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Article

Improving Sleep Disorder Diagnosis Through Optimized Machine Learning Approaches

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Abstract: The accurate diagnosis of sleep disorders such as obstructive sleep apnea and insomnia is extremely significant because of the significant health impacts that can occur. This is the research where we try to understand best ML approaches to predict sleep problems, using the Sleep Health and Lifestyle dataset available in Kaggle. ANOVA is used for feature selection and then resampling is performed using SMOTEENN for class imbalance . The seven classifiers that are used to derive the new engineered features are: RF, Gradient Boosting, Gaussian Naive Bayes, KNN, DT, LR and SVM. There are seven new features added in all. We use different ML techniques such as LR, RF, DT, SVM, ET, Extreme Gradient Boosting, Gradient Boosting, LightGBM, CatBoost, AdaBoost, Naive Bayes, Voting Classifier and Stacking Classifier. The designed feature Voting Classifier has good prediction performance, with a 97.3% accuracy for both 5 and 2 feature sets. With original features, Stacking Classifier gave 88.0% accuracy while with two features it gave 80.0% accuracy. To facilitate clinical decision assistance, explainable AI methods such as LIME and SHAP are integrated to interpret model predictions, hence boosting transparency.
Keywords: SMOTEENN, ANOVA test, feature engineering, classification, sleep disorder, machine learning classifiers, ensemble technique.

1. Introduction

Sleep plays a critical role in the regulation of physiological functions and recovery, and is essential for maintaining physical, cognitive and emotional health. Sleep is crucial in all age groups and for children and older people, sleep quality is especially problematic. In the short term not getting enough sleep can affect concentration and memory and increase the risk of accidents. In the longer term disturbed sleep has been associated to cardiovascular disease, obesity, diabetes and depression [7]. Hence, it is essential for health care to understand the sleep stages and to diagnose sleep disorders.

There are 4 phases of sleep: Alertness, N1, N2, N3 and REM (Rapid Eye Movement).Sleep is made up of Alertness, N1, N2, N3, and REM (Rapid Eye Movement). The brainwaves and physiological responses vary from one stage to the next. These are light sleep (Stage N1 and N2), slow wave sleep (Stage N3) related to restorative activities and REM associated with intense brain activity and vivid dreams [6]. It is crucial to identify these stages for sleep quality assessment and to diagnose diseases like insomnia, narcolepsy, and sleep apnea. The gold standard is the traditional polysomnography (PSG) which is resource intensive, expensive, and manual interpretation errors limit access [8].

Automated ML-based techniques have emerged as a popular solution to address these challenges. Sleep stage classification and accuracy improvement by DL and neural network models have been successfully applied [3]. ML frameworks also provide scalable methods for the analysis of sleep disturbances in elderly population [4]. The novelty has been brought in by using novel decision support methods like neutrosophic and hybrid clustering which have made the prediction more reliable [5,9]. Ensemble learning and random forest classifiers deal with complex data sets and are useful in identifying relevant features [10].

There has been recent progress, and we see the combination of categorisation and optimisation techniques. Multi-task learning is improved by genetic and reinforcement techniques, which boosts the accuracy of diagnosis

[1]. Bayesian optimization and gradient boosting provides good sleep disorder classification [2]. These approaches utilize domain knowledge together with clever computational models to produce therapeutically meaningful outcomes.

Overall aim of this project is to build an Automatic and Robust Sleep Disorder Detection and Classification System with advanced ML techniques with optimizing models and Data driven approaches to improve the accuracy of the system, reduce the burden of diagnosing the sleep disorders and make the system scalable for future clinical and at home sleep monitoring applications.

2. Related Work

To improve the accuracy of sleep problem diagnosis and their therapeutic value, in recent years, ML and DL methods have been broadly applied. Polysomnography is a conventional method which is resource intensive and prone to errors in manual scoring. This has inspired to develop patient friendly, accurate and scalable computational frameworks [11].

RF is a widely used technique for categorization of sleep disorder. Tareq [11] demonstrated that the use of RF models is effective for diagnosing multiple sleep disorders in structured healthcare datasets. The performance of the predicted classifiers was also good when Hidayat [10] applied RF classifiers to sleep health and lifestyle data. In a similar study, Zhang et al. [12] proposed a bed-integrated RF sensors for non-intrusive detection and prediction and demonstrated that sensor-based data can enhance the diagnostic accuracy without interfering patients' natural sleep.

DL algorithms have also found applications in sleep disorder studies. Wadichar et al. [13] designed a hierarchical system that combines CNN and RNN to capture spatial and temporal information, leading to an accurate diagnosis. Logistic regression is also explored, where Soni et al. [14] have taken it as a baseline model and highlighted data preprocessing is important for achieving reliable classification results.

Considering the role of lifestyle and behavioural factors also has been emphasised. Sravani et al. [15] performed the relation between Lifestyle with sleep disorders by pre-processing Lifestyle data using Ensemble learning. Similarly, Taher and Ayon [16] explored the performance of multiple ML approaches on lifestyle datasets, finding that the model performance highly depended on feature engineering and preprocessing techniques. The findings show the significance of contextual variables in modelling to predict sleep problems.

With predictive modeling, the use of ML for sleep-related issues has been expanding. Kumar et al. [17] leveraged lifestyle and health information to detect potential sleep disorders, demonstrating the potential of predictive analytics in anticipating the onset of sleep disorders. In sleep stage classification, Morokuma et al. [18] successfully demonstrated the advantage of multimodal inputs for higher detection accuracy with DL techniques, using the cardiorespiratory and body movement data.

Ensemble methods continue to be essential to improving robustness. Widasari et al. used bagged trees ensemble to classify sleep disorders according to sleep quality variables. It is designed so as to minimize variance and increase reliability. Recently, Jabid et al. [20] added the advanced optimization techniques to the classification model to attain high accuracy and emphasis on the optimization of algorithmic performance to attain clinical dependability.

3. Materials And Methods

The proposed approach will focus on enhancing the diagnosis of sleep disorders by utilizing the Kaggle Sleep Health and Lifestyle dataset with the aim of using improved ML algorithms to achieve this. It starts with a thorough preprocessing of the data, in which missing values are addressed, categorical data is encoded and features are standardized to ensure a uniform data set. For better classification reliability, we use ANOVA for feature selection and SMOTEENN to solve the problem of class imbalance. From strong classifiers, we add 7 new predictors to the data set using random forest, gradient boosting, SVM, etc. Various algorithms are then applied, such as LR, DT, LightGBM, CatBoost, AdaBoost and ensemble methods like Voting and Stacking, to give a strong classification. Explainable AI (XAI) techniques like LIME (Local Interpretable Model Explanations) and SHAP (SHapley Additive Perturbations) have been employed to gain insights into the most relevant contribution to the decision, ensuring the transparency of the model's decisions [21].

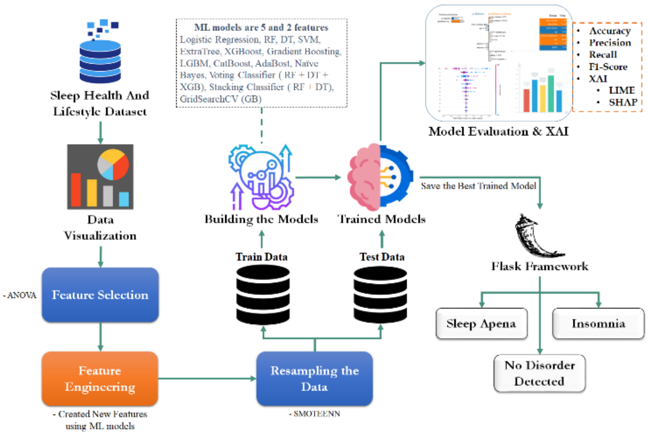


Fig. 1. System Architecture

The whole pipeline of ML based sleep abnormality prediction is shown in Fig. 1. Data with user information regarding sleep health and lifestyle is collected and processed with missing value treatment, encoding and standardization. ANOVA is used in order to select the features, and SMOTEENN is used to combat the class imbalance problem. The train and test sets are used to train different types of ML models and the accuracy, precision and recall are used to evaluate their performance. Finally, the trained models are deployed in a Flask app, which enables providing predictions with XAI interpretability (LIME and SHAP).

A) Data Set Collection

The Kaggle Sleep Health and Lifestyle contains 374 samples, 13 features of demographic, physiological and lifestyle factors related to sleep. Main features are: gender, age, occupation, sleep duration, sleep quality, physical activity level, stress level, BMI category, blood pressure, heart rate and daily steps. The class variable is Sleep Disorder, the classes are None, Sleep Apnea. Data collected encompasses behavioral and clinical characteristics for a comprehensive basis of the prediction of sleep health. The architecture allows for the study of linkages between lifestyle patterns, physiological signals and sleep disorders, making it suitable for ML diagnostic systems [22].

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Blood Pressure	Heart Rate	Daily Steps	Sleep Disorder
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	126/83	77	4200	None
1	2	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	None
2	3	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	None
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea

Fig. 2. DataSet Collection

B) Pre-Processing

The preparation process for the Sleep Health and Lifestyle dataset for ML task is important and includes pre-processing. It is the process of converting raw data into organized, structured and informative form for classification. Steps are data visualization to get insights, feature selection with ANOVA, producing new features using feature engineering and resampling using SMOTEENN [24] for handling class imbalance.

*Data Visualization:*The visualization of data is the basis of understanding the distribution and relations in a data set. The imbalance between classes (None and Sleep Apnea) can be visually shown through the visualization of target values. A correlation matrix shows linear relationships between numerical features such as stress, physical activity and sleep length. For categorical data such as gender, occupation, BMI category etc., bar charts and count plots are used. This exploratory study identifies dependencies, outliers and trends to help choose predictors prior to advanced modeling.

*Feature Selection:*Feature selection diminishes the dimensionality, enhances the computational efficiency and boosts predictive capabilities. The technique is based on ANOVA (Analysis of Variance) test to find significant predictors for classification of sleep disorder. ANOVA is used to identify characteristics that differentiate between groups, by comparing the difference between groups to the difference within groups. For example, the better discriminative ability is reflected in stress, sleep length, quality and BMI. The selection of the most useful features reduces noise, avoids overfitting and increases clinical relevance, making subsequent classifiers to focus on important predictors.

*Feature Engineering:*Feature engineering increases the dataset by producing extra predictor variables to model complex interactions among attributes. The outputs of the strong classifiers (RF, Gradient Boosting, SVM, LR, KNN, DT and Gaussian Naïve Bayes) are recalculated as new features in this stage. Each contributes to the probability scores which makes up machine derived predictors and extend the feature space. This can capture non-linear patterns, greatly enhance the learning capacity and predictive accuracy, and give more accurate modelling of sleep disorders detection.

*Resampling the Data:*One of the main problems in sleep disorder classification is the class imbalance: None class is more common than Sleep Apnea class. To solve this SMOTEENN (Synthetic Minority Over-sampling Technique with Edited Nearest Neighbors) is utilized. The synthetic samples in SMOTE are generated for minority classes and noisy misclassified samples are removed from majority classes in ENN. A combined method providing class distribution and adjustment of decision limits and quality of the datasets. Therefore, models trained on the resampled data results to a more fair, accurate and generalized classification result.

C) Train & Test:

The data set is divided in 80:20 for model construction (training and testing data sets). Training set (80%): It enables models to learn patterns and predict rules based on characteristics about health, lifestyle and sleep. The remaining 20 per cent is set aside for testing against test data. This separation enables to train without overfitting while ensuring that the evaluation is fair. It also takes note of the need for learning along with validation requirements. This results in higher accuracy, robustness and practical applicability to realistic settings.

D) Algorithms:

*Logistic Regression:*Uses a logistic function to predict probabilities of class membership. The model is interpretable, showing correlations between variables and outcomes, and setting a baseline to determine the significant health-related aspects that influence categorization. The model is useful for the study of the contribution of predictors to sleep problem detection.

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(W^T x + b)}} \quad (1)$$

*Random Forest:*Integrates numerous decision trees to obtain increased accuracy and decreased overfitting. Supports non-linear and complex relationships between features and is able to deal with high dimensional data. It also gives feature importance, highlighting the most important aspects that influenced the prediction, hence improving the reliability of the categorization of sleep disorders.

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \quad (2)$$

*Decision Tree:*Uses rules based on features to partition data into branches, for classification of observations. It can overfit complicated data, offers intuitive decision paths, interpretable results, and a clear understanding of the decision boundaries and insights into the relationship between characteristics and the sleep disorder categories.

$$I\,(i) = 1 - \sum_{i=1}^{k} p_i^2 \quad (3)$$

*Support Vector Machine (SVM):*It is optimized to separate the classes, and can use linear or non-linear boundaries through the use of kernel functions. Captures complex feature interactions, high generalization, categorizes similar features well and makes good predictions when data distributions vary.

$$minimize\ \frac{1}{2}\,||W||^2 + C\sum_{i=1}^{n} \xi_i \quad (4)$$

*Extra Trees Classifier:*Provides a way of introducing randomization in the splitting of trees to boost generalization and minimize the variation. It can effectively deal with data of sleep health that contain numerous features interacting with one another and are noisy and high-dimensional, accelerate training, and make valid predictions, particularly when numerous interacting features are difficult to categorize in datasets of sleep health.

*LightGBM:*Gradient boosting, grows the tree leaves-wise for speed and accuracy. Being able to effectively deal with very high-dimensional data, and reduce the size of the calculation and make very accurate predictions. Appropriate for real-time applications for fast and memory efficient classification of sleep disorders.

*CatBoost:*Constructs a sequence of decision trees. Categorical features do not require any heavy preprocessing. It helps to minimize overfitting, improves prediction performance, and can effectively manage categorical and mixed type data to enhance workflow and robustness in lifestyle and health related categorization tasks.

*AdaBoost:*Computes a combination of weak classifiers, assigning more weight to the misclassified cases. Increases the focus on hard data points, enhances the robustness of the model, reduces the downside bias and model level of generalization. Results in better and more accurate classification performance for sleep disorder data.

*Naive Bayes:*Estimate the probabilities of classes when the features are independent. Lightweight, interpretable, small or categorical datasets. Provides a baseline classification which may be used quickly to get insight into the feature-class relationships, and as a baseline to compare more complicated models in the context of sleep problem investigation.

*Extreme Gradient Boosting (XGBoost):*Sequential construction of a tree as a correction of previous errors, regularization. Capture complicated feature interactions Provide high accuracy and high scalability Reduce overfitting Effectively handle diverse and imbalanced dataset Support accurate sleep disorder categorization

$$\hat{y}_i = \sigma\left(\sum_{k=1}^{K} f_k(x_i)\right), f_k \in F \ (5)$$

*Gradient Boosting:*Makes mistakes in the past and optimizes models with iteration by gradient descent. Captures subtle non-linear patterns among interacting characteristics, improves accuracy, decreases prediction errors and provides robust classification in datasets with complicated interactions in sleep health data.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)(6)$$

*Voting Classifier:*Combines the results of various models using majority voting or probabilities. Applies the complementary evaluations of models to make sleep problem classification more robust and predictable and to yield consistent and reliable outcomes through the combination of the potential of multiple algorithms.

*Stacking Classifier:*Base model predictions are synthesized into meta-models for learning a variety of patterns. Improves generalization, combines the complimentary capabilities and maximizes the predictive performance to obtain more accurate and balanced classification results than each separate classifier for sleep disorder data.

*GridSearchCV:*It performs a grid search with exhaustive sampling (including cross-validation) to determine optimal hyperparameters. Increases the accuracy of the model, reduces overfitting, increases the robustness and robustness of the model, and determines the best configuration to make reliable predictions in complex sleep disorder classification tasks.

4. Experimental Results

*Accuracy:*The accuracy of a test is its ability to correctly identify patient and healthy cases. To determine the accuracy of a test, we need to know the number of true positive and true negative cases, among all the cases examined. In math, this is expressed as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (7)$$

*Precision:*Precision is concerned with the ratio of correct classifications of occurrences or samples to total number of occurrences or samples classified as positives. Thus the formula for determining the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (8)$$

*Recall:*In ML, recall is a measure of how well a model can find all instances of a certain class that are important. It is the proportion of positive observations that are correctly predicted by a model over the total number of observations that are predicted as positive; this represents the proportion of the class that is captured by the model.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (9)$$

*F1-Score:*The F1 score is a way to quantify how accurate a ML model is. Composes the precision and recall scores of the model. Accuracy measure is used to find out how many times a model predicted correctly on the whole dataset.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100 (10)$$

*Specificity:*This is done by dividing the number of people who test negative for a condition by the number of people who don't have a condition, including those who also tested positive for a condition (the "false positives").

$$Specificity = \frac{TN}{(TN + FP)} (11)$$

AUC-ROC Curve: The AUC-ROC Curve is a method to assess the performance of the classification problem over various threshold levels. ROC graphically displays the True Positive Rate and False Positive Rate. The AUC is the maximum discriminating ability of the model; the higher the AUC, the better the performance of the model.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} (12)$$

"Table. 1. Performance Evaluation – Engineered 5 Features"

ML Model	Accuracy	Precision	Recall	F1 Score	Specificity	AUC Score
Eng - Logistic Regression	0.893	0.888	0.846	0.862	0.931	0.957
Eng - Random Forest	0.973	0.958	0.958	0.958	0.989	0.973
Eng - Decision Tree	0.973	0.958	0.958	0.958	0.989	0.973
Eng - SVM	0.733	0.689	0.714	0.700	0.858	0.973
Eng - ExtraTree	0.973	0.958	0.958	0.958	0.989	0.973
Eng - Extreme GB	0.973	0.958	0.958	0.958	0.989	0.973
Eng - Gradient Boosting	0.973	0.958	0.958	0.958	0.989	0.973
Eng - LightGBM	0.973	0.958	0.958	0.958	0.989	0.973
Eng - CatBoost	0.973	0.958	0.958	0.958	0.989	0.973
Eng - AdaBoost	0.973	0.958	0.958	0.958	0.989	0.973
Eng - Naive Bayes	0.773	0.555	0.646	0.594	0.828	0.973

Eng - Voting Classifier	0.973	0.958	0.958	0.958	0.989	0.973
Eng - Stacking Classifier	0.947	0.924	0.943	0.932	0.977	0.973
Eng - GridSearch CV	0.947	0.931	0.930	0.930	0.973	0.973

The model performance is given in table 1. The Voting Classifier achieved the best accuracy and good prediction results.

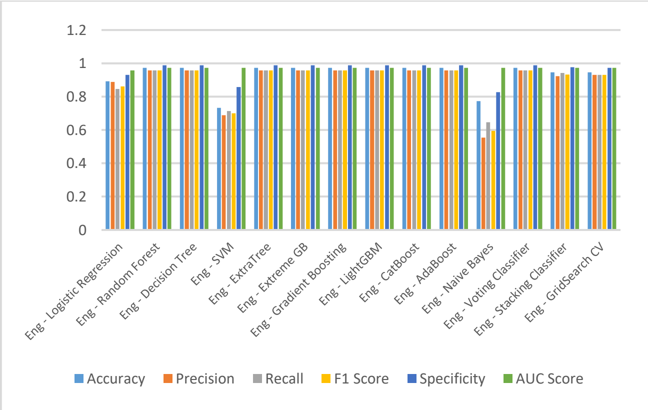
Table.2 Performance Evaluation – Engineered 2 Features

ML Model	Accuracy	Precision	Recall	F1 Score	Specificity	AUC Score
Eng - Logistic Regression	0.973	0.958	0.958	0.958	0.989	0.958
Eng - Random Forest	0.973	0.958	0.958	0.958	0.989	0.974
Eng - Decision Tree	0.973	0.958	0.958	0.958	0.989	0.974
Eng - SVM	0.973	0.958	0.958	0.958	0.989	0.974
Eng - ExtraTree	0.973	0.958	0.958	0.958	0.989	0.974
Eng - Extreme GB	0.973	0.958	0.958	0.958	0.989	0.974
Eng - Gradient Boosting	0.973	0.958	0.958	0.958	0.989	0.974
Eng - LightGBM	0.973	0.958	0.958	0.958	0.989	0.974
Eng - CatBoost	0.973	0.958	0.958	0.958	0.989	0.974
Eng - AdaBoost	0.973	0.958	0.958	0.958	0.989	0.974
Eng - Naive Bayes	0.773	0.555	0.646	0.594	0.828	0.974
Eng - Voting Classifier	0.973	0.958	0.958	0.958	0.989	0.974
Eng - Stacking Classifier	0.973	0.958	0.958	0.958	0.989	0.974

Eng - GridSearch CV	0.973	0.958	0.958	0.958	0.989	0.974

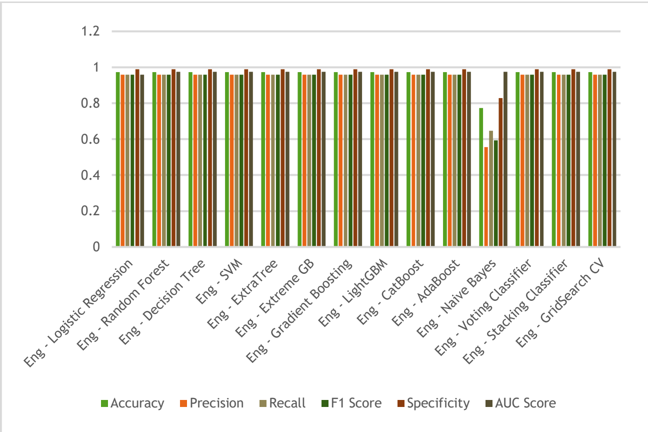
The results of the evaluation measures are summarized in Table 2 where the performance of various engineered-feature based categorization models is good.

Fig. 3. Comparison Graph – Engineered 5 Features



The performance comparison of engineered-feature-based models is displayed in Fig.3; Light green bars are Red, Green is Precision, Yellow is Recall, Orange is F1-Score, Red bars are Green and Grey is AUC-Score that demonstrates consistency of metrics and variation of computational time among techniques.

Fig.4 Comparison Graph – Engineered 2 Features



The performance of classifiers is shown in Fig.4, Comparison Graph – Engineered 2 Features, where green colour indicates Accuracy, orange indicates Precision, grey indicates Recall, dark blue indicates F1-Score, brown indicates Specificity and light brown indicates AUC-Score.

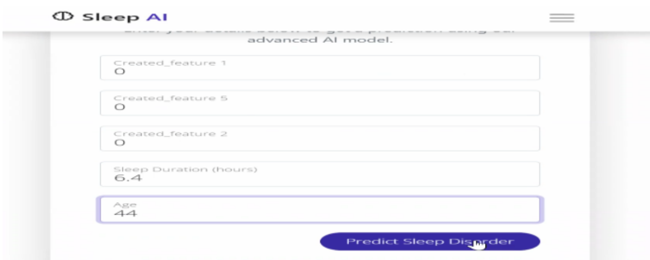


Fig.7 Upload Input Data – 5 Features

The "Upload Input Data" interface appears as in Figure 7. The users may enter five attributes to forecast sleep disorders with accuracy.

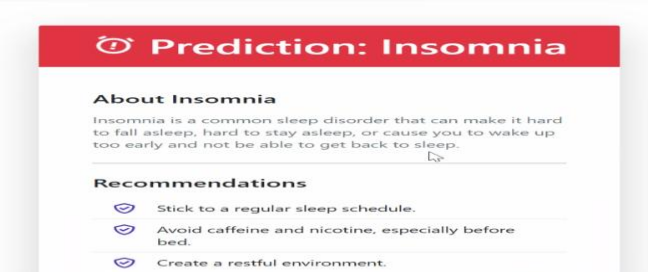


Fig.8 Predict Result

The prediction result and personalized recommendations are depicted in Figure 8, wherein the condition of the user is predicted as Insomnia.

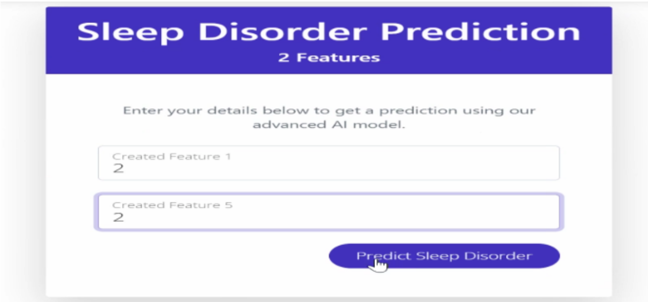


Fig.9 Upload Input Data – 2 Features

Figure 9 represents the prediction UI that will allow the user to enter two features to see the possible results of the sleep disorder.

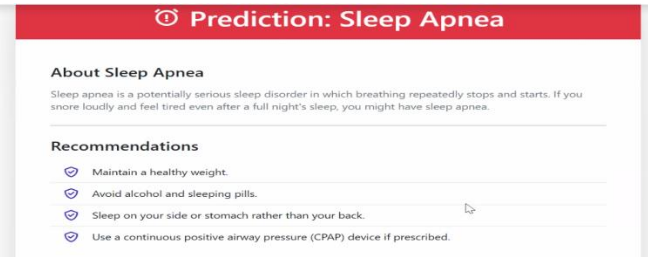


Fig.10 Final Outcome

The user's diagnosis, Sleep Apnea, is confirmed with the prediction result and the corresponding advice in Figure 10.

5. Conclusion

By introducing designed characteristics and powerful ML algorithms, together with enhanced resampling strategies, accurate prediction of sleep disorders was achieved. Normal and pathological sleep patterns were better separated after using feature selection and class balance based on ANOVA and SMOTEENN. Seven engineering features were added using RF, GB, GNB, KNN, DT, LR and SVM to improve the predictive performance. The Voting Classifier achieved the highest accuracy (97.3%) with a 5-feature model and the Stacking Classifier achieved 88% accuracy with 5 features and 80% with 2 features, which proves that engineered features are important in this case. The explainable AI techniques, LIME and SHAP, determined influential traits. The results indicate that ML models designed for specific features with designed XAI approaches can reliably support sleep disorder accurate and interpretable diagnosis.

Larger and diverse sleep recordings with EEG, ECG and breathing data can be used in the future to further enhance the generalization. Lifestyle, medical history and wearables can be integrated to improve accuracy, with the help of DL models such as CNNs and RNNs that can capture temporal dependencies and multimodal data integration. Advanced optimization strategies and ensemble approaches can further boost the performance, and the frameworks for real-time deployment allow for continuous monitoring, highlighting the potential for real-world and proactive use of ML to diagnose sleep disorders.

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