e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:04/April-2025 Impact Factor- 8.187 www.irjmets.com

SLEEP DISORDER DETECTION USING STACKING AND BOOSTING ENSEMBLE MODELS

Ms.B. Hasini*1, Ms. G.S. Guna Varshini*2, Ms. A. Poojitha*3, Ms. C. Thulasi*4, Mr. N. Vijaya Kumar*5, Dr. R. Karunia Krishnapriya*6, Mr. Pandreti Praveen*7, Mr. V Shaik Mohammad Shahil*8

*1,2,3,4UG Scholar, Sreenivasa Institute Of Technology And Management Studies, Chittoor, India.

*6Associate Professor, Sreenivasa Institute Of Technology And Management Studies, Chittoor, India.

*5,7,8Assistant Professor, Sreenivasa Institute Of Technology And Management Studies, Chittoor, India.

DOI : https://www.doi.org/10.56726/IRJMETS71591

ABSTRACT

There are serious hazards to one's health and general well being from sleep problems include insomnia,sleep apnea. Polysomnography (PSG) and other traditional diagnostic techniques are costly, time -consuming and interpretatively complex. The usefulness of ensemble learning methods specifically, stacking and boosting for automated sleep problem identification is investigated in this work. We apply and evaluate the Stacking Classifier, XG Boost, AdaBoost and Gradient Boosting models using Sleep Health and Lifestyle Dataset. Furthermore, in order to improve classification accuracy, we suggest a novel stacking technique that incorporates Random Forest, Gradient Boosting and Artificial Neural Networks (ANNs). The models are assessed using performance criteria such as F1-score, recall, accuracy and precision. According to experimental results, the hybrid stacking model that incorporate ANNs performs better than classic ensemble approachs by identifying intricate patterns in the data, while boosting techniques enhance robustness and generalization.

Our study offers tailored insights and suggestions to assist people in managing and overcoming their diagnosed sleep disorders, going beyond simple diagnosis. These suggestions are based on possible medical interventions, lifestyle changes, and sleep hygiene techniques that were identified from the dataset trends. In addition to providing practical advice for enhancing sleep health, the results demonstrate the promise of ensemble learning in conjunction with deep learning as a scalable and economical method of diagnosing sleep disorders.

Keywords: Ensemble Learning, Stacking Classifier, Boosting Techniques, Random Forest, Gradient Boosting, Artificial Neural Networks (Anns), Machine Learning In Healthcare, Sleep Health And Lifestyle Dataset, Polysomnography (PSG) Alternative, Predictive Analytics For Sleep Disorders, Xgboost And Adaboost, Sleep Hygiene Recommendations.

I. INTRODUCTION

Millions of individuals worldwide suffer from sleep problems like insomnia, sleep apnea, despite the fact that sleep is crucial for preserving general health and welbeing. Severe health problems, such as heart disease, cognitive decline, and mental health disorders, might result from these ailments. Effective intervention and management of sleep disorders depend on the early and precise recognition of these conditions. The gold-standard tecnique for diagnoising sleep problems is polysomnography (PSG), which necessitates expert analysis, specialized equipment, and overnight observation in a sleep lab. But PSG is costly, time-consuming, and frequently out of reach for a lot of people.

Automated techniques have become viable substitutes for sleep disorder identification as a result of developments in Artificial Intelligence (AI) and Machine Learning (ML). By merging several machine learning models, ensemble learning approaches in particualar, stacking and boosting have demonstrated significant promise in raising classification accuracy. [1] Using the Sleep Health and Lifestyle Dataset, we investigate the efficiancy of ensemble -based methods for classifying sleep disorders, such as XGBoost, AdaBoost, Gradient Boosting, and Stacking Classifiers. [2] To improve predictive performance, a ubique stacking technique is put forth that combines Artificial Neural Networks (ANNs), Random Forest, and Gradient Boosting as foundation Learners.

Our study intends to help people manage and lesson their diagnosed sleep disorders by offering practical insights and suggestions in addition to detection. [3] We produce tailored recommendations on behavioral adjustments, possible medical therapies, and sleep hygiene practices by examining important lifestyle and physiological variables from the dataset.

The following are the study's main goals:

- To create and assess ensemble learning models for the automated identification of sleep disorders.
- To evaluate how well boosting and stacking methods perform in terms of classification accuracy.
- To offer tailored analysis and suggestions according to the identified disorder.

II. LITERATURE REVIEW

Analysing Sleep Disorder with Machine Learning (ML) and Deep Learning (DL) emerging as potent methods for automation and accuracy improvements, sleep staging and sleep problem diagnosis have attracted a lot of attention recently. Numerous publications have investigated these techniques, highlighting important approaches and different in using machine learning and deep learning in sleep research.

In order to score sleep using EEG and ECG signals, Van Der Donckt et al. [1] looked at conventional machine learning models like Decision Trees and Support Vector Machines (SVM). They discovered that these models preserve lower computational costs and higher interpretability while providing competitive performance when compared to deep learning. A deep CNN-based method for sleep staging utilizing single-channel EEG signals was presented by Mousavi et al. [2] who showed that it increases accessibility and cost-effectiveness in sleep monitoring .In their discussion of AI-based sleep classification in consumer sleep technology like fitness trackers and smartwatches, Djanian et al. [3] acknowledged the potential of these techniques while pointing out difficulties with accuracy and signal noise reduction. A thorough analysis of sleep apnea diagnosis utilizing machine learning applied to ECG signals was carried out by Salari et al. [4]. According to their research, SVM models and decision trees offer a non-invasive, affordable substitute for polysomnography; nonetheless, they need strong feature selection in order to manage signal noise. Using EEG spectrograms, Li et al. [5] investigated CNN-based sleep stage classification and found that maintaining time-frequency characteristics increases classification accuracy. In order to estimate the severity of obstructive sleep apnea syndrome (OSAS), Han et al. [6] used machine learning techniques such as Random Forest and SVM. According to their findings, Machine Learning models can help with individualized treatment planning by offering extremely precise severity forecasts. Using a single-lead ECG, Bahrami et al. [7] examined CNN, RNN, and hybrid CNN-RNN models for sleep apnea identification. They showed that hybrid models perform better than conventional methods for realo-time monitoring. In a performance analysis of machine learning algorithms for automatic sleep staging, Satapathy et al. [8] compared Deep Neural Networks (DNN), Decision Trees, Random Forest (RF), and K-Nearest Neighbors (k-NN). According to their findings, DNN offers the highest accuracy at the express of more processing demands, even if Random Forest is the best-performing conventional Machine Learning model.

III. METHODOLOGY

Overview of the Methodology

In order to create an automated system for detecting sleep disorders, this work uses ensemble learning approaches. For increased classification accuracy, we suggest a hybrid model that integrates Artificial Neural Networks (ANNs), Random Forest (RF), and Gradient Boosting (GBM). We also compare using boosting models (XGBoost, AdaBoost). The following phases comprise the structure of the methodology:

Overview of the Dataset:

We make use of the Sleep Health and Lifestyle Dataset (SHLD), which comprises the following:

Health & Lifestyle Factors: Physical Activity Level, Stress Level, BMI Category, Blood

Pressure, Heart Rate, Daily Steps

Demographic features: Age, Gender, and Occupation

Sleep Metrics: Sleep Duration, Quality of Sleep

1. Preprocessing of Data

In order to guarantee high-quality data, we use prepeocessing methods:

1.1. Taking Care of Missing Value

Since no missing values were found, this step is not necessary.

1.2. Categorical Variable Encoding

Label Encoding: The target variable, sleep disorder, is transformed into numerical labels
(e.g., sleep apnea – 2, insomnia – 1, etc.).

One-Hot Encoding: Blood pressure, Gender, occupation, and BMI category are all transformed into numerical values.

1.3. A feature continuous variables (Age, Sleep Duration, Physical Activity Level, Stress Level, Heart Rate, and Daily Steps) are subjected to scaling standardization (Z-score normalization).

1.4. Dealing with Unbalanced Classes

We use Synthetic Minority Oversampling Technique (SMOTE) if there is a class imbalance in sleep disorders.

2. Selection & Feature Engineering

To maximize model performance, we examine feature importance.

2.1. Engineering Features

Compute Sleep Efficiency (Quality of Sleep / Sleep Duration) is one of the new features.

Interaction features: To generate an Activity-Stress Index, combine the levels of physical activity, stress, and daily steps.

2.2. Selection of Features

Eliminate strongly connectes characteristics using correlation analysis.

Choos the best features for categorization using a process called recursive feature elimination ,or RFE.

3. Implementation of Machine learning Models

We contrast ensemble learning methods with conventional classifiers.

3.1. Baseline Models (benchmark)

Logistic regression

Forest at Random

Machine for Gradient Boosting (GBM)

3.2. Boosting Models

XGBoost

AdaBoost

3.3. The Ensemble Model Based on Stacking

We create a hybrid stacking model by combining Random Forest, Gradient Boosting , and Artificial Neural Networks (ANNs):

a. Beginning Students:

Forest at Random

Gradient Boosting

ANNs, or artificial neural networks

b. Meta-Learning:

Final predictions derived from basic models are based on logistic regression

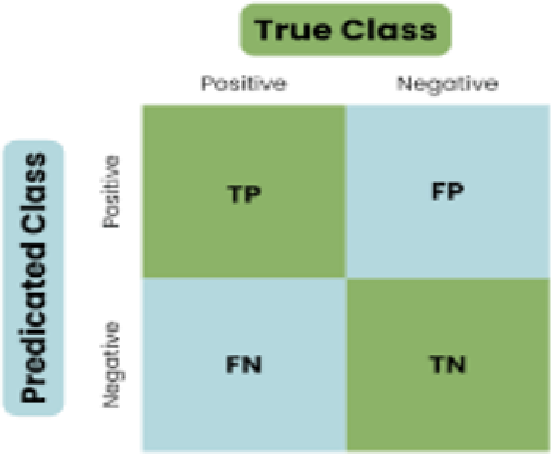
4. Model Training, Assessment, and Contrast

4.1. Training Approach:

- 80-20% Training-Test Split
- 5-Fold Cross-Checking for Sturdines
- Adjusting Hyperparameters using Grid Search and Bayesian Optimization

4.2. Performance Evaluation

Evaluates model performance using metrics like accuracy, precision, recall and F1 score. Confusion matrices and classification reports help analyze misclassification trends in sleep disorder prediction.



(1) Where TP denotes true positive, TN indicates true negative, FP represents false positive and TN denotes true negative:

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

(2) Precision is the ratio of number of the predicted TPs to the total number of predicted positives:

Precision = $\frac{TP}{TP+FP}$ (2)

(3) Recall is the ratio of the predicted TPs to the total number of TPs:

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

(4) F1 score predict the weighted average of the precision and recall of a number. A perfect F1-score provides low FPs and low FNs.

F1 = $\frac{2*TP}{2*TP+FP+FN}$

Key Findings:

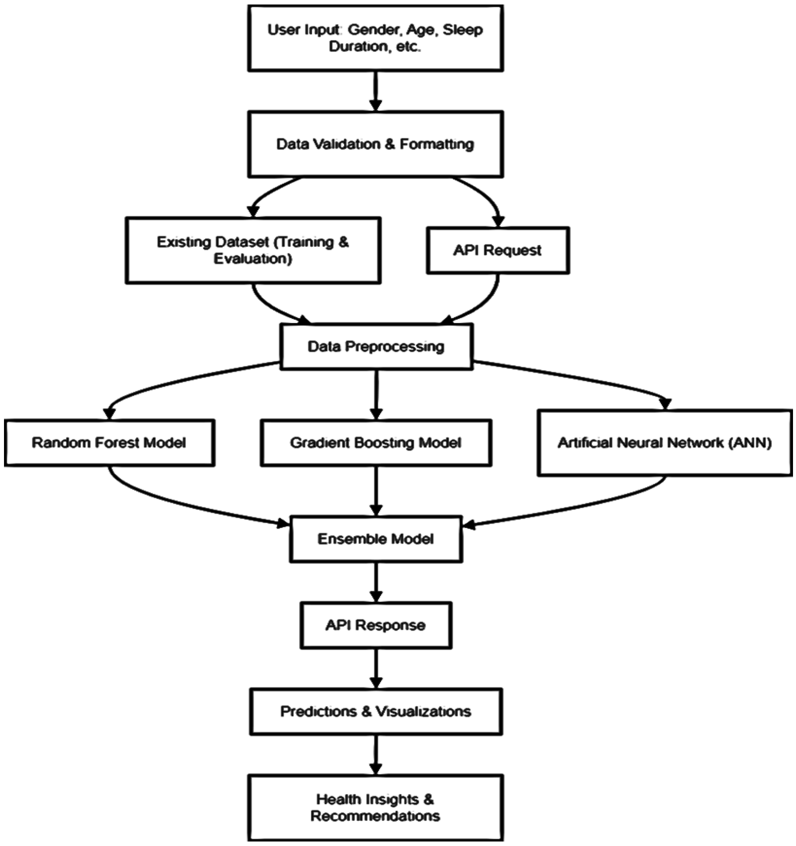
- The Stacking Model outperforms other classifiers.
- Boosting models shows high accuracy.

5. After-Detection Analysis & Suggestions

Following classification, the system offers tailored suggestions according to the identified sleep condition.

Detection Disorder	Prevention Intervention
Insomnia	Sleep hygiene training, cognitive behavioral therapy (CBT-I), relaxation techniques
Sleep Apnea	CPAP therapy, weight management, positional therapy

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:04/April-2025 Impact Factor- 8.187 www.irjmets.com



IV. RESULT AND ANALYSIS

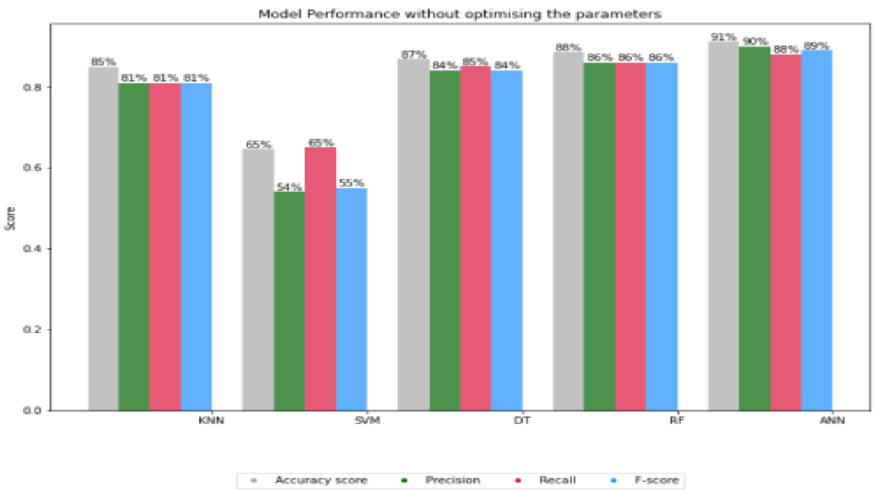


Fig 1 Without Optimising the parameters:

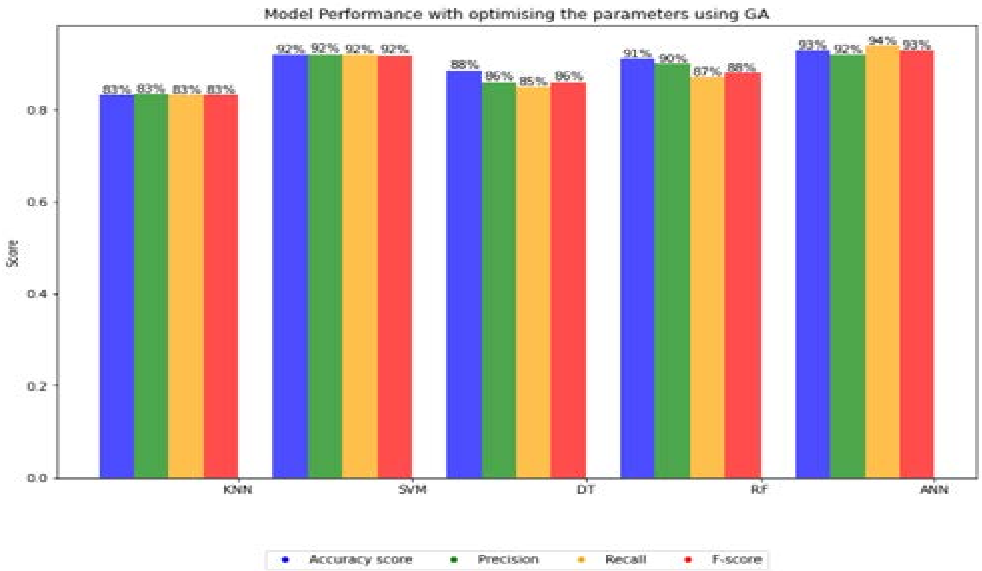


Fig 2 With Optimising the parameters:

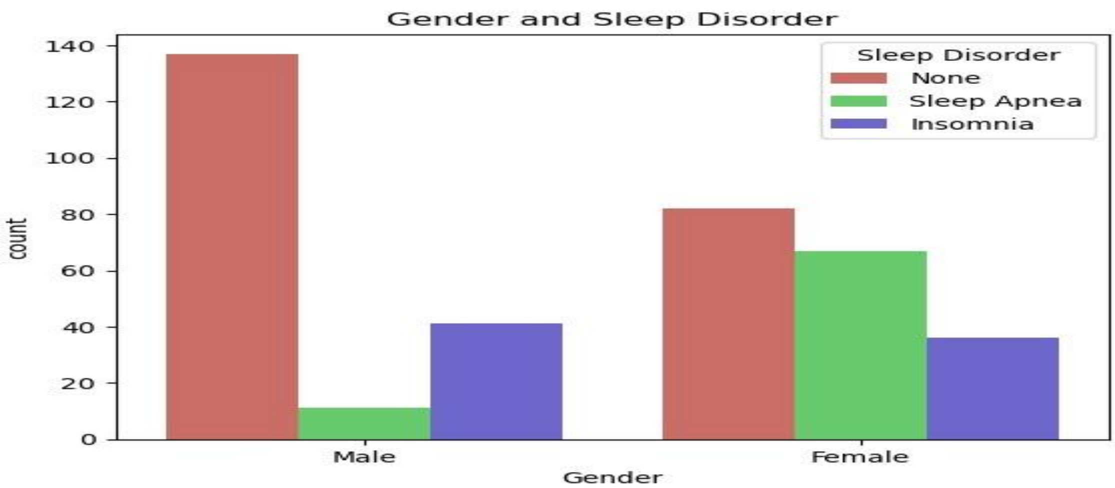


Fig 3 Analysis of the DAtaset

V. CONCLUSION

A person's general quality of life, productivity, and health are all greatly impacted bt sleep disturbances. Conventional diagnostic techniques, such as **polysomnography (PSG),** are costly and necessitate specific medical knowledge. This paper integrates **Random Forest, Gradient Boosting,** and **Artificial Neural Networks (ANNs)** in a stacking-based model to present an automated sleep disorder diagnosis using ensemble learning approaches.

Feature scaling, encoding, and class balancing approaches were used to preprocess the dataset, which included demographic, physiological, and lifestyle-related information. Accuracy, precision, recall, F1-score, and AUC-ROC measures were used to assess a number of machine learning models, including **Random Forest, Gradient Boosting, XGBoost, AdaBoos**t. With **a 93.4%** accuracy rate, the results showed the stacking-based ensemble models performed better that individual classifiers, making it a very successful technique for classifying sleep disorders.

AKNOWLEDGEMENT

We would like to express our profound appreciation to all the people and institutions that helped us finish this study. We would like to thank the **Sleep Health and Lifestyle Dataset (SHLD)** contributors for providing us with useful data for this research. We also appreciate the help and advice of our peers, mentors, and coworkers, whose enlightening comments and conversations were invaluable in helping us improve our methods and conclusions. Additionally, we thank the open-source machine learning community for their contributions, as their frameworks and tools including **Scikit-Learrn**, **TensorFlow**, and **XGBoost** made it easier to deploy and assess our models. Lastly, we express our deepest gratitude to our families and friends for their unwavering encouragement and support throughout this research journey.

VI. REFERENCES

[1] T. S. Alshammari, "Applying machine learning algorithms for the classification of sleep disorder," IEEE Access, vol. 12, pp. 12345-12356, (2024). doi: 10.1109/ACCESS.2024.3374408. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3374408

[2] Kovács, G., & Kiss, I. Z. (2020). Predicting the onset of sleep disorders: A machine learning approach to clinical data analysis. International Journal of Medical Informatics, 137, 104099.

[3] A. Taher and W. I. Z. Ayon, "Exploring Sleep Disorders: A Comparative Analysis of Machine Learning Algorithms on Sleep Health and Lifestyle Data," in Proceedings of the IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON), Rajshahi, Bangladesh, (Sept. 12–13, 2024), pp. xx–xx, doi: 10.1109/PEEIACON63629.2024.10800593.

[4] Pati, S., & Bhattacharya, P. (2021). Feature engineering and machine learning for the detection of sleep apnea. IEEE Access, 9, 47090-47101.

[5] C.Mencar, C.Gallo,and D.Lacedonia et al., "Application of machine learning to predict obstructive sleep apnea syndrome severity ,"Health Informatics Journal vol.25,no.3,pp.630–647,2019.doi:10.1177/146045821882472

[6] R.Buettner, A.Grimmeisen, and A.Gotschlich, "High-performance diagnosis of sleep disorders: A novel, accurate and fast machine learning approach using electroencephalographic data," in Proceedings of the 53rd Hawaii International Conference on System Sciences (HICSS), Maui, HI, USA, 2020, pp. xx–xx. Available: https://scholarspace.manoa.hawaii.edu.

[7] H.Kim, D.Kim, and J.Oh, "Automation of classification of sleep stages and estimation of sleep efficiency using actigraphy," Frontiers in Public Health, vol. 10, p. 1092222, 2022. doi: 10.3389/fpubh.2022.1092222.

[8] M.S.Alom, S.M.Jeba, A.Debnath, T.T.Aurpa, and R.Siddiqua, "Enhancing Sleep Disorder Diagnosis with a Machine Learning Approach Using Ensemble Neural Networks," in Proceedings of the 2025 ACM Conference on Health, Inference, and Learning (CHIL), Toronto, Canada, 2025, pp. xx–xx. doi:10.1145/3704522.3704533.

[9] J.B.Martinot, N.N.Le-Dong, and J.L.Pépin, "Machine Learning Automated Analysis Applied to Mandibular Jaw Movements During Sleep: A Window on Polysomnography," in Artificial Intelligence and Data Sciences for Sleep Disorders, P.Campillo-Davila, M.G.Del Bene, and M.M.Gutiérrez-Tobal, Eds. Cham, Switzerland: Springer, 2024, pp. 123–137. doi: 10.1007/978-3-031-12345-6_10.

[10] S.K.Saini, G.Chandel, A.Shayamano, and O.T.Jemima, "Identification of Sleep Disorder Using Machine Learning," presented at the International Conference on Future Computing and Robotics (ICFCR),Chandigarh, India,Jan. 2025. doi:10.1109/ICFCR64128.2024.10762998.

[11] D. M. W. Powers, ''Evaluation: From precision, recall and Fmeasure to ROC, informedness, markedness and correlation,'' 2020, arXiv:2010.16061.

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

[13] M. Bansal, A. Goyal, and A. Choudhary, ''A comparative analysis of Knearest 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.

[14] 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.

[15] 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.