Applying Machine Learning Algorithms for the Classification of Sleep Disorders

Vallem Pranith Reddy, V Sai Surya, P Rithvik Rao, Kalaiarasi M

Abstract: Sleep disorders, particularly sleep apnea, have an impact on people's health, and that reveals the need for a correct diagnosis. However, sleep experts use complex and time-consuming methods for the manual classification of the various sleep stages. Based on the Sleep Disorder Data which is available for public access and consists of 400 records and 13 attributes, this work introduces a machine learning classification model. A number of deep and techniques-based machine learning models are considered and their performance is evaluated in accurately diagnosing sleep disorders. Lifestyle parameters and sleep health characteristics are among the features in the dataset meaningful for discovering patterns, with patterns of which can be indicative of existing sleep-related disorders. Based on the models assessed, it was found that the model with the highest performances are bagged models particularly the Voting Classifier with RF and DT. The accuracy, precision, recall, and F1-score of the algorithm were 0.973, suggesting that the algorithm useful for sleep disorder classification and is reliable. These results imply that the proposed machine learning approaches provides an opportunity to make smarter, faster and more accurate sleep disorders diagnoses in order to enhance the possibilities of the physicians' decision-making process and patients' condition.

Index Terms* - *Machine learning algorithms, deep learning, classification, sleep disorder, Voting algorithm.

1. INTRODUCTION

Sleep is a vital physiological function necessary for physical and mental health. It helps strengthen the body and consolidate the brain and memories. Sleep quality significantly affects cognitive functions, especially in children and older adults, who are at an increased risk of accidents. Poor sleep can lead to various health issues, including heart disease, diabetes, and obesity. Despite its importance, sleep disorders are often underdiagnosed or misclassified due to the complexity of sleep stage evaluation. Physicians, medical professionals, and sleep experts must manually analyze polysomnography (PSG) records to assess sleep stages, a task that is prone to human error and is time-consuming for accurate classification [1].

According to the 2021 World Sleep Day survey by Philips, which polled over 13,000 adults in 13 countries, 55% of adults reported being dissatisfied with their sleep. Factors like the COVID-19 pandemic, sleep apnea, and insomnia were identified as key contributors to poor sleep quality. Specifically, 37% of participants mentioned that the pandemic negatively impacted their sleep, while 37% experienced insomnia, 29% snored, 22% had shift-work sleep disorder, and 12% suffered from sleep apnea [2]. These statistics highlight the widespread nature of sleep-related issues and the need for better diagnostic and classification systems.

Medical professionals classify sleep into five distinct stages: wakefulness, N1, N2, N3, and rapid-eye movement (REM). Wakefulness represents the alert state when individuals are aware of their surroundings, with fast and irregular brain waves. N1 is the lightest sleep stage where brain waves slow down, and muscles relax. N2 is a deeper stage, while N3 represents the deepest sleep stage, where awakening is difficult. REM sleep is characterized by rapid eye movements and brain waves similar to those during wakefulness. Each of these stages plays a critical role in the body's restoration and cognitive processes. PSG allows doctors to observe these stages by recording electroencephalogram (EEG) and electrocardiogram (ECG) signals to monitor the brain and body's activity during sleep [3], [4], [5].

To reduce human intervention in the classification and prediction of sleep stages, several researchers have developed automated techniques using machine learning algorithms (MLAs). These methods can be broadly categorized into conventional machine learning and deep learning algorithms. Traditional MLAs, such as support vector machines and decision trees, are typically applied to smaller datasets, requiring manual feature extraction to classify sleep stages based on signals like entropy and energy. In contrast, deep learning algorithms, inspired by the structure of the human brain, utilize neural networks to learn complex patterns from data automatically. These algorithms are especially beneficial for large, complex datasets and are seen as a potential replacement for traditional MLAs [6], [7]. The most common technique for sleep-stage classification involves the application of EEG signals as input for both traditional and deep learning models [8].

2. RELATED WORK

Various studies have explored the application of machine learning (ML) techniques for sleep disorder detection and classification, particularly focusing on obstructive sleep apnea (OSA), sleep stage classification, and sleep apnea detection using electrocardiogram (ECG) signals. The utilization of machine learning algorithms has significantly improved diagnostic accuracy and reduced the dependence on manual analysis, which can be time-consuming and prone to errors.

Kim et al. [9] proposed prediction models for obstructive sleep apnea in Korean adults using machine learning techniques. Their study utilized a range of ML algorithms to classify and predict the likelihood of OSA based on clinical data. The models demonstrated the potential of ML algorithms in identifying OSA, with the advantage of automated prediction systems, which can aid clinicians in diagnosing the condition more efficiently. The findings highlighted the importance of incorporating various features, including demographic, clinical, and physiological data, to enhance prediction accuracy. This study underscores the capability of machine learning to improve sleep apnea diagnosis by providing early detection mechanisms.

Mousavi et al. [10] investigated the use of deep convolutional neural networks (CNNs) for classifying sleep stages from single-channel EEG signals. Their work demonstrated the power of deep learning in automating sleep stage classification, a critical component of diagnosing sleep disorders such as sleep apnea and insomnia. CNNs, as a form of deep learning, are particularly effective in extracting hierarchical features from raw data, such as EEG signals, without requiring manual feature extraction. The study confirmed that CNNs could outperform traditional machine learning techniques in sleep stage classification, providing an efficient and accurate alternative to conventional methods.

Djanian et al. [11] reviewed the landscape of sleep classification using consumer sleep technologies and artificial intelligence (AI). Their review highlighted the growing trend of incorporating AI into consumer-grade sleep monitoring devices, such as wearable sleep trackers. These devices, combined with AI algorithms, have the potential to provide continuous and real-time monitoring of sleep quality, which can be crucial for individuals suffering from sleep disorders. The study found that AI-based consumer sleep technologies, particularly those employing deep learning, have significantly improved the accuracy of sleep stage detection and diagnosis. The integration of AI with wearable devices offers a promising direction for personalized sleep health management.

Salari et al. [12] conducted a comprehensive review of machine learning algorithms for detecting sleep apnea using ECG signals. The study focused on the application of ECG-based signal processing methods for sleep apnea detection, highlighting the efficacy of ML algorithms in analyzing ECG data for identifying apnea events. Machine learning models, such as support vector machines (SVMs) and random forests (RF), were shown to effectively classify sleep apnea events from single-lead ECG signals. The authors emphasized the importance of feature extraction techniques, which play a crucial role in enhancing model performance. This work provided valuable insights into how ECG-based sleep apnea detection could be optimized using machine learning, offering a non-invasive alternative to traditional sleep studies.

Li et al. [13] proposed a deep learning method for sleep stage classification using EEG spectrograms. Their approach involved converting raw EEG signals into spectrograms, which capture the frequency content of the signals over time. These spectrograms were then used as input to a deep neural network (DNN) for classification. The deep learning model was able to automatically learn relevant features from the spectrograms, achieving high classification accuracy for different sleep stages. This study highlighted the advantages of using deep learning for sleep stage classification, particularly in cases where traditional feature engineering methods may not suffice. The work demonstrated that deep learning techniques, particularly DNNs, could offer an efficient and accurate solution for automating sleep stage detection.

Han and Oh [14] explored the application of various machine learning techniques to predict the severity of obstructive sleep apnea syndrome. Their study compared the performance of several algorithms, including decision trees, random forests, and support vector machines, in predicting OSA severity based on patient data. The results indicated that ensemble methods, such as random forests, achieved better performance in predicting OSA severity compared to individual models. The authors highlighted the importance of considering multiple features, such as demographic and physiological data, to accurately predict the severity of sleep apnea. This study reinforced the idea that machine learning can be a valuable tool for assessing the severity of sleep disorders, providing clinicians with objective insights that aid in treatment planning.

Bahrami and Forouzanfar [15] focused on detecting sleep apnea from single-lead ECG using deep learning algorithms. They compared the performance of several deep learning models, including convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), in classifying sleep apnea events from ECG data. The study found that deep learning algorithms, particularly CNNs and LSTMs, outperformed traditional machine learning models in detecting sleep apnea. The authors concluded that deep learning algorithms have the potential to revolutionize sleep apnea detection by providing accurate, real-time analysis of ECG signals. This work contributed to the growing body of research on using ECG data for non-invasive sleep apnea detection and highlighted the advantages of deep learning in handling complex time-series data.

Satapathy et al. [16] conducted a performance analysis of various machine learning algorithms applied to automated sleep staging. Their study evaluated the effectiveness of algorithms such as support vector machines, random forests, and decision trees in classifying sleep stages based on feature sets extracted from EEG signals. The results demonstrated that ensemble methods, like random forests, yielded the highest performance in terms of accuracy and robustness. The authors emphasized that feature selection plays a crucial role in improving classification results and noted that different ML algorithms performed differently depending on the type of features used. This study provided insights into the optimal use of machine learning algorithms for sleep staging and highlighted the importance of selecting relevant features to improve model performance.

Bahrami and Forouzanfar [17] also explored the use of machine learning and deep learning algorithms for sleep apnea detection from single-lead ECG signals. Their comprehensive analysis compared multiple models, including CNNs[24], LSTMs, and traditional machine learning algorithms like support vector machines and random forests. The study found that deep learning algorithms, particularly CNNs, demonstrated superior performance in terms of accuracy and sensitivity. The authors concluded that deep learning techniques are highly effective for detecting sleep apnea from ECG signals, offering a promising alternative to traditional sleep apnea diagnosis methods, which typically require more invasive procedures such as polysomnography.

3. MATERIALS AND METHODS

This paper proposed a system to use some of the machine learning algorithms in diagnosing the sleep disorders which it believed would be effective given the strengths in use of the different algorithms. The system adopts different models, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF) and Artificial Neural Network (ANN) with Multi Layer Perceptron (MLP). These algorithms are built from the Sleep Disorder Data which includes numerous features concerning sleep health and habits. To improve the classification accuracy, the Voting Classifier is used, which included Decision Tree and Bagging with Random Forest. This approach to ensemble is aimed at increasing the level of the models' evaluation and enhancing the performance of each of them. The system can handle 400 records with 13 features as an attempt to diagnose sleep disorders such as sleep apnea. The proposed system shall

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act as a solid decision support system to the clinicians while delivering better health to patients.

Fig.1 Proposed Architecture

The image depicts a flowchart for a machine learning focused on sleep disorder classification. It starts with raw sleep disorder data, which undergoes pre-processing (data cleaning, visualization, and feature selection). The pre-processed data is then split into training and testing sets. Various machine learning models (SVM, KNN, Decision Tree, Random Forest, ANN-MLP[25], and Voting Classifier) are trained on the training data. The trained models are evaluated on the testing data using metrics like accuracy, precision, recall, F1-score, AUC score, specificity, and sensitivity.

i) Dataset Collection:

The dataset used in this study is the Sleep Health and Lifestyle Dataset, sourced from Kaggle [22]. It contains 400 observations with 13 features related to sleep and daily habits, such as gender, age, occupation, sleep duration, sleep quality, physical activity level, stress level, BMI category, blood pressure, heart rate, daily steps, and sleep disorder. The target variable, "Sleep Disorder," is categorized into three groups: none, sleep apnea, and insomnia. The dataset includes varied occupation data, with the most common being nurse (73 observations), doctor (71), and engineer (63), followed by other occupations such as lawyer (47), teacher (40), and salesperson (32). Pre-processing was done to standardize and replace labels for consistency in analysis.

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Bl Pres
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	12
1	2	Male	28	Doctor	6.2	6	60	8	Normal	12
2	3	Male	28	Doctor	6.2	6	60	8	Normal	12
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	14
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	14

Fig.2 Dataset Collection Table

ii) Pre-Processing:

In the pre-processing step, data processing involves cleaning and handling missing values, while data visualization helps identify patterns and outliers. Label encoding is applied to categorical variables, and feature selection techniques are used to identify the most relevant features for classification.

a) Data Processing: In the data processing step, duplicate data is identified and removed to ensure data consistency and accuracy. Duplicates can distort the analysis and model performance, so any repeated rows or observations are discarded. Next, drop cleaning is performed by handling missing or null values in the dataset. This involves either removing rows with missing values or imputing them using appropriate methods like mean, median, or mode, depending on the nature of the data. This step ensures that the dataset is clean, reducing noise and improving the quality of the machine learning models.

b) Data Visualization: Data visualization is a critical step in exploring the dataset and understanding the underlying patterns. By visualizing the data using charts, graphs, and plots, it becomes easier to identify trends, distributions, and potential outliers. Techniques like histograms, box plots, and scatter plots help analyze the distribution of numerical features, while bar plots are useful for categorical variables. Visualizations also help detect correlations between features and identify anomalies that could impact model performance. This step aids in feature engineering and better understanding of the data before applying machine learning algorithms.

c) Label Encoding: Label encoding is a technique used to convert categorical string data into numeric form. In datasets with categorical variables, such as "Gender" or "Sleep Disorder," machine learning algorithms cannot process string values directly. Therefore, label encoding is applied to convert these string labels into integers. For example, labels like "Male" and "Female" could be converted into 0 and 1, respectively. This step ensures that categorical variables are represented in a format suitable for machine learning models, allowing algorithms to interpret and learn from these features effectively during training and testing.

d) Feature Selection: Feature selection is the process of identifying and selecting the most relevant features (or variables) for building machine learning models. This step helps reduce the dimensionality of the dataset, improving model efficiency and preventing overfitting. By selecting the appropriate features, the model can focus on the most significant variables that contribute to the target variable. The process involves splitting the dataset into input features (X) and the target variable (y), where X represents the independent variables and y represents the dependent variable. Feature selection techniques, such as correlation analysis and recursive feature elimination, are applied to optimize the dataset.

iii) Training & Testing:

The dataset is split into training and testing subsets to evaluate the model's performance. Typically, 80% of the data is used for training the model, while the remaining 20% is reserved for testing. This division helps ensure that the model is trained on a substantial portion of the data and evaluated on unseen data to assess its generalization ability. The split is usually done using techniques like train_test_split from scikit-learn, which ensures random and unbiased division of the dataset into training and testing sets.

iv) Algorithms:

Support Vector Machine [18] is employed to classify sleep disorders by finding the optimal hyperplane that separates different classes in the dataset. It effectively handles high-dimensional data, making it suitable for identifying complex patterns in sleep patterns and activities, ultimately aiding accurate diagnosis.

K-Nearest Neighbours [23] algorithm classifies sleep disorders based on proximity to similar data points in the feature space. By evaluating the nearest neighbors of a given instance, KNN effectively identifies patterns and similarities, providing intuitive insights into sleep disorder classifications based on historical data.

Decision Tree [19] algorithm is utilized to create a model that predicts sleep disorder classifications through a series of binary decisions based on input features. Its transparent structure allows for easy interpretation, making it suitable for identifying key factors affecting sleep health and improving diagnosis accuracy.

Random Forest [20] aggregates multiple decision trees to enhance classification accuracy and robustness. By utilizing random subsets of features and data, it reduces overfitting and improves generalization. This ensemble approach effectively identifies important variables in sleep disorder diagnosis while providing reliable predictions.

Artificial Neural Networks [21] are employed to model complex relationships in the dataset, learning from input features to classify sleep disorders. The multilayer perceptron architecture enables the system to capture intricate patterns in sleep data, enhancing prediction capabilities and improving overall diagnostic outcomes.

The **Voting Classifier** combines predictions from multiple models, including decision trees and bagging classifiers with Random Forest. This ensemble method improves classification accuracy by leveraging the strengths of individual algorithms, reducing errors, and providing a more robust and reliable prediction for sleep disorders.

4. RESULTS & DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as

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positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

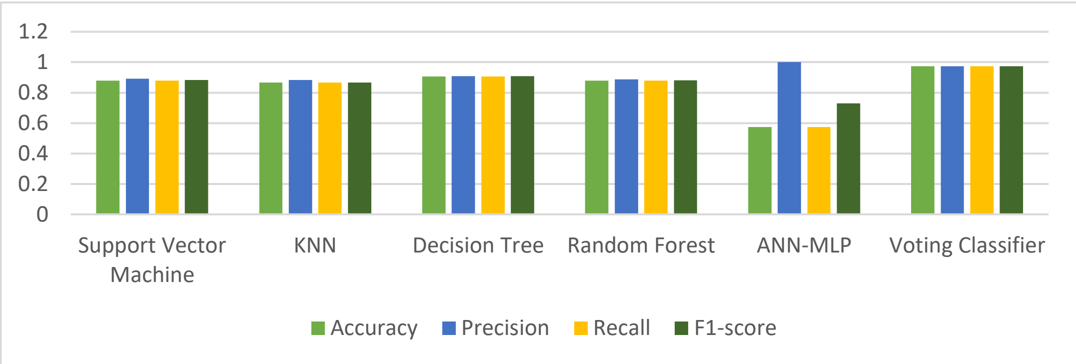
$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(1)$$

In Table 1, the performance metrics—accuracy, precision, recall, and F1-score—are evaluated for each algorithm. The Voting Classifier achieves the highest scores, with all metrics at 0.973%. Other algorithms' metrics are also presented for comparison.

Table.1 Performance Evaluation Metrics

ML Model	Accuracy	Precision	Recall	F1-score
Support Vector Machine	0.880	0.892	0.880	0.884
KNN	0.867	0.883	0.867	0.867
Decision Tree	0.907	0.909	0.907	0.908
Random Forest	0.880	0.887	0.880	0.881
ANN-MLP	0.573	1.000	0.573	0.729
Voting Classifier	0.973	0.973	0.973	0.973

Graph.1 Comparison Graphs



In Graph 1, accuracy is represented in light green, precision in blue, recall in light yellow, and F1-score in green. The Voting Classifier outperforms the other algorithms in all metrics, with the highest values compared to the remaining models. These details are visually represented in the above graph.

Fig. 3 Dash Board

The Fig. 3 shows the title page of a research paper titled "Applying Machine Learning Algorithms for the Classification of Sleep Disorders."

Fig. 4 Register Page

The Fig. 4 shows a user registration form with fields for username, full name, email, phone number, and password. It also includes a "Forgot Password?" link and a "Register" button.

Fig. 5 Login page

The Fig. 5 shows a login page with fields for username and password. The username field is pre-filled with "admin." A "Forgot password?" link is provided below the fields.

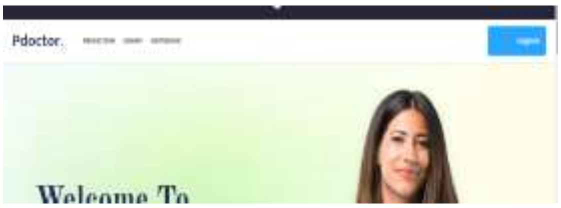


Fig.6 Main page

The Fig.6 shows the title page of a research paper titled "Applying Machine Learning Algorithms for the Classification of Sleep Disorders."

Fig. 7 Test case – 1

The Fig. 7 shows a sleep disorder prediction form. It collects patient information like age, gender, occupation, sleep duration, and more. After inputting data, the form predicts the risk of sleep disorder. In this case, the prediction is "NONE, PATIENT IS NOT SUFFERING FROM SLEEP DISORDER!"

Fig. 8 Test case - 2

The Fig. 8 shows a sleep disorder prediction form. It collects patient information like age, gender, occupation, sleep duration, and more. After inputting data, the form predicts the risk of sleep disorder. In this case, the prediction is "INSOMNIA, IS A COMMON SLEEP DISORDER THAT CAN MAKE IT HARD TO FALL ASLEEP OR STAY ASLEEP!"

Fig. 9 Test case – 3

The Fig. 9 shows a sleep disorder prediction form. It collects patient information like age, gender, occupation, sleep duration, and more. After inputting data, the form predicts the risk of sleep disorder. In this case, the prediction is "SLEEP APNEA, IS A POTENTIALLY SERIOUS SLEEP DISORDER IN WHICH BREATHING REPEATEDLY STOPS AND STARTS!"

5. CONCLUSION

This paper has established that with the help of machine learning algorithms it is indeed possible to classify sleep disorders by using data from Sleep Disorder Data set that is made available to the public. Comparing a range of deep learning and classical machine learning methods, the Voting Classifier, based on bagging with RF and DT showed the highest accuracy. Performance was satisfactory in all evaluation matrices with an accuracy of 97.3%, precision of 97.3%, recall of 97.3% and F1-score of 97.3%. These results suggest further that the Voting Classifier developed here is a highly reliable and robust system for classifying sleep disorders. These results showing steady improvements in almost all the tested measurement indicate that the model could be useful in providing precise and timely diagnosis of sleep disorders thus benefiting the patient and enhancing the clinical decisions. Based on the high classification accuracy, the Voting Classifier can be recommended as the useful instrument to automate the process of Sleep disorders' diagnostic, thus promoting more accurate diagnoses and better prognosis in individuals with Sleep disorders.

The ***future scope*** of this research includes the exploration of additional advanced machine learning techniques, such as deep learning architectures like Convolutional Neural Networks (CNNs) and recurrent networks for improved accuracy in sleep disorder classification. Integrating real-time data from wearable devices could enhance the system's predictive capabilities. Furthermore, expanding the dataset to include diverse populations and sleep disorders will improve model generalization.

REFERENCES

[1] F. Mendonça, S. S. Mostafa, F. Morgado-Dias, and A. G. Ravelo-García, ''A portable wireless device for cyclic alternating pattern estimation from an EEG monopolar derivation,'' Entropy, vol. 21, no. 12, p. 1203, Dec. 2019.

[2] Y. Li, C. Peng, Y. Zhang, Y. Zhang, and B. Lo, ''Adversarial learning for semi-supervised pediatric sleep staging with single-EEG channel,'' Methods, vol. 204, pp. 84–91, Aug. 2022.

[3] E. Alickovic and A. Subasi, ''Ensemble SVM method for automatic sleep stage classification,'' IEEE Trans. Instrum. Meas., vol. 67, no. 6, pp. 1258–1265, Jun. 2018.

[4] D. Shrivastava, S. Jung, M. Saadat, R. Sirohi, and K. Crewson, ''How to interpret the results of a sleep study,'' J. Community Hospital Internal Med. Perspect., vol. 4, no. 5, p. 24983, Jan. 2014.

[5] V. Singh, V. K. Asari, and R. Rajasekaran, ''A deep neural network for early detection and prediction of chronic kidney disease,'' Diagnostics, vol. 12, no. 1, p. 116, Jan. 2022.

[6] J. Van Der Donckt, J. Van Der Donckt, E. Deprost, N. Vandenbussche, M. Rademaker, G. Vandewiele, and S. Van Hoecke, ''Do not sleep on traditional machine learning: Simple and interpretable techniques are competitive to deep learning for sleep scoring,'' Biomed. Signal Process. Control, vol. 81, Mar. 2023, Art. no. 104429.

[7] H. O. Ilhan, ''Sleep stage classification via ensemble and conventional machine learning methods using single channel EEG signals,'' Int. J. Intell. Syst. Appl. Eng., vol. 4, no. 5, pp. 174–184, Dec. 2017.

[8] Y. Yang, Z. Gao, Y. Li, and H. Wang, ''A CNN identified by reinforcement learning-based optimization framework for EEG-based state evaluation,'' J. Neural Eng., vol. 18, no. 4, Aug. 2021, Art. no. 046059.

[9] Y. J. Kim, J. S. Jeon, S.-E. Cho, K. G. Kim, and S.-G. Kang, ''Prediction models for obstructive sleep apnea in Korean adults using machine learning techniques,'' Diagnostics, vol. 11, no. 4, p. 612, Mar. 2021.

[10] Z. Mousavi, T. Y. Rezaii, S. Sheykhivand, A. Farzamnia, and S. N. Razavi, ''Deep convolutional neural network for classification of sleep stages from single-channel EEG signals,'' J. Neurosci. Methods, vol. 324, Aug. 2019, Art. no. 108312.

[11] S. Djanian, A. Bruun, and T. D. Nielsen, ''Sleep classification using consumer sleep technologies and AI: A review of the current landscape,'' Sleep Med., vol. 100, pp. 390–403, Dec. 2022.

[12] N. Salari, A. Hosseinian-Far, M. Mohammadi, H. Ghasemi, H. Khazaie, A. Daneshkhah, and A. Ahmadi, ''Detection of sleep apnea using machine learning algorithms based on ECG signals: A comprehensive systematic review,'' Expert Syst. Appl., vol. 187, Jan. 2022, Art. no. 115950.

[13] C. Li, Y. Qi, X. Ding, J. Zhao, T. Sang, and M. Lee, ''A deep learning method approach for sleep stage classification with EEG spectrogram,'' Int. J. Environ. Res. Public Health, vol. 19, no. 10, p. 6322, May 2022.

[14] H. Han and J. Oh, ''Application of various machine learning techniques to predict obstructive sleep apnea syndrome severity,'' Sci. Rep., vol. 13, no. 1, p. 6379, Apr. 2023.

[15] M. Bahrami and M. Forouzanfar, ''Detection of sleep apnea from single-lead ECG: Comparison of deep learning algorithms,'' in Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA), Jun. 2021, pp. 1–5.

[16] S. Satapathy, D. Loganathan, H. K. Kondaveeti, and R. Rath, ''Performance analysis of machine learning algorithms on automated sleep staging feature sets,'' CAAI Trans. Intell. Technol., vol. 6, no. 2, pp. 155–174, Jun. 2021.

[17] M. Bahrami and M. Forouzanfar, ''Sleep apnea detection from single-lead ECG: A comprehensive analysis of machine learning and deep learning algorithms,'' IEEE Trans. Instrum. Meas., vol. 71, pp. 1–11, 2022.

[18] J. Ramesh, N. Keeran, A. Sagahyroon, and F. Aloul, ''Towards validating the effectiveness of obstructive sleep apnea classification from electronic health records using machine learning,'' Healthcare, vol. 9, no. 11, p. 1450, Oct. 2021.

[19] S. K. Satapathy, H. K. Kondaveeti, S. R. Sreeja, H. Madhani, N. Rajput, and D. Swain, ''A deep learning approach to automated sleep stages classification using multi-modal signals,'' Proc. Comput. Sci., vol. 218, pp. 867–876, Jan. 2023.

[20] O. Yildirim, U. Baloglu, and U. Acharya, ''A deep learning model for automated sleep stages classification using PSG signals,'' Int. J. Environ. Res. Public Health, vol. 16, no. 4, p. 599, Feb. 2019.

[21] S. Akbar, A. Ahmad, M. Hayat, A. U. Rehman, S. Khan, and F. Ali, ''IAtbP-Hyb-EnC: Prediction of antitubercular peptides via heterogeneous feature representation and genetic algorithm based ensemble learning model,'' Comput. Biol. Med., vol. 137, Oct. 2021, Art. no. 104778.

[22] (2023). Sleep Health and Lifestyle Dataset. [Online]. Available: http://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

[23] P. Tripathi, M. A. Ansari, T. K. Gandhi, R. Mehrotra, M. B. B. Heyat, F. Akhtar, C. C. Ukwuoma, A. Y. Muaad, Y. M. Kadah, M. A. Al-Antari, and J. P. Li, ''Ensemble computational intelligent for insomnia sleep stage detection via the sleep ECG signal,'' IEEE Access, vol. 10, pp. 108710–108721, 2022.

[24] Y. You, X. Zhong, G. Liu, and Z. Yang, ''Automatic sleep stage classification: A light and efficient deep neural network model based on time, frequency and fractional Fourier transform domain features,'' Artif. Intell. Med., vol. 127, May 2022, Art. no. 102279.

[25] I. A. Hidayat, ''Classification of sleep disorders using random forest on sleep health and lifestyle dataset,'' J. Dinda : Data Sci., Inf. Technol., Data Anal., vol. 3, no. 2, pp. 71–76, Aug. 2023.

[26] Hamouda, G. B., Rejeb, L., & Said, L. B. (2024). Ensemble learning for multi-channel sleep stage classification. Biomedical Signal Processing and Control, 93, 106184.

[27] Mukherjee, D., Dhar, K., Schwenker, F., & Sarkar, R. (2021). Ensemble of deep learning models for sleep apnea detection: an experimental study. Sensors, 21(16), 5425.

[28] Mostafa Monowar, M., Nobel, S. N., Afroj, M., Hamid, M. A., Uddin, M. Z., Kabir, M. M., & Mridha, M. F. (2025). Advanced sleep disorder detection using multi-layered ensemble learning and advanced data balancing techniques. Frontiers in Artificial Intelligence, 7, 1506770.

[29] Timplalexis, C., Diamantaras, K., & Chouvarda, I. (2019, October). Classification of sleep stages for healthy subjects and patients with minor sleep disorders. In 2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE) (pp. 344-351). IEEE.

[30] Rahman, M. A., Jahan, I., Islam, M., Jabid, T., Ali, M. S., Rashid, M. R. A., ... & Ali, M. A. (2025). Improving Sleep Disorder Diagnosis through Optimized Machine Learning Approaches. IEEE Access.

[31] Irfan, M., Siddiqa, H. A., Nahliis, A., Chen, C., Xu, Y., Wang, L., ... & Chen, W. (2023). An ensemble voting approach with innovative multi-domain feature fusion for neonatal sleep stratification. Ieee Access, 12, 206-218.

[32] Byeon, H. (2020, May). Exploring the predictors of rapid eye movement sleep behavior disorder for Parkinson's disease patients using classifier ensemble. In Healthcare (Vol. 8, No. 2, p. 121). MDPI.

[33] Revathy, P., Manju Bhargavi, N., Gunasekar, S., & Lohit, A. (2024, August). Voting Regressor Model for Timely Prediction of Sleep Disturbances Using NHANES Data. In International Conference on ICT for Sustainable Development (pp. 53-65). Singapore: Springer Nature Singapore.

[34] Haneef, R., Rao, N. M., & Gracewell, J. J. (2024, December). Applying Machine Learning Algorithms for the Classification of Sleep Disorders Accuracy and Automating Diagnosis with the Sleep Health Dataset. In 2024 International Conference on Sustainable Communication Networks and Application (ICSCNA) (pp. 1439-1443). IEEE.

[35] Sravani, G., Lavanya, B., Mithila, K., & Surendran, R. (2024, July). Exploring Sleep Disorder and Lifestyle Analysis Through Data Preprocessing and Ensemble Learning Techniques. In 2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS) (pp. 791-795). IEEE.