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SLEEPSENSE : MACHINE LEARNING APPROACHES FOR ACCURATE SLEEP DISORDER DIAGNOSIS

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Abstract : Sleep disorders such as insomnia and sleep apnea are growing public health concerns due to their impact on physical and mental well-being. Conventional diagnostic methods, including polysomnography, though accurate, are time-consuming, costly, and require clinical settings. The integration of machine learning (ML) and deep learning (DL) techniques has opened new avenues for automated, scalable, and cost-effective detection of sleep disorders. This paper presents a critical review of recent advancements in sleep disorder classification using ML and DL approaches. The reviewed studies utilize various data sources, including physiological signals and lifestyle attributes, applying methods such as feature extraction, hybrid model design, and ensemble learning. Algorithms like Random Forest, Support Vector Machines, and Convolutional Neural Networks demonstrate notable performance, with some achieving accuracies up to 99%. This review evaluates these models in terms of accuracy, robustness, and clinical relevance, while also addressing challenges such as data imbalance, computational complexity, and model interpretability. The findings aim to guide future research towards developing efficient, accurate, and interpretable systems for the early detection and diagnosis of sleep disorders.

IndexTerms - Sleep Disorders, Machine Learning, Deep Learning, EEG, Sleep Staging, Classification Models, Healthcare AI.

I. INTRODUCTION

Sleep plays a critical role in maintaining overall physical and mental well-being. Disruptions in sleep, when persistent, are linked to numerous health issues such as heart disease, depression, cognitive impairment, and a weakened immune system. Two of the most common sleep disorders are insomnia, which involves difficulty falling or staying asleep, and obstructive sleep apnea, marked by repeated interruptions in breathing during sleep. Early detection of these conditions is essential for timely treatment and better health outcomes.

Polysomnography (PSG) remains the standard diagnostic method, involving overnight observation in specialized clinics. However, its high cost, need for clinical infrastructure, and limited availability make it less accessible for widespread use. This has spurred significant interest in automated detection systems powered by machine learning (ML) and deep learning (DL). These technologies are capable of analyzing complex physiological signals—such as EEG and ECG—as well as behavioral and lifestyle data, to identify irregular sleep patterns.

This review explores recent advancements in applying ML and DL to sleep disorder detection. The research includes a variety of models, from traditional classifiers to deep neural networks, utilizing diverse data types. Through comparative analysis, this study highlights effective techniques and common challenges in developing intelligent, automated diagnostic tools for sleep disorders.

II. RELATED WORK

[1] A convolutional neural network (CNN)-based framework has been developed for evaluating sleep quality using electrocardiogram (ECG) signals. The system begins by segmenting raw ECG recordings into sleep episodes and extracting comprehensive time- and frequency-domain features to represent physiological variations across different sleep states. These features are passed through a multi-layer CNN, which automatically learns discriminative patterns associated with various sleep quality levels. The architecture was benchmarked against conventional models such as support vector machines (SVM) and k-nearest neighbors (KNN), and demonstrated superior classification accuracy, robustness, and potential for real-time implementation in wearable or home-based systems.

[2]A deep learning-based system was designed for automatic sleep stage classification using raw EEG signals, employing a hybrid architecture that combines 1D convolutional layers with Long Short-Term Memory (LSTM) units. The CNN layers effectively extract local spatial features from EEG waveforms, while the LSTM layers capture sequential dependencies and transitions among sleep stages over time. This model was evaluated on the publicly available Sleep-EDF dataset and achieved high classification performance across all major sleep stages, including Wake, N1, N2, N3, and REM. The automated nature of this model significantly reduces reliance on time-consuming manual scoring and increases reproducibility in sleep research and diagnostics.

[3] A context-aware, long-term monitoring system has been proposed for personalized sleep quality analysis using lifelog data captured from wearable devices. Unlike conventional models that treat all users homogeneously, this system dynamically adjusts its analytical models based on individual routines, sleep-wake cycles, and historical trends. The framework integrates multiple types of behavioral and biometric data collected over extended periods, allowing it to generate customized feedback and sleep hygiene recommendations. This approach is particularly valuable for users with chronic sleep disturbances or those engaged in lifestyle interventions aimed at improving sleep health.

[4] Recent literature surveys have emphasized the transformation of sleep monitoring practices from hospital-based polysomnography (PSG) to modern, tech-driven solutions that utilize mobile applications, wearable sensors, and AI-based algorithms. Various machine learning techniques, such as decision trees, random forests, and deep neural networks, have been applied to enhance the accuracy and accessibility of sleep analysis. These reviews underline the shift towards personalized and continuous monitoring systems that are capable of detecting sleep patterns and anomalies outside clinical settings. Challenges including data standardization, sensor calibration, and real-time feedback mechanisms were also identified as active areas of research.

[5] An innovative sleep quality assessment approach was introduced that leverages ambient and behavioral data, shifting away from traditional clinical sensor-based setups. The system collects environmental parameters like room temperature, humidity, and sound levels, along with behavioral metrics such as caffeine intake, physical activity, and smartphone usage. After applying principal component analysis (PCA) for dimensionality reduction, ensemble learning models including Random Forest and AdaBoost are trained to classify sleep quality into categories such as "Good" or "Poor." The system showed promising performance in uncontrolled, real-world environments, making it particularly suitable for non-invasive smart home applications where comfort and scalability are critical.

[6] A hierarchical diagnostic model was proposed to detect sleep disorders using a hybrid approach combining Convolutional Neural Networks (CNN) with Recurrent Neural Networks (RNN). This two-stage architecture first performs feature extraction from multimodal inputs such as EEG and EOG using CNN layers, followed by sequential modeling through RNNs. The model was tested on public datasets and was able to accurately classify sleep-related breathing disorders like sleep apnea, as well as neurological disorders affecting sleep patterns. The hierarchical structure of the model allows for stepwise refinement of predictions, improving diagnostic precision. It represents an advanced approach for clinical applications where early and accurate diagnosis is critical.

[7] The proposed System used Deep Belief Networks with Bayesian Optimization for sleep quality prediction, outperforming SVM and KNN. Highlighted the importance of hyperparameter tuning in improving model performance.

[8] This work integrates machine learning with a graphical user interface to build a user-friendly system for sleep disorder prediction. It presents an end-to-end pipeline involving data preprocessing, model training, and user interaction. While its core focus is on interface development, the underlying use of decision trees and support vector machines shows practical applications of ML in healthcare tools.

[9] Recent advancements in sleep analysis have leveraged deep learning methods to overcome the limitations of traditional statistical models, which often fail to capture non-linear patterns in physiological data. Models such as CNNs and LSTMs have shown improved accuracy in sleep stage classification by effectively modeling temporal and spatial features from EEG, ECG, and actigraphy signals. Despite these improvements, challenges remain in optimizing model performance and generalizability. A hybrid approach integrating Deep Belief Networks (DBNs) with Bayesian Optimization has been proposed to enhance prediction accuracy by fine-tuning hyperparameters efficiently. This method demonstrated superior results over conventional deep learning techniques by combining physiological and subjective data inputs. The integration of probabilistic optimization into deep learning frameworks presents a promising solution to address individual variability and improve the reliability of sleep quality estimation.

[10] This paper proposes a structured machine learning framework for classifying sleep stages using PSG data. It leverages techniques like Random Forest, AdaBoost, and Decision Trees, focusing on accurately segmenting sleep into NREM and REM stages. The study's novelty lies in building an intelligent system that not only detects disorders but also provides detailed sleep staging, aiding in comprehensive sleep analysis.

[11] This study explores various machine learning algorithms including SVM, KNN, and Decision Trees for detecting sleep disorders. The authors emphasize the importance of preprocessing PSG data and selecting relevant features to improve model accuracy. Their findings suggest that machine learning is a viable tool for early detection of sleep disorders, providing a strong foundation for building automated diagnostic systems.

[12] This research focuses on the detection of chronic insomnia using a combination of polysomnographic and clinical data. It applies machine learning models to identify patterns associated with insomnia and emphasizes the role of clinical variables such as sleep latency and REM sleep percentage. The study advocates for a multi-modal approach to improve the prediction of specific sleep conditions.

[13] The System proposed an AI-based wearable somnography system that detects sleep events and breathing irregularities using deep learning techniques, achieving an accuracy of 96%.

[14] This paper explores the potential of combining wearable sensor technology with deep learning to improve the diagnosis and assessment of sleep disorders. The study uses a chest-worn sensor to acquire optical, air-pressure, and acceleration signals from twenty healthy subjects during sleep. These signals are then processed to create five somnographic-like signals: breathing rhythm, chest effort, oxygen saturation (SpO2), body position, and acoustic signals.
A deep learning network was developed to classify these signals into three categories: signal quality (normal/corrupted), breathing patterns (normal/apnea/irregular), and sleep patterns (normal/snoring/noise).

[15] Recent advancements in automatic sleep staging have leveraged machine learning, including traditional methods and deep learning techniques like CNNs, RNNs, and Transformers. While CNNs and RNNs have been used to extract local and temporal features, Transformers have shown promise in modeling long-range dependencies. However, many existing methods either focus on local features while ignoring global context or employ naive approaches to fuse multimodal data, neglecting the cross-modality context relationship between signals like EEG and EOG. To address these limitations, this paper introduces CareSleepNet, a hybrid deep learning network that integrates a multi-scale Convolutional-Transformer Epoch Encoder for capturing both local and global features and a Cross-Modality Context Encoder to model the interdependencies between EEG and EOG.

[16] Machine learning techniques have been effectively utilized to distinguish between insomnia, sleep apnea, and normal sleep patterns. A comprehensive model named Serenity leveraged decision trees and ensemble methods to process features like respiration rate, heart rate variability, and sleep efficiency. This work highlighted the importance of integrating physiological and behavioral data to enhance detection accuracy.

[17] This paper investigates the autonomic dysfunction in REM Sleep Behavior Disorder (RBD) by assessing sleep structure and autonomic nervous system activity across sleep stages. The study innovatively combines a sleep transition model, using Markov chains, with heart rate variability (HRV) dynamics, modeled through a point-process approach, to assess instantaneous autonomic state. Previous research has shown the significance of sleep structure analysis using Markov chains and the limitations of standard HRV methods. This work builds upon existing methodologies to provide a more fine-grained assessment of autonomic dysfunction in RBD, with and without Parkinson's Disease (PD).

[18] This study investigates the impact of sleep-tracking applications on sleep quality through surveys conducted before and after app usage on a cohort of young adults. The increasing prevalence of sleep issues and the advancement of sleep-related technologies have spurred research into the effectiveness of sleep-tracking applications. Studies have explored the features and functionalities of these apps. Furthermore, research in smart home technologies and the integration of various systems, such as video surveillance and utility consumption prediction, highlights the growing interest in leveraging technology for improved living and well-being.

[19] This paper evaluates and compares multiple machine learning models such as Random Forest, Naïve Bayes, and Logistic Regression for classifying different sleep disorders. The study highlights how different classifiers perform on various datasets and stresses the need for model validation. It demonstrates the significance of choosing appropriate algorithms based on performance metrics like accuracy and precision.

[20] The study analyzed the effectiveness of sleep tracking applications, reporting a positive impact on sleep habits for users aged 18-20, with limited effects on older users.

III. COMPARATIVE ANALYSIS

The performance of various Machine learning models for sleep disorder detection has been thoroughly analyzed , with different studies utilizing distinct machine learning algorithms for tasks like sleep stage classification, disorder detection, and sleep quality prediction. The following table provides a comparative overview of these models, highlighting their accuracy, strengths, and limitations in each study.

Model	Accuracy Achieved	Strengths	Limitations
Ensemble Models	**94%**	Highest accuracy; combines strengths of multiple classifiers	May be computationally intensive and harder to interpret
Convolutional Neural Network	90–99%	Excellent for pattern recognition in signal data	Requires large data and longer training time
Random Forest	93%	High accuracy; good feature handling	May overfit if not tuned properly
Support Vector Machine (SVM)	92%	Strong with high-dimensional data	Performance drops with noisy or unscaled data
Decision Tree	90%	Simple and interpretable	Can overfit on small datasets
K-Nearest Neighbors (KNN)	89%	Easy to implement; no training phase	Sensitive to noise and scaling
Logistic Regression	88%	Good for baseline comparison	Limited in capturing complex relationships

IV. CHALLENGES

Data Imbalance: Unequal distribution of sleep disorder classes can lead to biased model predictions and poor generalization.

Noise in Physiological Signals: EEG and ECG signals often contain artifacts and noise, affecting model reliability if not properly cleaned.

High Dimensionality: Large feature sets can increase model complexity and the risk of overfitting without proper selection techniques.

Lack of Standardized Datasets: Differences in data formats and sources hinder model reproducibility and cross-study validation.

Model Interpretability: Complex models, especially deep learning (e.g., CNN), are difficult to interpret and explain.

Overfitting in Deep Models: Deep architectures can overfit when trained on limited or imbalanced data without proper regularization.

Preprocessing Complexity: Handling raw signals and structured data requires extensive preprocessing, often needing domain expertise.

Computational Requirements: Deep learning and ensemble models demand significant processing power and memory during training.

V. CONCLUSION

Machine learning is increasingly proving to be a powerful tool in identifying and diagnosing sleep disorders. It provides an efficient, scalable, and cost-effective alternative to traditional methods, which are often time-consuming and resource-intensive. Techniques such as SVM, Random Forest, KNN, CNN, and ensemble models have shown promising results in detecting conditions like insomnia and sleep apnea, using both physiological and lifestyle data.

However, there are still some key challenges to address. Issues like data imbalance, the complexity of preprocessing, and limited interpretability of certain models can hinder real-world applications. These obstacles highlight the need for continued research and refinement.

Looking ahead, future work should focus on creating more standardized and diverse datasets that combine clinical signals with behavioral data. There's also a growing need to develop models that are not only accurate but also transparent and easy to interpret—especially for use in clinical settings. Incorporating real-time monitoring through wearables and reducing the need for manual preprocessing can help bring these technologies closer to everyday healthcare**.**

In essence, the future of sleep disorder detection lies in making machine learning models more accessible, explainable, and integrated with the tools people already use, ultimately improving diagnosis and quality of care.

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