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Research Paper

Classification Of Sleep Disorder Using Advanced Machine Learning Technology

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***Abstract*— Sleep disorders, particularly insomnia and sleep apnea, significantly affect physical health, cognitive performance, and overall quality of life, making timely and accurate diagnosis essential. Conventional manual assessment of sleep-related conditions is time-consuming, subjective, and prone to diagnostic inconsistencies, motivating the adoption of intelligent classification techniques. A publicly available Sleep Health and Lifestyle dataset containing 400 instances with 13 attributes representing demographic, physiological, and lifestyle characteristics was utilized for analysis. Data preprocessing included duplicate removal, missing-value handling, feature extraction, label encoding, feature selection, class balancing using SMOTE, feature scaling with Min-Max normalization, and train–test splitting to improve model reliability. Multiple machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), Gaussian Naïve Bayes, Gradient Boosting, and a hybrid Voting Classifier integrating Decision Tree, Bagging, and Random Forest, were implemented and compared. Performance was assessed using accuracy, precision, recall, F1-score, confusion matrix, and classification report. The optimized Decision Tree achieved an accuracy of 90.7%, while the hybrid Voting Classifier delivered the highest classification accuracy of 97.3%, demonstrating superior predictive capability and robustness. The proposed intelligent classification framework enhances diagnostic performance and provides a practical foundation for efficient web-based sleep disorder assessment.**

Keywords*— *Sleep Disorder Classification, Machine Learning, Ensemble Learning, Voting Classifier, Sleep Health and Lifestyle Dataset, Healthcare Analytics.

I. INTRODUCTION

Sleep is a fundamental biological process that plays a critical role in maintaining physical health, mental well-being, and cognitive performance. Adequate sleep supports memory consolidation, tissue repair, metabolic regulation, and overall physiological balance. Disturbances in normal sleep patterns are associated with numerous chronic health conditions, including cardiovascular diseases, diabetes, obesity, depression, and impaired immune function. The growing prevalence of sleep-related disorders has become a major public health concern, affecting individuals of all age groups and reducing productivity and quality of life. Advances in healthcare technologies and intelligent diagnostic systems have created opportunities for improving the identification and management of sleep disorders through data-driven approaches. The increasing availability of digital health records and lifestyle-related information further enables the development of computational techniques capable of supporting clinical decision-making and reducing diagnostic complexity. Consequently, intelligent sleep disorder classification has emerged as an important area of investigation for enhancing healthcare efficiency and diagnostic reliability. [1] [2] [3]

Conventional diagnosis of sleep disorders primarily depends on manual examination of polysomnography (PSG) recordings and expert interpretation of multiple physiological signals. Although these methods remain clinically valuable, they require considerable time, specialized expertise, and extensive human effort, making large-scale screening difficult. Variations in expert interpretation may also introduce inconsistencies that affect diagnostic accuracy and reproducibility. Furthermore, increasing patient populations place additional pressure on healthcare systems, emphasizing the need for efficient and reliable decision-support mechanisms. Existing computational approaches have demonstrated encouraging performance; however, limitations related to classification accuracy, scalability, robustness, and adaptability continue to restrict their widespread clinical applicability. These challenges highlight the necessity for more dependable intelligent frameworks capable of delivering consistent and accurate sleep disorder classification across diverse patient profiles. [4] [5]

The primary objective is to develop an intelligent framework for accurately classifying sleep disorders using clinically relevant health and lifestyle information while improving prediction reliability and diagnostic consistency. The framework is designed to analyze multiple factors associated with sleep quality and generate dependable classification outcomes that assist healthcare professionals during diagnosis. It also aims to provide an accessible decision-support environment through an interactive web-based interface, enabling convenient data entry and prediction visualization. By emphasizing reliable classification, improved usability, and practical deployment, the proposed

framework contributes toward supporting early identification of sleep-related abnormalities and facilitating informed clinical decision-making. [6] [7] [8]

Accurate and efficient classification of sleep disorders has the potential to significantly improve patient care by enabling earlier diagnosis, personalized treatment planning, and continuous health monitoring. Intelligent classification systems can reduce the workload of medical professionals, minimize subjective interpretation, and provide consistent diagnostic assistance across different healthcare environments. Such advancements contribute to improved healthcare accessibility while supporting preventive medicine and long-term patient management. The integration of data-driven decision-support technologies into routine clinical practice represents a promising direction for enhancing diagnostic quality, optimizing healthcare resources, and improving overall quality of life for individuals affected by sleep disorders. [9] [10]

II. Related Work

Recent advances in intelligent healthcare have significantly improved the automated analysis of sleep disorders using machine learning and deep learning techniques. Early investigations primarily focused on physiological signals such as electroencephalography (EEG) and electrocardiography (ECG) to classify sleep stages and detect sleep-related abnormalities. Ilhan introduced ensemble and conventional machine learning methods for single-channel EEG-based sleep stage classification, demonstrating that ensemble learning can improve predictive consistency while maintaining computational efficiency, although performance remained dependent on handcrafted features and signal quality [11]. Yang et al. presented a reinforcement learning-based optimization framework for identifying convolutional neural network architectures for EEG state evaluation, achieving improved learning capability but requiring substantial computational resources and complex model optimization [12]. Kim et al. developed machine learning-based prediction models for obstructive sleep apnea using demographic and clinical information from Korean adults, highlighting the effectiveness of data-driven prediction while emphasizing the need for improved generalization across broader populations [13].

Deep learning techniques have further advanced automated sleep analysis by reducing the reliance on manual feature engineering. Mousavi et al. proposed a deep convolutional neural network for sleep stage classification using single-channel EEG signals, demonstrating high classification capability with simplified signal acquisition; however, the approach required extensive training data and computational power [14]. Li et al. utilized EEG spectrograms within a deep learning framework to classify sleep stages, reporting encouraging predictive performance through automatic feature extraction, although interpretability and deployment complexity remained important concerns [15]. Bahrami and Forouzanfar investigated deep learning algorithms for detecting sleep apnea from single-lead ECG signals and demonstrated that deep architectures can effectively identify apnea events while reducing dependence on multiple physiological channels, despite sensitivity to data quality and computational requirements [16].

Comparative analyses have also explored the effectiveness of traditional and advanced learning techniques for automated sleep analysis. Satapathy et al. evaluated multiple machine learning algorithms using automated sleep staging feature sets and observed that classifier performance varies considerably depending on feature representation and dataset characteristics, indicating the importance of selecting robust classification strategies [17]. Bahrami and Forouzanfar later presented a comprehensive comparison between machine learning and deep learning approaches for sleep apnea detection using ECG signals, concluding that although deep learning often provides superior predictive accuracy, increased computational complexity and reduced interpretability remain practical limitations for clinical adoption [18]. Ramesh et al. investigated obstructive sleep apnea classification using electronic health records and demonstrated the feasibility of utilizing structured clinical information for prediction, while noting challenges associated with data heterogeneity, missing information, and real-world deployment [19]. Yildirim et al. proposed an automated sleep stage classification framework using polysomnography (PSG) signals and deep learning, achieving promising diagnostic performance but relying heavily on complex PSG acquisition systems that may restrict routine clinical implementation [20].

Although previous investigations have demonstrated substantial progress in automated sleep disorder classification, several challenges remain unresolved. Many existing approaches depend on specialized physiological signals, computationally intensive deep learning architectures, or limited clinical datasets, reducing their scalability, interpretability, and practical applicability in routine healthcare environments. In addition, variability in patient characteristics and differences in data acquisition continue to influence classification reliability across diverse populations. These limitations emphasize the need for an intelligent classification framework that achieves high predictive performance while maintaining simplicity, accessibility, and practical deployment. The present approach addresses these gaps by utilizing readily available health and lifestyle information within a unified classification framework that enables reliable prediction and convenient web-based decision support, thereby contributing toward more efficient and accessible sleep disorder assessment.

III. Materials And Methods

The proposed system is designed to provide an accurate and reliable framework for classifying sleep disorders using the publicly available Sleep Health and Lifestyle dataset, which contains demographic, physiological, and lifestyle-related attributes associated with sleep health. The overall methodology follows a structured data-driven pipeline involving data acquisition, quality enhancement, transformation, model development, and performance evaluation to ensure dependable classification outcomes. To improve predictive capability, multiple machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN), are implemented and comparatively evaluated. A Genetic Algorithm is employed to optimize model parameters, enhancing classification efficiency and reducing model complexity. Furthermore, an ensemble Voting Classifier integrating

Decision Tree, Bagging, and Random Forest is incorporated to improve robustness, generalization, and predictive accuracy by leveraging complementary model decisions. The trained framework is deployed through a Flask-based web application with user authentication, enabling secure and user-friendly access for real-time prediction. This integrated methodology enhances diagnostic reliability, supports timely clinical decision-making, and provides an effective platform for practical sleep disorder assessment.

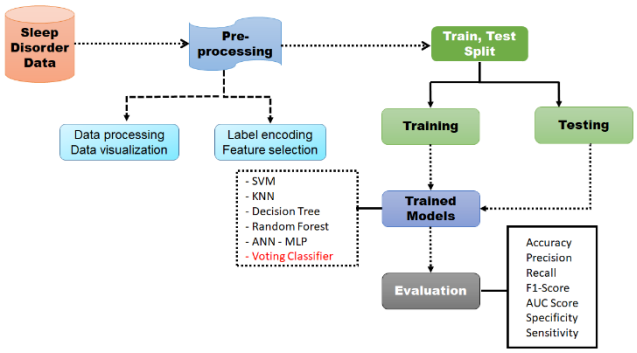

Fig. 1. System Architecture

The system architecture begins with the Sleep Disorder Dataset, which undergoes preprocessing to improve data quality through data processing, visualization, label encoding, and feature selection. The processed data is divided into training and testing subsets for model development and validation. Multiple machine learning algorithms, including SVM, KNN, Decision Tree, Random Forest, ANN-MLP, and the Voting Classifier, are trained and evaluated. Finally, the trained models are assessed using performance metrics such as Accuracy, Precision, Recall, F1-Score, AUC Score, Specificity, and Sensitivity to determine the most reliable classifier for sleep disorder prediction.

A) Dataset Collection:

The Sleep Health and Lifestyle Dataset was collected from the publicly available Kaggle repository and utilized to develop and evaluate the sleep disorder classification framework. The dataset comprises 400 patient records with 13 features, including demographic, physiological, and lifestyle-related attributes such as age, gender, occupation, sleep duration, stress level, physical activity, heart rate, blood pressure, BMI category, and daily steps. The target variable consists of three classes: No Disorder, Insomnia, and Sleep Apnea. Owing to its diverse health-related attributes and representative class distribution, the dataset provides a reliable benchmark for developing and validating machine learning models for accurate sleep disorder classification.

B) Pre-Processing:

Data preprocessing is a crucial stage that prepares the dataset for effective machine learning by improving data quality, transforming attributes, selecting relevant features, and creating reliable training and testing datasets for classification.

1. Data Pre-processing: Data preprocessing was performed to improve the overall quality and consistency of the sleep disorder dataset before model development. Duplicate records and incomplete or irrelevant entries were identified and removed to eliminate redundancy and reduce potential bias in the analysis. This process ensured that only valid and meaningful information was retained for subsequent stages. By enhancing data integrity and consistency, preprocessing improved the reliability of model training, reduced noise, and contributed to more accurate and robust classification performance.

2. Data Visualization: Data visualization was conducted to explore the characteristics and distribution of the dataset through graphical representations. Various visual analyses were used to examine relationships among demographic, physiological, and lifestyle attributes while identifying trends, patterns, and class distributions. This exploratory process facilitated a deeper understanding of the underlying data structure and helped reveal potential anomalies or imbalances. Effective visualization supported informed decision-making during model development and contributed to improved interpretation of classification outcomes.

3. Label Encoding: Label encoding was applied to transform categorical attributes into numerical representations that could be effectively processed by machine learning models. This transformation preserved the uniqueness of each category while ensuring compatibility with computational algorithms. Converting categorical information into standardized numerical values enabled efficient learning from demographic and lifestyle features without altering their original meaning. As a result, the classification models could process heterogeneous data more effectively, leading to improved prediction accuracy and computational efficiency.

4. Feature Selection: Feature selection was carried out to identify the most relevant predictor variables while separating them from the target class for sleep disorder classification. The selected features represented important demographic, physiological, and lifestyle characteristics that significantly contributed to the prediction process. Eliminating unnecessary or less informative attributes reduced data dimensionality and minimized redundant information. This process enhanced computational efficiency, improved model generalization, and enabled the classification framework to focus on the most influential factors affecting prediction performance.

C) Training and Testing:

The prepared dataset was divided into separate training and testing subsets to enable an unbiased evaluation of model performance. The training subset was used to learn classification patterns, while the testing subset independently assessed the predictive capability of the developed models. This separation ensured that evaluation was performed on previously unseen data, providing a realistic estimate of model generalization. Consequently, the train–test split reduced the risk of overfitting and improved the credibility and reliability of the experimental results.

D) Algorithms

Support Vector Machine (SVM): Support Vector Machine (SVM) is employed to perform accurate classification by identifying an optimal decision boundary that effectively separates different classes. Parameter optimization enhances its predictive capability, enabling improved generalization, robust performance, and reliable classification across complex feature spaces.

K-Nearest Neighbors (KNN): K-Nearest Neighbors (KNN) classifies instances by analyzing the similarity between new observations and their nearest neighboring samples. Its distance-based decision process effectively captures local data patterns, providing a simple yet reliable approach for accurate classification and consistent prediction performance.

Decision Tree Classifier: The Decision Tree Classifier generates classification outcomes through a sequence of hierarchical decision rules based on input attributes. Its interpretable structure simplifies decision-making while effectively identifying significant patterns, contributing to reliable prediction accuracy and improved model transparency.

Random Forest Classifier: Random Forest Classifier combines multiple decision trees to produce robust classification results through ensemble learning. By aggregating predictions from diverse trees, it reduces overfitting, improves generalization, enhances prediction stability, and delivers consistent performance across varying data distributions.

Multi-Layer Perceptron (ANN–MLP Classifier): The Multi-Layer Perceptron (ANN–MLP) models complex nonlinear relationships among input features through interconnected neural layers. Optimized parameter selection improves learning efficiency, enabling the classifier to capture intricate patterns and achieve enhanced predictive accuracy and generalization capability.

Voting Classifier: The Voting Classifier integrates predictions from Bagging Classifier, Random Forest, and Decision Tree models to generate a unified classification result. This ensemble strategy leverages the strengths of individual classifiers, improving robustness, reducing prediction errors, and achieving superior overall classification accuracy.

IV. Experimental Results

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:

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

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

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

Table.1 Performance Evaluation Table

ML Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine (SVM)	0.880	0.892	0.880	0.884
K-Nearest Neighbors (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

Table 1 presents the comparative performance of six machine learning models for sleep disorder classification using Accuracy, Precision, Recall, and F1-Score. The Voting Classifier achieved the best overall performance with a score of 0.973 across all evaluation metrics, demonstrating superior classification accuracy, robustness, and balanced predictive capability compared with the individual machine learning models.

Fig. 2 Comparison Graph

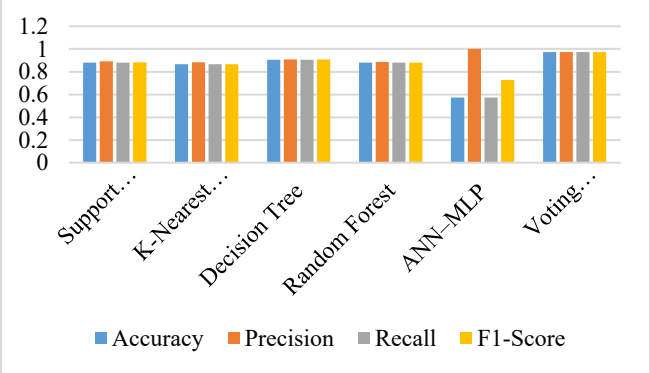

Fig.2 compares the performance of six machine learning models using Accuracy, Precision, Recall, and F1-Score. The Voting Classifier consistently achieved the highest values across all metrics, demonstrating superior predictive performance and overall classification effectiveness compared with the individual machine learning algorithms.

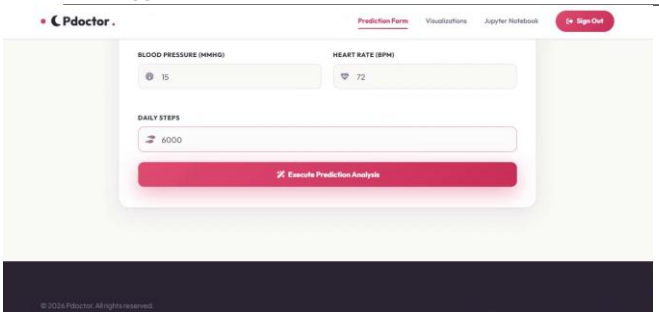

Fig.3 Enter the input data

Fig. 3 illustrates the prediction input interface of the sleep disorder classification system, where users enter health-related parameters such as blood pressure, heart rate, and daily steps. After submitting the information, the system processes the input and performs prediction analysis, providing an efficient and user-friendly interface for sleep disorder assessment.

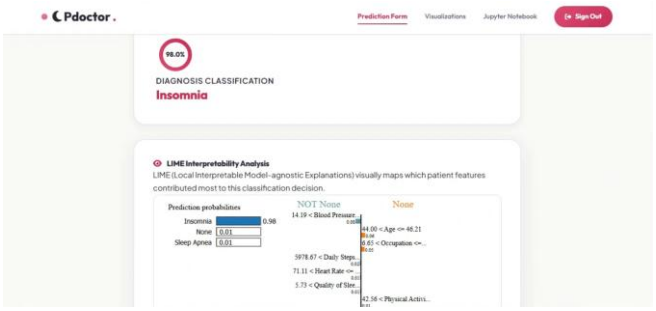

Fig.4 Predicted Result

Fig. 4 illustrates the prediction output of the sleep disorder classification system, where the model identifies Insomnia with a 98.0% confidence score. The interface also presents a LIME interpretability analysis, highlighting the most influential health-related features that contributed to the prediction, thereby improving result transparency and supporting reliable clinical decision-making.

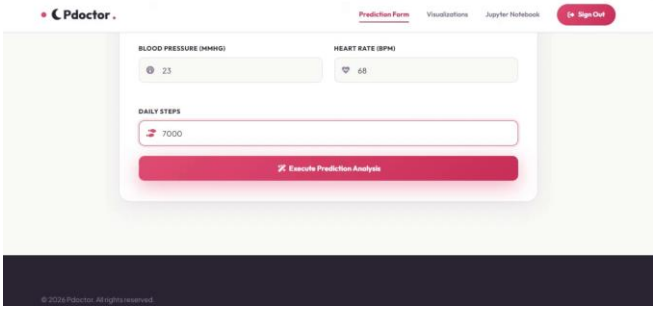

Fig.5 Enter the input data

Fig. 5 illustrates the prediction input interface of the sleep disorder classification system, where users enter health-related information, including blood pressure, heart rate, and daily steps. The submitted values are processed by the trained machine learning model to generate an accurate sleep disorder prediction through a simple and user-friendly interface.

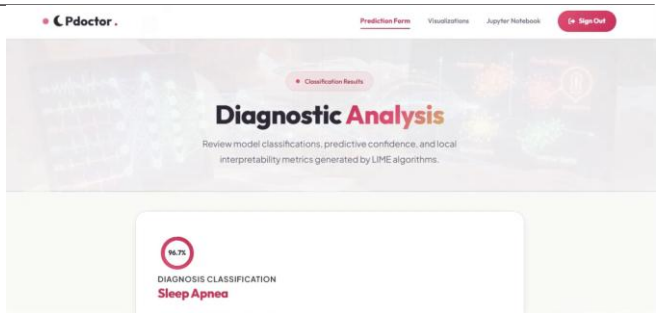

Fig.6 Predicted Result

Fig. 5 illustrates the diagnostic analysis output of the sleep disorder classification system, where the model predicts Sleep Apnea with a 96.7% confidence score. The interface presents the classification result along with predictive confidence, enabling reliable interpretation and supporting accurate clinical decision-making for sleep disorder assessment.

V. Conclusion

In conclusion, the primary objective of this system is to develop an intelligent and reliable framework for the accurate classification of sleep disorders, thereby supporting timely diagnosis and improving healthcare decision-making. The developed framework utilizes the publicly available Sleep Health and Lifestyle dataset containing demographic, physiological, and lifestyle-related information to classify sleep disorders effectively. Multiple machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN), were comparatively evaluated, while a Genetic Algorithm was employed for model parameter optimization to enhance predictive performance. Furthermore, an ensemble Voting Classifier integrating Decision Tree, Bagging, and Random Forest was implemented to improve classification robustness and overall accuracy. Experimental evaluation demonstrated the effectiveness of the proposed framework, with the ensemble model achieving a classification accuracy of 97.3%, outperforming the individual models and validating its reliability for sleep disorder prediction. The system is further strengthened through deployment as a secure Flask-based web application with user authentication, enabling practical and accessible real-time prediction. Overall, the developed framework provides an efficient, accurate, and dependable decision-support solution that reduces reliance on manual assessment, enhances diagnostic consistency, and contributes to automated clinical support for sleep disorder classification in real-world healthcare environments.

The developed sleep disorder classification system can be further enhanced by incorporating larger and more diverse clinical datasets to improve generalization across different populations. Integration with wearable devices and Internet of Things (IoT)-based health monitoring systems can enable continuous real-time sleep assessment. Advanced hybrid artificial intelligence models and explainable AI techniques can further improve prediction accuracy and transparency. Additionally, cloud-based deployment and mobile application support can increase accessibility, enabling

healthcare professionals and individuals to perform convenient and efficient remote sleep disorder screening.

REFERENCES

[1] 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.

[2] 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.

[3] 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.

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] 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.

[14] 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.

[15] 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.

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[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] F. Ordóñez and D. Roggen, ''Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition,'' Sensors, vol. 16, no. 1, p. 115, Jan. 2016.

[24] D. M. W. Powers, ''Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation,'' 2020, arXiv:2010.16061.

[25] F. Pedregosa, ''Scikit-learn: Machine learning in Python,'' J. Mach. Learn. Res., vol. 12, pp. 2825–2830, Nov. 2011.

[26] M. Bansal, A. Goyal, and A. Choudhary, ''A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning,'' Decis. Anal. J., vol. 3, Jun. 2022, Art. no. 100071.

[27] M. Q. Hatem, ''Skin lesion classification system using a K-nearest neighbor algorithm,'' Vis. Comput. Ind., Biomed., Art, vol. 5, no. 1, pp. 1–10, Dec. 2022.

[28] V. G. Costa and C. E. Pedreira, ''Recent advances in decision trees: An updated survey,'' Artif. Intell. Rev., vol. 56, no. 5, pp. 4765–4800, May 2023.

[29] 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.

[30] 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.