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Review of Artificial Intelligence Methods Used in the Analysis of Functional Near-Infrared Spectroscopy Data

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Abstract

Introduction. Recently, machine learning methods, which are core components of artificial intelligence, have gained popularity in analyzing neurophysiological data. Functional near-infrared spectroscopy (fNIRS) is actively used to study neurocognitive mechanisms. This technology for recording hemodynamic data has a number of advantages, including spatial resolution, non-invasiveness, and the feasibility to conduct studies in natural settings, which has made the technology popular among researchers. **Theoretical justification.** The analysis of fNIRS results relies on the sequence and selected methods for preliminary processing of raw data, as well as on the classification models employed. This review evaluates various preprocessing methods and examines the approaches to classifying fNIRS data. An essential aspect of preprocessing involves detecting and eliminating physiological artifacts from raw data, utilizing algorithms such as filtering, signal whitening, principal component analysis (PCA) and independent component analysis (ICA), short-channels removal. Methods such as wavelet filtering, spline interpolation, and Kalman filtering are employed to address motion artifacts. **Discussion.** The review aims to provide an in-depth exploration of machine learning methods, specifically recurrent neural networks (RNN) and convolutional neural networks (CNN), which have been used in various studies for analyzing fNIRS data. The review highlights that leveraging deep learning neural networks can streamline signal preprocessing while achieving higher accuracy compared to traditional approaches in processing neurocognitive data.

Keywords

functional near-infrared spectroscopy, neurophysiological data, machine learning methods, deep learning neural networks, convolutional neural networks, recurrent neural networks

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Introduction

Currently, there are several ways to register brain activation data in neurocognitive research. These methods are typically divided into invasive (which involves directly registering data from the cerebral cortex or its structures by inserting electrodes into brain tissue) and non-invasive (which involves registering data from the surface of the scalp). Non-invasive methods used to obtain brain activation signals include electroencephalography (EEG) (Light et al., 2010); magnetoencephalography (MEG) (Cohen, 1968); functional magnetic resonance imaging (fMRI) (Seliverstov, Seliverstova, Konovalov, Kotenkova, Illarioshkin, 2014); functional near-infrared spectroscopy (fNIRS) (Scholkmann et al., 2014; Pinti et al., 2018; Quaresima & Ferrari, 2019).

Functional NIRS register changes in the blood flow of local capillary networks, which are induced by the activation of brain neurons. This method uses near-infrared signals in the cerebral cortex to detect changes in hemoglobin concentration. There are two types of hemoglobin chromophore: oxyhemoglobin (HbO2) – oxygen-saturated, and deoxyhemoglobin (HHb), which is oxygen-free. FNIRS is a modern, non-invasive technology for measuring changes in concentrations of oxyhemoglobin, deoxyhemoglobin and total hemoglobin (Sitnikova & Malykh, 2021). FNIRS spectroscopy technology is based on two main principles: human tissue is relatively transparent to near-infrared light; hemoglobin is the primary absorbent of light in the near-infrared range. In this range, oxyhemoglobin and deoxyhemoglobin exhibit oxygen-dependent absorption, that varies across different wavelengths (Chen et al., 2020).

Recently, the use of machine learning technologies in the psychophysiology domain has gained popularity. Specifically, machine learning methods are actively employed to analyze fNIRS data in both neurocognitive research and for applications in brain-computer interfaces.

Theoretical background

Preprocessing of neurophysiological data using machine learning technologies

There is a different set of parameters and methods for signal cleaning and conversion, depending on the type of research and the machine learning model being used. However, there are several uniform steps in the signal preprocessing, which include converting the raw signal from different wavelength into optical density, and then into the concentration of oxy- and deoxy-hemoglobin. The conversion to total hemoglobin is optional. Multiple sources of signal interference can complicate signal interpretation and pose a significant challenge.

The main sources of noise may include head movements, changes in the optode (source and detector) scalp coupling index (SCI index), and changes in blood flow unrelated to neural activity. For example, the heart rate can be recorded by fNIRS and may be present in the neurophysiological signal. This occurs because near-infrared waves first pass through the meninges, skull, and scalp, and physiological changes in these tissues can cause changes in light absorption between source and detector that are not associated with functional changes in neural activity (Osharina, Ponchel, Aarabi, Grebe & Wallois, 2010). Overall, sources of physiological noise include heart rate, blood pressure fluctuations, respiratory rate, and scalp blood flow. Physiological noise can be removed using several techniques, including digital filtering, pre-whitening, and adaptive filtering. Techniques such as principal component analysis (PCA) and independent component analysis (ICA) can also be used to remove physiological noise from fNIRS signals. Additionally, registering short-wavelength channels has become increasingly common, allowing for the measurement of activation on the surface of the head (Brigadoi & Cooper, 2015). Each source of biological noise is characterized by its own frequency range in the recorded signal (Cordes et al., 2001; Blanco, Molnar & Caballero-Gaudes, 2018). Therefore, digital filtering can reduce and/or completely eliminate the influence of noise sources that occur in frequency ranges different from the frequency ranges of the brain activity signal evoked by the task (Cordes et al., 2001; Liu, Ayaz, & Shewokis, 2017). However, fluctuations in blood pressure (0.08–0.12 Hz) and heart rate at rest (1–1.5 Hz) tend to overlap with the frequency range of the task-related brain activation signal (Huppert, 2016).

In addition to signal filtering, physiological noise removal is available through signal pre-whitening (Blanco et al., 2018). Signal whitening is used to remove autocorrelated signals such as heart rate by decorrelating task-irrelevant physiological signals (Barker, Aarabi, & Huppert, 2013). Some researchers (Blanco et al., 2018; Barker, Aarabi, & Huppert, 2013) have determined pre-whitening filter coefficients using an iterative autoregressive model to reduce residual error in task-evoked activity estimated from a general linear model analysis (GLM) (Luke et al., 2021; Yücel et al., 2021). It is worth noting that the pre-whitening is sensitive to motion artifacts (Blanco et al., 2018); therefore, motion artifacts must be removed from the signal before applying this procedure.

Another source of artefacts in fNIRS signal is global blood flow in the scalp. Principal component analysis (PCA) is used to remove such artefacts associated with scalp blood flow (Zhang, Noah, & Hirsch, 2016). The effectiveness of using PCA is justified in case of one dominant source of variation. If there are several sources that significantly can influence the overall signal variation, then PCA may not provide the desired effect (Zhang, Noah, & Hirsch, 2016). Another option for removing the global blood flow component from the signal can be the use of ICA (Hyvärinen & Oja, 2000). For example, ICA was used to eliminate global blood flow interference during Gate experiments by exploiting temporal coherence between channels to identify large signal components with a high coefficient of spatial homogeneity (Kohno et al., 2007).

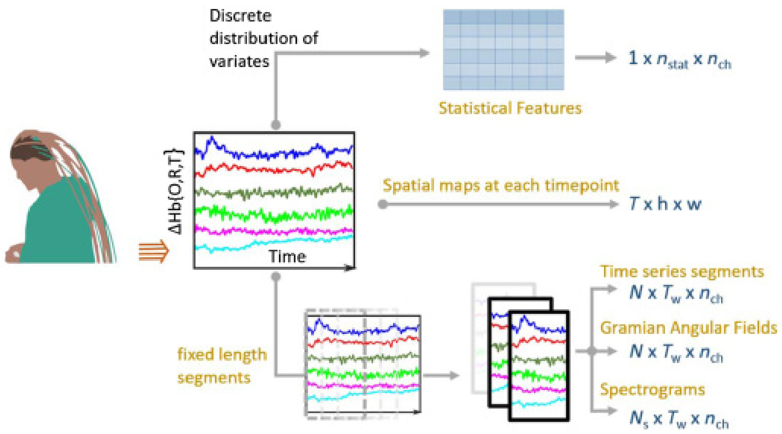
Improvements in fNIRS technology have led to the development of short wavelength channels (~8 mm source to detector distance) that are used to measure and remove scalp blood flow data from analysis (Gagnon, Yücel, Boas & Cooper, 2014; Funane et al., 2015; Nguyen, Yoo, Bhutta & Hong, 2018). Short distances prevent light from penetrating the cortical surface, limiting blood flow measurements in the scalp. Thus, adding short-wave channels as a regressor to the fNIRS model allows to reduce the noise from the blood flow of the scalp.

Another typical source of noise in the fNIRS signal is motion artifacts that occur during conversation or facial, head, and/or upper body movements (Izzetoglu, Chitrapu, Bunce, & Onaral, 2010; Jahani, Setarehdan, Boas, & Yücel, 2018). Motion can cause the optode shift, resulting in sharp high-frequency peaks, slow-wave drifts, or a shift in the baseline of the fNIRS signal (Jahani et al., 2018). To remove motion artifacts, methods such as wavelet filtering, spline interpolation, and Kalman filtering are used. Specifically, wavelet-based methods divide the fNIRS signal into wavelet coefficients and remove those that fall outside a predefined distribution (Molavi & Dumont, 2012; Robertson, Douglas, & Meintjes, 2010). Spline interpolation methods model motion artifacts as a series of spline functions and subtract them from the data, achieving significant error reduction (Scholkmann, Spichtig, Muehlemann, & Wolf, 2010). Thus, the authors (Jahani et al., 2018) showed that combining spline interpolation with a Savitzky-Golay filter can correct baseline shifts and high-frequency peaks without removing additional artifacts from the signal (Jahani et al., 2018).

Obtaining features and augmenting input data before analysis using artificial intelligence methods

After the preprocessing of fNIRS signal, time series of oxyhemoglobin, deoxyhemoglobin and the total change in hemoglobin are formed. Each research team decides which combination of signals to use for further analysis. Figure 1 presents various options for transforming oxy- and deoxy-hemoglobin in time series before analyzing using mathematical methods or training machine learning models (Eastmond, Subedi & Intes, 2022).

Figure 1
Options for extracting features from signal samples (Eastmond, Subedi & Intes, 2022)



Researchers employ the following approaches to transform the signal before using it in the models:

1. Discrete probability distribution of concentration changes and extraction of statistical features (such as mean, slope, variance, skewness, kurtosis, maximum and others). Statistical characteristics can describe the time series of oxy- and deoxy-hemoglobin and incorporate the distinctive features of the series. The drawback of this this approach is that researchers themselves determine the available features that the model will analyze. This approach is valid when using

machine learning methods such as random forests or support vector machines. However, for neural networks, this approach is not valid, as in this case, the neural network can't independently model original features from the raw signal.

2. In another approach, fNIRS data in the form of a spatial map or raw time series is used by machine learning model (Tanveer, Khan, Qureshi, Naseer & Hong, 2019; Ghonchi et al., 2020a; Saadati, Nelson & Ayaz, 2019). In some research, data segments are converted to the form of Gramian angle fields (Gao et al., 2020) or spectrogram maps (Chhabra, Shajil & Venkatasubramanian, 2020). This approach allows machine learning methods, particularly deep learning neural networks, to independently extract features from the input signal. In this case, nonlinear features may be formed that are not understandable to researchers.

Approaches based on manual feature extraction and artifact removal are a challenge for creating a real-time signal processing system, in particular brain-computer interfaces. Deep learning neural networks can solve this problem with a sufficient set of training data. At the same time, deep learning methods can be used both as independent classifiers and as a method for extracting features, which can be used subsequently in the classifier. This fact is due to the good parallelization of calculations in neural networks, as well as the ability of neural networks to study and extract unique feature maps. Thus, Tanveer et al. (2019) used deep learning neural networks to extract features that were used in a K-nearest neighbors' classifier.

Some researchers use raw data in the classifier. In these approaches, a neural network extracts feature maps, based on which classification layers recognize patterns of brain activity. In Rojas and colleagues (2020) research, raw fNIRS data was used as an input for a LSTM neural network, achieving a classification accuracy of 90.6%. In a study evaluating methods for motion artifact reduction (Kim, Lee, Dan, & Tak, 2022), the authors compared convolutional neural networks with wavelet denoising and autoregressive denoising. The results showed that the root mean square error is approximately two times lower compared to the best combination of wavelet and autoregressive noise reduction methods. The present research confirms that deep learning neural networks can classify brain activity patterns from raw, non-preprocessed data, bypassing the steps of data preprocessing and feature extraction. It is worth noting that this approach is actively developing and has demonstrated effectiveness on certain tasks.

Neurophysiological studies are often characterized by small sample size. Deep learning neural networks require large amounts of data to be effectively applied. Large data samples enable machine learning methods to develop the ability to generalize classifiers across a broad data set. Consequently, researchers have recently become interested in generating large samples of fNIRS data (artificially generating fNIRS data), using neural networks. using neural networks. The generated data is based on, but distinct from the original data set. Generative adversarial neural networks (GAN) are employed to address this issue. For example, in a study by Wickramaratne and Mahmud (2021), GANs were utilized to expand the fNIRS data set. When training a CNN on the original data set, an accuracy of 80% was achieved. However, when the data set was expanded with synthetic data using GANs, the trained CNN classifier achieved an accuracy of 96.67%. Similar results were observed in a study by Woo, Kang, and Hong (2020), where the addition of synthetic data increased the accuracy of the CNN classifier from 92% to 97%.

Artificial intelligence methods for analyzing fNIRS data

The fNIRS signal is converted into concentrations of oxyhemoglobin and deoxyhemoglobin, which can be considered as a multivariate time series. The numerous channels placed on the head's surface create multidimensionality. Modern neural network architectures aim to solve complex problems by minimizing the number of parameters required for training the network, utilizing innovative approaches to neural network structures.

Despite recent advancements in the field of machine learning, some researchers still rely on multilayer perceptron (MLP) neural networks. For instance, in a review by Naseer, Qureshi, Noori, and Hong (2016), a comparative analysis of classification accuracy between MLP and other methods such as kNN, Naive Bayes, SVM, LDA, and QDA was carried out. In a mental workload task, the MLP classifier achieved an accuracy of 96%, slightly outperforming certain classifiers such as QDA, Naive Bayes, and SVM. However, predefined feature extraction approaches were used for the classifiers the study. In another study by Erdoğan and colleagues (2019), MLP with predefined fNIRS features was used to classify imagined movements, achieving an accuracy of 96.3% for distinguishing between tasks involving finger tapping and resting state.

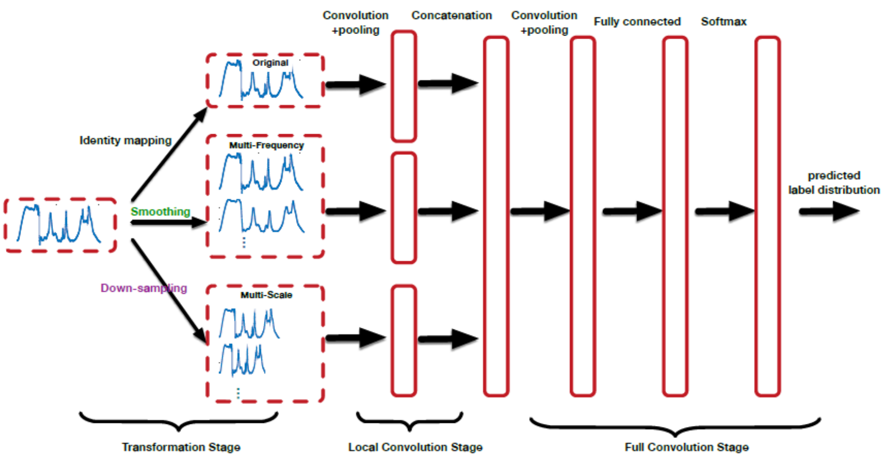
Recurrent neural networks (RNNs) specialize in processing sequences, such as time series, where the chronological order of events is crucial. This is achieved by using loops, that transfer information from the current layer to the previous ones, allowing for the processing of current data alongside previously processed data. However, a limitation of these architectures is the short-term memory, which hinders their ability to effectively handle long sequences while maintaining connections between data points. To address this issue, the long short-term memory (LSTM) neural network architecture was introduced as a solution (Hochreiter & Schmidhuber, 1997; Graves, 2012; Van Houdt, Mosquera & Nápoles, 2020).

Asgher et al. (2020) successfully tackled the challenge of mental workload analysis using LSTM, achieving an accuracy of 89.31%. Hamid et al. (2022) examined the distinction between walking and resting states with LSTM, achieving an accuracy of 78.97%. When compared to classical algorithms, the accuracy rates were as follows: kNN at 68.38%, SVM and LDA at 66.63% and 65.96%, respectively. In a study by Zhao, Li, Xu & Jin (2019), LSTM was employed to address a motor activity task, achieving an accuracy of 71.70%, surpassing the SVM accuracy of 66.6% on the same task. Wickramaratne & Mahmud (2020) demonstrated the efficacy of bidirectional LSTM architecture in classifying tasks like mental arithmetic, motor imagery, and resting state using fNIRS data, achieving a classification accuracy of 81.48%.

Another increasingly popular architecture neural networks for analyzing fNIRS data is convolutional neural networks (CNNs While CNNs are traditionally used for image processing, recent research has shown their effectiveness in handling time series data. Time series can be treated as one-dimensional vectors and convolved accordingly. For example, a multiscale convolutional neural network (MCNN) proposed by Cui, Chen, & Chen (2016) uses parallel convolution and pooling operations both on original time series and its transformations (scaling and smoothing of the series). The pooling results are concatenated into a single vector for further processing through fully connected and softmax layers (Fig. 2). This approach shows the possibilities to extract features from various transformations of the original time series.

Figure 2

MCNN neural network architecture (Cui, Chen & Chen, 2016)



Wang & Oates (2015) propose a method of using CNN to classify a time series by converting the original time series into an image to which CNN is applied. This approach involves constructing two matrices: the Gramian angular field (GAF), which retains all information about the series, except for the original boundaries of the values, and the Markov transition field (MTF), which preserves the original boundaries and values distribution. Figure 3 illustrates the structure and parameters of the neural network for processing GAF and MTF matrices.

The neural networks' architectures depicted in Figures 2 and 3 allow for the consideration of various key aspects of time series in classification tasks. However, they require representation of time series in various forms to extract unique feature maps. Specifically, the GAF matrix converts a row of N length into a matrix of size NxN. The authors suggest that their approaches also be extended to multidimensional time series.

The classification method based on multi-channel deep learning convolutional neural networks MC-DCNN, proposed in the research (Zheng, Liu, Chen, Ge & Zhao, 2014), offers a solution to increasing the dimensionality of time series. Figure 4 presents the architecture of this network, where each channel (row) serves as an input for eight convolutions of size 1x5. Subsequently, an average pooling of size 1x2 is applied to each convolution result. The following layer applies four convolutions of size 1x5 and another average pooling of size 1x2 to the rows. The resulting vectors are then concatenated and used in the fully connected layer.

Figure 3

GAF-MTF-CNN architecture (Wang & Oates, 2015)

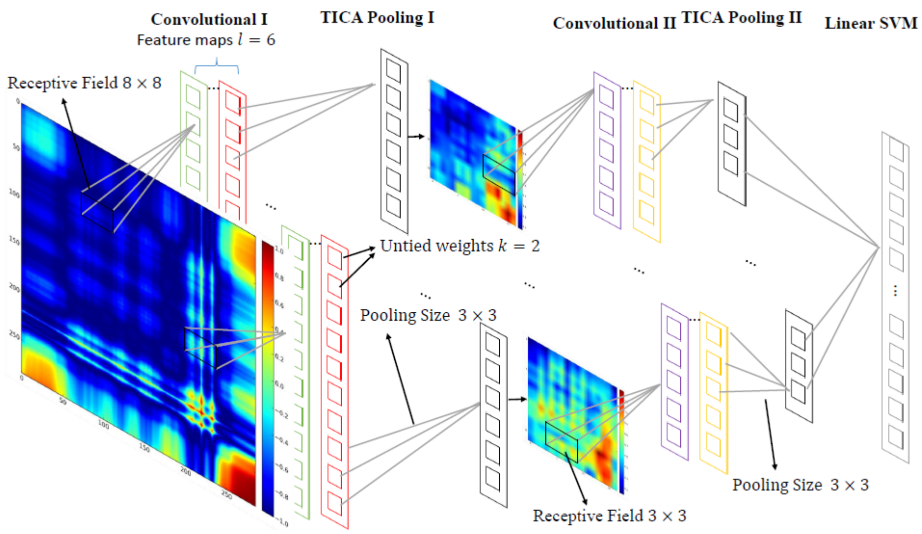
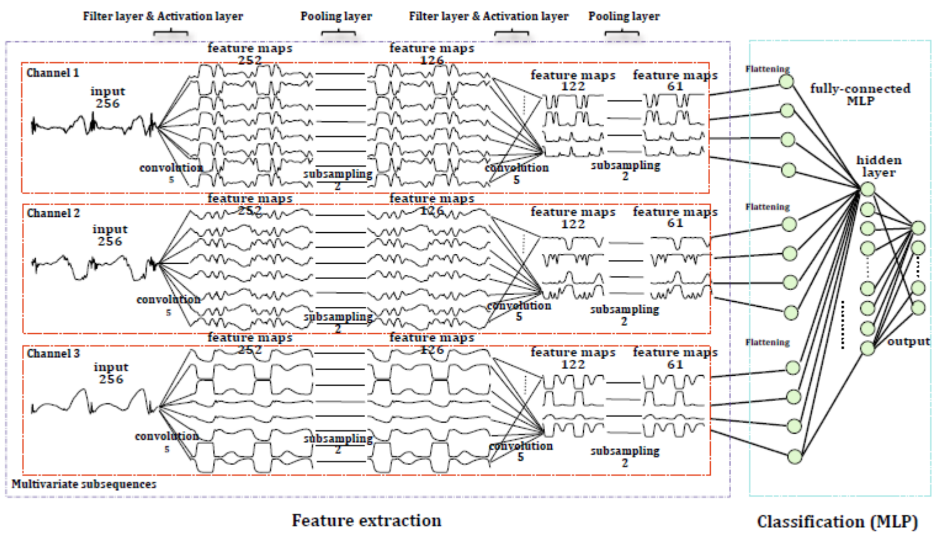


Figure 4

MC-DCNN network architecture (Zheng et al., 2014)



In conclusion, convolutional neural networks provide effective options for analyzing time series data. Kwon & Im (2021) addressed the problem of classifying mental calculation of arithmetic problems using CNN, achieving an accuracy of 71.2%, surpassing the LDA classifier's accuracy of 65.74% under similar conditions. Wickramaratne and Mahmud (2021) also employed CNN for classifying mental arithmetic tasks, achieving an accuracy of 87.14%. Ho et al. (2019) utilized CNN for classifying mental workload tasks by converting signals to spectrograms and applying two-dimensional convolutions, resulting in an accuracy of 82.77%. In another study by Hakimi, Jodeiri, Mirbagheri & Setarehdan (2020), CNN was used to analyze mental states during stress and resting states, achieving an accuracy of 98.69%. Trakoolwilaiwan, Behboodi, Lee, Kim & Choi (2018) achieved an accuracy of 92.68% using CNN for motor movement classification tasks. Ortega & Faisal (2021) examined differences between left- and right-handed grasping tasks, reducing the dimensionality of time series data using PCA before applying CNN, resulting in an accuracy of 77%. The classification of motor movements becomes much more difficult if the movements are imaginary. When dealing with imaginary motor movements, Ma et al. (2021) utilized a residual neural network (ResNet) to achieve an accuracy of 98.6%.

Discussion

Various artificial intelligence methods, particularly machine learning techniques for analyzing hemodynamic data obtained by NIRS, are discussed in the review. The analysis of scientific research literature revealed the advantages and disadvantages of most commonly used methods for preprocessing the raw signal before applying them to specific neural network models. Thus, the discrete probability distribution of concentration changes of oxy- and deoxyhemoglobin and the extraction of statistical features are often used in the preprocessing of neurocognitive data in applying random forests and support vector machines. Whereas constructing spatial maps or original time series allow deep learning neural networks to independently extract features from the input signal. In general, artificial intelligence algorithms require denoised data to function effectively. studies have shown that arbitrary feature extraction and artifact removal can cause problems in real-time signal processing and subsequent use in brain-computer interfaces. However, deep learning neural networks can efficiently handle this task with a sufficient training dataset. Deep learning neural networks are employed both as independent classifier models and as feature extraction methods that are subsequently used in any classifier model. This approach is highly promising and continues to evolve actively. Despite modern AI methods, such as deep learning neural networks, being capable of summarizing and interpreting the original "raw" data, the data preprocessing step remains crucial and mandatory, especially with small samples of neurocognitive data.

An important challenge in the application of deep learning neural networks is the requirement for large datasets, while research on neurocognitive mechanisms typically involves small sample sizes. A potential solution to this challenge currently is generating artificial fNIRS data from existing small sets of registered data using generative adversarial neural networks (GAN).

The most common methods for analyzing preprocessed and denoised fNIRS data include convolutional neural networks (CNN) and recurrent neural networks (RNN), particularly with LSTM (long short-term memory) architecture. The review indicated that applying these deep learning neural networks reduces the number of signal preprocessing stages while achieving high classification accuracy.

Therefore, the primary applications of artificial intelligence methods (Orrù et al., 2020), particularly those based on deep learning, for processing and analyzing neurocognitive data are:

(1) feature extraction or data augmentation (Gao et al., 2022; Lu, et al., 2020; Yücel et al., 2021);

(2) signal classification in brain-computer interfaces (Dolmans, Poel, van't Klooster & Veldkamp, 2021; Glorot, Bordes & Bengio, 2011; Dargazany, Abtahi & Mankodiya, 2019; Saadati, Nelson & Ayaz, 2019);

(3) analysis of neurocognitive mechanisms (Tanveer et al., 2019; Gao et al., 2020; Ma et al., 2020; Wang et al., 2021; Sirpal et al., 2019; Xu et al., 2019; Yang et al., 2020; Ortega & Faisal, 2021; Ghonchi et al., 2020b; Chiarelli et al., 2018; Sun et al., 2020; Cooney, Folli & Coyle, 2021).

Conclusion

The key findings of the theoretical review on using machine learning technologies for processing and analyzing neurophysiological data are:

- the hierarchical structure of deep learning neural networks allows for the potential learning of features directly from raw or minimally preprocessed data, thereby diminishing the necessity for multi-stage processing and feature extraction pipelines when analyzing fNIRS data;
- features derived through deep learning neural networks more precisely capture task-induced neural activation in the brain compared to those manually extracted using traditional methods;
- deep learning methods exhibit superior performance levels in analyzing fNIRS data.

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Conflict of Interest Information

The authors have no conflicts of interest to declare.