ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika *et. al.,* / International Journal of Engineering & Science Research

Applying Machine Learning Algorithms for the Classification of Sleep Disorders

Chitikinavelu Devika
PG scholar, Department of MCA, DNR College, Bhimavaram, Andhra Pradesh.
V.Sarala
(Assistant Professor), Master of Computer Applications, DNR college, Bhimavaram, Andhra Pradesh.

Abstract: Sleep disorders significantly impact overall health and well-being, necessitating accurate identification and classification for timely intervention. This study applies various machine learning algorithms, including Random Forest, Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), XGBoost, and Artificial Neural Network (ANN), to predict sleep disorders using a dataset sourced from Kaggle. Key attributes analyzed include Gender, Age, Sleep Duration, Sleep Quality, Stress Level, Blood Pressure, and Body Mass Index (BMI). A comparative analysis of algorithmic performance reveals that XGBoost achieves the highest accuracy of 90.66%, outperforming other methods. The best-performing algorithm is further utilized to predict sleep disorders, offering a robust framework for diagnosis and potential treatment recommendations.

Keywords : Machine Learning , Sleep Disorder , Recommendation

I. INTRODUCTION:

Sleep is a crucial biological process essential for maintaining both physical and mental well-being. It plays a key role in enhancing the body's strength, while also supporting memory consolidation and brain function. The quality of sleep significantly influences cognitive abilities, particularly in vulnerable groups such as children and elderly drivers, who are at a higher risk of accidents due to impaired cognitive performance from poor sleep. Insufficient sleep can have serious health consequences, including increased risks for conditions like heart disease, diabetes, and obesity.

Sleep assessments, often conducted through polysomnography (PSG), require careful evaluation by physicians and medical experts. However, manual classification of sleep stages from PSG data is time-consuming and prone to human error, leading to variability in the results of sleep-stage assessments. [1][2]

Philips conducts an annual World Sleep Day survey to assess global attitudes and behaviors related to sleep. In the 2021 survey, over 13,000 adults across 13 countries participated, revealing that only 55% of adults were satisfied with their sleep. The remaining 45% experienced dissatisfaction with their sleep quality due to factors such as the COVID-19 pandemic, sleep apnoea, and insomnia. Specifically, 37% of respondents reported that the pandemic negatively impacted their ability to sleep well. In addition, 37% experienced insomnia, 29% snored, 22% suffered from shift-work sleep disorder, and 12% had sleep apnoea. [1][2]

Medical professionals and sleep experts assess sleep quality by analyzing the different stages of sleep, which are classified into five stages: wakefulness, N1, N2, N3, and rapid-eye movement (REM). During wakefulness, individuals are conscious and aware of their surroundings, with fast and irregular brain waves. N1 is the lightest sleep stage, where brain waves slow down, and muscles relax. N2 is a deeper sleep stage, followed by N3, the deepest sleep stage, where waking someone is particularly difficult. REM sleep, characterized by rapid eye movements, is when brain waves resemble those of wakefulness. Each of these stages is essential for specific physiological functions. During sleep, the brain and body remain highly active, and doctors use polysomnography (PSG) to monitor brain and body activity, recording electroencephalogram (EEG) and electrocardiogram (ECG) signals[3][4][5]. To reduce human intervention and increase efficiency, researchers have developed algorithms for classification and prediction, aiming to automate the analysis and prediction of sleep patterns and actions.

Sleep-stage classification techniques can be categorized into traditional machine learning algorithms (MLAs) and deep learning algorithms. Traditional MLAs are suitable for smaller datasets, offering faster implementation and simplicity, with manual feature engineering to extract characteristics like signal entropy and energy for classifying sleep stages. [6][7] In contrast, deep learning algorithms, inspired by the human brain's structure, use neural networks to automatically learn complex patterns from larger datasets, eliminating the need for manual feature extraction. These algorithms are particularly effective for tasks involving large, intricate datasets, such as sleep-stage classification using electroencephalogram (EEG) signals.

Sleep-stage classification techniques can be divided into traditional machine learning algorithms (MLAs) and deep learning algorithms. Traditional MLAs are simple and work well with small datasets, relying on manual feature engineering to extract characteristics like signal entropy and energy. In contrast, deep learning algorithms use neural networks to automatically learn complex patterns from large datasets, eliminating the need for manual feature extraction. These algorithms are particularly effective for tasks involving complex or large data, such as classifying sleep stages using EEG signals.[8]

This study reviews research on sleep disorders, highlighting challenges such as data collection, which often includes noisy and uncertain data, such as missing information, from patients across various hospitals. The dataset's limitations arise from its collection at a single sleep clinic, leading to biased results that may not be generalizable and could influence decision-making. Additionally, there is a lack of natural sleep-stage datasets. [9] Feature extraction from the dataset is necessary for training models and selecting discriminative features, which often requires significant computational effort to identify suitable machine learning algorithms (MLAs). [10] This study addresses the challenges posed by sleep disorders, particularly in modern lifestyles, where neglecting sleep can lead to serious health issues. Given that sleep is vital to human health, the application of machine learning techniques to classify sleep disorders is crucial for improving well-being and quality of life.

Machine learning algorithms (MLAs) have been applied to sleep disorder classification, but to the authors' knowledge, there has been a lack of comprehensive evaluations in this area. This article contributes in two significant ways: 1) providing an overview of existing studies and research on sleep disorder classification, and 2) offering a thorough evaluation of traditional MLAs alongside deep learning algorithms. The study also compares the performance of the proposed algorithm with state-of-the-art machine learning algorithms, using default parameters for classification in the context of sleep disorders.

LITERATURE SURVEY:

Sleep disorder classification is essential for improving quality of life, as disorders like sleep apnoea can severely affect health. Expert sleep-stage classification is challenging and prone to human error. This paper compares deep learning algorithms and traditional machine learning algorithms (MLAs) for sleep disorder classification, proposing an optimized method using the publicly available Sleep Health and Lifestyle Dataset. A genetic algorithm was used to fine-tune the parameters of different MLAs. The study evaluates algorithms like k-nearest neighbours, support vector machine, decision tree, random forest, and artificial neural network (ANN). The results show significant performance differences, with the ANN achieving the highest classification accuracy of 92.92%, outperforming other algorithms in precision, recall, and F1-score. [1]

Healthy sleep is vital for overall well-being, but many sleep disorders can impair both the quality and duration of sleep. Accurate and convenient detection methods are crucial for identifying these disorders. In this study, the authors proposed an AI-enabled algorithm, named the Sleep Disorder Network (SDN), for the automatic classification of four major sleep disorders: insomnia (INS), periodic leg movement (PLM), REM sleep behavior disorder (RBD), and nocturnal frontal-lobe epilepsy (NFE). The SDN,

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika ***et. al.,*** **/ International Journal of Engineering & Science Research**

built using deep convolutional neural networks, can analyze the complex, cyclic rhythms of sleep disorders that affect ECG patterns. The algorithm was trained on a dataset from the CAP Sleep Database, consisting of single-lead ECG signals from 35 subjects, including control and sleep disorder groups. After preprocessing and segmenting the ECG data, the SDN achieved high classification performance with F1 scores of 99.0%, 97.0%, 97.0%, 95.0%, and 98.0% for the CNT, INS, PLM, RBD, and NFE groups, respectively. This AI-enabled method offers a promising approach for sleep disorder classification based solely on single-lead ECG signals, providing a useful tool for sleep monitoring and screening. [2]

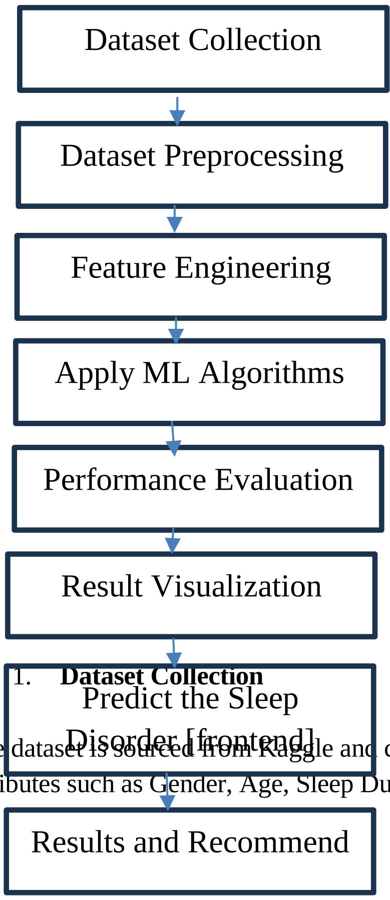
This study proposes an automated method using EEG signals to identify six sleep disorders: insomnia, NFLE, narcolepsy, RBD, PLM, and SDB. By applying a novel triplet half-band filter bank (THFB) to extract EEG subbands and features, and using machine learning algorithms, the system achieves high classification accuracies, with up to 99.2% for insomnia and 98.8% for RBD and SDB. The method offers a fast, efficient, and accurate way to diagnose sleep disorders, potentially improving diagnosis in sleep clinics and home settings. [3]

This study explores the use of machine learning (ML) models to identify sleep disorders based on a dataset of 400 individual records, including demographic, lifestyle, sleep, and health data. The dataset differentiated between individuals with no sleep disorder, insomnia, and sleep apnea. Several ML models were evaluated, including logistic regression, decision trees, ensemble methods like RandomForest and XGBClassifier, support vector machines, and neural networks, using metrics such as accuracy, precision, recall, and F1 score. Ensemble methods, especially RandomForest and XGBClassifier, outperformed others, achieving accuracy and precision up to 0.93, proving their effectiveness in managing complex datasets. The study advocates for using advanced ensemble techniques in diagnostic tools for sleep disorders to improve predictive accuracy and reliability in healthcare. Further research is needed to refine these models for clinical application. [4]

Classifying sleep disorders is vital for improving health, as conditions like sleep apnea can severely affect well-being. Traditional methods are often error-prone, making machine learning algorithms (MLAs) essential for accurate diagnosis. This study compares various MLAs using the Sleep Health and Lifestyle Dataset, which is processed through label encoding and MinMax scaling. The dataset is split into training, testing, and validation sets, with K-fold cross-validation used for performance estimation and hyperparameter tuning to optimize accuracy. Among the models tested, Gradient Boosting achieved the highest classification accuracy at 93.80%, outperforming Random Forest (90.26%), Logistic Regression (91.15%), and AdaBoost (91.15%). Gradient Boosting's superior performance is attributed to its ability to sequentially optimize weak learners and capture complex patterns. The study highlights the importance of optimized MLAs, thorough preprocessing, and hyperparameter tuning for accurate sleep disorder classification. [5]

Proposed Method

Proposed method block diagram is shown as below,



1. **Dataset Collection**

The dataset is sourced from Kaggle and comprises attributes such as Gender, Age, Sleep Duration,

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika ***et. al.,*** **/ International Journal of Engineering & Science Research**

Sleep Quality, Stress Level, Blood Pressure, and BMI. These features are key indicators of sleep health and serve as inputs for classification models.

2. **Data Preprocessing**

Initial exploration is performed using data visualization tools like pandas to inspect attributes and their distributions.

A correlation matrix is generated to assess relationships among features, identifying significant predictors of sleep disorders.

3. **Feature Engineering and Splitting**

The dataset is split into training and testing sets to ensure unbiased evaluation of models. Standard preprocessing techniques are applied to normalize and clean data.

4. **Machine Learning Model Development**

Several algorithms are implemented using the sklearn and xgboost libraries:

Random Forest: Achieved 88% accuracy.

Decision Tree: Attained an accuracy of 86%.

SVM: Performed with the lowest accuracy of 64%.

KNN: Matched the Decision Tree with 86.66% accuracy.

XGBoost: Demonstrated the best performance with 90.66% accuracy.

ANN: A deep learning approach, though it underperformed compared to XGBoost.

5. **Performance Metrics**

Metrics such as accuracy, precision, recall, and F1-score are computed for all models to facilitate a comprehensive performance comparison.

6. **Visualization**

Graphs and plots illustrate algorithm performance, attribute relationships, and classification trends. Examples include gender-based sleep disorder distributions and BMI category visualizations.

7. **Prediction and Recommendation System**

The XGBoost model, as the best-performing algorithm, is integrated into the application for real-time prediction.

Users input attribute values (e.g., age, stress level) to classify sleep disorders like Sleep Apnea.

The system provides tailored recommendations for managing identified disorders.

8. **Outcomes**

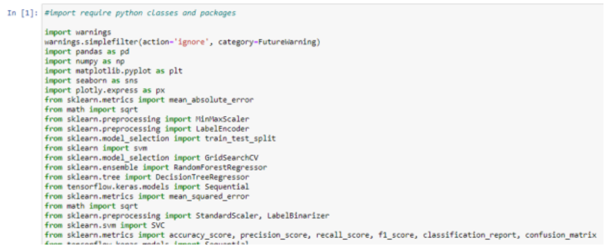
The approach ensures high accuracy in identifying sleep disorders while enabling actionable insights into their management.

- XGBoost's superior accuracy solidifies its role as the primary predictive model in the application.

Results

To identify sleep disease in this application different machine learning algorithms.

The dataset collected from Kaggle.com has different attributes as Gender, Age, Sleep Duration, Quality of Sleep, Stress Level, Blood Pressure, etc.



```
In [1]: #import require python classes and packages

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.metrics import mean_absolute_error
from math import sqrt
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from tensorflow.keras.models import Sequential
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.preprocessing import StandardScaler, LabelBinarizer
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, confusion_matrix
```

Fig: Import Libraries

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika ***et. al.,*** **/ International Journal of Engineering & Science Research**

Loading the required libraries for sleep disorder classification. Different machine learning algorithms are loaded from sklearn library.

```
df = pd.read_csv('data.csv')
df.head()
```

	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: Dataset first 5 records

Showing first five records from dataset using head function from pandas.

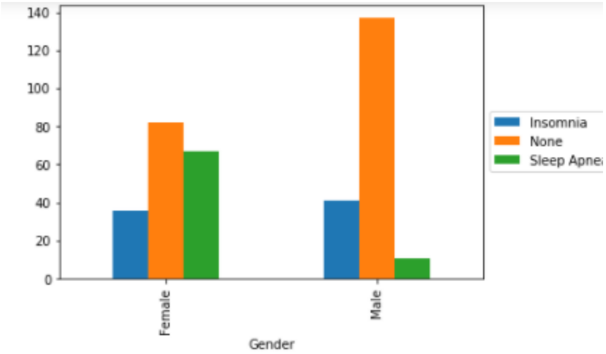


Fig. Male and Female Genders vs. Sleep Disorders

In this graph we plotted male and female gender on x-axis and on y-axis we are displaying count of sleep disorders.

	index	BMI Category
0	Normal Weight	216
1	Overweight	148
2	Obese	10

Fig: Count of BMI category for each index

Dataframe is shown where index and BMI Category are the columns displayed.

Analysing the data with different attributes such as Gender Vs Sleep Disorder.

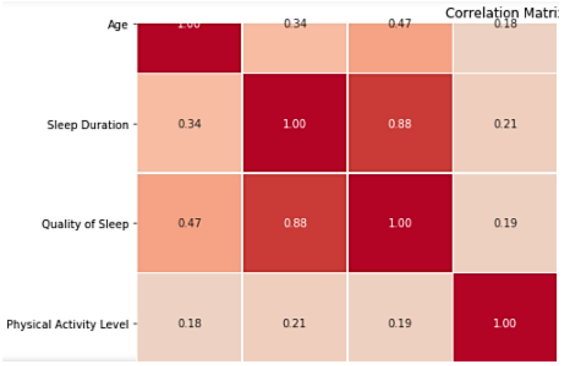


Fig: Correaltion Matrix of Dataset

This is correlation matrix for checking the relations between each attribute from the dataset. Value, -1 indicates that there is inverse correlation between the attributes , 0 indicate that there is no proper correlation between the attributes and 1 indicates that there is linear correlation between the attributes.

```
#split dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,random_state=42)
print("Total records found in dataset = "+str(X.shape[0]))
print("Total features found in dataset= "+str(X.shape[1]))
print("80% dataset for training : "+str(X_train.shape[0]))
print("20% dataset for testing  : "+str(X_test.shape[0]))
```

```
Total records found in dataset = 374
Total features found in dataset= 12
80% dataset for training : 299
20% dataset for testing  : 75
```

Fig: Data Splitting for training and testing

Data is prepared and splits into training and testing.

```
Random Forest Accuracy  : 88.0
Random Forest Precision : 84.09738409738411
Random Forest Recall    : 82.55813953488372
Random Forest FMeasure  : 82.96146044624747
```

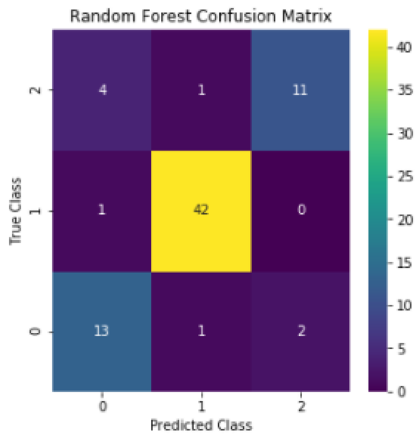


Fig: Random Forest Performance

This is Random Forest algorithm performance which gives accuracy 88%.

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika *et. al.,* / International Journal of Engineering & Science Research

```
Decision Tree Accuracy  : 86.66666666666667
Decision Tree Precision : 83.33980833980834
Decision Tree Recall    : 81.78294573643412
Decision Tree FMeasure  : 82.19517692134325
```

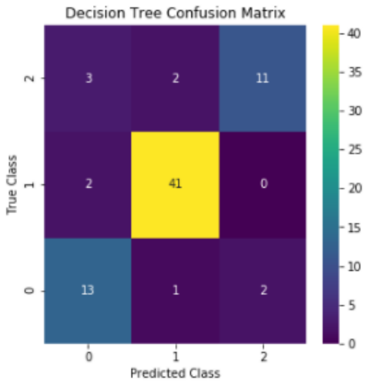


Fig: Decision Tree

Decision tree is giving bit less accuracy as compared to Random forest i.e.86%.

```
SVM Accuracy  : 64.0
SVM Precision : 56.71717171717172
SVM Recall    : 43.75
SVM FMeasure  : 42.33144022134848
```

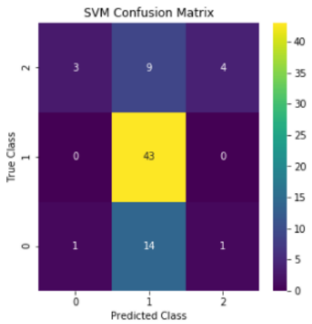


Fig: SVM Performance

SVM is giving lowest accuracy i.e. 64%

```
KNN Accuracy  : 86.66666666666667
KNN Precision : 84.30819826168663
KNN Recall    : 81.78294573643412
KNN FMeasure  : 81.69952898635069
```

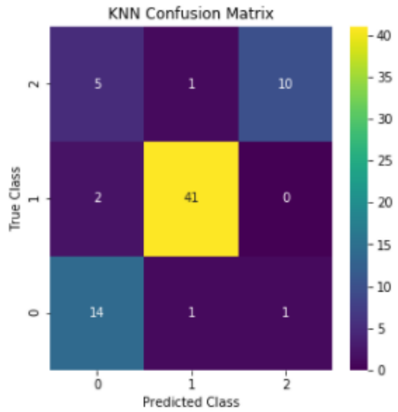


Fig: KNN Performance

KNN is giving same accuracy as Decision Tree i.e. 86.66%

```
XGBoost Accuracy  : 90.66666666666666
XGBoost Precision : 87.79040404040404
XGBoost Recall    : 86.7248062015504
XGBoost FMeasure  : 87.22423062662217
```

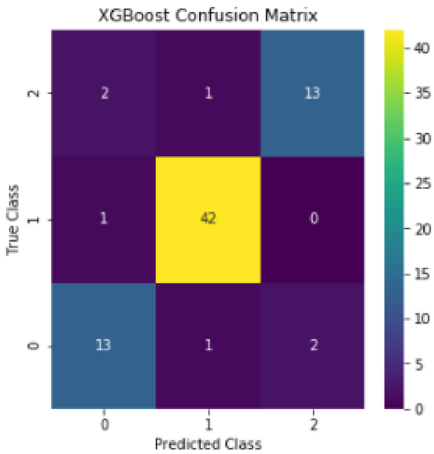


Fig: XGBoost Performance

XGBoost is giving highest accuracy among all algorithms i.e. 90.66.

```
ANN Accuracy  : 57.333333333333336
ANN Precision : 19.11111111111111
ANN Recall    : 33.33333333333333
ANN FMeasure  : 24.293785310734464
```

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/367-374
Chitikinavelu Devika ***et. al.,*** **/ International Journal of Engineering & Science Research**

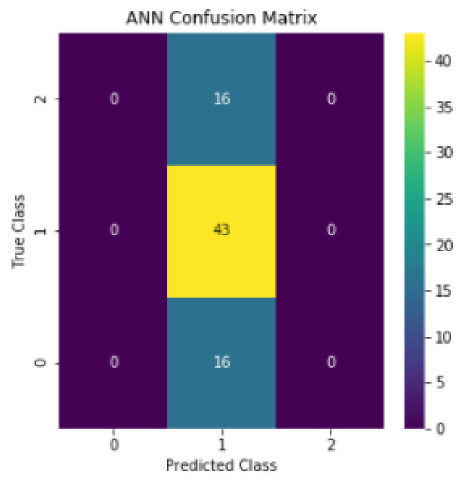


Fig: ANN Performance

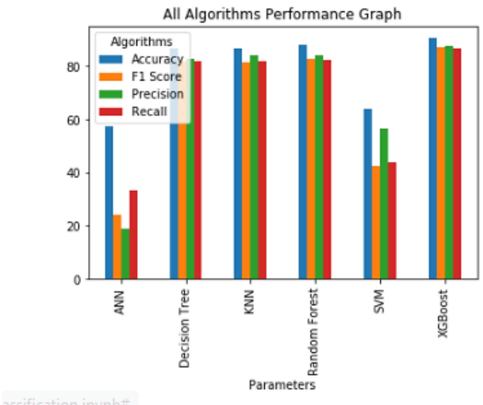


Fig: All algorithms performance graph

From above graphs. We can see that XGBoost is giving highest accuracy and ANN is giving low.

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	Random Forest	84.097384	82.558140	82.961460	88.000000
1	Decision Tree	82.795091	81.782946	81.832207	86.666667
2	SVM	56.717172	43.750000	42.331440	64.000000
3	KNN	84.308198	81.782946	81.699529	86.666667
4	XGBoost	87.790404	86.724806	87.224231	90.666667
5	ANN	19.111111	33.333333	24.293785	57.333333

Fig: Performance metrics of all algorithms

So here data frame of comparison of machine learning algorithms such as Random forest , Decision tree , SVM , KNN, XGBoost , ANN are compared for sleep disorder prediction.

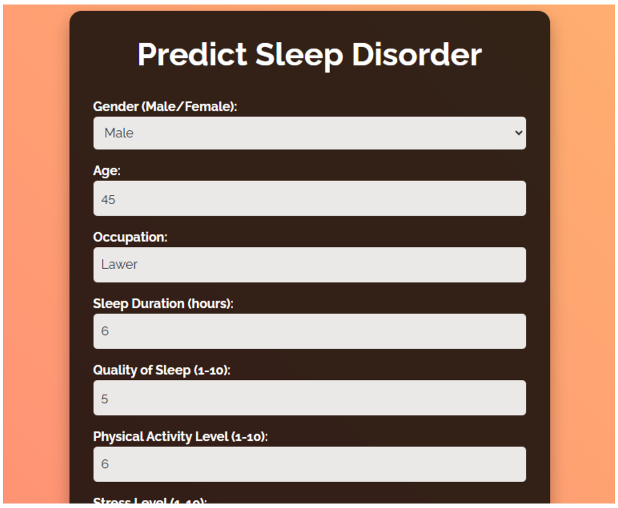


Fig: Predict Sleep Disorder with attributes.

After entering all values, type of sleep disorder can be predicted. Best performing algorithm is used for prediction of sleep disorder.

Fig: Prediction of Sleep disorder

Sleep disorder is predicted as Sleep Apnea and it will also tell how to cure this disorder.

REFERENCES

1. Rajbhandari, Ereena, Abeer Alsadoon, P. W. C. Prasad, Indra Seher, Tran Quoc Vinh Nguyen, and Duong Thu Hang Pham. "A novel solution of enhanced loss function using deep learning in sleep stage classification: predict and diagnose patients with sleep disorders." *Multimedia*

Tools and Applications 80 (2021): 11607-11630.

2. Urtnasan, Erdenebayar, Eun Yeon Joo, and Kyu Hee Lee. "Ai-enabled algorithm for automatic classification of sleep disorders based on single-lead electrocardiogram." *Diagnostics* 11, no. 11 (2021): 2054.
3. Sharma, Manish, Jainendra Tiwari, Virendra Patel, and U. Rajendra Acharya. "Automated identification of sleep disorder types using triplet half-band filter and ensemble machine learning techniques with eeg signals." *Electronics* 10, no. 13 (2021): 1531.
4. Airlangga, Gregorius. "EVALUATING MACHINE LEARNING MODELS FOR PREDICTING SLEEP DISORDERS IN A LIFESTYLE AND HEALTH DATA CONTEXT." *JIKO (Jurnal Informatika dan Komputer)* 7, no. 1 (2024): 51-57.
5. Taher, Abrar, and Walid Ibn Zinnah Ayon. "Exploring Sleep Disorders: A Comparative Analysis of Machine Learning Algorithms on Sleep Health and Lifestyle Data."
6. F. Mendonça, S. S. Mostafa, F. Morgado-Dias, and A. G. Ravelo-García, ‘‘A portable wireless device for cyclic alternating pattern estimation from an EEG monopolar derivation,’’ Entropy, vol. 21, no. 12, p. 1203, Dec. 2019.
7. Y. Li, C. Peng, Y. Zhang, Y. Zhang, and B. Lo, ‘‘Adversarial learning for semi-supervised pediatric sleep staging with single-EEG channel,’’ Methods, vol. 204, pp. 84–91, Aug. 2022.
8. E. Alickovic and A. Subasi, ‘‘Ensemble SVM method for automatic sleep stage classification,’’ IEEE Trans. Instrum. Meas., vol. 67, no. 6, pp. 1258–1265, Jun. 2018.
9. D. Shrivastava, S. Jung, M. Saadat, R. Sirohi, and K. Crewson, ‘‘How to interpret the results of a sleep study,’’ J. Community Hospital Internal Med. Perspect., vol. 4, no. 5, p. 24983, Jan. 2014.
10. V.Singh,V.K.Asari,andR.Rajasekaran,‘‘Ad eepneuralnetworkforearly detection and prediction of chronic kidney disease,’’ Diagnostics, vol. 12, no. 1, p. 116, Jan. 2022.
11. J. Van Der Donckt, J. Van Der Donckt, E. Deprost, N. Vandenbussche, M. Rademaker, G. Vandewiele, and S. Van Hoecke, ‘‘Do not sleep on traditional machine learning: Simple and interpretable techniques are competitive to deep learning for sleep scoring,’’ Biomed. Signal Process. Control, vol. 81, Mar. 2023, Art. no. 104429.
12. H. O. Ilhan, ‘‘Sleep stage classification via ensemble and conventional machinelearning methodsusingsingle channel EEGsignals,’’ Int. J. Intell. Syst. Appl. Eng., vol. 4, no. 5, pp. 174–184, Dec. 2017.
13. Y. Yang, Z. Gao, Y. Li, and H. Wang, ‘‘A CNNidentified by reinforcement learning-based optimization framework for EEG-based state evaluation,’’ J. Neural Eng., vol. 18, no. 4, Aug. 2021, Art. no. 046059
14. Y. J. Kim, J. S. Jeon, S.-E. Cho, K. G. Kim, and S.-G. Kang, ‘‘Prediction modelsforobstructivesleepapneainKoreana dultsusingmachinelearning techniques,’’ Diagnostics, vol. 11, no. 4, p. 612, Mar. 2021.