IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 3, December 2023

Brain Computer Interface using Deep Learning

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Abstract: *Human-generated thoughts and signals are non-stationary and nonlinear due to the complexity of the human brain. Therefore, the difficult part is to create a system that can extract deeper insights from the human brain. Once these deeper insights are obtained, BCI applications will function more effectively. Devices known as brain-computer interfaces allow its users to communicate with computers only through their brain activity, which is often detected by electroencephalography (EEG). The use of deep learning in brain computer interfaces (BCIs) is investigated in this work. Reviewing previous research and findings on brain computer interfaces (BCIs) and how they work with deep learning methods is the main goal of the study. It looks at how signal processing, feature extraction, and classification in BCIs have been improved via the use of deep learning. The goal of the research is to present a thorough review of the state of innovations and improvements in this sector as of right now. illuminating the possible advantages and difficulties of using deep learning to BCIs*

Keywords: deep learning, computer, brain language, EEG, and brain-computer interface

I. INTRODUCTION

A computer-based device known as a Brain-Computer Interface (BCI) gathers brain signals, processes them, and converts them into commands that are sent to an output device so that a desired action may be performed. In order for a user to communicate with an external device using an active BCI, they must actively modify their brain signals. Six essential components function together effortlessly in a BCI system. First, electrodes are used to capture electrophysiological signals that come from the patient's brain and constitute the basic responses of the neurons. These brain reactions are then recorded and examined using signal gathering apparatus. The process of feature extraction then extracts discriminative components while decreasing the amount of data required for additional classification tasks. The translation algorithm then comes into play with these translated parts. These translated features are transformed into usable control signals by the Translation Algorithm, which is essential for establishing communication between the user and external devices. These control signals are then deciphered by the Control Interface, which converts them into instructions and actions for particular output devices. Lastly, the feedback system acts as a guide, helping the person to fine-tune their brain activity for improved interaction and control. BCIs come in three varieties: invasive, semi-invasive, and non-invasive. Sensors are applied to the scalp in non-invasive brain-computer interfaces (BCIs) to measure electrical potentials generated by the brain (EEG) or the magnetic field (MEG). With semi-invasive BCIs, a craniotomy is necessary to place electrodes on the brain's exposed surface for electrocorticography (ECoG). During neurosurgery, invasive BCIs are placed right into the brain's gray matter, providing the best signal quality but also increasing the risk of scar tissue accumulation over time. Brain-computer interfaces (BCIs) have been transformed by convolutional neural networks (CNNs), which do away with the need for human feature engineering by automatically extracting meaningful features from neural data. They can recognize cognitive states and identify complex patterns in EEG or other neural recordings thanks to their hierarchical processing ability. This dynamic synergy advances neural signal processing and maximizes the potential of BCIs. The combination of convolutional neural networks (CNNs) and brain-computer interfaces (BCIs) ushers in a new era of seamless human-technology interaction in this quickly changing landscape. .. This discovery advances our knowledge of how the brain works and ushers in a new era of seamless mind-machine communication for neurotechnology. CNNs are a game-changer in BCI, providing more reliable and intuitive systems for tasks like cognitive state recognition and motor imagery classification. This dynamic synergy advances neural signal processing and maximizes the potential of BCIs. The combination of convolutional neural networks (CNNs) and brain-computer interfaces (BCIs) opens a new era of seamless human-technology interaction in this quickly changing

DOI: 10.48175/568

landscape. These Brain Computer Interface Using developments promise improved communication as well as a greater comprehension of brain functions. BCI technology is based on the complex interaction of electrodes, signal processing, and translation algorithms, and it has enormous potential applications in assistive technology and medical rehabilitation. Brain-computer interfaces (BCIs) have emerged as a transformative technology with far-reaching implications for human-computer interaction, medical rehabilitation, and our understanding of the brain. By bridging the gap between the human brain and external devices, BCIs hold the promise of restoring lost functions, enhancing communication, and revolutionizing the field of neurotechnology.One of the most compelling applications of BCIs lies in the realm of assistive technology. For individuals with severe motor impairments, BCIs offer a lifeline for regaining control over their lives. By decoding brain signals associated with movement intentions, BCIs can enable paralyzed individuals to operate prosthetics, navigate wheelchairs, and even interact with computers using their thoughts alone. In medical rehabilitation, BCIs are poised to accelerate the recovery process for individuals suffering from neurological disorders such as stroke, spinal cord injuries, and amyotrophic lateral sclerosis (ALS). By providing a direct channel for communication between the brain and affected muscles, BCIs can facilitate neuroplasticity, the brain's remarkable ability to reorganize itself, potentially restoring lost motor function. Beyond their therapeutic applications, BCIs also hold the potential for enhancing human capabilities in healthy individuals. Imagine controlling external devices with mere thoughts, navigating virtual worlds with unparalleled precision, or even augmenting our cognitive abilities. BCIs open up a new frontier for human-computer interaction, blurring the lines between mind and machine. The advancement of convolutional neural networks (CNNs) has revolutionized the field of BCIs. CNNs, a type of artificial intelligence, excel at extracting meaningful patterns from complex data, making them ideally suited for analyzing brain signals. By employing CNNs, researchers have developed BCIs that can recognize cognitive states, classify motor imagery, and even translate thoughts into speech. The integration of CNNs into BCIs has unlocked a new era of seamless human-technology interaction. With more reliable and intuitive systems, BCIs are poised to transform the way we interact with the world around us, blurring the lines between human and machine. As BCI technology continues to evolve, it promises to revolutionize our understanding of the brain, leading to new insights into its intricate workings and unlocking novel therapeutic approaches for neurological disorders. The future of BCIs is bright, filled with the potential to enhance human capabilities, restore lost functions, and transform our relationship with technology.

II. LITERATURE SURVEY

[1].With a focus on approaches like CNNs and RNNs, the paper offers a thorough analysis of deep learning techniques used in EEG-based Brain-Computer Interfaces (BCIs).It draws attention to the potential advantages of deep learning, specifically its ability to independently extract complex EEG patterns, which may improve the accuracy and dependability of BCI systems. The study recognizes difficulties with data scarcity, model interpretability, and computational complexity, highlighting the need for more study in these areas.

[2]. To enable advanced motor Brain-Computer Interfaces (BCIs), the paper uses Convolutional Neural Networks (CNNs) for processing Stereo-Electroencephalography (SEEG) data. CNNs are particularly good at picking up complex spatial patterns, which could improve the accuracy and dependability of BCIs in motor control applications. Although offering encouraging progress, obstacles include the requirement for high-quality SEEG data, interpretability of the model, and computational resources for training and implementation.

[3]. In order to classify EEG signals associated with motor execution in Brain-Computer Interaction (BCI) systems, the paper presents a deep learning technique. Deep learning models show promise in automatically deciphering complex patterns from EEG data, which could improve the classification accuracy of BCIs. Although promising, difficulties with data quality, model interpretability, and computational resources point to areas that need further study.

[4]. With a particular focus on tasks involving motor imagery, the paper investigates deep learning models in EEG-based Brain-Computer Interfaces. The potential benefits of deep learning reside in its ability to learn intricate EEG patterns on its own, which could improve the accuracy and adaptability of BCI.Data quality issues, interpretability difficulties, and possible computational demands are among the limitations, highlighting areas that warrant further study in the development of BCIs..

[5]. The use of deep learning in continuous control Brain-Computer Interfaces (BCIs) is examined in this paper. Deep learning models can improve the accuracy and adaptability of continuous control BCI by independently identifying patterns from EEG data. The paper identifies potential interpretability issues and data limitations and makes recommendations for future research directions in real-time BCI applications.

[6].A thorough analysis of deep learning algorithms used in EEG signal decoding applications is given in this paper. Deep learning shows promise in automatically deciphering intricate patterns from EEG data, which could improve decoding precision. Recognizing difficulties with data interpretability and quality, the study makes recommendations for future research aimed at improving EEG signal decoding efficiency.

[7]. In biomedical engineering, deep learning algorithms have become increasingly popular, especially for interpreting EEG data to determine brain states. This paper offers a thorough review of the state-of-the-art applications, widely used algorithms, common scenarios, developments, and difficulties in EEG decoding tasks. It outlines the fundamentals of deep learning for EEG decoding, explores applications in cognitive neuroscience, brain-computer interfaces, and the diagnosis of brain disorders, and highlights upcoming difficulties with parameter selection, computational complexity, and generalization abilities.

[8]. Using deep learning techniques, the paper presents a novel approach to direct thought-to-text translation using EEG signals. By avoiding traditional input methods, this method has the potential to revolutionize communication for people with limited motor function. Nevertheless, difficulties include translation accuracy, subject-specific data requirements, and ethical issues. In order to improve usability and performance, more research is necessary.

[9]. In order to improve signal processing for better Brain-Computer Interface (BCI) performance, the paper focuses on the application of deep learning algorithms in BCIs. It recognizes possible restrictions on the interpretability of deep learning models, the quality of the data, and the computational capacity for real-time BCI applications.The deep learning algorithm showed flexibility by independently deriving intricate patterns from EEG data, which could improve the usability and accessibility of BCIs.

[**10**].The paper presents a novel deep convolutional neural network for ERP-based Brain-Computer Interfaces (BCIs), called EEG-inception, and shows how it can potentially improve classification accuracy and adaptability. Restrictions include the need for computational resources for real-time BCI applications, potential sensitivity to data quality, and difficulties with model interpretability.

[11]. The study uses deep learning methods to optimize P300-based Brain-Computer Interfaces (BCIs) with the goal of raising signal-to-noise ratios and classification accuracy. Acknowledging constraints in interpretability and computational capacity, the research advances brain computer interfaces (BCIs) by utilizing flexible deep learning model.

[12]. The paper streamlines the Brain-Machine Interface (BMI) setup process by introducing a deep learning based method for automatically choosing the most informative channels. Potential sensitivity to data quality and the difficulty of interpreting decisions made by deep learning models in relation to channel selection are limitations. Although there may be benefits in automation and optimization, the paper might not go into great detail about certain application domains or ethical issues with BMI technology.

[13].A thorough review of EEG-based Brain-Computer Interfaces (BCIs) is given in this paper, covering methods such as SSVEPs, ERPs, and motor imagery. It emphasizes the possibility of direct communication with external devices while addressing constraints like signal noise, individual variability, and ethical issues. To improve BCI usability and performance in real-world applications, the review recommends standardizing protocols, enhancing signal processing, and implementing user-centered design.

[14]."EEGNet" introduces a neural network specifically designed for Brain-Computer Interfaces (BCIs) based on EEG. EEGNet performs competitively in classification tasks by processing EEG signals efficiently through the use of depthwise separable convolutions. The study emphasizes the need for additional research to confirm its robustness and investigate customized applications in particular BCI tasks by acknowledging potential sensitivity to electrode placement and individual EEG characteristics.

[15]. He et al.'s chapter from 2020 offers a thorough introduction to Brain-Computer Interfaces (BCIs), encompassing a range of methods such as EEG, ECoG, fNIRS, and invasive recordings. It stresses the need for customized strategies and user-centered design while addressing drawbacks like subject-specific neural responses, possible signal artifacts, and ethical issues. BCIs provide important insights into neural activity and brain function, and they hold promise for use in neurorehabilitation, cognitive neuroscience research, and brain-controlled assistive technologies.

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[16]. In order to preserve both temporal and spatial features, the paper presents a novel 3D representation method for EEG data in motor imagery (MI) classification tasks. To process the distinct 3D EEG representation, a specialized multi-branch 3D convolutional neural network (CNN) is used, which improves classification accuracy and allows for effective feature extraction. The experimental results show cutting-edge performance with dramatically lower subject-to-subject variability. The framework's ability to function well even with fewer electrodes is another indication of its practical promise.

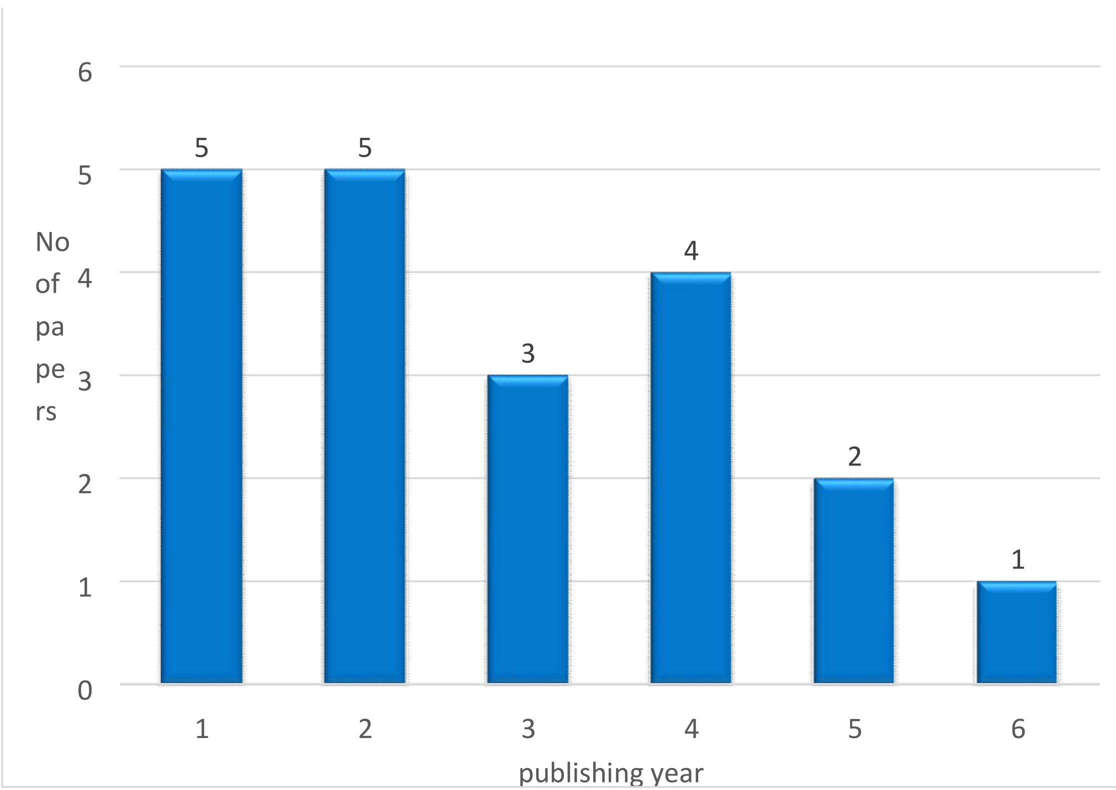
[17]. The deep learning framework NeuroAiR, intended to identify airwriting gestures, is presented in this paper. Using neural signals captured from the scalp, NeuroAiR emphasizes a non-invasive method of obtaining input data for deciphering airwriting movements. The main objective is to use the NeuroAiR deep learning framework to accurately interpret airwriting gestures, enabling communication and device control.

[18]. Focuses on developing best practices for analyzing deep learning models in Brain-Computer Interfaces (BCIs) that are based on EEG. Seek to improve the field of EEG-based BCI's comprehension and utilization of deep learning approaches. places special emphasis on enhancing deep learning models' interpretability for real-world use in braincomputer interfaces.

[19]. Focuses on using Electrocorticography (ECoG) for brain-computer interfaces by integrating deep learning. Particularly contrasts hand-crafted features with end-to-end learned features in terms of efficacy. Examines developments in brain-computer interface technology based on ECoG.

[20]. During mathematical computations, the paper uses deep learning techniques to classify Electroencephalograms (EEGs).It offers a system for classifying EEG patterns linked to mathematical task-related cognitive processes.

III. GRAPHICAL REPRESENTATION



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IV. METHODOLOGY

[1]

1.Data Collection and Preprocessing:

Data Collection: In this study, we utilized EEG datasets obtained from reputable sources. These datasets were chosen due to their relevance to the targeted BCI applications and their availability for research purposes.

Preprocessing: Prior to model training, the EEG data underwent several preprocessing steps to enhance the quality of the input. These steps included bandpass filtering to remove noise outside the desired frequency range. Additionally, we applied artifact removal techniques, referencing methods, etc. A common average reference was employed to mitigate the effects of common noise sources.

2. Feature Selection: Relevant features were extracted from the preprocessed EEG data to serve as inputs for the deep learning models. We selected a combination of time-domain and frequency-domain features, including specific features, e.g., spectral power, entropy measures, etc. These features were chosen based on their established effectiveness in capturing meaningful information for the intended BCI tasks.

3. Deep Learning Models: Convolutional Neural Networks (CNNs):CNNs were used to effectively identify spatial patterns within EEG data. They are well-suited for tasks that involve grid-like data, which is perfect for processing multichannel EEG recordings. The CNN consisted of layers specialized in detecting different features. These layers include convolutional layers that scan the data for patterns, pooling layers that downsample the information, and fully connected layers for making predictions. Activation functions, like ReLU, were used to introduce non-linearity, allowing the network to learn complex relationships.

Long Short-Term Memory Networks (LSTMs): LSTMs were employed to capture temporal dependencies in the EEG time series data. They excel at modeling sequential patterns and are particularly useful for tasks involving time-varying EEG signals. The LSTM network was composed of memory cells that can store and process information over time steps. It includes input, forget, and output gates to control information flow. These gates enable the network to selectively remember or forget information. LSTMs are well-suited for tasks where understanding the context over time is crucial, like analyzing EEG data.

4. Training and Validation: Training Procedure: We used the Adam optimizer with a learning rate of 0.001 to facilitate efficient model training. The batch size was set to 32to balance computational efficiency and model convergence. Validation Set: The dataset was divided into training and validation sets .The validation set was crucial for monitoring the model's performance during training and preventing overfitting.

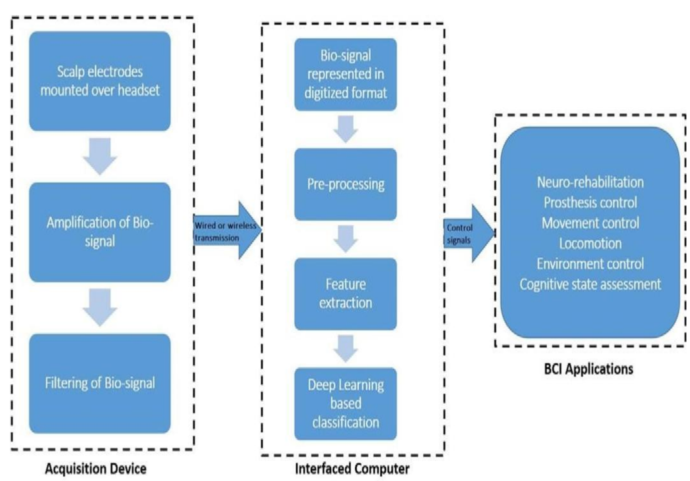

FIGURE 3
An architecture of BCI based on EEG data.

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5. Evaluation Metrics: The models were evaluated using a range of standard metrics including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). These metrics were chosen to provide a comprehensive assessment of the model's classification performance for the specific BCI applications.

[2]

1. Data Collection and Preprocessing: EEG signals were recorded using specific equipment and electrode placements based on the international 10–10 system. Impedance of electrodes was kept below 5 k ohms before data acquisition. Eye-movement activity was monitored using EOG electrodes. EEG data was segmented based on specific time windows and excluded epochs with extreme amplitudes or gradients.

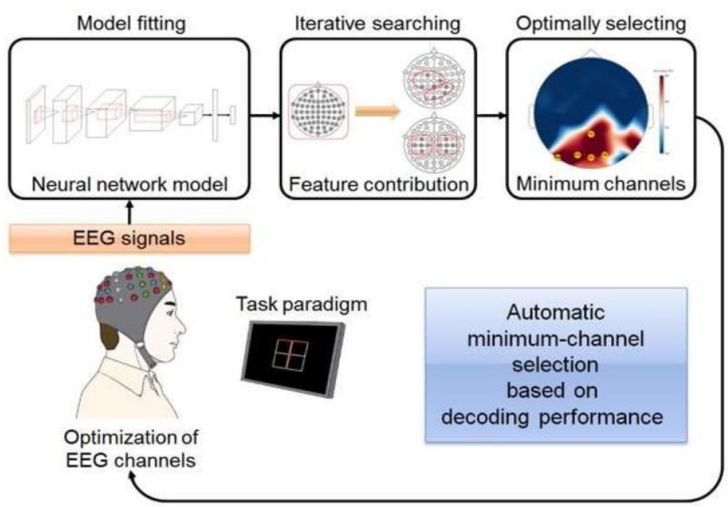
2. Feature Extraction: Features were extracted from EEG epochs to be used as input for the compact CNN model.

3. Deep Learning Models (Compact CNN): This model is versatile and can be applied to different BCI paradigms, regardless of the number of channels or decoding classes. The CNN model is designed to perform both feature extraction and classification for each subject's EEG data. The study also outlines the technical details of the CNN architecture, including weight initialization, optimizer settings, and training methodology. Additionally, a validation set is used to monitor and select the best-performing model. The model is evaluated using various EEG datasets, demonstrating its effectiveness in minimum-channel selection across different BCI paradigms.

4. Validation Set: The dataset was split into training, validation, and test subsets at a ratio of 5:1:2.The model was trained using the training set, and performance was monitored on the validation set.

5.Evaluation Metrics:Decoding accuracy was used as the primary evaluation metric.Equivalence tests were employed to statistically compare decoding accuracies obtained using minimally selected channels with those using all channels.Pearson's correlation coefficients were computed to assess the relationship between decoding accuracies.

6.Comparisons with Other Algorithms: LDA and ConvNet algorithms were introduced for channel selection comparison. Standard sets of channels were analyzed for performance comparison.



[3]

1.Data Collection: EEG signals are collected, presumably from subjects participating in different tasks or scenarios relevant to the application areas (BCI, cognitive psychology, disease detection).

2.Data Preprocessing: The collected EEG signals undergo preprocessing steps to enhance their quality and prepare them for the subsequent decoding process.Preprocessing may include filtering, artifact removal, and other techniques to clean and standardize the EEG data.

3.Deep Learning models:

1.Convolutional Neural Network (CNN):Effective for image classification, CNN uses convolution to learn local patterns in data. Typically consists of hierarchical convolutional layers and pooling.

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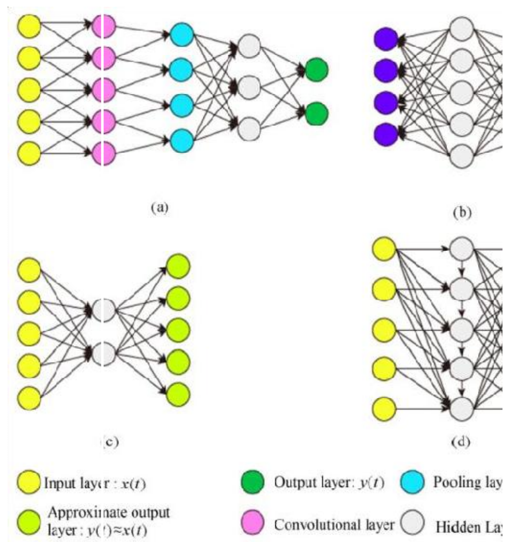
2, Deep Belief Network (DBN):A generative probability model composed of Restricted Boltzmann Machines (RBM). Utilizes unsupervised learning for pre-training and supervised learning for fine-tuning. Suitable for dimensionality reduction, image compression, and digital recognition.

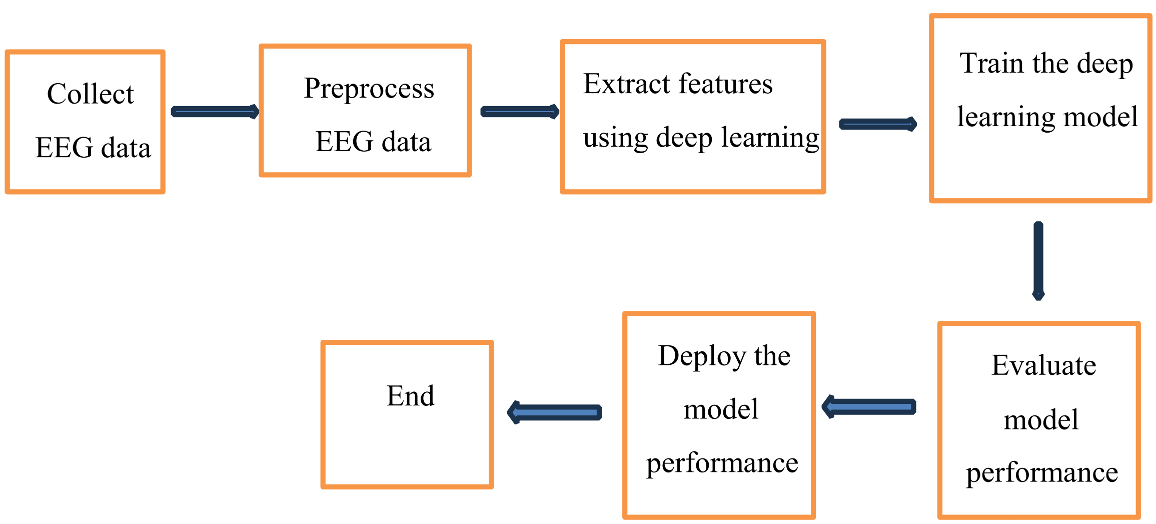
3.Auto-Encoder (AE):Composed of an encoder function and a decoder function.Uses a feedforward acyclic neural network structure similar to MLP.Typically employed for dimensionality reduction and learning data representation.

4,Recurrent Neural Network (RNN):Used for processing sequence data, including EEG signals.Contains self-connected hidden layers, providing feedback connections.Effective for processing time series data and capturing time information.

4..Performance Evaluation: The performance of each deep learning model is likely assessed using relevant metrics such as classification accuracy, sensitivity, specificity, or other measures depending on the application area.



V. CASE STUDY



VI. RESULTS AND DISCUSSIONS

References	Dataset	Max. accuracy (%)	Algorithms used
Rammy et al. (2020)	BCI competition IV	100	CNN
Wilaiprasitporn et al. (2019	DEAP	99.90	CNN, RNN
Amber et al. (2019)	DRYAD	99.60	CNN
Dang et al. (2021)	CMB-MIT	99.56	CNN
Li Y. et al. (2020)	EEGMMIDB	97.36	R-CNN
Fares et al. (2019)	ImageNet-EEG	97.30	Bi-LSTM
Hwang et al. (2020)	SEED	96.77	CNN
Arnau-González et al. (2017)	DREAMER	94.01	CNN
Huang et al. (2022)	Physionet	92.00	CNN
Chakladar et al. (2020)	STEW	82.57	Bi-LSTM
Völker et al. (2018)	Flanker task	81.70	CNN
Saha et al. (2019)	KARA	77.90	CNN+LSTM
Tiwari et al. (2021)	Emotiv	72.00	CNN

VII. CONCLUSION

Brain-Computer Interface (BCI) with deep learning is like creating a super connection between our minds and computers. This is super useful, especially for people who have trouble moving because it lets them control things just by thinking. Deep learning, which is like a smart computer helper, makes BCI understand our thoughts even better. But, we still have some things to figure out, like making it work really well and keeping our thoughts private.Looking ahead, this mix of BCI and deep learning isn't just for helping people who need it. It can make a big difference in healthcare, games, virtual reality, and how we learn new things. As this technology gets better, it could change how we use computers, making it easier and more fun. So, the combination of BCI and deep learning is like opening a door to lots of cool possibilities, making our connection with technology more natural and exciting. In simple terms, it's like making friends with computers in a way that makes our lives better and more interesting

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