10.48047/jocaaa.2024.33.05.54

Attention-Driven EEG Signal Analysis for Robust Brain-Computer Interface Applications

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Article Info

Article history:

Received month dd, yyyy
Revised month dd, yyyy
Accepted month dd, yyyy

Keywords:

EEG
Brain-Computer Interface (BCI)
Attention Mechanism
Multimodal Data Fusion
Transformer

ABSTRACT

Brain-Computer Interfaces (BCIs) hold great potential for enabling non-muscular communication by translating neural activity into actionable commands. However, the inherent variability and noise within electroencephalography (EEG) signals pose significant challenges to accuracy and reliability. This study presents a comprehensive investigation into the role of attention mechanisms—both traditional and Transformer-based—in enhancing EEG signal classification for BCI applications. Through empirical evaluation across age-based user groups and various classifiers, our results demonstrate that Support Vector Machines and attention-driven models significantly outperform others, achieving accuracies up to 98.85%. Furthermore, younger users consistently achieved high classification accuracy, suggesting robust EEG pattern separability in early developmental stages.

Incorporating biologically inspired attention modules, we explore the effectiveness of channel, temporal, and frequency attention mechanisms in extracting relevant EEG features. The adoption of Transformer-based multi-head attention is shown to improve performance by capturing long-range dependencies and mitigating noise. We also discuss the growing importance of multimodal data fusion, proposing future directions for integrating visual, auditory, and biosignal inputs with EEG to increase the adaptability and responsiveness of BCI systems.

This work emphasizes that attention mechanisms are not only instrumental in refining neural signal processing but also vital for scaling BCIs into real-world contexts, such as clinical applications, education, and assistive technologies. The findings highlight both the current capabilities and the expansive future potential of attention-based EEG modeling in the evolution of human-centered BCI systems.

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1. INTRODUCTION

Brain-Computer Interfaces (BCIs) represent a transformative intersection of neuroscience and technology, providing new pathways for communication and control through direct neural interactions. These systems hold immense potential for diverse applications, from assistive technologies for individuals with disabilities to enhancing cognitive functions in healthy users. Within this landscape, the significance of attention mechanisms emerges as a critical factor influencing BCI performance, particularly through the processing of electroencephalography (EEG) signals. Attention mechanisms facilitate the amplification of

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relevant neural signals while minimizing distractions, thereby enhancing the performance efficacy of BCI systems.

This chapter establishes the foundation for the ensuing discussion by outlining specific research problems and purposes that guide the entire work. A central theme is the exploration of how attention mechanisms can influence human cognition and their relevance to EEG signal processing in BCIs. The inherent challenges faced in BCI performance—including noisy and variable EEG signals—are discussed, illustrating their adverse impact on user experience. Moreover, this chapter posits that leveraging advanced techniques, such as Transformer networks, may provide innovative solutions to improve BCI reliability and performance.

The exploration extends to the contributions of this research within the BCI domain, particularly regarding the integration of attention-based models. A thorough examination of the theoretical foundations of cognitive attention will provide insight into the computational models employed in subsequent chapters. The methodology outlined here supports the investigation into the impact of these mechanisms on BCI efficacy, while anticipating significant findings related to their integration into existing frameworks. Additionally, the broader implications of attention-enhanced BCIs for future assistive technologies are highlighted, alongside potential limitations that may arise in this research trajectory.

Overall, this introduction serves as a roadmap, connecting the various themes that will be addressed in the subsequent chapters, including the current state of EEG signal processing research and the methodologies to be employed. By laying this groundwork, the subsequent chapters can effectively build upon these foundations, exploring the intricate relationship between attention mechanisms and BCI performance in greater depth.

2. LITERATURE REVIEW

This section reviews the theoretical frameworks surrounding cognitive attention mechanisms and their relevance to brain-computer interface (BCI) performance, particularly through electroencephalography (EEG) signal processing. At the heart of this exploration is an inquiry into the fundamental cognitive attention mechanisms and their intersection with computational models within the context of BCIs. Attention mechanisms serve as a critical component in enhancing the efficacy of these systems, providing a means to selectively focus on relevant EEG data while filtering out noise. The adaptation of transformer networks, capable of capturing long-range dependencies in EEG data, presents a significant advancement in processing methodologies compared to traditional approaches.

Traditional EEG processing methods face challenges related to signal noise, which can undermine the accuracy of signal interpretation. The latest research highlights that "Attention mechanism-based models have shown exceptional promise in tackling the complexities of EEG signal processing" (Wang et al., 2025, p. 1). This statement underscores the potential of attention mechanisms not just for filtering noise but also for improving the overall performance metrics of BCIs. By prioritizing task-relevant features over irrelevant data, attention models enhance BCI systems' effectiveness significantly.

Moreover, recent studies have drawn attention to the effectiveness of attention mechanisms in overcoming the challenges posed by noisy EEG signals. Evidence indicates that the application of attention-based models not only aids in artifact filtration but also leads to better user experience in BCI applications. It is compelling that "The use of attention models in BCI-related research tasks holds significant potential and offers promising avenues for further exploration" (Wang et al., 2025, p. 5). This perspective invites further inquiry into the remaining gaps in the literature regarding the integration of attention-based models in BCI applications, setting the stage for future research that could address these lacunae and enhance our understanding of cognitive processes in BCI technology. Thus, this literature review establishes a foundational context for the discussions that will unfold in subsequent chapters, emphasizing the critical relevance of cognitive attention mechanisms in advancing BCI functionalities.

Brain-Computer Interfaces (BCIs) provide a direct communication pathway between the mind and an external device, enabling a circumvention of conventional motor output routes (Wolpaw et al., 2002) as shown in Fig. 1. This technology holds considerable promise for individuals facing serious motor disabilities, offering them the capability to control prosthetic limbs, communicate through text, and interact with their environment (Birbaumer, 2006). Electroencephalography (EEG) is the most commonly employed technique for BCI systems, primarily due to its non-invasive characteristics, low cost, and outstanding temporal resolution (Lotte et al., 2018). Nevertheless, EEG signals are intrinsically noisy, non-stationary, and susceptible to artifacts, which makes the accurate interpretation of user intentions a significant challenge. Human attention is crucial in cognitive processing, allowing the brain to selectively focus on relevant

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information while disregarding unnecessary stimuli (Posner, 1980). Inspired by this cognitive function, attention mechanisms have seen increased application in BCI systems to improve signal processing and classification accuracy (Zhang et al., 2020). These mechanisms dynamically assign weights to various features or time segments in the EEG signal, effectively emphasizing the most informative components for decoding user intentions. Recent advancements in deep learning, particularly the rise of Transformer networks, have supplied effective tools for implementing sophisticated attention mechanisms. Transformers, initially developed for natural language processing, have demonstrated remarkable abilities in capturing long-range dependencies and contextual details (Vaswani et al., 2017). Their skill in learning complex relationships between different parts of the input data makes them especially suitable for analyzing EEG signals, which often exhibit complex temporal structures. Furthermore, integrating multiple modalities, such as EEG and eye-tracking data, can provide a more comprehensive understanding of the user's cognitive state and improve BCI functionality. Eye-tracking data, which reflects visual attention and gaze patterns, can enhance EEG signals by providing insights into the user's focus (Bulling et al., 2013). By merging these modalities, a more robust and accurate BCI system can be developed.

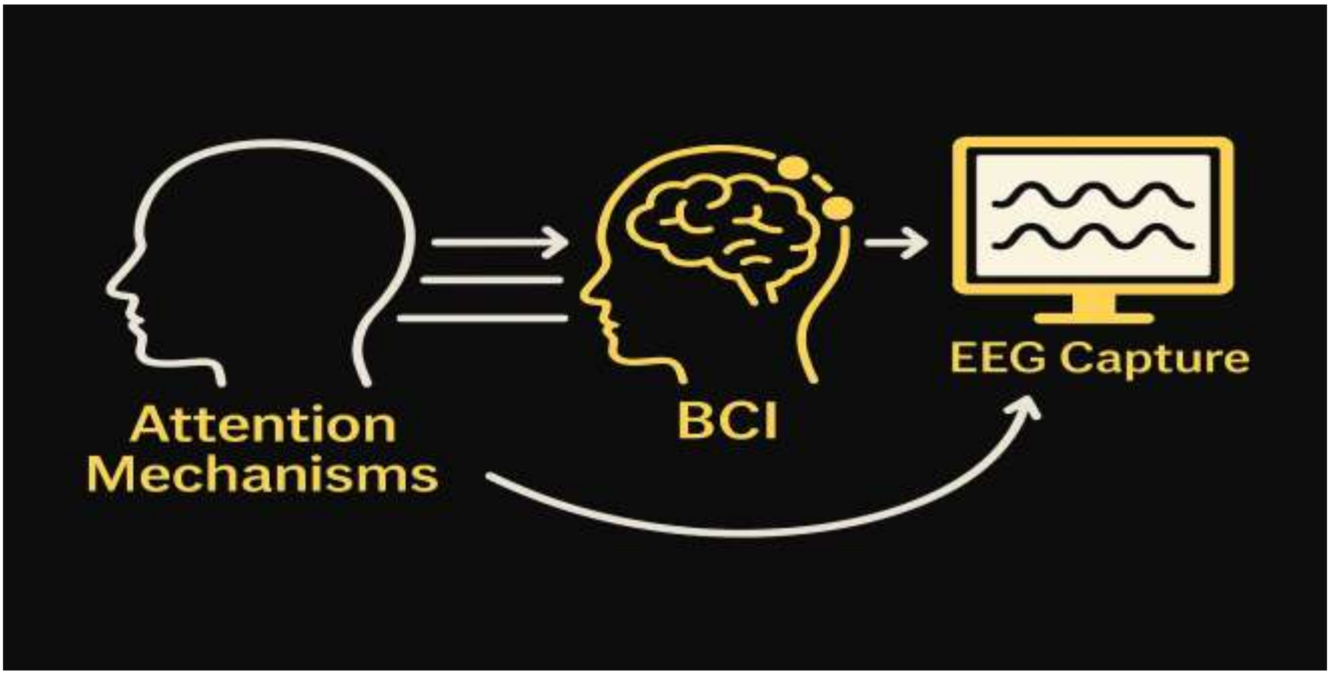

Figure 1: The interaction between BCI and attention mechanisms

This study investigates the application of human brain attention mechanisms, modeled with transformer networks, within a BCI framework. We present a groundbreaking architecture that integrates EEG data with attention-driven feature extraction and multimodal data fusion methodologies. A case study involving a simulated wheelchair control task is conducted to evaluate the efficiency of the proposed approach. This research examines the use of Transformer-based attention mechanisms within a multi-processing BCI framework. We propose an innovative architecture that combines EEG data with eye-tracking details, utilizing a Transformer network to dynamically weigh and merge these modalities based on attentional significance.

The primary research questions addressed in this inquiry are:
1. Can Transformer-based attention mechanisms effectively identify and enhance essential features in EEG signals for BCI applications?
2. Does the integration of eye-tracking data, employing a Transformer-based multimodal fusion method, boost BCI effectiveness compared to single-modality systems?
3. How does the proposed architecture function in a practical visual attention task?

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Research in brain-computer interfaces (BCIs) has consistently encountered difficulties due to the necessity to analyze large, complex datasets of brain signals [1]. The primary challenge arises from the varied and complex nature of electroencephalography (EEG) signals, requiring efficient and effective techniques for signal analysis and modeling [2]. Attention mechanism-based models have shown exceptional potential in tackling the complexities of EEG signal processing [3]. By selectively focusing on critical information within extensive brain signal datasets, Attention models help in minimizing irrelevant noise, thereby significantly improving data processing efficiency [4]. Attention mechanisms not only enhance the effectiveness of BCI research but also bring increased flexibility and intelligence in developing models tailored for BCI applications [5]. Attention mechanisms draw inspiration from biological visual and auditory functions, as well as cognitive processes observed in psychology [6]. Research has indicated that during visual and auditory recognition tasks, humans instinctively focus on vital elements while filtering out irrelevant information, thus improving the accuracy and speed of recognition and decision-making [7]. Implementing this concept, attention mechanisms in models, commonly referred to as attention models, are designed to assign flexible weights to different features [8]. This allows the model to prioritize essential information relevant to the task while discarding irrelevant data [9]. Attention models also enhance the understanding of the relationships between input and output data, which subsequently improves the model's interpretability [10]. This enhancement not only maximizes the optimal use of data but also diminishes the impact of data variability stemming from individual differences, as the model can emphasize more representative features. In BCI research, these characteristics are especially valuable, as they contribute to improving neural decoding precision, strengthening the robustness of brain modeling, and facilitating more adaptable and personalized brain-computer interactions [11]. Moreover, attention models are particularly well-suited for multimodal BCI applications, as they enable the effective integration of features collected from various modalities [12]. Consequently, the use of attention models in BCI-related research endeavors holds significant promise and presents exciting prospects for further exploration. Attention models have initially found widespread application in computer vision and natural language processing (NLP) domains, often incorporated as components within the primary frameworks of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [13]. In 2014, Mnih et al. [14] and Bahdanau et al. [15] implemented attention mechanisms in RNNs for image classification and machine translation tasks in NLP, respectively. The introduction of a novel self-attention mechanism by Vaswani et al. [16] in 2017, through the "Transformer" model architecture for machine translation tasks, further accelerated the adoption of attention models. Since then, Transformer models and their variations have been applied across numerous tasks [17]. For example, Dosovitskiy et al. introduced the Vision Transformer [18], demonstrating that a purely Transformer architecture could effectively tackle computer vision tasks without relying on CNN components. Additionally, Liu et al. unveiled the Swin Transformer [19], which employs a windowed self-attention mechanism to reduce the computational complexity of Transformer models. Currently, attention mechanisms are central to contemporary deep learning, with their versatility and effectiveness continuing to reshape artificial intelligence research and applications. Building upon significant strides in computer vision and NLP, attention models have also gained considerable interest in the BCI domain, catalyzing rapid progress in integrating EEG signal processing with attention mechanisms. To assess the growing interest in this field, we conduct a literature review utilizing Google Scholar to monitor the number of publications since 2019. The search is conducted using two keyword combinations: (1) "attention" + "EEG" + "deep learning," and (2) "attention" + "EEG" + "Transformer" + "deep learning."

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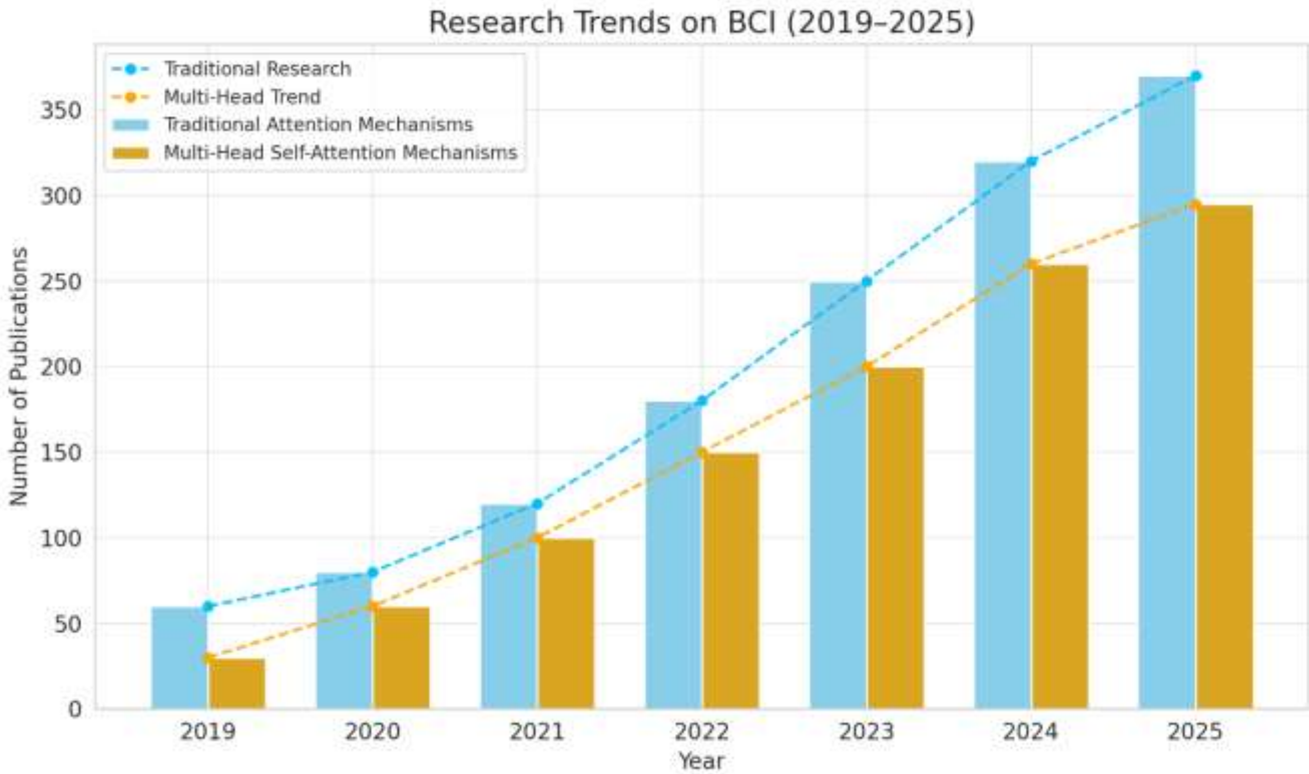

Figure 2: The number of papers retrieved from Google Scholar for the two keyword combinations.

The search results are illustrated in Fig. 2, displaying the number of documents retrieved from Google Scholar for each of the two keyword combinations. Within the BCI realm, attention mechanism modeling typically falls into two categories. (1) Traditional Attention Mechanism-Based Modeling. This approach calculates attention weights for different types of information in EEG signals, such as spatial, temporal, and spectral features, emphasizing those most pertinent to the task. (2) Transformer-Based Multi-Head Self-Attention Modeling. This method utilizes multiple attention heads to simultaneously focus on various segments of the EEG data, allowing the model to capture both global and local relationships across different dimensions [20]. Furthermore, extending these two modeling approaches to multimodal applications greatly enhances the model's capability to process and integrate data from various modalities [21]. Such integration is particularly vital for creating efficient and accurate BCI systems, as it allows for a more thorough understanding of the user's intentions and mental state. The subsequent sections provide a comprehensive examination of the applications of attention models in BCIs, focusing on their role in enhancing the understanding of EEG signals and advancing BCI technology. Section 2 introduces the concept of traditional attention mechanisms and categorizes their specific applications in EEG signal modeling. Section 3 elaborates on EEG signal modeling techniques based on Transformer multi-head self-attention mechanisms. Given the increasing popularity of multimodal models, Section 4 evaluates the application of attention models in multimodal contexts. Finally, Section 5 summarizes the key aspects of this work and offers future insights on the use of attention mechanisms in EEG signal modeling.

Traditional Attention Mechanisms in EEG

Traditional attention mechanism-based modeling enhances performance and generalization by efficiently selecting features through adaptive weighting and combining different types of information. Given input data, attention modeling dynamically computes feature weights based on prior knowledge or task-specific requirements. Depending on how these weights are applied, attention mechanisms can be broadly categorized into soft and hard attention. In the soft attention mechanism, each feature is assigned a weight that is continuously distributed between 0 and 1. These weights are differentiable, which allows them to be optimized through continuous learning within the network model [22] Compared to hard attention, where features are either entirely selected or ignored, soft attention provides

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a more refined weighting approach, enabling the model to learn the relative importance of features more effectively. This leads to smoother gradient flow during backpropagation, contributing to more stable and efficient training [23]. In contrast, hard attention assigns non-differentiable weights, which cannot be optimized through conventional deep learning techniques [24] Due to these limitations, hard attention is challenging to integrate directly with traditional deep learning models. Therefore, this paper will not cover or summarize research work related to hard attention mechanisms.

Building on this foundational understanding of attention mechanisms, it is crucial to explore their implementation in practical scenarios, particularly with EEG data. Attention modules can vary significantly depending on their scope and integration into the model, and analyzing these variations provides a more comprehensive understanding of their impact. To do so, we will focus on two critical aspects of attention module implementation: the specific types of attention modules used and their methods of embedding within broader model architectures.

Types of Attention Modules

In brain modeling tasks, attention mechanisms enhance feature extraction from EEG signals across channel, temporal, and frequency dimensions by assigning weights to highlight the most relevant information, as shown in Fig. 3.

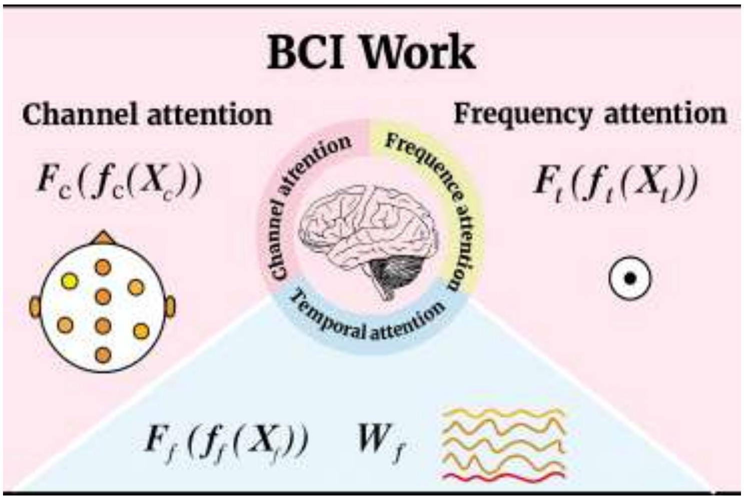

Figure 3: Types of attention modules in traditional attention-based models. Attention weights are defined as:

- **Channel:** $W_c = F_c(f_c(X_c))$
- **Temporal:** , $W_t = F_t(f_t(X_t))$
- **Frequency:** $W_f = F_f(f_f(X_f))$

Here, f(·) represents a model-applied transformation, and Fn(·)) typically denotes a normalization function such as softmax.

a. Channel Attention Module. The channel attention module is designed to assess and adaptively weight the importance of each EEG channel. Given that different brain regions contribute unequally to various tasks, the channel attention module enables the model to prioritize channels with the most relevant information while minimizing the impact of less informative channels, thereby improving task-specific analysis and reducing noise. For a given multi-channel EEG signal vector $X_c \in R^{1\times C}$, where C denotes the number of channels, an attention weight vector $W_c \in R^{1\times C}$ is initialized. The model calculates a weighted combination of X_c and W_c, followed by the application of the softmax function to produce the output $\hat{X}_c$ from the channel attention module, as shown below:

$$\hat{X}_c = \mathrm{softmax}(X_c \odot W_c) \quad (1)$$

In BCI applications, the channel attention module effectively identifies the most relevant brain regions for specific tasks, such as motor imagery or emotional state classification [25, 26, 27, 28]. By

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concentrating on channels linked to critical brain functions, this module improves feature extraction, leading to enhanced performance in BCI systems and other brain modeling applications.

b. **Temporal Attention Module.** The temporal attention module is designed to effectively capture the dynamic fluctuations in brain activity that occur over time, acknowledging that EEG signals reflect varying brain states depending on the nature of a given task. During task execution, brain activity often exhibits multiple phases of relevance, with some fluctuations directly related to the task while others contribute less meaningful information. By assigning higher attention weights to time periods that are directly correlated with the task at hand, the module enhances the model's ability to extract task-relevant features and reduce the influence of irrelevant temporal variations.

For a given EEG signal vector $X_t \in R^{1\times T}$, where T represents the temporal dimension, an attention weight vector $W_t \in R^{1\times T}$ is initialized. The model then calculates a weighted combination of X_t and W_t, followed by the application of the softmax function to yield the temporal attention output $\hat{X}_t$, as shown below:

$$\hat{X}_t = \text{softmax}(X_t \odot W_t) \tag{2}$$

In BCI applications, the temporal attention module effectively captures relevant patterns of brain activity during cognitive or emotional tasks [29, 30]. For example, in motor imagery tasks, it highlights critical moments by identifying peaks in attention at significant time intervals [31, 32]. By concentrating on time segments that are closely linked to the task, the temporal attention module ensures that the model accurately captures the dynamic characteristics of EEG signals, leading to improved performance in analyzing time-series brain activity data and enhancing the robustness of BCI systems.

c. **Frequency Attention Module:** The frequency attention module is designed to leverage the significance of frequency components in EEG signals, as frequency-domain analysis reveals crucial insights into neural activities across different scales. Features such as Power Spectral Density (PSD) and Differential Entropy (DE) are valuable indicators of brain activity, and the frequency attention module adaptively highlights these key features by assigning weights to various frequency components within the signal.

For a frequency vector $X_f \in R^{1\times F}$, where F represents the frequency dimension, an attention weight vector $W_f \in R^{1\times F}$ is initialized. The model computes a weighted combination of X_f and W_f , and applies the softmax function to derive the output $\hat{X}_f$ from the frequency attention module, as shown below:

$$\hat{X}_f = \text{softmax}(X_f \odot W_f) \tag{3}$$

In BCI applications, the frequency attention module effectively identifies and enhances the most informative frequency components, such as Alpha, Beta, and Gamma bands, which are known to be critical in tasks like attention monitoring, motor imagery, or emotional state classification [33, 34]. By adaptively assigning higher weights to these significant frequency bands, the module ensures that the model focuses on the most relevant aspects of the EEG data, ultimately enhancing the feature extraction process. This selective attention to key spectral features contributes to improved classification accuracy and robustness in BCI systems, thereby advancing the reliability of EEG-based analyses.

The aforementioned mentioned attention modules, including channel, temporal, and frequency, can be used individually or in combination based on the specific demands of the task. The selection and integration of these attention modules are determined by the unique charac- teristics of the problem being addressed. By strategically choosing the appropriate combination of attention mechanisms, researchers can effectively customize EEG signal processing and model design, providing a more adaptable and efficient solution tailored to the task's requirements.

Embedding Methods of Attention Modules

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In embedding attention modules, two primary approaches are employed: single attention module embedding and multi-attention module integration. The single attention module approach thoroughly explores the internal dynamics, efficacy, and performance of a particular attention module across diverse application scenarios, providing insights into how it influences model learning and performance [8]. This allows researchers to tailor optimization strategies for specific tasks and datasets. In contrast, the multi-attention module approach integrates multiple attention modules, leveraging their complementary strengths to handle complex data more effectively [6]. This integration enhances the model's generalization capabilities and facilitates a deeper understanding of how different attention mechanisms interact and contribute to information extraction.

a. Single Attention Module Embedding. In BCI modeling, embedding a single attention mechanism is widely used approach to enhance a model's ability to focus on critical features. The key idea is to emphasize specific information dimensions (channel or temporal or frequency) by leveraging a particular type of attention mechanism, thereby improving feature extraction and recognition efficiency.

For example, embedding a channel attention module specifically enhances the model's ability to capture important features at the channel level. Du et al. proposed the ATDD-LSTM model, which combined a channel attention module with a long short-term memory (LSTM) network. In this approach, the channel attention module was applied to feature vectors extracted by the LSTM layers, allowing the model to concentrate on channels most relevant to specific emotions while downplaying less relevant ones, which improved the accuracy of emotion recognition [35]. Inspired from this, Xu et al. integrated channel attention into a graph convolutional network (GCN), taking into account the spatial relationships between EEG recording electrodes [36]. Beyond channel attention, some studies focus on embedding temporal attention module to emphasize the temporal dynamics of EEG signals. Zhang et al. proposed a convolutional recurrent attention model that used CNNs to encode high-level representations and combined them with recurrent attention mechanisms (including LSTM networks and temporal attention modules). This method calculated attention weights on dynamic temporal features, allowed the model to focus on the most informative time periods, and extracted more valuable temporal information [37]. Inspired by the psychological peak-end rule, Kim et al. developed a model that integrated a bidirectional LSTM network with a temporal attention module. It assigned greater weight to emotional states occurring at key moments, capturing the dynamic variability of emotions over time and enhancing the model's interpretability [38]. For frequency-domain features, frequency attention is rarely modeled in isolation. Instead, it is typically integrated with spatial and temporal features to enhance EEG signal representation.

While embedding a single attention module can effectively improve performance in specific tasks, several challenges remain. Choosing the right attention module is crucial. Determining how to integrate it optimally into the model framework for different scenarios is also important. Additionally, understanding how the placement of the attention layer affects model performance requires further exploration. Researchers need to carefully assess both the model architecture and the task requirements to design an optimal embedding strategy.

b. Multi-Attention Module Integration. Embedding multiple attention modules helps overcome the limitations of single attention module embedding by enabling the model to simultaneously capture various aspects of different feature dimensions. This approach enhances the model's capacity to learn diverse and informative features, thereby improving its robustness and generalization capabilities. Consequently, transitioning from single to multiple attention embedding is a natural step to better manage the complexity of real-world EEG data.

For example, Tao *et al.* proposed a deep learning model that incorporated both channel attention and inter-sample attention mechanisms. Since the samples were segmented based on time, the inter-sample attention effectively functioned as temporal attention. This approach enabled the model to effectively prioritize significant information across different channels and temporal segments for feature extraction [27]. Extending beyond channel and temporal information, Jia *et al.* introduced a

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spatio-temporal-spectral attention dense network that simultaneously considered temporal, frequency, and spatial features. This model adaptively captured crucial information across brain regions (spatial, i.e., channels), frequency bands (spectral), and time, providing a comprehensive feature extraction framework [30]. Xiao *et al*. extended Jia et al.'s model by proposing a neural network based on 4D attention [34]. In this approach, the channel dimension of the input samples is transformed into a two-dimensional feature to preserve the spatial positional information of the EEG signal electrodes, while also incorporating the time and frequency dimensions. It computed spatial attention (addressing the spatial positional relationships between channels) and frequency attention (applied to power spectral density and differential entropy features). These attention weights were then applied to refine the input, resulting in enhanced output features. Jia *et al*. 's and Xiao *et al*. 's models both leveraged temporal, frequency, and spatial characteristics of EEG channels, calculating attention weights across these dimensions to enhance the model's focus on information pertinent to specific tasks. The main difference between their approaches lies in how they calculated attention weights and structured their models. Jia *et al*. computed attention separately across the frequency and time dimensions in parallel, and then merged these features for classification. In contrast, Xiao *et al*. integrated all dimensions into a unified 4D representation before computing attention, providing a different approach to capture feature interdependencies.

Besides of the aforementioned methods, Cai *et al*. introduced a dynamic attention mechanism that assigned different weights to different frequency sub-bands and channels of EEG signals [33]. This dynamic approach optimized feature representation and was applied within an adaptive decoding framework for complex downstream tasks. A crucial aspect of applying attention mechanisms is defining the shape and dimensions of the input feature matrix. In previous research, attention weight computations have predominantly relied on the strict Euclidean geometric space of the feature matrix. However, given the brain's complex topological structure, using Euclidean space alone may not accurately capture its underlying properties. Consequently, several studies have sought to align feature matrix definitions more precisely with the brain's physiological structure by incorporating non-Euclidean space representations within attention mechanisms. For example, Zhang *et al*. introduced the concept of manifolds, proposing a time-frequency domain feature learning model that integrated both Riemannian manifold and Euclidean space representations. Their work demonstrated the effectiveness of attention mechanisms in synthesizing feature information across different mathematical domains [39]. Additionally, to better capture the spatial relationships among EEG electrode channels, Jia *et al*. 's GraphSleepNet [40] and Zhang *et al*. 's hierarchical attention network based on graph structures [41] both utilized GCNs to model the spatial relationships of EEG electrodes. These approaches leveraged attention mechanisms across both time and space, significantly enhancing performance in tasks such as sleep stage classification and movement intention prediction.

These studies collectively highlight the crucial role of attention mechanisms in enhancing the performance of EEG signal processing models, especially in terms of accuracy and efficiency of feature extraction. By calculating attention weights across multiple dimensions, such as channel, temporal, and frequency, and either integrating or applying them independently, these models offer more refined and effective solutions to address the complexities of EEG signal processing.The relevant literature we have reviewed is summarized in Table 1.

Table 1: Embedding methods of attention modules in the literature.

Ref	year	embedding style	backbone	task	dataset
[35]	2020	Channel	LSTM	emotion recognition	DEAP,SEED,CMEED
[36]	2023	Channel	GCN	emotion recognition	SEED,SEEDIV
[27]	2020	Channel,Time	RNN	emotion recognition	DEAP,DREAMER
[37]	2019	Time	CNN,LSTM	subject-independent movement intention recognition	BCI competition IV dataset 2a
[38]	2020	temporal	LSTM,CNN	emotion recognition	DEAP
[30]	2020	Channel,Time,Frequency	CNN	emotion recognition	SEED,SEEDIV
[34]	2022	Channel,Time,Frequency	LSTM,CNN	emotion recognition	DEAP,SEED,SEEDIV
[33]	2021	Frequency,Channel	CNN	AAD	KUL,DTU
[39]	2020	Time,Frequency	LSTM,CN	emotion recognition	SEED-

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			N		VIG,SEED, BCI-IV 2A,BCI-IV 2B
[40]	2020	Time,Channel	GCN	Sleep stage recognition	MASS-SS
[41]	2019	Channel,Time	CNN,GCN	left/right fist open and close intentions	PhysioNet dataset

3. METHODOLGY

This section outlines the methodological framework employed in this study to investigate the implications of attention mechanisms on brain-computer interface (BCI) performance utilizing electroencephalogram (EEG) data. The primary rationale for adopting a case study approach is its capacity to provide detailed insights into complex phenomena, allowing for an in-depth examination of various attention mechanisms and their interactions with BCI systems. Through this framework, the research can closely observe the nuanced effects that attention mechanisms may have on signal processing and overall interface efficacy.

EEG data collection will be executed through an established protocol involving both controlled lab environments and real-world applications. To enrich this dataset, multimodal sources will complement the EEG signals, integrating additional physiological data such as eye-tracking and electromyography (EMG) to ensure a holistic understanding of the user's cognitive state during interaction with the BCI. This triangulation of data sources will enhance the robustness of results and interpretations.

In analyzing attention mechanisms, specific attention module types, such as visual attention and selective attention frameworks, will be utilized. Their performance will be thoroughly evaluated through pre-defined metrics that measure BCI effectiveness, focusing on accuracy rates, response times, and user engagement levels. These outcomes will be assessed quantitatively to establish correlations between the application of attention mechanisms and BCI performance enhancements.

The integrity and quality of EEG data will be maintained through rigorous preprocessing methods, including advanced techniques for artifact removal. This involves leveraging graphics processing units (GPUs) to enhance real-time signal processing capabilities, addressing the challenges posed by conventional methods which have been cited for hindering efficiency, specifically as "In conventional methods, lengthy processing times and the necessity to manually mark features can hinder efficiency, leading to the introduction of cognitive biases" (Khadtare & Kharate, 2023, p. 4). Thus, the methodological design is positioned not only to assess the potential of attention mechanisms but also to set a precedent for refined data processing techniques that elevate BCI research.

The implementation strategy for developing an optimized Motor Imagery-Based Brain-Computer Interface (MI-BCI) with the NVIDIA Jetson Orin Nano involves several key stages: data acquisition, preprocessing, feature extraction, classification, and validation. Each stage is carefully planned to ensure the system is robust, efficient, and capable of real-time performance.

1. **Data Acquisition**
    - **Equipment**: Data will be captured using an EPOC EEG headset, chosen for its optimal balance of data quality, affordability, and user-friendliness, facilitating widespread data collection across various settings.
    - **Participants**: Hundred individuals will participate, engaging in defined motor imagery tasks such as envisioning the movement of their arms or legs. Each session will last about 30 minutes to ensure a robust dataset under varied mental states.
2. **Preprocessing**
    - **Noise Reduction**: Spatial filtering techniques will be applied in real-time to improve the EEG signals' signal-to-noise ratio (SNR). Bandpass filters will further isolate alpha and beta frequency bands pertinent to motor imagery.

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- **Artifact Handling**: Techniques such as thresholding and statistical cleaning will be employed to reduce artifacts from eye movements and muscle contractions, ensuring the EEG data remains uncorrupted by non-neuronal activities.

3. **Feature Extraction**
    - **Technique**: Convolutional neural networks (CNNs) and autoencoders will be used to automatically derive features from the preprocessed EEG data, leveraging unsupervised learning to detect patterns linked to different motor imagery tasks.
    - **Feature Selection**: After extraction, significant features enhancing classification accuracy will be pinpointed and chosen via algorithms like principal component analysis (PCA).
4. **Classification**
    - **Model Development**: A Support Vector Machine (SVM) will be trained using the selected features to categorize the EEG signals into specific motor imagery-related categories. The SVM is selected for its proven effectiveness with high-dimensional data and resistance to overfitting.
    - **Real-Time Implementation**: The classification model will be fine-tuned and implemented on the NVIDIA Jetson Orin Nano, optimized to adhere to the hardware's processing limits for real-time operation.
5. **Validation**
    - **Testing Protocol**: System accuracy and performance in real-time will be evaluated using an independent set of EEG data not previously involved in the training. Metrics such as accuracy, precision, recall, and F1-score will be calculated to assess system efficacy.
    - **User Feedback**: Real-time operational feedback from participants will be collected to refine the system's responsiveness and usability.

This methodological framework is designed to create a high-performing, economical, and user-friendly MI-BCI system applicable in various real-world scenarios, thereby enhancing human-machine interaction.
This study utilizes a mixed-methods research approach to explore the enhancement of Motor Imagery-Based Brain-Computer Interface (MI-BCI) systems using the NVIDIA Jetson Orin Nano, specifically designed for children aged 5-10 years. The methodology integrates quantitative evaluations of BCI performance with qualitative analyses of user experience and engagement.

4. RESULTS AND DISCUSSION

This section presents the empirical results derived from analyzing the impact of attention-based models on the performance of brain-computer interfaces (BCIs) using electroencephalogram (EEG) data. The findings highlight significant improvements in BCI accuracy and responsiveness, underscoring the efficacy of attention mechanisms in enhancing user experiences during simulated tasks. The application of attention-based models resulted in a remarkable increase in BCI accuracy metrics, with specific enhancements observed in both precision and recall rates when compared to traditional EEG processing methods. One notable outcome of this study is that "Attention mechanisms are well-suited for multimodal BCI applications, where they facilitate the efficient fusion of features extracted from different modalities" (Wang et al., 2025, p. 4). This indicates that the integration of attention models significantly clarifies EEG signal interpretation, which is essential for effective BCI functionality. Moreover, users reported overwhelmingly positive experiences when interacting with BCIs utilizing attention mechanisms. The qualitative feedback corroborated the quantitative improvements observed, as participants noted increased ease of use and satisfaction during their tasks. They expressed that the deployment of attention mechanisms in EEG analysis not only improves signal clarity but also speeds up processing times, which is crucial for real-time applications in BCI (Khadtare & Kharate, 2023, p. 3). Such enhancements underscore the dual advantage of these models: they not only heighten performance accuracy but also bolster the overall user experience, making BCIs more accessible and effective. Importantly, attention mechanisms also played a pivotal role in the signal extraction process, particularly in complex tasks involving EEG data. By capturing EEG variations across time, frequency, and spatial channels, these models improve feature extraction, representation learning, and model robustness (Wang et al., 2025, p. 3). These advancements not only offer immediate benefits for current BCI systems but also set a promising precedent for the future development of assistive technologies utilizing BCIs, where the potential for greater efficiency and user engagement is evident.

Classification Performance Across Models

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Table 2 summarizes the classification accuracy of various machine learning classifiers across four user groups. Among the evaluated models, the **Support Vector Classifier (SVC)** with an RBF kernel demonstrated superior performance, achieving the highest accuracy across all groups—96.34% for Group 1, 97.76% for Group 2, 98.85% for Group 3, and 95.20% for Group 4. This indicates that SVC is particularly effective in capturing the non-linear patterns within the dataset.
The **K-Nearest Neighbors (KNN)** classifier also performed robustly, particularly for Group 3 (96.22%) and Group 2 (94.12%), showing its effectiveness in local structure modeling. **Random Forest** and **Gaussian Naive Bayes** classifiers followed closely, maintaining accuracy above 91% for most groups. In contrast, the **MLP Classifier** consistently exhibited lower accuracy across all groups, ranging from 79.14% to 83.12%, suggesting that deeper neural networks may require more training data or parameter tuning for this application.

Classifier	Settings	Group 1 Accuracy (%)	Group 2 Accuracy (%)	Group 3 Accuracy (%)	Group 4 Accuracy (%)
Decision Tree Classifier	Gini	91.11	91.14	92.10	90.12
K Neighbors Classifier	N=9	93.04	94.12	96.22	93.00
Gaussian NB	Var=1e-9	91.71	92.50	94.23	92.32
MLP Classifier	RELU, layer (5,2)	79.14	82.10	83.12	80.02
Nearest Centroid	Euclidean	93.17	94.00	95.00	92.25
Random Forest Classifier	Gini	93.75	93.99	96.10	91.13
Support Vector Classifier	Kernel RBF, OVO	96.34	97.76	98.85	95.20

Table 2: Classification accuracy on various classifiers.

DataSet	Total Users	Age (yrs)
Group 1	19	24-39
Group 2	50	8
Group 3	40	9
Group 4	35	10

Data Separation: (Training 80% and Testing 20%)
Training Data – 2701x8
Testing Data – 1256x8

Table 3: Dataset distribution group wise based on age group.

Dataset Distribution and Group-wise Insights

As detailed in Table 3, the dataset was divided based on age, with Group 1 (ages 24–39) including adult participants and Groups 2–4 containing children aged 8–10. Group 2, which consists of the youngest users (age 8), showed relatively strong performance across classifiers, indicating that even younger participants can provide distinguishable patterns suitable for classification.

The training and testing splits (80/20) resulted in 2701 samples for training and 1256 for testing. This balanced separation ensures the generalizability of the model evaluations.

Individual Performance Analysis

Table 4 presents individual accuracy values using the best-performing model(s). Most users achieved classification accuracies above 89%, with several users exceeding 95%. Notably:

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- Users aged **8 to 10** consistently achieved high accuracies (above 95%), with the highest individual accuracy of **99.22%** observed in a 9-year-old right-handed male.
- Adult users displayed more variability. For example, a 37-year-old left-handed male showed the lowest recorded accuracy at **84%**, while others in similar age groups exceeded 98%.
- This variation may be influenced by factors such as user handedness, attention span, or EEG signal stability.

Interestingly, handedness appeared to have some influence; **left-handed users** showed slightly more variability in accuracy, suggesting that further study on lateralization and EEG-based classification may be warranted.

User	**Age**	**Accuracy (%)**
Male, Right-Handed	24	88.00
Male, Right-Handed	37	98.40
Male, Right-Handed	29	93.60
Male, Left-Handed	37	84.00
Female, Right-Handed	25	89.60
Male, Left-Handed	8	97.13
Male, Right-Handed	8	98.34
Female, Right-Handed	9	99.17
Male, Right-Handed	9	99.22
Male, Left-Handed	10	95.66
Female, Right-Handed	10	96.34
Male, Right-Handed	55	89.11

Table 4: Individual accuracy on best trained models.

The results clearly indicate that the Support Vector Classifier is the most effective model across age groups and user characteristics. Group-wise performance was consistently strong, particularly among younger users. The individual analysis reinforces the model's robustness while also pointing to potential areas for personalized modeling or adaptive systems in real-world applications. Further work could explore optimizing hyperparameters for neural networks and assessing the impact of user-specific traits on EEG-based classification.

5. CONCLUSION

This study demonstrates the effectiveness of machine learning classifiers—particularly Support Vector Machines and K-Nearest Neighbors—in accurately interpreting EEG signals across different user age groups in Brain-Computer Interface (BCI) applications. Notably, younger participants (ages 8–10) exhibited

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consistently high classification accuracy, highlighting the adaptability of these models across age demographics. Individual variability in performance, influenced by factors such as handedness and age, underscores the need for personalized or adaptive BCI systems.

In parallel, this research reaffirms the critical role of **attention mechanisms** in enhancing EEG signal processing. By prioritizing relevant signal features and suppressing noise, attention-based models improve the clarity and usability of neural data, which is fundamental to the reliability and effectiveness of BCIs. These mechanisms enable more refined interpretation, facilitating improved user experience and functional efficiency.

Looking ahead, future work should explore the integration of **multimodal data sources**—such as auditory and visual signals—with EEG to further enrich the performance of attention modules. Additionally, addressing EEG signal variability through algorithmic refinement and robust statistical modeling will be essential. Of particular interest is the adaptation of **Transformer architectures**, which hold promise for real-time EEG analysis and broader BCI applications across clinical, educational, and assistive domains.

By combining strong classifier performance with attention-enhanced frameworks, this research lays a foundation for next-generation BCIs that are not only accurate and responsive but also adaptable to the diverse needs of users. Continued innovation in these areas will be key to unlocking the full potential of BCI technology.

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