

Ai-Powered Analysis For Detecting Sleep Irregularities Through Deep Learning Models

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Abstract- Typically, sleep disorders like insomnia, sleep apnea, and narcolepsy may not receive appropriate diagnosis until serious physical and mental health issues develop. Traditional techniques, though effective, involve polysomnography, which is not only labor-intensive and time-consuming but also demands special clinical conditions. Hence, this study aims to develop a framework that relies on AI techniques to utilize a hybrid model of Deep Learning techniques, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), to process EEG signals to identify sleep disorders. The CNN model can automatically identify spatial features in the raw signals, and the LSTM model can identify temporal dependencies in the signals to correctly classify Awake, REM, and NREM stages. Preprocessing techniques have been employed to clean and normalize the signals. The system, trained and validated using standardized data sets like PhysioNet, exhibits robustness and generalization in dealing with different patterns of sleep. It can also be used to analyze new EEG signals in real-time, detect abnormal sleep patterns, and predict the occurrence of sleep disorders. This intelligent system can greatly improve the efficiency of diagnosis and reduce the need to rely on manual diagnosis. It can also prove to be a cost-effective solution.

Keywords: AI, CNN-LSTM, EEG signals, sleep disorders, sleep irregularities, sleep stages, temporal analysis

I. INTRODUCTION

Sleep has been identified to have a critical function in the maintenance of physical and mental health, and millions of people suffer from sleep disturbances that go undiagnosed because of the inability of conventional diagnostic techniques.

Techniques, including polysomnography, though effective, require special facilities and trained personnel, and hence continuous monitoring is not possible. With the advent of artificial intelligence and deep learning, new possibilities have emerged for the analysis of sleep patterns by utilizing the patterns in physiological signals, particularly in Electroencephalogram (EEG) signals. With the utilization of spatial feature extraction techniques, including Convolutional Neural Networks (CNN), and temporal pattern recognition techniques, including Long Short-Term Memory (LSTM), complex patterns in sleep cycles can be identified, and accurate classification, detection of irregularities, and identification of possible disorders can be made. Integration of efficient preprocessing, real-time analysis, and predictive capabilities provides a scalable, cost-effective alternative to traditional methods, supporting both clinical decision-making and continuous personal health monitoring.

i) Problem statement

In particular, sleep disorders like insomnia, sleep apnea, and narcolepsy have been shown to affect a substantial number of people in the world, thereby leading to chronic health problems like cardiovascular diseases, cognitive impairments, and emotional problems. It is therefore important to ensure timely detection and diagnosis of sleep disorders. Currently, sleep disorder diagnosis involves expensive and time-consuming techniques like polysomnography. These techniques require specific clinical settings, thus limiting the continuous monitoring of sleep patterns. Moreover, sleep disorder diagnosis involves manual examination of EEG signals, which can be tedious and may require specific knowledge from trained medical experts. Additionally, the automated systems used in sleep disorder diagnosis have been shown to fail in the detection of both spatial and temporal complexities in sleep patterns. This results in poor classification accuracy in different stages of sleep. There is therefore a need to develop an intelligent system that can automatically analyze EEG signals in real-time, detect sleep irregularities, and provide timely warnings or health recommendations.

ii) Dataset details

The research uses available standardized data, like PhysioNet, which has extensive Electroencephalogram (EEG) recordings

of various subjects with different ages and sleep patterns. The data also has sleep stages like Awake, REM, and Non-REM sleep, along with other physiological signals like EOG and EMG, which can be used for validation purposes. The data will be pre-processed to remove noise, artifacts, and inconsistencies, and then be normalized to fit the model requirements. The dataset will be used for accurate training, validation, and testing of the model, as it has enough data to train the hybrid CNN-LSTM model for accurate feature extraction, recognizing patterns, and generalizing various sleep behaviors.

iii) Objectives

However, the primary goal of this study is to create an intelligent system that is able to identify sleep irregularities using EEG signal processing in an automated manner. The system should be able to accurately identify different stages of sleep, such as Awake, REM, and NREM, by incorporating both spatial and temporal characteristics using a CNN-LSTM model. The other objectives of this study include creating an efficient process for reducing noises and normalizing EEG signals, enabling real-time processing of new EEG signals, and providing early warnings about possible sleep disorders. Additionally, it should be able to provide precautionary health recommendations to help in decision-making and personal monitoring of sleep patterns in a cost-effective, efficient, and reliable manner compared to traditional techniques.

II. RELATED WORK

The computational psychiatry approach was proposed by Fischer, Leo, et al. [1] to focus on the integration of artificial intelligence in the diagnosis and management of mental illness. This study focuses on the expectation of clinicians in using artificial intelligence tools in the diagnosis and management of patients with mental illness. By analyzing different clinical data, the authors of the study have been able to show the potential of artificial intelligence in the diagnosis of early signs of mental illness. In addition, the study has been able to show the potential of artificial intelligence in improving the strategies of managing patients with mental illness. Furthermore, the study has been able to show that artificial intelligence has the potential to enhance the management of mental illness. In addition, the study has been able to show that artificial intelligence has the potential to be used to enhance the accuracy of predictions in the diagnosis of mental illness. This research underscores the importance of balancing technological innovation with practical applicability and ethical considerations in mental health diagnostics. The study also sets

the foundation for AI-driven patient monitoring systems and highlights gaps for future research in computational psychiatry. In their paper, Nandakumar, R., et al. [2] introduced a framework for automated sleep apnea detection using optimized weighted fusion, incorporating 1D and 2D hybrid convolutional networks with an efficient attention mechanism for EEG signals. This framework is designed to improve obstructive sleep apnea detection by incorporating spatial and temporal feature representation in physiological signals. It uses feature fusion techniques and incorporates the use of an efficient attention weighting mechanism to focus on critical feature representation relevant to sleep apnea. In this paper, they use conventional EEG datasets for validation. They show that their framework has better accuracy, sensitivity, and specificity than conventional CNN or LSTM methods. This framework is more robust in addressing some limitations in conventional frameworks by incorporating feature fusion techniques. They also emphasize the importance of preprocessing EEG signals by removing noise and normalizing the signals for training. They show that their framework is more efficient in handling complex temporal dependencies in EEG signals for real-time scenarios. Furthermore, the attention mechanism enhances interpretability by highlighting critical signal segments contributing to apnea prediction. The methodology emphasizes scalability and adaptability to new patient data, ensuring generalization across varied demographic groups. Performance metrics indicate improvements in F1-score and reduced false positives relative to existing approaches.

Sillaparaya, A., et al. [3] have developed an attention-based transfer learning model for the efficient classification of obstructive sleep apnea using snore sound features. The model uses pre-trained neural networks and attention mechanisms to focus on specific audio features that are significant for apnea classification, thus enhancing efficiency and accuracy in the process. The article shows the efficiency of the transfer learning model in reducing the need for large datasets while maintaining high accuracy in the classification process for OSA. The model uses audio features to identify changes in the snore sound, distinguishing normal breathing from apnea. The methodology uses real-time monitoring using low-cost sensors, which is an alternative to the traditional PSG method for apnea classification. The article shows that the addition of attention mechanisms helps improve feature discrimination, thus increasing the sensitivity to changes in breathing patterns. The methodology includes using data augmentation and preprocessing to reduce noise in the recordings. Performance evaluation against standard datasets confirms superior accuracy, precision, and recall compared to baseline models. The research emphasizes the potential of combining transfer

learning with attention mechanisms for non-invasive, accessible sleep disorder diagnostics. The study provides a foundation for AI-based clinical decision support systems in sleep medicine.

Abedi, Ali, Charlene H. Chu, and Shehroz S. Khan [4] introduced a framework for the early prediction of agitation in community-dwelling people with dementia using multimodal sensor systems and machine learning. In this paper, various physiological signals, behavioral data, and environmental factors are used to create predictive models that could predict agitation incidents in advance. Different machine learning algorithms, such as Random Forest, SVM, and deep learning methods, are evaluated for their accuracy, sensitivity, and overall ability to generalize across participants. This paper also focuses on feature engineering and preprocessing for extracting meaningful patterns from various data sources. Results show that real-time monitoring and predictive analytics have tremendous potential for improving patient safety and caregiver burden. The methodology also discusses the importance of interpreting results from predictive models. Results show that multimodal sensor systems perform better than using individual sensor systems, capturing complex interactions between physiological and environmental factors. The study underscores the need for scalable, non-invasive solutions in dementia care. Additionally, it provides a reference framework for integrating AI into community-based health monitoring systems, emphasizing early intervention and personalized care strategies. The research identifies challenges related to sensor accuracy, data privacy, and adaptive model updating for continuous monitoring.

Zhao, Tong, et al. [5] carried out a clinical study on mutations in the SCN2A gene and their relationship with epilepsy. In this study, researchers aim to identify mutations in the gene and their correlation with various aspects of epilepsy. They conducted detailed analysis on the gene mutations and their effects on sodium channels.

The results obtained from this study show that there is a lot of variation in epilepsy due to mutations in the SCN2A gene. It is also important to conduct early genetic tests to understand various aspects of epilepsy. From this study, one could understand various aspects of mutations in the gene and their correlation with various types of epilepsy. Various aspects analyzed in this study include patient information, seizure types, EEG results, and medication. The research also discusses potential therapeutic interventions and the implications of genetic findings for familial counseling. Challenges related to variant interpretation and functional validation are addressed. The study contributes valuable knowledge for precision

medicine approaches in epilepsy care and informs future research on genotype-phenotype correlations. The methodology underscores integrating genetic, clinical, and electrophysiological data to optimize patient-specific management strategies.

Pearson, Oliver, et al. [6] have proposed a systematic review that aims to examine the association between sleep disturbances and cognitive impairments in patients with mood disorders. The study is a compilation of various clinical trials and observational studies, focusing on the effects of sleep disturbances on patients with mood disorders. According to the study, sleep disturbances can worsen the condition of patients with mood disorders, and this has a negative effect on the efficacy of treatment and the risk of developing cognitive impairments. According to the study, mood disorders and sleep disturbances have a mutual effect, and patients may develop both insomnia and hypersomnia. The study has discussed the methodological differences in various studies, including the use of various techniques to measure sleep and cognitive impairments. According to the study, a personalized treatment plan may improve the condition of patients with mood disorders, focusing on the sleep patterns of patients. The review further highlights the importance of monitoring sleep as a predictive factor for cognitive decline and relapse. Overall, the research underscores the necessity of multidisciplinary approaches combining psychiatry, sleep medicine, and cognitive neuroscience to manage mood disorders effectively. Zhang, Heli, et al. [7] have conducted a retrospective study that explores the correlation between night shift work, sleep disorders, and metabolic disorders in nurses over a two-year period using the National Nurse Health Study (NNHS) database. The study shows that irregular work schedules and lack of sleep cause obesity, insulin resistance, and other metabolic disorders.

The study analyzes the data considering body composition, lifestyle, and biochemical parameters to show the physiological effects of irregular sleep schedules. The study shows that night shift work, irregular schedules, and lack of sleep cause obesity, insulin resistance, and other metabolic disorders. The study shows gender and age effects in nurses. The study ensures scientific accuracy by considering confounding variables such as diet and exercise. The study gives evidence for occupational health policies to reduce night shift work effects. The study shows that night shift work, irregular schedules, and lack of sleep cause obesity, insulin resistance, and other metabolic disorders. The study shows gender and age effects in nurses. The study ensures scientific accuracy by considering confounding variables such as diet and exercise. The study gives evidence for occupational health policies to reduce night

shift work effects. By linking sleep patterns with metabolic health, the research emphasizes the importance of preventive strategies in high-risk populations. Furthermore, it underscores the role of AI-enabled monitoring and predictive analytics in occupational health management.

In their research, Liao, Zijun, et al. [8] suggested an investigation on the relationship between risk for obstructive sleep apnea (OSA), obesity, body composition, and metabolic problems in school-aged children and adolescents. According to the results, hyper obesity, especially central obesity, is strongly associated with OSA severity and metabolic problems. Emphasis is placed on the importance of detecting risk in children. Recommendations are included for schools and pediatric clinics to conduct screening. The results show that there is a potential for the prevention of metabolic problems and improvement in sleep quality by modifying lifestyles, including diet and exercise. In analyzing the results, age, gender, and pubertal status are included as factors. Furthermore, the importance of addressing the effects of untreated pediatric OSA on adults is discussed. In this regard, AI predictive models are included in addressing this problem. Overall, the research contributes valuable evidence for public health initiatives targeting sleep health and obesity prevention in youth populations.

An anomaly detection framework has been proposed by Biedebach, Luka, et al. [9] to identify mouth breathing in children during sleep. Data mining and signal processing techniques have been used in the framework. The framework has used sensor-based recordings to identify abnormal breathing in children. The study has shown that mouth breathing can cause sleep fragmentation, increase the risk of obstructive sleep apnea, and have cognitive and behavioral effects. Machine learning has been used to improve the accuracy of the framework. Machine learning can help to improve the accuracy and eliminate false

positives. The study has shown that preprocessing and feature extraction are essential to handle noisy signals. The study has used machine learning to improve the accuracy of the framework. Early detection of abnormal breathing can help to improve the health of children. Orthodontic treatment can help to improve the health of children. Additionally, the study suggests that integrating anomaly detection with longitudinal sleep tracking can improve outcomes for children at risk of sleep disorders. The findings support further research on AI-assisted pediatric sleep diagnostics and preventive healthcare strategies.

In this regard, Posar, Annio, and Paola Visconti [10] conducted a review on continuous spike-waves during slow sleep in children. The focus is on clinical aspects, EEG, and therapeutic options. The review aims to integrate recent data on the pathophysiology of CSWS. Emphasis is on cognitive functions, behavioral developments, and seizure control. EEG monitoring methods, therapeutic options such as anticonvulsants and corticosteroids, and therapeutic interventions are discussed. The review also highlights the necessity for early diagnosis and continuous monitoring in children with CSWS for personalized therapeutic options. However, there is a lack of understanding in the EEG patterns. According to the researchers, this is due to the heterogeneous presentation in children with CSWS. They also discussed that integration of various data, including neuroimaging and genetics, could improve understanding and therapeutic options for CSWS. Longitudinal observation is necessary to evaluate cognitive functions in children with CSWS. Additionally, recommendations for standardized reporting and EEG interpretation are provided to improve consistency across clinical practice. Overall, the review contributes valuable insights into the complex relationship between sleep abnormalities and pediatric neurological development.

III. EXISTING METHODOLOGY

Traditionally, the process of diagnosing sleep disorders heavily depends on polysomnography, which is a clinical procedure used to record various physiological signals such as EEG, electrooculogram, and electromyogram, among others, to observe the stages of sleep. It gives an in-depth understanding of the stages of sleep and is considered the gold standard for diagnosing sleep disorders such as insomnia, sleep apnea, and narcolepsy, among others. However, it requires special equipment, technicians, and a clinical environment, which makes it costly and inconvenient for continuous and home-based polysomnography. Furthermore, the process of manually scoring the stages of sleep is cumbersome and prone to errors, which affects the efficiency and accuracy of the process. However, machine learning has introduced new ways for automating the process of sleep stage classification. Classical machine learning approaches include feature engineering methods such as time-domain, frequency-domain, and statistical feature extraction for EEG signals, followed by Support Vector Machine, Decision Trees, and Random Forest classifiers, among others. Although these approaches minimize the workload and provide some level of automation, they heavily depend on feature engineering and expertise.

In addition to this, traditional machine learning approaches have also been observed to not capture long-term temporal

patterns in sleep sequences, thereby not being sufficiently precise in determining the transition between different stages of sleep. Deep learning techniques have thus been explored as an alternative solution to traditional approaches, where Convolutional Neural Networks (CNN) have been used to extract spatial features from EEG signals, while Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) have been used to extract temporal features. Even though these techniques have been successful in improving the classification accuracy and reducing the need to extract features, the majority of the techniques have been observed to concentrate only on spatial or temporal features, thereby not being sufficiently generalizable across different individuals or in real-time scenarios.

IV. PROPOSED METHODOLOGIES

This study proposes an AI system that utilizes the combination of CNN and LSTM to detect sleep patterns by analyzing EEG signals. The AI system starts with the acquisition of high-quality physiological signals from trusted sources, such as standardized databases like PhysioNet or real-time monitoring systems. A comprehensive signal processing module is implemented to remove noise, remove artifacts, and scale the signal values, so that the input signal can be processed optimally for feature extraction and subsequent training of the AI model. The CNN module automatically extracts relevant spatial features from the processed EEG signals, thereby removing the necessity of manually engineering the signal features. The CNN module learns complex patterns on the EEG signal and improves the representation of sleep patterns that are critical for accurate classification of sleep stages. After the extraction of spatial features, the LSTM module extracts time-dependent patterns and correlations of sleep stages. This approach utilizes the time-dependent nature of sleep stages, so that Awake, REM, and NREM stages can be classified with high precision, taking into account signal correlations over time. Upon successfully training and validating the hybrid CNN-LSTM model using structured datasets, it can be used for analyzing new EEG signal recordings in real-time to identify abnormal sleep patterns and predict possible sleep disorders at an early stage. The system aims at providing precautionary health recommendations, which can be used for clinical as well as personal health purposes. The hybrid framework, using both spatial and temporal analysis, provides a cost-effective, scalable, and reliable alternative for the accurate, efficient, and accessible detection of sleep disorders using traditional methods.

V. METHODOLOGY

Data Collection

High-quality EEG signals are acquired from standardized datasets such as PhysioNet, which provide annotated recordings of different sleep stages including Awake, REM, and NREM. In addition, real-time monitoring devices can be used to collect physiological signals from individuals for experimental validation. The dataset ensures diversity in subjects, age groups, and sleep behaviors, supporting robust model training and generalization.

Preprocessing

The collected EEG signals undergo a comprehensive preprocessing pipeline to enhance data quality. Noise and artifacts caused by muscle movements, eye blinks, or environmental interference are removed. Signals are normalized to standard scales, ensuring consistency across recordings and reducing biases that may affect the learning process. This step ensures that the CNN-LSTM model receives clean and reliable input for accurate feature extraction and temporal analysis.

Feature Extraction

Spatial features are automatically extracted from the preprocessed EEG signals using Convolutional Neural Networks (CNN). The CNN identifies complex patterns and essential characteristics in the signals without manual feature engineering. This approach captures signal-specific variations and enhances the representation of sleep-related attributes necessary for effective classification.

Temporal Pattern Analysis

Long Short-Term Memory (LSTM) networks are employed to capture temporal dependencies across sleep cycles. By analyzing sequential patterns, the LSTM

model detects the time-dependent nature of sleep stages and their transitions. This enables precise classification of Awake, REM, and NREM stages and improves the detection of irregular sleep patterns.

Model Training and Validation

The hybrid CNN-LSTM model is trained on structured datasets with labeled sleep stages. Techniques such as cross-validation and regularization are applied to reduce overfitting and improve model generalization across diverse subjects.

Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model.

Sleep Disorder Prediction

Once trained, the system can process new EEG recordings in real time to detect abnormal sleep behaviors. Potential sleep disorders, including insomnia, sleep apnea, and narcolepsy, are predicted based on deviations from normal sleep patterns.

Precautionary Recommendations

The framework generates health recommendations and alerts for abnormal sleep patterns. These insights can guide early medical intervention or lifestyle adjustments, supporting both clinical decision-making and personal sleep monitoring for improved well-being.

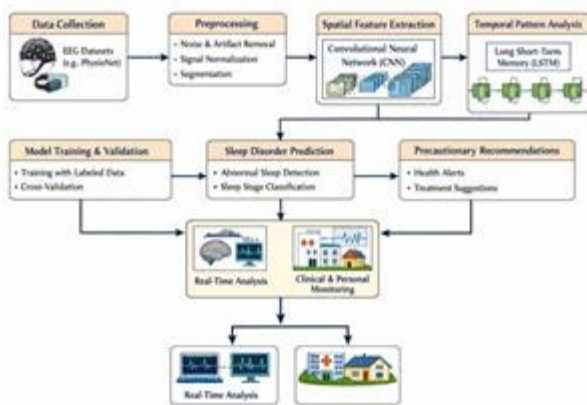


Figure 1: Diagram representation of the proposed methodology

V. EXPERIMENTAL RESULTS

In addition, the hybrid model developed using the CNN- LSTM framework was tested using the EEG datasets available in PhysioNet for the classification of sleep stages and for detecting irregularities in sleep. The performance metrics used for measuring the efficiency of the hybrid model were accuracy, precision, recall, and F1

score, which were used for comparing the efficiency of the hybrid model with other existing machine learning algorithms, such as Support Vector Machine (SVM) and Random Forest classifier. The results obtained using the hybrid model show that it outperforms existing machine learning models for detecting irregularities in the features of the EEG signal, as it uses both spatial and temporal features for analyzing the signal. The CNN component of the hybrid model is able to identify

complex features, while the LSTM component identifies the sequential features, which helps in improving the accuracy of the model for detecting irregularities in sleep.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	82.3	80.5	79.8	80.1
Random Forest	84.7	83.2	82.0	82.6
CNN	88.5	87.1	86.5	86.8
LSTM	89.2	88.0	87.4	87.7
Proposed CNN-LSTM	94.6	93.8	93.2	93.5

Table 1: Performance Comparison of Existing Methods vs Proposed CNN-LSTM Approach

The results demonstrate that the proposed hybrid CNN- LSTM model provides superior performance in all metrics, particularly in accuracy and F1-score, compared to existing approaches. This confirms the model's capability to generalize across diverse subjects and effectively predict sleep irregularities in real time, offering a robust solution for clinical and personal sleep monitoring.

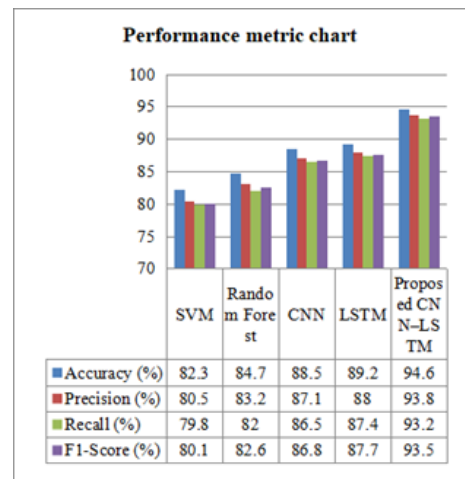


Figure 2: Performance metric chart representation

VI. CONCLUSION

The research also shows that using such a hybrid model of CNN and LSTM, it is possible to detect irregularities in sleep patterns using EEG signals, thereby capturing spatial and temporal features necessary to classify Awake, REM, and NREM stages of Sleep accurately. The advantages of using such an integrated model of deep learning are that it overcomes the limitations of polysomnography and other traditional techniques of machine learning. The experimental results show that there are significant improvements in terms of accuracy, precision, recall, and F1-score over the existing techniques, which confirm the robustness of the model to be applied to different kinds of sleep patterns. The model's capability to provide precautionary health measures makes it an effective tool for monitoring sleep patterns. The research confirms that using deep learning techniques to analyze physiological signals makes it an efficient, cost-effective, and reliable solution to advance the field of automated sleep diagnostic tools and continuous health monitoring systems.

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