iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VII **Month of publication:** July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84408

Sleep Disorder Prediction Using Machine Learning Techniques

Syed Shabbeer Ahmad[1], Asra Fatima[2]
[1]Professor & Head , Department of Computer Science and Engineering Muffakham jah college of engineering and technology Telangana, Hyderabad ,India
[2]Student, Department of Computer Science and Engineering Muffakham jah college of engineering and technology Telangana , Hyderabad, India

Abstract: Sleep problems, especially sleep apnoea, have an impact on people's health, which indicates the necessity for a correct diagnosis. Sleep experts, however, have highly complex and time-consuming methods to manually identify the various sleep stages. We present here a ML classification model, publicly available for use that has 13 features and 400 records and relates to the Sleep Disorder Data. We investigate and evaluate the effectiveness of numerous DL models based on techniques for reliable diagnosis of sleep disorders. The data includes important lifestyle indicators and sleep health measures that are useful in identifying patterns. Patterns may be indicative of other sleep disorders. The bagged models, and especially the Voting Classifier with RF and DT, have the best performance among the models considered. The method achieved accuracy, precision, recall and F1-score values of 0.973, which means the method is useful for the sleep disorder classification and reliable. The results indicate that the proposed ML methods offer the potential for more intelligent, faster and precise sleep disorders diagnosis, benefiting the physicians' decision making process and the patient's health.
"Index Terms: Machine learning algorithms, deep learning, classification, sleep disorder, Voting algorithm."

I. INTRODUCTION

Sleep is an important physiological process which plays a vital role in one's physical and mental well being. It helps to strengthen the body and consolidate the brain and memories. Quality of sleep has a big influence on cognitive abilities, especially for youngsters and elderly adults, who are at greater risk of accidents. From heart disease to diabetes and obesity, poor sleep can cause a host of health issues. Although sleep disorders are important they are often underdiagnosed and misclassified due to the difficulty of evaluating sleep stages. PSG records are analysed manually by physicians, medical professionals, and sleep experts to evaluate the sleep stages. It is susceptible to human errors and it is time-consuming to be used for the proper classification [1].

Philips polled more than 13,000 people in 13 countries to find that sleep dissatisfaction was high among adults (55%). The factors of COVID-19 pandemic, sleep apnoea and insomnia were found to be poor sleep quality. In particular, 37% of those who participated reported that the pandemic had a negative impact on their sleep, 37% reported insomnia, 29% snored, 22% reported shift-work sleep disturbance, and 12% reported sleep apnoea [2]. These figures demonstrate how common sleep problems are and highlight the importance of new diagnosis and classification methods.

Medical specialists divide sleep into five separate stages: alertness, N1, N2, N3 and REM. Wakefulness is a state of alertness in which people are aware of their environment, with rapid and irregular brain waves. N1 is the lightest stage of sleep, characterised by slower brain waves and relaxation of muscles. N2 is a deeper stage and N3 is the deepest stage of sleep. Awakening is difficult in this stage. During REM sleep, the eye moves quickly and the brain waves look like those of an awake person. Each of these stages plays an important part in the body's recovery and the brain's cognitive functions. Through PSG, doctors can record data from the EEG and ECG – which record the activity of the brain and body while a person is sleeping – to monitor these stages [3, 4, 5].

Automated strategies using MLAs have been developed by numerous researchers to minimise human intervention in classification and prediction of sleep stages. Traditional ML algorithms and DL algorithms are some of the methods that can be broadly categorized. For smaller data sets, traditional ML algorithms like neural networks, SVM and decision tree are used and manual feature extraction is required to classify sleep stages, such as entropy and energy. In contrast, DL algorithms are motivated by the structure of the human brain and learn complex patterns from data automatically using neural networks. These algorithms are particularly suitable for huge and complicated datasets and are considered as a possible alternative to classic MLAs [6], [7]. EEG signals are one of the most popular ways to categorise sleep stages using traditional and DL models [8].

II. RELATED WORK

Many studies applied ML to sleep disorder detection and classification like OSA, sleep stage classification and ECG-based detection. ML algorithms have enhanced the accuracy of diagnosis and replaced the manual analysis that is tedious and prone to errors. Similarly, like Kim et al. [9] did with Koreans, we trained many ML systems to predict OSA risk using clinical data. The models demonstrate the potential of automated predictions, such as machine learning, for earlier detection of OSA during ongoing care. Demographic, clinical and physiological parameters were predictive of improvement. According to this study, ML can help to improve the diagnosis of sleep apnoea, identify it early on and make it more accurate.

Mousavi et al. [10] suggest a single-channel EEG sleep stage classification method based on Deep CNN. Using DL to detect sleep stages automatically for insomnia and sleep apnoea. CNNs based on DL can automatically extract the hierarchy of the EEG. The traditional ML performs less accurately and slower in sleep stage classification when compared to CNN. Djanian et al. [11] explored sleep classification techniques and AI in sleep studies. AI is becoming more popular for wearable sleep trackers. These sensors and AI algorithms track sleep quality as it happens to correct sleep problems. DL consumer AI gadgets enhanced sleep stage diagnosis, according to research. The wearable AI gadgets provide personalised sleep health.

Salari et al. [12] analysed the ML sleep apnoea diagnosis from ECG. The study has found that ML algorithms can identify sleep apnoea in ECG signals. Single-lead ECGs are used for the diagnosis of sleep apnoea by RFs and SVMs. The authors pointed out that the characteristics of the model are influenced by the feature extraction methods. The researchers found ML can significantly enhance sleep apnoea detection without the use of an ECG. Li et al. used DL and EEG spectrogram to classify sleep stages [13]. The time-frequency content is similar to an EEG spectrogram. DNNs clustered spectrograms. The DL algorithm that is based on learning spectrogram characteristics is able to accurately classify sleep stages. This work demonstrated that feature engineering is unnecessary and that DL can be used to classify sleep stages. DL, particularly DNNs can be applied to automate sleep stage recognition. Han, Oh [14] estimated OSA severity using ML. Patient data were used to test the following ML algorithms for severity prediction of OSA: DT, RF, and SVM. The models predicted the severity of OSA with higher accuracy than the RF model. The authors suggest using demographic and physiological factors to predict sleep apnoea severity. The study concluded that ML is capable of objectively recognizing the severity of sleep disorders and helping clinicians address patients. Bahrami and Forouzanfar [15] developed a system for detecting sleep apnoea using single-lead ECG that leverages DL. ECG-based sleep apnoea classification was done using CNN and LSTMs. CNNs and LSTMs achieved better performance in sleep apnoea diagnosis than ML models. DL sleep apnoea detection may be affected by real time ECGs. This research brings in additional ECG data to be used for non-invasive sleep apnoea detection, and DL algorithms can be used to process complex time-series data.

ML-based automatic sleep staging comparison. Satapathy et al. (16). Using SVM, RF and DT, sleep stages were classified from EEG data feature sets. Ensembles of RF were most error-tolerant. The authors found that feature selection aided the classification and that ML systems were found to be different in their performance for different types of features. Using ML, sleep stages were performed and variables for model enhancement were identified. Bahrami and Forouzanfar [17] developed a ML approach and DL approach for sleep apnoea detection from single-lead ECGs. CNNs, LSTMs, SVMs and RF were thoroughly explored. The survey indicated that CNNs were more accurate and sensitive. Using ECG signals for DL to detect sleep apnoea instead of polysomnography.

III. MATERIALS AND METHODS

We suggested a technique to diagnose sleep issues using ML algorithms which were effective due to their strengths. Various models, such as SVM, KNN, DT, RF, ANN with Multi Layer Perceptron are used. These algorithms are developed using different sleep health and behaviour information supplied by Sleep Disorder Data. Voting Classifier is an improvement of classification accuracy using DT and Bagging with RF. The ensemble approach has been found to improve the model performance and evaluation. The system can be trained with 400 records with 13 features, which is used to detect sleep disorders like sleep apnoea. The proposed technique will help professionals to take informed decisions and enhance patient well-being.

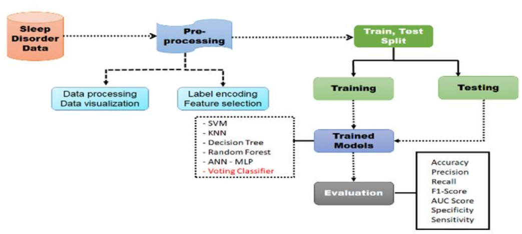


Fig.1 Proposed Architecture

The illustration shows a flowchart for a ML based sleep disorder classification. It starts with raw data on sleep disorders, pre-processing these data (data cleaning, visualisation and feature selection). Then the preprocessed data is divided into training and testing set. Various ML algorithms such as SVM, KNN, DT, RF, ANN-MLP[25] and Voting Classifier are trained with the training set. Test performance of the trained models is evaluated on the test data using various measures such as accuracy, precision, recall, F1 score, AUC score, specificity and sensitivity.

A. Dataset Collection

The dataset used in this work is Sleep Health and Lifestyle Dataset from Kaggle [22]. It contains 400 observations and 13 aspects related to sleep and daily activities such as gender, age, occupation, sleep duration, sleep quality, physical activity level, stress level, BMI category, blood pressure, heart rate, daily steps and sleep problem. The target variable "Sleep Disorder" is divided into three classes: none, sleep apnoea and insomnia. The dataset's vocations are diverse, with nurse (73 observations), doctor (71) and engineer (63) being the most frequent, followed by lawyer (47), teacher (40) and salesperson (32). Standardised/replaced 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

B. Pre-Processing:

Pre-processing stage involves data cleaning and filling in missing data in the data. Patterns and outliers are easily identified with the help of data visualisation. The Categorical variables are label encoded . Feature selection techniques to select most relevant features for classification .

1) *Data Processing:* At this stage, duplicate data is identified and deleted to ensure consistency and accuracy of the data. If duplicate rows/observations exist, they are eliminated prior to the analysis and model performance as they can skew the analysis and performance of the model. After that, missing values (and null values) in the data set are controlled during cleaning. In this step we either delete the row with the missing value or fill with the correct value that may be the mean, median or mode depending on the type of data. This stage ensures that the data is of high quality and free from noise, resulting in improved performance of the ML models.
2) *Data Visualization:* Data visualisation involves creating visual representations of the data, which can help identify patterns and trends. Patterns, distributions and outliers can be easily identified using data visualisation techniques such as charts, graphs and plots. Histograms, box plots, scatter plots and bar graphs can be used to analyze numerical and categorical data. Visualisations are also useful in identifying relationships between features and identifying abnormalities that may negatively affect the performance of the model. This is useful when working with feature engineering, and when understanding the data prior to applying ML algorithms.
3) *Label Encoding:* Encoding of categorical string data as numbers. ML algorithms are not directly able to understand string values of categorical data like "Gender" or "Sleep Disorder." Therefore, we need to use label encoding to re-encode these string labels into integer. The labels Male and Female can be changed to 0 and 1, for instance. This is a key step in preparing categorical variables for use by ML models, so that ML algorithms can become familiar with and learn it during training and testing.
4) *Feature Selection:* It is a process of identifying and choosing the most relevant feature (or variable) and designing ML models. This is for reducing the dimensionality of the data set, which increases the efficiency and prevents overfitting of the model. By picking the right features the model can concentrate on the most important variables contributing to the target variable. In the procedure, we separate the input features (X) from the target variable (y). X is the independent variables and y is the dependent variables. Feature selection techniques such as correlation analysis and recursive feature elimination are used for data set optimisation.

C. Training & Testing:

The dataset is divided into training and testing sets to assess the performance of the model. Usually 80% of the data is used to train the model and 20% of the data is utilised to test the model. This is a split to keep the largest portion of data used to train the model, and the remaining portion of data used to test the model and determine its generalisation capacity. Typically, the split is performed in a manner to ensure that it is a random split, and the data is split evenly, such as using the train_test_split method from scikit-learn to divide the data set into training and testing sets.

D. Algorithms

Random Forest [20] is a method that uses multiple DT to improve classification accuracy and robustness. Reduces overfitting and increases generalisation by using random selections of features and data. The ensemble approach is effective for diagnosis of sleep disorders by finding relevant variables and at the same time provides reliable forecasts.

$$G = 1 - \sum_{j=1}^{c} p_j^2 \ (1)$$

Where, p_j is the probability of class j in a node

The sleep disorders are classified using SVM [18] which finds the optimum hyperplane separating various classes of data in the data set. It can effectively deal with high-dimensional data, allowing it to identify complex patterns in sleep behavior and activities, thereby facilitating accurate diagnosis.

$$f(x) = sign(w^T x + b)(2)$$

where:

- w is the weight vector,
- x is the input feature vector,
- b is the bias term,
- sign(·) is the sign function determining the class label.

K-Nearest Neighbours [23] algorithm is used to detect sleep disorders based on the distance between similar data points in the feature space. The concept behind KNN is to identify patterns and similarities by analysing the nearest neighbours of a given instance. It gives an easy-to-understand analysis on sleep disorder diagnosis based on previous data.

Decision Tree [19] technique is used to develop a model which predicts the sleep disorder classes via a series of binary judgements based on input features. The clear format is easy to interpret. This can be beneficial in the detection of significant elements that have an effect on sleep health and enhance the precision of diagnosis.

Artificial Neural Networks [21] are used to model complex relationships in the data set and to learn from the input features to classify sleep disorders. The MLP architecture enables to learn complex patterns in sleep data, which results in improved prediction skills and overall diagnosis results.

A Voting Classifier – This is a combination of many models. The models used are DT and Bagging Classifiers using RF. The ensemble approach increases the classification rate, reduces the error rate and provides a more stable and reliable prediction for sleep disorders by combining the strengths of the individual algorithms.

$$\hat{y} = arg\,max \frac{1}{N} \sum_{i=1}^{N} p_i(c|x)(3)$$

IV. RESULTS AND DISCUSSION

1) Accuracy: The accuracy of test is the capability of the test to correctly differentiate between the patient and healthy. A test's accuracy can be assessed by determining the percentages of true positive and true negative cases in all cases tested. This can be expressed mathematically as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} (4)$$

2) Precision: Proportion of cases or samples correctly classified out of the total number of samples that are labeled as positive. And the formula for calculating the precision is given by:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} (5)$$

3) Recall: Recall measures a ML model's ability to recover all of the relevant instances of a given class. It is the ratio of true positive prediction over the total positive prediction and it shows how complete is the model in covering positive instances of a class.

$$Recall = \frac{TP}{TP + FN} (6)$$

4) F1-Score: F1 score is a ML evaluation statistic to estimate the accuracy of the model. It is a combination of precision and recall scores of a model. The accuracy measure is the percentage of correct predictions of the model on the total data set.

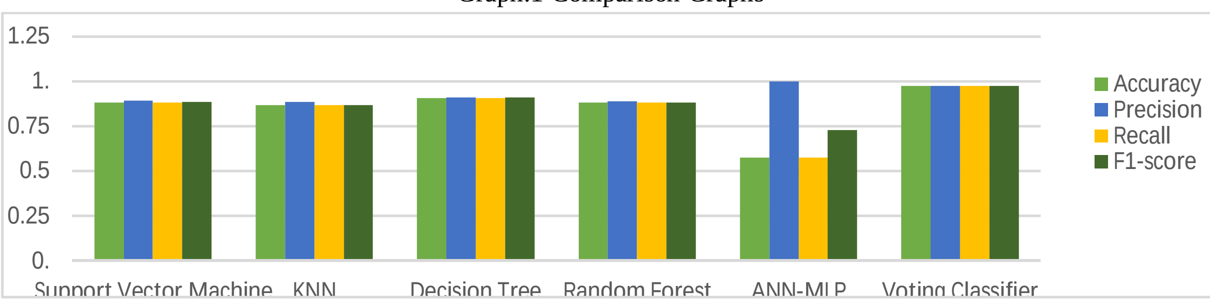
$$F1Score = 2 * \frac{RecallXPrecision}{Recall + Precision} * 100(7)$$

The accuracy, precision, recall and F1-score for each method is explored in Table 1. All the metrics are 0.973 and Voting Classifier has the highest. Metrics of other algorithms are also included 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, the accuracy is depicted with light green colour, precision in blue, recall in light yellow and F1-score in green. The Voting Classifier performs better than the other algorithms for all the metrics, with the highest values with the rest of the models. These facts are illustrated in the above graph.

V. CONCLUSION

The ML algorithms used in this article have shown that classification of sleep disorder can be realized by using public Sleep Disorder Data set. The VC, constructed using bagging with RF and DT obtained the maximum accuracy as compared to a selection of DL and classical ML techniques. The performance was good in all the evaluation matrices with accuracy 97.3%, precision 97.3%, recall 97.3% and F1-score 97.3%. These results also show that the VC developed here is a very reliable and robust approach for classifying sleep disorders. The results presented below provide consistent improvements in practically all evaluated measures which shows that the model can be effective in delivering accurate and quick diagnosis of sleep problems, therefore helping the patient and improving the clinical decisions. With the high classification accuracy, the Voting Classifier may be recommended as the useful equipment to automate the process of Sleep disorders' diagnostic, thus more accurate diagnoses and better prognosis in individuals with Sleep disorders are promoted.

The scope of this research for the future will be exploring other advanced ML methods to achieve high accuracy in sleep disorder categorisation, specifically DL architectures like the CNN and recurrent networks. The system's prediction powers could be improved by including real-time data from wearable devices. In addition, the generalisation of the model can be further enhanced by further expanding the variety of population and sleep disorders in the data set.

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.