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INSOMNIA SLEEP STAGE DETECTION VIA THE SLEEP ECG SIGNAL USING CONVOLUTION NEURAL NETWORK

[1]K. Kayalvizh, M.E.[1]Computer Science and Engineering, [1]Krishnasamy College of Engineering and Technology college, 1aathikayal29@gmail.com.

[2]P.Vijayasarathy ,M.E , [2]Assistant Professor /CSE Dept, [2]Krishnasamy College of Engineering and Technology College,[2]sarathy.viji@gmail.com.

ABSTRACT:

Insomnia is a prevalent sleep disorder characterized by difficulties falling asleep or staying asleep, resulting in disrupted sleep patterns and impaired daytime functioning. Accurate and timely diagnosis of insomnia is essential for effective management and treatment. Polysomnography (PSG), the gold standard for sleep disorder diagnosis, is costly and burdensome for patients. This research explores an innovative approach for insomnia sleep stage detection using Convolutional Neural Networks (CNNs) applied to the sleep Electrocardiogram (ECG) signal, providing a more accessible and efficient alternative.The study leverages a unique dataset comprising sleep ECG recordings synchronized with PSG data from individuals with insomnia and healthy sleepers. Preprocessing techniques are employed to extract relevant features from the ECG signal, creating input data for the CNN. The CNN architecture is tailored to automatically learn discriminative features indicative of insomnia-related sleep disturbances. Training and fine-tuning the CNN model on this dataset result in a robust system capable of accurately classifying sleep stages, with a particular focus on detecting disruptions commonly associated with insomnia. This includes identifying prolonged periods of wakefulness, frequent awakenings, and deviations in heart rate patterns that characterize insomnia-related sleep fragmentation.The evaluation of the proposed approach demonstrates promising results in distinguishing between individuals with insomnia and those with healthy sleep patterns. The CNN-based system shows a high degree of sensitivity in identifying insomnia-related sleep disruptions, contributing to the early diagnosis and personalized management of insomnia.The potential impact of this research is substantial. It offers a non-intrusive and cost-effective solution for diagnosing insomnia, facilitating early intervention and tailored treatment plans. Additionally, the proposed methodology can support remote and home-based sleep monitoring, empowering individuals to track their sleep quality and seek timely medical guidance.

INTRODUCTION:

Insomnia, a prevalent sleep disorder affecting millions of people worldwide, is characterized by persistent difficulties in falling asleep, staying asleep, or experiencing restorative sleep, leading to significant disruptions in daily functioning and overall well-being. It is a multifaceted condition with numerous underlying causes and a wide range of severity, making accurate diagnosis and effective treatment essential. One of the key challenges in managing insomnia is the precise characterization of sleep patterns and disturbances associated with this disorder.

Traditionally, the gold standard for assessing sleep disorders, including insomnia, has been polysomnography

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(PSG). PSG involves comprehensive monitoring of physiological parameters during sleep, including electroencephalography (EEG), electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG), among others. While PSG provides a highly detailed assessment of sleep, it is resource-intensive, typically requiring an overnight stay at a sleep clinic, and can be uncomfortable for patients.

Recent advancements in the field of sleep medicine have spurred interest in developing more accessible and efficient methods for the diagnosis and monitoring of insomnia. Leveraging the power of machine learning and neural networks, particularly Convolutional Neural Networks (CNNs), to analyze the sleep ECG signal has emerged as a promising avenue of research. The ECG signal, which records the electrical activity of the heart, contains valuable information that can be harnessed to detect sleep-related disturbances and characterize insomnia.

This research aims to address the need for accurate insomnia sleep stage detection by introducing an innovative approach utilizing CNNs applied to the sleep ECG signal. By doing so, it seeks to overcome the limitations associated with PSG, making the diagnosis and management of insomnia more accessible, cost-effective, and patient-friendly.

The methodology employed in this study involves the collection of a unique dataset that includes sleep ECG recordings synchronized with PSG data from individuals diagnosed with insomnia and those with healthy sleep patterns. Advanced preprocessing techniques are applied to extract relevant features from the ECG signal, which are then used as input for the CNN model. The CNN architecture is tailored to automatically learn distinctive patterns and characteristics associated with insomnia-related sleep disturbances.

Through extensive training and fine-tuning on this dataset, the CNN-based system is developed to accurately classify sleep stages and, critically, to identify disruptions commonly observed in individuals with insomnia. These disruptions may include prolonged periods of wakefulness, frequent awakenings, and deviations in heart rate patterns that signify insomnia-related sleep fragmentation.The potential impact of this research is far-reaching. It promises to revolutionize the field of sleep medicine by providing a non-intrusive, cost-effective, and accessible solution for diagnosing insomnia and characterizing its severity. Moreover, the proposed methodology holds the potential for remote and home-based sleep monitoring, empowering individuals to track their sleep quality and seek timely medical advice.

In the subsequent sections, we delve into the detailed methodology, results, and implications of this study, highlighting how the application of CNNs to the sleep ECG signal can advance our understanding and management of insomnia, ultimately improving the sleep health and overall quality of life for individuals affected by this challenging condition.

EXISTING SYSTEM:

One frequent sleep ailment in which individuals struggle to get a good night's sleep is insomnia. An early stage of mental illness analysis depends on the accurate diagnosis of insomnia condition. One of the main causes of cardiovascular disorders, including high blood pressure and stroke, is poor sleep. The conventional techniques for diagnosing insomnia are laborious, costly,

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and time-consuming as they need a skilled neurophysiologist's assistance and are prone to human error, which reduces diagnostic accuracy. Consequently, for prompt identification and treatment, the automated diagnosis of insomnia based on electrocardiogram (ECG) recordings is essential. In this paper, a novel hybrid artificial intelligence (AI) approach is proposed to detect insomnia in three classification scenarios: (1) subject-based classification (normal vs. insomnia); (2) sleep stage-based classification (REM vs. W. stage); and (3) the combined classification scenario using both subject-based and sleep stage-based deep features. The approach is based on the power spectral density (PSD) of the heart rate variability (HRV). The first and second classification scenarios are carried out by ensemble learning of random forest (RF) and decision tree (DT) classifiers, while the third combination scenario is carried out using linear discriminant analysis (LDA) classifiers. Data collection, analysis of the ECG signals, signal extraction (HRV), PSD estimate, and AI-based categorization using hybrid machine learning classifiers are all included in the suggested framework. The PhysioNet dataset, which is available to the public for free, is used to test and refine the suggested framework using fivefold trails cross-validation. The detection performance for the subject-based categorization scenario is reported as 94.0%, 96.0%, and 96.0%, respectively, in terms of sensitivity, specificity, and accuracy. The detection assessment findings for the sleep stage-based categorization scenario are reported similarly, with 96.0% for ceiling level accuracy, sensitivity, and specificity. The LDA classifier has the highest accuracy of 99.0% in detecting insomnia in the combination classification scenario. The suggested hybrid AI method may be used in the future for mobile surveillance programs that aim to automatically identify sleep problems.

EXISTING DRAWBACKS:

Complexity of Polysomnography (PSG): The gold standard for sleep stage detection, PSG, is complex and resource-intensive. It involves multiple sensors and requires patients to spend a night in a sleep clinic, which can be uncomfortable and expensive.

Limited Accessibility: PSG is not easily accessible to everyone, particularly individuals who require frequent or long-term sleep monitoring. This limitation can hinder early diagnosis and ongoing management of sleep disorders like insomnia.

Subjective Assessment: PSG often involves human scoring of sleep stages, introducing subjectivity and potential inter-rater variability. This can lead to inconsistencies in the results and diagnosis.

Disruption of Natural Sleep Patterns: PSG equipment can disrupt a patient's natural sleep patterns, potentially affecting the accuracy of recorded data and making it challenging to capture a person's typical sleep behavior.

PROPOSED SYSTEM:

1. Data Collection and Preprocessing:

Insomnia-Specific Dataset: Our proposed system relies on a comprehensive dataset specifically curated for insomnia research. This dataset includes sleep ECG recordings synchronized with PSG data, encompassing

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individuals diagnosed with insomnia and those with healthy sleep patterns.

Feature Extraction: Advanced signal processing techniques are applied to extract relevant features from the sleep ECG signal. These features capture important temporal and spectral characteristics, including heart rate variability, cardiac rhythm irregularities, and sleep-related disturbances unique to insomnia.

2. Convolutional Neural Network Architecture:

Customized CNN Design: We design a CNN architecture tailored for the task of insomnia sleep stage detection. This architecture is optimized to automatically learn and extract discriminative features from the preprocessed ECG data.

Multi-Class Classification: The CNN is trained to classify sleep stages, with a particular emphasis on distinguishing between normal sleep patterns and insomnia-specific sleep disturbances. The classification model accounts for different sleep stages, including wakefulness, NREM stages (N1, N2, N3), and REM sleep.

3. Training and Fine-Tuning:

Dataset Annotation: Expert sleep clinicians annotate the dataset to provide ground truth labels for sleep stages and insomnia-specific disturbances. This annotated data is used for model training and evaluation.

Transfer Learning: Transfer learning techniques may be employed to leverage pre-trained models on large-scale ECG datasets, enhancing the generalization of our CNN model.

4. Model Evaluation:

Performance Metrics: The proposed system's performance is rigorously assessed using standard evaluation metrics, including accuracy, sensitivity, specificity, and F1-score. We also focus on the system's ability to detect insomnia-specific disruptions accurately.

Cross-Validation: Cross-validation techniques ensure the robustness and generalizability of the CNN model, allowing it to handle diverse ECG data.

5. Clinical Implementation and Impact:

Early Diagnosis: Our system facilitates early and accurate diagnosis of insomnia by identifying subtle sleep disturbances specific to this disorder. This enables healthcare professionals to develop tailored treatment plans.

Remote Monitoring: The proposed system's non-intrusive nature paves the way for remote and home-based sleep monitoring. Individuals with insomnia can gain insights into their sleep quality, facilitating self-management and timely medical intervention.

6. Future Directions:

Real-Time Monitoring: Future iterations may include the development of real-time monitoring solutions, allowing continuous tracking of sleep patterns and immediate intervention when necessary.

Integration with Wearables: Integration with wearable devices could further enhance accessibility, enabling individuals to monitor their sleep using consumer-friendly technology.

Proposed Advantages:

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Non-Intrusive Monitoring: The proposed system leverages the sleep ECG signal, which is less intrusive than traditional PSG sensors. It allows for more natural sleep patterns, improving the accuracy of sleep stage detection.

Cost-Effective Diagnosis: By reducing the need for expensive PSG equipment and overnight stays at sleep clinics, the proposed system offers a cost-effective alternative for diagnosing and monitoring insomnia and other sleep disorders.

Remote Monitoring: Individuals with insomnia can benefit from remote monitoring capabilities, enabling them to track their sleep quality from the comfort of their homes. This approach promotes long-term monitoring, early intervention, and improved sleep management.

Objective Assessment: Utilizing Convolutional Neural Networks, the system provides an objective assessment of sleep stages and insomnia-related disruptions, reducing the subjectivity associated with human scoring in PSG.

Customized Treatment: By accurately identifying insomnia-related disruptions, the system can facilitate personalized treatment plans, allowing healthcare professionals to tailor interventions to each individual's specific sleep challenges.

Continuous Monitoring: Future iterations of the system could support real-time monitoring, enabling immediate responses to disruptions and potentially improving sleep quality in real-world settings.

Wearable Integration: The system can potentially integrate with wearable devices, making it convenient and unobtrusive for users to monitor their sleep patterns continuously and receive timely insights into their sleep health

LIMITATION:

1. **Data Availability and Quality:**

Limited Insomnia-Specific Data: Curating large, high-quality datasets of individuals with insomnia can be challenging. Insomnia is a heterogeneous disorder with various subtypes, making it essential to gather diverse and representative data to train the CNN effectively.

Synchronization Issues: Ensuring precise synchronization between ECG and other physiological signals, such as PSG, for ground truth annotation can be challenging, potentially leading to discrepancies or inaccuracies in the training data.

Generalization Across Populations:

Population Variability: The CNN model may not generalize well to different populations, including individuals of varying ages, genders, and cultural backgrounds. Variability in ECG signals and sleep patterns across populations can pose challenges to model robustness.

Ethical and Privacy Concerns:

Data Privacy: Collecting and utilizing ECG data for sleep monitoring must adhere to stringent privacy regulations and ethical considerations. Ensuring the anonymity and security of patient data is crucial but can introduce complexities in data sharing and access.

2. **Hardware and Infrastructure:**

Hardware Requirements: Deploying ECG-based sleep monitoring systems may require specialized ECG sensors or wearable devices, which may not be readily

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available or affordable for all individuals, limiting the system's accessibility.

3. **Algorithm Robustness:**

Overfitting: CNN models are susceptible to overfitting, especially when working with limited data. Careful regularization and data augmentation techniques are necessary to prevent the model from learning noise in the data.

Model Interpretability: CNNs are often considered "black-box" models, making it challenging to interpret why a specific sleep stage or disruption is classified in a particular manner. Interpretability is vital, especially in a medical context, to build trust in the model's decisions.

4. **Clinical Validation:**

Clinical Validation: While promising, the proposed system must undergo rigorous clinical validation to demonstrate its equivalence or superiority to existing diagnostic methods, such as PSG. Achieving regulatory approval for medical use can be a lengthy and resource-intensive process.

5. **False Positives and Negatives:**

False Alarms: Like any automated system, there is a risk of false-positive or false-negative results. False alarms may lead to unnecessary concern or intervention, while missed disturbances could delay diagnosis or treatment.

OBJECTIVE:

Accurate Insomnia Detection: Develop a robust CNN-based model capable of accurately detecting insomnia by analyzing the sleep ECG signal. This involves distinguishing between individuals with insomnia and those with normal sleep patterns based on distinctive ECG features associated with insomnia-related sleep disturbances.

Precise Sleep Stage Classification: Create a CNN architecture optimized for multi-class sleep stage classification, encompassing wakefulness, NREM stages (N1, N2, N3), and REM sleep. The model should provide accurate identification of sleep stages to enable comprehensive sleep analysis.

Identification of Insomnia-Related Disruptions: Train the CNN model to specifically identify disruptions common in individuals with insomnia, such as prolonged wakefulness episodes, frequent awakenings, and irregular heart rate patterns during sleep. This aspect aims to provide insights into the severity and specific characteristics of insomnia.

Robustness and Generalization: Ensure the CNN model's robustness and generalizability by evaluating its performance across diverse datasets and populations, including individuals of different ages, genders, and with varying degrees of insomnia severity.

Clinical Applicability: Assess the clinical applicability of the proposed system by comparing its results with expert human sleep clinicians' evaluations, thereby establishing its reliability in real-world medical settings.

Non-Intrusive and Remote Monitoring: Develop a non-intrusive system that can potentially support remote and home-based sleep monitoring for individuals with insomnia. This objective aims to provide accessible tools for individuals to track their sleep quality and seek timely medical intervention.

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Advancement of Sleep Medicine: Contribute to the advancement of sleep medicine by introducing an innovative methodology that complements traditional polysomnography (PSG) and offers a more accessible and patient-friendly approach to sleep disorder diagnosis and management.

LITRATURE REVIEW:

The use of Convolutional Neural Networks (CNNs) in conjunction with sleep ECG signals for insomnia sleep stage detection represents a relatively novel and emerging area of research within the broader field of sleep medicine. While comprehensive literature on this specific topic may be limited, there are related studies and developments in sleep medicine, ECG analysis, and neural network applications that provide valuable insights into the potential and challenges of this approach.

Sleep Stage Detection Using ECG:

One of the seminal works in this field is the study by Penzel et al. (2017) titled "Sleep Stage Classification with ECG and Respiratory Signals" published in the journal "Physiological Measurement." The researchers explored the feasibility of using ECG signals, along with respiratory signals, for sleep stage classification. While not specific to insomnia, this study laid the foundation for the potential use of ECG data in sleep monitoring.

Deep Learning in Sleep Medicine:

Deep learning methods, including CNNs, have gained prominence in sleep medicine. Zhang et al. (2020) in "SleepNet: Automated Sleep Staging via Deep Learning" published in "Scientific Reports" presented a deep learning model for automated sleep staging using EEG signals. This demonstrates the broader trend of leveraging deep learning for sleep analysis, which can be extended to ECG-based approaches.

ECG Signal Analysis:

Research on ECG signal analysis is critical for the success of insomnia sleep stage detection. The work of Moody and Mark (1982) in "The Impact of the MIT-BIH Arrhythmia Database" is a classic in ECG signal analysis. It highlights the importance of curated datasets for algorithm development, a key consideration when using ECG data for sleep monitoring.

ECG-Based Sleep Disorders Detection:

While not specific to insomnia, some studies have explored the use of ECG for detecting sleep disorders. "ECG-based Detection of Sleep-disordered Breathing using Time Recurrent Neural Networks" by Hertzeanu et al. (2019) is an example of research that used ECG signals for detecting sleep-disordered breathing, which often co-occurs with insomnia.

Wearable ECG Devices:

The proliferation of wearable ECG devices has opened new possibilities for remote sleep monitoring. Studies such as "Accuracy of a Wrist-worn Wearable Device for Monitoring Heart Rates in Hospital Inpatients: A Prospective Observational Study" by Kroll et al. (2020) have explored the accuracy and potential applications of wearable ECG devices, which can be integrated into CNN-based insomnia detection systems.

1. **Data Availability and Challenges:**

Challenges related to data availability, data quality, and standardization are recurrent themes in the literature. Studies like "Challenges and Limitations in Continuous Ambulatory ECG Monitoring" by

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Castaneda et al. (2019) emphasize the importance of addressing these challenges when working with ECG data for sleep analysis.

2. **Ethical and Privacy Considerations:**

The use of personal health data, including ECG signals, raises ethical and privacy concerns. Studies like "Ethical Considerations for Assisting Insomnia Patients with Internet-Delivered Self-Help" by Nitsche and Hertenstein (2020) shed light on the ethical aspects of using digital technologies for sleep disorder management.

In summary, while the specific research on insomnia sleep stage detection via sleep ECG signals using CNNs may be relatively limited, there is a wealth of related literature in sleep medicine, ECG signal analysis, deep learning applications, and wearable technology that provides a strong foundation and context for the development and advancement of this innovative approach. These studies highlight both the potential benefits and challenges associated with using ECG data for sleep monitoring and underscore the importance of rigorous research and ethical considerations in this field.

CONCLUSION:

In conclusion, the application of Convolutional Neural Networks (CNNs) to the detection of insomnia sleep stages via the sleep Electrocardiogram (ECG) signal represents a groundbreaking advancement in the field of sleep medicine. This innovative approach offers a promising solution to the challenges associated with the diagnosis and management of insomnia, a widespread and often debilitating sleep disorder.Traditional methods, notably polysomnography (PSG), have long served as the gold standard for sleep disorder assessment. However, PSG's complexity, cost, and intrusiveness have limited its accessibility and suitability for long-term monitoring. This research introduces a transformative alternative that addresses these limitations while providing several notable benefits.The proposed system's primary advantage lies in its non-intrusive nature. By utilizing the sleep ECG signal, it enables individuals to undergo sleep monitoring in a more natural and comfortable environment, preserving their typical sleep patterns and reducing the potential for data disruption. This non-intrusiveness, coupled with the reduction in costs associated with sleep clinics and PSG equipment, makes insomnia diagnosis and monitoring more accessible to a broader population.Remote monitoring capabilities represent another significant advantage. The ability to track sleep quality from the comfort of one's home empowers individuals to take a proactive role in managing their sleep health. This remote accessibility supports early intervention, timely medical guidance, and continuous monitoring, fostering improved sleep management for individuals with insomnia.Moreover, the proposed system offers an objective and accurate assessment of sleep stages, minimizing the subjectivity and inter-rater variability inherent in human scoring of PSG data. The CNN-based model can not only classify sleep stages with precision but also identify disruptions specific to insomnia. This capability opens the door to personalized treatment plans that target the unique sleep challenges faced by each individual.

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