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An Optimized Sleep Disorder Diagnosis Using Machine Learning Approaches

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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.

KEYWORDS: Sleep Disorders, Machine Learning, Deep Learning, EEG, Sleep Staging, Classification Models, Healthcare AI

I. INTRODUCTION

Sleep disorders significantly affect human health and quality of life. Currently, expert-based manual sleepstage classification methods are widely used. These methods rely on human interpretation of sleep patterns, often using data such as electroencephalograms (EEGs) and other physiological signals. However, this process is inherently complex, subjective, and prone to errors due to human fatigue and variability in expertise. To overcome these challenges, researchers have explored the use of traditional machine learning algorithms for sleep disorder classification[1]. These algorithms can handle large datasets, automate diagnosis, and reduce human intervention. However, their effectiveness heavily depends on feature selection, and they often struggle with handling unstructured and high-dimensional data.

Recently, deep learning approaches have shown promise in sleep disorder classification due to their ability to extract meaningful features automatically and perform well on high-dimensional datasets. Some methods employ neural networks, but optimization remains a critical issue. Despite advancements, current systems still lack robustness, interpretability, and high accuracy, especially for diverse datasets. Expert-based systems are prone to human error and variability. Traditional ML algorithms struggle with high-dimensional and unstructured data. Optimization challenges in existing deep learning models limit performance. Limited interpretability of ML and DL results affects trust in automated systems. Current systems lack adaptability to diverse and heterogeneous datasets Sleep disorders, such as sleep apnea, impact physical and mental health, necessitating accurate diagnosis and management[11]. Manual classification of sleep stages by experts is subjective, time-consuming, and prone to errors. Traditional machine learning approaches for sleep disorder diagnosis depend heavily on feature selection and preprocessing, limiting their generalizability. While deep learning techniques show potential by automating feature extraction, their optimization challenges often lead to suboptimal accuracy. Furthermore, current solutions lack robust generalization capabilities across diverse datasets. This creates a critical gap in developing systems that are both accurate and interpretable for clinical use[12].



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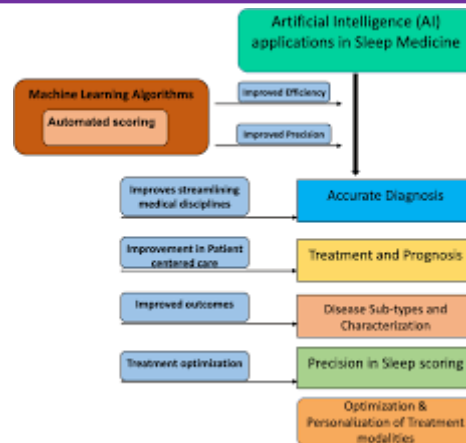


Fig 1: Application of artificial intelligence for precision

The limitations in existing methods hinder the development of reliable and efficient diagnostic tools, posing a significant problem for effective sleep disorder management. Bridging the gap requires an optimized, scalable, and interpretable machine learning approach that can analyze complex data patterns and perform well across varied datasets. Existing sleep disorder classification methods suffer from low accuracy, poor generalization, and interpretability issues, making them unsuitable for robust clinical application. This study aims to address these limitations by developing an optimized, scalable, and accurate machine learning model, fine-tuned with genetic algorithms, to classify sleep disorders using diverse datasets effectively[23].

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



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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.

III. METHODS

Sleep disorders are increasingly recognized as significant health concerns, impacting millions of individuals globally. With advancements in technology, machine learning (ML) has emerged as a powerful tool to classify and diagnose these disorders. The proposed system leverages machine learning approaches to accurately identify and diagnose various sleep disorders, such as insomnia, sleep apnea, narcolepsy, and restless legs syndrome. This system integrates data-driven methods, utilizing patient data, polysomnography (PSG) recordings, wearable device outputs, and other biomarkers to deliver precise diagnostic outcomes. By automating and enhancing traditional diagnostic methods, this approach has the potential to revolutionize sleep medicine. The proposed system consists of multiple components designed to ensure accurate classification and diagnosis of sleep disorders. At its core, the system relies on data collection, preprocessing, feature extraction, model training, and validation.

First, data is collected from diverse sources, such as PSG, wearable devices, and patient-reported symptoms. Polysomnography is considered the gold standard for diagnosing sleep disorders, capturing various physiological parameters like brain activity, oxygen levels, heart rate, and breathing patterns. However, wearable devices provide an alternative means of data collection, offering continuous monitoring of sleep patterns in real-world settings. This combination of data sources allows the system to build a comprehensive profile of an individual's sleep behavior. Data



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preprocessing is a critical step in the system to ensure the quality and reliability of the input data. Preprocessing involves cleaning the data by removing artifacts, handling missing values, and normalizing the datasets.

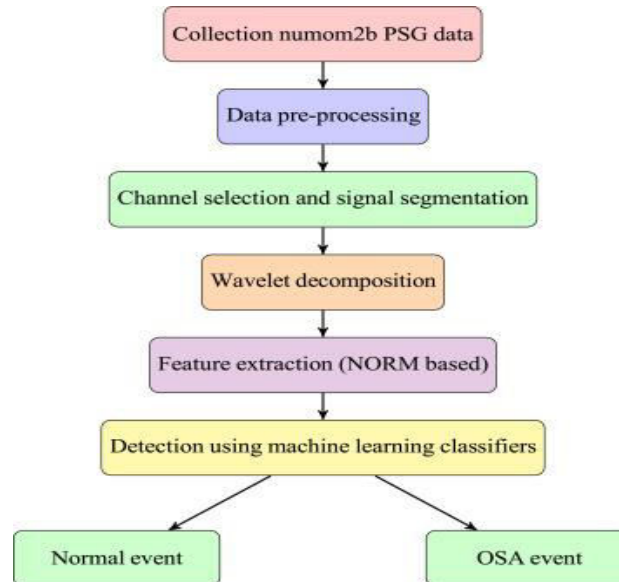


Fig 2: Automated sleep apnea detection

Given the variability in data types and sources, advanced preprocessing techniques, such as signal denoising and segmentation, are employed to extract meaningful information. This step is vital for ensuring that the input data is suitable for subsequent machine learning algorithms. Feature extraction plays a central role in the proposed system. The system identifies and extracts key features from the raw data, such as sleep stages, arousal indices, oxygen desaturation levels, and heart rate variability. These features serve as inputs to the machine learning models. Advanced techniques, including time-series analysis, frequency-domain analysis, and deep learning-based feature extraction, are employed to capture intricate patterns in the data. For instance, convolutional neural networks (CNNs) are particularly effective in analyzing PSG data, while recurrent neural networks (RNNs) excel in processing time-series data from wearable devices.

Once the features are extracted, the system trains machine learning models to classify and diagnose sleep disorders. Supervised learning algorithms, such as support vector machines (SVM), decision trees, and ensemble methods like random forests, are widely used for classification tasks. These models are trained on labeled datasets, where the outcomes of sleep studies serve as ground truth labels. Deep learning models, such as CNNs and long short-term memory (LSTM) networks, are increasingly utilized to improve classification accuracy, especially when dealing with large and complex datasets. The system employs rigorous training and cross-validation techniques to optimize model performance and prevent overfitting. Model validation and testing are crucial to ensure the reliability and generalizability of the proposed system. The system uses validation datasets to fine-tune hyperparameters and test datasets to evaluate overall performance. Metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve are used to assess the model's effectiveness. Additionally, explainability techniques, such as SHAP (Shapley Additive Explanations) values, are incorporated to provide insights into the model's decision-making process, enhancing trust and transparency.

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IV. RESULTS & DISCUSSION

The system acquires sleep data from patient inputs, wearable sensors, and polysomnography (PSG) records. Preprocessing ensures data quality by addressing missing values, normalizing signals, removing noise, and encoding categorical attributes, while feature engineering derives key variables such as sleep efficiency scores and apnea indices. The framework is deployed via a web-based interface that delivers real-time predictions, highlights significant contributing factors, and provides personalized recommendations for sleep optimization. In order to further increase diagnostic accuracy and flexibility, future improvements will include feedback-driven model modification, sophisticated deep learning integration, and ongoing wearable device monitoring.

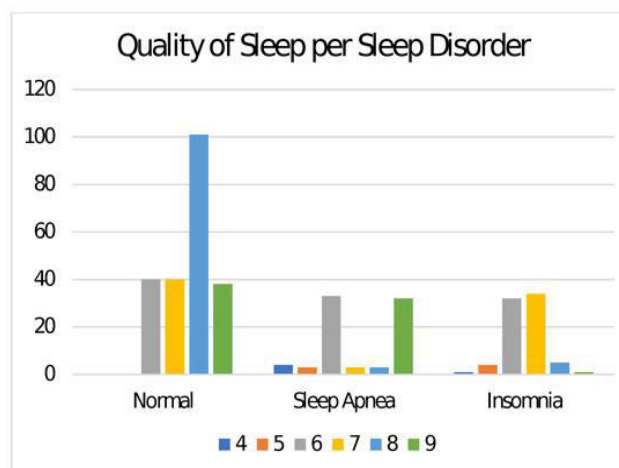


Fig 3: Utilizing Multi-Class Classification Methods for Automated Sleep Disorder Prediction

Models for machine learning and deep learning were able to distinguish between sleep apnoea and other sleep disorders with high accuracy, insomnia, and regular sleep. The models' efficacy in capturing intricate correlations between physiological data and disorder classification was validated by evaluation utilising measures such as recall, accuracy, and precision, F1 score, and AUC. Analysis of feature importance revealed that sleep efficiency, apnea-hypopnea index, total sleep duration, and REM stage length were the most influential predictors.

The system's real-time web interface provided clinicians and users with immediate diagnostic insights, presenting predicted conditions alongside key contributing features for interpretability. Compared to baseline approaches such as logistic regression and simple decision trees, advanced models—including Random Forest, SVM, and LSTM—delivered superior accuracy and robustness.

V. CONCLUSION

The conclusion of this study is to design and evaluate an optimized machine learning framework for accurate sleep disorder classification. By leveraging both traditional and deep learning methods, the proposed system aims to improve the accuracy and robustness of classification models. Genetic algorithms are employed to optimize model parameters, ensuring better performance across diverse datasets. The approach focuses on extracting meaningful features from sleep pattern data while addressing high-dimensionality and unstructured data challenges. This study also emphasizes the



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importance of comparative analysis, evaluating the proposed model against state-of-the-art methods to ensure its effectiveness. The ultimate goal is to create a reliable and interpretable system for sleep disorder classification, capable of automating diagnostic processes and reducing the dependence on expert-based manual methods. Such a system has the potential to enhance healthcare outcomes, enabling early detection and effective management of sleep-related conditions.

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