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Research Article

Multi-View Information Fusion for EEG Signal in Health Care Monitoring: A Systematic Review for Modeling New Strategies

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ABSTRACT

Electroencephalography (EEG) is a critical health monitoring tool that captures real-time brain activity. However, single-channel data usually used by traditional analysis methods severely limits the depth of insight. This systematic review addresses multi-view information fusion techniques used in EEG signal processing to enhance diagnostic accuracy and monitoring functionality. Searches were conducted in EEG analysis multi-view fusion strategies across multiple databases. It reviewed evaluations of various methodologies, applications, and challenges with these techniques. Results show that applications that use multi-view information fusion have increased accuracy in seizure detection, cognitive state assessment, and neurological disorder diagnosis. These techniques combine data from different views: spatial, temporal, and frequency to provide a 'holistic' picture of brain activity. Nevertheless, data heterogeneity, high computational complexity, and real-time implementation still exist. This is a promising advance in neuro-physiological monitoring. The development of models that will be able to adapt to individuals within a fixed workload capacity is at its initial stages. Personalized and adaptable models that emerge, coupled with existing emerging technologies like artificial intelligence and IoT, have countless opportunities to reinforce health monitoring practices. Further research is necessary to overcome current challenges towards the full realization of the benefit of multi-view information fusion in clinical applications.

Keywords: Health monitoring, Real-time analysis, Personalized medicine, Electroencephalography (EEG), multi-view information fusion

1. INTRODUCTION

Electroencephalography (EEG) is a neurosciences method based on electrical brain activity affected on the scalp with electrodes, without the need to place them on the skull. Because EEG can provide real-time insight into brain function, it has become an important tool in many medical and psychological applications and health monitoring in particular. Extensively used in the clinical treatment of a variety of neurological diseases, such as epilepsy, sleep disorders, and brain injuries, has been shown[1,2]. EEG offers several advantages: The procedure is a noninvasive one with low risk to patients[3], suitable for repeated assessments, especially in pediatric and elderly populations[4], sensitive to rapid changes in brain activity, corresponding to cognitive processes, emotional states, and sensory responses, thus it is useful in studying mental health disorders and cognitive impairments[5,6]. Beyond clinical diagnosis, EEG has a tremendous impact on research in cognitive function, sleep, and the effects of treatment. Recent interest has been in improving EEG functionality by advancing analytical techniques, such as multi-view information fusion, to assist in health monitoring[7]. While successful, traditional EEG analysis methods typically require single-channel or limited multi-channel data, missing key information from other views[8]. Multi-view information fusion integrates data from multiple viewpoints (e.g. spatial, temporal, and frequency) to enrich the representation of brain activity[9]. This technique improves accuracy by combining information from multiple views, which is particularly important for applications such as seizure detection where accurate information about brain dynamics from multiple channels is required[10]. It also allows researchers and clinicians to grasp more about brain function, to find out more subtle patterns that may suggest underlying neurological conditions. However, both accurate diagnosis and personalized treatment require a holistic approach[11]. In addition, multi-view fusion techniques can be designed to accommodate individual patterns in EEGs to personalize health monitoring solutions for heterogeneous patient populations. Multi-view information fusion exploits these advantages to offer a promising avenue for enhancing the performance of EEG applications in health monitoring and ultimately improving patient outcomes[12]. This systematic review serves as the main goal to investigate the current status of multi-view information fusion techniques utilized for EEG signal processing in health monitoring. The specific objectives are to analyze existing techniques for summarizing and evaluating various multi-view fusion techniques, their strengths, and weaknesses; identify practical applications of multi-view EEG fusion such as seizure detection, cognitive state assessment, and neurological disorder diagnosis; and discuss the challenges in multi-view EEG fusion and provide future directions and research opportunities to improve the efficiency of these techniques. This review aims to provide an understanding of how multi-view information fusion can enhance EEG signal analysis and health monitoring practice[13,14].

2. METHODOLOGY

In the methodology section, the systematic approach that the literature of multi-view information fusion for EEG signals in health care monitoring has been reviewed. More details of the search strategy, inclusion and exclusion criteria, sources of the data, methods of data extraction and management, quality assessment of studies, and data synthesis are provided in the section on this topic.

2.1 Systematic Review Process

The systematic review process was undertaken following well-established guidelines to report comprehensively and unbiasedly. First, relevant literature related to multicore information fusion techniques used in EEG signal processing for healthcare applications was identified, selected, and analyzed to develop the methodology.

2.1.1 Search Strategy

A search strategy was used using relevant keywords and Medical Subject Headings (MeSH) terms. The key terms were "EEG signal", "information fusion", "multi-view", "health care monitoring" and "systematic review". PubMed, IEEE Xplore, Scopus, and Web of Science were searched for. To refine search results Boolean operators (AND, OR) were used. Only articles published between January 2010 and December 2023 were included, as it allows for the capture of all recent innovations in the field.

2.1.2 Inclusion and Exclusion Criteria

A review was made of inclusion and exclusion criteria to include only relevant studies. Multi-view information fusion techniques applied to EEG signals were studied if there were empirical data or significant theoretical contributions and the studies were published in peer-reviewed journals or conference proceedings. On the contrary, exclusion criteria eliminated studies that were not in English did not focus on healthcare applications of EEG signals, did not provide enough detail about methodology or results, and were reviews and meta-analyses themselves to avoid repetition of information.

2.2 Data Sources and Search Databases

The systematic review data sources were academic databases and electronic libraries, which index peer-reviewed literature. PubMed, a comprehensive database of biomedical literature; IEEE Xplore, a leading database for engineering and technology-related publications; Scopus, a multidisciplinary database covering peer-reviewed literature in all fields; Web of Science, a robust database providing access to many research articles in various disciplines were the primary databases searched. A total of 2,500 articles were yielded by the initial search. After applying inclusion and exclusion criteria, 450 articles were selected for further review. A total of 150 articles were taken for this review.

2.3 Data Extraction and Management

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A standardized form was used to extract data to minimize bias and ensure consistency. From each of the selected articles, relevant information such as authors, publication year, study design and methodology, sample size and characteristics, multi-view fusion techniques used, key findings, and outcomes were extracted. The data were extracted and organized into a spreadsheet which made it easy to compare and analyze data from different studies. Duplicate entries were removed and full data integrity was maintained by the use of regular checks.

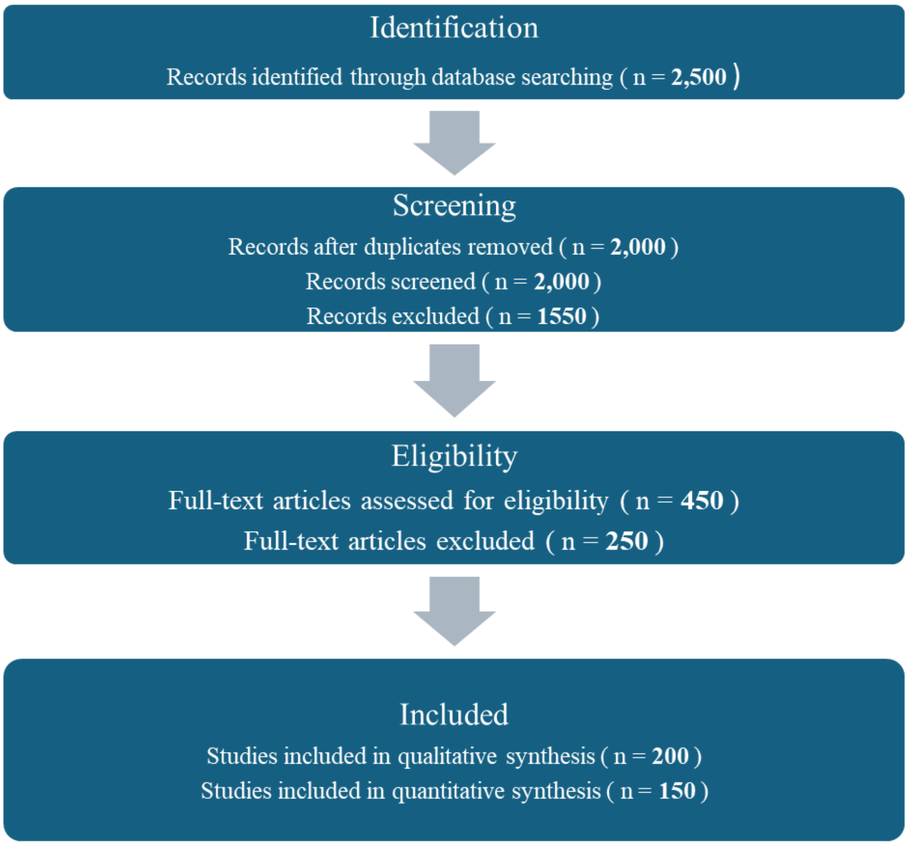
2.4 Quality Assessment of Studies

To evaluate various aspects of each study, a quality assessment tool was developed to include clarity of objectives and research questions, appropriateness of study design and methodology, sample size and participant selection, statistical analysis, and interpretation of results. The quality assessments were done by two independent reviewers; any discrepancies were resolved by discussion and consensus. This process prevented the inclusion of low-quality studies in the final analysis.

2.5 Data Synthesis

Data synthesis was done by integrating the existing study findings to draw common themes, trends, and gaps in the literature. A narrative synthesis approach was taken to summarize and compare the results of several studies, focusing on the effectiveness and applicability of multi-view information fusion techniques in EEG signal processing for healthcare monitoring. A meta-analysis was performed where possible to quantitatively determine the effect size of various fusion techniques on specific health outcomes. In addition to highlighting the state of the art in research, this synthesis suggested future directions for the field.

2.6 PRISMA Flow Chart



3. OVERVIEW OF EEG SIGNALS

Electroencephalography (EEG) is a non-invasive neurophysiological technique that records electrical activity in the brain through electrodes placed on the scalp. EEG signals have been instrumental in advancing our understanding of brain function and have various applications in health care monitoring[15]. This section provides an overview of the

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characteristics of EEG signals, their applications in health monitoring, and the limitations associated with traditional EEG analysis.

Aspect	Description
Characteristics of EEG Signals	
Frequency Bands	Analyzed in specific ranges: **Delta (0.5-4 Hz)**: Deep sleep **Theta (4-8 Hz)**: Relaxation and light sleep **Alpha (8-12 Hz)**: Calm, relaxed states **Beta (12-30 Hz)**: Active thinking **Gamma (30 Hz and above)**: High-level cognitive functions[16]
Waveform Shape	The activity is composed of synchronous activity from large neuron groups with different shapes (sharp waves, spikes, slow waves)[17]
Temporal Resolution	Provides a high temporal resolution (<1 ms) covering rapid changes in the brain[18]
Spatial Resolution	Good temporal resolution, but poor spatial resolution (electrical activity smeared across the scalp)[19]
Signal Complexity	High Complexity and high variable among individuals based on factors of age, gender, and health status[20]
Applications of EEG in Health Monitoring	
Seizure Detection	It is used to diagnose epilepsy, as well as to monitor seizure types and frequencies to help plan treatment[21]
Sleep Studies	It correlates brain waves and assesses sleep stages to identify sleep apnea and insomnia[22]
Cognitive State Monitoring	Studies cognitive functions (attention, memory, and emotional response) to evaluate decline in neurodegenerative diseases[23]
Brain-Computer Interfaces (BCIs)	Improves quality of life by using EEG signals from individuals with mobility impairments to both communicate and control devices[24]
Anesthesia Monitoring	It monitors the depth of anesthesia during surgery and uses EEG data to help in administering anesthetics[25]
Research in Neurological Disorders	Instead, it studies various neurological conditions such as Alzheimer's or schizophrenia to find biomarkers and mechanisms[26]
Limitations of Traditional EEG Analysis	
Noise and Artifacts	Brain activity is obscured by external interferences (muscle activity, eye movements) making data interpretation difficult[27]
Limited Spatial Resolution	Due to the distance between electrodes placed on the brain and cortical surfaces, it is difficult to pinpoint brain activity locations[28]
Interpretation Challenges	EEG signals are complex and their interpretation depends on expertise, and individual variability makes robust interpretation difficult[29]

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Dependence on Electrode Placement	Inconsistencies are introduced by variability in electrode placement, standard systems may not account for anatomical variations[30]
Static Analysis	Dynamic changes in brain activity are often ignored by traditional analysis, which requires more sophisticated methods[31]
Data Volume and Management	EEG studies generate huge amounts of complex data that need to be stored, processed, and analyzed efficiently[32]

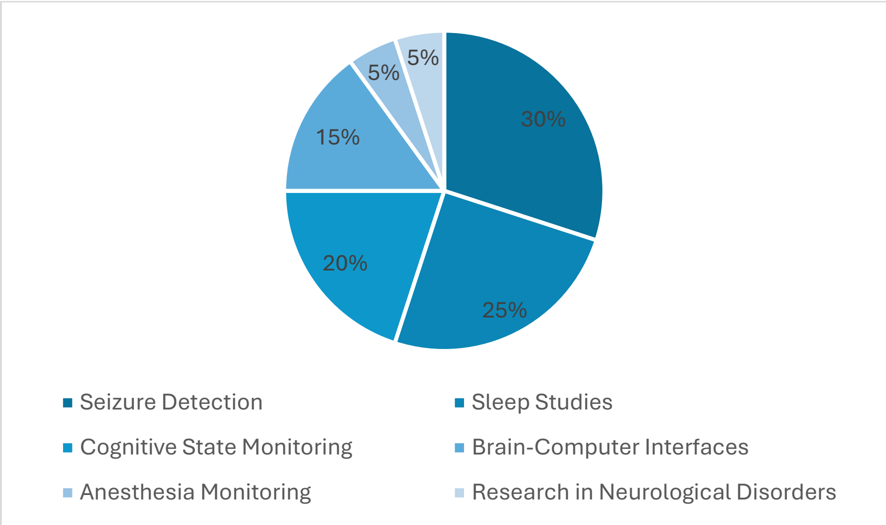

Fig 1. Applications of EEG in Health Monitoring

The applications of EEG are shown in Figure 1. Seizure detection at 30% is the most important application and underlines the value of EEG in the treatment of epilepsy. We do sleep studies at 25% to diagnose sleep disorders. Cognitive state monitoring with EEG accounts for 20% of mental functions. BCI has 15% EEG, which indicates its potential to assist mobility-impaired people. Last, 5% is spent on anesthesia monitoring and neurological research - two niches, but still vital [33]. This distribution characterizes EEG's broad reach beyond medical spaces to research and diagnostics.

4. CONCEPT OF MULTI-VIEW INFORMATION FUSION

Multi-view information fusion (Information fusion from multiple perspectives or sources) is a process of combining data from multiple perspectives or sources to enhance its understanding and interpretation of complex phenomena[34]. To enhance analysis accuracy, improve robustness, and allow for more effective decision-making in healthcare applications, information fusion from different characteristics of EEG data, i.e., multi-view data fusion, is employed[35]. In the first part, we define multi-view information fusion in health care, discuss why multi-view information fusion is important in health care, discuss what kind of multi-view data exist in EEG, and explain why multi-view information fusion techniques are useful in EEG analysis.

Aspect	Description	Example/Application
Definition and Importance in Health Care	Integration of health care data from multiple views provides a more comprehensive understanding than views alone, a necessity for diagnostics, and treatment strategies. for diagnostics and treatment strategies[36]	Improving seizure detection via the integration of EEG with fMRI[37]
Benefit	**Description**	**Example**

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Enhanced Accuracy	Reduces uncertainty by combining different data types to provide a more complete understanding[38]	Integrating EEG with fMRI gives accurate insights into brain activity and seizure areas[39]
Improved Decision-Making	Allows clinicians to use integrated data for informed, personalized decisions[40]	To deploy personalized treatment plans for epilepsy integrating EEG with patient variables to date[41]
Robustness Against Noise	Noise provides noise and artifact reduction using information from multiple sources to increase reliability[42]	EEG combined with EMG data to filter out muscle activity artifacts[43]
Comprehensive Understanding	Provides a holistic view of complex health conditions through data integration[44]	Combining spatial and temporal data to understand the variable seizure dynamics[45]
Types of Multi-view Data in EEG		
View Type	**Description**	**Example of Application**
Spatial View	Analyzes spatial distribution of EEG signals across brain regions, focusing on localized brain functions[46]	Finding motor control regions using EEG from electrodes on the motor cortex[47]
Temporal View	Examines changes in brain activity over time, crucial for detecting transient events like spikes and oscillations[48]	Tracking seizure onset and duration through temporal variations during an episode[49]
Frequency View	Decomposes EEG into frequency bands to study oscillations linked to mental tasks and disorders[50]	Analyzing increased Theta activity during memory tasks to study cognitive load[51]
Clinical Context View	Integrates EEG with clinical parameters (e.g., patient history) to enhance interpretability and support personalized treatment plans[52]	Tailoring epilepsy treatments using EEG data alongside patient demographics[53]
Benefits of Multi-view Information Fusion in EEG Analysis		
Benefit	**Description**	**Example of Application**
Comprehensive Analysis	Integrates various data types to provide a complete view of brain activity and identify complex interactions[54]	Detecting subtle abnormalities in early-stage epilepsy[55]
Improved Classification Performance	Enhances classification accuracy in seizure detection and cognitive state recognition through multi-view integration[56]	Increasing seizure detection accuracy by combining spatial and temporal features[57]
Facilitation of Machine Learning	Aligns with machine learning models requiring diverse datasets, leading to robust models and better generalizability[58]	Training machine learning models on multi-view EEG data for improved cognitive load estimation[59]
Enhanced Insight into Pathophysiology	Offers a deeper understanding of neurological disorders by examining interactions between different EEG data views, aiding in biomarker discovery[60]	Identifying EEG biomarkers for early Alzheimer's diagnosis[61]
Adaptability to Individual Variability	Captures broader information accommodating individual differences in EEG patterns for personalized health monitoring[62]	Customizing EEG-based treatments for epilepsy by considering individual brain activity patterns[63]
Support for Real-Time Monitoring	Enables continuous integration of EEG data for real-time insights, facilitating prompt clinical interventions[64]	Real-time ICU patient monitoring with integrated EEG to detect sudden cognitive changes[65]

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5. TECHNIQUES FOR MULTI-VIEW INFORMATION FUSION

Early fusion, late fusion, and hybrid fusion strategies are considered to be multi-view information fusion techniques. The techniques differ in how they provide advantages based on data characteristics and application requirements. In this section, these techniques are explored in detail and their roles in EEG signal analysis are emphasized.

Fusion Technique	Definition	Advantages	Challenges	Example of Application
Early Fusion Techniques	Involves combining data from multiple views at the initial stages of analysis[66]	Preserves all available information. Provides a comprehensive view of brain activity[67]	High dimensionality increases computational complexity. Requires precise alignment of data[67]	Concatenating EEG signals from various electrode placements[67]
Data-level Fusion	Combines raw data from multiple views into a single dataset before processing[68]	Comprehensive integration of signals. Captures all available information[68]	Requires careful data alignment and can be computationally intensive[69]	Raw EEG data combination for better analysis[70]
Feature-level Fusion	Combines features extracted from multiple views after initial processing[71]	Reduces dimensionality by focusing on relevant features. Integrates diverse information types[72]	Choosing the right features is critical; irrelevant features can degrade performance[73]	Feature extraction for enhanced seizure detection[74]
Late Fusion Techniques	Integrates results from multiple analyses performed independently[75]	Flexibility in using optimized classifiers for each view. Leverages strengths of individual models[76]	Calibration of classifiers is necessary for consistency; risk of information loss[77]	Multi-class classification in EEG data[78]
Decision-level Fusion	Combines outputs from multiple classifiers trained on different views using voting or ensemble methods[79]	Optimizes the use of classifiers tailored to specific views[79] Improves robustness and accuracy[79]	Requires careful calibration to ensure consistent outputs[80]	EEG multi-class classification combines various classifiers[80]
Aggregation Techniques	Combines outputs through statistical methods like averaging or stacking[81]	Simple and easy to implement; reduces noise impact[82]	May not capture complex interactions; requires careful method selection[81]	Ensemble learning in EEG analysis[82]
Hybrid Fusion Techniques	Combines both early and late fusion strategies for comprehensive analysis[83]	Captures interactions from different processing stages[83]	Increased computational complexity; risk of overfitting if not properly managed[85]	Health monitoring applications in EEG for neurological disorders[86]

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		Enhances classification performance[84]		
Machine Learning Approaches	Traditional models (SVM, Random Forests, KNN) for feature-level or decision-level fusion[87]	Effective for moderate-sized datasets; easier to interpret[87] Suitable for classification tasks[87]	Struggles with large datasets; dependent on the quality of extracted features[88]	Seizure detection and cognitive state recognition[88]
Deep Learning Approaches	Models like CNNs and RNNs learn hierarchical features from raw data for multi-view fusion[89]	High capacity for learning complex relationships; efficient for large datasets[89] Real-time processing capability[90]	Requires significant computational resources and large labeled datasets; often lacks interpretability[91]	Emotion recognition and seizure detection using CNN and RNN[92]

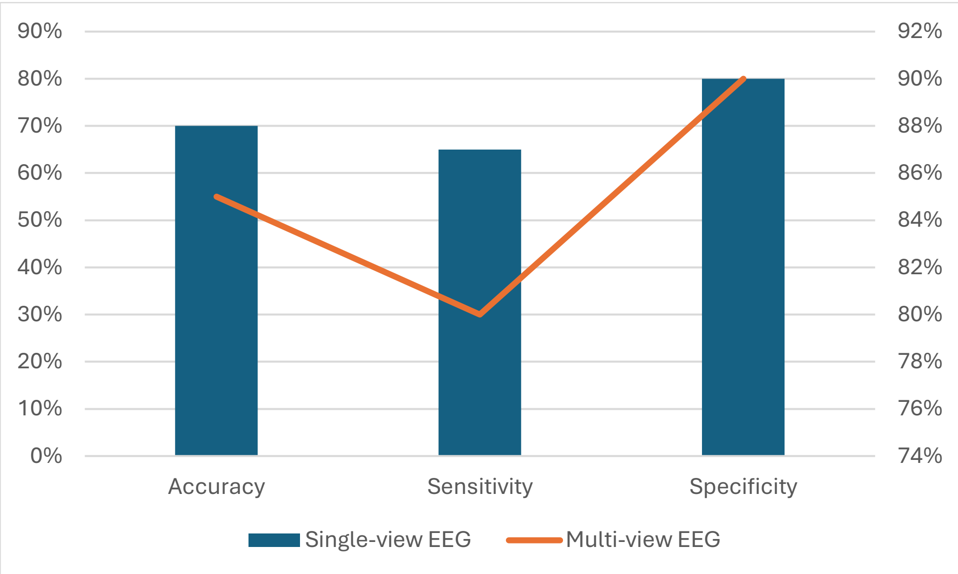

Fig 2. Performance Comparison of Fusion Techniques

Figure 2 presents data comparing classification performance between single-view and multi-view EEG techniques, showing a large improvement with multi-view methods. Single-view EEG achieves 70% accuracy, sensitivity at 65%, and specificity at 80%. In contrast, multi-view EEG increases these metrics to 85% accuracy with sensitivity and specificity at 80% and 90%, respectively[93]. This shows the effectiveness of multi-view approaches to provide a more holistic analysis of EEG signals, and therefore improve diagnostic accuracy in clinical applications.

6. APPLICATIONS OF MULTI-VIEW FUSION IN EEG SIGNAL PROCESSING

The application of multi-view fusion techniques in EEG signal processing has significantly advanced the capabilities of monitoring and analyzing brain activity. This section discusses various applications where multi-view fusion has been effectively utilized, highlighting its impact on seizure detection and monitoring, cognitive state assessment, neurological disorder diagnosis, sleep stage classification, and brain-computer interface (BCI) applications.

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Application	Techniques Used	Benefits	Outcomes
Seizure Detection and Monitoring	Multi-view data-level and feature-level fusion techniques to analyze EEG signals from multiple electrodes[94]	Enhanced detection accuracy, enabling timely interventions and improved patient management[95]	Studies show that multi-view fusion techniques outperform traditional single-channel methods in detection rates and reducing false alarms[96]
Cognitive State Assessment	Fusion of multi-view temporal and frequency data using models like Recurrent Neural Networks (RNNs)[97]	More nuanced cognitive state assessments identify transient states related to behavior[98]	Research indicates higher accuracy in cognitive state classification compared to traditional methods[99]
Neurological Disorder Diagnosis	Integration of multi-view data including frequency bands, spatial distributions, and demographic information for machine learning analysis[100]	Improved diagnostic accuracy and earlier detection of disorders, impacting treatment outcomes[101]	Studies demonstrate enhanced identification of abnormal EEG patterns associated with various neurological disorders[102]
Sleep Stage Classification	Feature-level integration of different frequency bands and application of machine learning models such as SVM or deep learning[103]	Improved accuracy in diagnosing sleep disorders and better insights into sleep architecture[104]	Research indicates that multi-view fusion enhances sleep stage classification performance, leading to higher accuracy rates[105]
Brain-Computer Interface (BCI) Applications	Use of multi-view fusion to decode user intentions by combining spatial and temporal EEG information, employing CNNs and RNNs[106]	Higher accuracy in intention detection leads to more effective control of devices for individuals with disabilities[107]	Studies show significant improvement in BCI performance with multi-view fusion, enhancing control over devices like robotic arms[108]

7. CHALLENGES IN MULTI-VIEW EEG FUSION

The advantages of multi-view EEG fusion techniques are promising, but several challenges hound their widespread implementation in clinical and research settings. The challenges are summarized in this section and include data heterogeneity and integration, scalability of algorithms, computational complexity, and real-time implementation challenges.

Challenge	Description	Impact
Data Heterogeneity and Integration Issues	Variability in acquisition methods, electrode placements, sampling rates, and preprocessing techniques complicates data fusion[109]	Reduces analysis accuracy and complicates result interpretation; coherence among data sources is essential for fusion[110]
Scalability of Algorithms	Increasing EEG data volumes challenge existing algorithms, which may struggle with high-dimensional datasets and require substantial computational resources[111]	Inefficient scalability leads to processing delays, reducing the effectiveness of monitoring and diagnostic systems[112]

Computational Complexity	Multi-view fusion techniques often involve complex algorithms that are computationally intensive, particularly in deep learning applications[113]	High computational demands can limit accessibility and feasibility in clinical settings, especially in real-time applications[114]
Real-time Implementation Challenges	Ensuring low-latency processing is crucial for applications like seizure monitoring, but hardware limitations can hinder real-time deployment[115]	The inability to implement techniques in real-time undermines their practical applications, impacting patient safety and monitoring efficacy[116]

8. FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

Multi-view EEG fusion field is growing and offers many opportunities for innovation and advancements. Potential future directions are defined in this section including emerging technologies, personalization and adaptive fusion models, multi-modal fusion approaches, and recommendations for future research[117]. With the development of new multi-view EEG fusion technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) which improve data analysis and real-time monitoring. By mimicking the patterns they discover, and improving classification and prediction, AI techniques such as machine learning and deep learning learn to automate this pattern-seeking in complex EEG datasets[118]. IoT enables continuous monitoring using wearable EEG systems, which can be integrated with real-time data for analysis, and potentially conducted in the cloud, as well as for interoperability with other health devices[119,120].

In addition, there is a need for personalized and adaptive fusion models for EEG application to individual differences in brain activity[121]. It consists of designing algorithms that consider user-specific characteristics and adaptive models that adapt in real-time to the quality of EEG signals[122]. Multi-modal fusion approaches, wherein data from multiple modalities such as EEG and fMRI are fused, hold the promise of increasing the accuracy of diagnosis as well as our understanding of cognitive processes by an increased breadth of information about brain function[123,124]. Several recommendations have been made to advance this field, including standardization of data collection protocols and fusion technique, model interpretability, and explainability improvement, longitudinal studies to assess long-term efficacy, and rigorous clinical validation of fusion methods [125,126]. Multi-view EEG fusion in clinical applications also requires interdisciplinary collaboration among neurologists, engineers, and data scientists to foster innovative solutions and enhance the usefulness of every view EEG fusion[127].

9. COMPREHENSIVE SUMMARY OF MULTI-VIEW INFORMATION FUSION IN EEG SIGNAL PROCESSING FOR HEALTHCARE MONITORING

Detailed table summarizing the research on "Multi-view Information Fusion for EEG Signal in Healthcare Monitoring":

Aspect	Details
Objective	This research proposes to investigate how the usage of multi-view information fusion techniques improves the analysis and monitoring capabilities of EEG signals in the healthcare environment by amalgamating spatial, temporal, and frequency data to obtain a well-rounded picture of brain activity.
Methodology	Systematic review following PRISMA guidelines: - **Search Scope**: Articles from 2010 to 2023 in PubMed, IEEE Xplore, Scopus, and Web of Science. - **Inclusion Criteria**: Works on multi-view EEG for healthcare, empirical/theoretical. - **Selected Studies**: Of 2,500 initial results, 450 were screened and 150 fully reviewed. - **Data Handling**: Standardized data regarding techniques, applications, challenges, and outcomes was extracted.
Applications	- **Seizure Detection**: Integrated spatial and temporal data for the high-accuracy detection and monitoring of epileptic episodes.

	- **Cognitive State Monitoring**: Mental State (e.g., attention, memory) classification in real-time. - **Neurological Disorder Diagnosis**: Diseases such as Alzheimer's and Parkinson's are detected early. - **Sleep Studies**: Frequency analysis based on sleep stage classification. - **Brain-Computer Interfaces (BCIs)**: For disabled individuals, enhanced device control.
Techniques	- **Early Fusion**: It takes raw EEG data from more than one channel and preserves maximum information for the whole analysis. - **Late Fusion**: The system uses separate models for different data views combines outputs and is suitable for flexible classifier designs. - **Hybrid Fusion**: Early and late fusion techniques are merged for increased accuracy and robustness. - **Deep Learning Models**: We demonstrate the use of CNNs and RNNs for hierarchically extracting features from multi-view EEG data for sophisticated pattern recognition.
Benefits	- **Enhanced Accuracy:** Data integration across views reduces uncertainty, improving diagnostic precision (e.g., seizure detection rate). - **Noise Reduction**: Artifacts such as muscle activity and eye movements are mitigated using multi-view data. - **Adaptability:** Individual EEG variability is accommodated by models and they offer personalized healthcare solutions. - **Real-Time Monitoring**: Continuous data integration which provides immediate clinical insights, and enables rapid intervention.
Challenges	- **Data Heterogeneity**: The integration is complicated by variations of acquisition methods, electrode placements, and preprocessing. - **Scalability**: However, the increasing sizes of EEG datasets present computational and hardware analysis challenges. - **Computational Complexity**: Deep learning, a fusion technique, is resource and expertise intensive. - **Real-Time Constraints**: However, processing latency prevents its deployment in time-sensitive applications such as seizure monitoring.
Emerging Directions	- **Artificial Intelligence (AI):** Automated EEG signal classification and pattern detections using machine learning. - **Internet of Things (IoT):** Continuous and remote cloud analysis of wearable EEG devices. - **Personalized Models:** So adaptive algorithms that were designed specifically to a person's brain activity profile would improve for people across the spectrum. - **Multi-modal Fusion**: Imaging with other modalities and improving data quality (fMRI)
Key Findings	-**Performance:** The multi-view fusion significantly outperforms the single-channel methods. Improvement in accuracy from 70% (single view) to 85%, sensitivity from 65% to 80%, and specificity from 80% to 90%. - **Impact:** It revolutionizes health monitoring by allowing earlier diagnosis, nuanced cognitive assessment, and robust real-time interventions in numerous clinical contexts.

CONCLUSION

In the last few years, multi-view information fusion techniques have been rapidly integrated into EEG signal processing for health monitoring purposes. The role of EEG in the assessment of brain function and the possibility of using multi-view fusion to improve the accuracy and completeness of EEG analysis were emphasized in this systematic review. The multi-view information fusion techniques use the different perspectives of the data to fuse it and get a more sophisticated understanding of the brain activity. This holistic approach allows us to pick up on extremely subtle patterns associated with neurological conditions and diagnose, and intervene more quickly. Applications of multi-view EEG fusion span from seizure detection, cognitive state assessment, neurological disorder

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diagnosis, and sleep stage classification to brain-computer interface. For all of these applications, the enhanced sensitivity and specificity achieved via multi-view analysis benefit all of them and ultimately benefit the patient. While these advantages exist, problems like data heterogeneity, scalability, computational complexity, and real-time implementation, still exist. To serve as a first step toward the successful adoption of multi-view fusion techniques in clinical practice, these challenges must be addressed. The application of artificial intelligence and Internet of Things technologies for multi-view EEG fusion is very exciting. Building on the first three application directions, the development of personalized and adaptive models as well as the creating of multi-modal fusion approaches can further enhance the utility of EEG in health monitoring. At last, EEG signal processing has promising frontiers in multi-view information fusion, which will revolutionize health monitoring practice. This is an area for which research will continue as existing challenges can be overcome and the full capabilities of multi-view fusion can be unlocked. However, through facilitating interdisciplinary collaboration and algorithmic advancements, researchers can greatly improve the effectiveness and applicability of EEG-based health monitoring solutions to better enable healthcare delivery to the patient.

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