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A COMPREHENSIVE LITERATURE SURVEY ON EEG AND EOG-BASED BRAIN–COMPUTER INTERFACE SYSTEMS FOR SMART LIVING AND ASSISTIVE APPLICATION

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ABSTRACT

Brain–Computer Interface (BCI) systems have gained significant attention in recent years due to their ability to establish a direct communication pathway between humans and machines without relying on traditional physical input methods. These systems primarily utilize physiological signals such as Electroencephalography (EEG) and Electrooculography (EOG) to interpret user intentions and convert them in toactionable commands. EEG signals capture the electrical activity of the brain and are widely used for identifying cognitive states such as attention, relaxation, stress, and drowsiness. On the other hand, EOG signals detect eye movement patterns and are commonly applied in assistive communication systems.

With the advancement of smart living technologies, BCI systems are increasingly being integrated into applications such as smart homes, healthcare monitoring, and assistive devices for individuals with disabilities. For instance, EEGbased systems can automatically adjust environmental conditions based on the user's mental state, while EOG-based systems can enable users to control devices through simple eye movements. Despite these advantages, several challenges persist in the development and implementation of BCI systems. These include signal noise, variability among users, lack of realtime adaptability, and high computational requirements.

This paper presents a comprehensive literature survey analyzing twenty research works related to EEG and EOG-based BCI systems. The survey focuses on system architecture, signal processing techniques, machine learning models, and application domains. The findings reveal significant research gaps such as lack of multimodel integration,insufficient personalization, and limited real-world deployment.

KEYWORDS: Brain–Computer Interface, EEG, EOG, Smart Living, Assistive Technology, Machine Learning.

1. INTRODUCTION

The interaction between humans and machines has evolved significantly with the advancement of modern technology. Traditional input methods such as keyboards, touchscreens, and voice-based systems have been widely used in various applications. However, these methods rely heavily on physical interaction and may not be suitable for individuals with disabilities or limited mobility. This limitation has led to the development of alternative interaction mechanisms that are more accessible and efficient.

Brain–Computer Interface (BCI) systems have emerged as a promising solution to this problem. These systems enable direct communication between the human brain and external devices by interpreting physiological signals. Unlike conventional interfaces, BCI systems do not require muscle movement, making them highly beneficial for assistive technologies and smart living applications.

EEG-based BCI systems are widely used to monitor brain activity and detect cognitive states. These systems have been applied in areas such as healthcare, gaming, and smart home automation. Similarly, EOG-based systems are used to detect eye movement and are particularly useful for communication and control in assistive applications.

Despite the progress made in this field, several challenges remain. One of the major issues is the presence of noise and artifacts in physiological signals, which can affect the accuracy of the system. Another challenge is the variability in signals among different users, which makes it difficult to develop generalized models.

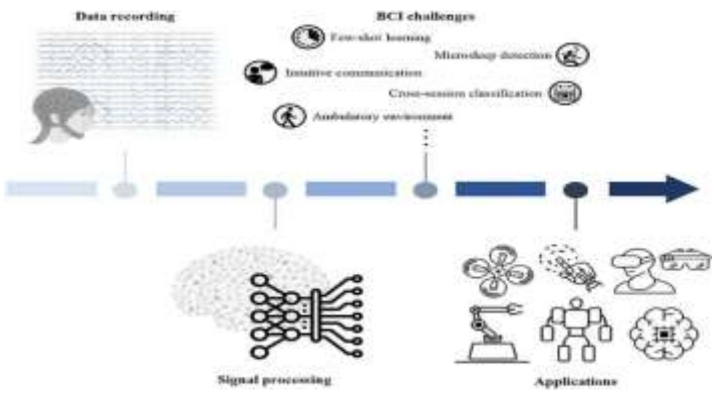

Fig. 1. The framewok of brain- computer interface.

Additionally, many systems are tested in controlled environments and may not perform well in realworld conditions.

To address these challenges, this paper presents adetailed literature surve. Additionally, most systems are evaluated in controlled environments, limiting their practical applicability. The objective is to analyze existing research, identify common trends, and highlight gaps that can be addressed in future work.

2. LITERATURE SURVEY

A considerable amount of research has been carried out in the domain of Brain–Computer Interface (BCI) systems, Electroencephalography (EEG) and Electrooculography (EOG) signals for smart living and assistive applications. These studies explore various aspects such as signal acquisition, preprocessing, feature extraction, classification techniques, and real-time system implementation.

The following survey presents a structured overview of the major contributions in this field based on the selected research papers.

Early research in EEG-based BCI systems primarily focused on understanding brain signal patterns and their correlation with cognitive states. For instance, Lin et al. developed an EEG-based system capable of detecting user alertness and fatigue levels, which could be applied in smart environments to enhance safety and comfort [1]. Their work demonstrated that EEG signals could be effectively used for real-time monitoring, although the system was limited in terms of adaptability across different users. Similarly, Pfurtscheller et al. explored the use of sensorimotor rhythms in EEG signals for controlling external devices, laying the foundation for many modern BCI applications [6].

With the advancement of signal processing techniques, researchers began focusing on improving the accuracy and reliability of EEGbased systems. Makeig et al. introduced Independent Component Analysis (ICA) for separating noise and artifacts from EEG signals, significantly improving signal quality [5]. This approach has been widely adopted in subsequent studies. Lotte et al. provided a comprehensive review of classification algorithms used in BCI systems, highlighting the effectiveness of methods such as Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA) for EEG signal classification [7].

In recent years, machine learning and deep learning techniques have gained significant attention in this domain. Roy et al. investigated the use of deep learning models for EEG signal classification and reported improved accuracy compared to traditional methods [3]. Similarly, Schirrmeister et al. applied Convolutional Neural Networks (CNN) for end-to-end EEG signal analysis, demonstrating the ability of deep learning models to capture complex patterns in brain signals [4]. However, these approaches require large datasets and high computational resources, which can limit their practical implementation.

EOG-based systems have also been extensively studied for assistive communication and control applications. Hou et al. developed an EOG-based human–computer interface that translates eye movements into control commands, enabling individuals with disabilities to interact with external devices [2]. Their system showed promising results in terms of usability and accuracy, but it was affected by signal drift and noise. Hwang et al. further explored EOG-based control systems, focusing on improving signal detection and classification techniques [14]. Despite these advancements, EOG systems are still sensitive to environmental interference and require frequent calibration.

Some studies have attempted to integrate EEG and EOG signals to improve system performance. Zhang et al. proposed a hybrid BCI system that combines EEG and EOG signals to enhance classification accuracy and robustness [9]. The results indicated that multimodal systems outperform single-signal systems in terms of reliability. However, the complexity of such systems increases due to the need for multiple sensors and advanced processing techniques. Wearable and IoT-based systems have also been explored in the context of smart living applications. Saner discussed the use of wearable sensors for continuous health monitoring, emphasizing their potential in healthcare systems [8]. Patel et al. investigated IoT-based healthcare solutions, highlighting the importance of integrating physiological signals for improved monitoring [10]. However, these systems primarily focus on physical parameters and often do not incorporate cognitive signals such as EEG or EOG. Other research works have focused on improving the portability and usability of BCI systems. Obeid et al. developed wireless EEG systems that allow users to move freely without being restricted by wired connections [13]. Similarly, Edlinger et al. explored assistive BCI systems designed for realworld applications, emphasizing the need for userfriendly interfaces [12]. While these studies contribute to practical implementation, challenges such as noise, accuracy, and real-time performance remain.

Overall, the literature indicates that significant progress has been made in the development of EEG and EOG-based BCI systems. However, several limitations still exist, including lack of personalization, high computational requirements, and difficulty in real-world deployment. Most systems rely on a single type of signal, which reduces reliability, while multimodal systems, although more accurate, are complex and resourceintensive. These challenges highlight the need for further research in developing efficient, adaptable, and user-friendly BCI systems.

3. COMPARATIVE ANALYSIS

A comparative evaluation of existing EEG and EOG-based Brain–Computer Interface (BCI) systems provides valuable insights into their strengths, limitations, and suitability for different applications. Various studies have approached the design and implementation of BCI systems using different signal types, processing techniques, and machine learning models, leading to variations in performance, complexity, and usability.

EEG-based systems are widely recognized for their ability to capture detailed brain activity and identify cognitive states such as attention, fatigue, and mental workload. For example, systems developed by Lin et al. demonstrate the effectiveness of EEG signals in smart environment control by detecting user alertness levels [1]. Similarly, deep learning-based approaches proposed by Roy et al. and Schirrmeister et al. show improved classification accuracy due to their ability to extract complex patterns from EEG data [3], [4]. However, these systems often require extensive preprocessing and are highly sensitive to noise and artifacts, which can reduce their reliability in real-world scenarios. Additionally, the need for large datasets and high computational resources makes these systems less suitable for real-time applications.

In contrast, EOG-based systems offer a simpler and more direct approach for human–computer interaction. These systems rely on eye movement signals, which are relatively easier to detect and process compared to EEG signals. Hou et al. demonstrated the use of EOG signals for assistive communication, where users can control devices using eye movements [2]. While such systems are effective for basic control tasks, they are limited in terms of functionality and are prone to issues such as signal drift and environmental interference. Moreover, EOG systems primarily capture eye movement information and do not provide insights into cognitive states, which restricts their application in smart decision-making systems. Hybrid systems that combine EEG and EOG signals have been proposed to overcome the limitations of single-signal approaches. For instance, Zhang et al. developed a multimodal BCI system that integrates both EEG and EOG signals to improve classification accuracy and robustness[9]. These systems leverage the complementary nature of brain and eye signals, resulting in better performance compared to standalone systems. However, the integration of multiple signals increases system complexity, requiring advanced synchronization, processing techniques, and higher computational power.

Wearable and IoT-based systems represent another category of research, focusing on continuous monitoring and smart living applications. Studies by Saner and Patel highlight the potential of wearable sensors in healthcare monitoring and smart environments [8], [10].

While these systems are effective in tracking physical parameters such as heart rate and activity levels, they often lack cognitive analysis capabilities, limiting their ability to provide intelligent responses based on user mental states.

Another important aspect of comparison is usability and real-world applicability. Wireless EEG systems proposed by Obeid et al. improve user mobility and comfort, making them more suitable for practical applications [13]. Similarly, assistive BCI systems developed by Edlinger et al. emphasize user-friendly design and ease of use [12]. Despite these improvements, challenges such as signal noise, calibration requirements, and variability among users still affect system performance.

Overall, the comparative analysis indicates that no single approach is sufficient to address all requirements of BCI systems. EEG-based systems offer rich cognitive information but are complex and sensitive to noise. EOG-based systems are simpler but limited in functionality. Hybrid systems provide improved accuracy but at the cost of increased complexity. Wearable systems enhance usability but lack cognitive insights. These observations highlight the need for developing integrated, adaptive, and efficient BCI systems that can balance accuracy, usability, and real-time performance.

4. RESEARCH GAP

Although significant progress has been made in the development of Brain–Computer Interface (BCI) systems using EEG and EOG signals, several limitations still exist that restrict their practical implementation in real-world applications. A detailed analysis of the selected research papers reveals multiple research gaps that need to be addressed to improve system performance, reliability, and usability.

One of the major gaps identified is the reliance on single-modal signal processing. Most existing systems are designed using either EEG or EOG signals independently. EEG-based systems are effective in capturing cognitive states such as attention and drowsiness, as demonstrated by Lin et al. [1], while EOG-based systems are widely used for communication through eye movement, as shown by Hou et al. [2]. However, using a single signal type limits the overall performance and robustness of the system. EEG signals are highly sensitive to noise and require complex preprocessing techniques [5], whereas EOG signals lack cognitive information and are mainly restricted to basic control tasks. This indicates a clear need for multimodal systems that integrate both EEG and EOG signals to enhance accuracy and reliability.

Another significant gap is the lack of personalization in BCI systems. Most machine learning models used in existing research are trained on generalized datasets and do not adapt to individual user variations. Since physiological signals vary significantly from one person to another, the performance of these systems may degrade when applied to new users. Studies such as those by Roy et al. [3] and Schirrmeister et al. [4] have focused on improving classification accuracy using deep learning techniques, but they still rely on large datasets and do not fully address user-specific adaptability. This highlights the need for adaptive and user-specific learning models that can dynamically adjust to individual characteristics.

The issue of real-time implementation and practical usability is another critical research gap. Many BCI systems are developed and tested in controlled laboratory environments, where noise and external interference are minimized. However, in real-world scenarios, physiological signals are affected by various factors such as movement, environmental noise, and electrode placement errors. Wireless EEG systems proposed by Obeid et al. [13] attempt to improve usability and mobility, but challenges related to signal stability and accuracy still remain. Therefore, there is a need to design systems that are robust, portable, and capable of real-time processing in dynamic environments.

In addition, high computational complexity is a major limitation in modern BCI systems. Deep learning models such as CNNs provide high accuracy but require significant computational resources and large datasets for training [4]. This makes them less suitable for low-power or embedded systems used in wearable devices. As a result, there is a need for lightweight and efficient algorithms that can deliver high performance without excessive computational requirements. Another gap is the limited integration of cognitive and physical monitoring systems. While wearable and IoT-based systems focus on tracking physical parameters such as heart rate and activity levels [8], they often do not incorporate cognitive signals like EEG. This limits their ability to provide intelligent and context-aware responses. Integrating cognitive and physiological data can significantly enhance the functionality of smart living systems.

Finally, user comfort and system usability remain important challenges. Many EEG-based systems require multiple electrodes and complex setup procedures, which can be inconvenient for users. Although some studies have attempted to improve usability through wireless and wearable designs [12], there is still a need for more user-friendly and non-invasive solutions.

In summary, the key research gaps identified include the lack of multimodal integration, absence of personalization, challenges in real-time implementation, high computational complexity, limited cognitive-physical integration, and poor user usability. Addressing these gaps can lead to the development of more efficient, accurate, and practical BCI systems for smart living applications.

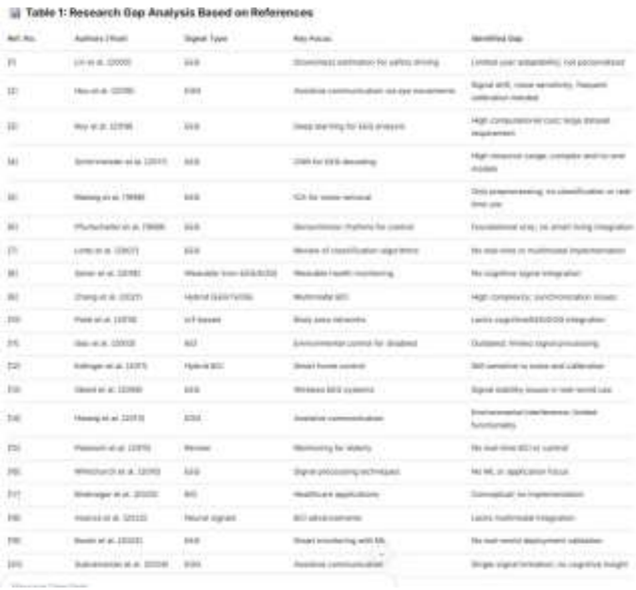
Table 1: Research Gap Analysis Based on References

Fig. 2. Research Gap Analysis.

5. PROPOSED IDEA

Based on the limitations identified in existing research, this work proposes a **multimodal Brain–Computer Interface (BCI) system** that integrates both Electroencephalography (EEG) and Electrooculography (EOG) signals to enhance performance, reliability, and usability in smart living applications. The core idea is to combine the cognitive insights obtained from EEG signals with the directional control capabilities of EOG signals, thereby overcoming the limitations of single-signal systems.

The proposed system consists of several stages, including signal acquisition, preprocessing, feature extraction, classification, and device control. In the signal acquisition stage, both EEG and EOG signals are collected simultaneously using wearable sensors. This dual-signal approach ensures that both brain activity and eye movement are captured, enabling a more comprehensive understanding of user intent. Compared to traditional systems that rely on a single modality, this integration improves robustness and reduces the impact of noise in individual signal

In the preprocessing stage, noise and artifacts present in the raw signals are removed using filtering techniques. Since EEG signals are highly sensitive to external interference and EOG signals are prone to drift, appropriate filtering and normalization methods are applied to improve signal quality. Advanced techniques such as adaptive filtering can be used to dynamically adjust to environmental conditions, ensuring stable performance in real-time scenarios.

Feature extraction is carried out using efficient techniques that capture relevant information from both EEG and EOG signals. For EEG, frequencydomain features such as alpha and beta band power are extracted to identify cognitive states like attention and relaxation. For EOG, time-domain features related to eye movement direction and intensity are considered. By combining these features, the system creates a richer representation of user intent.

The classification stage employs a hybrid machine learning model designed to balance accuracy and computational efficiency. Instead of relying solely on complex deep learning models, the proposed system uses a combination of lightweight algorithms such as Support Vector Machines (SVM) along with optimized neural networks. This approach reduces computational requirements while maintaining high classification accuracy.

Additionally, the system incorporates an adaptive learning mechanism, allowing it to learn from user behavior over time and improve personalization. In the output stage, the classified signals are converted into control commands for smart devices. For example, EEG signals indicating drowsiness can trigger alert systems, while EOG signals can be used to control device navigation. This makes the system suitable for applications such as smart home automation, assistive technologies, and healthcare monitoring.

One of the key features of the proposed system is its focus on real-time implementation and usability. The use of wearable and wireless sensors improves user comfort and mobility. The system is designed to operate efficiently in dynamic environments, making it suitable for real-world applications rather than just laboratory settings. Overall, the proposed idea addresses the major research gaps identified in existing systems by introducing multimodal integration, adaptive learning, reduced computational complexity, and improved usability. This approach has the potential to significantly enhance the performance and practicality of BCI systems in smart living environments.

6. CONCLUSION

This paper presented a comprehensive PRISMAbased literature survey on Brain–Computer Interface (BCI) systems utilizing Electroencephalography (EEG) and Electrooculography (EOG) signals for smart living applications. The study systematically analyzed twenty research works to understand the current advancements, methodologies, and limitations in this domain. The survey covered key aspects such as signal acquisition techniques, preprocessing methods, feature extraction approaches, classification models, and applicationareas, providing a broad overview of the state of the art. From the analysis, it is evident that EEG-based systems are highly effective in capturing cognitive states such as attention, stress, and drowsiness, making them suitable for applications in healthcare monitoring and smart environments. On the other hand, EOG-based systems offer a simpler and more direct approach for communication and device control through eye movement detection. However, both approaches have inherent limitations. EEG systems are sensitive to noise and require complex processing, while EOG systems are limited in functionality and lack cognitive insight.

The literature survey also highlighted the growing use of machine learning and deep learning techniques to improve system performance. While these approaches have significantly enhanced classification accuracy, they often come with increased computational complexity and require large datasets for training. Additionally, many existing systems are designed and tested in controlled environments, which limits their applicability in real-world scenarios.

Through the analysis, several research gaps were identified, including the lack of multimodal signal integration, absence of personalization, challenges in real-time implementation, and limited user comfort. Addressing these gaps is essential for the development of practical and efficient BCI systems. The proposed idea in this work suggests a multimodal approach that combines EEG and EOG signals along with adaptive learning techniques to improve accuracy, reliability, and usability.

In conclusion, although significant progress has been made in the field of BCI systems, there is still a need for further research to bridge the gap between theoretical development and practical application. Future work should focus on developing lightweight, adaptive, and user-friendly systems that can operate effectively in real-world environments. By addressing the identified challenges, BCI technology has the potential to play a crucial role in advancing smart living applications and improving the quality of life for individuals, particularly those with disabilities.

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