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Deep Learning in EEG: Advance of the Last Ten-Year Critical Period

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***Abstract*—Deep learning has achieved excellent performance in a wide range of domains, especially in speech recognition and computer vision. Relatively less work has been done for EEG, but there is still significant progress attained in the last decade. Due to the lack of a comprehensive and topic widely covered survey for deep learning in EEG, we attempt to summarize recent progress to provide an overview, as well as perspectives for future developments. We first briefly mention the artifacts removal for EEG signal and then introduce deep learning models that have been utilized in EEG processing and classification. Subsequently, the applications of deep learning in EEG are reviewed by categorizing them into groups such as brain-computer interface, disease detection, and emotion recognition. They are followed by the discussion, in which the pros and cons of deep learning are presented and future directions and challenges for deep learning in EEG are proposed. We hope that this paper could serve as a summary of past work for deep learning in EEG and the beginning of further developments and achievements of EEG studies based on deep learning.**

***Index Terms*—Deep Learning, Electroencephalogram (EEG), Classification, Brain-Computer Interface, Disease, Emotion, Sleep, Mental State**

I. Introduction

MACHINE learning technology has benefited to diverse domains in our modern society [1], [2]. Deep learning, a subcategory of machine learning technology, has been showing excellent performance in pattern recognition [3], dramatically improving classification accuracy. It is worth noting that new world records were created by using deep learning in many competitions such as ImageNet Competition [4]. The research outcomes of deep learning in speech recognition [5] and computer vision [6] have been successfully utilized to develop practical application systems, which are remarkably influencing our life and even changing our lifestyle.

Deep learning is an enhanced variant of traditional neural network, which is thought to be established based on the inspiration of hierarchical structure existing in visual cortex of the human brain. The adjective 'deep' in the term of deep learning describes the attribute of multiple processing layers forming a long-cascaded architecture. The extracted information becomes more and more abstract from the lowest layer to the highest layer. This is one of the advantages for the deep learning as information expression could be more meaningful when passing onto a higher layer. Meanwhile, deep learning suffers from the issues of slow convergence and high computation demand. These disadvantages have been released by introducing training strategies such as dropout [7] and batch normalization [8], and the availability of high-performance computers. The high performance is not only due to the capacity improvement of central processing units, but also new computing units such as graphic processing unit and tensor processing unit. These new computing units are designed to suit matrix manipulation, which greatly reduce computational time in deep learning. Moreover, the availability of large scale of data and increased capacity of data storage also promote the use of deep learning.

Electroencephalogram (EEG) signal was first recorded by Hans Berger in the year of 1924 [9], which manifests underlying brain activity. Multiple electrodes can be set to record EEG signal by placing them on different locations of the scalp and temporal fluctuations in voltage can be captured in a high resolution (e.g., in milliseconds) by using a high sampling rate. With the advantages of multi-channel recording and high temporal resolution, EEG has been applied to numerous domains from brain-computer interface [10], [11], [12], [13], to emotion [14], [15], to cognition [16], to brain diseases [17]. EEG processing methodology is evolved from simple methods such as mean and amplitude comparison to complicated methods such as connectivity topology and deep learning. In particular, deep learning exhibits better performance in EEG classification (a.k.a., recognition or identification) compared to conventional methods (e.g., support vector machine). By using deep learning, discriminative features could be extracted without handcraft, which requires specific knowledge and expertise. It could avoid the low performance derived from unsuitable handcrafted features. However, deep learning is not a destination because model architecture and parameters have to be set manually. A good classification performance is usually not obtained by just feeding data into a deep learning model. This is because the target signal is much weaker than the background signal and noise, resulting in a low signal-to-noise ratio. Therefore, artifacts removal is commonly adopted to remove artifacts so that the signal-to-noise ratio can be improved before feeding into a deep learning model. This

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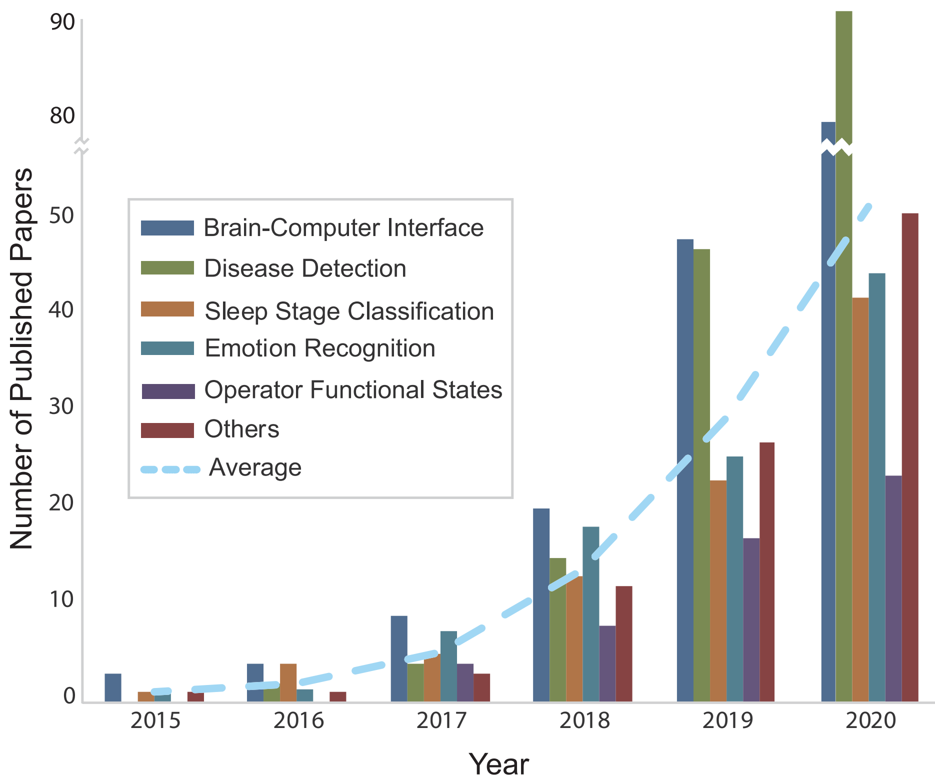

Fig. 1. Numbers of the published papers in each year. Note that numbers before 2015 are omitted because of rare papers.

is quite different compared to image or video processing, where image or video is directly fed into a deep learning model. To date, different kinds of deep learning models have been employed to process and classify EEG signal. Cecotti et al. used convolutional neural network (CNN) to extract features from steady-state visual evoked potential in 2008 [18]. Li et al. employed denoising autoencoder to classify two classes of motor imagery using EEG recorded from 14 electrodes on the sensorimotor cortex [19]. Tsiouris et al. applied recurrent neural network (RNN) to capture sequential relationships for seizure detection [20]. A survey covering six EEG-based applications was done in 2019, where studies were reviewed separately for task type, model type and so on [21]. A more specialized survey on motor imagery classification can be found in [22]. A distribution summary showing which disease is dominantly targeted in the studies of deep learning-based disease diagnosis can be found in [23]. If you want to read a survey on brain-computer interface (more beyond motor imagery), it can be found in Section 5 of [24]. If a wide range of topics of deep learning in EEG is sought, this survey can be an option.

Although EEG domain is far behind compared to the domains such as computer vision [25] and speech recognition [26] in terms of adopting deep learning, significant progress has been achieved in the last decade. It is time to summarize the achievements of deep learning in EEG for the past 10 years and discuss current existing issues and future directions. The searching criterion [”Deep Learning” AND ”EEG” AND ”Classification” OR ”Recognition” OR ”Identification”] was used for literature retrieval in the Web of Science in March 2020. After manual selection, 193 papers were included in this survey. During the revision in February 2021, we applied the same searching criterion to find newly-published literature after the previous searching and selected 20 papers to be included in this survey. After the acceptance, seven more papers were further included, but they were not used to update the figures and tables due to the constrained time.

As shown in Fig. 1, the majority of these papers were published after 2017 while there was a rapid increase from the year of 2019. In 2019, the number of papers in the topic of brain-computer interface and disease detection are significantly more than the other topics. In 2020, the numbers of the published papers in more topics are rapidly increased, although disease detection is still a leading topic. The rapid increase of the published papers about deep learning in EEG is continued in 2021. The remainder of the survey is organized as follows. In Section II, artifacts removal is briefly introduced. This is followed by the detailed descriptions of all deep learning models which have been applied to EEG in Section III. In this section, we also mention the advantages and limitations of each deep learning model. Subsequently, the applications of deep learning in EEG are detailed along with publicly available EEG datasets used in these applications in Section IV. Finally, discussions are given and future directions are drawn at the end of the survey. All abbreviations used in this survey are listed in Table I.

II. Artifacts Removal

In general, artifacts are larger than that we intend to extract from EEG signal in terms of scale, leading to a low signal-to-noise ratio (SNR). In order to improve SNR, EEG signal is preprocessed to remove or mitigate the effect of artifacts on the signal before the signal is further processed. For example, a notch filter [16] is effective for eliminating the interference of power line. Independent component analysis [27] is usually utilized to remove eye movements-related and muscular activity-related artifacts. Classical methods of artifacts removal and their targeted artifacts are summarized in Table II.

When deep learning emerges, the step of artifacts removal is kept. EEG signal is preprocessed as usual to remove artifacts before inputting into a deep learning model. This is an effective way as all artifacts removal methods can be applied with deep learning models to be of both benefits inherited from the artifacts removal methods and deep learning models. This is also a natural and straightforward way that researchers are able to easily implement. However, an independent step of artifacts removal is not always necessary. The first several layers in a deep learning model could be functioned as artifacts removal, where noise is removed through the layers. To this end, a few attempts were done. For example, Supratak et al. inputted raw EEG data into a CNN for the classification of sleep stages. Their study showed that an acceptable performance can be achieved without an independent step of artifacts removal [28]. In addition, Bahador et al. mapped the correlation of EEG channels into a 2D space and used a CNN model to learn representations related to particular artifacts. With respect to artifact detection, this method outperformed spectrogram-based CNNs [29]. Moreover, no auxiliary reference signal was required in their method.

III. Deep Learning Models

In this section, we describe each fundamental deep learning model. Their variants and combinations are not included as they share the similar rationale with fundamental models. A deep learning model is a hierarchical structure, comprising layers through which data are mapped into more and more abstract. Whatever a deep learning model is, there are an input layer, an output layer, and one or more hidden units (see Fig. 2(A)). The hidden unit might be one of the layer structures illustrated in Fig. 2(B) or their combinations. In the following subsections, we introduce classical deep learning models where typical units illustrated in Fig. 2(B) are embedded.

A. Restricted Boltzmann Machine and Deep Belief Networks

A restricted Boltzmann machine (RBM) [30] is an undirected graph model (see Fig. 2(B): RBM Unit), which has a visible layer $\mathbf{v} = (v_1, v_2, \ldots, v_n)$ and a hidden layer $\mathbf{h} = (h_1, h_2, \ldots, h_n)$. Connections exist only between visible layer $\mathbf{v}$ and hidden layer $\mathbf{h}$ and there are no connections between nodes within the visible layer or hidden layer. The energy function for an RBM is defined as:

$$E(\mathbf{v}, \mathbf{h}) = -\mathbf{v}^T \mathbf{W} \mathbf{h} - \mathbf{a}^T \mathbf{v} - \mathbf{b}^T \mathbf{h} \tag{1}$$

where $\mathbf{W}$ is the weight matrix, $\mathbf{a}$ and $\mathbf{b}$ are bias vectors. The joint probability of $\mathbf{v}$ and $\mathbf{h}$ is constructed in terms of E:

$$P(\mathbf{v}, \mathbf{h}) = \frac{1}{Z} e^{-E(\mathbf{v}, \mathbf{h})} \tag{2}$$

where Z is a normalizing constant defined as:

$$Z = \sum_{\mathbf{v}, \mathbf{h}} e^{-E(\mathbf{v}, \mathbf{h})} \tag{3}$$

The marginal distribution over the visible variables is obtained as:

$$P(\mathbf{v}) = \frac{1}{Z} \sum_{\mathbf{h}} e^{-E(\mathbf{v}, \mathbf{h})} \tag{4}$$

The conditional probabilities can be described as:

$$P\left(h_j = 1 | \mathbf{v}\right) = \sigma\left(\mathbf{W}_j \mathbf{v} + b_j\right) \tag{5}$$

$$P\left(v_i = 1 | \mathbf{h}\right) = \sigma\left(\mathbf{W}_i \mathbf{h} + a_i\right) \tag{6}$$

where σ is logistic function defined as:

$$\sigma(x) = \left(1 + e^{-x}\right)^{-1} \tag{7}$$

A deep belief network (DBN) is constructed by stacking multiple RBMs [31]. Each RBM in the DBN is trained using an unsupervised manner at first. Then, the output of previous RBM is inputted into the next RBM. All RBMs are fine-tuned together by supervised optimization.

B. Convolutional Neural Network

Convolutional neural network (CNN) [32] is good at capturing spatial information of data (see Fig. 2(B): Convolutional Unit). Most CNNs consist of two types of layers: convolutional layer and pooling layer.

In specific, a convolutional layer has filters k_{ij}^l, the size of which is usually much smaller than the dimension of input data and forms a locally connected structure. Filter at layer l can produce feature maps $\mathbf{X}_j^l$ by convolving with the input $\mathbf{X}_i^{l-1}$ plus biases b_j^l. These features are subjected to a non-linear transformation $f(\cdot)$ and can be mathematically expressed as:

$$\mathbf{X}_j^l = f\left(\sum_{i=1}^{M^{l-1}} \mathbf{X}_i^{l-1} * k_{ij}^l + b_j^l\right) \tag{8}$$

Where M^{l-1} represents the number of feature maps in layer $l-1$, and $*$ denotes convolution operation.

A pooling layer is responsible for feature selection and information filtering. Two kinds of pooling operations are widely used: max pooling and average pooling. In max pooling, maximum value is mapped from a sub-region by pooling operator. In average pooling, the average value of a sub-region is selected as the result. A fully-connected layer is usually located at the last part of a CNN. It transforms a 1D vector and sends the output to its following layer through an activation function.

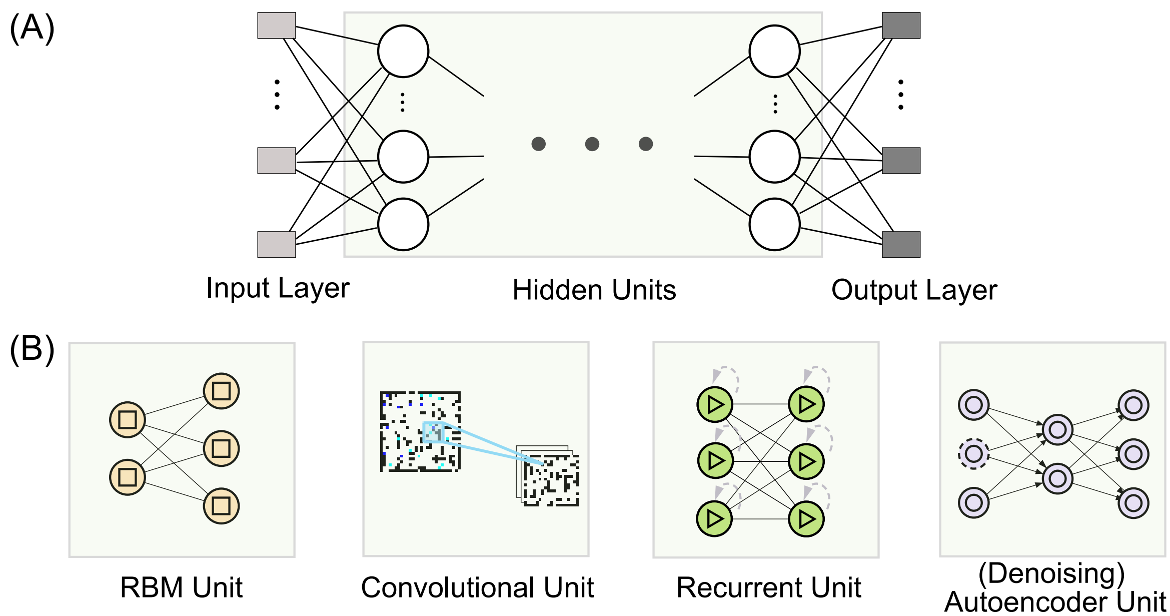

Fig. 2. (A) Generic framework of a deep learning model. (B) Classical units that are employed in a deep learning model.

Weight sharing and sparse connections are two basic strategies in CNN models, which lead to dramatic reduction in the number of parameters. These strategies are helpful to reduce training time and enhance training effectiveness. Moreover, they also mitigate the overfitting problem while retaining a good capability of complex feature extraction.

C. Recurrent Neural Networks

Recurrent neural network (RNN) [33] was developed to deal with sequential data because of its unique recurrent structure (see Fig. 2(B): Recurrent Unit), which allows previous outputs to be used as inputs while having hidden states. It is widely used in applications that need to extract sequential information, such as natural language processing, speech recognition, and EEG classification.

1) GRU: Gated Recurrent Unit (GRU) [34] has two gates, reset $\mathbf{r}_t$ and update $\mathbf{z}_t$. Let $\mathbf{x}_t$ be the input at time step t to a GRU layer and $\mathbf{h}_t$ be the output vector. The output activation is a linear interpolation between the activation from the previous time step and a candidate activation $\hat{\mathbf{h}}_t$.

$$\mathbf{h}_t = \mathbf{z}_t \odot \mathbf{h}_{t-1} + (1 - \mathbf{z}_t) \odot \tilde{\mathbf{h}}_t \tag{9}$$

where $\mathbf{z}_t$ decides the interpolation weight, which is computed by:

$$\mathbf{z}_t = f\left(\mathbf{W}_z \mathbf{x}_t + \mathbf{U}_z \mathbf{h}_{t-1} + \mathbf{b}_z\right) \tag{10}$$

where $\mathbf{W}$ and $\mathbf{U}$ are weight matrices for the update gate, $\mathbf{b}$ is a bias vector, and $f(\cdot)$ is a non-linear function (usually sigmoid function). The candidate activation is also controlled by an additional reset gate and computed as follows:

$$\tilde{\mathbf{h}}_t = g\left(\mathbf{W}_h \mathbf{x}_t + \mathbf{U}_h \left(\mathbf{r}_t \odot \mathbf{h}_{t-1}\right) + \mathbf{b}_h\right) \tag{11}$$

where $\odot$ represents an element-wise multiplication and $g(\cdot)$ is often a non-linear tanh function. The reset gate is computed in a similar manner as the update gate:

$$\mathbf{r}_t = f\left(\mathbf{W}_r \mathbf{x}_t + \mathbf{U}_r \mathbf{h}_{t-1} + \mathbf{b}_r\right) \tag{12}$$

2) LSTM: Different from GRU, Long Short-Term Memory (LSTM) [35] has three gates, input $\mathbf{i}_t$, output $\mathbf{o}_t$, and forget gates $\mathbf{f}_t$. Each LSTM cell has an additional memory component $\mathbf{c}_t$. The gates are calculated in a similar manner as the GRU but LSTM has additional memory components.

$$\mathbf{i}_t = f\left(\mathbf{W}_i \mathbf{x}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{b}_i\right) \tag{13}$$

$$\mathbf{o}_t = f\left(\mathbf{W}_o \mathbf{x}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{b}_o\right) \tag{14}$$

$$\mathbf{f}_t = f\left(\mathbf{W}_f \mathbf{x}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{b}_f\right) \tag{15}$$

A memory component is updated by forgetting the existing content and adding a new memory component as:

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t \tag{16}$$

where $\hat{\mathbf{c}}_t$ can be computed by:

$$\hat{\mathbf{c}}_t = g\left(\mathbf{W}_c \mathbf{x}_t + \mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{b}_c\right) \tag{17}$$

The updated equation for the memory component is controlled by the forget and input gates. Then, the output of the LSTM unit is computed from the memory modulated by the output gate according to the following equation:

$$\mathbf{h}_t = \mathbf{o}_t \odot g\left(\mathbf{c}_t\right) \tag{18}$$

D. Autoencoder and Stacked Autoencoder

Autoencoder (AE) is a symmetrical structure with two layers [36] (see Fig. 2(B): Autoencoder Unit).

An encoder learns latent representation from the input data while a decoder restores the latent representation as close to the input data as possible. The goal of an autoencoder is to minimize the reconstruction error between the input and the output.

Given the inputs $\mathbf{x} \in \mathbf{R}$, the encoding process first maps it into a latent representation $\mathbf{h} \in \mathbf{R}$ through a weight matrix $\mathbf{W}_v$, bias $\mathbf{b}_v$, and an activation function $f(\cdot)$:

$$\mathbf{h} = f\left(\mathbf{W}_v \mathbf{x} + \mathbf{b}_v\right) \tag{19}$$

Then the decoding process transforms the latent representation $\mathbf{h}$ into the reconstruction $\mathbf{y}$ through a weight matrix $\mathbf{W}_h$, bias $\mathbf{b}_h$, and an activation function $g(\cdot)$:

$$\mathbf{y} = g\left(\mathbf{W}_h \mathbf{h} + \mathbf{b}_h\right) \tag{20}$$

To simplify the network architecture, the tied weights strategy $\mathbf{W}_v = \mathbf{W}_h = \mathbf{W}$ are usually employed. The parameters to be determined are $\{\mathbf{W}, \mathbf{b}_v, \mathbf{b}_h\}$. The training of an autoencoder is to minimize the loss:

$$\arg\min_{\mathbf{W}, \mathbf{b}_v, \mathbf{b}_h} \mathcal{J}\left(\mathbf{W}, \mathbf{b}_v, \mathbf{b}_h\right) \tag{21}$$

Given the training samples $\mathbf{D}_n$, the loss function is defined as:

$$\mathcal{J}\left(\mathbf{W}, \mathbf{b}_v, \mathbf{b}_h\right) = \frac{1}{N_{D_n}} \sum_{\mathbf{x} \in \mathbf{D}_n} L(\mathbf{x}, \mathbf{y}) \tag{22}$$

where L is the error of the reconstruction and N_{D_n} is the number of the training samples.

Stacked autoencoder (SAE) is a neural network, where autoencoders are connected one another to form a cascade.

E. Others

In addition to the aforementioned models, there are other models aiming to solve particular shortcomings existing in the above models. For example, capsule network (CapsNet) was proposed to overcome the shortcoming that CNN does not well capture the relationships between the parts of an image [37]. When it applied to fMRI [38] and EEG [15], it is expected to capture comprehensive relationships among brain regions, channels, or frequencies, and so on. To shorten training time, extreme learning machine (ELM) was proposed, where the weights of hidden layers are randomly assigned and fixed during the training [39]. Weight randomization is also implemented in echo state network (ESN) [40]. ESN is a recurrent neural network where the weights of hidden layers are randomly and sparsely assigned and fixed while the weights of output layer can be tuned. Spiking neural network (SNN) is a biologically inspired model and has been used to explore brain activity patterns in [41]. Deep polynomial network (DPN) uses a quadratic function to process its inputs and is able to learn features between different samples or dimensions. It was implemented in [42] to utilize features from multiple views for motor imagery classification, including common spatial pattern, power spectral density, and wavelet packet transform. In addition, some variants of deep learning models were proposed by using different training strategies, such as generative adversarial network.

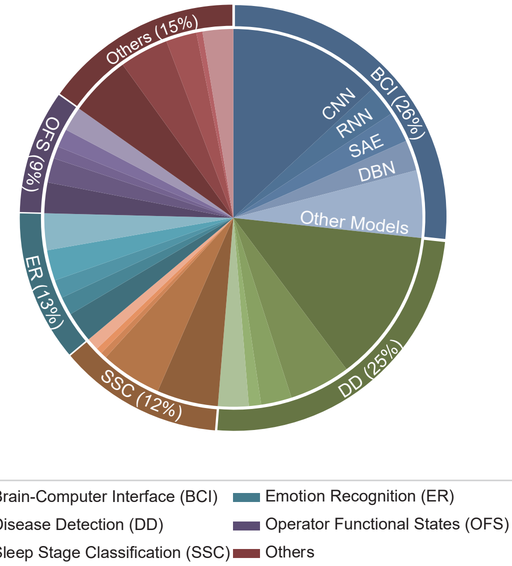

Fig. 3. Percentages of application topics and deep learning models. The outer ring represents paper percentages for each topic. The models within each topic are distinguished from the darkest to lightest colors, which stand for CNN, RNN, SAE, DBN, and other models in order.

IV. Applications

We summarized applications, in which deep learning was utilized for EEG processing and classification, in this section. For your convenience, we group diverse applications into six topics, which are brain-computer interface (see Table III for the details of studies), disease detection (see Table IV), emotion recognition (see Table V), operator functional states (see Table VI), sleep stage classification (see Table VII), as well as the applications other than above topics (see Table VIII). According to statistics, the majority of selected papers belong to the topics of brain-computer interface (account for 26%) and disease detection (account for 25%). The percentages of each topic and the percentages of each model used in each topic are illustrated in Fig. 3. In addition, we collected the information of the publicly available datasets which had been used in the studies and listed them in Table IX.

A. Brain-Computer Interface

A brain-computer interface (BCI) can be defined as a system that decodes brain activity and translate user's intentions into messages or commands for the purposes of communication or the control of external devices, and more. In this topic, deep learning was mainly applied to establish motor imagery (MI)- and P300-based BCIs (see Fig. 4).

Transfer learning is utilized to mitigate the cost of re-training or solve the problem of data lack in the target domain. A deep learning model trained on the data collected from a session or a subject can be transferred to classify/recognise the data of another session or another subject with a fine-tuning. In some cases, the fine-tuning is omitted. In general, the fine-tuning positively contributes to the performance. The extent of fine-tuning was investigated in a recent study[43]. It shows

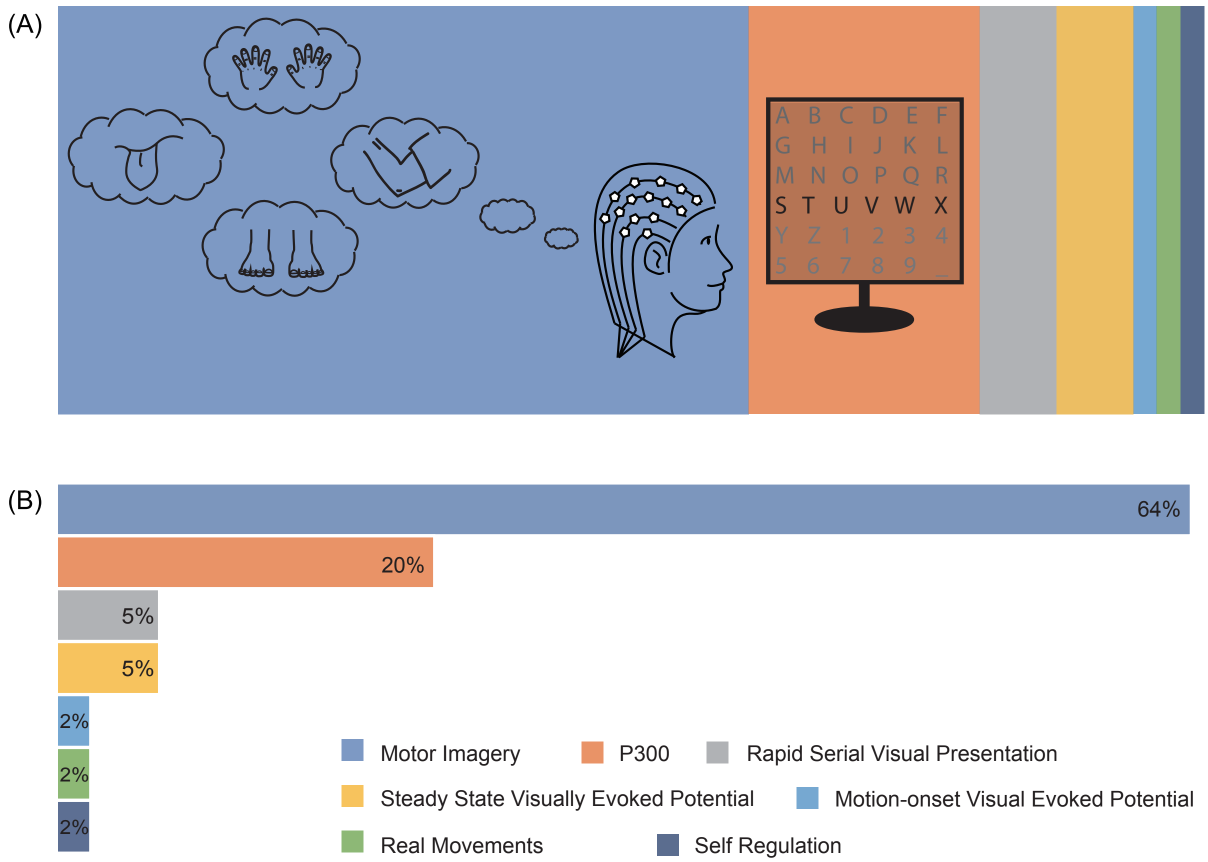

Fig. 4. (A) Paradigms of brain-computer interface. (B) Percentages of the selected papers for each paradigm by the year of 2020

that the best performance of motor imagery classification was achieved when all layers were tuned except the first hidden layer under the condition of a low learning rate. Another study comparing cross-session transferring and cross-subject transferring demonstrated that the cross-session transferring was feasible and the cross-subject transferring was inefficient [44]. With the combination of transfer learning and CNN, Hang et al. proposed a deep domain adaption network [45]. They used maximum mean discrepancy to minimize the distribution discrepancy between target and source subjects and used the center-based discriminative feature learning method to make deep features closer to corresponding class centers. The evaluation on BCI Competition datasets (i.e., Dataset IVa of Competition III and Dataset IIa of Competition IV) demonstrated a good classification performance. In the study of cross-subject transferring [46], network weights were transferred. Dose et al. used a pool of data to obtain a universal model of CNN [47]. This model was then adapted based on a small amount of data from a subject before applying to this subject. Their results showed that an average improvement of 6$\sim$9% was achieved for motor imagery classification in terms of classification accuracy.

Transferring can also be conducted between domains. A CNN-based model (VGG-16) trained on image data (the data from ImageNet) was transferred to recognize EEG data by freezing the parameters in the first several layers and fine-tuning the parameters in the last several layers using an EEG dataset [48]. The performance was better than that of support vector machine. Similar to the domain of image recognition, the amount of EEG data can also be increased by augmentation procedure. Li et al. produced new samples by adding noise into EEG data [49]. They claimed that adding noise into amplitudes of power spectra was superior to that adding noise into EEG time series in terms of classification accuracy. Zhang et al. used intrinsic mode functions derived from empirical mode decomposition to generate new EEG samples so that the total number of samples was increased [50].

Classical models such as CNN and RNN were originally developed for image or speech recognition, so they did not well match the characteristics of EEG signal. They should be adapted before applying to EEG recognition. Li et al. designed a CNN-based network consisted of three blocks to capture spatial and temporal dependencies [49]. Multi-channel raw EEG signals were fed into temporal convolutional layer and spatial convolutional layer successively in the first block. In the second block, a standard convolutional layer and a dilated convolutional layer were utilized to extract temporal information at different scales while reducing the number of parameters. The extracted features were finally used for motor imagery classification in the third block. In another CNN-based network [51], a layer was fed by all outputs from previous layers and its output was inputted to all following layers.

By using such dense inter-layer connections, information loss could be reduced. In [50], EEG signals were transformed into tensors and fed into a CNN-like network where convolution were replaced with complex Morlet wavelets, resulting in parameter reduction. Wavelet kernel was also used to learn time-frequency features [46]. Their results demonstrated that wavelet kernels can provide faster convergence rate and higher classification accuracy compared to plain CNN. Alazrai et al. used CNN to extract features from time-frequency images, which were transformed using a quadratic time-frequency distribution [52]. The methods were compared to a support vector machine, and it suggested that CNN can achieve good performance in MI tasks of the same hand.

In order to accelerate the training course and alleviate the overfitting problem, Liu et al. adjusted the number and position of batch normalization layers in a CNN-based network for P300 detection [8]. Kshirsagar et al. employed leaky rectified linear unit activation function at each convolutional layer [53]. To evaluate whether the number of convolutional layers needs to be adjusted for different BCI tasks and find out an optimal structure, Lawhern et al. compared networks with different numbers of convolutional layers [54]. Their results showed that deep CNN (i.e., five convolutional layers) tended to perform better on the oscillatory BCI dataset than on the event-related potential BCI dataset, while shallow CNN (i.e., two convolutional layers) achieved better performance on the event-related potential BCI dataset. Apart from CNN, Lu et al. used a DBN (i.e., three RBMs and an output layer) to extract features of motor imagery [44]. Some studies aimed to compare performances of different deep learning models. For example, Pei et al. compared SAE and CNN in the classification of reaching movements [55]. They found that SAE was better than CNN and suggested that poorer performance in CNN might be due to the lack of training data. One year later, another study comparing between these two models showed that SAE had satisfactory performance in some trials, but inefficient to those trials of the subjects who were less attentive in P300 detection, while CNN performed well in terms of accuracy and information transfer rate [53].

The combination of deep learning model and traditional model or the mixture of two or more types of deep learning models is applied to EEG classification. For example, SAE was combined with support vector machine to classify EEG signal [56]. SAE was also combined with CNN to develop a new model [57], where CNN layers were used to extract features from 2D time-frequency images (obtained by Fourier transform over EEG signals) and SAE was further used to extract features. In [58], the features extracted by CNN were fed into an autoencoder for cross-subject MI classification. This combination achieved a better accuracy for the cross-subject classification, but worse for the subject-specific classification, compared to the combination of CNN and multilayer perceptron (MLP). Zhang et al. presented a hybrid network comprised of CNN and LSTM, in which EEG signals were sequentially processed through common spatial pattern, CNN, and LSTM [59]. The idea of using CNN and LSTM to extract spatial and temporal features was also conceived by Yang et al. [60]. However, they inserted a discrete wavelet transformation (DWT) between CNN and LSTM, which led to better performance in the MI classification compared to that of pure combination of CNN and LSTM.

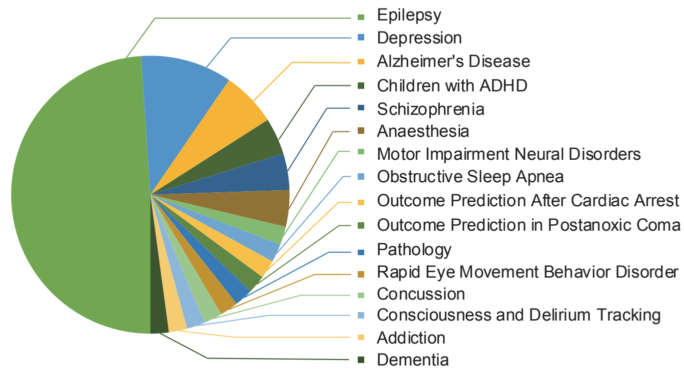

Fig. 5. Percentages of the selected papers across diseases.

In addition to P300- and MI-based BCIs, deep learning models also applies to the other BCIs, including motion-onset visual evoked potentials [61] and self-paced reaching movements [55]. Nguyen et al. developed a steady state visually evoked potential (SSVEP)-based BCI speller system, in which only one channel was used [62]. They used fast Fourier transform to extract features from this channel and then fed the features into a CNN model. According to their results, frequency resolution and time window length influence classification performance. The frequency resolution of 0.0625 Hz and time window of 2s were optimal for the five-class classification [62]. Waytowich et al. proposed a compact CNN to deal with asynchronous problem in SSVEP classification [63]. It outperformed canonical correlation analysis (CCA) and combined-CCA.

B. *Disease Detection*

Machine learning could benefit disease diagnosis by providing assistant information and preliminary diagnostic results. In this topic, deep learning models were also widely employed to detect a variety of diseases (see the distribution of the selected papers over diseases in Fig. 5). In this subsection, commonly used models and model designing strategies were introduced at first, including the examples of single or hybrid models, as well as the detailed architecture (e.g., layer settings). Afterwards, we described other techniques that have an influence on the performance of deep learning.

CNN is a deep learning model, which has been widely adopted for the detection of brain diseases (e.g., seizure detection [64] and schizophrenia identification [65]). Cao et al. stacked multiple CNNs to classify epileptic signals. In this study, the proposed model was compared to a few classification algorithms (i.e., Support Vector Machine (SVM), k-Nearest Neighbours (kNN), ELM) under different conditions (i.e., 1. Two-class, seizure/non-seizure; 2. Three-class, interictal/preictal/ictal; 3. Five-class, interictal/three preictal states/ictal) [66]. To enhance the performance of epilepsy classification, original binary labels, namely interictal epileptiform discharge (IED) and non-IED, were converted into multiple labels used for model training [67]. Specifically, samples were further divided into five subclasses according to spatial distribution and morphology of EEG waveforms and were then fed into a CNN model for the training. A new sample was first classified to one of these subclasses and then the final classification result (IED versus non-IED) was obtained by applying a threshold at the last layer. Compared to the CNN model training with binary labels, the training with further finer tags could enhance the discriminative power of the model and led to better performance in the most subjects.

When CNN is combined with other models, classification performance can be improved. In [68], CNN and autoencoder (AE) were combined to learn robust features in an unsupervised way. The integrated network had an encoder consisting of convolution and down-sampling and a decoder consisting of deconvolution and up-sampling. Their results demonstrated that CNN+AE is superior to principal component analysis (PCA) and sparse random projection (SRP) in epilepsy related feature extraction. In [69], a hybrid model combining CNN, AE, and LSTM achieved remarkable prediction of seizure. Combined deep learning model was used for pre-training and latent representation learning. By this, the accuracy of focal and non-focal classification was improved [70]. However, model combination is not always positive to the performance improvement. Some studies showed that performance may decline in some cases. For instance, Mumtaz et al. combined CNN and LSTM to detect unipolar depression. Their results showed that the hybrid model did not outperform single model of CNN [71].

Beyond the selection of deep learning models, model settings also vary across studies. Tsiouris et al. found that overfitting problem can be mitigated by shuffling input EEG segments, which could replace the dropout role partially [20]. Qiu et al. applied data corruption in the stacked autoencoder for seizure detection [72]. Specifically, they designed a denoising sparse autoencoder, in which some of the input data were set to zero. This improved model robustness and reduced overfitting problem. In addition, performance is also influenced by the condition of data recording. Mumtaz et al. found that unipolar depression can be more accurately detected using the EEG recorded under the condition of eyes open compared to that of eyes closed [71]. In the study of attention deficit hyperactivity disorder (ADHD) detection using a CNN model, EEG signals at different channels were rearranged to make adjacent channels together in the connectivity matrix to improve accuracy [73]. Moreover, Tsiouris et al. shuffled interictal and preictal segments of EEG to avoid the overfitting in seizure detection [20]. Yuan et al. used a channel-aware module to enhance the capability of feature learning and concentrate on important and relevant EEG channels [74]. Daoud et al. computed the statistical variance and entropy of the channels, and selected those with the highest variance entropy product for seizure prediction [69].

The performance of deep learning for disease detection is affected by EEG data arrangement. For example, EEG data are reshaped into 2D format before inputting into a deep learning model. In [75], EEG data were transformed into 2D images of spectral powers. Then, these images were fed

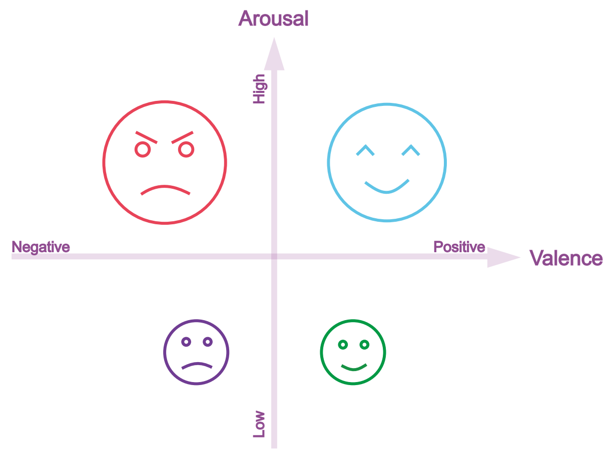

Fig. 6. Four illustrative emotions classified based on the scores of arousal and valence.

into a CNN network for distinguishing Alzheimer's disease and mild cognitive impairment from healthy controls. To differentiate patients with schizophrenia [76], Pearson correlation coefficients were calculated between channels and assembled as a correlation matrix. Correlation matrices of each subject were fed into a CNN network. Moreover, fast Fourier transform [77] and continuous wavelet transform [78] were used to transform EEG data into 2D images for motor impairment neural disorders and epilepsy classification, respectively. Wei et al. further converted 2D images into 3D stacked images according to the mutual correlation intensity between channels [79]. To utilize comprehensive information from different data forms, Tian et al. used three CNNs to respectively obtain features existing in the time, frequency, and time-frequency domain, and then ultilized these features for seizure detection [80]. By comparing with the methods that ultilizing features from only one domain, the proposed method exhibited better performance. According to the study comparing among raw EEG signal, Fourier transform, wavelet transform, and empirical mode decomposition, raw signals and empirical mode decomposition were better than the others in distinguishing focal EEG from non-focal EEG, while Fourier transform was best in ictal and non-ictal classification [81]. To handle the problem of inadequate data, sliding time window was used to split continuous EEG signal into segments with partial overlapping to increase the data amount in [82]. Cao et al. developed an interactive system to help experts label the new data, and the data can be added to fine-tune the deep learning model to gradually improve the interictal-ictal continuum classification accuracy [17].

C. Emotion Recognition

Emotion conveys lots of underlying information during conversations and is part of communication between people. People can understand emotion by reading facial expression, voice tone, and gestures. From the perspective of artificial intelligence, emotion can be recognized based on the data of facial expression [83], eye movement measures [84], EEG [85], or galvanic skin response signal [86]. According to the arousal and valence, emotion can be categorized into different classes (see Fig. 6). Based on the statistics of the included papers in this survey, the studies mainly aimed to classify three classes (i.e., positive, neutral, and negative) or more classes (partitioned based on the scores of arousal and valence). Within these papers, the datasets named 'SEED' [87] and 'DEAP' [88] were frequently used to evaluate deep learning models for emotion recognition.

SEED dataset was published by the BCMI laboratory at the Shanghai Jiao Tong University [87]. For this dataset, 62 channels were used to collect EEG data from 15 subjects when they were watching positive, negative, and neutral video clips. The data were collected from the subjects three times with an interval of one week or longer. Thus, it enables cross-session investigations. Zheng et al. demonstrated the stable patterns of EEG signals over time for emotion recognition [89]. Besides, they found that differential entropy could provide better performance than other features such as differential asymmetry and rational asymmetry. Using this dataset, Yang et al. proposed a hierarchical network which consists of subnetwork node, and this method boosted 5%-10% accuracy [90]. Li et al. trained a CNN and accomplished around 88% of recognition accuracy based on features of the gamma band [91]. Zhang et al. proposed a two-layer RNN model to extract spatial and temporal features, respectively. The first layer of their model is an RNN layer that takes EEG signals from electrodes as inputs. The outputs of the first layer were concatenated along the time dimension and fed into the second RNN layer. The performance evaluated on the SEED dataset was 89.5% [83]. In [92], Zeng et al. used an architecture that adapted from SincNet (a CNN-based network proposed for speaker recognition [93]) to classify emotion. Their results demonstrated that the adapted SincNet (i.e., three convolutional layers and three fully connected layers) was promising for emotion classification, reaching an accuracy of around 95% as evaluated on the SEED dataset.

Another dataset named 'DEAP' [88], was collected from 32 subjects when they watched 40 one-minute-long music videos. Perceptual emotion was assessed in terms of arousal, valence, liking, and dominance. Studies using this dataset have showed that deep learning was successful and effective to classify emotion categories based on EEG. [85], [94]. Even using raw EEG as the input, LSTM achieved an acceptable accuracy of around 85% in the emotion classification [95]. In [96], various handcrafted EEG features (e.g. sample entropy, mean, and power spectral density) were fed into three stacked autoencoders in a parallel way for voting. Chao et al. also designed a parallel architecture to process EEG signal. However, they used DBN as the basic unit [97]. To improve the classification performance and utilize strengths of different models. Li et al. combined CNN and LSTM to extract representations from multi-channel EEG, in which CNN was used to learn inter-channel and inter-frequency correlation while LSTM was used to extract contextual information [98]. The model combination was also used in [99], where feature extraction was done by graph convolutional networks, temporal information was memorized by LSTM, and classification was done by a SVM. The same idea of model combination was also used in [100], where CNN was used for feature extraction.

Besides the two commonly used datasets (i.e., SEED and DEAP), Serap Aydın used affective video clips to induce nine emotional states (fear, anger, happiness, sadness, amusement, surprise, excitement, calmness, and disgust) and investigated gender effect on emotion recognition [101]. This paper revealed that emotion is more affected by individual experience than gender. Zhu et al. designed an experiment to explored the emotion in the scenario of two-person interaction. In their experiment, two person need to rate their emotions induced by the same piciture one by one. They extracted the intra-brain and inter-brain phase synchronization features from emotional EEG signals and applied a CNN model to evaluate [102]. As we know, deep learning needs parameter tuning and it is time-consuming. To mitigate this problem, various strategies were proposed. Hemantha et al. modified the back-propagation neural network by arranging layers in a circular manner that the output can access the parameters of the input and hidden layers [103]. This modification reduced convergence time by around 20%. Jirayucharoensak et al. used principal component analysis for dimension reduction to lower computation cost [104]. Gao et al. utilized gradient priority particle swarm optimization to optimize parameters of a CNN model [105].

D. Operator Functional States

The operator functional states (OFS) describe the mental states of operators in specific working conditions [106]. Two of them are mental workload and mental fatigue. In specific, mental workload is a measure of cognitive resources consumed in the human working memory while mental fatigue is identified by an accumulated process of a disinclination of effort and drowsiness. To date, deep learning was used to identify mental states based on EEG signal. For example, drivers' [107] [108] [109] [110] and pilots' [111] fatigue was monitored for the purposes of preventing fatigued operation.

Generalization is one of the important metrics to evaluate a model. In the classification of operator functional states, large variance across subjects is challenging. Many studies employed subject-specific classifiers. For example, Tao et al. fused multiple ELMs and Naive Bayesian model to build a subject-specific classifier. This ensemble model with fine-tuned hyper-parameters was of the higher subject-specific accuracy in mental workload assessment [112]. In the study of [113], Zhang et al. selected the most relevant EEG channels for each subject and used these subject-specific channels for calculating weights between the input layer and the first hidden layer in the DBN. In contrast to the subject-specific models, the cross-subject model aims to have a general model for tolerating variance of subjects. For example, Heron et al. used multi-path convolutional layers and bi-directional LSTM layers to learn frequency and temporal features over subjects. This model achieved low variance in performance across subjects and showed better generalization compared to subject-specific models [114]. Another cross-subject model was proposed using an adaptive DBN with the weights of the first hidden layer iteratively updated to track the EEG changes in a new subject [115]. When different tasks were used to induce mental workload, the induced workload might be variable across tasks. The cross-task workload classification was made by using a CNN+RNN model [116]. Another study used transfer learning strategy to improve model generalization for the classification of mental workload [117].

Multiple kinds of features can be fused to improve assessment performance of mental workload. Gao et al. presented a temporal convolutional block to extract sequential information of EEG. The block orderly consists of a 1D convolution, a rectified linear activation, and a batch normalization. Temporal convolutional blocks and dense layers for spatial feature fusion were combined to form a novel network. Their results showed that this architecture can achieve higher accuracy for fatigue classification, when compared to these networks that replace convolutional block by 1D convolution [109]. Zhang et al. proposed a two-stream CNN network to learn spectral and temporal features [118]. One stream of CNN was fed by power spectral density topographic maps and the other was fed by topographic maps of amplitude distributions. At the same year (2019), they designed another network for the same propose of learning spectral and temporal features for mental workload classification. In this network, CNN with 3D kernels were first applied to EEG cubes, then extracted features from CNN were flatten to 1D vectors and fed to a bidirectional LSTM for further processing and classification [116]. Both models (i.e. two-stream CNN and CNN+LSTM) showed a significant improvement in mental workload classification.

E. Sleep Stage Classification

Sleep stage classification helps us understand the course of sleep to assess sleep quality and diagnose sleep-related disorders. Table X briefly summarized the characteristics of each sleep stage. With the aid of EEG recording, sleep quality can be assessed objectively. In the processing of sleep quality, sleep staging is a precedent step. To date, deep learning has been applied to sleep staging. For instance, LSTM model was used for sleep stage classification based on a single channel EEG [119]. CNN+LSTM model was proposed to classify sleep stages [120] [28] and detect sleep spindles [121].

Sleep consists of a sequence of stages. Therefore, temporal information should be useful for sleep stage classification. Morlet wavelets [122] and time-frequency representations [119] [123] were applied to retain temporal information in the extraction of spectral features. These extracted features were then learned by deep learning models for sleep stage classification, showing promising performance. Using the time-frequency representation of EEG, CNN model achieved good performance [124]. In another study, the CNN was combined with LSTM to capture both temporal and spatial information for sleep stage classification [125]. The CNN was also combined with attention mechanism for sleep stage classification [126]. In contrast to the supervised learning, unsupervised learning can perform with unlabeled data, which is preferable when the data labelling is expensive or very time-consuming. Zhang et al. presented a CNN model with a greedy layer-wise training strategy, in which complex-valued k-means was utilized to train filters used in the convolution with unlabeled EEG data [127]. In [128], unsupervised sparse DBN was used to extract features. Subsequent classifiers (e.g., kNN or SVM) performed well on sleep stage classification by using these unsupervised-extracted features. Jaoude et al. demonstrated that a large training data can help validate classification performance. They trained a deep learning model (CNN+RNN) on sleep data from more than six thousand participants and tested on several publicly available datasets. The model achieved as good as humam experts in sleep staging accuracy [129]. Usually, the numbers of samples for each sleep stage are unbalanced. To date, several methods have been proposed to release this issue, including the class-balanced random sampling [122], data augmentation [130], class-balance training set design [28], and synthetic minority oversampling technique [131].

F. Others

Those studies that cannot be grouped into the above topics are presented in this subsection. A summary table with key information of those studies is prepared (see Table VIII). On the one hand, EEG with deep learning can be used for person identification [132], [133], age and gender prediction [134]. On the other hand, it can also be used to decode brain activity related to vision, audio [135], and pain [136]. In a study of image classification [137], LSTM was used to extract EEG features while CNN was used to extract image features. This study claimed that features extracted from EEG could help image classification so that classification performance was improved. In [138], a CNN+LSTM hybrid network was used to extracted visual representations from EEG, and a generative adversarial network was applied to reconstruct images from the learnt EEG representations. Deep learning and EEG were also applied to understand brain functions and structure. These studies aimed to understand functional brain connectivity [139], speech laterality [140], as well as memory under specific conditions. For example, Baltatzis et al. investigated the brain's activity of different people (ever experienced school bullying or not) to different stimuli (2D videos or Virtual Reality) [141]. Doborjeh et al. used EEG and spiking neural network to decode how the brain react to various commercial brands (locally familiar or not) [142]. Arora et al. studied the memory loss after seizure surgery [143].

V. Discussion

In this survey, we reviewed the researches of deep learning in EEG for the last ten years, which is a critical period for the development of deep learning used in EEG. An introduction about deep learning in EEG was first presented in the first section. Subsequently, we presented classical methods of artifacts removal which is an important step in EEG processing. We detailed prevalent deep learning models, followed by the comprehensive reviews on different applications that used deep learning to process and classify EEG signals. These applications were categorised into several topics for presentation. The increase in the number of published papers suggested that the research of deep learning in EEG are expanding over time.

Although remarkable achievements were obtained, challenges and limitations still exist, which need to be addressed. We discuss them below and provide our perspectives.

The performance of deep learning-based classification should be further improved. Although the published papers showed the advantages of deep learning in EEG classification and demonstrated that deep learning is superior to conventional methods, the performance is much lower compared to the performance achieved by deep learning in image or speech classification [25], [26]. The reasons for the lower performance are mainly due to two aspects: EEG signal itself and deep learning models. On the one hand, EEG signal is non-stationary and much variable over time, which makes the extraction of robust features difficult. An effective solution for this problem is to partition continuous EEG signal into short segments, which can be seen as a stationary signal. However, this is only an approximation but not a final solution. When performing cross-subject classification or cross-session classification, EEG over subjects or sessions is largely variable, making the above problem more dominant. On the other hand, most deep models are originally proposed to process other signals (e.g., images) rather than EEG. Although certain adaptions of the models have been done, the performance is still not ideal because of mismatch between the models and EEG characteristics. Taking CNN as an example, it is more suitable for image processing. Raw images can be directly fed into the CNN. However, this is not the case when applying to EEG signals. Although we have seen some studies, in which raw EEG was fed into CNN directly without pre-processing, it is not mainstream. The mainstream is still to pre-process EEG before feeding into a deep learning model because the pre-processing is very effective for removing noises to improve signal-to-noise ratio. Another advantage of the pre-processing step is that EEG data can be transformed into other representations and/or reorganised to facilitate the following processing in the deep learning model. For instance, spectral power density is one of the most widely used feature for EEG signal. Without a separate pre-processing step, this kind of feature cannot be obtained because temporal EEG signal cannot be transformed into spectral domain within the deep learning model.

Available data size in EEG studies is significantly smaller than that available in image or speech studies [25], [26]. As we know, the deep learning model requires extensive training and a large data size can benefit model training to a great extent. Compared to the millions of training data in image or speech recognition, the scale of training data is much less in EEG classification, only from tens, hundreds, or at most thousands of participants. One potential solution for the lack of EEG data in the model training is the use of transfer learning. Deep learning model can be trained by the data which are not collected at the moment and the trained model can be used for recognition or classification on the new collected EEG data after fine-tuning or even without fine-tuning [44], [45], [46]. Unlike image classification, for which there are mature existing pre-trained models (e.g., ImageNet pre-trained VGG model), there is no publicly available pre-trained model for EEG classification. If VGG model is directly applied to EEG, reorganization of EEG has to be done in order to meet the input data format of VGG model. This reorganization might lead to information loss and give detrimental effect on the EEG classification. In addition, there is no idea how well a model trained on images can be tuned to classify EEG signal.

Based on the effectiveness comparison of transfer learning, greater performance improvement was observed in image classification compared to EEG classification. This might be due to the lack of effective training framework and strategies that are suitable for transferring EEG patterns. There was an attempt to transfer the model trained on images to EEG classification [48]. This transferring is across distinct modalities. It is likely to have a better performance when transferring across relevant modalities. As we know, there are different modalities (e.g., functional near-infrared spectroscopy (fNIRS) and EEG) that can be used to measure underlying brain activity. A deep learning model can be trained on one modality and then fine-tuned by the other modality to classify signals of that modality. Or, different modalities can be used together to train a deep learning model so that the training can be benefited from the complementary information existing in the different modalities. It is a fusion of modalities. It has been seen that classification performance was elevated by feature fusion in the case of using conventional classifiers [144]. The fusion could be done at the different stages of the classification process (e.g., at the beginning of initial feature fusion or at the later stage of decision fusion [145], [146]). Wu et al. utilized both EEG and Electrooculogram (EOG) to classify the level of vigilance by fusing the features extracted from EEG and EOG [147]. In the future, more extensive research should be carried out to elevate the development of fusion in deep learning models. Especially, to address how to effectively fuse multiple modalities in deep learning models for neurophysiological signal classification and analysis. Of course, collecting adequate data is a straightforward solution for the lack of EEG data. However, this results in new issues, such as cost increase and time delay. If data collection involves different institutes, extra communication effort should be paid to coordinate the data collection. Meanwhile, computation demand will be increased with the increase of data size, which requires to upgrade computational hardware or replace with the new generation hardware (e.g., central processing unit (CPU) and graphics processing unit (GPU)). As mentioned in [148], cloud computing service is an effective way to share hardware resources so that the hardware cost in individual institutes will be reduced. Using the cloud computing service, data protection and privacy have to be considered, especially for clinical data.

When applying a deep learning model to EEG, we need to adapt the deep learning model in compliance with the characteristics of EEG. For example, how to arrange the input data or how to set kernel size should be considered. EEG signal is usually not directly used and commonly transformed before feeding into a deep learning model. There are strong relationships among temporal domain, spectral domain, and spacial domain. It is important these relationships should be kept as much as possible when arranging the input data. When EEG channels are stacked along a dimension, their spacial layout is distorted. In this case, kernels, such as square kernel, that usually-used in image recognition are no longer effective for EEG classification. A column kernel (covering all channels) is a better choice, which has been supported by the study in [149]. Further, Wang et al. extended the column kernel by considering brain anatomic structure to develop multiple kernels with the sizes matching brain region sizes, achieving a better performance in schizophrenia identification compared to the usually-used kernels, such as square kernel [38].

We believe deep learning models should be changed to be more flexible. The trained model can be adapted dynamically in real-time as needed. This is not limited to dynamic parameter tuning. Ideally, model architecture can also be adjusted when needed. Also, we hope the newly-developed deep learning model could perform multiple tasks at the same time in the future. Please see the detailed description in [150].

Apart from the purposes of deep learning-based EEG classification, deep learning may also be a useful tool to reveal neural mechanisms of the brain. When a deep learning model achieves a satisfactory classification performance, it captures essential differences existing between the classes. Therefore, we can look at what information the deep learning model focuses on to roughly infer the underlying associated brain activity. For example, Goh et al. presented spatial distribution of brain activations associated with lower limb movements by probing into the model of spatio-spectral representation learning [149]. We expect that advanced deep learning models developed in the future could reversely decompose EEG signal back into the representation in the brain to reveal underlying brain mechanisms. It is unrealistic at the current stage, but paying efforts to make progress towards to this target.

A prominent advance we need to mention is the EEGNet [54], which is proven effective for different BCI paradigms. Another promising model is SincNet, which was initially proposed for speaker recognition and also well for the classification of EEG signal [92]. New deep learning architectures, such as capsule network [38], are also required to enhance the chance of success of EEG applications.

Lastly, a mix of different deep learning units has been increasingly seen, which integrates the characteristics of these units to benefit data learning. Because there is not definite guidance to set optimal deep learning architecture (e.g., model depth and model width) currently, model complexity might be considered to determine the model architecture. The model should have enough capacity for learning information in accordance with classification tasks while its complexity should be kept as low as possible to minimize computational cost.

VI. Conclusion

Our survey is a glimpse of what have been done for the deep learning in EEG over the past ten years. There are still many researches currently on-going at laboratories and hospitals, dealing with challenges we mentioned above and beyond. We hope that our survey can provide the researchers who are working in this field with a summary and facilitate their researches.

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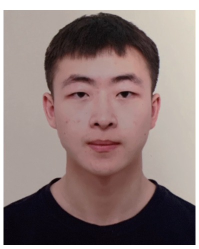

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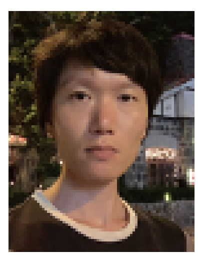

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TABLE I
THE ABBREVIATIONS IN THIS SURVEY

Abbreviation	Full Name
AD	Alzheimer's Disease
ADHD	Attention Deficit Hyperactivity Disorder
AE	Autoencoder
BCI	Brain-Computer Interface
CAM-ICU	Confusion Assessment Method for the ICU
CapsNet	Capsule Network
CJD	Creutzfeldt-Jakob Disease
CNN	Convolutional Neural Network
DBCS	Deep Blind Compresed Sensing
DBN	Deep Belief Network
DMCCA	Deep Multiset Canonical Correlation Analysis
DN-AE-NTM	Deep Network Autoencoder Neural Turing Machine
DPN	Deep Polynomial Network
DTI	Diffusion Tensor Imaging
DWT	Discrete Wavelet Transformation
EEG	Electroencephalogram
ELM	Extreme Learning Machine
EOG	Electrooculogram
ESN	Echo State Network
fMRI	functional Magnetic Resonance Imaging
fNIRS	functional Near-Infrared Spectroscopy
GPED	Generalized Periodic Epileptiform Discharge
GRU	Gated Recurrent Unit
HC	Healthy Controls
IED	Iterictal Epileptiform Discharge
kNN	k-Nearest Neighbor
LSTM	Long Short-Term Memory
MCI	Mild Cognitive Impairment
MI	Motor Imagery
MLP	Multilayer Perceptron
NREM	Non-Rapid Eye Movement
OFS	Operator Functional States
PCA	Principal Component Analysis
PLED	Periodic Lateralized Epileptiform Discharge
RASS	Richmond Agitation-Sedation Scale
RBM	Restricted Boltzmann Machine
REM	Rapid Eye Movement
RNN	Recurrent Neural Network
RPD	Rapidly Progressive Dementia
RSVP	Rapid Serial Visual Presentation
SAE	Stacked Autoencoder
SAN	Subject Adaption Network
SNN	Spiking Neural Network
SNR	Signal-to-Noise Ratio
SRP	Sparse Random Projection
SSRL	Spatio-Spectral Represemtation Learning
SSVEP	Steady State Visually Evoked Potentials
SVM	Support Vector Machine

TABLE II: Typical Methods for Artifacts Removal

Methods	Target Artifacts	Property
Notch Filter	Line Noise	Signal distortion in specific frequencies
Band-Pass Filter	Artifacts concentrated on a particular frequency band	Preclude certain frequency signals
Independent Component Analysis	Ocular and muscular noise removal	Decompose channels into independent components
Reject Contaminated Data Segments	Ocular noise, muscular noise etc., which are difficultly mitigated	Reject gross eye movement and occasional recording artifacts
Wavelet Transformation Analysis	Ocular and muscular noise removal	Signals are reconstructed based on the corrected coefficient
Common Average Reference	Artifacts equivalently affect all channels	Amplitudes can be overall reduced
Z-Score Calculation	Noisy channels or time periods	Generates zero-mean data with unitary variance
Denoise AutoEncoder	General Noises	Denoise in an unsupervised manner

TABLE III: Key Information of Papers about Brain-Computer Interface

Authors	Models	Paradigms	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Ma et al. 2020 [151]	CNN	MI	Rest, Right Hand, and Right Elbow	Private: 25 Participants, 64 Channels, 1000 Hz
Zhang et al. 2019 [50]	CNN	MI	Left, Right Hand	BCI Competition II Dataset III
Xu et al. 2019 [48]	CNN	MI	Left, Right Hand	BCI Competition IV Dataset 2b
Zhu et al. 2019 [152]	CNN	MI	Left, Right Hand	1. Private: 25 Participants, 15 Channels, 1000 Hz 2. BCI Competition IV Dataset 2b
Lu et al. 2017 [44]	DBM	MI	Left, Right Hand	BCI Competition IV Dataset 2b
Chiarelli et al. 2018 [153]	DNN	MI	Left, Right Hand	Private: 15 Participants, 128 Channels, 250 Hz
Tayeb et al. 2019 [154]	CNN, LSTM, CNN+LSTM	MI	Left, Right Hand	1. Private: 20 Participants, 32 Channels, 256 Hz 2. BCI Competition IV Dataset 2b
Dai et al. 2019 [155]	CNN+AE	MI	Left, Right Hand	BCI Competition IV Dataset 2b
Ha et al. 2019 [156]	CapsNet	MI	Left, Right Hand	BCI Competition IV Dataset 2b
Shi et al. 2019 [157]	CNN	MI	Left, Right Hand	Private: - Participants, 118 Channels, - Hz
Wang et al. 2018 [158]	CNN, LSTM	MI	Left, Right Hand	Private: 14 Participants, 11 Channels, 256 Hz
Tabar et al. 2017 [57]	CNN, SAE, CNN+SAE	MI	Left, Right Hand	1. BCI Competition II Dataset III 2. BCI Competition IV Dataset 2b
Amin et al. 2019 [159]	CNN	MI	Left Hand, Right Hand, Feet, and Tongue	1. High Gamma Dataset [160] 2. BCI Competition IV Dataset 2a
Amin et al. 2019 [58]	CNN, MLP, AE	MI	Left Hand, Right Hand, Feet, and Tongue	1. BCI Competition IV Dataset 2a 2. High Gamma Dataset [160]
Li et al. 2019 [51]	CNN	MI	Left Hand, Right Hand, Feet, and Tongue	BCI Competition IV Dataset 2a
Hassanpour et al. 2019 [161]	DBN, SAE	MI	Left Hand, Right Hand, Feet, and Tongue	BCI Competition IV Dataset 2a
Zhang et al. 2019 [59]	CNN+LSTM	MI	Left Hand, Right Hand, Feet, and Tongue	BCI Competition IV Dataset 2a
She et al. 2018 [162]	ELM	MI	Left Hand, Right Hand, Feet, and Tongue	BCI Competition IV Dataset 2a
Uribe et al. 2019 [163]	ELM	MI	Left Hand, Right Hand, Feet, and Tongue	BCI Competition IV Dataset 2a
Lei et al. 2019 [42]	MMDPN	MI	Idle, Preparation, Walking Imagery, and Restoration	Private: 9 Participants, 32 Channels, 512 Hz
Duan et al. 2017 [164]	ELM	MI	Cortical Positivity and Negativity	BCI Competition II Dataset Ia

Alazrai et al. 2019 [52]	CNN	MI	Rest, Grasp-Related (Small Diameter, Lateral, and Extension-Type), Wrist-Related (Ulnar/Radial Deviation. Flexion/Extension), Fingers-Related (Flexion and Extension of The Index, The Middle, The Ring, The Little, and The Thumb Finger)	Private: 22 Participants (18 Able-Bodied and 4 with Transradial Amputations), 16 Channels, 2048 Hz
Hang et al. 2019 [45]	CNN	MI	1. Right Hand, Foot 2. Left Hand, Right Hand, Feet, and Tongue	1. BCI Competition III Dataset IVa 2. BCI Competition IV Dataset IIa
Yang et al. 2018 [60]	CNN+LSTM	MI	1. Left Hand, Right Foot 2. Left, Right Hand 3. Left Hand, Tongue	1. Private: 6 Participants, 64 Channels, 500 Hz 2. BCI Competition III Dataset - 3. BCI Competition IV Dataset -
Zhao et al. 2019 [46]	CNN	MI	1. Left Hand, Right Hand, Feet, and Tongue 2. Left, Right Hand 3. Elbow Flexion/Extension, Forearm Supination/Pronation, Hand Open/Close	1. BCI Compeition IV Dataset 2a 2. BCI Compeition IV Dataset 2b 3. From Ofner et al., 15 Participants, 61 Channels, 512 Hz
Wu et al. 2019 [165]	CNN	MI	1. Left Hand, Right Hand, Feet, and Tongue 2. Left, Right Hand	1. BCI Competition IV Dataset 2a 2. BCI Competition IV Dataset 2b 3. High Gamma Dataset [160]
Majidov et al. 2019 [166]	CNN	MI	1. Left Hand, Right Hand, Feet, and Tongue 2. Left, Right Hand	1. BCI Competition IV Dataset 2a 2. BCI Competition IV Dataset 2b
Li et al. 2019 [49]	CNN	MI	1. Left Hand, Right Hand, Feet, and Tongue 2. Left Hand, Right Hand, Feet, and Rest	1. BCI Competition IV Dataset 2a 2. High Gamma Dataset [160]
Dose et al. 2018 [47]	CNN	MI	Left/Right Fist or Both Fists/Both Feet	EEG Motor Movement/MI Dataset
Tang et al. 2019 [167]	DBN	MI	Left, Right Hand	Private: 7 Participants, 14 Channels, 128 Hz
Xu et al. 2018 [168]	CNN	MI	1. Left, Right Hand 2. Left Hand, Right Hand, Feet, and Tongue	1. BCI Competition II Dataset III 2. BCI Competition IV Dataset 2a
Kwon et al. 2020 [169]	CNN	MI	Left and Right Hnad	Private: 54 Participants, 62 Channels, 1000 Hz
Mammone et al. 2020 [170]	CNN	MI	Elbow Flexion/Extension, Forearm Supination/Pronation, Hand Open/Close, Resting	BNCI Horizon Dataset
Zhang et al. 2020 [171]	CNN+LSTM	MI	1. Left/Right Fist Open and Close 2. Left hand, right hand, feet, and tongue	1. PhysioNet Dataset 2. BCI Competition IV Dataset 2a
Chen et al. 2020 [172]	CNN	MI	1. Left hand, right hand, feet, and tongue 2. Right hand and feet	1. BCI Competition IV Dataset 2a 2. SMR-BCI Dataset
Jeong et al. 2020 [173]	CNN+LSTM	Reaching Movements and MI	Left, Right, Forward, Backward, Up, and Down	Private: 15 Participants, 64 Channels, 1000 Hz

Ding et al. 2015 [39]	ELM	-	Cortical Positivity and Negativity	BCI Competition II Dataset Ia
Ma et al. 2017 [61]	DBN	mVEP	Target Stimulus Signal and The Standard Stimulus Signal	Private: 11 Participants, 10 Channels, 1000 Hz
Gao et al. 2015 [174]	ANN	P300	P300 and Non-P300	Private: 5 Participants, 32 Channels, 2048 Hz
Kundu et al 2019 [56]	SAE	P300	P300 and Non-P300	1. BCI Competition II Dataset IIb 2. BCI Competition III Dataset II 3. BNCI Horizon Dataset
Kshiragar et al. 2019 [53]	SAE, CNN	P300	P300 and Non-P300	Private: 10 Participants, 16 Channels, 500 Hz
Liu et al. 2018 [8]	CNN	P300	P300 and Non-P300	1. BCI Competition III Dataset II 2. BCI Competition II Dataset IIb
Farahat et al. 2019 [175]	CNN	P300	P300 and Non-P300	Private: 19 Participants, 29 Channels, 508.63 Hz
Solon et al. 2019 [176]	CNN	P300	P300 and Non-P300	Private: 67 Participants, 64 Channels, - Hz
Vareka et al. 2017 [177]	SAE	P300	P300 and Non-P300	Private: 25 Participants, 19 Channels, 1000 Hz
Morabbi et al. 2018 [178]	DBN	P300	P300 and Non-P300	EPFL BCI Dataset
Ditthapron et al. 2019 [179]	CNN+LSTM+AE	P300	P300 and Non-P300	1. From Citi et al. [180], 12 Participants, 64 Channels, 2048 Hz 2. BCI Competition III Dataset II 3. From Schreuder et al. [181], 10 Participants, 60 Channels, 240 Hz 4. From Acqualagna et al. [182], 13 Participants, 63 Channels, 250 Hz 5. EEG Database Data Set/UCI EEG Dataset 6. From Treder et al. [183], 11 Participants, 63 Channels, 200 Hz
Lawhern et al. 2018 [54]	CNN	P300, MI, etc.	1. P300 and Non-P300 2. Correct and Incorrect 3. The Left Index, Left Middle, Right Index, and Right Middle Finger 4. Left Hand, Right Hand, Feet, and Tongue	1. Private: 15 Participants, 64 Channels, 512 Hz 2. BCI Challenge 3. Private: 13 Participants, 256 Channels, 1024 Hz 4. BCI Competition IV Dataset 2a
Boloukian et al. 2020 [184]	DN-AE-NTM	P300, MI, etc.	1. P300 and Non-P300 2. Alcoholic and Control 3. Left/Right Fist or Both Fists/Both Feet	1. From Hoffmann et al. [185], 9 Participants (5 with disablement and 4 able-bodied), - Channel, - Hz 2. EEG Database Data Set/UCI EEG Dataset 3. EEG Motor Movement/Imagery Dataset
Pei et al. 2018 [55]	SAE	Reaching Movements	Left, Central and Right	Private: 5 Participants, 32 Channels, 256 Hz
Chen et al. 2019 [186]	CNN	RSVP	Target and Non-Target	From Touryan et al. [187], 10 Participants, 64 Channels, 512Hz
Manor et al. 2015 [188]	CNN	RSVP	Target and Non-Target	Private: 15 Participants, 64 Channels, 256 Hz
Manor et al. 2016 [189]	CNN	RSVP	Target and Non-Target	Private: 15 Participants, 64 Channels, 256 Hz

Nguyen et al. 2019 [62]	CNN	SSVEP	6.67, 7.5, 8.57, 10, and 12 Hz	Private: 8 Participants, 1 Channel, 128 Hz
Liu et al. 2020 [190]	DMCCA	SSVEP	6, 8, 9, and 10 Hz	Private: 10 Participants, 8 Channels, 250 Hz
Waytowich et al. 2018 [63]	CNN	SSVEP	12 SSVEP Stimuli Flashed at Frequencies Ranging from 9.25 Hz To 14.75 Hz in Steps of 0.5 Hz	From Nakanishi et al. [191], - Participants, - Channel, 2048 Hz

'-' indicates that the information is unavailable

TABLE IV: Key Information of Papers about Disease Detection

Author	Models	Categories	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Doborjeh et al. 2016 [41]	SNN	Addiction	Healthy, Addiction Treated, and Addiction Not Treated Subjects	Private: 74 Participants, 26 Channels, - Hz
Ieracitano et al. 2019 [75]	CNN	Alzheimer's Disease	1. AD vs. HC, AD vs. MCI, MCI vs. HC 2. AD, MCI, and HC	Private: 189 Participants (63 AD, 63 MCI, 63 HC), 19 Channels, 1024 Hz
Bi et al. 2019 [192]	DBN	Alzheimer's Disease	1. AD, HC, and MCI 2. Identification: determine EEG spectral image come from which person 3. Verification: wheather two EEG spectral images come from the same person	Private: 12 Participants (4 HC, 4 MCI, and 4 AD), 64 Channels, 500 Hz
Morabito et al. 2016 [193]	SAE, MLP	Alzheimer's Disease	CJD/RPD, CJD/HC, and CJD/AD	Private: 76 Participants, 19 Channels, - Hz
Hayase et al. 2019 [194]	MLP	Anaesthesia	-	Private: 30 Participants, - Channels, 128 hZ
Liu et al. 2019 [195]	CNN	Anaesthesia	Anesthetic Ok, Deep, and Light	Private: 50 Participants, - Channel, - Hz
Park et al. 2020 [196]	CNN	Anesthesia	-	VitalDB
Kim et al. 2018 [197]	CNN, LSTM, DNN	Brain Disease	1. Normal and Dementia 2. Normal and Alcoholism	EEG Database Data Set/UCI EEG Dataset
Chen et al. 2019 [73]	CNN	Children with ADHD	Adhd and Controls	Private: 107 Participants (50 Children with ADHD and 57 Controls), 128 Channels, 1000 Hz
Chen et al. 2019 [198]	CNN	Children with ADHD	Adhd and Controls	Private: 107 Participants (50 Children with ADHD and 57 Controls), 62 Channels, 1000 Hz
Boshra et al. 2019 [199]	CNN	Concussion	Normal and Concussion	Private: 54 Participants (26 with Concussion and 28 Controls), 64 Channels, 512 Hz
Sun et al. 2019 [200]	CNN+LSTM	Consciousness and Delirium Tracking	1. Rass: -5, -4, -3, -2, -1, 0 2. Cam-Icu: 0, 1	Private: 295 Participants (174 for RASS and 121 for CAM-ICU), 4 Channels, 250 Hz
Ay et al. 2019 [201]	CNN+LSTM	Depression	Normal and Depression	From Acharya et al. [202], 30 Participants (15 Depressed and 15 Normal), 1 Channel (FP1-T3, FP2-T4), 256 Hz
Acharya et al. 2018 [203]	CNN	Depression	Depression and Normal	Private: 30 Participants (15 Deoressed and 15 Normal), FP1-T3 and FP2-T4 Channel, 256 Hz
Li et al. 2019 [204]	CNN	Depression	Depression and Normal	Private: 28 Participants (14 Deoressed and 14 Normal), 16 Channels, 250 Hz
Mumtaz et al. 2019 [71]	CNN, CNN+LSTM	Depression	Depression and Normal	Private: 63 Participants (33 Deoressed and 30 Normal)
Zhu et al. 2019 [205]	MDAE	Depression	Mild Depression and Normal	Private: 51 Participants (24 Mild Deoression and 27 Normal), 16 Channels, 250 Hz
Bouallegue et al. 2020 [206]	RNN+CNN	Autism and Epilepsy	1. Normal and Autistic 2. Normal and Seizure	1. Private: 19 Participants (10 normal and 9 autistic), 16 Channels, 256 Hz 2. CHB-MIT Scalp EEG database 3. From Andrzejak et al.[207], 10 participants (5h healthy and 5 epileptic patients)

Cao et al. 2020 [66]	CNN+ELM	Epilepsy	1. Seizure/Non-Seizure 2. Interictal, Preictal, Ictal 3. Interictal, Three Preictal States, Ictal	1. CHB-MIT Scalp EEG database 2. Private: 10 Participants, 18 Channels, 256 Hz
Daoud et al. 2020 [70]	CNN+AE+MLP	Epilepsy	Focal and Non-Focal	1. From Andrzenak et al.[208], 5 epileptic patients 2. From Andrzejak et al.[207], 10 participants (5h healthy and 5 epileptic patients)
Tsiouris et al. 2018 [20]	LSTM	Epilepsy	Preictal and Interictal	CHB-MIT Scalp EEG Database
Yuan et al. 2019 [74]	AE	Epilepsy	Ictal and Non-Ictal	CHB-MIT Scalp EEG Database
Karim et al. 2019 [209]	SAE	Epilepsy	Healthy and Epileptic Activiy	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Ullah et al. 2018 [82]	CNN	Epilepsy	1. Seizure, and Non-Seizure 2. Normal, Interical, and Ictal	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
San-Segundo et al. 2019 [81]	CNN	Epilepsy	1. Focal and Non-Focal 2. Healthy/Ictal, Ictal/Non-Ictal, Healthy/ Non-Focal/Ictal, and Healthy/Focal/Ictal	1. The Bern-Barcelona EEG Database 2. Epileptic Seizure Recognition Data Set
Wen et al. 2018 [68]	CNN+AE	Epilepsy	1. Health With Eyes Open/Closed (A, B), Interictal (C, D), and Ictal (E) 2. Epileptic Seizure and Non-Epileptic Seizure	1. From Andrzejak et al.[207], 10 Participants (5 Healthy and 5 Epileptic Patients) 2. CHB-MIT Scalp Database
Acharya et al. 2018 [64]	CNN	Epilepsy	Noraml, Preictal, and Seizure	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Qiu et al. 2018 [72]	SAE	Epilepsy	Normal, Interictal, and Ictal	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Turk et al. 2019 [78]	CNN	Epilepsy	1. A and B 2. A, B, and E 3. A, C, D, and E 4. A, B, C, D, and E	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Thara et al. 2019 [210]	LSTM	Epilepsy	1. Seizure and Non-Seizure 2. Preictal, Interictal, and Ictal	From Bonn University, 500 Participants (missing detial)
Sayeed et al. 2019 [211]	DNN	Epilepsy	1. Normal and Ictal 2. Normal. Interictal, and Ictal	From Andrzejak et al.[207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Hosseini et al. 2017 [27]	CNN, SAE	Epilepsy	Interictal, and Preictal	1. Private: 9 Participants, 70 Channels, 1000 Hz 2. From Upenn and the Mayo Clinic [212] [213], 2 Participants, 15 Channels, 5000 Hz
Hussein et al. 2019 [214]	LSTM	Epilepsy	1. Normal and Seizure 2. Normal, Inter-Ictal, and Ictal 3. Health With Eyes Open/Closed (A, B), Interictal (C, D), and Ictal (E)	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)

Abdelhameed et al. 2019 [215]	CNN+AE	Epilepsy	1. Normal and Ictal 2. Normal. Interictal, and Ictal	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
He et al. 2019 [7]	CNN	Epilepsy	Five Classes: Health With Eyes Open/Closed (A, B), Interictal (C, D), and Ictal (E)	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Cao et al. 2019 [17]	CNN+LSTM	Epilepsy	Iic Patterns and Others	From MGH, over 2500 Participants, 20 Channels, - Hz
Akut 2019 [216]	CNN	Epilepsy	1. Normal and Ictal 2. Normal. Interictal, and Ictal	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Emami et al. 2019 [217]	CNN	Epilepsy	Seizure and Non-Seizure	1. Private: 8 Participants, 19 Channels, 1000 Hz 2. Private: 16 Participants, 19 Channels, 500 Hz
Daoud et al. 2019 [69]	MLP, CNN, LSTM, SAE	Epilepsy	Interictal and Preictal	CHB-MIT Scalp EEG Database
Tian et al. 2019 [80]	CNN	Epilepsy	Seizure and Non-Seizure	CHB-MIT Scalp EEG Database
Wei et al. 2018 [79]	CNN	Epilepsy	Interictal, Preictal, and Ictal	Private: 13 Participants, 22 Channels, 500 Hz
Antoniades et al. 2017 [67]	CNN	Epilepsy	IED and Non-IED	Private: 18 Participants, 20 Channels, 200 Hz
Baloglu et al. 2019 [218]	CNN+LSTM	Epilepsy	Normal/Ictal, Interictal/Ictal, Normal/Epilepsy, Nonictal/Ictal, Normal/Interictal/Ictal	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Oshea et al. 2019 [219]	CNN	Epilepsy	Seizure and Non-Seizure	1. Private: 18 Participants, 8 Channels, 256 Hz 2. Helsinki Dataset
Vrbancic et al. 2018 [77]	CNN	Motor Impairment Neural Disorders	Normal and Motor Impairments	CSU BCI collection
Jansen et al. 2018 [220]	ANN	Obstructive Sleep Apnea	OSA Patients and Controls	From Klosch et al. [221], 247 Participants (50 Patients and 197 Controls), 6 Channels, - Hz
Jonas et al. 2019 [222]	CNN	Outcome Prediction after Cardiac Arrest	Favorable and Unfavorable Outcome	Private: 267 Participants, 19 Channels, 250 Hz
Hofmejer et al. 2018 [223]	CNN	Outcome Prediction in Postanoxic Coma	Good and Poor	Private: 456 Participants, - Channels, - Hz
Amin et al. 2019 [224]	CNN	Pathology	Normal and Pathology	TUH Abnormal EEG Dataset
Ruffini et al. 2019 [225]	CNN	REM Behavior Disorder (RBD)	1. HC and Parkinson'S Disease (PD) 2. HC+ RBD Vs. PD+Dementia with Lewy Bodies(DLB)	Private: 206 Participants (121 with Idiopathic RBD), 14 Channels, 256 Hz
Naira et al. 2019 [76]	CNN	Schizophrenia	Normal and Schizophrenia	From Piryatinska et al. [226], 84 Participants (39 Healthy and 45 with Schizophrenia), 16 Channels, 128 Hz
Oh et al. 2019 [65]	CNN	Schizophrenia	Normal and Schizophrenia	Private: 28 Participants (14 with Schizophrenia and 14 Normal), 19 Channels, 250 Hz
Phang et al. 2020 [227]	CNN	Schizophrenia	Normal and schizophrenia	Lomonosov Moscow State University Dataset

TABLE V: Key Information of Papers about Emotion Recognition

Authors	Models	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Jirayucharoensak et al. 2014 [104]	SAE	Happy, Pleased, Relaxed, Excited, Neutral, Calm, Distressed, Miserable, and Depressed	DEAP Dataset
Zheng et al. 2014 [14]	DBN	Positive and Negative	Private: 6 Participants, 62 Channels, 1000 Hz
Al-Nafjan et al. 2017 [85]	DNN	Excitement, Meditation, Boredom, and Frustration	DEAP Dataset
Alhagry et al. 2017 [95]	LSTM	High/Low Arousal, High/Low Valence, High/Low Liking	DEAP Dataset
Li et al. 2017 [98]	CNN+LSTM	High/Low Valence, High/Low Arousal	DEAP Dataset
Yin et al. 2017 [228]	SAE	High/Low Valence, High/Low Arousal	DEAP Dataset
Bozhkov et al. 2017 [40]	ESN	Positive and Negative	Private: 26 Participants, 21 Channels, 1000Hz
Zheng et al. 2017 [89]	ELM	1. High/Low Valence, High/Low Arousal 2. Positive, Neutral, and Negative	1. DEAP Dataset 2. SEED Dataset
Yang et al. 2018 [90]	Hierarchical Network	Positive, Neutral, and Negative	SEED Dataset
Chen et al. 2018 [229]	DBN	Happy, Calm, Sad, and Fear	Private: 10 Participants, 16 Channels, 128Hz
Hemanth et al. 2018 [103]	DNN	Happy, Sad, Relaxed, and Angry	DEAP Dataset
Choi et al. 2018 [94]	LSTM	High/Low Valence, High/Low Arousal	DEAP Dataset
Kwon et al. 2018 [86]	CNN	High/Low Valence, High/Low Arousal	DEAP Dataset
Bagherzadeh et al. 2018 [96]	SAE	High/Low Valence, High/Low Arousal	DEAP Dataset
Chao et al. 2018 [97]	DBN, RBM	Pleasant, Unpleasant, Aroused, and Relaxed	DEAP Dataset
Li et al. 2018 [91]	CNN	Positive, Neutral, and Negative	SEED Dataset
Kim et al. 2018 [230]	DBN	Relaxed, Fear, Joy and Sad	Private: 25 Participants, 64 Channels, 1000Hz
Teo et al. 2018 [231]	DNN	1. Like and Dislike 2. Rest and Excited	Private: 16 Participants, 9 Channels, - Hz
Zheng et al. 2019 [84]	RBM, AE	Happy, Sad, Fear, and Neutral	SEED-IV Dataset
Chao et al. 2019 [15]	CapsNet	High/Low Arousal, High/Low Valence, High/Low Dominance	DEAP Dataset
Chen et al. 2019 [232]	GRU	High/Low Valence, High/Low Arousal	DEAP Dataset
Balan et al. 2019 [233]	DNN	No, Low, Medium, and High Fear	DEAP Dataset
Zhang et al. 2019 [83]	RNN	Positive, Neutral, and Negtive	SEED Dataset

Zeng et al. 2019 [92]	CNN	Positive, Neutral, and Negtive	SEED Dataset
Gao et al. 2020 [105]	CNN	Happy, Sad, and Fear	Private: 15 Participants, 30 Channels, 1000 Hz
Serap Aydin 2020 [101]	LSTM	Fear, Anger, Happiness, Sadness, Amusement, Surprise, Excitement, Calmness, Disgust	Private: 23 Participants, 16 Channels, 128 Hz
Cimtay et al. 2020 [234]	CNN	1. Positive and Negative 2. Positive, Neutral, and Negative	1. SEED Dataset 2. DEAP Dataset 3. LUMED Dataset
Kim et al. 2020 [235]	CNN+LSTM, LSTM	1. Low and High 2. Low, Medium, and High	DEAP Dataset
Kim et al. 2020 [236]	CNN+LSTM	High/Low Valence, High/Low Arousal	DEAP Dataset
Zhu et al. 2020 [102]	CNN	Anger, Disgust, Neutral, and Happy	Private: 40 Participants, 62 Channels, 1000 Hz

TABLE VI: Key Information of Papers about Operator Functional States

Authors	Models	Categories	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Chai et al. 2017 [110]	DBN	Fatigue	Alert and Fatigue	Private: 43 Participants, 32 Channels, 2048 Hz
Zeng et al. 2018 [108]	CNN	Fatigue	Sober and Fatiuge	Private: 10 Participants, 16 Channels, 256 Hz
Yin et al. 2018 [106]	ELM	Fatigue	Low and High Mental Workload Levels	Private: 14 Participants, 11 Channels, 500 Hz
Ma et al. 2019 [107]	PCANet	Fatigue	Awake and Fatigue	Private: 6 Participants, 32 Channels, 500 Hz
Gao et al. 2019 [109]	CNN	Fatigue	Alert and Fatigue	Private: 8 Participants, 30 Channels, 1000 Hz
Jeong et al. 2019 [237]	CNN+LSTM	Mental State and Drowsiness	1. Alert and Drowsy 2. Very Alert, Fairly Alert, neither Alert nor Sleepy, Sleepy but No Effort to Keep Awake, and Very Sleepy	Private: 8 Participants, 30 Channels, 1000 Hz
Zhang et al. 2017 [113]	DBN	Mental Workload	1. Unloaded/Low/Normal/High Level 2. Unloaded/Very/Low/Low/ Medium/High/Very High/Overloaded Level	Private: 6 Participants, 15 Channels, 500 Hz
Yin et al. 2017 [238]	SAE	Mental Workload	Low and High	Private: 7 Participants, 11 Channels, 500 Hz
Hefron et al. 2018 [114]	CNN+LSTM	Mental Workload	Low and High	Private: 8 Participants, 128 Channels, 4096 Hz
Jiao et al. 2018 [239]	CNN	Mental Workload	4 Levels (1, 2, 3, and 4)	Private: 13 Participants, 64 Channels, 500 Hz
Yang et al. 2019 [240]	SAE	Mental Workload	Low and High	Private: 8 Participants, 11 Channels, 500 Hz
Tao et al. 2019 [112]	ELM	Mental Workload	Low and High	Private: 8 Participants, 11 Channels, 500 Hz
Zhang et al. 2019 [116]	CNN+LSTM	Mental Workload	Low and High	Private: 20 Participants, 16 Channels, 1000 Hz
Yin et al. 2019 [117]	DAE	Mental Workload	Low and High	1. Private: 14 Participants, 11 Channels, 500 Hz 2. DEAP Dataset
Zhang et al. 2019 [118]	CNN	Mental Workload	Low, Medium, and High	Private: 17 Participants, 16 Channels, 1000 Hz
Wu et al. 2019 [111]	CAE	Mental Workload and Fatigue	Normal, Mild Fatigue, and Excessive Fatigue	Private: 40 Participants, 1 Channel, - Hz
Yin et al. 2017 [115]	DBN	Mental Workload and Fatigue	1. Low, Medium and High Mental Workload 2. Low, Medium and High Fatigue	Private: 8 Participants, 11 Channels, 500 Hz
Li et al. 2017 [16]	DBN, SAE	Mental Workload and Fatigue	Engagement Levels	Private: 15 Participants, 32 Channels, 200 Hz

TABLE VII: Key Information of Papers about Sleep Stage Classification

Authors	Models	Dimension	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Yildirim et al. 2019 [241]	CNN	EEG, EOG	W, N1, N2, N3, N4, REM	1. Sleep-EDF Database 2. Sleep-EDF Database Expanded
Patanaik et al. 2018 [242]	CNN	EEG, EOG,	W, N1, N2, N3, REM	Private: Healthy Adolescents and Adults, Sleep Disorders Patients, Parkinson's Disease Patients
Yuan et al. 2019 [243]	CNN+GRU	EEG, EOG, EMG	W, S1, S2, SWS, REM	UCD Database
Zhang et al. 2019 [244]	CNN+LSTM	EEG, EOG, EMG	W, N1, N2, N3, REM	SHHS
Chapotot et al. 2010 [245]	MLP	EEG, EOG, EMG	W, N1, N2, N3, Paradoxical Sleep, and Movement Time	Private: 13 Participants, 4 Channels, 128 Hz
Malafeev 2018 [246]	LSTM, CNN+LSTM	EEG, EOG, EMG	W, N1, N2, N3, REM	Private: 18 Healthy Participants, 12 Channels, 256 Hz Private: 28 patients with narcolepsy and hypersomnia, 6 Channels, 200 Hz
Zhang et al. 2016 [128]	DBN	EEG, EOG, EMG	W, S1, S2, SWS, REM	UCD Database
Phan et al. 2019 [247]	CNN	EEG, EOG, EMG	W, N1, N2, N3, REM	1. MASS Database 2. Sleep-EDF Database
Chambon et al. 2018 [248]	CNN	EEG, EOG, EMG	W, N1, N2, N3, REM	MASS Database
Jaoude et al. 2020 [129]	CNN+RNN	EEG, EOG, EMG	W, N1, N2, N3, REM	1. Private: 6341 Participants, 6 channels, - Hz 2. Private: 93 participants, 6 channels, - Hz 3. From Rosen et al. [249], 243 patients 4. From Bakker et al. [250], 49 patients
Biswal et al. 2018 [251]	CNN+RNN	EEG, EMG	Sleep Staging, Sleep Apnea, and Limb Movements	1. SHHS Database 2. From Massachusetts General Hospital Sleep Lab, 10000 Participants, 6 EEG Channels, 200 Hz
Sors et al. 2018 [252]	CNN	Single Channel EEG	W, N1, N2, N3, REM	SHHS
Kulkarni et al. 2019 [121]	CNN+LSTM	Single Channel EEG	Spindles, Non-Spindles in N2 and N3 Stages	1. MASS Database 2. The DREAMS Sleep Spindles Database 3. From Blank et al. [253], 5 Participants, 2 Channels, 200-512 Hz 4. From Redline et al. [254], 5 Participants, 2 Channels, 200-512 Hz 5. Private: 18 Epileptic Patients, 1 Channel, 512 Hz
Tsinalis et al. 2016 [122]	SAE	Single Channel EEG	W, N1, N2, N3, REM	Sleep-EDF Database Expanded

Zhang et al. 2018 [127]	CNN	Single Channel EEG	W, S1, S2, SWS, REM	1.UCD Database 2.MIT-BIH Polysomnographic Database
Mousavi et al. 2019 [130]	CNN	Single Channel EEG	W, N1, N2, N3, N4, REM	Sleep-EDF Database
Supratak et al. 2017 [28]	CNN+LSTM	Single Channel EEG	W, N1, N2, N3, REM	1. MASS Databse 2. Sleep-EDF Database
Dong et al. 2018 [119]	LSTM	Single Channel EEG	W, N1, N2, N3, REM	Private:62 Participants, 20 Channels, - Hz
Zhang et al. 2020 [124]	CNN	Single Channel EEG	W, S1, S2, SWS, REM	1.UCD Database 2. MIT-BIH Polysomnographic Database
Bresch et al. 2018 [120]	CNN+LSTM	Single Channel EEG	W, N1, N2, N3, REM	1. The SIESTA Normative Database 2. Private: 29 Participants, 1 Channel, 1000 Hz
AlMeer et al. 2019 [255]	DNN	Single Channel EEG	W, N1, N2, N3, REM	Sleep-EDF Database
Qu et al. 2020 [256]	CNN	Single channel EEG	W, N1, N2, N3, REM	1. MASS Database 2. Sleep-EDF Database
Hartmann et al. 2019 [123]	LSTM	Multiple Channels EEG	Consecutive Activation Phases and Background Phase	CAP Sleep Database
Charnbon et al. 2019 [257]	CNN	Multiple Channels EEG	Spindles, K-complexes, and Arousals	1. MASS Database 2. Stanford Sleep Cohort Dataset [258], 26 Participants, 1 Channel (C4 or C3), 128 Hz 3. WisConsin Sleep Cohort Dataset [259], 30 Participants, 1 Channel (C4 or C3), 200 Hz 4. MESA
Jeon et al. 2019 [125]	CNN+LSTM	Multiple Channels EEG	W, N1, N2	Private: 218 Pediatric Participants, 32 Channels, 200 Hz
Chriskos et al. 2020 [131]	CNN	Multiple Channels EEG	N1, N2, N3, REM	Private: 22 Participants, 19 Channels, - Hz

TABLE VIII: Key Information about Other Applications

Authors	Models	Categories	Classes	Data (Private/Public: No. of Participants, No. of Channels, Sampling Rate)
Kaushik et al. 2019 [134]	LSTM	Age and Gender Prediction	Class from 0 to 5, Varies from Age and Gender	From Kaur et al. [260], 60 Participants (35 males and 25 females), 14 Channels, - Hz
Wulsin et al. 2012 [261]	DBN	Anomaly Detection	5 Classes: Spike and Sharp Wave, GPED and Triphasic, PLED, Eye Blink, and Background	Private: 11 Participants, 17 Channels, 256 Hz
Anem et al. 2019 [262]	CNN+LSTM	Artifacts Removal	-	-
Jacob et al. 2019 [263]	-	Artificial Muscle Intelligence System	Grasp, Release, Rollup, Rolldown, and Rollup Release	Private: 20 Participants (10 Healthy and 10 Paralyzed), 16 Channels, - Hz
Huang et al. 2018 [135]	CNN	Auditory Salience	4923 Classes of Video Classification	Private: - Participants, 128 Channels, 2048 Hz
Yang et al. 2018 [264]	SAE	Automatic Ocular Artifacts Removal	-	BCI Competition IV Dataset 1
Jiang et al. 2019 [137]	CNN+LSTM	Brain Imaging Classification	40 Classes of Images	ImageNet-EEG Dataset [265]
Baltatzis et al. 2017 [141]	CNN	Bullying Incidences Identification	Bullying 2D/VR, Non-Bullying 2D/VR	Private: 18 Participants, 256 Channels, 250 Hz
Toraman et al. 2019 [140]	CNN	Cerebral Dominance Detection	Left and Right-Hemisphere Dominance	Private: 67 Participants (35 Right-Hand Dominat and 32 Left-Hand Dominat), 18 Channels, - Hz
Doborjeh et al. 2018 [142]	SNN	Classification of Familiarity of Marketing Stimuli	Familiar and Unfamiliar Brands	Private: 20 Participants, 19 Channels, 256 Hz
Croce et al. 2019 [266]	CNN	Classification of Independent Components	Brain ICs and Artifact ICs	Private: - Participants, 128 Channels, 500 Hz
Zheng et al. 2020 [138]	LSTM+CNN, GAN	Decoding Human Brain Activity	40 Classes of Images	From Spampinato et al. [265], 6 Participants, 128 Channels, 1000 Hz
Ming et al. 2019 [267]	SAN	EEG Data Analysis	1. Different Vigilance Stages 2. P300 and Non-P300	1. Private: - Participants, - Channel, 500 Hz 2. From Wu et al., 18 Participants, 64 Channels, 512 Hz
Nagabushanam et al. 2019 [268]	LSTM	EEG Signal Classification	-	From Bonn University, - Participants, 20 Channels, - Hz
Hua et al. 2019 [139]	SAE	Functional Brain Network	High and Low Proficiency Operators	Private: 20 Participants, 8 Channels, 1000 Hz
Goh et al. 2018 [149]	SSRL	Gait Pattern Classification	Free Walking, Exoskeleton-Assisted Walking at Zero, Low, and High Assistive Forces	Private: 27 Participants, 20 Channels, 1000 Hz
Fares et al. 2019 [269]	LSTM	Image Classification	40 Classes of Images	From Spampinato et al. [265],6 Participants, 128 Channels, 1000 Hz
Akbari et al. 2019 [270]	DNN	Intelligible Speech Recognition	-	Private: 5 Participants, - Channel, 3000 Hz
Antoniades 2018 [271]	CNN	Mapping Scalp EEG to iEEG	-	Private: 18 Participants, 32 Channels (12 FO and 20 Scalp), 200 Hz
Bird et al. 2019 [272]	MLP, LSTM	Optimise the Topology of ANN	1. Relaxed, Concentrative, and Neutral 2. Positive, Neutral, and Negative 3. 0 to 9 Imaginary EEG	1. EEG Brainwave Dataset: Mental State 2. EEG Brainwave Dataset: Feeling Emotions 3. MindBigData Dataset

Wang et al. 2019 [133]	CNN	Person Identification	-	1. From PhysioNet (missing detail), 109 Participants, 64 Channels, 160 Hz 2. Private: 59 Participants, 46 Channels, 250 Hz
Ozdenizci et al. 2019 [132]	CNN	Person Identification	-	Private: 10 Participants, 16 Channels, 256 Hz
Singhal et al. 2018 [273]	DBCS	Reconstruction and Analysis of Biomedical Signals	-	1. From Andrzejak et al. [207], 10 Participants (5h Healthy and 5 Epileptic Patients) 2. BCI Competition II and III
Gogna et al. 2017 [274]	SAE	Reconstruction and Analysis of Biomedical Signals	-	From Andrzejak et al. [207], 10 Participants (5 Healthy and 5 Epileptic Patients)
Jang et al. 2019 [275]	CNN	Seizure Detection of Mice	Seizure and Non-Seizure	Private: Total 4704h of EEG Recording, 1000 Hz
Arora et al. 2018 [143]	LSTM	Successful Episodic Memory Encoding Prediction	Successful and Unsuccessful Recall	From UT Southwesetern Medical Center: 30 Participants (15 Dominat and 15 Non-Dominant Hemisphere), 13 and 17 Channel (8-14 Contacts per Electrode), 1000 Hz
Yu et al. 2020 [136]	CNN	Tonic Cold Pain Assessment	No Pain, Moderate Pain, and Sever Pain	Private: 32 Participants, 32 Channels, 500 Hz
Ogawa et al. 2018 [276]	LSTM	Video Classification	Liked Video and Not Liked Video	Private: 11 Participants, 1 Channel, 1024 Hz
Said et al. 2018 [277]	SAE	Vital Signs Compression and Energy Efficient Delivery	-	DEAP Dataset

TABLE IX: A Summary of Datasets Mentioned in This Survey

Dataset Name	Modality	Data Information	Category	URL
BCI Challenge	EEG	26 Participants, 56 Channels, 600 Hz	P300 and Non-P300	https://www.kaggle.com/c/inria-bci-challenge
BCI Competition Data	EEG	Multiple Datasets	Multiple Categories	http://www.bbci.de/competition
BNCI Horizon	EEG	Multiple Datasets	Multiple Categories	http://bnci-horizon-2020.eu/database/data-sets
CAP Sleep Database	EEG, EOG, EMG, ECG	16 Participants, 3 EEG Channels	W, S1, S2, S3, S4, and REM	https://physionet.org/content/capslpdb/1.0.0
CHB-MIT Scalp EEG Database	EEG	22 Participants, 23 Channels, 256 Hz	Ictal Activity, Siezure Onset, and Offset	https://physionet.org/content/chbmit/1.0.0
CSU BCI Collection	EEG	Vary with data sets in the database	Normal and Motor Impairments	https://www.cs.colostate.edu/eeg
DEAP Dataset	EEG and Physiological Signals	32 Participants, 32 Channels, 512 Hz	Scores For Arousal, Valence, Iiking, Dominance and Familiarity	http://www.eecs.qmul.ac.uk/mmv/datasets/deap
EEG Brainwave Dataset: Feeling Emotions	EEG	2 Participants, 4 Channels, - Hz	Positive, Neutral, and Negative	https://www.kaggle.com/birdy654/eeg-brainwave-dataset-feeling-emotions
EEG Brainwave Dataset: Mental State	EEG	4 Participants, 4 Channels, - Hz	Relaxed, Concentrating, and Neutral	https://www.kaggle.com/birdy654/eeg-brainwave-dataset-mental-state
EEG Database Data Set/UCI EEG Dataset	EEG	122 Participants, 64 Channels, 256 Hz	Alcoholic and Control	https://archive.ics.uci.edu/ml/datasets/eeg+database
EEG Motor Movement/Imagery Dataset	EEG	109 Participants, 64 Channels, 160 Hz	Left/Right Fist or Both Fists/Both Feet	https://physionet.org/content/eegmmidb/1.0.0
EPFL BCI Dataset	EEG	9 Participants, 34 Channels, 2047 Hz	P300 and Non-P300	https://www.epfl.ch/labs/mmspg/research/page-58317-en-html/bci-2/bci_datasets/emotion_dataset/
Epileptic Seizure Recognition Data Set	EEG	500 Participants, - Channels, 173.61 Hz	Healthy With Eyes Open/Closed, Patients during Seizure/Interictal from Hippocampal Location/Interictal from Epileptogenic Zone	https://archive.ics.uci.edu/ml/datasets/Epileptic+Seizure+Recognition
MASS Database	EEG, EOG, EMG, ECG	200 Participants, 4–20 EEG Channels, 256Hz	W, N1, N2, N3, and REM	http://www.ceams-carsm.ca/en/MASS
MESA	EEG, EOG	6814 Participants, Fz-Cz, Cz-Oz, C4, 256Hz	Arousal Level	https://www.sleepdata.org/datasets/mesa
MindBigData	EEG	Vary with data sets in the dataset	Brain Reaction from Seeing A Digit (0 to 9)	http://www.mindbigdata.com/opendb
MIT-BIH Polysomnographic Database	EEG, ECG, EOG, EMG, Respiration Signals, and Physiological Signals	60 subjects, 7 PSG Channels, 250 Hz	W, N1, N2, N3, N4, and REM	https://www.physionet.org/content/slpdb/1.0.0
SEED Dataset	EEG and Eye Movement	15 Participants, 62 Channels, 1000Hz	Positive/Neutral/Negative and Happy/Sad/Neutral/Fear	https://bcmi.sjtu.edu.cn/home/seed/
SHHS	EEG, EOG, EMG	6,441 Participants, C4-A1 and C3-A2, 125 Hz	W, N1, N2, N3, N4, and REM	https://sleepdata.org/datasets/shhs/
Sleep-EDF Database Expanded	EEG, EOG, EMG	61 Participants, Fpz-Cz and Pz-Oz, 100 Hz	W, S1, S2, S3, S4, and REM	https://physionet.org/content/sleep-edfx/1.0.0

Sleep-EDF Database	EEG, EOG, EMG	20 Participants, Fpz-Cz and Pz-Oz, 100 Hz	W, N1, N2, N3, and REM	https://physionet.org/content/sleep-edf/1.0.0
The Bern-Barcelona EEG Database	EEG	5 Participants, 7500 Pairs of Signals, 512 or 1024 Hz	Focal and Non-Focal	https://www.upf.edu/web/mdm-dtic/datasets
The SIESTA Normative Database (cross-institute)	EEG, EOG, EMG, ECG	292 Participants, 6 EEG Channels, Variable (minimum 100Hz)	W, N1, N2, N3, and REM	http://ofai.at/siesta/database.html
UCD Database	EEG and Physiological Signals	25 Participants, C3–A2 and C4–A1, 128Hz	W, S1, S2, Sws, and REM	https://physionet.org/content/ucddb/1.0.0
LUMED Dataset	EEG and Physiological Signals	11 Participants, 8 Channels, 500 Hz	Negative and Positive Valence	https://www.dropbox.com/s/xlh2orv6mgweehq/LUMED_EEG.zip?dl=0

TABLE X
A BRIEF SUMMARY OF SLEEP STAGES

Sleep Stages	Main Features of EEG in Each Stage	Brief Description
Wake	Alpha Waves	Before Sleep
Stage N1 NREM	Low-Voltage Theta Waves	Blood Pressure Falls
Stage N2 NREM	Theta Waves with K Complexes and Sleep Spindles	Cardiac Activity Decrease
Stage N3 NREM	High-Amplitude Delta Waves	High Threshold for Arousal
Stage REM Sleep	Low-Amplitude Theta Waves	Blood Pressure and Pulse Rate Increase