International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Sleep Disorder Classification with Ensemble Based Machine Learning Models

P.Prasanna
Assistant Professor
Department of Computer Science and Engineering
TKRCET Autonomous, Hyderabad, India
prasanna@tkrcet.com

P.Manoj Kumar
Student,
Department of Computer Science and Engineering
TKRCET Autonomous, Hyderabad, India
manojkumarpottabathini@gmail.com

S.Vaishanvi
Student,
Department of Computer Science and Engineering
TKRCET Autonomous, Hyderabad, India
vaishnavidurga66@gmail.com

V.Aryan Sriram
Student,
Department of Computer Science and Engineering
TKRCET Autonomous, Hyderabad, India
aryansriram.1@gmail.com

P.Varun Reddy
Student,
Department of Computer Science and Engineering
TKRCET Autonomous, Hyderabad, India
pallevarunreddyy@gmail.com

Abstract: Sleep disorders, in particular sleep apnea, have a negative impact on the health of people, so it is important to diagnose them correctly. However, the manual classification of the individual sleep stages is complex and labor intensive in nature and is used by sleep experts. In this paper, a machine learning classification model based on publicly available Sleep Disorder Data, which contains 400 records and 13 attributes, is presented. Various deep learning and technique-driven machine learning models are reviewed and their effectiveness in accurately detecting sleep disorders is evaluated. The variables of lifestyle measures and sleep health measurements are of great importance in the dataset to determine the trends that can be used to suggest the presence of sleep-related conditions. The analysis of the models showed that the best-performing models are bagged models, namely, the Voting Classifier with the help of the Random Forest and Decision Tree algorithms. The algorithm accuracy, precision, recall, and F1-score were 0.973, which means that it can be used to categorize sleep disorders and is reliable. The results indicate that the suggested machine learning methods have the potential for more intelligent, rapid, and precise diagnostics of sleep disorders, hence improving physicians' decision-making and patients' conditions.

"Index Terms - *Machine learning algorithms, deep learning, classification, sleep disorder, Voting algorithm".*

I. INTRODUCTION

Sleep is a vital process that is important in both the physical and mental health. It strengthens the body and improves mental functioning and memory. Sleep has significant effects on cognitive abilities, especially in children and the elderly who are at a greater risk of accidents. Poor sleep may lead to many health issues, including cardiovascular diseases, diabetes, and obesity. Despite its importance, sleep disorders are often undiagnosed or misdiagnosed due to the complexity of testing sleep phases. At present, medical practitioners and sleep specialists have to manually analyze polysomnography (PSG) data to identify sleep stages that can be easily manipulated by human error and is labor-intensive to classify properly [1].

The 2021 survey of the World Sleep Day by Philips, which surveyed more than 13,000 respondents in 13 countries, had found that 55% of adults were not satisfied with their sleep. Factors like COVID-19 epidemic, sleep apnea, and insomnia were identified as influential factors on sleep quality. In particular, 37% of them said that the pandemic negatively impacted their sleep, 37% developed insomnia, 29% snored, 22% had shift-work sleep problem, and 12% sleep apnea [2]. These results highlight the widespread nature of sleep-related disorders and the need to have better diagnostic and classification systems.

The healthcare practitioners divide sleep into five distinct phases which include alertness, N1, N2, N3 and rapid eye movement (REM). Wake is defined as the state of alertness of human beings where they are aware of their surroundings and this is represented by quick and irregular brain waves. The first stage of sleep is N1, which is marked by decreased activity of brain waves and muscle relaxation. N2 is a deeper level and N3 is the lowest level of sleep, which is hard to wake up. REM sleep is characterized by rapid eye movements and brain waves similar to those which occur during waking. All these stages are critical in the recovery and mental processes of the body. PSG allows doctors to measure these stages, recording electroencephalogram (EEG) and electrocardiogram (ECG) signals to measure brain and body activity during sleep [3], [4], [5].

In order to reduce the number of human factors in the classification and prediction of sleep stages, many researchers have developed the automated methodologies using machine learning algorithms (MLAs). These approaches can be broken down into classic machine learning and deep learning algorithms. Traditional machine learning models, including support vectors machines and decision trees, tend to be applied to smaller datasets, and human feature extraction is required to determine sleep stages based on features like entropy, and energy. On the other hand, the deep learning algorithms, which are designed to replicate the structure of the human brain, use a neural network to identify complex patterns in the data on their own. These approaches are especially beneficial to large, complex datasets and are considered as a possible alternative to traditional machine learning approaches [6], [7]. The most common approach to sleep-stage classification is the one that takes EEG signals as the input to conventional and deep learning models [8].

II. RELATED WORK

Many studies have used machine learning to detect and classify sleep disorders like obstruction sleep apnea, sleep stage classification, and ECG based detection. Algorithms based on machine learning have improved diagnostic accuracy and reduced manual analysis, which is manually inspected and therefore error-prone. Kim et al. [9] utilized machine learning to predict obstructive sleep apnea in Koreans. Many machine learning methods identified and predicted the probability of obstructive sleep apnea with clinical information. Models suggest that machine learning and automated prediction systems could help physicians to diagnose obstructive sleep apnea faster. Predictive accuracy was increased with demographic, clinical, and physiological characteristics. It is proposed in this study that machine learning used early on may be beneficial in the diagnosis of sleep apnoea.

Mousavi et al. [10] applied deep convolutional neural networks in the detection of sleep phases in single-channel EEG. Apply deep learning to automatically identify sleep stages to diagnose insomnia and sleep apnea. EEG hierarchies can be identified automatically by the use of deep learning convolutional neural networks. Compared to the conventional machine learning algorithms, Convolutional Neural Networks (CNNs) classify the stages of sleep in a faster and more accurate way. Djanian et al. [11] examined sleep technologies and artificial intelligence in sleep classification on the side of consumers. Sleep trackers are progressively using artificial intelligence. These AI algorithms and sensors measure the quality of sleep in real-time, helping to address sleep disorders. The study showed that the AI-based consumer sleep devices (especially those based on deep learning) improved the identification of sleep stages. Individualized sleep health is achieved through wearable AI devices.

Salari et al. [12] explored the identification of sleep apnoea based on machine learning algorithms on ECG data. The study says that sleep apnea can be detected by machine learning algorithms based on ECG signal analysis. Random Forests and Support Vector Machines are able to detect sleep apnea on single-lead electrocardiograms. The authors declared that methodologies of feature extraction affect the performance of the model. This study showed that machine learning could be used to improve sleep apnoea detection using the ECG, without sleep tests. Li et al. applied the method of deep learning and EEG spectrograms to detect sleep stages [13]. EEG spectrograms keep track of frequency composition over time. These spectrograms were classified using deep neural networks. Our deep learning approach acquired spectrogram features to precisely differentiate sleep states. As demonstrated by this paper, deep learning is applicable in classifying sleep stages where feature engineering fails. Sleep stage recognition can be effectively automated using deep learning, and especially deep neural networks. Han, Oh [14] carried out a comparative study of machine learning techniques to predict the intensity of obstructive sleep apnea (OSA). Data on patients was used to compare decision trees, random forests, and support vectors machines to predict the severity of obstructive sleep apnea (OSA). Random forests performed better than models to predict OSA severity. The authors believe that demographic and physiological information can predict the extent of sleep apnoea. This paper proved that machine learning could help quantitatively evaluate the extent of sleep disorders and guide specialists in

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their treatment. Bahrami and Forouzanfar [15] used deep learning to detect sleep apnea using single-lead ECG. To predict sleep apnea using electrocardiogram data, we used Convolutional Neural Networks and Long Short-Term Memory networks. CNNs and LSTMs performed better than machine learning models in diagnosis of sleep apnoea. Sleep apnoea could be revolutionized with deep learning methods of real-time ECG data. This paper showed that deep learning was able to efficiently process complex time-series data, and improved the use of ECG data to non-invasively detect sleep apnea.

Satapathy et al. [16] made a comparison of machine learning methods of staging sleep automatically. The classification of sleep stages was assessed based on the feature set of the EEG data and the support vectors machines, random forests, and decision trees. Forests of random trees demonstrated the best performance in terms of accuracy and strength. The authors found that the selection of features improves classification and machine learning techniques performed differently depending on the type of features used. This study exemplified how to stage sleep using machine learning techniques and to choose the factors that are crucial to improve the efficiency of the model. Bahrami and Forouzanfar [17] recognized single-lead ECGs of sleep apnoea using machine learning and deep learning models. A comprehensive comparison of CNNs, LSTMs, SVMs and random forests. The poll determined that CNNs exhibited greater accuracy and sensitivity. Deep learning is capable of detecting sleep apnea with ECG signals instead of polysomnography.

III. MATERIALS AND METHODS

We proposed a way of diagnosing sleep disorders through machine learning algorithms which proved to be effective because of the strengths they have. Support Vector Machine, K-Nearest Neighbors, Decision Tree, Random Forest, and Artificial Neural Network with Multi-layer perception model are the various models used. Sleep Disorder Data provides a few sleep health and habit measures that were used in the creation of these algorithms. The Voting Classifier uses Decision Trees and Bagging using Random Forest to boost its accuracy in classification. This group method improves the evaluation and effectiveness of models. The medical device is able to handle 400 records with 13 features to diagnose sleep issues like sleep apnea. The suggested methodology will help professionals to make knowledgeable decisions and improve health of patients.

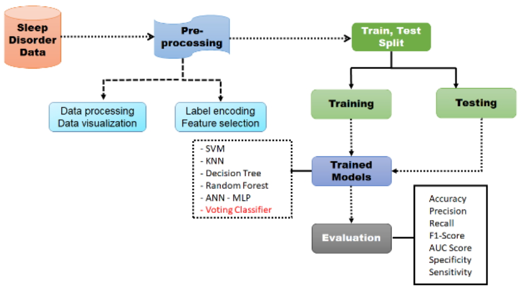

Fig.1 Proposed Architecture

The diagram shows a machine learning model flowchart that focuses on classifying sleep disorders. The procedure starts with raw data on sleep disorders, which undergo pre-processing, comprising of data cleaning, visualization, and feature identification. The processed data is then separated into training and testing data. There are several machine learning models: SVM, KNN, Decision Tree, Random Forest, ANN-MLP[25], and Voting Classifier, which are trained on the training data. The trained models are evaluated on the testing data based on the measures of accuracy, precision, recall, F1-score, AUC score, specificity and sensitivity.

A) Dataset Collection:

The current paper makes use of Sleep Health and Lifestyle Dataset which is available on Kaggle [22]. The sample consists of 400 observations and 13 parameters which are relevant to sleep and daily habits such as sex, age, professionalism, sleep time, quality of sleep, physical activity, stress, body mass index, blood pressure, heart rate, number of steps each day, and sleeping disorders. Sleep Disorder is the target variable that has three categories; none, sleep apnea and insomnia. Our dataset includes variety of occupational data, the most common being nurse (73 observations), doctor (71), and engineer (63), and other occupations, including lawyer (47 observations), teacher (40 observations), and salesperson (32 observations). Standardization of the labels was performed in pre-processing to replace labels in the analysis.

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Bl Pres
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	12
1	2	Male	28	Doctor	6.2	6	60	8	Normal	12
2	3	Male	28	Doctor	6.2	6	60	8	Normal	12
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	14
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	14

Fig.2 Dataset Collection Table

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B) Pre-Processing:

In the pre-processing stage, the data is processed through cleansing and the treatment of absent values and data visualization helps in identifying patterns and anomalies. Categorical data are encoded using label encoding, but feature selection techniques are used to decide on the most relevant ones to use in classification.

i) Data Processing: In data processing stage, duplicates are identified and removed in order to ensure consistency and accuracy of data. The redundant entries can bias the analysis and compromise the model performance and hence, any duplicate rows or observations are removed. Data cleansing is then performed by dealing with missing or null values in the data. This involves either deleting rows which contain no values or filling the values in by appropriate methods like mean, median or mode depending on the nature of the data. This procedure guarantees the dataset's cleanliness, minimizing noise and enhancing the quality of the machine learning models.

ii) Data Visualization: Data visualization is a critical process that is needed to analyze the dataset and understand the patterns that are inherent. The visualization of data using charts, graphs, and plots can help to identify trends, distributions, and possible outliers. Histograms, box plots, and scatter plots help to analyze the distributions of numerical features, and bar graphs are useful with categorical variables. Visualizations can be used to identify the correlation between features and find anomalies that can influence the work of models. This step simplifies feature engineering and improves an understanding of the data before applying machine learning algorithms.

iii) Label Encoding: Label encoding This is a technique used to encode and convert the data in categories in the form of strings to numbers. The machine learning algorithms do not understand the values represented by strings in the dataset when it contains category variables, e.g., Gender or Sleep Disorder. Label encoding is therefore used to encode these string labels into integers. As an example, the words "Male" and Female could be represented by 0 and 1 respectively. This step will ensure that categorical variables are properly coded to fit machine learning models, allowing algorithms to effectively understand and learn these characteristics during training and testing.

iv) Feature Selection: The process of selecting the most relevant features (or variables) and including them in the machine learning models is called feature selection. This step reduces the dimension of the dataset, improving model performance and reducing overfitting. With the choice of the relevant characteristics, the model will be able to focus on the most significant variables that affect the target variable. This process involves separating the data into input variables (X) and the target variable (y), where X represents the independent variables, and y represents the dependent variable. The dataset is improved by using techniques such as correlation analysis and recursive feature reduction.

C) Training & Testing:

The data is separated into training and testing to determine the effectiveness of the model. Typically, 20% of the data is used to train the models, and the remaining 80% is used to test. This split is what makes the model be trained on a large percentage of the data and tested on new data to determine its generalization ability. The split is usually done with the help of the train test split functions of scikit-learn that ensures a random and unbiased splitting of the data into training and testing segments.

D) Algorithms:

Random Forest [20] is a collection of decision trees that is designed to enhance the accuracy and robustness of classification. The random selection of features and data reduces overfitting and improves the generalization. This team technique is effective in identifying important variables in the diagnosis of sleep disorders and provides reliable predictions.

$$G = 1 - \sum_{j=1}^{c} p_j^2 \ (1)$$

In this respect, pj is the likelihood of class j in a node.

The **Support Vector Machine** [18] is used to classify sleep disorders based on the optimum hyperplane to separate different classes in the data. It is capable of handling high-dimensional data, which make it suitable in identifying the complex trends in sleep patterns and activities, therefore, making it suitable in making accurate diagnosis.

$$f(x) = sign(w^T x + b)(2)$$

where:

- w is the weight vector,
- x is the input feature vector,
- b is the bias term,

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ISSN: 3068-272X www.ijdim.com Original Research Paper

- sign(·) is the sign function determining the class label.

K-Nearest Neighbours algorithm spies sleep disorders based on the closeness to similar data points within the feature space. KNN finds patterns and similarities by looking at the closest neighbors of a given instance, and provides the intuitive information on the diagnosis of the sleep disorder based on past information.

The Decision Tree method is used to create a model which predicts the classification of sleep disorders using a series of binary decisions based on input features. The basic structure enables easy interpretation, which makes it suitable to identify the critical factors affecting sleep health and improve the accuracy of the diagnosis.

To categorize sleep disorders, Artificial Neural Networks [21] are used to construct complex interactions between the data, getting knowledge based on the input variables. The multilayer perceptron architecture enables the system to detect intricate patterns in sleep data, therefore, increasing the predictive accuracy and improving the diagnostic outcomes.

The Voting Classifier combines the forecasts of a large number of models, including decision trees and bagging classifiers, such as Random Forest. This combination approach improves the accuracy of classification by leveraging the capabilities of multiple algorithms, reducing errors, and providing a more robust and reliable prediction of sleep disorders.

$$\hat{y} = \arg max \frac{1}{N} \sum_{i=1}^{N} p_i(c|x) (3)$$

IV. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is the ability of a test to differentiate between a patient and a healthy case. The ratio of true positives and true negatives of all analyzed cases should be calculated to determine the accuracy of a test. This mathematically can be written as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (4)$$

Precision: Precision tests the percentage of correctly identified cases out of positive cases. As a result, precision is calculated as the following formula:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (5)$$

Recall: Recall is a machine learning metric used to evaluate the ability of a model to recognize all the relevant examples of a particular class. It is the ratio of the correctly forecasted positive counts to the actual counts and it reflects on the effectiveness of a model to detect the occurrence of a given class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (6)$$

F1-Score: F1 score is used to assess how accurate a machine learning model is. It combines the precision and recall measures of a model. The accuracy measure is the rate of correct predictions on a model on the whole dataset.

$$F1\, Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (7)$$

The results of the performance measures (accuracy, precision, recall and F1-score) of each algorithm are presented in Table 1. The Voting Classifier has the highest scores, and the metrics are all of 0.973. Alternative algorithm metrics are also given.

Table.1 Performance Evaluation Metrics

ML Model	Accuracy	Precision	Recall	F1-score
Support Vector Machine	0.880	0.892	0.880	0.884
KNN	0.867	0.883	0.867	0.867
Decision Tree	0.907	0.909	0.907	0.908
Random Forest	0.880	0.887	0.880	0.881
ANN-MLP	0.573	1.000	0.573	0.729
Voting Classifier	0.973	0.973	0.973	0.973

Graph.1 Comparison Graphs

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ISSN: 3068-272X www.ijdim.com Original Research Paper

In Graph 1, accuracy is shown in light green, precision in blue, recall in light yellow, and F1-score in green. The Voting Classifier outperforms any other algorithm in all aspects, having the highest values in comparison to the other models. The above information is depicted in the graph above.

V. CONCLUSION

This study shows that machine learning algorithms can be useful to classify sleep disorders by utilizing publicly available information in the Sleep Disorder Data set. The most accurate of the numerous deep learning and classical machine learning methods was the Voting Classifier which relied on bagging with Random Forest and Decision Trees. The performance was good in all the evaluation measures with an accuracy of 97.3, the precision of 97.3, the recall of 97.3 and the F1-Score of 97.3. It shows that the Voting Classifier developed in this case is an extremely reliable and robust approach to the classification of sleep disorders. The findings indicate stable improvements in almost all the considered measures, which proves that the model can be useful in providing precise and timely diagnoses of sleep disorders, benefiting patients and enhancing clinical decision-making. The Voting Classifier can be suggested as a useful tool in terms of improving the process of sleep disorder diagnosis automation since it has a high classification accuracy and can help to increase the level of diagnostic accuracy and improve the prognoses of patients with this condition.

The future focus of this study includes exploring more advanced machine learning models, like deep learning models like Convolutional Neural Networks (CNNs) and recurrent networks, to increase the accuracy of sleep disorder classification. The integration of wearable devices-based real-time data can enhance predictive capabilities of the system. Moreover, augmenting the dataset to encompass varied demographics and sleep problems will enhance model generalization.

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