International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 1 (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 22, No. 1, 2026

Peer Reviewed, Referred & Indexed Journal

Research

HYBRID ENSEMBLE VOTING MODEL FOR ENHANCED SLEEP DISORDER DIAGNOSIS

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Abstract: Since sleep-related problems have a substantial impact on people's health and quality of life, accurate classification of sleep disorders is crucial for efficient diagnosis and treatment. Even though individual deep learning and machine learning models have shown encouraging outcomes, model bias and overfitting frequently limit their performance. This study offers an ensemble learning-based extension for the categorization of sleep disorders that integrates predictions from several machine learning models in order to overcome these difficulties. To increase robustness and classification accuracy, the outputs of optimized base classifiers are aggregated using a voting classifier. Experiments on the Sleep Health and Lifestyle Dataset show that the suggested ensemble strategy outperforms individual models with an accuracy of 97.3%. Additionally, to improve system usability and real-time user engagement, a Flask-based web interface with secure user authentication is created. The suggested extension offers an automated framework for diagnosing sleep disorders that is dependable, accurate, and easy to use.

Keywords— Sleep Disorder Classification, Ensemble Learning, Voting Classifier, Machine Learning, Artificial Neural Network, Flask Framework, Healthcare Analytics.

Received: 31-01-2026 Accepted: 05-03-2026 Published: 12-03-2026

1. INTRODUCTION

A good night's sleep is essential for maintaining both your physical and mental wellbeing. A good night's sleep fortifies the body and improves memory and cognitive retention. Sleep quality has an impact on cognitive function, especially in young people and elderly drivers who are more likely to be involved in incidents. Not getting enough sleep can cause a variety of health issues, including diabetes, heart disease, and exhaustion. Manual study of polysomnography (PSG) recordings by physicians, specialists, medical professionals, and experts may result in different interpretations of sleep phases.

Manually categorizing sleep stages is time-consuming and prone to inaccuracy. Every year on World Sleep Day, Philips conducts a poll to determine how people think and behave around sleep. Throughout 2021, the research had an impact on roughly 13,000 people in 13 nations. Although 55% of respondents stated they were generally satisfied, 47% were unhappy with the quality of their sleep. Sleep apnea, sleeplessness, and the 2019 coronavirus disease (COVID) pandemic all contributed to their difficulty falling asleep. According to the study, 37% of respondents reported that the epidemic made it harder for them to sleep soundly. Furthermore, 37% of respondents reported difficulty falling asleep, 29% snore, 22% had a sleep disorder related to working shifts, and 12% had sleep apnea. Medical practitioners and sleep specialists can assess the quality of sleep by studying the sleep system, which is separated into stages. Your sleep cycle has five stages: rapid-eye movement (REM), non-REM, profound sleep, and awakening. People are in the waking stage of awareness when they are fully aware of their immediate environment. During our conscious states, our brain waves are rapid and unpredictable. The first stage of sleep, N1, is defined by relaxed muscles and sluggish brain waves..

2. LITERATURE SURVEY

Sleep instability can be assessed using cyclic alternating patterns, which are long-lasting periodic activity with two alternate EEG patterns. Each one-second epoch of the electroencephalogram signal is visually inspected by experts to rate this pattern, which is a laborious and prone process. To overcome these challenges, a home monitoring system was developed that automatically scores the cyclic alternating pattern by analyzing a single electroencephalogram derivation. Two recurrent networks (long short-term memory and gated recurrent unit) and one one-dimension convolutional neural network were developed and tested in order to determine the optimal classifier for the cyclic alternating pattern phase. The best accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (76%, 75%, 77%, and 0.752) are found in the network with long short-term memory. Performance metrics of 76%, 71%, 84%, and 0.778 were obtained by subjecting the classified epochs to a finite state machine in order to identify cyclic alternating pattern cycles. Because the performance is in the upper bound of the experts' projected agreement range and far higher than the inter-scorer agreement of many experts, the clinical analysis device is usable [6].

Children's complicated sleep structures necessitate pediatric sleep staging, even with advancements in autonomous sleep staging for adults. Physicians' epoch-by-epoch annotation burden is significantly reduced by semi-supervised learning, which trains networks with both labeled and unlabeled data. Semi-supervised methods like as pseudo-labeling are useless due to the class-imbalance issue in the sleep staging task. In order to provide more reliable pseudo-labels for network enhancement, this study suggests a Bi-Stream Adversarial Learning network (BiSALnet). Adversarial learning is used by the teacher and student branches of two-stream networks. The discriminator enhances its discrimination while the similarity measurement function lessens the divergence between the outputs from the Student and Teacher branches. To capture the relevant feature distribution properties for the Student branch, we employ a strong symmetric positive definite (SPD) manifold structure. Through the combination of convolutional features and SPD matrix nonlinear complex information, the attention feature fusion module enhances the classification of sleep stages. Pediatric data from a nearby hospital is used to assess the BiSALnet. Experiments show that our method obtains 0.80 classification accuracy, 0.73 kappa, and 0.76 F1-score. We use the well-known public dataset Sleep-EDF to show the generality of our approach. Our BiSALnet performs well with 0.91 accuracy, 0.85 kappa, and 0.77 F1-score. With minimal labeled data, we were able to attain comparable results using cutting-edge supervised methods [7].

Sleep disorders are diagnosed and treated using sleep scoring. Because sleep specialists must visually review large volumes of data, which is time-consuming, subjective, and prone to error, automated sleep scoring is crucial. For the diagnosis and investigation of sleep issues, automated sleep stage classification is crucial. This study suggests a reliable three-module approach for single-channel EEG-based automatic sleep stage classification. The first module used multiscale principal component analysis to denoise Pz-Oz electrode signals. In the second module, the discrete wavelet transform (DWT) is used to extract the most informative features, and DWT subband statistical values are generated. In the third module, retrieved characteristics were fed into an ensemble classifier that used a rotational support vector machine. By merging SVM with main component analysis, the proposed classifier enhances SVM classification. With a Cohen's kappa coefficient of 0.88, the five-stage sleep classification had 91.1% accuracy and 84.46% sensitivity for all patients. Findings on classification performance demonstrate that a single-channel EEG can be used for home care and medical applications to track sleep [8].

With growing public awareness of sleep disorders, primary care physicians and other health care professionals are referring more patients to sleep specialists for sleep testing. The sleep study report's technical and clinical facts must be understood. It illuminates sleep pathophysiology and patient symptoms. This article shows primary care physicians how to easily interpret polysomnography results. This helps understand and treat sleep abnormalities and consequences [9].

Since skin cancer is one of the most prevalent and deadly types of cancer, patient outcomes depend heavily on early diagnosis and detection. Particularly in lesion detection and classification, deep learning (DL) can enhance automated skin disease diagnosis. Complex features, image noise, intra-class variance, inter-class similarity, and data imbalance are challenges for DL-based skin cancer detection. This review discusses recent studies and novel approaches such as feature fusion, hybrid models, and data augmentation. The integration of DL models into clinical processes is also covered in the study, demonstrating how deep learning could revolutionize clinical decision-making and the identification of skin diseases. This thorough and transparent evaluation synthesizes current deep learning advances for skin disease diagnosis using a novel

PRISMA-based methodology and challenge-oriented taxonomy. For next dermatological AI research, novel approaches such as hybrid CNN-Transformer architectures and uncertainty-aware models are highlighted [10].

3. METHODOLOGY

i) Proposed Work:

The suggested methodology builds on the baseline sleep disorder classification system by using an ensemble learning approach to improve prediction accuracy and robustness. Initially, the Sleep Health and Lifestyle Dataset is preprocessed to account for missing values, standardize feature scales, and decrease bias. Multiple optimized base classifiers, such as Support Vector Machine, k-Nearest Neighbors, Decision Tree, Random Forest, and Artificial Neural Network, are trained independently using adjusted hyperparameters. The predictions made by these models are then coupled with a voting classifier, which aggregates the individual outputs to form a final class label, eliminating model bias and overfitting. Performance is evaluated using standard classification measures, and the ensemble model improves accuracy by 97.3%. To support real-time use, the final ensemble model is incorporated into a Flask-based web application with secure user identification, allowing for quick user interaction and deployment in actual sleep disorder diagnosis settings.

The proposed project aims to enhance the sleep disorder classification system by utilizing an ensemble learning framework that combines optimized machine learning and deep learning models for improved diagnostic accuracy and robustness. Individual classifiers, including Support Vector Machine, k-Nearest Neighbors, Decision Tree, Random Forest, and Artificial Neural Network, are trained on preprocessed sleep health and lifestyle data. Each model contributes a prediction based on previously acquired patterns, and a voting classifier is used to combine these results into a single, final judgment. This ensemble technique eliminates individual model restrictions, lowers overfitting, and increases generalization, resulting in a 97.3% improvement in accuracy over standalone classifiers.

In addition to enhancing classification performance, the proposed project focuses on practical deployment and usability. The completed ensemble model is linked into a Flask-based web application, allowing for real-time prediction and user interaction. Secure user authentication procedures are implemented to control access to sensitive data and system functions. This deployment-oriented strategy changes the suggested system from a theoretical model to a user-friendly diagnostic assistance tool, making it suited for real-world healthcare settings and aiding effective sleep problem assessment by medical experts.

ii) System Architecture:

The proposed approach for sleep disorder categorization uses a combination of machine learning and deep learning techniques, with the Sleep Health and Lifestyle Dataset serving as the foundation. It starts with data pretreatment, which involves cleaning and normalizing raw sleep and lifestyle data to account for missing, noisy, or biased information. The preprocessed data is then fed into a number of machine learning models, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Decision Tree, Random Forest, and Artificial Neural Network (ANN). These models are refined by a Genetic Algorithm, which fine-tunes each algorithm's parameters to increase classification accuracy. The ANN, with its deep learning capabilities, is praised for its capacity to achieve greater accuracy. The system architecture ensures reliable data handling and classification, making it suitable to a wide range of patient groups. The end result is a highly accurate classification of sleep disorders, offering critical insights for better diagnosis and therapy, all while reducing computing time and enhancing performance efficiency..

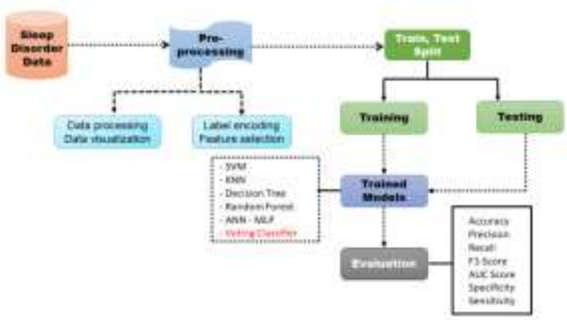

Fig 1 Proposed architecture

iii) Modules:

a. Data Collection and Acquisition Module

This module is responsible for collecting the Sleep Health and Lifestyle Dataset from Kaggle, which contains attributes related to sleep patterns, lifestyle habits, and health indicators required for sleep disorder classification.

b. Data Preprocessing and Normalization Module

The collected data is cleaned by handling missing values and normalized to ensure uniform feature scaling. This step reduces noise and improves the learning efficiency of machine learning models.

c. Feature Selection Using Genetic Algorithm Module

This module applies a Genetic Algorithm to select the most relevant features by iteratively performing population initialization, fitness evaluation, selection, crossover, and mutation, resulting in an optimized feature subset.

d. Model Training Module

Optimized features are used to train multiple machine learning and deep learning models, including KNN, SVM, Decision Tree, Random Forest, and ANN, enabling individual learning of sleep disorder patterns.

e. Ensemble Voting Module

Predictions from all trained models are combined using a voting classifier to generate a final decision. This ensemble approach improves robustness, reduces overfitting, and enhances classification accuracy.

f. Model Evaluation Module

The performance of individual and ensemble models is evaluated using accuracy, precision, recall, and F1-score metrics to ensure reliable assessment of classification effectiveness.

g. Web Deployment Module

The final ensemble model is deployed using a Flask-based web application with secure user authentication, allowing real-time prediction and user interaction in practical diagnostic scenarios.

IV.ALGORITHMS

a) k-Nearest Neighbors (KNN)

The k-Nearest Neighbors algorithm is a distance-based supervised learning method that classifies sleep disorders by comparing a test sample with its k nearest training samples in the feature space. It uses distance metrics such as Euclidean distance to measure similarity between data points. In the proposed system, KNN benefits from Genetic Algorithm-based feature selection, which reduces dimensionality and improves neighborhood accuracy. The final class label is assigned based on majority voting among the nearest neighbors, making KNN effective for capturing local patterns in sleep-related data.

b) Support Vector Machine (SVM)

Support Vector Machine is a powerful classification algorithm that identifies an optimal hyperplane to separate different sleep disorder classes with maximum margin. It is particularly effective for high-dimensional datasets and can handle nonlinear relationships using kernel functions. In this work, SVM is trained on optimized features obtained through Genetic Algorithm selection, which enhances its generalization capability and reduces classification error. This makes SVM a reliable classifier for distinguishing complex sleep disorder patterns.

c) Decision Tree (DT)

Decision Tree is a rule-based classification algorithm that divides the dataset into smaller subsets based on feature conditions, forming a hierarchical tree structure. Each internal node represents a decision rule, while leaf nodes correspond to class labels. The simplicity and interpretability of Decision Trees make them suitable for understanding how sleep-related features influence classification outcomes. In the proposed system, Decision Trees provide fast predictions and serve as an important component in the ensemble framework.

d) Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using random subsets of training data and features. The diversity among trees helps reduce overfitting and improves overall prediction stability. In the proposed approach, Random Forest effectively handles noisy and imbalanced sleep data, contributing robust predictions to the ensemble voting classifier. Its ability to model complex feature interactions enhances classification reliability.

e) Artificial Neural Network (ANN)

Artificial Neural Network is a deep learning model composed of interconnected neurons organized in multiple layers. It learns complex nonlinear relationships between input features and output classes through backpropagation. In this system, ANN plays a key role by achieving high classification accuracy due to its capability to capture intricate sleep disorder patterns. When combined with optimized features, ANN significantly improves learning efficiency and overall model performance.

f) Genetic Algorithm (GA)

The Genetic Algorithm is an evolutionary optimization technique inspired by natural selection. It is used in this work for selecting the most relevant features and tuning model parameters. GA operates through population initialization, fitness evaluation, selection, crossover, and mutation to iteratively improve solutions. By eliminating irrelevant and redundant features, GA enhances model accuracy while reducing computational complexity.

g) Ensemble Voting Classifier

The ensemble voting classifier combines the predictions of all trained models to generate a final classification decision. Each classifier contributes equally through majority voting, ensuring balanced decision-making. This ensemble approach minimizes the weaknesses of individual models, reduces overfitting, and improves generalization. As a result, the proposed ensemble model achieves a superior classification accuracy of 97.3%, demonstrating its effectiveness in sleep disorder diagnosis.

4. EXPERIMENTAL RESULTS

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

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

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Fig 2:Results no disease Predicted

Fig 3:Disease Predicted

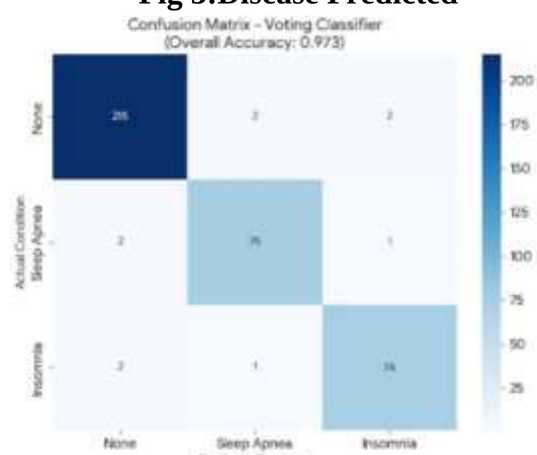

Fig 4: Confusion Matrix of Voting Classifier

This figure illustrates the confusion matrix of the proposed ensemble voting classifier for sleep disorder classification. The model accurately classifies most instances of normal sleep, sleep apnea, and insomnia, achieving an overall accuracy of 97.3% with minimal misclassification. The strong diagonal dominance indicates high reliability and robust multi-class prediction performance.

Fig3 Multi-class ROC Curve of Voting Classifier

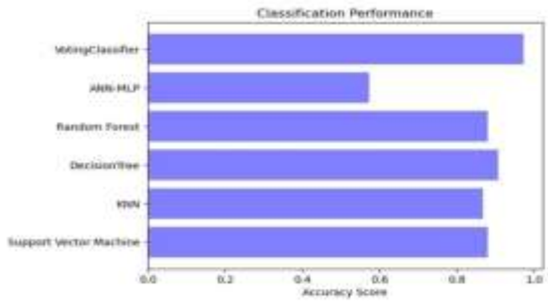

Fig 5: Accuracy Performance Comparison

This figure compares the accuracy of different machine learning and deep learning models for sleep disorder classification. The ensemble voting classifier outperforms individual classifiers, achieving the highest accuracy of 97.3%. The results demonstrate the effectiveness of ensemble learning in improving overall classification performance.

5.CONCLUSION

This paper introduces an improved model for identifying sleep disorders that combines MLAs with a genetic algorithm to successfully determine the optimal values for each model's hyperparameters. This paper used a real-world dataset, the Sleep Health and Lifestyle Dataset, to evaluate several cutting-edge MLAs for classifying sleep issues. Even without expert qualities, MLAs may be able to identify sleep disorders based on high-dimensional sleep data. The optimized ANN with GA outperformed all other MLAs, with 92.92% accuracy. The exam results showed an F1-score of 91.93%, recall of 93.80%, and accuracy of 92.01%. Despite this, there is insufficient information. The purpose of this study was to investigate challenges in classifying sleep disorders using MLA. Large datasets are necessary to train and evaluate models for this challenge. GA-enhanced MLAs improve classification accuracy for sleep disorders. In the future, researchers will employ unsupervised learning to build MLAs, test them on a new model, and compare their performance to the best models on the market.

6.FUTURE SCOPE

This study will broaden its focus to look at more advanced machine learning techniques in an effort to improve the classification accuracy of sleep disorders. Recurrent networks and convolutional neural networks (CNNs), two varieties of deep learning architectures, may be used in these methods. Incorporating real-time data from wearable devices might enhance the system's predictive capabilities. Increasing the variety of the dataset in terms of individuals and sleep disorders also helps to improve the generalisability of the model.

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