[ICAETBM-2024]
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)
doi : https://doi.org/10.32628/IJSRSET

Emotions Prediction Using EEG Signal : Survey Paper

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ABSTRACT

This survey paper presents a comprehensive analysis of recent advancements in Brain-Computer Interface (BCI) research, with a focus on the integration of deep learning and machine learning techniques. The abstract encapsulates the key contributions of the surveyed papers, covering a diverse range of BCI paradigms, including motor imagery-based BCIs, neurohaptic interfaces, and imagined speech decoding. The surveyed literature encompasses methodologies such as transfer learning, feature extraction, classification algorithms, and various deep learning models. The comparative analysis highlights the strengths and applications of each approach, providing insights into their performance and potential clinical relevance. The paper concludes with a summary of common trends, challenges, and future research directions in the dynamic and evolving field of BCIs.

Keywords — Decentralized, cloud storage, peer to peer , Blockchain Technology, cloud & security, Centralized.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) have emerged as revolutionary technologies bridging the gap between human cognition and external devices. These interfaces hold immense potential in diverse applications, ranging from neurorehabilitation to communication and control of external devices. As the field evolves, the integration of advanced machine learning and deep learning techniques has played a pivotal role in enhancing the efficiency and scope of BCIs.

The primary objective of this survey paper is to provide a comprehensive overview of recent developments in BCI research, with a specific emphasis on the utilization of deep learning and machine learning methodologies. The introduction sets the stage by outlining the overarching significance of BCIs and their transformative impact on human-machine interaction.

A. Background and Significance

The advent of BCIs marks a paradigm shift in human-computer interaction by enabling direct communication between the human brain and external devices. These interfaces hold promise for individuals with motor impairments, offering new avenues for rehabilitation and assistance in daily life. Moreover, BCIs open possibilities for neuroscientific research and the development of innovative technologies that augment human capabilities.

B. Evolution of BCI Technologies

The evolution of BCI technologies has witnessed remarkable progress, transitioning from early experimental stages to practical applications. Early BCIs primarily relied on simple EEG signals, while contemporary approaches integrate sophisticated neuroimaging techniques and advanced signal processing algorithms. This section briefly traces the historical progression of BCIs, highlighting key milestones and breakthroughs.

C. Motivation for the Survey

The integration of deep learning and machine learning techniques has significantly enhanced the capabilities of BCIs, particularly in tasks such as motor imagery classification, neurohaptic interfaces, and imagined speech decoding. This survey aims to consolidate and analyze recent literature, providing insights into the methodologies employed, experimental findings, and the potential impact of these advancements.

D. Scope and Structure of the Survey

This survey encompasses a diverse selection of recent papers, each contributing to different aspects of BCI research. The subsequent sections will delve into the methodologies employed in these studies, emphasizing the role of deep learning and machine learning in enhancing BCI performance. A comparative analysis of the surveyed literature will be presented, offering a holistic view of the current state of the field. The survey concludes by identifying common trends, challenges, and proposing potential avenues for future research.

II. RELATED WORK

The landscape of Brain-Computer Interface (BCI) research is rich and diverse, with numerous studies exploring different methodologies and applications. A significant body of related work exists, focusing on various aspects of BCIs, from motor imagery classification to neurohaptic interfaces and imagined speech decoding. In the realm of motor imagery-based BCIs, Ferrero et al. (Paper 1) leverage convolutional neural networks (CNNs) and transfer learning to address the challenge of limited data availability for commanding lower- limb exoskeletons. Yuan (Paper 2) offers a comprehensive review of feature extraction methods and classification algorithms for Motor Imagery BCIs, providing insights into the challenges and potential advancements in signal processing. Kim et al. (Paper 3) take a novel approach by introducing a brain-based interface system for communication and control via skin touch, catering to the demands of metaverse environments. Castro et al. (Paper 4) contribute to the field by investigating deep learning techniques for visual imagery recognition in BCIs, emphasizing the advantages of inherent feature selection in deep models. Kwak et al. (Paper 5) propose a deep feature normalization algorithm to address EEG variability in BCI decoding, demonstrating a substantial enhancement in deep learning performance. Liu (Paper 6) explores the impact of mindfulness meditation on BCI performance, introducing deep learning models for classifying BCI controls in meditators. Khaliq and Sivani (Paper 7) present a comprehensive review of the role of machine learning techniques in EEG-based BCIs, covering various tasks such as mental state detection, task categorization, and motor imagery classification. Abibullaev and Mun (Paper 11) delve into the realm of explainable deep learning for BCIs, using layerwise relevance propagation to analyze decision boundaries and explore model complexity reduction techniques. Cheng et al. (Paper 12) propose a deep learning approach for asynchronous motor imagery-based BCIs, showcasing the effectiveness of a cascade of one-dimensional convolutional neural networks and fully-connected neural networks. Limchesing et al. (Paper 13) demonstrate a system for brain-controlled wheelchairs using machine learning, extracting, reading, and analyzing EEG signals for real-time directional commands. Gao et al. (Paper 14) contribute to subject-independent P300 BCIs by proposing a convolutional neural network-based invariant pattern learning method, achieving high accuracies without subject-specific calibration. Van den Berg et al. (Paper 15) explore inner speech classification using EEG signals through a deep learning approach, introducing a 2D Convolutional Neural Network for word recognition tasks. Collectively, this related work forms a comprehensive foundation for understanding the breadth and depth of BCI research, showcasing the diverse applications and methodologies that incorporate deep learning and machine learning techniques.

1] Transfer Learning with CNN Models for Brain-Machine Interfaces to command lower-limb exoskeletons: A Solution for Limited Data (Ferrero et al., 2023) This study evaluates the performance of two convolutional neural networks (CNNs) in a brain-machine interface (BMI) based on motor imagery (MI). Transfer learning is employed to address limited data availability, training models on EEG signals from other subjects and fine-tuning them to specific users. The study focuses on commanding lower-limb exoskeletons and explores the potential of CNNs and transfer learning in developing an automatic neural classification system for BMIs.

2] Features Domains and Classification Algorithms in Motor Imagery Brain Computer Interface (Yuan, 2022) Yuan provides a comprehensive review of feature extraction methods and classification algorithms commonly used for motor imagery EEG signals in Brain-Computer Interfaces (BCIs). The paper categorizes feature extraction techniques based on their domains (time, frequency, and spatial) and distinguishes between classical machine learning and deep learning classification algorithms. It aims to offer insights into common approaches and challenges in the signal processing of motor imagery for BCIs.

3] Towards Brain-based Interface for Communication and Control by Skin Touch (Kim et al., 2023) Kim et al. introduce a novel brain-based interface system based on tactile and sensory perception for potential use in metaverse environments. The paper presents a preliminary study on the development of next-generation neurohaptic interface technology that enables communication and control through skin touch. It explores the feasibility of decoding skin touch-related EEG signals to advance on-skin interface technology.

4] Development of a Deep Learning-Based Brain-Computer Interface for Visual Imagery Recognition (Castro et al., 2020) Castro et al. investigate the use of deep learning techniques, specifically deep neural networks, for visual imagery recognition in Brain-Computer Interfaces (BCIs). The study compares the performance of deep learning models against traditional classifiers and highlights the advantages of deep learning models, particularly in handling the chaotic and nonlinear nature of EEG signals.

5] Deep feature normalization using rest state EEG signals for Brain-Computer Interface (Kwak et al., 2021) Kwak et al. propose a feature normalization method using rest state EEG signals to address EEG variability issues in BCI decoding. The paper introduces a decoding structure trained with normalized features and demonstrates that the deep feature normalization algorithm significantly enhances the performance of conventional deep learning algorithms.

6] Deep Learning for Meditation's Impact on Brain-Computer Interface Performance (Liu, 2022) Liu explores the impact of mindfulness meditation on Brain- Computer Interface (BCI) performance. Using feed-forward neural network (FFNN) and convolutional neural network (CNN) models, the study classifies BCI controls for meditators. The research introduces optimal preprocessing methods and novel experimental designs to enhance the accuracy rates compared to traditional predictive methods.

7] The Role of EEG-based Brain Computer Interface using Machine Learning Techniques: A Comparative Study (Khaliq and Sivani, 2022) Khaliq and Sivani present a comprehensive review and comparative study of EEG-based Brain-Computer Interfaces (BCIs) using machine learning techniques. The paper covers various BCI tasks, including mental state detection, task categorization, emotional state classification, and motor imagery classification. The study assesses feature extraction, selection, and classification approaches, highlighting advancements in BCI applications.

8] Reinforcement Learning for Decoding Imagined Speech Neural Signals This paper aims to establish reinforcement learning techniques in the decoding of imagined speech neural signals. The study focuses on providing alternative natural communication pathways for individuals unable to communicate verbally due to physical or neurological limitations. Reinforcement learning, based on deep learning algorithms, is employed to decode imagined speech neural signals, showcasing its potential in imagined speech decoding for BCIs.

9] Employing Deep Learning and Discrete Wavelet Transform Approach to Classify Motor Imagery Based Brain Computer Interface System (Ghafari and Azizi, 2022) Ghafari and Azizi propose an efficient deep learning approach for extracting features from EEG signals using a combination of convolutional neural networks and discrete wavelet transform in a Motor Imagery (MI)-BCI system. The study demonstrates remarkable accuracy and high performance compared to traditional approaches, eliminating the need for explicit feature selection and reducing processing costs significantly.

10] Towards Neurohaptics: Brain-Computer Interfaces for Decoding Intuitive Sense of Touch (Cho et al., 2021) Cho et al. introduce neurohaptics, a brain-computer interface system for decoding touch sensations. The paper presents a preliminary study on recognizing users' intentions based on haptic and sensory perception. Using EEG signals acquired during touching designated materials, the study evaluates classification performances through machine learning and deep learning approaches, confirming the feasibility of decoding actual touch and touch imagery in EEG signals.

11] Explainable Deep Learning for Brain-Computer Interfaces through Layerwise Relevance Propagation (Mun and Abibullaev, 2023) Mun and Abibullaev investigate the application of Layerwise Relevance Propagation (LRP) in explainable deep learning for Brain-Computer Interfaces (BCIs). The study employs LRP to analyze decision boundaries and evaluate the contribution of each input feature in deep learning models. The research aims to enhance transparency and interpretability in BCI models, providing insights into the underlying neural processes.

12] Deep Learning for Asynchronous Motor Imagery-Based Brain-Computer Interface (Cheng et al., 2021) Cheng et al. propose a deep learning approach for asynchronous motor imagery-based Brain-Computer Interfaces (BCIs). The study introduces a cascade of one-dimensional convolutional neural networks (1D CNNs) and fully-connected neural networks for decoding EEG signals related to motor imagery. The approach aims to address the asynchrony issue in motor imagery tasks, showcasing improved accuracy and robustness compared to traditional methods.

13] Machine Learning for Real-time Directional Control of Brain-Controlled Wheelchairs using EEG Signals (Limchesing et al., 2022) Limchesing et al. present a system for brain-controlled wheelchairs using machine learning techniques. The study involves real-time wheelchairs, contributing to the development of assistive technologies.

14] Subject-Independent P300 Brain-Computer Interface using Convolutional Neural Network-based Invariant Pattern Learning (Gao et al., 2021) Gao et al. propose a subject-independent P300 Brain- Computer Interface (BCI) utilizing a convolutional neural network (CNN)-based invariant pattern learning method. The study focuses on overcoming the challenges of subject-specific calibration by introducing a CNN architecture capable of learning invariant patterns across different users. The results indicate high accuracies in P300 BCI applications without the need for individualized training.

15] Inner Speech Classification using EEG Signals: A Deep Learning Approach (Van den Berg et al., 2022) Van den Berg et al. explore inner speech classification using EEG signals through a deep learning approach. The study introduces a 2D Convolutional Neural Network (CNN) for word recognition tasks based on inner speech signals. The research aims to contribute to the understanding of neural extraction, reading, and analysis of EEG signals to enable

Table I. COMPARATIVE ANALYSIS OF EXISTING LITERATURE SURVEY

Author	**Algorithms**	**Observation**	**Limitations**
Ferrero et al. (2023)	Transfer learning with CNNs	Evaluated CNN performance in BMI for lower-limb exoskeletons using transfer learning.	Limited data availability in BMI, need for automatic neural classification system.
Yuan (2022)	Various feature extraction and classification algorithms	Comprehensive review of feature extraction and classification methods for motor imagery BCIs.	Identifies challenges and gaps in signal processing for BCIs, offers insights into common approaches.
Kim et al. (2023)	Novel brain-based interface system	Preliminary study on neurohaptic interface technology for communication and control through skin touch.	Explores decoding skin touch-related EEG signals, potential advancements in on-skin interface technology.
Castro et al. (2020)	Deep learning for visual imagery recognition	Investigates the use of deep neural networks for visual imagery recognition in BCIs.	Highlights advantages of deep learning in handling chaotic and nonlinear EEG signals.
Kwak et al. (2021)	Deep feature normalization	Proposes feature normalization using rest state EEG signals to address EEG variability in BCIs.	Demonstrates significant performance enhancement of deep learning algorithms with deep feature normalization.
Liu (2022)	Deep learning for meditation impact	Explores the impact of mindfulness meditation on BCI performance using FFNN and CNN models.	Introduces optimal preprocessing methods and novel experimental designs for improved accuracy rates.
Khaliq and Sivani (2022)	Comprehensive review and comparative study	Reviews EEG-based BCIs using machine learning techniques across various tasks.	Assesses feature extraction, selection, and classification approaches, highlighting advancements and challenges.
Unpublis hed (2022)	Reinforcement learning for imagined speech	Establishes reinforcement learning techniques in decoding imagined speech neural signals.	Focuses on providing alternative communication pathways for individuals unable to communicate verbally.
Ghafari		Proposes a deep learning approach for MI-BCI using convolutional neural networks	Demonstrates remarkable accuracy and high performance, eliminating the

and Azizi (2022)	Deep learning with discrete wavelet transform	and discrete wavelet transform.	need for explicit feature selection.
Cho et al. (2021)	Neurohaptics for decoding touch sensations	Introduces neurohaptics for decoding touch sensations in BCIs based on EEG signals.	Evaluates classification performances through machine learning and deep learning approaches.
Mun and Abibulla ev (2023)	Explainable deep learning using Layerwise Relevance Propagation	Investigates the application of LRP in explainable deep learning for BCIs.	Aims to enhance transparency and interpretability in BCI models, providing insights into neural processes.
Cheng et al. (2021)	Deep learning for asynchronous motor imagery	Proposes a deep learning approach for asynchronous motor imagery-based BCIs.	Addresses the asynchrony issue in motor imagery tasks, showcasing improved accuracy and robustness.
Limchesi ng et al. (2022)	Machine learning for brain-controlled wheelchairs	Presents a system for brain-controlled wheelchairs using machine learning techniques.	Demonstrates real-time extraction and analysis of EEG signals for enhancing the performance of brain- controlled wheelchairs.
Gao et al. (2021)	Subject-independent P300 BCI	Proposes a subject-independent P300 BCI using CNN-based invariant pattern learning.	Overcomes challenges of subject-specific calibration, achieving high accuracies in P300 BCI applications.
Van den Berg et al. (2022)	Inner speech classification using EEG	Explores inner speech classification using EEG signals through a deep learning approach.	Contributes to understanding neural correlates of inner speech, potential applications in BCIs for linguistic tasks.

CONCLUSION

In conclusion, the surveyed literature reveals a dynamic landscape in Brain-Computer Interface (BCI) research, showcasing diverse approaches and methodologies. The studies explored various applications, from motor imagery- based control of lower-limb exoskeletons to decoding skin touch and tactile perception in the metaverse. Advances in deep learning, transfer learning, and neurohaptic interfaces have demonstrated promising results in enhancing the performance and versatility of BCIs. The comparative analysis highlights the significance of transfer learning with convolutional neural networks in addressing limited data availability, the effectiveness of deep learning models in EEG signal processing, and the potential of neurohaptic interfaces for intuitive communication and control. Additionally, studies focused on feature normalization, meditation's impact on BCI, and explainable deep learning contribute valuable insights into addressing challenges and improving system robustness. Despite the advancements, challenges such as the chaotic nature of EEG signals, variability across subjects, and the need for interpretability persist. The studies collectively underscore the importance of ongoing research to [ance their practical applications in real- world scenarios. Future endeavors should focus on refining algorithms, addressing subject-specific variations, and promoting the seamless integration of BCIs into daily activities, ultimately advancing the field towards more accessible and effective neurotechnological solutions.

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