand-crafted features (e.g., CSP, band powers). Li et al. [103] processed EEG signals with discrete wavelet transformation and then applied a DBN-AE based on denoising AE. They achieved an accuracy of 73.86% over a local MI EEG dataset. The authors also used denoising AE to generate the missing values in incomplete EEG signals such as an EEG segment with a portion of data removed (unevenly spaced). Rekar et al. [160] employed an AE model for feature extraction followed by a KNN classifier, which achieved an accuracy of 72.38% in binary classification over a local dataset.

Nurse et al. [146] proposed a model combining MLP with Genetic Algorithm (GA) where the GA was used for optimal hyper-parameter selection (e.g., the number of hidden layers in MLP) and the MLP worked as the classifier. Zhang et al. [252] combined AE with an XGBoost classifier to recognize the EEG signals in a multi-person scenario. The authors also proposed a complex framework by combining LSTM with reinforcement learning to classify multi-modality signals [248, 253].

(iii) *Hybrid models.* Several studies proposed hybrid models for the recognition of MI EEG [41]. Fraiwan et al. [50] combined DBN with MLP for neonatal sleep state identification. Twelve features were extracted from the time and frequency domain of the sleeping EEG signals, which were refined by a designed DBN-AE. After that, the MLP classifier gave an accuracy of 80.4% on a public dataset. Tabar et al. [198] combined the time, frequency and location information of the EEG signals as the input data which would be fed into a CNN for high-level feature extraction. The features were classified through a DBN-AE with seven AEs while the hidden layer of AE only had two nodes which corresponded to the probability of the two labels. Tan et al. [200] proposed a complicated system to achieve multimodal EEG classification. A denoising AE was employed for dimensional reduction. A multi-view CNN combined with RNN was proposed to discover the latent temporal and spatial information from the low-dimension representations. They obtained an average accuracy of 72.22% over the IIa dataset from BCI competition IV.

(3) **Emotional EEG.** The emotion of an individual can be evaluated by three aspects: the valence, arousal, and dominance. Each aspect can be rated by an integer between 1 to 9 or can be divided into positive and negative. The combination of the three aspects forms the emotions which are familiar to us like fear, sadness, anger. The subject's EEG signals could be used to predict the affective state.

(i) *Discriminative models.* In the beginning, the basic MLP is adopted to classify manually extracted features when deep learning first arose [234]. Frydenlund et al. [51] extracted the average and standard deviation of each EEG band and then fed them into an MLP for emotional affect estimation.

However, CNN is the most popular in the area of EEG based emotion prediction [105, 117]. Li et al. [105] proposed a hierarchical CNN to implement the EEG-based emotion classifier (positive, negative and neutral) in a movie-watching task. Differential Entropy (DE) is calculated as the main feature. This paper first proposes that converting multi-channel EEG signals into a 2-D matrix, which takes advantage of the spatial dependencies among EEG channels. For the emotion recognition task, this paper compared the proposed CNN with a DBN-AE and demonstrated that

CNN has better performance than DBN, which is similar to [77]. Wang et al. [216] employed a CNN algorithm to classify emotional EEG signals. Of note is the fact that they augmented the training set by generating new EEG samples by adding Gaussian noise to the original samples. Li et al. [106] proposed a novel hierarchical convolutional neural network (HCNN) to recognize the subject's emotional state (positive, neutral, and negative) and obtained an accuracy of 88.2%. In the HCNN structure, each convolutional kernel only has localized receptive field, so the kernels can capture the correlations among adjacent electrodes, which might be of great value for the recognition task.

RNN and its variants are another group of widely used discriminative models. Talathi [199] utilized a discriminative deep learning model composed of GRU cells to detect early seizure disease and achieved competitive performance. Zhang et al. [244] proposed a spatial-temporal recurrent neural network (STRNN) to integrate the feature learning from both spatial and temporal information. To capture those spatially co-occurring variations of human emotions, a multidirectional RNN layer can capture long-range contextual cues by traversing the spatial regions of each temporal slice along with different directions. Then, a bi-directional temporal RNN layer is further used to learn the discriminative features characterizing the temporal dependencies of the sequences produced by the spatial RNN layer.

(ii) *Representative models*. DBN, especially DBN-RBM, is widely used for unsupervised representation ability in emotion recognition [53, 107, 110]. For instance, Xu et al. [227] proposed a DBN-RBM algorithm with three RBMs and an RBM-AE to predict the subject's affective state. Nevertheless, it is not a strictly semi-supervised method: the model reported by [227] is composed of unsupervised feature representation and a supervised softmax layer. The authors also tried to manually extract the PSD features from 14 narrow-down bands of the EEG signals and then fed them into DBN-RBM for classification [228]. For Alzheimer's Disease diagnosis, Zhao et al. [254] adopted DBN-RBM with three RBMs to extract informative representations after filtering (0.5 ~ 30 Hz). The proposed representative model is combined with a traditional classifier (SVM) and achieved an accuracy of 92%. Another work combined DBN-RBM with Hidden Markov Model (HMM) and achieved an accuracy of 87.62% in a local dataset [258].

Compared to other repetitive models, D-RBM only appears in a few studies. Zheng et al. [255, 256] introduced a D-RBM with five hidden RBM layers to investigate critical frequency bands and channels in emotion recognition. The authors claimed that they employed a DBN-RBM; however, the RBMs are trained jointly. Thus it is regarded as D-RBM in this survey. Jia et al. [85] proposed an interesting algorithm which is composed of RBMs. The algorithm contains a channel selection component and an RBM classifier. The data from each EEG channel are reconstructed through RBM; then, the channels with high error are eliminated. Then the representative features of the residual channels are sent to D-RBM for affective state recognition.

Emotion is affected by many subjective and environmental factors, such as gender, fatigue, etc. Yan et al. [118, 230] investigated the differences between males and females in emotion recognition using EEG and eye movement data. They proposed a novel model called Bimodal Deep AutoEncoder (BDAE) which is, however, actually formed by RBMs. The BDAE received both EEG and eye movement features and shared the information in a fusion layer which connected with an SVM classifier. The results showed that the fearful emotion is more diverse among women compared with men, and men behave more diversely on the sad emotion compared with women. Moreover, individual differences in fear are more pronounced than in the other three emotions for females.

To overcome the mismatched distribution among the samples collected from different subjects or different experimental sessions, Chai et al. [34] proposed an unsupervised domain adaptation technology which is called the subspace alignment autoencoder (SAAE). SAAE combined an AE

and a subspace alignment solution, which could take advantage of both nonlinear transformation and a consistency constraint. The proposed approach obtained a mean accuracy of 77.88% in a person-independent scenario.

(iii) *Hybrid models.* One commonly-used hybrid model is a combination of RNN and MLP. For example, Alhagry et al. [8] employed an LSTM architecture for feature extraction from emotional EEG signals, and the features are forwarded into an MLP for classification, which got 85.65%, 85.45%, and 87.99% accuracy on arousal, valence, and liking classes, respectively. Furthermore, Yin et al. [237] proposed a multi-view ensemble classifier to recognize emotions using multimodal physiological signals. The ensemble classifier contains several D-AEs with three hidden layers and a fusion structure. Each D-AE receives one physiological signal (e.g., EEG, EOG, EMG) and then sends the outputs of D-AE to a fusion structure which is composed of another D-AE. At last, an MLP classifier classifies the mixed features. Kawde et al. [90] implemented an affect recognition system by combining a DBN-RBM for effective feature extraction and an MLP for classification.

(4) **Mental Disease EEG.** A large number of researchers exploited EEG signals to diagnose neurological disorders, especially epileptic seizures [240].

(i) *Discriminative models.* CNN is widely used in the automatic detection of epileptic seizures [3, 173, 211, 218]. For example, Johansen et al. [87] adopted CNN to work on the high-passed filtered (≥ 1 Hz) EEG signals of epileptic spikes and achieved an AUC of 94.7%. Acharya et al. [4] employed a CNN model with 13 layers (5 convolutional layers, five pooling layers, and three fully-connected layers) on depression detection. The method was evaluated on a local dataset with 30 subjects (15 normal and 15 depressed) and achieved the accuracies of 93.5% and 96.0% using EEG signals from the left and right hemisphere, respectively. Morabito et al. [138] exploited a CNN structure to extract suitable features of multi-channel EEG signals to classify Alzheimer's Disease from a prodromal version of dementia (Mild Cognitive Impairment, MCI) and age-matched Healthy Controls (HC). The EEG signals are filtered in bandpass (0.1 ~ 30 Hz) and finally achieved an accuracy of around 82% for three-class classification.

In some research, the discriminative model is only employed for feature extraction. For example, Ansari et al. [10] used CNN to extract the latent features which are fed into a Random Forest classifier for the final seizure detection in neonatal babies. Chu et al. [38] employed CNN for feature extraction which was sent to a random forest for schizophrenia recognition.

REM Behavior Disorder (RBD) may cause many mental disorder diseases like Parkinson's disease (PD). Ruffini et al. [164] described an Echo State Networks (ESNs) model to distinguish RBD from healthy individuals. ESN, as a particular class of RNN, implements nonlinear dynamics with memory and seem ideally poised for the classification of complex time series data. The central concept in ESNs and related types of so-called fireservoir computationf systems is to have data inputs drive a semi-randomly connected, large, fixed recurrent neural network (the fireservoirf) where each node/neuron in the reservoir is activated in a nonlinear way.

(ii) *Representative models.* For disease detection, one commonly used method is adopting a representative model (e.g., DBN) followed by a softmax layer for classification [209, 229]. Page et al. [149] adopted DBN-AE to extract useful features from seizure EEG signals. The extracted features were fed into a traditional logistic regression classifier for seizure detection. Al et al. [7] proposed a multi-view DBN-RBM structure to analyze EEG signals from depressed patients. The proposed approach contains multiple input pathways, composed of two RBMs, while each corresponded to one EEG channel. All the input pathways would merge into a shared structure which is composed of another RBMs. The results showed that the multi-view DBN-RBM achieved competitive results. Yuan et al. [239] extract EEG context features in parallel by using global principal component

analysis (GPCA), deep denoising AE, and EEG embeddings, respectively. The multi-features are concatenated into a fixed-length feature vector for seizure classification.

Some papers favor preprocessing the EEG signals through dimensionality reduction methods such as PCA and ICA [78] while others prefer to direct fed the raw signals to the representative model [111]. Lin et al. [111] proposed a sparse D-AE with three hidden layers to extract the representative features from epileptic EEG signals while Hosseini et al. [78] adopted a similar sparse D-AE with two hidden layers.

(iii) *Hybrid models.* A popular hybrid method is a combination of RNN and CNN. Shah et al. [176] investigated the performance of CNN-LSTM on seizure detection after channel selection. They used a reduced number of channels ranging from 8 to 20, and achieved sensitivities between 33% and 37% with false alarms in the range of 38% and 50%. Golmohammadi et al. [56] proposed a hybrid architecture for automatic interpretation of EEG that integrates temporal and spatial context for sequential decoding of EEG events. 2D and 1D CNNs capture the spacial features while LSTM networks capture the temporal features. The authors claimed sensitivity of 30.83% and a specificity of 96.86% on the well-known TUH EEG seizure corpus.

In the detection of early-stage Creutzfeldtfi?!Jakob Disease (SJD), Morabito et al. [139] combined D-AE and MLP together. The EEG signals of SJD were first filtered by bandpass (0.5~70 Hz) and then fed into a D-AE with two hidden layers for feature representation. At last, the MLP classifier obtained the accuracy of 81~ 83% in a local dataset. Convolutional autoencoder, replacing the fully-connected layers in a standard AE by convolutional and de-convolutional layers, is applied to extract the seizure features in an unsupervised manner [223].

(5) **Data augmentation.** Generative models such as GAN can be used for data augmentation in BCI classification [1]. Palazzo et al. [150] first demonstrated that brain activity EEG signals encode visually-related information that enables to discriminate between visual object categories accurately. Then, they extracted a more compact class-dependent representation of EEG data using recurrent neural networks. At last, they used the learned EEG manifold to condition image generation employing GANs, which, during inference, will read EEG signals and convert them into images. Kavasidis et al. [88] aiming at converting EEG signals into images. The EEG signals were collected when the subjects were observing images on a screen. An LSTM layer was employed to extract the latent features from the EEG signals, and the extracted features were regarded as the input of a GAN structure. The generator and the discriminator of the GAN were both composed of convolutional layers. The generator was supposed to generate an image based on the input EEG signals after the pre-training. Abdelfattah et al. [1] adopted a GAN on seizure data augmentation. The generator and discriminator are both composed of fully-connected layers. The authors demonstrated that GAN outperforms AE and VAE. After the augmentation, the classification accuracy increased dramatically from 48% to 82%.

(6) **Others** Other researchers have explored a wide range of interesting topics. The first one is how EEG affected by audio/visual stimuli. This differs from the potentials evoked by audio/visual stimulations because the stimuli in this phenomenon are constant instead of fluctuating at a particular frequency. Stober et al. [190, 191] claimed that EEG signals of rhythm perception might contain enough information to distinguish different rhythm types/genres or even identify the rhythms themselves. The authors conducted an experiment where 13 participants were stimulated by 23 rhythmic stimuli including 12 East African and 12 Western stimuli. For the 24-category classification, the proposed CNN achieved a mean accuracy of 24.4%. After that, the authors exploited convolutional AE for feature learning and CNN for classification and achieved an accuracy of 27% for 12-class classification [192]. Sternin et al. [189] adopted CNN to extract discriminative features from the EEG signals to distinguish whether the subject was listening or imaging music.

Similarly, Sarkar et al. [170] designed two deep learning models to recognize the EEG signals invoked by audio or visual stimuli. For this binary classification task, the proposed CNN and DBN-RBM with three RBMs achieved the accuracy of 91.63% and 91.75%, respectively. Furthermore, the spontaneous EEG could be used to distinguish the user's mental state (logical versus emotional) [21].

Moreover, some researchers focus on the impact of cognitive load[180] or physical workload [58] on EEG . Bashivan et al. [23] first extracted informative features through wavelet entropy and band-specific power which were fed into a DBN-RBM for further refining. At last, an MLP is employed for cognitive load level recognition. The authors, in another work [22], also aimed to find representations that are invariant to inter- and intra-subject differences from multi-channel EEG time-series in the context of the mental load classification task. They transformed EEG activities into a sequence of topology-preserving multi-spectral images and then trained a recurrent-convolutional network to preserve the spatial, spectral, and temporal features of the EEG signals. Yin et al. [236] collected the EEG signals from different mental workload levels (e.g., high and low) for binary classification. The EEG signals were filtered by a low-pass filter, transformed to the frequency domain and the power spectral density (PSD) was calculated. The extracted PSD features were fed into a denoising D-AE structure for future refining. They finally achieved an accuracy of 95.48%. Li et al. [108] worked on the recognition of mental fatigue level including alert, slight fatigue, and severe fatigue. They adopted a simple DBN-RBM to extract the related features from single-channel EEG.

In addition, EEG based driver fatigue detection is a popular area of research[33, 45, 65, 65, 67]. Huang et al. [82] designed a 3D CNN to predict reaction time in drowsy driving. This is useful to reduce traffic accidents. Hajinorozi et al. [64] adopted a DBN-RBM to handle the EEG signals which were processed by ICA. They achieved an accuracy of around 85% in binary classification ('drowsy' or 'alert'). The strength of this paper is that they evaluated the DBN-RBM on three levels: time samples, channel epochs, and windowed samples. The experiments showed that the channel epoch level provided the best performance. San et al. [169] combined deep learning models with a traditional classifier to detect driver fatigue. The model contains a DBN-RBM structure followed by an SVM classifier, which achieved a detection accuracy of 73.29%. Almogbel et al. [9] investigated the drivers' mental state under high workload and low workload. A proposed CNN is claimed to detect the driver's cognitive workload directly based on the raw EEG signals.

Research into detection of eye state has shown exceedingly high accuracy. Narejo et al. [141] explored the detection of eye state (closed or open) based on EEG signals. They tried a DBN-RBM with three RBMs and a DBN-AE with three AEs and achieved a very high accuracy of 98.9%. Reddy et al. [159] tried a simpler structure, MLP, for eye state detection and got a slightly lower accuracy of 97.5%.

There are still a lot of promising areas that have not drawn much attention to date. Baltatzis et al. [18] adopted CNN to detect school bullying through EEG when watching the specific video. They achieved 93.7% and 88.58% for binary and four-class classification. Khurana et al. [91] proposed deep dictionary learning that outperformed several deep learning methods. Volker et al. [215] evaluated the use of Deep CNN in a flanker task, which achieved an averaging accuracy of 84.1% within subject and 81.7 on unseen subjects. Zhang et al. [246] combined CNN and graph network to discover the latent information from the EEG signal.

Miranda-Correa et al. [137] proposed a cascaded framework by combining RNN and CNN to predict individuals' affective level and personal factors (Big-five personality traits, mood, and social context). An experiment conducted by Putten et al. [157] attempted to identify the user's gender based on their EEG signals. They employed a standard CNN algorithm and achieved the binary

classification accuracy of 81% over a local dataset. The detection of emergency braking intention could help to reduce the responses time. Hernandez et al. [73] demonstrated that the driver's EEG signals could distinguish braking intention and normal driving state. They combined a CNN algorithm which achieved the accuracy of 71.8% in binary classification. Behncke et al. [24] applied deep learning, a CNN model, in the context of robot assistive devices. They attempted to use CNN to improve the accuracy of decoding robot errors from EEG while the subject watching the robot both during an object grasping and a pouring task.

Teo et al. [203, 204] tried to combine the BCI and recommender system, which predicted the user's preference by EEG signals. A cohort of 16 users was shown 60 bracelet-like objects as rotating visual stimuli (a 3D object) on a computer display while their preferences and EEGs were recorded. Then, an MLP algorithm was adopted to classify whether the user liked or disliked the object. This exploration got the prediction accuracy of 63.99%. Some researchers have tried to explore a common framework which can be used for various BCI paradigms. Lawhern et al. [99] introduced a compact CNN for EEG-based BCI. The authors described the use of depth-wise and separable convolutions to construct an EEG-specific model which encapsulates well-known EEG feature extraction concepts for BCI. The proposed EEGNet is evaluated on four BCI paradigms: P300 visual-evoked potentials, error-related negativity responses (ERN), movement-related cortical potentials (MRCP), and sensory-motor rhythms (SMR).

5.2.2 Evoked Potential. (1) **ERP** In most situations, ERP signals are analyzed in terms of the P300 peak. Likewise, almost all the studies on P300 are based on the ERP paradigm. Therefore, in this section, a majority of the P300 related publications are introduced in the subsection of VEP/AEP according to the paradigm.

(i) **VEP** VEP is one of the most popular subcategories of ERP [63, 187, 235]. Ma et al. [136] worked on motion-onset VEP (mVEP) by extracting representative features through deep learning. They used improved multi-level compressed sensing combined with a genetic algorithm as the first stage to compress the original mVEP EEG. The compressed signals were sent to a DBN-RBM algorithm to capture the more abstract high-level features. Maddula et al. [123] filtered the P300 signals to visual stimuli using a bandpass filter (2 ~ 35 Hz) and then fed them into a proposed hybrid deep learning model for further analysis. The model included a 2D CNN structure to capture the spatial features, followed by an LSTM layer for temporal feature extraction. Liu et al. [116] combined a DBN-RBM representative model with an SVM classifier for concealed information test and achieved a high accuracy of 97.3% over a local dataset. Gao et al. [52] employed an AE model for feature extraction followed by an SVM classifier. In the experiment, each segment contains 150 points which were divided into five time-steps, and each step had 30 points. This model achieved an accuracy of 88.1% over a local dataset. A wide range of P300 related studies are based on the P300 speller [179] which allows the user to write characters, as introduced in Section 3.3.2. Cecotti et al. [29] tried to increase the P300 detection accuracy for more precise word-spelling. A new model was presented based on CNN, which including five low-level CNN classifiers with the different feature set and the final high-level results are voted by the low-level classifiers. The highest accuracy reached 95.5% over the dataset II from the third BCI competition. Liu et al. [115] proposed a Batch Normalized Neural Network (BN³) which is a variant of CNN in P300 speller. The proposed method consists of six layers, and the batch normalization was operated in each batch. Kawasaki et al. [89] employed an MLP model to detect P300 segments from non-P300 segments and achieved the accuracy of 90.8%.

(ii) **AEP** A few works focused on the recognition of AEP. For example, Carabez et al. [28] proposed and tested 18 CNN structures to identify and classify single-trial AEP signals. In the experiment, the auditory stimuli following the oddball paradigm were presented via earphones from six different virtual directions. The authors found that the models that consider data from

both the time and space domains and those that overlap in the pooling process usually offer better results regardless of the number of CNN layers. The AEP signals are bandpass filtered between $0.1 \sim 8$ Hz and downsampled from 256 Hz to 25 Hz. The experimental results showed that the downsampled data works better.

(iii) RSVP Among various VEP diagrams, RSVP has attracted much attention [59]. In the analysis of RSVP, a number of discriminative deep learning models (e.g., CNN [29, 112, 185] and MLP [131]) have achieved great success. A common preprocessing method used in RSVP signals is frequency filtering. The pass bands are generally ranged from $0.1 \sim 50$ Hz [126, 178]. Cecotti et al. [30] worked on the classification of ERP signals in the RSVP paradigm. This paper proposed a CNN algorithm with a layer dedicated to spatial filtering for the detection of the specific target in RSVP. In the experiment, the images of faces and cars were regarded as target or non-target, respectively. Each image was presented for 500 ms and immediately replaced by the subsequent image. In each session, the target probability was 10%. The proposed model offered an AUC of 86.1%. Yoon et al. [238] provided a way to analyze the spatial and temporal features of ERP. The authors trained a CNN with two convolutional layers whose feature maps represented spatial and temporal features of the event-related potential. The results demonstrated that literate subjects' ERP shows a high correlation between the occipital lobe and parietal lobe, whereas illiterate subjects only show the correlation between neural activities from the frontal lobe and central lobe. Most importantly, they found that the P700 may be used to distinguish illiterate and literate subjects when the P300 peak is not shown in some subjects' ERP signals. Hajinorozi et al. [66] adopted a CNN model for cross-subject and cross-task detection of RSVP. CNN was designed to capture both temporal and spatial features. The experimental results showed that CNN worked good in cross-task but failed to get satisfying performance in the cross-subject scenario. Mao et al. [130] compared three different deep learning models in the prediction of whether the subject had seen the target or not. The MLP, CNN, and DBN models obtained the AUC of 81.7%, 79.6%, and 81.6%, respectively. The author also applied a CNN model to analyze the RSVP signals for person identification [132].

Representative deep learning models are also applied in RSVP. Vareka et al. [212] verified if deep learning performs well for single trial P300 classification. They conducted an RSVP experiment while the subjects were asked to recognize the target from non-target and distractors. The A DBN-AE was implemented and compared with some non-deep learning algorithms. The DBN-AE was composed of five AEs while the hidden layer of the last AE only has two nodes which can be used for classification through softmax function. Finally, the proposed model achieved the accuracy of 69.2%. Manor et al. [127] applied two deep learning models to deal with the RSVP signals after lowpass filtering ($0 \sim 51$ Hz). The discriminative CNN achieved the accuracy of 85.06%. Meanwhile, the representative convolutional D-AE achieved the accuracy of 80.68%.

(3) SSEP. Most deep-learning based studies in the SSEP field focus on SSVEP, such as [6, 98]. SSVEP are neural oscillations from the parietal and occipital regions of the brain evoked from flickering visual stimuli. Attia et al. [14] aimed at finding an appropriate intermediate representation of SSVEP. A hybrid method combining CNN and RNN was proposed to capture the meaningful features from the time domain directly, which achieved an accuracy of 93.59%. Waytowich et al. [221] applied a compact CNN model to directly work on the raw SSVEP signals without any hand-crafted features. The reported cross subject mean accuracy was approximately 80%. Thomas et al. [205] first filtered the raw SSVEP signals through a bandpass filter ($5 \sim 48$ Hz) and then operated discrete FFT on consecutive 512 points. The processed data were classified by a CNN (69.03%) and an LSTM (66.89%) independently.

Perez et al. [153] adopted a representative model, a sparse AE, to extract the distinct features from the SSVEP from multi-frequency visual stimuli. The proposed model employed a softmax layer for

the final classification and achieved an accuracy of 97.78%. Kulasingham et al. [96] classified SSVEP signals in the context of a guilty knowledge test. The authors applied DBN-RBM and DBN-AE independently and achieved the accuracy of 86.9% and 86.01%, respectively. Hachem et al. [62] investigated the influence of fatigue on SSVEP through an MLP model during wheelchair navigation. The goal of this study was to seek the key parameters to switch between manual, semi-autonomous, and autonomous wheelchair command. Aznan et al. [16] explored SSVEP classification where the signals were collected through dry electrodes. The dry signals were more challenging for the lower SNR than standard EEG signals. This study applied a CNN discriminative model and achieved the highest accuracy of 96% over a local dataset.

5.2.3 ERD/ERS. ERD/ERS is not widely used in BCI due to drawbacks like unstable accuracy cross subjects [81]. In most situations, the ERD/ERS is regarded as a specific feature of EEG powers for further analysis [41, 198]. In particular, the ERD/ERS were calculated as relative changes in power concerning baseline [37]:

$$\text{ERD/ERS} = \frac{P_e - P_b}{P_b}$$

, where P_e denotes the average power over a one-second window during the event and P_b denotes the baseline average power in a one-second window preceding the event. Generally, the baseline refers to the rest state. For example, Sakhavi et al. [167] calculated the ERD/ERS map and analyzed the different patterns among different tasks. The analysis demonstrated that changes in energy should be considered because static energy is not sufficiently discriminatory for some tasks.

5.3 fNIRS

Up to now, only a few researchers have focussed on deep learning based fNIRS. Naseer et al. [143] analyzed the difference between two mental tasks (mental arithmetic and rest) based on fNIRS signals. The authors manually extracted six features from the prefrontal cortex fNIRS and compared six different classifiers. The results demonstrated that the MLP with the accuracy of 96.3% outperformed all the traditional classifiers including SVM, KNN, naive Bayes, etc. Huve et al. [83] classified the fNIRS signals which were collected from the subjects during three mental states including subtractions, word generation, and rest. The employed MLP model achieved an accuracy of 66.48% based on the hand-crafted features (e.g., the concentration of OxyHb/DeoxyHb). After that, the authors study mobile robot control through fNIRS signals and got a binary classification accuracy of 82% (offline) and 66% (online) [84]. Chiarelli et al. [37] exploited the combination of fNIRS and EEG for left/right MI EEG classification. Sixteen features extracted from fNIRS signals (eight from OxyHb and eight from DeoxyHb) were fed into an MLP classifier with four hidden layers.

On the other hand, Hiroyasu et al. [75] attempted to detect the gender of the subject through their fNIRS signals. The authors employed a denoising D-AE with three hidden layers to extract distinctive features to be fed into an MLP classifier for gender detection. The model was evaluated over a local dataset and achieved the average accuracy of 81%. This paper also pointed out that, compared with PET and fMRI, fNIRS is cheaper and can measure cerebral blood flow changes with higher temporal resolution.

5.4 fMRI

Recently, several deep learning methods have been applied to fMRI analysis, especially on the diagnosis of cognitive impairment [213, 222].

(1) Discriminative models

Among the discriminative models, CNN is a promising model to analysis fMRI [182]. For example, Havaei et al. [71] presented brain tumor segmentation approaches based on fMRI. A novel CNN algorithm was proposed, which can capture both the local features and the global features simultaneously. The convolutional filters have a different size. Thus, the small-size and large-size filter could exploit the local and global features, independently. Tu et al. [208] used simultaneous EEG-fMRI dataset to demonstrate that the temporal and spatial hierarchical correspondences between the multi-stage processing in CNN and the activity observed in the EEG and fMRI. Sarraf et al. [171, 172] applied deep CNN to recognize Alzheimer's Disease based on fMRI and MRI data. Morenolopez et al. [133] employed a CNN model to deal with fMRI of brain tumor patients for three-class recognition (normal, edema, or active tumor). The model was evaluated over BRATS dataset and obtained the F1 score of 88%. Hosseini et al. [79] employed CNN for feature extraction. The extracted features were classified by SVM for the detection of an epileptic seizure.

Furthermore, Li et al. [109] proposed a data completion method based on CNN. Specifically, the information from fMRI data is used to complete positron emission tomography (PET), then a classifier is trained based on both fMRI and PET data. In the model, the input data of the proposed CNN is an fMRI patch with shape [15, 15, 15] and the output is a PET patch with shape [3, 3, 3]. There are two convolutional layers with ten filters each to mapping the input to output. The experiments illustrated that the classifier trained by the combination of fMRI and PET (92.87%) outperformed the one trained by solo fMRI (91.92%).

Moreover, Koyamada et al. [95] used a nonlinear MLP to extract common features from different subjects. The model is evaluated over a dataset from the Human Connectome Project (HCP).

(2) *Representative models* A wide range of publications demonstrated the effectiveness of representative models in recognition of fMRI data [26, 194]. Hu et al. [80] demonstrated the advantages of deep learning in diagnosing brain disease and providing clinical decision support in Alzheimer's disease detection. Firstly, the fMRI images were converted to a matrix to represent the activity of 90 brain regions. Secondly, a correlation matrix was obtained by calculating the correlation between each pair of brain regions to represent the functional connectivity between different brain regions. Furthermore, a targeted AE was built to classify the correlation matrix, which was sensitive to AD. The proposed approach achieved an accuracy of 87.5%. Plis et al. [156] employed a DBN-RBM with three RBM components to extract the distinctive features from ICA processed fMRI and finally achieved an average F1 measure of above 90% over four public datasets. Suk et al. [195] compared the effectiveness of DBN-RBM and DBN-AE on Alzheimer's disease detection. The experimental results showed that the former obtained the accuracy of 95.4% which was slightly lower than the latter (97.9%). Suk et al. [196] applied a D-AE model to extract latent features from the resting-state fMRI data on the diagnosis of Mild Cognitive Impairment (MCI). The latent features are classified by SVM and achieved an accuracy of 72.58%. Ortiz et al. [147] proposed a multi-view DBN-RBM to receive the information of MRI and PET simultaneously. The learned representations were sent to several simple SVM classifiers which were ensembled to form a stronger, high-level classifier by voting.

(3) *Generative models*

The reconstruction of natural images based on fMRI data has attracted lots of attention [68, 175, 181, 244]. Seeliger et al. [175] proposed a deep convolutional GAN for reconstructing visual stimuli from fMRI. The objective was to create an image similar to the presented stimulus image through a well-trained generator. The generator is composed of four convolutional layers to convert the input fMRI to a natural image. Han et al. [68] focused on the generation of synthetic multi-sequence fMRI using GAN. The generated image can be used for data augmentation for better diagnostic accuracy or physician training to help better understand various diseases. The authors applied the

existing Deep Convolutional GAN (DCGAN) [158] and Wasserstein GAN (WGAN) [13] and found that the former works better. Shen et al. [181] presented a novel image reconstruction method, in which the pixel values of a generated image are optimized to make its features, which is decoded by MLP, similar to those decoded from the real fMRI.

5.5 EOG

In most situations, the EOG signals are regarded as artifacts which should be removed from the collected EEG. However, they can also be used as informative signals to deploy EOG based BCI. Although a number of researchers focussed on EOG analysis, only a limited number of papers utilized deep learning. For example, Xia et al. [224] attempted to detect the subjects' sleep stage only using EOG signals. They employed a DBN-RBM for feature representation and a HMM for classification. Moreover, EOG has been widely used as a supplementation of other signals (e.g., EEG) in several research topics such as emotion detection [90, 118, 218], sleep stage recognition [49, 197], and driving fatigue detection [45].

5.6 MEG

Garg et al. [54] worked on the refining of MEG signals by removing the artifacts like eye-blanks and cardiac activity. The MEG signals were decomposed by ICA first and then classified by a 1-D CNN model. Finally, the proposed approach achieved the sensitivity of 85% and specificity of 97% over a local dataset. Hasasneh et al. [70] also focused on artifact detection (cardiac and ocular artifacts). The proposed approach used CNN to capture temporal features and MLP to extract spatial information. Shu et al. [183] employed a sparse AE to learn the latent dependencies of MEG signals in the task of single word decoding. The results demonstrated that the proposed approach is advantageous for some subjects although it didn't produce an overall increase in decoding accuracy. Cichy et al. [40] applied a CNN model to recognize visual objects based on MEG and fMRI signals.

5.7 Discussion

In this section, we first analyze what is the most suitable deep learning models for BCI signals. Then, we will summarize the popular deep learning models in BCI research. We hope this survey could help our readers to select the most effective and efficient methods when dealing with BCI signals. In Table 5, we summarize the BCI signals and the corresponding deep learning models of the state-of-the-art papers. Hybrid models are divided into three parts: the combination of RNN and CNN, the combination of representative and discriminative models, and others. Figure 20 illustrated of the publications proportion for crucial BCI signals and deep learning models.

5.7.1 BCI Signal based Discussion. Our investigations above reveal that studies on non-invasive signals dominate the BCI research. Among the summarized 238 publications, there are only seven focused on invasive BCI and most of them worked on ECoG instead of intracortical signals. One important reason result in this phenomena is that the invasive BCI has a higher requirement on the hardware and experiment environments. For example, the collection of ECoG signals needs a volunteer patient and a surgeon who can operate craniotomy which makes most researchers unqualified. Moreover, there are few public datasets of invasive brain signals. Therefore, most people can not access the invasive data. In terms of the classification of invasive signals, CNN-related algorithms often have higher ability to recognize the spikes from cortical neurons.

Besides, among the non-invasive signals, the studies on EEG is far more than the sum of all the other BCI paradigms (fNIRS, fMRI, EOG, and MEG). Furthermore, there are about 70% of the EEG papers concentrate on spontaneous EEG (133 publications). For better understanding, we split the spontaneous EEG into several aspects: sleeping, motor imagery, emotional, mental disease, data

Table 5. The summary of BCI studies based on deep learning models. Repre + Discri represents the hybrid models which combined representative and distinctive models.

BCI Signals				Deep Learning Models										
				Discriminative Models			Representative Models			Generative Models		Hybrid Models		
				MLP	RNN	CNN	AE (D-AE)	RBM (D-RBM)	DBN DBN-AE	DBN-RBM	VAE	GAN	LSTM+CNN	Repre + Discri
Non-invasive Signals	EEG	Spontaneous EEG	Sleeping EEG, MI EEG, Emotional EEG, Mental Disease EEG, Data Augmentation, Others	Invasive		[93]	[12, 77]					[225]	[11, 77] [226]	
				[27, 177]	[27, 207]	[214],[35], [186, 206], [27, 49]				[201, 241]		[197] [27]	[50]	[128], [44, 129]
				[37],[193]	[249], [245, 247]	[100], [210], [145],[242], [86],[99], [69, 232], [202]	[104, 160] [252]		[103]	[97, 162], [121]	[41]	[200, 250]	[198],[46]	[146, 248], [167, 219] [253]
				[51]	[244]	[105],[117], [216], [106, 218]	[34],[230], [118]	[255, 256] [85]		[85],[227], [110],[228], [107, 258]		[137]	[53, 90] [237]	[8]
				[240]	[199],[164]	[211],[4], [3],[138], [173],[79], [10, 87] [77]	[239],[111], [139, 229], [223]		[149]	[209, 254]		[176]	[77, 78], [7, 56]	
				Data Augmentation		[24], [82], [18],[190], [180],[215],[73], [9, 157]	[236],[45]		[141]	[64],[141], [108, 169]		[1, 41], [150] [88]		
				[159, 203] [234]	[180]	[65, 65] [38, 189]						[65, 65]	[192],[23, 33]	[246]

Table 5. The summary of BCI studies based on deep learning models (continued)

augmentation, and others. First, the classification of sleeping EEG mainly depends on discriminative and hybrid models. Among the nineteen studies about sleeping stage classification, there are six that employed CNN and modified CNN models independently while two papers adopted RNN models. Three studies used hybrid models built based on the combination of CNN and RNN. Second, in terms of research on MI EEG (30 publications), independent CNN and CNN-based hybrid models are widely used. As for representative models, DBN-RBM is often applied to capture the latent features from the MI EEG signals. Third, there are twenty-five publications related to spontaneous emotional EEG. More than half of them employed representative models (such as D-AE, D-RBM, especially DBN-RBM) for unsupervised feature learning. Most affective state recognition works recognize the user's emotion as positive, neutral, or negative. Some researchers take a further step to classify the valence, and the arousal rate, which is more complex and challenging. Fourth, research on mental disease diagnosis is promising and attractive. The majority of the related research focuses on the detection of epileptic seizures and Alzheimer's Disease. Since the detection is a binary classification problem, many studies can achieve a high accuracy like above 90%. In this area, the standard CNN model and the D-AE are prevalent. One possible reason is that CNN and AE are the most well-known and effective deep learning models for classification and dimensionality reduction. Fifth, several publications focus on GAN based data augmentation. At last, about thirty studies investigated other spontaneous EEG such as driving fatigue, audio/visual stimuli impact, cognitive/mental load, and eye state detection. These studies extensively apply standard CNN models and variants.

Moreover, apart from spontaneous EEG, evoked potentials also attracted much attention. On the one hand, in ERP, VEP and the subcategory RSVP has drawn lots of investigations because visual stimuli, compared to other stimuli, are easier to present and more applicable in the real world (e.g., P300 speller can be used for brain typing). For VEP (21 publications), 11 studies applied discriminative models and six works adopted hybrid models. In terms of RSVP, CNN is the most prevalent algorithm employed. Additionally, five papers focused on the analysis of AEP signals. On the other hand, among the steady-state related researches, only SSVEP has been studied using deep learning models. Most of them only applied discriminative models on the recognition of the target image. At last, few papers attempted to investigate the ERD/ERS singles. Several publications utilized ERD/ERS to analyze the signals and calculated the ERD/ERS value as a distinct feature.

Furthermore, beyond the diverse EEG paradigms, a wide range of papers paid attention to fNIRS and fMRI. fNIRS images are rarely studied by deep learning and the majority of studies just employed the simple MLP models. We believe more attention should be paid to the research on fNIRS for the high portability and low cost relative to fMRI. As for the fMRI, twenty-three papers proposed deep learning models to the classification. The CNN model is widely used for its outstanding performance in feature learning from images. There are also several papers interested in image reconstruction based on fMRI signals. One reason why fMRI is so popular is that several public datasets are available on the internet although the fMRI equipment is expensive. EOG has mainly been regarded as noise instead of a useful signal. However, it enables individuals to communicate with the outer world by detection of the user's eye movement. MEG signals are mainly used in the medical field, where deep learning algorithm are not much employed. Thus, we only found very few studies on MEG. The sparse AE and CNN algorithms have a positive influence on the feature refining and classification of MEG.

5.7.2 Deep Learning Model-based Discussion. In this section, we will discuss the deep learning models which are applied in BCI systems. First of all, in a high-level view, the discriminative models, especially CNN, are most widely adopted in the summarized 238 publications. This is reasonable because almost all the BCI issues can be regarded as a classification problem. CNN algorithms

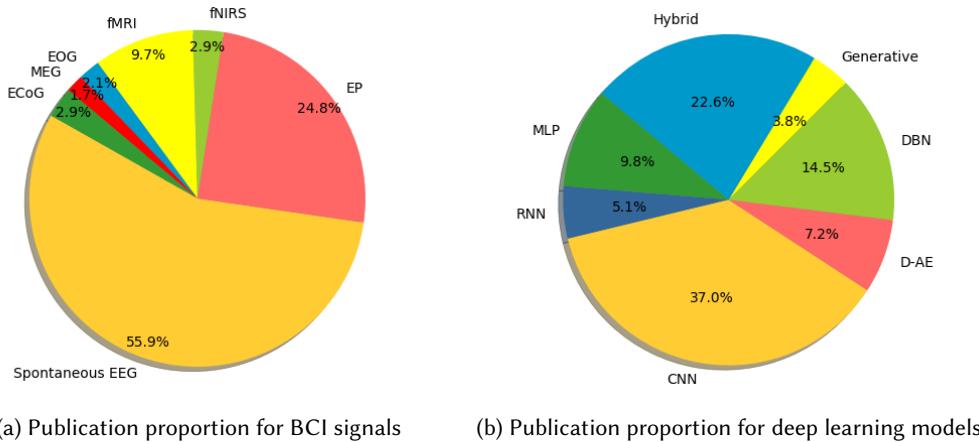


Fig. 20. Illustration of the publications proportion for crucial BCI signals and deep learning models.

account for more than 70% of discriminative models. We provide several possible reasons. First, the design of CNN is powerful enough to extract the latent discriminative features and spatial dependencies from the EEG signals for classification. As a result, CNN structures are adopted for classification in some studies while adopted for feature engineering in some other studies. Second, CNN has been achieved great success in some research areas (e.g., computer vision) which makes it extremely famous and easy to implement (through the available public code). Thus, BCI researchers have more chance to understand and apply CNN on their works. Third, some BCI approaches (e.g., fMRI, MEG) naturally form two-dimension images conducive to processing by CNN. Meanwhile, other 1-D signals (e.g., EEG) could be converted into 2-D images for further analysis by CNN. Here, we provide several methods converting 1-D EEG signals (with multiple channels) to a 2-D matrix: 1) convert each time-point²¹ to a 2-D image; 2) convert a segment into a 2-D matrix. For the first situation, suppose we have 32 channels, and we can collect 32 elements (each element corresponding to a channel) at each time-point. As described in [105], the collected 32 elements could be converted into a 2-D image based on the spatial position as shown in Figure 6. For the second situation, suppose we have 32 channels, and the segment contains 100 time-points. The collected data can be arranged as a matrix with the shape of [32, 100] where each row and column refers to a specific channel and time-point, respectively. Fourth, there are a lot of variants of CNN which are suitable for a wide range of BCI scenarios. For example, single-channel EEG signals can be processed by 1-D CNN. In terms of RNN, only about 20% of discriminative model based papers adopted RNN, which is much less than we expected since RNN has demonstrated powerful in temporal feature learning. One possible reason for this phenomena is that processing a long sequence by RNN is time-consuming and the EEG signals generally form a long sequence. For example, sleeping EEG signals are usually sliced into segments of 30 seconds, which has 3000 time-points for a 100 Hz sampling rate. For a sequence with 3000 elements, through our preliminary experiments, RNN takes more than 20 times as long to train as CNN. Moreover, MLP is not popular due to its inferior effectiveness (e.g., non-linear ability) to the other algorithms because of its simple deep learning architecture.

Additionally, for the representative models, DBN, especially DBN-RBM, is the most popular model for feature extraction. DBN is widely used in BCI because of two advantages: 1) it is an

²¹Time-point represents one sampling point. For example, we can have 100 time-points if the sampling rate is 100 Hz.

efficient procedure to learn the top-down generative parameters that determine how the variables in one layer depend on the variables in the layer above; 2) the values of the latent variables in every layer can be inferred by a single, bottom-up pass that starts with an observed data vector in the bottom layer and uses the generative weights in the reverse direction. However, most work that employs the DBN-RBM model were published before 2016, indicating DBN is currently not popular. It can be inferred that the researchers prefer to use DBN for feature learning followed by a non-deep learning classifier before 2016; but recently, an increasing number of studies prefer to adopt CNN or hybrid models for both feature learning and classification.

Moreover, generative models are rarely employed independently. The GAN and VAE based data augmentation and image reconstruction are mainly focused on fMRI and EEG signals. It has been demonstrated that a trained classifier will achieve more competitive performance after data augmentation. Therefore, this is a promising research prospect in the future.

Last but not least, there are fifty-three publications proposing hybrid models for BCI studies. Among them, the combinations of RNN and CNN make up about one-fifth. Since RNN and CNN are known to have excellent temporal and spatial feature extraction ability, it is natural to combine them for both temporal and spatial feature learning. Another type of hybrid models is the combination of representative and discriminative models. This is easy to understand because the former is employed for feature refining and the latter is employed for classification. There are twenty-eight publications using this type of hybrid deep learning model, covering almost all types of BCI signals. The adopted representative models are mostly AE or DBN-RBM, while the adopted discriminative models are mostly CNN. Furthermore, there are twelve papers proposed other hybrid models, such as two discriminative models. For example, several studies proposed the combination of CNN and MLP where the CNN structure is used to extract spatial features which are fed into an MLP for classification.

6 BCI APPLICATIONS

Deep learning models have contributed to various BCI applications including health care, smart environments, security, affective computing, etc. In Table 7, we summarized deep learning based BCI paradigms. The papers focused on signal classification without a specific application are not listed in this table. Therefore, the publication numbers in this table are lower than in Table 5.

6.1 Health Care

In the health care area, deep learning based BCI systems mainly work on the detection and diagnosis of mental diseases such as sleeping disorders, Alzheimer's Disease, epileptic seizure, and other disorders. In the first place, for the sleeping disorder detection, most studies are focused on sleep-stage detection based on sleeping spontaneous EEG. In this situation, the researchers do not need to recruit patients with sleeping disorders because the sleeping EEG signals can be easily collected from healthy individuals. In terms of the algorithm, it can be observed from Table 7 that the DBN-RBM and CNN are widely adopted for feature engineering and classification. Ruffini et al. [164] went one step further by detecting REM Behavior Disorder (RBD) which may cause neurodegenerative diseases such as Parkinson's disease. They achieved an average accuracy of 85% in recognition of the RBD from healthy controls.

Moreover, fMRI is widely used in the diagnosis of Alzheimer's Disease. By taking advantage of the high spatial resolution of fMRI, the diagnosis achieved an accuracy of above 90% in several studies. Another reason that contributes to competitive performance is the binary classification paradigm. Additionally, several publications aim to diagnose AD based on spontaneous EEG [138, 254].

Table 7. Summary of deep learning based BCI applications. The ‘local’ dataset refers to private or not publicly available dataset and the public datasets (with links) will be introduced in Section 6.9. In the signals, S-EEG, MD EEG, and E-EEG separately denote sleeping EEG, mental disease EEG, and emotional EEG. The single ‘EEG’ refers to the other subcategory of spontaneous EEG. In the models, RF and LR denote to random forest and logistic regression algorithms, respectively. In the performance column, ‘N/A’, ‘sen’, ‘spe’, ‘aro’, ‘val’, ‘dom’, and ‘like’ denote not-found, sensitivity, specificity, arousal, valence, dominance, and liking, respectively.

BCI Applications	Reference	Signals	Deep Learning Models	Dataset	Performance
Sleeping Quality Evaluation	Vilamala et al. [214]	S-EEG	CNN	Sleep-EDF	0.86
	Chambon et al. [35]	S-EEG	Multi-view CNN	MASS session 3	N/A
	Zhang et al. [241]	S-EEG	DBN + voting	UCD	0.9131
	Tsinalis et al. [206]	S-EEG	CNN	Sleep-EDF	0.82
	Sors et al. [186]	S-EEG	CNN	SHHS	0.87
	Manzano et al. [128]	S-EEG	CNN + MLP	Sleep-EDF	0.732
				University	
	Shahin et al. [177]	S-EEG	MLP	Hospital in Berlin	0.9
	Manzano et al. [129]	S-EEG	CNN, MLP	Sleep-EDF	0.686/0.689
	Supratak et al. [197]	EEG, EOG	CNN + LSTM	MASS/Sleep-EDF	0.862/0.82
	Xia et al. [224]	EOG	DBN-RBM + HMM	Sleep-EDF	0.833
	Ruffini et al. [164]	S-EEG	RNN	Local	0.85
	Fraiwan et al. [50]	S-EEG	DBN-AE + MLP	Local	0.804
	Tan et al. [201]	S-EEG	DBN-RBM	Local	0.9278 (F1)
	Fernandez et al. [49]	EEG, EOG	CNN	SHHS	0.9 (F1)
Health Care	Biswai et al. [27]	S-EEG	RNN	Local	0.8576
	Hu et al. [80]	fMRI	D-AE + MLP	ADNI	0.875
	Morabito et al. [138]	MD EEG	CNN	Local	0.82
	Suk et al. [195]	fMRI	DBN-AE; DBN-RBM	ADNI	0.979; 0.954
	Zhao et al. [254]	MD EEG	DBN-RBM	Local	0.92
	Sarraf et al. [171]	fMRI	CNN	ADNI	0.9685
	Sarraf et al. [172]	fMRI	CNN	ADNI	0.999
	Bhatkoti et al. [26]	fMRI, PET	AE + MLP	ADNI	0.7922
	Ortiz et al. [147]	fMRI, PET	DBN-RBM + SVM	ADNI	0.9
	Li et al. [109]	fMRI	CNN + LR	ADNI	0.9192
Seizure Detection	Tsiouris et al. [207]	MD EEG	LSTM	CHB-MIT	~0.99
	Yuan et al. [240]	MD EEG	Attention-MLP	CHB-MIT	0.9661
	Yuan et al. [239]	MD EEG	D-AE + SVM	CHB-MIT	0.95
	Ullah et al. [211]	MD EEG	CNN + voting	UBD	0.954
	Lin et al. [111]	MD EEG	D-AE	UBD	0.96
	Hosseini et al. [78]	MD EEG	D-AE + MLP	Local	0.94
	Page et al. [149]	MD EEG	DBN-AE + LR	N/A	0.8 ~ 0.9
	Golmohammadi et al. [56]	MD EEG	RNN+CNN	TUH	Sen: 0.3083; Spe: 0.9686
	Wen et al. [223]	MD EEG	AE	Local	0.92
	Acharya et al. [3]	MD EEG	CNN	UBD	0.8867
	Schirmeister et al. [173]	MD EEG	CNN	TUH	0.854
	Hosseini et al. [79]	MD EEG	CNN	Local	N/A
	Talathi et al. [199]	MD EEG	GRU	BUD	0.996
	Kiral et al. [93]	EcoG	MLP	Local	Sen: 0.69
	Johansen et al. [87]	MD EEG	CNN	Local	0.947 (AUC)
	Ansari et al. [10]	MD EEG	CNN + RF	Local	0.77

Table 7. Summary of deep learning based BCI applications (Continued).

BCI Applications	Reference	Signals	Deep Learning Models	Dataset	Performance	
Seizure Detection	Hosseini et al. [77]	EEG, EcoG	CNN	Local	0.96	
	Shah et al. [176]	MD EEG	CNN+ LSTM	TUH	Sen: 0.39; Spe: 0.9037	
	Turner et al. [209]	MD EEG	DBN-RBM + LR	Local	N/A	
Health Care	Others:					
	Garg [54]	MEG	CNN	Local	Sen: 0.85, Spe: 0.97	
	Hasasneh et al. [70]	MEG	CNN + MLP	Local	0.944	
	Acharya et al. [4]	MD EEG	CNN	Local	0.935 ~ 0.9596	
	Al et al. [7]	MD EEG	DBN-RBM + MLP	Local	0.695	
	Morenolopez et al. [133]	fMRI	CNN	BRATS	0.88 (F1)	
	Havaei et al. [71]	fMRI	Multi-scale CNN	BRATS	0.88 (F1)	
	Shreyas et al. [182]	fMRI	CNNC	BRATS	0.83	
Depression	Antoniades et al. [12]	EcoG	CNN	Local	0.8751	
	Antoniades et al. [11]	EEG, EcoG	AE + CNN	Local	0.68	
	Pilis et al. [156]	fMRI	DBN-RBM	Combined	0.9 (F1)	
Brain Tumor	Chu et al. [38]		CNN + RF + Voting	Local	0.816, 0.967, 0.992	
	Morabito et al. [139]	MD EEG	D-AE	Local	0.81 ~ 0.83	
	Suk et al. [196]	fMRI	AE + SVM	ADNI2	0.7258	
Smart Environment	Robot Control	Behncke et al. [24]	EEG	CNN	0.75	
	Exoskeleton Control	Huve et al. [84]	fNIRS	MLP	0.82	
	Smart Home	Kwak et al. [98]	SSVEP	CNN	0.9403	
		Zhang et al. [247]	MI EEG	RNN	EEGMMI	0.9553
Brain Communication	Kawasaki et al. [89]	VEP	MLP	Local	0.908	
	Cecotti et al. [31]	VEP	CNN + Voting	The third BCI competition, Dataset II	0.955	
	Zhang et al. [250]	MI EEG	LSTM-CNN + AE	Local	0.9452	
	Cecotti et al. [31]	VEP	CNN	The third BCI competition, Dataset II	0.945	
	Maddula et al. [123]	VEP	RCNN	Local	0.65~0.76	
	Liu et al. [115]	VEP	CNN	The third BCI competition, Dataset II	0.92 ~ 0.96	
Security	Identification	Zhang et al. [249]	MI-EEG	Attention-based RNN	EEGMMI + local	0.9882
		Koike et al. [94]	VEP	MLP	Local	0.976
	Authentication	Mao et al. [132]	RSVP	CNN	Local	0.97
		Zhang et al. [245]	MI EEG	Hybrid	EEGMMI + local	0.984
Affective Computing	Mioranda et al. [137]	E-EEG	RNN + CNN	AMIGOS	0.7	
	Jia et al. [85]	E-EEG	DBN-RBM	DEAP	0.8 ~ 0.85 (AUC)	
	Li et al. [105]	E-EEG	Hierarchical CNN	SEED	0.882	
	Xu et al. [227]	E-EEG	DBN-AE, DBN-RBM	DEAP	0.86 (F1)	
	Liu et al. [117]	E-EEG	CNN	Local	0.82	
	Frydenlund et al. [51]	E-EEG	MLP	DEAP	N/A	
	Yin et al. [237]	E-EEG	Multi-view D-AE + MLP	DEAP	Aro: 0.7719; Val: 0.7617	
	Chai et al. [34]	E-EEG	AE	SEED	0.818	
	Kawde et al. [90]	EEG, EOG	DBN-RBM	DEAP	Aro: 0.7033; Val: 0.7828; Dom: 0.7016	
	Li et al. [110]	E-EEG	DBN-RBM	DEAP	Aro: 0.642, Val: 0.584, Dom: 0.658	

Table 7. Summary of deep learning based BCI applications (Continued).

BCI Applications	Reference	Signals	Deep Learning Models	Dataset	Performance
Affective Computing	Xu et al. [228]	E-EEG	DBN-RBM	DEAP	Aro:0.6984, Val:0.6688, Lik: 0.7539
	Zheng et al. [258]	E-EEG	DBN-RBM + HMM	Local	0.8762
	Alhagry et al. [8]	E-EEG	LSTM + MLP	DEAP	Aro:0.8565, Val:0.8545, Lik: 0.8799
	Li et al. [75]	E-EEG	CNN DBN-RBM + MLP	SEED	0.882
	Zhang et al. [255, 256]	E-EEG	DBN-RBM + MLP	SEED	0.8608
	Liu et al. [118]	EEG, EOG	AE	SEED, DEAP	0.9101, 0.8325
	Gao et al. [53]	E-EEG	DBN-RBM + MLP	Local	0.684
Drive Fatigue Detection	Zhang et al. [244]	E-EEG	RNN	SEED	0.895
	Hung et al. [82, 82]	EEG	CNN	Local	0.572 (RMSE)
	Hajinoroози et al. [64]	EEG	DBN-RBM	Local	0.85
	Hung et al. [82]	EEG	CNN	Local	
	Du et al. [45]	EEG, EOG	D-AE + SVM	Local	0.094 (RMSE)
	San et al. [169]	EEG	DBN-RBM + SVM	Local	0.7392
	Almogbel et al. [9]	EEG	CNN	Local	0.9531
	Hachem et al. [62]	SSVEP	MLP	Local	0.75
	Chai et al. [33]	EEG	DBN + MLP	Local	0.931
	Hajinoroози et al. [65, 65]	EEG	CNN	Local	0.8294
Mental Load Measurement	Naseer et al. [143]	fNIRS	MLP	Local	0.963
	Yin et al. [236]	EEG	D-AE	Local	0.9584
	Hennrich et al. [72]	fNIRS	MLP	Local	0.641
	Bashivan et al. [22]	EEG	R-CNN	Local	0.9111
	Bashivan et al. [21]	EEG	DBN + MLP	Local	N/A
	Bashivan et al. [23]	EEG	DBN-RBM	Local	0.92
	Li et al. [108]	EEG	DBN-RBM	Local	0.9886
School Bullying	Baltatzis et al. [18]	EEG	CNN	Local	0.937
	Stober et al. [190]	EEG	CNN	Local	0.776
Music Detection	Stober et al. [192]	EEG	AE + CNN	Open MIIR	0.27 for 12-class
	Stober et al. [191]	EEG	CNN	Local	0.244
Number Choosing	Sternin et al. [189]	EEG, EOG	CNN	Local	0.75
	Waytowich et al. [221]	SSVEP	CNN	Local	0.8
Other Applications	Cichy et al. [40]	fMRI, MEG	CNN	N/A	N/A
	Manor et al. [126]	RSVP	CNN	Local	0.75
	Cecotti et al. [29]	RSVP	CNN	Local	0.897 (AUC)
	Hajinoroози et al. [66]	RSVP	CNN	Local	0.7242 (AUC)
	Perez et al. [153]	SSVEP	AE	Local	0.9778
	Shamwell et al. [178]	RSVP	CNN	Local	0.7252 (AUC)
	Xie et al. [225, 226]	EcoG	RNN+CNN	BCI Competition IV	N/A
Finger Traектор Guilty Knowledge Test	Kulasingham et al. [96]	SSVEP	DBN-RBM; DBN-AE	Local	0.869; 0.8601
	Liu et al. [116]	EEG	DBN-RBM	Local	0.973
Concealed Information Test	Volker et al. [215]	EEG	CNN	Local	0.841
	Narejo et al. [141]	EEG	DBN-RBM	UCI	0.989
Flanker Task	Reddy et al. [159]	EEG	MLP	Local	0.975
	Teo et al. [203]	EEG	MLP	Local	0.6399
Eye State	Hernandez et al. [73]	EEG	CNN	Local	0.718
	Hiroyasu et al. [75]	fNIRS	D-AE + MLP	Local	0.81
User Preference Emergency Braking Gender Detection	Putten et al. [157]	EEG	CNN	Local	0.81

Another area that has attracted much attention is the diagnosis of epileptic seizure. Seizure detection is mainly based on mental disease spontaneous EEG and occasionally on ECoG signals. The popular deep learning models in this scenario are independent CNN and RNN, along with hybrid models combining RNN and CNN. Some models integrated deep learning models for feature extraction and traditional classifiers for detection [149, 209]. For example, Yuan et al. [239] applied a D-AE in feature engineering followed by SVM for seizure diagnosis. Ullah et al. [211] adopted voting for post-processing, which proposed several different CNN classifiers and predicted the final result by voting.

Furthermore, there are a lot of other healthcare issues which can potentially be solved by BCI systems. Cardiac artifacts in MEG signals can be automatically detected by deep learning models[54, 70]. Several modified CNN structures are proposed to detect brain tumors based on fMRI from the public BRATS dataset [71, 133, 182]. The literature demonstrates the effectiveness of deep learning models in the detection of a number of mental disorders such as depression [4], Interictal Epileptic Discharge (IED) [12], schizophrenia [156], Creutzfeldt-Jakob Disease (CJD) [139], and Mild Cognitive Impairment (MCI) [196].

6.2 Smart Environment

The smart environment is a promising application scenario for BCI in the future. With the development of Internet of Things (IoT), an increasing number of smart environments can be connected to BCI. For example, an assisting robot can be used in smart home [247, 253], in which the robot can be controlled by brain signals of the individuals. Moreover, Behncke et al. [24] and Huve et al. [84] investigated how to control a robot based on the visual stimulated spontaneous EEG and fNIRS signals. BCI controlled exoskeletons could help people with damaged to the motor control in the lower limbs in walking and daily activities [98]. In the future, research on brain-controlled appliances may be beneficial to the elderly people and the disabled in creating smart homes and smart hospitals.

6.3 Brain Communication

The biggest advantage of BCI, compared to other human-machine interface techniques, is that BCI enables patients who have lost most motor abilities, like speaking, to communicate with the outer world. Deep learning technology has substantially improved the efficiency of brain signal based communications. One typical paradigm which enables individual to type without any motor system is the P300 speller which can convert the user's intent into text [89]. Powerful deep learning models allow the BCI systems to recognize P300 segments from non-P300 segments while the former contains the communication information of the user [31]. At a higher level, representative deep learning models can help to detect what character (as shown in Figure 12b) the user is focusing on and print it on the screen to chat with others [31, 115, 123].

Additionally, Zhang et al. [250] proposed a hybrid model combined RNN, CNN, and AE to extract informative features from MI EEG to recognize what letter the user wants to type. The proposed interface including 27 characters (26 English alphabets and the space bar) and all of them are separated by 3 character blocks (each block contains 9 characters) in the initial interface. Overall, there are three alternative selections, and each selection will lead to a specific sub-interface which includes 9 characters. Again, the $9 = 3 \times 3$ characters are divided into three character blocks, and each of them contains nine characters. Again, the $9 = 3 \times 3$ characters are divided into three character blocks, and each of them is connected to a lower level interface. In the bottom level, each block represents only one character. However, compared to P300 speller, the MI-based protocols

have lower information transform rate because it requires three operations to find the specific letter at the bottom level.

6.4 Security

The security field is a common area of interest for BCI researchers. The security problem can be divided into identification (also called recognition) and authentication (also called verification) aspects. The former generally is a multi-class classification problem, and its aim is to recognize the identity of the test-person [249]. The latter usually is a binary classification problem, which only cares whether the test-person is authorized or unauthorized [245].

The existing biometric identification/authentication systems are mainly based on individuals' unique intrinsic physiological features (e.g., face, iris, retina, voice, and fingerprint). However, the state-of-the-art person identification systems are vulnerable, e.g., anti-surveillance prosthetic masks can thwart face recognition, contact lenses can trick iris recognition, vocoders can compromise voice identification, and fingerprint films can deceive fingerprint sensors. In this perspective, the EEG (Electroencephalography) based biometric person identification systems are emerging as promising alternatives due to their high attack-resilience. An individual's EEG signals are virtually impossible to mimic for an imposter, thus making this approach highly resilient to spoofing attacks encountered by other identification techniques. Koike et al. [94] have adopted deep neural networks to identify the user's ID based on VEP signals while Mao et al. [132] applied CNN for person identification based on RSVP signals. Zhang et al. [249] proposed an attention-based LSTM model and evaluated it over both public and local datasets. The authors [245] then combined EEG signals with gait information to introduce a dual-authentication system with a hybrid deep learning model.

6.5 Affective Computing

The affective states of a user provide critical information for many applications such as personalized information (e.g., multimedia content) retrieval or intelligent human-computer interface design [227]. Recent research illustrated that deep learning models can enhance the performance of affective computing. Emotion can be defined according to several dimensions. Dimensional models of emotion attempt to conceptualize human emotions by defining where they lie in two or three dimensions. The most widely used circumplex model states the emotions are distributed in two dimensions: arousal and valence. The arousal refers to the intensity of the emotional stimuli or how strong the emotion is. The valence refers to the relationship within the person who experiences the emotion (positive to negative). In some other models, the dominance and liking dimensions are used instead.

Some papers only attempt to classify the user's emotional state into a binary (positive/negative) or three-category (positive, neutral, and negative) problem and seek to identify them using deep learning algorithms [51]. A range of publications adopted CNN and its variants to classify emotional EEG signals [105, 117, 216]. The DBN-RBM is the most representative deep learning model used to discover concealed features from emotional spontaneous EEG [227, 256]. Xu et al. [227] applied a DBN-RBM as specific feature extractors for the affective state classification problem using EEG signals.

Furthermore, at a more fundamental level, some researchers aim for the recognition of a positive/negative state for each specific emotional dimension. For example, Yin et al. [237] proposed a multiple-fusion-layer based ensemble classifier of AE for recognizing emotions. Each AE consists of three hidden layers to filter the unwanted noise in the physiological features and derives the stable feature representations. The proposed model was evaluated over the benchmark DEAP and achieved the arousal of 77.19% and valence of 76.17%. Mioranda et al. [137] presented a

multi-task cascaded deep neural network which jointly predicts people's affective levels (valence and arousal) and personal factors using EEG signals recorded in response to the presentation of affective multimedia content.

6.6 Driver Fatigue Detection

Vehicle driver's ability to maintain optimal performance and attention is essential to ensure the safety of the traffic. EEG signals have been proven to be useful in evaluating peoples cognitive state during specific tasks [9]. Generally, the driver is regarded as being in an alert state if the reaction time is below or equal to 0.7 seconds and in a fatigued state if the reaction time is higher or equal to 2.1 seconds. Hajinorozi et al. [64] considered the prediction of driver's fatigue from EEG signals by extracting the distinct features. They explored an approach based on DBN for dimensionality reduction.

The detection of driver fatigue is crucial because the drowsiness of the driver may lead to accidents. Additionally, driver fatigue detection is feasible in the real world. In terms of the hardware, the equipment used to collect EEG signals is off-the-shelf and portable enough to be used in a car. Moreover, the price of an EEG headset is affordable for most people. In terms of the algorithms, deep learning models have greatly enhanced the performance of fatigue detection. As we summarized, the EEG based driving drowsiness can be recognized with high accuracy (82% ~ 95%).

The future scope of driver-fatigue detection is in the self-driving scenario. As we know, in most self-driving situations (e.g., Automation level 3²²), the human driver is expected to respond appropriately to a request to intervene, which necessitates that the driver should maintain an alert state. Therefore, we believe the application of BCI based drive fatigue detection will benefit the development of the self-driving car.

6.7 Mental Load Measurement

Evaluation of operator mental workload levels via ongoing electroencephalogram (EEG) is quite promising in Human-Machine collaborative task environments to alert when the operator performance is degraded[236]. The human operator works as a vital component in automation systems for decision making and strategy development. However, unlike machines or computers, the human functional states cannot always fit the task requirements due to limited working memory and time-dependent psychophysiological experience. Therefore, In such a case, operator performance degradation caused by abnormal cognitive states, e.g., high working stress or distraction, is considered to be a crucial factor for catastrophic accidents [152].

A number of researchers have focussed on this topic. The mental workload can be measured from fNIRS signals or spontaneous EEG. Naseer et al. [143] analyzed and compared the classification accuracies of six different classifiers, including five traditional classifiers and a MLP classifier for a two-class mental task (mental arithmetic and rest) using fNIRS signals. The experiment results showed that the MLP outperformed the traditional classifiers like SVM, kNN and achieved the highest accuracy of 96.3%. Bashivan et al. [23] presented a statistical approach, a DBN model, to predict cognitive load from single trial EEG. Before the DBN, the authors manually extracted the wavelet entropy and band-specific power from theta, alpha and beta bands. Finally, the experiments demonstrated the recognition of cognitive load across four different levels with an overall accuracy of 92% during execution of a memory task.

²²https://en.wikipedia.org/wiki/Self-driving_car

Table 10. The summary of public dataset for BCI systems. ‘# Sub’, ‘# Cla’, and S-Rate denote the number of subject, the number of class, and the sampling rate, respectively. FM denote finger movement while BCI-C denote the BCI competition. The datasets may contain more biometric signals (e.g., ECG) but we only list the channels related to BCI.

BCI Signals		Name Link	# Sub	# Cla	S-Rate	# Channel
Inv-asive	FM EcoG	BCI-C IV ²³ , Dataset IV	3	5	1000	48 ~ 64
	MI EcoG	BCI-C III ²⁴ , Dataset I	1	2	1000	64
EEG	Sleeping EEG	Sleep-EDF ²⁵ : Telemetry	22	6	100	2 EEG, 1 EOG, 1 EMG
		Sleep-EDF: Cassette	78	6	100, 1	2 EEG (100Hz), 1 EOG (100Hz), 1 EMG (1Hz)
		MASS-1 ²⁶	53	5	256	17/19 EEG, 2 EOG, 5 EMG
		MASS-2	19	6	256	19 EEG, 4 EOG, 1EMG
		MASS-3	62	5	256	20 EEG, 2 EOG, 3 EMG
		MASS-4	40	6	256	4 EEG, 4 EOG, 1 EMG
	Seizure EEG	MASS-5	26	6	256	20 EEG, 2 EOG, 3 EMG
	MI EEG	SHHS ²⁷	5804	N/A	125, 50	2 EEG (125Hz), 1 EOG (50Hz), 1 EMG (125Hz)
		CHB-MIT ²⁸	22	2	256	18
	Emotional EEG	TUH ²⁹	315	2	200	19
		EEGMMI ³⁰	109	4	160	64
		BCI-C II ³¹ , Dataset III	1	2	128	3
		BCI-C III, Dataset III a	3	4	250	60
		BCI-C III, Dataset III b	3	2	125	2
		BCI-C III, Dataset IV a	5	2	1000	118
		BCI-C III, Dataset IV b	1	2	1001	119
	Others EEG	BCI-C III, Dataset IV c	1	2	1002	120
		BCI-C IV, Dataset I	7	2	1000	64
		BCI-C IV, Dataset II a	9	4	250	22 EEG, 3 EOG
		BCI-C IV, Dataset II b	9	2	250	3 EEG, 3 EOG
		AMIGOS ³²	40	4	128	14
VEP	SEED³³	SEED ³³	15	3	200	62
		DEAP ³⁴	32	4	512	32
fMRI	Open MIR³⁵	Open MIR ³⁵	10	12	512	64
MEG	BCI-C II, Dataset II b	1	36	240	64	
	BCI-C III, Dataset II	2	26	240	64	
ADNI³⁶	ADNI ³⁶	202	3	N/A	N/A	
	BRATS ³⁷ 2013	65	4	N/A	N/A	
BCI-C IV, Dataset III		2	4	400	10	

²³ <http://www.bbci.de/competition/iv/>

²⁴ <http://www.bbci.de/competition/iii/>

²⁵ <https://physionet.org/physiobank/database/sleep-edfx/>

²⁶ <https://massdb.herokuapp.com/en/>

²⁷ <https://physionet.org/pn3/shhpsgdb/>

²⁸ <https://physionet.org/pn6/chbmit/>

²⁹ https://www.isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml

³⁰ <https://physionet.org/pn4/eegmmidb/>

³¹ <http://www.bbci.de/competition/ii/>

³² <http://www.eecs.qmul.ac.uk/mmv/datasets/amigos/readme.html>

³³ <http://bcmi.sjtu.edu.cn/seed/download.html>

6.8 Other Applications

Apart from the aforementioned key applications, there are still some interesting scenarios, such as recommender system [203] and emergency braking [73] to which deep learning based BCI can be applied. One possible topic is the recognition of a visual object, which may be used in guilty knowledge test [96] and concealed information test [116]. The neurons of the participant will produce a pulse when he/she suddenly perceives a familiar object. Based on the theory, visual target recognition mainly uses RSVP signals. Cecotti et al. [29] investigated the performance of CNNs in terms of their architecture and how they are evaluated. Specifically, the authors aimed to build a common model target recognition which can work for various subjects instead of a specific subject. They addressed the change of performance that can be observed between specifying a neural network for a single subject, or by considering a neural network for a group of subjects, taking advantage of a larger number of trials from different subjects.

Other researchers have investigated whether it is possible to distinguish the subject's gender using fNIRS [75] or spontaneous EEG [157]. Hiriayasu et al. [75] adopted deep learning to recognize the gender of the subject based on the cerebral blood flow. The experiment results suggested that there exists a relation between cerebral blood flow changes and biological information. Putten et al. [157] tried to discover the sex-specific information from the brain rhythms and adopted a CNN model to recognize the participant's gender. This paper illustrated that fast beta activity (20 ~25 Hz), and its spatial distribution is one of the main distinctive attributes.

6.9 Benchmark Datasets

In this section, we extensively explore the benchmark datasets which can be used in deep learning based BCI. As listed in Table 10, we provide 31 reusable public datasets with download links, which cover most BCI signals. The BCI competition IV (BCI-C IV) contains five datasets. We give the access link at the first dataset. For better understanding, we present the number of subjects, the number of classes (how many categories), sampling rate and the number of channels of each dataset. In the '# Channel' column, the default channel is EEG signals.

7 FUTURE DIRECTIONS

Although deep learning has increased the performance of BCI systems, technical and usability challenges remain. The technical challenges concern the classification ability in complex BCI scenarios; and the usability challenges refer to limitations in large scale real-world deployment. In this section, we introduce these challenges and point out the possible solutions.

7.1 General Framework

Until now, we have introduced several types of BCI signals (e.g., spontaneous EEG, ERP, fMRI) and deep learning models that have been applied for each type. One promising research direction for deep learning based BCI is to develop a general framework that can handle various BCI signals regardless of the number of channels used for signal collection, the sample dimensions (e.g., 1-D or 2-D sample), and stimulation types (e.g., visual or audio stimuli), etc. The general framework would require two key capabilities: the attention mechanism and the ability to capture latent features. The former guarantees the framework can focus on the most valuable parts of input signals and the latter enables the framework to capture the distinctive and informative features.

³⁴<https://www.eecs.qmul.ac.uk/mmv/datasets/deap/>

³⁵https://owenlab.uwo.ca/research/the_openmiir_dataset.html

³⁶<http://adni.loni.usc.edu/data-samples/access-data/>

³⁷<https://www.med.upenn.edu/sbia/brats2018/data.html>

The attention mechanism can be implemented based on attention scores or by various machine learning algorithms such as reinforcement learning. The attention scores can be inferred from the input data and work as a weight to help the framework to pay attention to the parts with high attention scores. Reinforcement learning has been shown to be able to find the most valuable part through a policy search [248]. CNN is the most suitable structure for capturing features in various levels and ranges. In the future, CNN could be used as a fundamental feature learning tool and be integrated with suitable attention mechanisms to form a general classification framework.

7.2 Person-independent Classification

Until now, most BCI classification tasks focus on person-dependent scenarios, where the training and the testing sets come from the same person. The future direction is to realize person-independent classification so that the testing data will never appear in the training set. High-performance person-independent classification is necessary for the wide application of BCI Systems in the real-world.

One possible solution to achieving this goal is to build a personalized model with transfer learning. A personalized effective model can adopt a transductive parameter transfer approach to construct individual classifiers and to learn a regression function that maps the relationship between data distribution and classifier parameters [257]. Another potential solution is mining the subject-independent components from the input data. The input data can be decomposed into two parts: a subject-dependent component, which depends on the subject and a subject-independent component, which is common for all subjects. A hybrid multi-task model can work on two tasks simultaneously, one focusing on person identification and the other on class recognition. A well-trained and converged model ought to extract the subject-independent features in a class recognition task.

7.3 Semi-supervised and Unsupervised Classification

The performance of deep learning models highly depends on the size of training data, which requires expensive and time-consuming manual labeling to collect abundant class labels in a wide range of scenarios such as sleeping EEG. While supervised learning requires both observations and labels for the training, unsupervised learning requires no labels and semi-supervised learning only requires partial labels [85]. Therefore, they are more suitable for problems with little ground truth data available.

Zhang et al. proposed an Adversarial Variational Embedding (AVAE) framework that combines a VAE++ model (as a high-quality generative model) and semi-supervised GAN (as a posterior distribution learner) [251] for robust and effective semi-supervised learning. Jia et al. [85] proposed a semi-supervised framework by leveraging label information in feature extraction and integrating unlabeled information to regularize the supervised training.

Two methods may enhance unsupervised learning: one is to employ crowd-sourcing to label the unlabeled observations; the other is to leverage unsupervised domain adaption learning to align the distribution of source BCI signals and the distribution of target signals with a linear transformation.

7.4 Hardware Portability

Poor portability of hardware has prevented the wide application of BCI systems in the real world. In most scenarios, users would like to use small, comfortable, or even wearable BCI hardware to collect brain signals and to control appliances and assistant robots.

Currently, there are three types of EEG collection equipment: the unportable, the portable headset, and ear-EEG sensors. The unportable equipment (e.g., Neuroscan, Biosemi) has high

sampling frequency, channel numbers, and signal quality but is expensive. It is suitable for physical examination in hospital. The portable headsets (e.g., Neurosky, Emotiv EPOC) have 1 ~ 14 channels and 128~ 256 sampling rate but may cause discomfort for users after a long-time use. The ear-EEG sensors, which are attached to the outer ear, have gained increasing attention recently but remain mostly at the laboratory stage [148]. The ear-EEG platform comprises a set of electrodes placed inside each ear canal, together with additional electrodes in the concha of each ear [135]. The EEGGrids, to the best of our knowledge, is the only commercial ear-EEG. It has multi-channel sensor arrays placed around the ear using an adhesive³⁸ and is even more expensive. An promising future direction is to improve the usability by developing a cheaper (e.g., lower than 200\$) and more comfortable (e.g., can last longer than 3 hours without feeling uncomfortable) wireless ear-EEG equipment.

8 CONCLUSION

In this paper, we systematically survey the recent advances in deep learning models for Brain-Computer Interface. Compared with traditional methods, deep learning not only enables to learn high-level features automatically from BCI signals but also depends less on manual-crafted features and domain knowledge. We summarize BCI signals and dominant deep learning models, followed by discussing state-of-the-art deep learning techniques for BCI and identifying the suitable deep learning algorithms for each BCI signal type. Finally, we overview deep learning based BCI applications and point out the open challenges and future directions.

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³⁸<http://ceegrid.com/home/concept/>

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