Brain-Computer Interface Signal Decoding Technology Based on Deep Learning

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Abstract: With a special emphasis on the potential of sophisticated classification algorithms to improve overall system performance, this review article offers a thorough examination of the most recent developments in brain-computer interface (BCI) systems. The paper examines various methodologies, including adaptive learning, deep learning, and hybrid models, and evaluate their impact on decoding complex brain signals. Key findings highlight the superior efficacy of deep learning approaches such as LSTM-FCN and 1D CNN in improving accuracy and robustness. Transfer learning combined with advanced CSP algorithms also shows significant improvements in handling limited training data. Furthermore, the integration of deep learning with the EEG2Code method achieves remarkable information transfer rates. These advancements demonstrate transformative potential for BCI applications in healthcare, assistive technologies, and human-computer interaction. However, challenges remain in aligning algorithmic complexity with brain signal characteristics and ensuring practical deployment for end-users. Future research should focus on optimizing algorithms for real-time functionality, personalizing BCI systems, and exploring novel decoding modalities to further advance this transformative field.

1 INTRODUCTION

The emerging field of brain-computer interfaces (BCIs)aims to establish a direct communication link between the human brain and external devices. This innovative technology holds the promise of transforming human interaction with the environment, especially for individuals with motor impairments. BCIs work by decoding the electrical activity of the brain, often measured through electroencephalography (EEG), and translating it into control signals for various applications, such as assistive devices, gaming, and even complex tasks like continuous pursuit.

The development of BCI systems follows a multi-stage process, starting with data acquisition where raw brain signals are captured. After these signals are examined, significant features are extracted, and computers classify these traits to determine the user's intents. BCI systems' efficacy is dependent upon the accurate interpretation of brain signals which include functional near-infrared spectroscopy (fNIRS) data and electroencephalograms. Current developments in EEG-based Brain-Computer Interface technology showed enormous possibilities. As reviewed by Värbu et al. (Värbu et al., 2022), EEG-BCI systems interpret brain signals to facilitate interactions between the brain and external devices. Initially developed for medical purposes to aid patients in regaining independence, these systems have expanded into non-medical domains, enhancing efficiency and personal development for healthy individuals. Over the years, the field has seen the evolution of classification algorithms from traditional machine learning techniques, such as linear discriminant analysis (LDA), to more advanced deep learning models like convolutional neural networks (CNNs).

The first step in the multi-stage process of developing BCI systems is data acquisition, which involves recording unprocessed brain signals. After these signals are examined, significant features are extracted, and computers classify these traits to determine the user's intents. The effectiveness of BCI systems has to rely upon the accurate interpretation of cerebral signals like electroencephalograms and functional near-infrared spectroscopy data. Classification algorithms have evolved throughout time in the field, progressing from more traditional machine learning methods such as linear discriminant

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analysis (LDA) to more advanced deep learning models such as convolutional neural networks (CNN). CNNs are frequently used because they can find significant features from raw EEG data, eliminating the requirement for costly preprocessing and laborious feature engineering (Hossain et al., 2023). Performance in a number of BCI applications, such as driver attention monitoring, emotion recognition, and motor imagery categorization, has increased as a result.

2 TWO NEW DEVELOPMENTS IN BRAIN-COMPUTER INTERFACE SYSTEMS: AN EMPHASIS ON MACHINE LEARNING TECHNIQUES AND CLASSIFICATION ALGORITHMS

2.1 Overview of Classification Algorithms in BCIs

In their thorough evaluation and analysis of brain-computer interface (BCI) systems, Mansoor et al. highlight the features and improvements of these systems utilizing a variety of classification methods (Mansoor et al., 2020). To improve the preciseness and dependability of BCI systems, the authors investigate the application of deep learning, transfer learning, adaptive classifiers, matrix and tensor classifiers, and other methods. They offer an organized summary of recent techniques for feature extraction, data collection, and categorization.

The study highlights the effectiveness of adaptive classifiers in acquiring accurate results compared to static classification techniques. It also emphasizes the potential of deep learning techniques, particularly in achieving faster processing speeds and higher classification accuracy, for real-time BCI implementation. The authors compare different classification algorithms, noting the trade-offs between performance and computational requirements. For instance, linear discriminant analysis (LDA) is highlighted for its suitability in online BCI systems due to its low computational demand, despite its linearity potentially providing poor results on com-plex nonlinear EEG data.

The paper concludes that while artificial neural networks (ANN) offer high accuracy for non-invasive BCI techniques, their complex architecture may not always align with the inherent characteristics of brain signals. The authors suggest that further research is needed to enhance accuracy for healthcare applications and propose that future BCI systems could support multiplatforms and be controlled via smartphones for fail-safe mechanisms. The study's conclusions encourage the creation of more precise and approachable BCI systems, which could completely transform how people utilize assistive technology and technology in general.

2.2 Advanced Machine Learning Approaches

An innovative machine-learning method for brain-computer interfacing (BCI) was presented by Zhihan Lv et al. with the goal of increasing the classification accuracy of electroencephalogram (EEG) signals (Lv et al., 2021). To create a data categorization model, the authors integrate an enhanced Common Spatial Pattern (CSP) method with a transfer learning approach. A time-domain filter is incorporated into the enhanced CSP algorithm to better capture the temporal properties of EEG signals. The transfer learning algorithm is used to apply knowledge gained from one task to solve another related task, which is particularly useful in BCI where data often comes from different individuals with varying data distributions.

The effectiveness of the proposed algorithms, Adaptive Composite Common Spatial Pattern (ACCSP) and Self Adaptive Common Spatial Pattern (SACSP), is verified using a public EEG dataset. The results demonstrate that both actual and imagined movements show higher classification accuracy when comparing left and right-hand movements at different speeds versus same speeds. Traditional algorithms achieved a baseline accuracy of 76.62%, while the ACCSP and SACSP algorithms improved this to 83.58%, representing a 6.96% increase. Notably, the ACCSP method's classification accuracy outperforms the conventional CSP algorithm when the training sample size is modest (e.g., 10 samples).

The work demonstrates that integrating transfer learning with an updated CSP algorithm could substantially boost the categorizing performance of BCI systems. This is especially important since it tackles the issues of lengthy training periods and poor classification accuracy in BCI, which are crucial for real-world uses including intelligent perception, assistive medicine, and human-computer interaction. The study suggests that future BCI technology may further improve applications in gesture tracking and video gaming by utilizing these cutting-edge machine-learning approaches, based on the improved categorization accuracy shown in this study.

2.3 Deep Learning Models for EEG Signal Classification

Elsayed et al. provides a valuable deep learning approach for brain-computer interaction (BCI) systems, specifically focusing on motor execution (ME) electroencephalogram (EEG) signal classification (Elsayed et al., 2021). The authors propose a User-Independent Hybrid Brain-Computer Interface (UIHBCI) model for identifying data from fourteen channels of the electroencephalogram (EEG) which capture the brain reactions of nine individuals. Three steps make up the model: signal processing, Deep Belief Network (DBN) classification, and Independent Component Analysis with Automatic EEG artifacts Detector method (ICA-ADJUST) feature extraction.

The study employs two assessment models—Audio/Video (A/V) and Male/Female (M/F)—to identify relevant multisensory elements of multichannel EEG that suggest certain mental behaviors. When applied independently to these two models, the DBN outperforms other cutting-edge algorithms such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Hybrid Steady-State Visual Evoked Potential Rapid Serial Visual Presentation Brain-computer Inter-face (Hybrid SSVEP-RSVP BCI). Even applied with Brain-computer Interface Lower-Limb Motor Recovery (BCI LLMR), yielding overall classification rates of 94.44% for the A/V model and 94.44% for the M/F model.

The outcomes demonstrate the efficacy of the integration of signal processing, feature extraction, and DBN classification in BCI systems by showing that the suggested UIHBCI model is successful in classifying ME EEG signals.

2.4 The Comparative Study of Deep Learning and Machine Learning for fNIRS-BCI

Research contrasted deep learning with conventional machine learning methods for interpreting brain signals using functional near-infrared spectroscopy (fNIRS) in the context of brain-computer interfaces (BCI) (Lu et al., 2020). The purpose of the study is to ascertain which method processes fNIRS data for mental arithmetic tasks more effectively. Alongside the deep learning technique, namely the long short-term memory-fully convolutional network (LSTM-FCN), the traditional machine learning techniques, such as linear discriminant analysis (LDA), decision trees, support vector machines (SVM), K-Nearest Neighbor (KNN), and collective techniques, were assessed.

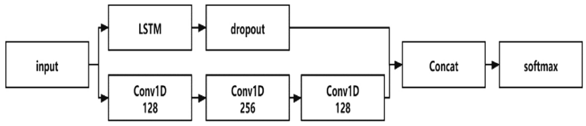

Figure 1: Mechanism of LSTM-FCN for fNIRS-BCI Data (Lu et al.,2020).

The fNIRS-BCI dataset used in the study was collected from eight subjects performing mental arithmetic tasks. Figure 1 depicts the LSTM-FCN architecture for fNIRS-BCI data. The data first underwent preprocessing to reduce physiological noise. Subsequently, feature extraction was performed to identify relevant channels and time periods. The classical machine learning methods required strict feature extraction and screening, while the LSTM-FCN model was designed to automatically learn features from the raw data.

According to the results, SVM outperformed the other conventional approaches, achieving an average accuracy of 91.0% for tasks related to the subject and 83.0% for tasks unrelated to the subject. However, with an accuracy of 95.3% for tasks relevant to the subject and 97.1% for tasks unrelated to the subject, the deep learning technique LSTM-FCN considerably surpassed the traditional methods. Interestingly, LSTM-FCN demonstrated its stability and efficacy in decoding fNIRS-BCI data by achieving 100% accuracy for several participants despite varying network dropout rates.

The study comes to the conclusion that deep learning—specifically, the LSTM-FCN model—is a more viable method for analyzing fNIRS-BCI data than traditional machine learning techniques because of its higher accuracy and capacity to automatically learn features. This finding is significant as it highlights the potential of deep learning to handle complex and dynamic brain signal data, which is crucial for advancing BCI applications in areas such as assistive technologies and cognitive research.

2.5 Deep Learning for EEG-Based Mental State Decoding

In order to decode mental states from electroencephalogram (EEG) data in non-invasive brain-computer interfaces (BCI), Dongdong Zhang and colleagues created a deep learning-based method (Zhang et al., 2019). The study addresses the challenge of accurately predicting mental states using EEG, which has traditionally suffered from limited accuracy and generalization. The authors suggest a brand-new 1D convolutional neural network (CNN) architecture that uses different-length filters to extract data from various EEG signal frequency bands. The goal of this strategy is to increase prediction accuracy and feature extraction.

The researchers looked at a dataset of 25 hours of EEG recordings from five patients who were undertaking a low-intensity control task. To maintain inter-channel correlations, the data were preprocessed using a bandpass filter and standardized. In order to enable robust feature extraction, a relatively deep network was trained for the proposed 1D CNN employing a Resnet-like structure. The model's performance was evaluated using fivefold cross-validation.

The results demonstrate significant improvements over traditional prediction methods such as KNN and SVM. The proposed model achieved an accuracy of 96.40% in predicting mental states, outperforming traditional algorithms and other published deep learning architectures. In the more challenging common-subject paradigm, the proposed model achieved a prediction accuracy of 53.22%, surpassing the performance of existing methods including EEG Net, FBCSP Shallow Net, and Deep Conv Net.

The study's findings highlight the effectiveness of using 1D convolutional neural networks for EEG feature extraction and mental state prediction. This technique presents an appealing option to further develop both the precision and generality within BCI systems, possibly broadening its applications in monitoring mental states in a variety of real-world situations

2.6 Continuous Pursuit Tasks in BCI

The use of deep learning (DL)-based decoders for continuous pursuit (CP) activities has been examined in noninvasive brain-computer interfaces (BCI) which incorporate electroencephalography (EEG) (Forenzo et al., 2024). Using motor imagery, users perform CP tasks by tracking a moving target in 2D space, a process that requires dynamic and continuous control. The researchers developed a novel labeling system to enable supervised learning with CP data, which lacks clear labels for traditional supervised learning methods. They trained DL-based decoders using two architectures: EEGNet and a modified PointNet, shown as Fig2. The performance of these DL models was evaluated over multiple online sessions with 28 human participants.

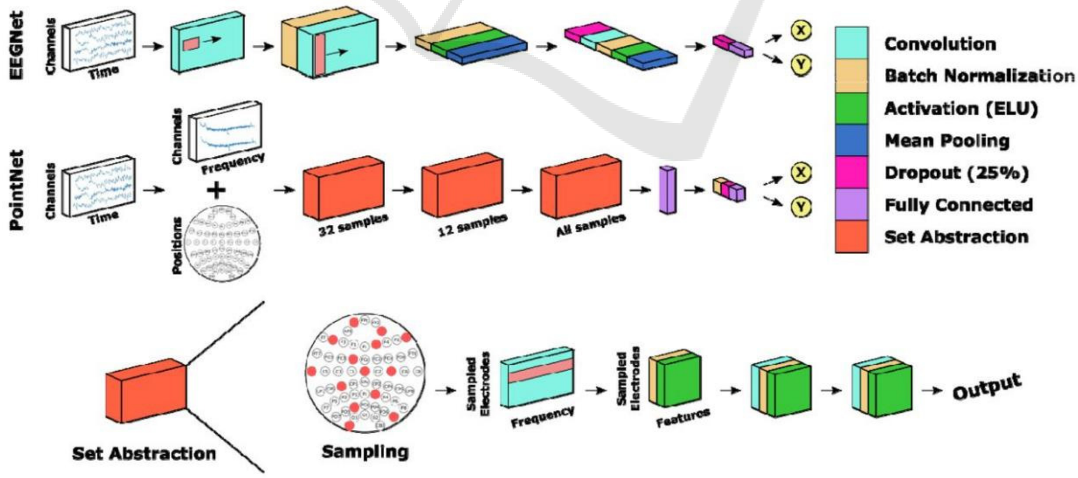

Figure 2: The Implementing of EEGNet and PointNet Architecture (Forenzo et al., 2024).

The results showed significant improvements in the performance of DL-based models as more training data became available. In the very last period, both DL models surpassed a standard autoregressive decoder. Specifically, the normalized mean squared error (NMSE) be-tween the cursor and target dropped from an initial value to 0.43 for EEGNet and 0.56 for PointNet every session. Furthermore, during the course of sessions, the correlation between the target and cursor positions grew, with EEGNet reaching a greater correlation by the last session. The study also investigated transfer learning and mid-session recalibration to enhance performance. Although transfer learning failed to significantly improve early session performance, mid-session recalibration demonstrated promising benefits in several cases.

All things considered, the study indicates how well DL-based decoders perform BCI in hard tasks like CP, indicating that they may be utilized to expand BCI applications in practical situations while also enhancing the quality of life for normal people and people with motor impairments.

2.7 Deep Learning for High-Speed BCI Systems

To forecast visual input properties from EEG data, deep learning and the EEG2Code technique have been combined (Nagel & Spüler, 2019). The disclosed BCI system is by far the quickest, since the authors demonstrate that an individual may use this method in an online BCI to obtain an information transfer rate (ITR) of 1237 bits per minute. The top person can distinguish between 500,000 distinct stimuli with 100% accuracy utilizing just 2 seconds of EEG data in a simulated online exercise with 500,000 targets.

The study uses deep learning, namely a convolutional neural network (CNN), with the EEG2Code approach to generate a nonlinear model that forecasts random stimulation patterns according to VEP feedbacks. Figure 3 depicts a demonstration of the EEG2Code CNN model. The authors suggest that EEG signals include more information than is commonly supposed. However, they also mention a ceiling effect, which suggests that, not less than for BCIs that rely on stimuli that are visual, more powerful decoding approaches may not necessarily result in greater BCI control.

The results highlight a significant improvement in classification accuracy and ITR when using deep learning compared to the previous ridge regression model. The technique increased the ITR from 232 bits/min to 701 bits/min, a 202% improvement, while also improving the pattern prediction accuracy from 64.6% to 74.9%. In a passive BCI environment, the top subject obtained an online ITR of 1237 bits/min. The system reached an average utility rate of 175 bits/min for asynchronous self-paced BCI spelling, Users can create an average of 35 error-free letters each minute.

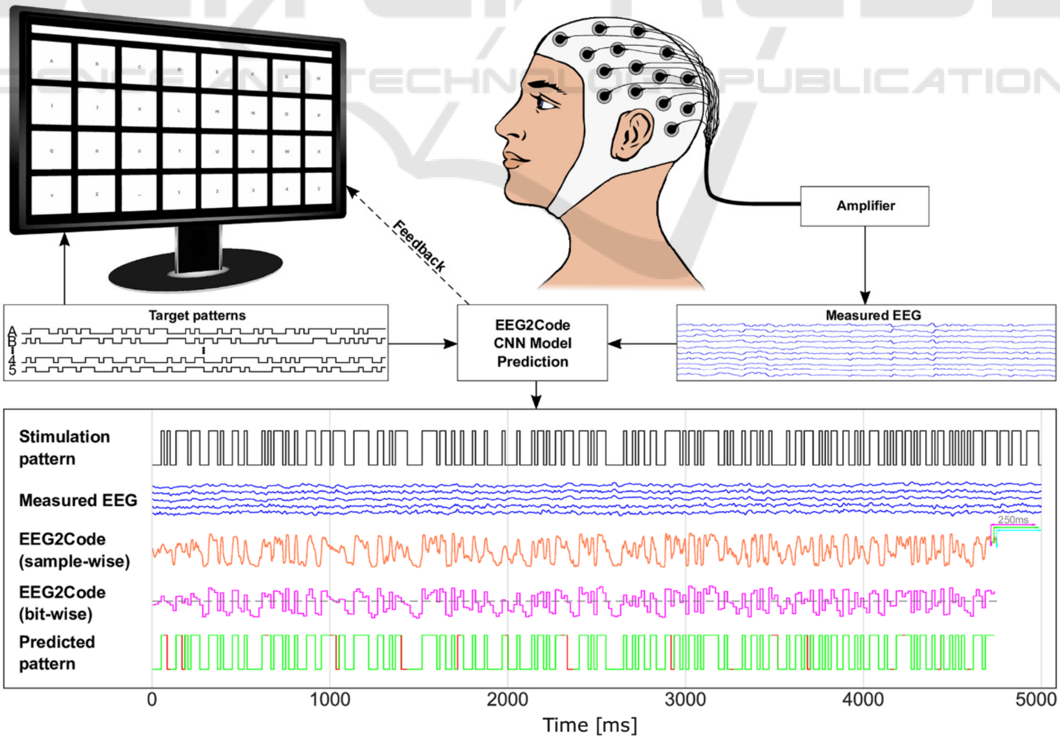

Figure 3: Example of the EEG2Code CNN Pattern Prediction (Nagel & Spüler, 2019).

The authors come to the conclusion that although the method they outlined may be able to gather a significant quantity of data from EEG signals, the maximum number of targets and the minimum trial duration are still limitations for genuine BCI control. They highlight two important points: the need to make sure BCI systems continue to be feasible for end-user applications, and the difference between brain signal decoding performance and actual BCI control performance.

3 CONCLUSION

This review research focuses on the substantial breakthroughs in brain-computer interface (BCI) systems made available through judicious application of advanced classification algorithms. Among various advances, deep learning techniques such as LSTM-FCN and 1D CNN have demonstrated superior capabilities in decoding intricate brain signals, offering better accuracy and robustness compared to traditional methods. The symbiotic relationship between transfer learning and enhanced CSP algorithms has also been validated, particularly in overcoming the challenges of limited training data. Building upon these advances, the integration of deep learning with the EEG2Code method has achieved unprecedented information transfer rates, revealing the untapped potential of EEG signals in BCI applications. Despite these advancements, the alignment of algorithmic complexity with brain signal characteristics and the practical deployment of BCI systems for end-users remain ongoing challenges. As highlighted in the review by Samal and Hashmi (Samal & Hashmi, 2024), the continuous advancements in non-invasive and portable sensor technologies, such as EEG-based BCIs, are expected to significantly enhance the precision and real-time capabilities. As BCI technology evolves, it shows great promise in revolutionizing multiple fields, from assistive healthcare to human-computer interaction and neuroscience research, heralding a new era of more intuitive and effective BCI systems.

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