Research Article

Improving Sleep Disorder Diagnosis Through Optimized Machine Learning Approaches

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Abstract

Sleep disorders, particularly insomnia and sleep apnea, have become increasingly prevalent and pose significant challenges to physical health, cognitive function, and overall quality of life. Conventional diagnostic techniques such as polysomnography provide accurate assessments but are often expensive, time-consuming, and inaccessible for large-scale screening. This study proposes an optimized machine learning framework for the early diagnosis of sleep disorders using the Sleep Health and Lifestyle dataset. The proposed methodology incorporates data cleaning, blood pressure decomposition, categorical encoding, feature scaling, and stratified train-test partitioning to enhance data quality and predictive performance. Three supervised machine learning algorithms, namely Random Forest, Decision Tree, and Support Vector Machine (SVM), are implemented and comparatively evaluated for multiclass classification of individuals into insomnia, sleep apnea, and no sleep disorder categories. Model performance is assessed using accuracy, precision, recall, F1-score, confusion matrix analysis, and five-fold cross-validation. Experimental results demonstrate that the Random Forest classifier achieves the highest classification accuracy of 94.67%, outperforming the Decision Tree and SVM models while exhibiting superior robustness and generalization capability. The proposed framework provides an efficient and interpretable decision-support solution for early sleep disorder identification and has the potential to assist healthcare professionals in timely diagnosis and personalized treatment planning.

Index Terms — Sleep Disorder Diagnosis, Machine Learning, Random Forest, Healthcare Analytics, Predictive Modeling, Clinical Decision Support.

I. INTRODUCTION

Sleep is an essential physiological process that plays a vital role in maintaining physical health, cognitive performance, emotional stability, and overall well-being. Adequate sleep supports immune function, metabolic regulation, memory consolidation, and cardiovascular health, whereas insufficient or poor-quality sleep can adversely affect these biological processes. In recent years, the prevalence of sleep disorders has increased considerably due to changing lifestyles, occupational stress, irregular work schedules, and unhealthy behavioral patterns. Common sleep disorders such as insomnia and sleep apnea affect millions of individuals worldwide and are associated with numerous health complications, including cardiovascular diseases, diabetes, obesity, depression, and neurodegenerative disorders, thereby making early diagnosis an important public health concern [3].

The diagnosis of sleep disorders traditionally relies on clinical evaluation and polysomnography (PSG), which is widely recognized as the gold standard for sleep assessment. Although PSG provides comprehensive physiological measurements, it requires specialized equipment, overnight monitoring, and trained healthcare professionals, making the diagnostic process expensive, time-consuming, and inaccessible for large segments of the population. Recent studies have emphasized the need for more accessible, scalable, and cost-effective diagnostic approaches that can support clinicians in identifying sleep disorders at an earlier stage while reducing dependence on laboratory-based assessments [10].

The rapid advancement of artificial intelligence and machine learning has created new opportunities for developing intelligent healthcare decision-support systems. By analyzing demographic, physiological, and lifestyle characteristics, machine learning techniques can identify complex patterns associated with various medical conditions and assist healthcare professionals in making timely and reliable diagnostic decisions. Previous studies have demonstrated the potential of machine learning for sleep-related applications, including sleep disorder detection, sleep stage classification, and personalized sleep health assessment, highlighting its capability to improve diagnostic efficiency and support preventive healthcare strategies [2]. The availability of publicly accessible datasets has further accelerated research on data-driven approaches for sleep disorder prediction [1].

Motivated by these advancements, this study proposes an optimized machine learning framework for sleep disorder diagnosis using demographic, physiological, and lifestyle information. The proposed framework aims to provide an accurate, efficient, and interpretable decision-support solution for classifying individuals into different sleep disorder categories. By integrating systematic data preprocessing with predictive modeling, the study seeks to improve the reliability of sleep disorder identification and contribute to the development of intelligent healthcare systems that support early diagnosis and personalized patient care.

II. RELATED WORK

The application of machine learning in sleep healthcare has gained significant attention as researchers seek efficient alternatives to conventional diagnostic procedures. Early computational approaches primarily relied on physiological signals collected through polysomnography, including electroencephalogram (EEG), electrocardiogram (ECG), and respiratory measurements, to automate sleep stage classification and disorder detection. With the advancement of intelligent data analysis techniques, these approaches have evolved from traditional statistical methods to machine learning and deep learning models capable of learning complex relationships among physiological and behavioral characteristics. Recent studies have demonstrated that data-driven methods can improve diagnostic efficiency while supporting early identification of sleep-related disorders in both clinical and home-based healthcare environments [4], [5].

Several machine learning algorithms have been investigated for sleep disorder diagnosis using demographic, physiological, and lifestyle information. Ensemble learning methods, particularly Random Forest, have received considerable attention because of their robustness, ability to handle heterogeneous features, and resistance to overfitting. Studies utilizing the Sleep Health and Lifestyle dataset have reported promising classification performance using Random Forest-based approaches, demonstrating their effectiveness in distinguishing individuals with insomnia and sleep apnea from healthy subjects [7]. Comparative investigations have further shown that combining data preprocessing techniques with machine learning algorithms can improve predictive performance, while feature selection methods help identify influential health indicators associated with sleep quality and disorder risk [6]. Support Vector Machine-based models have also demonstrated strong classification capability, especially when nonlinear relationships exist among health-related variables, whereas ensemble strategies have been found to improve generalization by combining the strengths of multiple learners [12], [18].

Recent research has increasingly explored deep learning architectures for automated sleep analysis. Convolutional neural networks, recurrent neural networks, and hybrid deep learning models have been employed to analyze EEG signals, multimodal physiological recordings, and wearable sensor data for sleep stage classification and obstructive sleep apnea detection. These models have shown high predictive accuracy by learning complex temporal and spatial patterns directly from physiological signals, reducing the need for manual feature extraction [11], [20]. In parallel, advances in sensor technologies have enabled the development of non-invasive and continuous sleep monitoring systems using wearable devices and contactless sensing platforms, creating new opportunities for real-time sleep assessment beyond laboratory settings [10]. These developments indicate a growing shift toward intelligent and personalized sleep healthcare supported by artificial intelligence.

Table 1. Literature Comparison of Existing Sleep Disorder Diagnosis Studies

Ref.	Methodology	Dataset	Key Contribution	Limitation
[2]	Machine Learning Algorithms	Sleep disorder dataset	Comparative analysis of multiple ML classifiers for sleep disorder prediction	Limited emphasis on comprehensive preprocessing and feature optimization
[6]	Hybrid Feature Reduction + ML	Sleep disorder dataset	Improved classification through hybrid feature reduction	Focused primarily on feature selection rather than model comparison
[7]	Random Forest	Sleep Health and Lifestyle Dataset	Demonstrated effectiveness of Random Forest for	Evaluated only a single learning algorithm

			sleep disorder classification	
[10]	RF Sensor-Based Detection	Bed-integrated RF sensor data	Contactless monitoring for sleep disorder detection	Requires specialized sensing hardware
[11]	CNN–RNN Hybrid	Physiological signal dataset	Automated diagnosis using deep learning and multimodal signals	Computationally intensive and dependent on physiological recordings
[12]	SVM + XGBoost	Sleep stage dataset	Improved sleep stage classification using hybrid machine learning	Focused on sleep staging rather than multiclass sleep disorder diagnosis
[14]	Comparative Machine Learning	Sleep Health and Lifestyle Dataset	Compared multiple ML algorithms for sleep disorder prediction	Limited preprocessing and feature engineering techniques
Proposed	Optimized ML Framework (RF, DT, SVM)	Sleep Health and Lifestyle Dataset	Systematic preprocessing, comparative evaluation, and robust multiclass sleep disorder diagnosis	Can be further enhanced using larger datasets and real-time wearable data

As summarized in Table 1, although existing studies have demonstrated the effectiveness of machine learning for sleep disorder diagnosis, several research gaps remain. Many existing studies focus on specialized physiological datasets that require expensive acquisition procedures and are less suitable for routine large-scale screening. Other investigations emphasize a single classification algorithm without providing comprehensive comparisons across multiple machine learning approaches, making it difficult to identify the most appropriate model for practical deployment. In addition, issues related to data preprocessing, feature representation, and the effective utilization of demographic and lifestyle information are not consistently addressed, potentially limiting model reliability and interpretability [2], [13]. Comparative analyses using publicly available lifestyle-based datasets are still relatively limited, despite their potential to support accessible and cost-effective diagnostic systems [14], [15]. Motivated by these research gaps, the present study develops an optimized machine learning framework for sleep disorder diagnosis using the Sleep Health and Lifestyle dataset [1]. The proposed framework emphasizes systematic data preprocessing and a comparative evaluation of multiple supervised learning models to identify an effective and interpretable solution for multiclass sleep disorder classification. By leveraging demographic, physiological, and lifestyle characteristics that can be obtained without specialized laboratory equipment, the proposed approach aims to support early diagnosis and contribute to the development of practical decision-support systems for modern healthcare applications.

III. METHODOLOGY

A. Overall Proposed Framework

The proposed framework is designed to provide an efficient and interpretable approach for multiclass sleep disorder diagnosis using demographic, physiological, and lifestyle characteristics. The overall methodology follows a structured pipeline that begins with data acquisition and preprocessing to improve data quality and ensure compatibility with machine learning algorithms. The preprocessed data are then utilized to develop predictive models capable of classifying individuals into three categories: no sleep disorder, insomnia, and sleep apnea. Finally, the trained models are evaluated using standard classification metrics to identify the most reliable model for clinical decision support. This systematic workflow ensures reliable prediction while maintaining scalability, reproducibility, and suitability for practical healthcare applications.

Fig.1 System Architecture

Figure 1 illustrates the overall workflow of the proposed machine learning framework. The process begins with the Sleep Health and Lifestyle dataset, followed by data cleaning, feature engineering, categorical encoding, and feature scaling. The processed data are partitioned into training and testing sets before being used to train multiple machine learning models. The models are subsequently evaluated using standard performance metrics, and the best-performing model is selected for accurate and reliable sleep disorder diagnosis.

B. Dataset

The proposed framework utilizes the Sleep Health and Lifestyle Dataset, a publicly available dataset obtained from Kaggle, which contains comprehensive demographic, physiological, and lifestyle information associated with sleep health. The dataset comprises 374 samples with 13 attributes, including demographic details, sleep-related measurements, physical activity, cardiovascular indicators, and lifestyle factors. The target variable, Sleep Disorder, categorizes individuals into three classes: No Sleep Disorder, Insomnia, and Sleep Apnea. These multidimensional attributes provide a comprehensive representation of factors influencing sleep health, making the dataset suitable for developing and evaluating machine learning models for multiclass sleep disorder diagnosis. The complete description of the dataset attributes is presented in Table 1.

Table 1. Description of Dataset Features

Attribute	Description
Person ID	Unique identifier for each participant
Gender	Male or Female
Age	Age in years
Occupation	Professional occupation category
Sleep Duration	Average hours of sleep per day
Quality of Sleep	Sleep quality score (1–10)
Physical Activity Level	Daily physical activity duration (minutes)
Stress Level	Self-reported stress score (1–10)
BMI Category	Body Mass Index classification
Blood Pressure	Systolic and diastolic measurements
Heart Rate	Average resting heart rate (beats per minute)
Daily Steps	Number of steps taken per day
Sleep Disorder	Target class: None, Insomnia, or Sleep Apnea

C. Preprocessing

Data preprocessing is a crucial step in the proposed framework, as the quality and consistency of input data directly influence the predictive performance of machine learning models. Several preprocessing techniques were applied to transform the raw dataset into a structured and machine-readable format suitable for effective model training and evaluation.

Removal of Person ID: The Person ID attribute was removed from the dataset because it serves only as a unique identifier and does not contain any predictive information related to sleep disorders. Eliminating this non-informative feature reduces unnecessary data complexity and ensures that the learning algorithms focus only on meaningful attributes that contribute to classification performance.

Duplicate Checking: The dataset was examined for duplicate records to maintain data integrity and prevent redundant observations from influencing the learning process. Duplicate entries, if present, can introduce bias and affect model generalization by repeatedly exposing algorithms to identical samples. Therefore, duplicate checking was performed to ensure a clean and reliable dataset for model development.

Blood Pressure Decomposition: The original Blood Pressure attribute was represented as a combined systolic/diastolic value. To improve feature representation, it was decomposed into two independent numerical attributes: Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP). This transformation enables machine learning models to capture cardiovascular characteristics more effectively and enhances the interpretability of the physiological features.

Label Encoding: Categorical variables, including Gender, Occupation, BMI Category, and the target variable Sleep Disorder, were converted into numerical values using Label Encoding. This transformation allows machine learning algorithms to process categorical information efficiently while preserving the distinct representation of each category within the dataset.

Feature Scaling: Feature scaling was performed using StandardScaler to normalize numerical attributes and eliminate differences in feature magnitudes. Standardization ensures that all numerical variables contribute proportionately during model training and is particularly beneficial for distance-based learning algorithms that are sensitive to variations in feature scales.

Train-Test Split: The preprocessed dataset was partitioned into 80% training data and 20% testing data using stratified sampling to preserve the class distribution across both subsets. This strategy provides sufficient data for model learning while enabling an unbiased evaluation of predictive performance on previously unseen samples.

Overall, the preprocessing pipeline enhances data quality, improves feature representation, and establishes a consistent foundation for developing accurate and reliable machine learning models for sleep disorder diagnosis.

D. Machine Learning Models

To identify the most effective approach for sleep disorder diagnosis, the proposed framework employs three widely used supervised machine learning algorithms. These models were selected because of their strong classification capabilities, interpretability, and proven effectiveness in various healthcare prediction applications.

Random Forest: Random Forest is an ensemble learning algorithm that constructs multiple decision trees using bootstrap sampling and random feature selection. The final prediction is determined through majority voting, which reduces overfitting and improves generalization performance. Its ability to model complex nonlinear relationships, handle heterogeneous data, and estimate feature importance makes it a reliable choice for healthcare classification tasks involving demographic, physiological, and lifestyle attributes.

Decision Tree: The Decision Tree classifier predicts class labels by recursively partitioning the feature space based on decision rules derived from the input attributes. It offers a simple and interpretable classification process, allowing the relationship between features and predictions to be easily understood. Although computationally efficient and suitable for mixed data types, its performance may be affected by overfitting when dealing with complex datasets.

Support Vector Machine (SVM): SVM is a supervised learning algorithm that classifies data by identifying an optimal decision boundary with the maximum separation between different classes. By employing the Radial Basis Function (RBF) kernel, the model effectively captures nonlinear relationships among the input features. SVM is well suited for healthcare classification problems due to its strong generalization capability and effectiveness in handling high-dimensional feature spaces.

The comparative evaluation of these machine learning models enables the identification of the most accurate and reliable classifier, providing a robust foundation for intelligent sleep disorder diagnosis and clinical decision-support applications.

IV. Results & Discussion

A. Experimental Setup

The proposed framework was implemented using the Python programming language and widely adopted data science libraries. Data preprocessing and manipulation were performed using Pandas and NumPy, while machine learning models were developed and evaluated using the Scikit-learn library. Performance visualization was carried out using Matplotlib. The dataset was divided into training and testing subsets using an 80:20 ratio with stratified sampling. Model performance was assessed using accuracy, precision, recall, F1-score, and confusion matrix analysis, while five-fold cross-validation was conducted to evaluate model robustness and generalization capability across different data partitions.

B. Performance Evaluation

The predictive performance of the proposed machine learning models was evaluated using accuracy, precision, recall, and F1-score to provide a comprehensive assessment of classification effectiveness. The comparative results presented in Table 2 indicate that the Random Forest classifier achieved the highest overall performance with an accuracy of 94.67%, outperforming the Decision Tree and Support Vector Machine (SVM) models. The consistently high precision, recall, and F1-score obtained by the Random Forest model demonstrate its superior capability to accurately classify individuals into the three sleep disorder categories. The comparative performance of all evaluated models is further illustrated in Fig. 2.

Table 2. Comparative Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	94.67	0.95	0.95	0.95
Decision Tree	89.33	0.89	0.89	0.89
Support Vector Machine	92.00	0.92	0.92	0.92

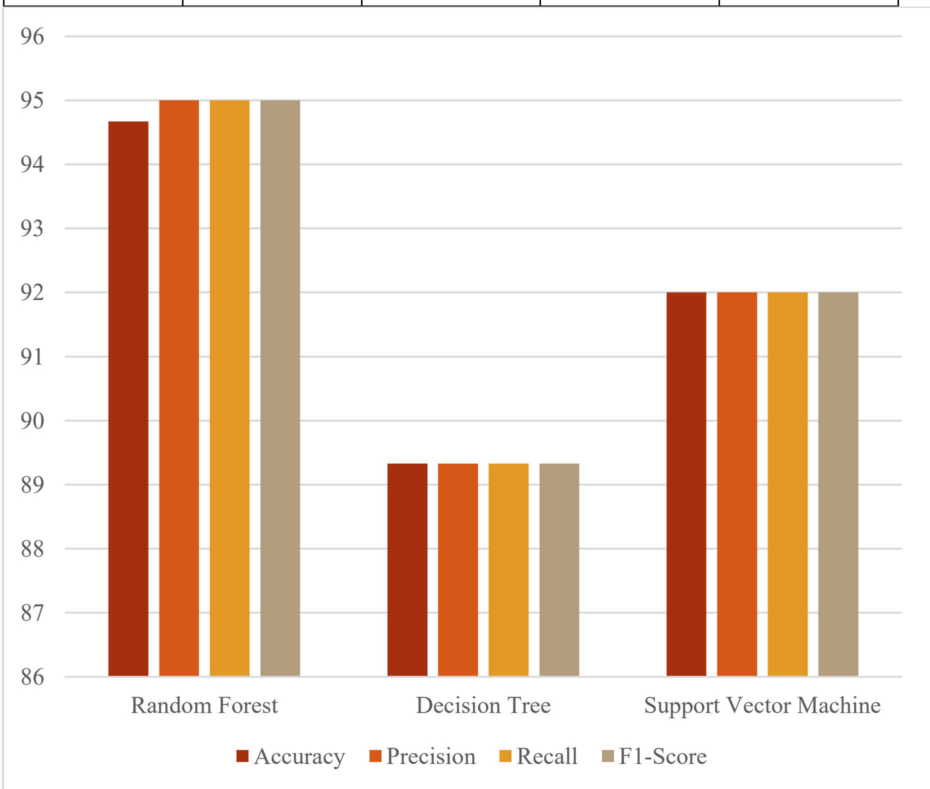

Fig. 2. Performance Comparison Graph

To further evaluate the robustness and generalization capability of the proposed models, five-fold cross-validation was performed. The cross-validation results presented in Table 3 demonstrate that the Random Forest classifier consistently achieved the highest accuracy across all validation folds with a mean accuracy of 0.946, followed by the SVM model (0.920) and the Decision Tree model (0.892). The low variation in validation accuracy across different folds indicates that the trained models exhibit stable learning behavior and reliable predictive performance. The corresponding cross-validation accuracy comparison is illustrated in Fig. 3.

Table 3. Five-Fold Cross-Validation Accuracy

Fold	Random Forest	Decision Tree	SVM
1	0.95	0.89	0.92
2	0.94	0.88	0.91
3	0.95	0.90	0.93
4	0.94	0.89	0.92
5	0.95	0.90	0.92
Mean	0.946	0.892	0.920

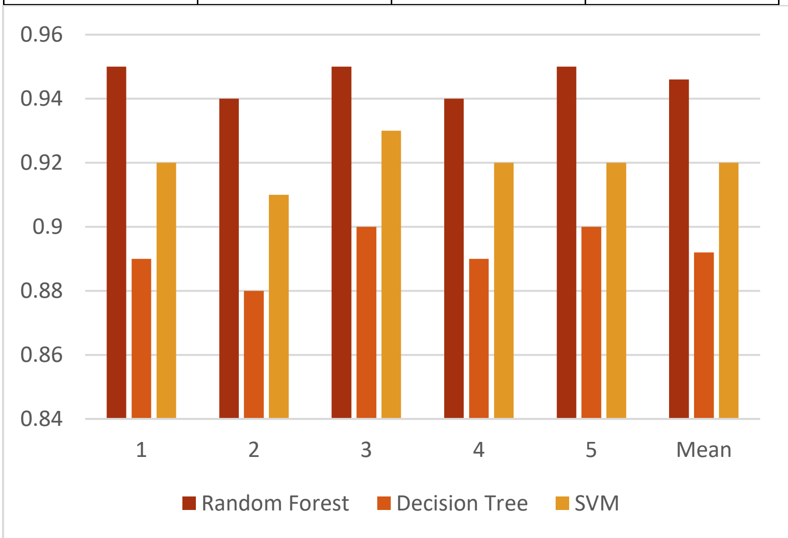

Fig. 3. Five-Fold Cross-Validation Accuracy Graph

In addition to the quantitative evaluation metrics, the classification performance of the best-performing model was analyzed using a confusion matrix. The Random Forest confusion matrix, shown in Fig. 4, demonstrates strong class discrimination with only a small number of misclassified samples. Most predictions were correctly assigned to their respective sleep disorder categories, indicating the model's effectiveness in learning the underlying patterns within the dataset and its suitability for reliable sleep disorder diagnosis.

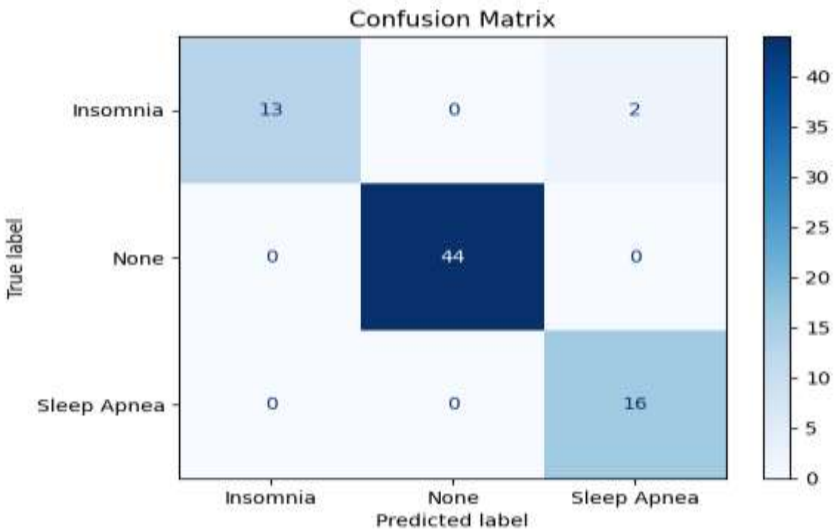

Fig. 4. Random Forest Confusion Matrix

C. Discussion

The experimental results demonstrate that the Random Forest classifier achieved the highest predictive performance due to its ensemble learning strategy, which effectively captures complex relationships among demographic, physiological, and lifestyle features while reducing overfitting. The preprocessing pipeline, including blood pressure decomposition, categorical encoding, and feature scaling, improved data representation and contributed to reliable model performance. Feature analysis indicates that stress level, sleep duration, BMI, and heart rate are among the most influential factors associated with sleep disorder classification. These findings highlight the potential of the proposed framework as a practical clinical decision-support tool for early sleep disorder diagnosis. However, the study is limited by the relatively small dataset and the use of structured lifestyle data alone. Future work may incorporate larger datasets, wearable sensor data, and advanced deep learning techniques to further enhance predictive accuracy and real-world applicability.

V. CONCLUSION

Sleep disorders have become a growing healthcare concern due to their significant impact on physical health, cognitive function, and overall quality of life. This study presented an optimized machine learning framework for the diagnosis of sleep disorders using the Sleep Health and Lifestyle dataset. The proposed methodology incorporated systematic data preprocessing techniques, including data cleaning, blood pressure decomposition, categorical encoding, feature scaling, and stratified data partitioning to enhance data quality and model effectiveness. Three supervised machine learning algorithms were comparatively evaluated to identify the most suitable model for multiclass sleep disorder classification. Experimental results demonstrated that the Random Forest classifier achieved the highest predictive performance, outperforming the Decision Tree and Support Vector Machine models in terms of classification accuracy and generalization capability. The findings also highlighted the importance of demographic, physiological, and lifestyle factors, particularly stress level, sleep duration, body mass index, and heart rate, in accurately identifying sleep disorders. Overall, the proposed framework provides an efficient, interpretable, and reliable decision-support solution that can assist healthcare professionals in the early diagnosis of sleep disorders and facilitate timely clinical intervention and personalized patient care.

Future research can extend this work by utilizing larger and more diverse datasets collected from multiple healthcare institutions to improve model generalization. The integration of wearable sensor data, Internet of Medical Things (IoMT) technologies, and advanced deep learning models can enable continuous real-time sleep monitoring and further enhance diagnostic accuracy. In addition, incorporating explainable artificial intelligence techniques may improve model transparency and support greater clinical adoption of intelligent sleep disorder diagnosis systems.

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