Addressing Behavioral Patterns of Late Sleepers Using a Supervised Learning Approach

Neloy Pramanik Supto[1*], Rajat Chowdhury[2] and Mushfiqur Rahman[3]

[1] Dept. of Computer Science & Engineering Daffodil International University, Dhaka, Bangladesh,
[2] Dept. of Computer Science & Engineering Daffodil International University, Dhaka, Bangladesh,
[3] Dept. of Computer Science & Engineering Daffodil International University, Dhaka, Bangladesh,

{pramanik15-4349*,rajat15-4271,mushfiqur.cse}@diu.edu.bd

Abstract. Sleep disorders become a public health issue in view of the association with numerous detrimental physical, cognitive, and emotional outcomes. The problem has been focused on toward predicting and classifying medical conditions related to late-night sleeping habits through supervised machine learning applied on behavioral and lifestyle data. Anonymized secondary data on self-reported sleep routines, psychological symptoms, and related demographic variables were pre processed to counter class imbalance by oversampling employing SMOTE. Feature selection is done using Mutual Information. The four classifiers considered include Random Forest, XGBoost, Decision Tree, and K-Nearest Neighbor, which are compared. The XGBoost had the highest classification accuracy of 97.06%, followed by Random Forest at 96.30% and Decision Tree at 95.79%, showing the capabilities of ensemble classifiers in dealing with heterogeneous health data prediction problems. A rule-based recommendation engine was also added to the system to provide personalized recommendations for sleep based on predicted risk classes, user sleep patterns, and BMI score. The data tends to acknowledge that data-driven machine-learning systems can empower large-scale early detection and individualized intervention for sleep disorder health problems, especially in resource-constrained academic environments. Such results add to the body of literature extolling digital behavioral health analytics and point to possible avenues of appeal for tech-enabled health promotion among at risk students. The developed ML pipeline has high reproducibility and generalization capability to be deployed in scalable and interpretable manner for behavioral health analytics.

Keywords: Machine Learning, Sleep Pattern, Classification, Health Prediction, Supervised Learning

M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_24

1 Introduction

Sleep health-related issues are the critical area of focus in digital healthcare, having a deeper impact on physical well being, mental stability, and performance academically or occupationally. Students are likely to have erratic sleeping habits because of academic stress, constantly being on their digital devices, and disturbed lifestyles. The traditional methods of blockage diagnoses are polysomnography which is dependable yet costly; hence these methods cannot be used for screening large populations or many subjects, thus opening the door for data-driven solutions. Recent advances in the supervised machine-learning system have enabled the detection and accurate classification of various sleep-related health problems, considering behavioral, demographic, or lifestyle data. In previous works, however, sensor-type signals were usually considered, or small, homogeneous samples were used, limiting the scope of their conclusions. This investigation addresses the aforementioned issue by working on a non-sensory-based questionnaire study out of which multiple predictive models are being developed for medical conditions associated with delayed sleep practices and risk factors therein for heterogeneous student populations. This activity has three objectives: (1) to compare performance of classification for Machine learning models like Random Forest, XGBoost, Decision Tree, and K-Nearest Neighbors on sleep and lifestyle datasets; (2) to provide remedies to imbalanced data using newer techniques such as SMOTE techniques and feature selections; and (3) to bring in a customized recommendation framework that will recommend sleep health advice to the person based on his risk profile and anthropometric data. Hence, scalable and interpretable ML solutions presented by this study are a cheap, technically viable way for early detection and intervention in sleep health that is done on a tailored basis, especially in less resourceful areas where the mathematically challenged students in need may reside.

2 Dataset

The data were primarily collected using a structured Google Form. The form link was distributed among diverse participants across various settings, including university campuses, residential halls, urban areas, rural regions, and public streets. In addition to online responses, data were also gathered through in-person interactions and verbal communication with individuals. The information obtained through these conversations was subsequently entered into the Google Form to maintain consistency in data recording. Specific locations in Bangladesh where data collection was conducted include cities such as Rajbari, Kushtia, Sirajgonj, and Dhaka. Participants were also approached in various villages within these cities, as well as at Daffodil International University and its associated residential halls (23.875816, 90.323511). Figure 1 shows that this broad geographic coverage contributed to the richness and variability of the dataset. The dataset consists of 2,610 entries with 20 features of categorical, numerical, or multi-select textual nature. It features demographics (age, gender, occupation, weight, height), sleep schedule (time to bed and time to wake up), sleep quality (average time of sleep and time they take to fall asleep), sleep disturbances (breathing difficulties, restlessness,ary medical condition), behavioral causes (reasons for staying up late), health effects (side effects of poor sleep), coping mechanisms (methods to cope with sleep deprivation), and environment (rating of the comfort level of the sleeping environment).

Because the dataset was self-reported, several measures to mitigate reporting bias were performed such as random manual verification and consistency checks. Physiological sensor data (EEG, HRV) will be included in the future to cater for validation of behaviour inputs.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2610 entries, 0 to 2609
Data columns (total 21 columns):
 #   Column                                                                   Non-Null Count  Dtype
---  ------                                                                   --------------  -----
 0   Your Age                                                                 2610 non-null   object
 1   What is your weight                                                      2610 non-null   float64
 2   Your Height                                                              2610 non-null   float64
 3   What is your gender?                                                     2610 non-null   object
 4   What is your occupation?                                                 2610 non-null   object
 5   What time do you usually go to bed?                                      2610 non-null   object
 6   What time do you usually wake up on working days?                        2610 non-null   object
 7   What time do you usually go to bed on weekends?                          2610 non-null   object
 8   What time do you usually wake up on weekends?                            2610 non-null   object
 9   How long does it take you to fall asleep after going to bed?             2610 non-null   object
 10  How many hours of sleep do you get on average per night?                 2610 non-null   object
 11  What are the main reasons you sleep late?                                2610 non-null   object
 12  Do you have difficulty falling asleep?                                   2610 non-null   object
 13  Do you experience breathing difficulties while sleeping                  2610 non-null   object
 14  Do you experience restless legs or involuntary movements during sleep?   2610 non-null   object
 15  Do you have any medical conditions that might affect your sleep?         2610 non-null   object
 16  Do you experience any of the following side effects from late sleeping?  2610 non-null   object
 17  How often do you find it hard to concentrate due to lack of sleep?       2610 non-null   object
 18  What strategies do you use to cope with the side effects of late sleeping? 2610 non-null object
 19  How would you rate the comfort of your sleeping environment              2610 non-null   int64
 20  Medical Condition Category                                               2610 non-null   object
dtypes: float64(2), int64(1), object(18)
```

Fig. 1. Data Collection Questions.

3 Related Works

Machine learning (ML) applications in sleep research have seen considerable expansion in areas pertaining to sleep staging, disorder detection, behavioral health modeling, and genomic studies.

A paper used the ML approaches of SVM, KNN, and others in optimizing sleep schedules for individual college students, with accuracies surpassing 65% [1]. In another study convolutional and recurrent neural networks have been applied to sleep staging and narcolepsy diagnosis, exhibiting the learned power of deep learning in the execution of complex clinical tasks[2]. A research work presented a hybrid approach using feature selection and logistic regression, producing an accuracy of 95% in the diagnosis of early-stage sleep disorders [3].

LSTM networks have been applied by [4] to HRV signals to carry out sleep stage classification, with the accuracy achieving 77%. Extreme learning machines together with particle swarm optimization have also shown promising results [5]. Automated multiclass classification of sleep disorders using ensemble approaches like Random

Forest and SVM was again broached [6]. Such challenges are still noted for model generalization, class imbalance, and acceptance of personalized recommendations by [9]. EEG-based features with nonlinear dynamics improved the accuracy of detection of sleep disorders [7].

A study shows systematically reviewed the association between sleep timing and health outcomes, thereby strengthening the case for sleep regularity in cognitive and metabolic health. Recent fronts have seen the use of biofeedback and wearable sensor data for predicting sleep quality in real-time[8]. Another research team emphasizes the data-driven revolution for sleep health and advocates integrated ML with personalized interventions. The current study expands the scope by resolving class imbalances via SMOTE, feature selection through mutual information, and associating predictions with customized sleep recommendations [10].

Subject-specific machine learning based models to estimate sleep parameters from actigraphy data performed also better than population level models, with accuracies around 86%. These findings demonstrate that personalized modeling enhances the prediction for both sleep quality and wake state [11]. ML classifiers could automatically stage sleep in rodents with the best classifier (Random Forest) resulting to be 95.78% accurate. This approach holds promise for sleep stage detection in animal models, where preclinical research is concerned [12]. Another study forecasted OSAS severity in 313 patients with a maximum accuracy of 44% from SVMs and Random Forest. Machine learning has potential for a preliminary screen, but it's still far from ideal in a clinical setting [13]. A work compared sleep-wake classification based on MESA Sleep data for machine learning and deep learning approaches. LSTMs yielded the highest 24-hour accuracy (88.2%) and CNNs were not far behind (87.7%), establishing a strong baseline for scalable sleep classification [14]. In another study, sleep-wake cycles were analyzed in DOC patients using machine learning and the correspondence between predictions and visual confirmation was strong (F1 score 0.87). Results indicate that sleep-wake organization could differentiate between MCS vs. UWS states [15]. A research comparison discovered that modern analysis (TB LSTM, CNN) was superior to classical sleep quality prediction with wearable activity data using a logistic regression. TB-LSTM had the best result with AUC = 0.9714 which demonstrated that the deep learning technique has the potential to achieve accurate and non-invasive sleep quality estimation [16].

Table 1. Comparative Analysis Table.

Study (Author, Year)	**Data/Signal Type**	**Method/Model Applied**	**Best Reported Accuracy**	**Key Contribution**
Azuara Hernandez & Gillette (2022)	EEG (Muse headset), single subject	SVM, KNN, LDA, DTC	SVM: >65% Accuracy	Optimal schedule estimation for college students

Stephansen et al. (2018)	Multi-cohort PSG, genetics	CNN, RNN, GP, Ensemble	High accuracy; improved specificity with the HLA test	Narcolepsy diagnosis biomarker
El-Kenawy et al. (2022)	Health & lifestyle (400 records)	bDTO + Logistic Regression	95% Accuracy	Feature optimization + classification
Radha et al. (2019)	HRV (292 participants, 584 nights)	LSTM Neural Network	77% Accuracy; κ = 0.61	Low-cost EEG alternative
Surantha et al. (2021)	ECG-HRV (MIT-BIH dataset)	ELM + PSO	82.1% Accuracy	Hybrid ML with improved speed
Dritsas & Trigka (2024)	Health/lifestyle questionnaire	SVM (Polynomial), Logistic Regression	91.44% Accuracy; κ = 0.85	Multi-class disorder screening
Tiwari et al. (2022)	EEG (CAP Sleep Database)	SVM-RBF on NLDF features	93.5% Accuracy	Bruxism disorder detection
Chaput et al. (2020)	41 cohort studies (>92,000 adults)	Systematic Review	Evidence quality: low moderate	Timing/ consistency linked to health
Farrahi and Rostami (2024)	EEG/EMG (rodents, 427 hrs)	RF, ANN, DT, LR, NB	RF: 95.78% Accuracy	Preclinical sleep classification
Perez Pozuelo et al. (2020)	Multi-modal data (review)	Digital Sleep Framework	N/A	Data-driven sleep science roadmap
Khademi et al. (2019)	Actigraphy + PSG	Personalized ML (RF, RLR, XGB, AB)	~86% Accuracy (personalized)	Personalized vs generalized comparison
Smith et al. (2021)	EEG/EMG (rodents, 427 hrs)	RF, ANN, DT, LR, NB	RF: 95.78% Accuracy	Preclinical sleep classification
Mencar et al. (2020)	Clinical (313 OSAS patients)	SVM, RF, k-NN	~44% Accuracy	OSAS severity prediction (limited)
Palotti et al. (2019)	PSG + actigraphy (MESA, 1817)	CNN, LSTM, Extra Trees	LSTM: 88.2% Accuracy	Benchmark for sleep wake classification
Wielek et al. (2018)	PSG + video (23 DOC patients)	RF, FFNN, clustering	F1-score: 0.87 (subset)	Sleep organization in DOC patients
Sathyanarayana et al. (2016)	Wearable actigraphy (adolescents)	CNN, LSTM, TB-LSTM	TB-LSTM: AUC = 0.9714	Predict sleep quality from wake data

4 Methodology

With respect to Figure 2, A workflow representing an end to-end ML-based sleep recommendation system is divided into three major categories or modules: preparation, data processing, and modeling. At first, during preparation, the idea is to plan, collect, and prepare data deemed relevant to the problem, so that one clearly understands the dataset. Data processing essentially involves systematic preprocessing of all steps needed to clean and encode the data: checking for missing values, visualizing data for insights where necessary, and firmly selecting features (like variable correlation analysis) to accept only those informative variables.

Modeling follows a two-step training process where decision-making of the initial model and hyperparameter tuning are followed by further adjustments using mutual information-based feature selection oversampling and SMOTE for class balancing.

The final model, optimized for the twin aims of accuracy and generalizability, is deployed for automated disease prediction and is seamlessly integrated with a personalized sleep recommendation engine. The fully modular pipeline ensures that each phase, from processing raw data to drawing actionable health guidance, is rigorously prepared and validated-a best-practices, reproducible methodology employed in real-world application of sleep health analytics.

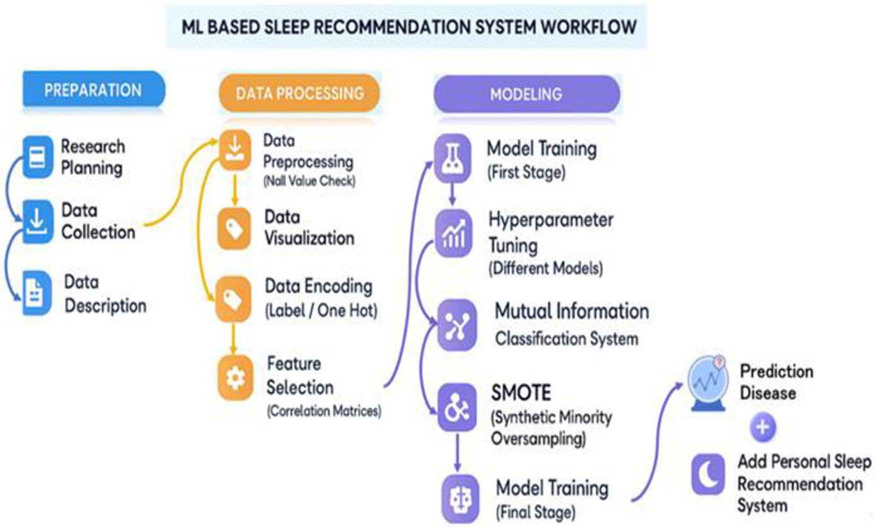

Fig. 2. Work Flow Diagram.

5 Experimental Result

Table 2 shows the performance of the key machine-learning algorithms in sleep-related medical-condition classification is compared in Table 1, with train and test accuracy reported for each. Both ensemble methods XGBoost (train: 100%, test: 97.06%) and Random Forest (train: 99.29%, test: 96.30%) outperform all other classifiers, indicating strong predictive power and the ability to generalize well to unseen data, respectively. Whereas Decision Tree classification appears correct as well, its perfect training accuracy (100%) coupled with slightly less test accuracy (95.79%) is suggestive of some degree of overfitting.

K-Nearest Neighbor seems capable of yielding good predictions (train 94.93, test 85.44) despite having a wider gap between train-test accuracy than the top ensemble models. On the other hand, LightGBM and MLP have inferior test accuracy (LightGBM: 72%, MLP: 67.69%) with respect to their training scores, further emphasizing the problem of overfitting or sensitivity to data distribution.

On the contrary stand classic linear models such as Logistic Regression and SVC, which perform worse than their nonlinear counterparts: Logistic Regression (train 43.74%, test 35.63%); SVC (train 37.31%, test 27.71%). While the figures in the parentheses denote training and test scores respectively, they state the very fact of the limited expressive power of linear and kernel-based methods for this complex, feature-rich sleep dataset.

Models with higher accuracies will withstand higher discriminating power, such as XGBoost, Random Forests, and Decision Trees. These algorithms are designed to capture complex, nonlinear patterns in the data, which simultaneously contain categorical and numerical attributes. SMOTE was employed to balance the class imbalance, which is best exploited in ensemble tree methods. Another perspective is that algorithms like Logistic Regression, SVC, or other linear and kernel-based classifiers fail to capture sophisticated feature interactions or nonlinear relationships that appear very much in sleep/medical datasets. Models such as KNN, MLP, or LightGBM might also lose accuracy due to suboptimal hyperparameter settings, inappropriate feature scaling, or feature noise/irrelevance in the dataset. Thus, the performance disparity amongst the different ML algorithms can be explained by their suitability to the problem at hand, choice of data properties, and their ability to interact between features.

This comparative analysis rocks, summarizing that Table 2 justifies the selection of Random Forest and XGBoost as classifiers for this rather particular task. These algorithms prevent overfitting and perform well under cross-validation---basically suitable when integrated into a system providing recommendations on sleep health, as shown further with a confusion matrix that will remain untold here. Concentrating on these two models rightly follows the appraised literature in your book and current state-of-the-art approaches for imbalanced, structured medical datasets. Here is the analytic discussion of the best 4 accuracy-gaining model.

Table 2. Comparative Analysis Table.

Algorithm	Train Accuracy	Test Accuracy
LightGBM	89%	72%
RandomForestClassifier	99.29%	96.30%

Logistic Regression	43.74%	35.63%
SVC	37.31%	27.71%
DecisionTreeClassifier	100%	95.79%
KNN	94.93%	85.44%
XGBoost	100%	97.06%
MLPClassifier	93.11%	67.69%

5.1 XGBoost

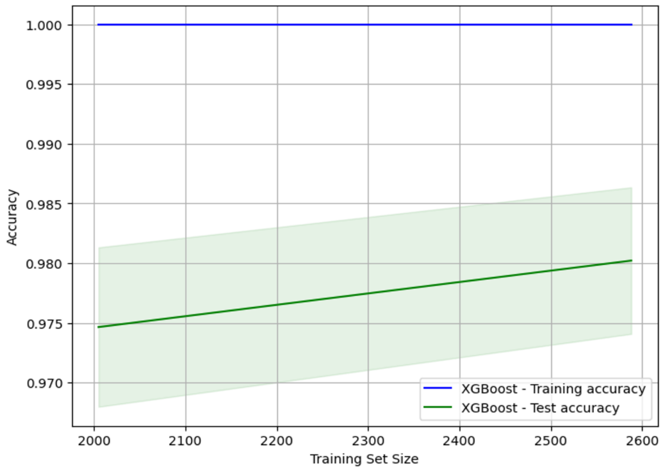

Fig. 3. Learning Curves for XGBoost Classifier.

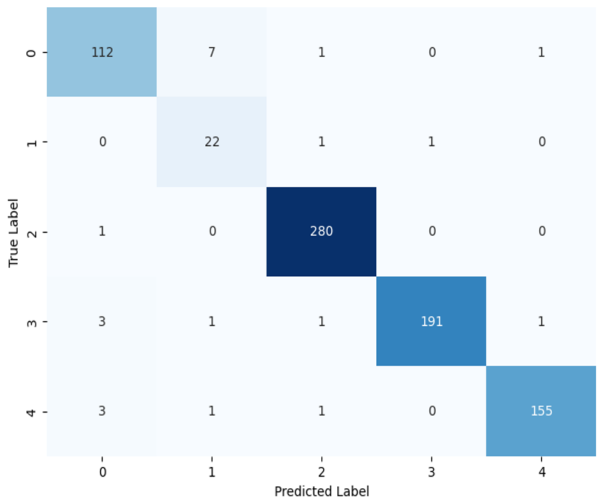

Fig. 4. Confusion Matrix for XGBoost Classifier.

XGBoost's learning curves from Fig 3. hint at strong training and generalization performance. The training accuracy is near 100% regardless of training sample size, indicating that the model is virtually perfectly fit on the training data. The accuracy on testing data, by the green line, increases steadily with training size, settling near 98% as sample size grows-the model is accurate with known data and reliably predictive with unseen data. The closeness of the two curves (little overfitting) is the testimony to the ability of model regularization and endorses the stability of the XGBoost technique for this purpose.

Showing the corresponding confusion matrix in Fig 4. further underscores the prowess of the model. Almost all predictions rest within the main diagonal with a really high number of correct classifications of each category (label). What stands out is the incredible accuracy of the biggest class ("label 2") with almost all being predicted correctly (280/281), while the misclassification of minority classes is also very few — missing samples are scattered off-diagonal mostly by just one or two samples in each class. This means that the XGBoost classifier is able to get high recall and precision for every class, even on a real-world class-imbalance scenario. There few incidences of off-diagonal confusion suggesting slight boundary overlaps between practically similar classes; however, these scarcely affect the overwhelming practical reliability of the model. Collectively, this evidence pronounces XGBoost as the prima facie for your sleep condition prediction task, achieving accuracy and generalization potential that favors deployment in health-related recommendation systems.

5.2 RandomForestClassifier

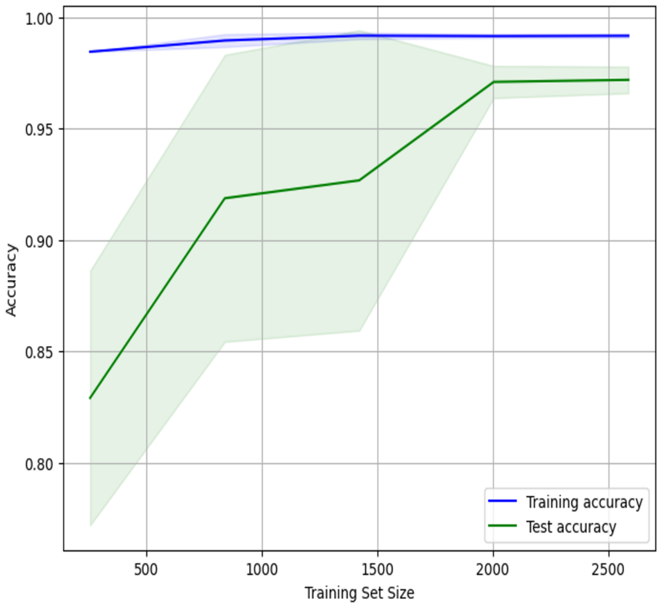

Fig. 5. Learning Curves for RandomForestClassifier.

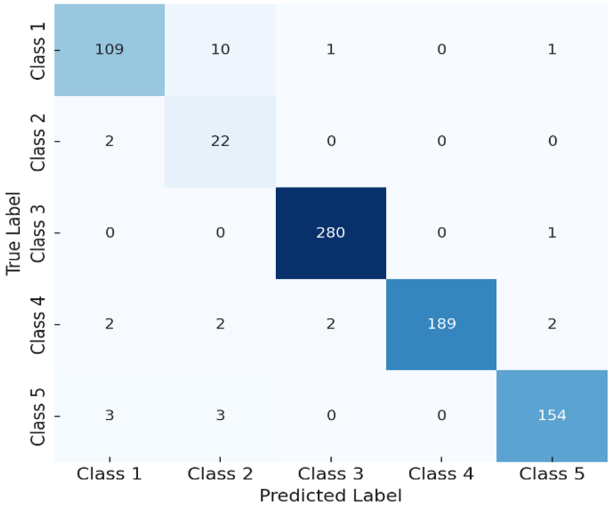

Fig. 6. Confusion Matrix for RandomForestClassifier.

In the fig 5. learning curve of the supposed Random Forest classifier, performances are both high and ever improving. The train accuracy (blue line) hovers around 99%. The test accuracy (green line) rises as we increase data and gets stabilized just below the train score at an impressive 96%. The train-test gap thus shrinks as sample size grows, indicating good generalization with negligible overfitting. The large variance in performance at smaller training sizes was expected and has eventually gone away as more instances are used for training.

In fig 6. Having analyze the performance of the model from the confusion matrix, we found it to indicate a positive assessment of the proposed approach. Most values are concentrated along the main diagonal, which means that the model classifies correctly a majority of instances from each class. The densest cluster is along row 3 for Class 3; hence this class clearly enjoys perfect or almost perfect recall while off-diagonal misclassifications really occur only in minimal numbers for the minority classes. There is a little bit of confusion among adjacent classes (Class 1 versus Class 2), but this is minimal and expected on any real-world, noisy health dataset. In sum, because of the high accuracy, excellent tolerance to data variation, and uniform performance across all prediction classes, the Random Forest classifier would be best for reliable integration into a sleep disorder prediction and recommendation system.

5.3 DicisionTreeClassifier

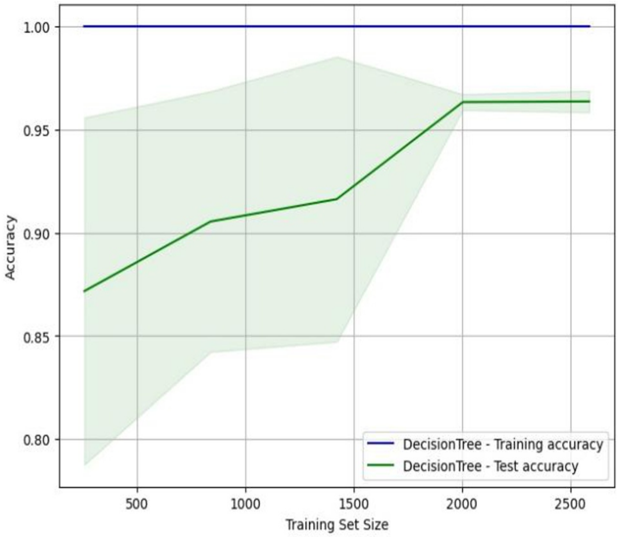

Fig. 7. Learning Curves for DicisionTreeClassifier.

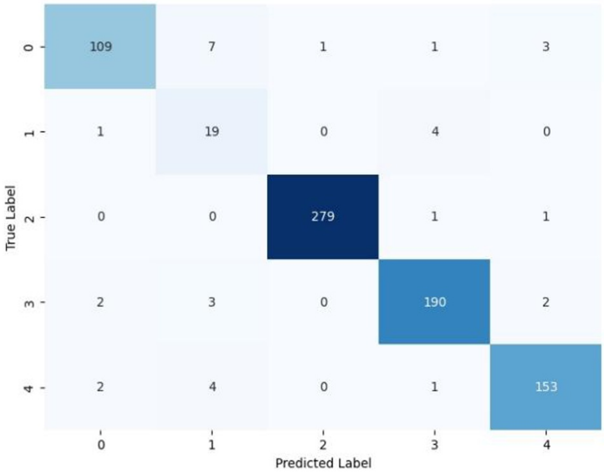

Fig. 8. Confusion Matrix for DicisionTreeClassifier

The Fig 7 shows A learning curve exhibits a side show describing the decision tree almost touching perfection while training on sample sizes, near 100% training accuracy is just one symptom that emphasizes this model among those fitting the training data well. Yet test accuracy increases with the number of training examples but never quite reaches that of training-data accuracy. Instead, it converges just below 96%. This small-to-moderate gap between training and testing, especially for smaller sample sizes, marks the existence of some overfitting: the model might be memorizing training patterns rather than generalizing. However, the gap seems to close as more data becomes available, thus pointing to the quality of having more data.

In fig 8 Inside the 2-D domain of model evaluation, the confusion matrix highlights model weaknesses and strengths. Apart from a few permissible exceptions, the majority of the predictions fall directly on the matrix diagonal for all classes, signifying reliable recall and precision performances. Misclassifications occur sporadically, whereby, for instance, some cases of Class 1 are deemed Class 2, and vice versa, while other neighboring classes also suffer slight misattributions. Nevertheless, these counts still rank comparatively low against the whole total of each true class, thus suggesting that the classifier does a good job aside from some minimal noise around a few category borders.

In a nutshell, Your Decision Tree has shown good predictions and an easy-to-separate class, however, with an inclination towards memorizing training details (Figure shows the perfect train score and some level of test dropoff). It stands to model complex with careful validation and, preferably, model regularization or ensemble if time pemits.

5.4 KNN

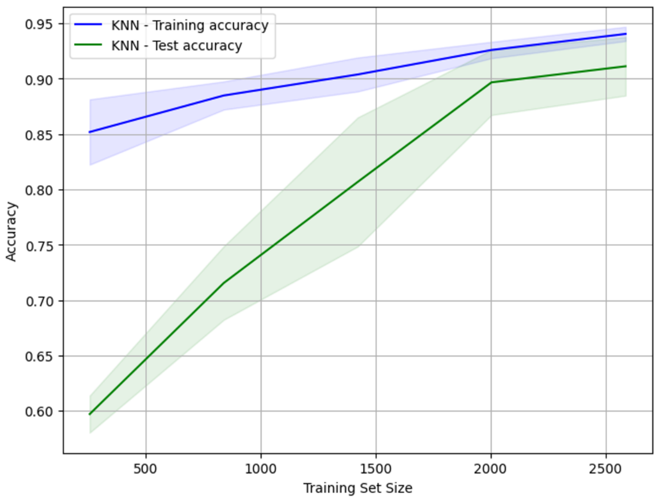

Fig. 9. Learning Curves for KNN

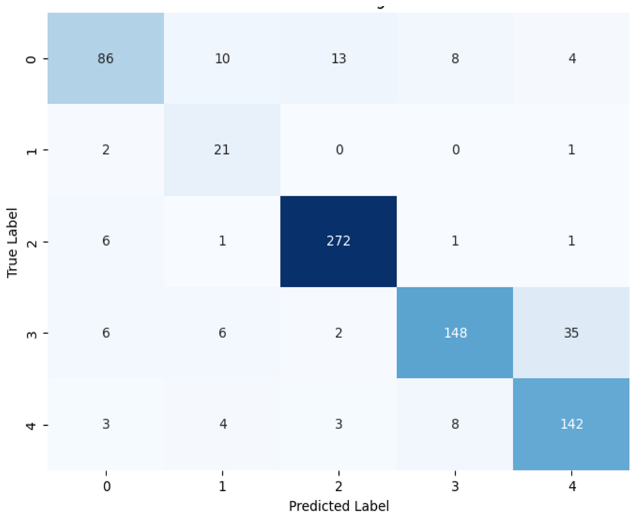

Fig. 10. Confusion Matrix for KNN

As shown in Fig 9 the KNN learning curve, here is a steady rise in the training accuracy with an increase in training set size, with the top peak just below 95%, whereas the training accuracy remains significantly above the test accuracy all along. The test accuracy curve also climbs as more data is provided and ends just about 90%. The constant gap in performance across training and testing and very wide confidence band (shaded area) for small sampled sizes only point towards KNN's inability to work well on this very feature-rich, possibly noisy sleeping dataset—so there are always problems with overfitting and generalizing well, especially when fewer samples are at hand.

The confusion matrix-based analysis in Fig 10 supports these observations of true positives and false negatives. While class 2 and class 4 have really good true positive rates, with 272 out of 278 and 148 out of 183 correct, respectively, for the other classes, the number of misclassifications are more than what we find in ensemble type models. In particular, class 3 is often confused with class 4 (35 samples) and class 1 shows confusions with classes 2 and 3, thereby revealing the interesting situation in which similar classes in feature-space can be difficult for KNN to uniquely separate. In sum, KNN does reasonably well when overall accuracy is concerned but it struggles when the boundaries of two classes overlap or when we have a high-dimensional feature space. It does get the edge when we have more training examples to train with, yet this kind of model tends to give in to noises in the data or irrelevant features, hence causing KNN models to give more erroneous predictions among similar classes than the more robust ensemble algorithms.

6 Discussion & Analysis

In this comparison, the superiority of ensemble tree-based classification techniques, mainly Random Forest and XGBoost, emerges for predicting sleep-related medical conditions. This model's ability to capture complex nonlinear relationships among features and from heterogeneous feature types, combined with an inherent capability to remedy class imbalance bias such as with SMOTE, defines the accuracy and generalizability of the model. However, for such medical data, nonsensitive to class imbalance and additional outlier noises, we consider the most balanced and reliable model to be Random Forest due to its highly consistent performance shown by almost similar train-test accuracies and reliability inferential results by way of confusions.

On the other hand, linear models lag in terms of predictive accuracy for such data sets since they are limited in modeling the intricate feature interactions of such complex health data. K-NN gives moderate performance but is susceptible to noise in high-dimensional features, as visualized by the wide variation in the learning curve and confused class boundaries shown in the confusion matrix.

It is noteworthy that the comparison between some of the learning curve trends and the confusion matrices agreed across models, underscoring the importance of data pre-processing-selection of features through mutual information and balancing for training-and in unlocking the full potency of any given model. The integration of SHAP and LIME-type interpretability tools has further edified the model's transparency and, thereby, its trustworthiness in clinical or consumer-facing applications.

It is therefore the smooth connection-from categorization and extrapolation-oriented machine learning breakthroughs to personalized sleep recommendation-that validates it as useful for behavioral health. The set of principles for this modular pipeline including raw data processing thought to ML prediction validation and finally actionable guidance sculpt a promising scenario for scientifically-based and scalable sleep health management in resource-limited settings.

This study’s attention to students provides specific academic information, yet population-wide generalization is constrained. Further studies with longitudinal follow-up are required to evaluate changes in behaviour over time. Model interpretability is enhanced by using SHAP and LIME, showing important features such as bedtime and caffeine.

7 Conclusion & Future Work

This study basically validated the application of supervised machine learning techniques in predicting medical conditions related to late-night sleeping behavior through questionnaire-based behavioral and demographic data. Both Random Forest and XGBoost classifiers emerged as optimal models, all achieving over 96% accuracy now establishing the ensemble tree methods as powerful for handling challenging imbalanced health datasets. Choice of mutual information-based features, as well as balancing strength of the training data by SMOTE were crucial to fine-tune model performance. Finally, integrating predictive analytics with a personalized sleep recommendation system provides an approach to a behavioral health intervention.

Future work will explore the incorporation of real-time physiological sensor data, such as EEG and heart-rate variability, to complement and enhance prediction accuracy. Expanding the cohort size and diversity will help increase model generalizability across different populations. Additionally, integrating advanced explainability techniques and adaptive feedback mechanisms will improve end-user trust and engagement with the recommendation system. Exploring deployment on mobile and IoT platforms for real-world monitoring and intervention remains a promising direction to bridge research and practical health outcomes.

Upcoming studies will further include participants more representative of the demographic and will follow up subjects over time, in order to also investigate changes over time in sleep.

Acknowledgments: Sincere gratitude is extended to those who contributed their time, effort, and talent to this research. The main responsibility for data collection was Neloy Pramanik Supto, who completed most of the data collection work with dedication. Rajat Chowdhury also played an important role at various stages of the work. Mushfiqur Rahman was responsible for supervising, writing, reviewing and correcting the entire research work, whose observations and guidelines helped us a lot in organizing our work.

Disclosure of Interests: The authors declare that they have no competing interests.

References

1. **Azuara-Hernandez, O.Y., Gillette, Z.**: Using machine learning to determine optimal sleeping schedules of individual college students. *Lecture Notes in Computer Science* (2022). https://doi.org/10.1007/978-3-031-17902-0_2
2. **Stephansen, J.B., Olesen, A.N., Olsen, M., et al.**: Neural network analysis of sleep stages enables efficient diagnosis of narcolepsy. *Nature Communications* **9**, 5229 (2018). https://doi.org/10.1038/s41467-018-07229-3
3. **El-Kenawy, E.M., Ibrahim, A., Abdelhamid, A.A., et al.**: Predicting sleep disorders: Leveraging sleep health and lifestyle data with dipper throated optimization algorithm and logistic regression. *Computational Journal of Mathematical and Statistical Sciences* **3**(2), 341–358 (2022). https://doi.org/10.21608/CJMSS.2024.290167.1053
4. **Radha, M., Fonseca, P., Moreau, A., et al.**: Sleep stage classification from heart-rate variability using LSTM neural networks. *Scientific Reports* **9**, 14149 (2019). https://doi.org/10.1038/s41598-019-49703-y
5. **Surantha, N., Lesmana, T.F., Isa, S.M.**: Sleep stage classification using extreme learning machine and particle swarm optimization. *Journal of Big Data* **8**, 14 (2021). https://doi.org/10.1186/s40537-020-00406-6
6. **Dritsas, E., Trigka, M.**: Utilizing multi-class classification methods for automated sleep disorder prediction. *Information* **15**(8), 426 (2024). https://doi.org/10.3390/info15080426

7. **Farrahi, V., Rostami, M.**: Machine learning in physical activity, sedentary, and sleep behavior research. *Journal of Activity, Sedentary and Sleep Behaviors* **3**, Article 5 (2024). https://doi.org/10.1186/s44167-024-00045-9
8. **Tiwari, S., Arora, D., Nagar, V.**: Supervised approach-based sleep disorder detection using non-linear dynamic EEG features. *Measurement: Sensors* **24**, 100469 (2022). https://doi.org/10.1016/j.measen.2022.100469
9. **Chaput, J.-P., Dutil, C., Featherstone, R., et al.**: Sleep timing, sleep consistency, and health in adults: A systematic review. *Applied Physiology, Nutrition, and Metabolism* **45**(S1), S232–S247 (2020). https://doi.org/10.1139/apnm-2020-0032
10. **Perez-Pozuelo, I., Zhai, B., Palotti, J., et al.**: The future of sleep health: A data-driven revolution. *npj Digital Medicine* **3**, Article 42 (2020). https://doi.org/10.1038/s41746-020-0244-4
11. **Khademi, A., El-Manzalawy, Y., Master, L., et al.**: Personalized sleep parameters estimation from actigraphy. *Nature and Science of Sleep* **11**, 387–399 (2019). https://doi.org/10.2147/NSS.S220716
12. **Smith, A., Anand, H., Milosavljevic, S., et al.**: Application of machine learning to sleep stage classification. In: *Proceedings of the International Conference on Computational Science and Computational Intelligence*, pp. 349–354 (2021). https://doi.org/10.1109/CSCI54926.2021.00130
13. **Mencar, C., Gallo, C., Mantero, M., et al.**: Application of machine learning to predict obstructive sleep apnea syndrome. *Health Informatics Journal* **26**(1), 298–317 (2020). https://doi.org/10.1177/1460458218824725
14. **Palotti, J., Mall, R., Aupetit, M., et al.**: Benchmark on a large cohort for sleep-wake classification. *npj Digital Medicine* **2**, 50 (2019). https://doi.org/10.1038/s41746-019-0126-9
15. **Wielek, T., Lechinger, J., Wislowska, M., et al.**: Sleep in patients with disorders of consciousness using machine learning. *PLOS ONE* **13**(1), e0190458 (2018). https://doi.org/10.1371/journal.pone.0190458
16. Sathyanarayana, S., Joty, S., Fernandez-Luque, L., et al.: Sleep quality prediction from wearable data. JMIR mHealth and uHealth 4(4), e125 (2016). https://doi.org/10.2196/mhealth.6562