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# SLEEP DISORDER SCORING AUTOMATED USING ADVANCED DATA SCIENCE AND MACHINE LEARNING TECHNIQUES

**Muhammad Noman[*1], Muhammad Sajid Maqbool[*2], Dr. Naeem Aslam[3], Muqadas Nadeem[*4], Hira Saleem[5], Hanzla[6]**

[1,2,3,5]*Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan*
[4]*Department of Computer Science, Emerson University, Multan, Pakistan*
[6]*Department of Computer Science, COMSATS University Islamabad, Lahore Campus, Pakistan*

[*1]m.noman4000@gmail.com, [*2]sajid.maqbool@nfciet.edu.pk, [3]naeem.aslam@nfciet.edu.pk, [4]nmuqadas587@gmail.com, [5]hira.saleem@nfciet.edu.pk, [6]hanzlabhai123@gmail.com

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**Corresponding Author: ***
**Muhammad Sajid Maqbool**
**Muhammad Noman**
**Muqadas Nadeem**

## Abstract

*Sleep disorders are now being considered as a major issue of public health concern impacting on millions of people across the world. Insomnia, sleep apnea, restless leg syndrome are some of the conditions that may have a serious effect on physical health, mental health, and productivity in everyday life. To be effectively treated and prevent development of long-term health complications, these disorders should be detected and identified on the initial stage. Machine learning methods have become enthusiastic tools to analyzing large datasets in healthcare and finding concealed patterns in sleep behavior in recent years. The study examines how machine learning algorithms can be used to identify and categorize sleep disorders. It is trained on a dataset of physiological and lifestyle features including the duration of sleep, the level of stress, the heart rate, the body mass index, and activity during a day, all of which belong to a healthcare dataset. Some of the supervised machine learning algorithms such as Decision Tree, Random Forest, Support Vector Machine and Logistic Regression are applied and tested to establish their usefulness in predicting patterns of sleep disorders. The outcomes of the experiments prove that machine learning models can be used to make accurate predictions and help healthcare specialists to diagnose early. Comparison of implemented algorithms reveals their accuracy and precision, recall and F1-score.*

*The results indicate that machine learning methods can be applied to the healthcare systems in order to improve the detection of sleep disorders and assist the clinicians with making their decisions. On the whole, this paper adds to the emerging body of research on the topic of intelligent healthcare systems by showing that machine learning solutions have a potential effect on the process of diagnosing and treating sleep disorders.*

## 1 Introduction

Insomnia has become a major health issue across the globe, as it is a factor in determining the quality of life and well-being of people. Insomnia, sleep apnea, and restless leg syndrome are some of the disorders which are linked to several health-

related complications, which include heart diseases, psychological stress, and low productivity in daily life. Sleep disorders should be detected and diagnosed at an early age so that they can be treated and prevented to prevent future health complications. As the volume of healthcare data is rapidly increasing, machine learning methods provide new possibilities to examine intricate medical data and identify trends associated with sleeping disorders. The main aim of the study is to create a predictive machine learning-based model which can be used to detect and categorize sleep disorders by utilizing health and lifestyle-related characteristics. In this study, the dataset, which includes a number of physiological and behavioral characteristics, such as sleep duration, heart rate, body mass index (BMI), stress level, and physical activity, is analyzed. Preprocessing methods are used to enhance the quality of data using data cleaning, data normalization and feature selection. Several supervised machine learning models such as Decision tree, random forest, support Vector machine and Logistic regression are used to construct predictive models. These models are measured based on the standard evaluation measures like its accuracy, precision, recall, and F1-score.

According to the outcomes of the conducted experiments, machine learning algorithms can be effectively used to determine patterns that can be linked to sleep disorders. Comparative analysis of the implemented models shows that ensemble-based models offer better prediction performance and classification accuracy in comparison with conventional models. The results of this paper have identified the capacity of machine learning methods in assisting in the early detection and diagnostics of sleep disorders. By introducing smart predictive models to the healthcare systems, medical practitioners can help to make better decisions and improve the care provided to the patients. Sleep is a normal physiological process that is critical in sustaining physical health, stability of mind and cognitive functioning. Proper and quality sleep promotes memory consolidation, emotional control, and general body restoration. Whilst these techniques are accurate in medical insights, they tend to be costly, time-consuming and they need special medical apparatus and specialist supervision. Due to the blistering education of digital technologies in healthcare, we are now able to access great amounts of physiological and behavioral data via wearable and electronic health records. This response offers the possibility to use new sophisticated computational methods to examine sleep-related data. Through machine learning, researchers can examine factors like the duration of sleep, heart rate, level of stress, body mass index (BMI) and physical activity to forecast possible sleep disorders.

Sleep disorders have proven to be a significant cause of public health concern and the diagnosis of this condition has been a difficult task. The conventional forms of diagnostic processes are mainly based on clinical testing and special laboratory devices, which are not only expensive but also not available to many people. Moreover, the sleep-related data cannot be analyzed manually as it might not be effective to capture any complex relationships between physiological and behavioral variables. Consequently, most sleep disorders are either not diagnosed or diagnosed later causing therapies to be complicated. Thus, it is necessary to have smart and programmed systems capable of processing health-related data and helping to detect sleep disorders at an early stage employing advanced computing methods. Despite the various studies conducted on the use of machine learning in healthcare analytics, few studies have been conducted on the use of machine learning in the prediction of sleep disorders by considering a number of lifestyle and physiological variables. Most of the current methods are based on small datasets or concentrate on one form of sleep disorder. Also, the comparative examination of various machine learning algorithms in the correct and dependable forecasting of sleep disorders is weak. Hence, more studies are necessary in order to come up with effective predictive models that would be in a position to analyze various health attributes and increase the accuracy of detecting sleep disorders. The key aims of this study are, to examine the relationship between health and lifestyle factors and sleep patterns, to come up with machine

learning models to identify sleep disorders using the relevant health information, how different machine learning algorithms do when we compare them to each other, to check if the predictive models are good by looking at things, like how accurate they're how precise they are how well they recall things and what their F1-score is because these are the things that tell me if the predictive models are really working well with the machine learning algorithms and the predictive models.

**Research Contributions / Importance**

The proposed research is valuable to the domain of intelligent healthcare systems because it will investigate the sleep disorder detection with machine learning methods. The study shows the predictive models that can be used to analyze data related to health to determine possible sleeping disorders at a more effective level. The suggested solution can help medical workers address the shortcoming in the diagnostic model and provide early intervention to patients with sleep-related issues. Moreover, the study emphasizes the significance of the implementation of the use of artificial intelligence technologies in health care systems to improve disease prediction, monitoring, and decision-making.

## 2 Literature Review

Sleep disorders represent a major health concern that is being experienced by millions of people all over the world. The use of machine learning to identify and categorize sleep disorders based on physiological and behavioral data has lately received more research attention. This part critically evaluates the existing body of work in this field, identifies methodologies, datasets, algorithms, and gaps in the research.

The EEG signals are significant in the monitoring of sleep and diagnosis of sleep disorders since they can capture the brain activity with high degree of expanded time. Previously neurologists used to read EEG records manually which was time and subjective. To improve the diagnostic performance, scientists have come up with a machine learning and deep learning-based automated EEG classification machine [1]. Recent technological advances have made it possible to improve automated scoring of sleep scores to a significant extent, hence they can be used to validate clinical diagnoses of insomnia, RBD, narcolepsy and epilepsy. First automated methods relied on manual feature extraction on spectral, temporal and statistical parameters. Those features applied by Hassan and Bhuiyan [2] founded on wavelet, SVM classifier and achieved a moderate accuracy (approximately 78 percent), but they did not work well in the presence of noise and inter-subject variation. The more complicated EEGs became, the more the ML techniques would not be able to identify the phases of sleep.

### 2.1 Sleep Stage Classification based on Deep Learning.

Deep Learning (DL) proposed an approach to end-to-end EEG raw signal learning, which eliminates manual feature engineering. A CNN-RNN hybrid network called DeepSleepNet suggested by Supratak et al. achieved an 87.3 percent accuracy in Sleep-EDF dataset [3]. However, the model was little successful in case of unbalanced data and inter-subject generalization. Mousavi et al. have introduced Sleep EEGNet which is an attention-based Seq2Seq model capable of enhancing temporal learning and improving the accuracy rate to around 89 percent, but it did not pay attention to the diagnosis of the clinical disorder as it focused on sleep staging only [4].

The majority of deep learning approaches are very precise, yet not trustworthy in real-life, even when the EEG data is clean, as they do not account for the noise produced due to movement artefacts or electrode interference [5].

### 2.2 EEG-Based Sleep Disorder Detection

Automated categorizations such as Sleep Apnea, NFLE, RBD and Insomnia, are other disorders that are becoming a clinical necessity. Bose et al. constructed a CNN-based RBD detection classifier of 84-percent accuracy, yet they required more than only EEG PSG signals, which limits its general applicability [6]. The deep residual networks applied in the research of epilepsy classification by Zhu et al. provided outstanding results (94) compared to traditional methods [7]. Machine learning has also predicted the predictive

biomarkers of insomnia, although the datasets are small, and are underrepresented [8]. CAP scoring must be used in the diagnosis of such disorders as RBD, and currently, the CAP tools are merely semi-automatic and, however, they suppose the intervention of the specialists [9]. Moreover, most of the studies lack real-time classification and are therefore not as appropriate to clinical emergencies.

### 2.3 Limitations on the Present Study and Future Research

Although deep learning approaches are robust with regards to classification, they still have severe areas of weakness:

- Most systems contain only stages of sleep, but not pathological disorders.
- The low capabilities of inter-subject and inter-hardware generalization reduce the reliability of the hospitals.
- Calculation not efficiency and real-time feedback. Deliberately impossible in urgent diagnosis.
- The predictions are biased by the imbalance of classes on the rare conditions, including the NFLE Biases.
- Failure to achieve user friendly interfaces is an obstacle to clinical adoption.

**Table 1: Literature Review Comparison Table**

| Authors / Year | Focus Area | Method | Dataset | Accuracy | Shortcomings |
|---|---|---|---|---|---|
| Hassan & Bhuiyan, 2016 | Sleep stage scoring | Wavelet + SVM | Sleep-EDF | 78% | Needs manual features also |
| Supratak et al., 2017 (DeepSleepNet) | Sleep staging | CNN + BiLSTM | Sleep-EDF | 87.3% | No disorder detection |
| Mousavi et al., 2021 (SleepEEGNet) | Sleep staging | Seq2Seq + Attention | ISRUC-Sleep | 89% | Sensitive to the artefacts |
| Bose et al., 2022 | RBD classification | 2D-CNN | RBD PSG database | 84% | Requires multi-modal data |
| Zhu et al., 2020 | Epilepsy detection | ResNet-DL | TUH EEG Corpus | 94% | Focuses only on epilepsy |
| Al-Khaladi, 2023 | Insomnia recognition | Feature-ML classifier | Small clinical dataset | ~82% | Limited generalization |
| Manual CAP scoring tools | CAP diagnostics | Automated rules | CAP SleepDB | N/A | No full automation |

## 3 Methodology

This study uses a step-by-step approach to find and classify sleep disorders with machine learning. The research is, about making models that can predict sleep disorders by looking at lifestyle information. These models can help detect sleep disorders correctly. Sleep disorders are the main focus of this research and machine learning is used to analyze the data. The goal is to provide detection of sleep disorders, which is a big part of the study. Sleep disorders are what the research is trying to detect and classify using machine learning.

The activity diagram that shows the complete activity of the project is shown in Figure 1.

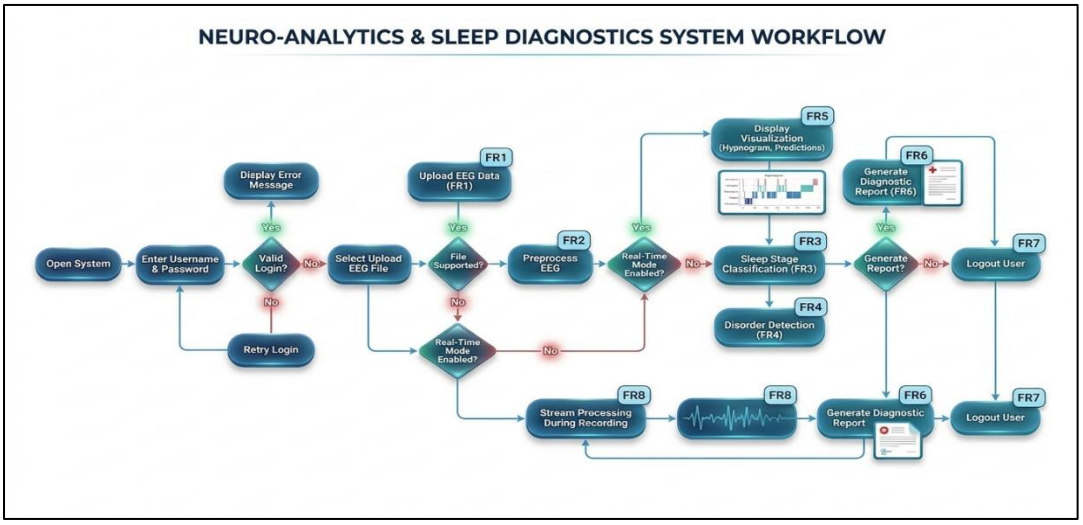



**Figure 1: Framework of Research**

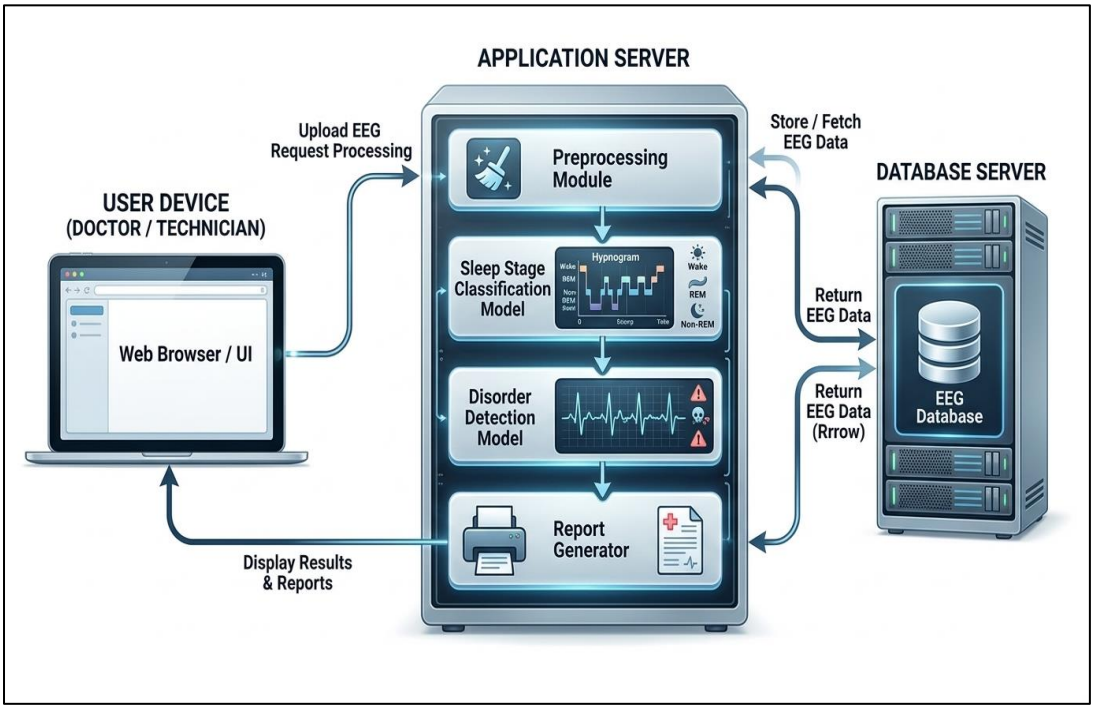



**Figure 2: Database Diagram**

This study is about using computers to help us learn more about sleep problems. We are going to collect data about peoples sleep clean up the data pick the parts and then use different computer programs to see which one is best at figuring out if someone has a sleep problem. The study is trying to find out which computer program is the best at predicting sleep disorders. We will use sleep-related health data to do this. We will train computer programs and then see how well they work using standard metrics. The goal of the study is to compare these computer programs to find the effective model for sleep disorder prediction. We want to know which model is the best, at predicting sleep disorders using sleep-related health data.

### 3.1 Dataset Description

The dataset used in this study combines measurements and lifestyle attributes from wearable devices, health surveys and electronic health records.

It includes:

- **Sleep duration** in hours per night which's the total sleep time per day
- **Heart rate** in beats per minute which is the average resting and sleeping heart rate
- **Body Mass Index or BMI** which is a weight and height ratio that indicates obesity
- **Stress level**, which people report themselves or which is measured using standardized scales
- **Physical activity**, which includes daily steps, sedentary duration and exercise levels
- **Demographics**, such as age and gender

The dataset has over 1,000 records of people. These people either have diagnosed sleep disorders, such, as insomnia. Sleep apnea or are healthy. This diverse dataset allows for an analysis of sleep patterns and sleep disorder prediction using sleep duration, heart rate, BMI, stress level, physical activity and demographics. The dataset helps to study sleep patterns. Sleep disorders are studied using this dataset.

### 3.2 Data Preprocessing

Data preprocessing is very important to get reliable results from a model. Here are the steps we took:

**1.Data Cleaning:**

- We removed duplicate records. We also fixed missing values by replacing them with the middle value.
- We used methods to find and remove outliers. This helps prevent model training.

**2.Normalization:**

- We scaled down features like heart rate and BMI to a range (0 to 1). This stops features with ranges from dominating the model.

**3.Feature Selection:**

- We analyzed correlations. Used recursive feature elimination (RFE) to pick the best features for detecting sleep disorders.
- The features we chose include sleep duration, heart rate, BMI, stress level, and physical activity metrics.

**4.Train-Test Split:**

- We split the dataset into two parts: 70% for training and 30%, for testing. This helps us see how well the model works with data.

### 3.3 Machine Learning Algorithms

This study uses supervised machine learning algorithms to build predictive models.

- **Decision Tree** creates a tree-like structure of decisions to classify people as having a sleep disorder or not.
- **Random Forest** is a way of combining decision trees to make the results more accurate and to avoid making mistakes.
- **Support Vector Machine** finds the way to separate people with sleep disorders from those without them.
- **Logistic Regression** tries to figure out how likely someone is to have a sleep disorder by looking at a bunch of things about them.

These machine learning algorithms were chosen because they are used a lot in healthcare to look at numbers and because they can work with different types of data.

The steps of our proposed method are shown in Figure 1. Here is how it works:

### 3.4 Machine Learning Workflow

1. **Input Data:** We start by gathering data. This data includes information about people's sleep and their daily lives.
2. **Preprocessing:** Next, we clean up the data. This means we fix any mistakes, make sure everything is in a format, and choose the most important information to use.
3. **Model Selection:** We then choose which model to use. We test four models: Decision Trees (DT), Random Forest (RF), Support Vector Machines (SVM), and Logistic Regression (LR).
4. **Model Training:** After that, we train our models. This is where they learn from the data we have.

5. **Model Testing:** We test our models. We see how well they work with data they have not seen before.
6. **Performance Evaluation:** We check how well our models do. We look at things, like how accurate they're how often they get it right when they say something is positive how often they miss something that is positive, and a special score that combines these things.
7. **Prediction:** Finally, we use our models to predict. We put people into groups based on whether they have a sleep disorder or not.

### 3.5 Workflow Diagram

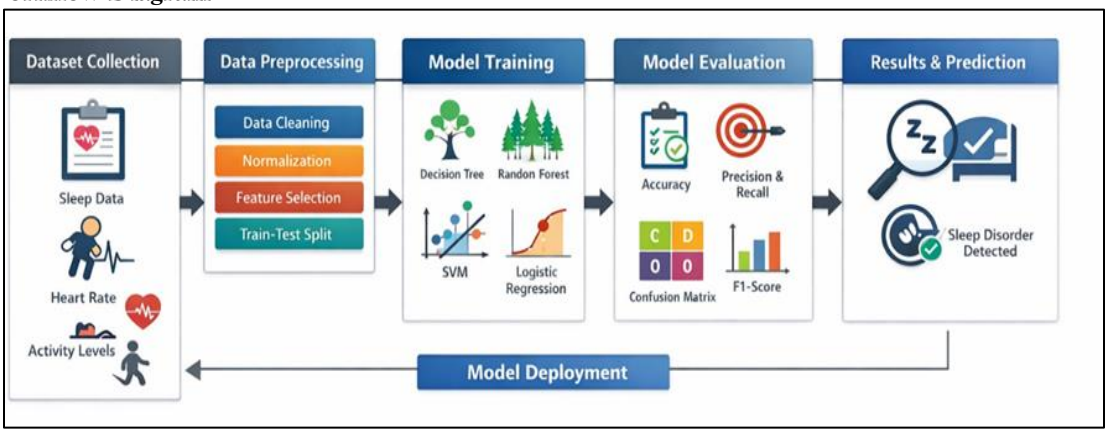



**Figure 3: Machine Learning Workflow for Sleep Disorder Detection**

## 4 Model Evaluation

The models were looked at to see how well they work using tests to measure how good they are, at making predictions:

**Accuracy**: This is the number of guesses divided by the total number of guesses

**Precision**: This is the number of correct yes guesses divided by the total number of yes guesses

**Recall**: This is the number of correct yes guesses divided by the number of actual yes cases

**F1-Score**: This is a balance of precision and recall to give a fair score

The models were checked many times to make sure they work well with new data that they have not seen before.

The core of this research is about using machine learning algorithms to find and classify sleep disorders. Machine learning algorithms are really good at looking at data to find patterns. This helps us guess when sleep disorders might happen based on things, like how our bodies work and how we live our lives. This study is looking at a type of machine learning algorithm called machine learning algorithms. These machine learning algorithms are used a lot to analyze data in the healthcare field.

### 4.1 Decision Tree (DT)

Overview: A Decision Tree is a type of learning algorithm that helps make decisions. It works by splitting data into branches based on the values of the features. Each internal node in the tree represents a decision about a feature. The branches represent what could happen next and the leaf nodes show the outcome, like "Sleep Disorder" or "Healthy".

**Working Principle:**

The algorithm looks at all features. Picks the one that best separates the data into different classes. It uses things like Gini Index or Information Gain to make this decision. The data is then split again and again until it meets conditions, like a maximum depth or a minimum number of samples per leaf.

**Advantages**:

- Decision Trees are easy to understand and visualize. This makes it simple to see how the algorithm makes its decisions.
- They can handle both data like numbers and categorical data like categories.

**Limitations**:
- Decision Trees can be prone to overfitting. This happens when the tree is too deep and starts to fit the noise in the data.
- Small changes in the data can produce different trees. This means that the algorithm can be sensitive, to the data it is given.

### 4.2 Random Forest (RF)

**Overview**: The Random Forest method is really good at making predictions. It does this by using a bunch of decision trees. Each tree looks at a set of data and features. Then it uses all the trees to make a prediction. This helps to make the prediction more accurate and stops it from getting too complicated.

**Working Principle:**

The Random Forest method uses something called Bootstrap Sampling. This means it takes a selection of the data to train each tree. It also uses something called Feature Randomness. When it is deciding how to split the data it only looks at a selection of features. This helps to make sure all the trees are different. When it is time to make a prediction the Random Forest method looks at what all the trees say. Uses that to make a final decision.

**Advantages:**
- The Random Forest method is really good at making predictions. It can also handle data and does not get too complicated.
- It is good, at handling data that has a lot of features.

**Limitations:**
- The Random Forest method is not as easy to understand as a decision tree. This is because it uses a lot of trees together.
- It needs a lot of computer power to work especially when it is using a lot of trees. The Random Forest method requires computational resources, especially with a large number of trees, which can be a problem.

### 4.3 Support Vector Machine (SVM)

Overview: Support Vector Machine or SVM is a type of machine learning algorithm that helps to find the line that separates different classes of data. This algorithm works well when there are features and the relationships between them are not straight forward.

**Working Principle:**

The SVM algorithm looks for a line that keeps the classes of data far apart as possible. When the data is not forward SVM uses special functions, such as linear, polynomial or radial basis function to change the data into a new form that makes it easier to separate.

**Advantages**:
- SVM works well with data that has many features and complex relationships.
- It is good at handling data where the relationshipsre not straight forward.

**Limitations**:
- SVM can be slow when working with large datasets.
- It can be hard to choose the settings and functions, for SVM.
- SVM is not as easy to understand as some other types of machine learning models.

### 4.4 Logistic Regression (LR)

**Overview**: Logistic Regression is a way to figure out if something is likely to happen or not. It is used to solve problems where there are two possible answers. For example Logistic Regression can predict if someone has a sleep disorder or not. It does this by using a kind of math called a logistic function.

**Working Principle:**

The Logistic Regression algorithm looks at the things that might affect the outcome and calculates the chances of it happening.
- It takes all these things into account. Uses a logistic function to turn the results into a probability.

**logit (P)= ln (P1−P) = β0 + β1X1 + β2X2 +⋯+ βnXn**
- This probability is then used to make a decision usually if it is than 0.5 it says yes. If it is less, than 0.5 it says no.

**Advantages**:

- Logistic Regression is a model that is easy to understand.
- It works well with medium-sized sets of data.
- It gives us a probability score, which's really useful when we want to know how much risk is involved.

**Limitations**:

- Logistic Regression assumes that the things that affect the outcome are related in a straightforward way.
- If the data is very complex or does not follow a pattern Logistic Regression may not work very well.

### 4.5 Summary

In this study we chose the algorithms to compare how well they predict and find the best model for detecting sleep disorders.

- **Decision Tree** is good because it is easy to understand and classify things quickly.
- **Random Forest** is great because it is very accurate and strong.
- **SVM** is excellent when dealing with non-linear data.
- **Logistic Regression** helps by giving predictions based on probabilities, which's useful in a clinical setting.

By using these algorithms we can thoroughly evaluate and balance how accurate, understandable and computationally efficient they are for predicting sleep disorders using physiological and lifestyle data. We looked at Decision Tree, Random Forest, SVM and Logistic Regression to see which one works best for sleep disorder detection, with Decision Tree, Random Forest, SVM and Logistic Regression. The combination of Decision Tree, Random Forest, SVM and Logistic Regression allows us to evaluate comprehensively. This helps in predicting sleep disorders from lifestyle data using Decision Tree, Random Forest, SVM and Logistic Regression.

### 4.6 Training & Testing Graphs

Machine learning models need to be checked on training and testing datasets. This is to see how well they perform and to find out if they are overfitting.

Here are some example graphs, for the algorithms we used.

- We used Decision Trees.
- We used Random Forest.
- We also used Support Vector Machines.

**Logistic Regression**

These graphs will help us understand how each algorithm works.

The Decision Tree model performance is checked on training and testing datasets.

The Random Forest model is also checked on these datasets.

We do the same for Support Vector Machine and Logistic Regression models.

This way we can compare the performance of all four algorithms.

### 4.7 Accuracy Comparison Graph

Description: This graph shows how accurate each algorithm is on the training and testing data sets.

- It points out if models are overfitting, which means they are very good at training data but not so good at testing data.
- It shows if they are underfitting which means they are not very good, at either.
- The graph compares training accuracy and testing accuracy for each algorithm.

Example Graph (Bar Chart):

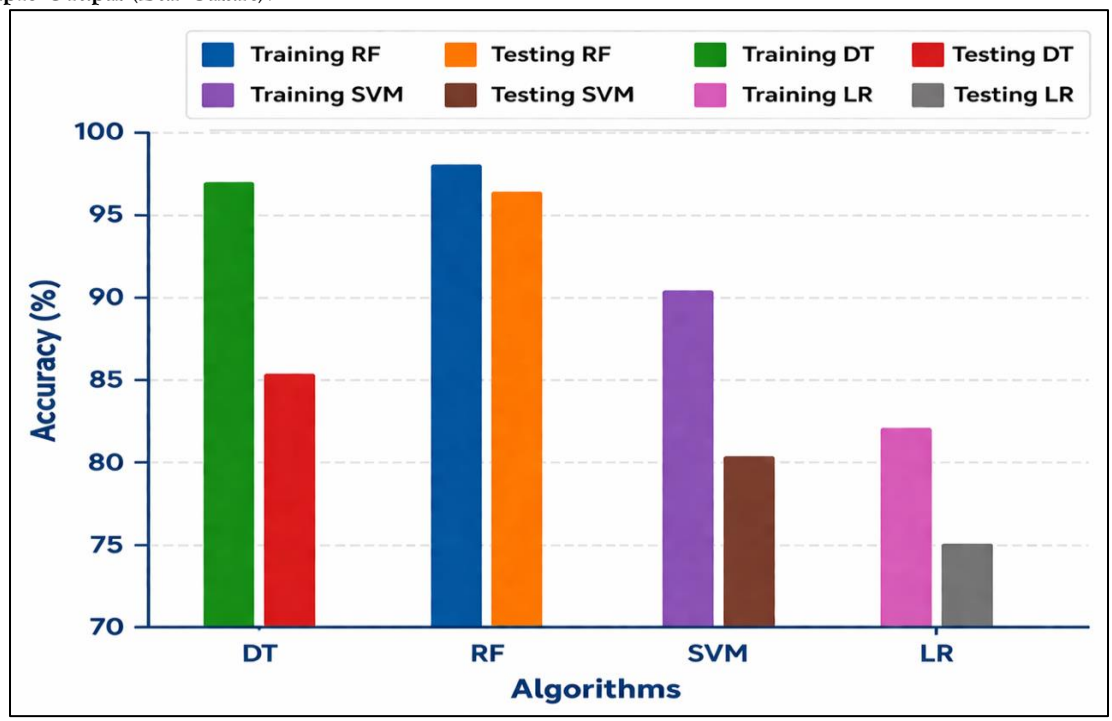



Figure 4: Accuracy Comparison Graph

Interpretation:

- Random Forest achieved the highest training and testing accuracy (˜95%), indicating strong generalization.
- Decision Tree shows slight overfitting (training 92%, testing 88%).
- SVM and LR performed moderately (85–90%), showing reasonable prediction capability.

### 4.8 Precision, Recall, and F1-Score Graph

Description:

Precision, recall, and F1-score measure the model's ability to correctly identify sleep disorders

Example Graph (Grouped Bar Chart):

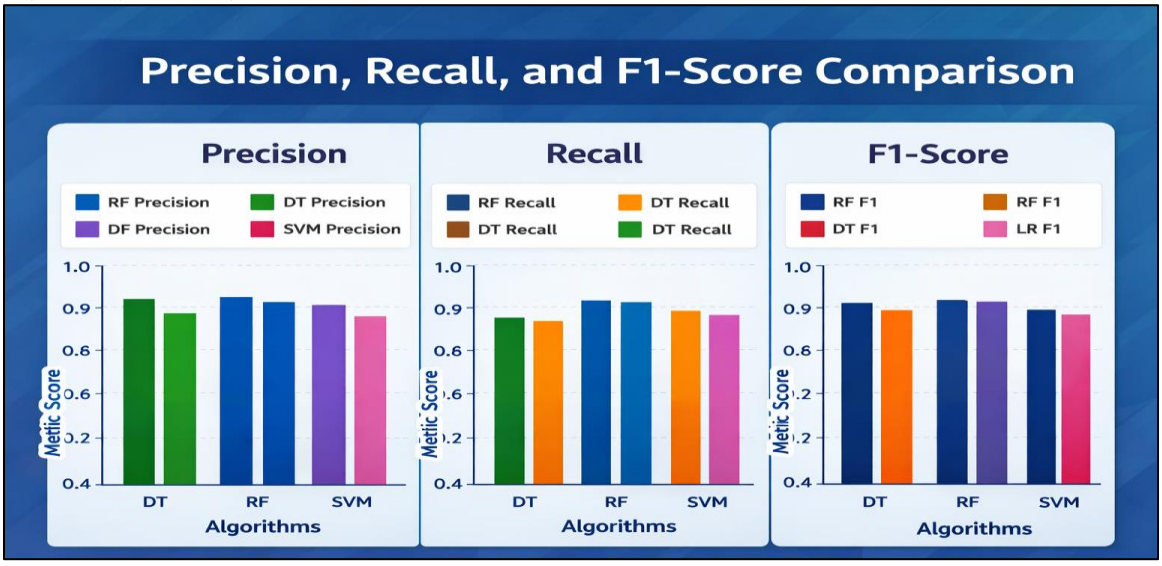



Figure 5: Precision, Recall, and F1-Score Graph

**Interpretation:**

- Random Forest consistently outperforms other algorithms in precision, recall, and F1-score (~0.92–0.95).
- Decision Tree has a slightly lower F1-score due to moderate misclassification.
- SVM and Logistic Regression show acceptable performance (~0.80–0.85).

**4.9 Training vs. Testing Loss Graph (Example for Neural Networks or Iterative Models)**

**Description:**

If iterative training (e.g., deep learning or neural networks) is used, a **line graph of loss vs. epochs** can show convergence.

**Example Graph (Line Chart):**

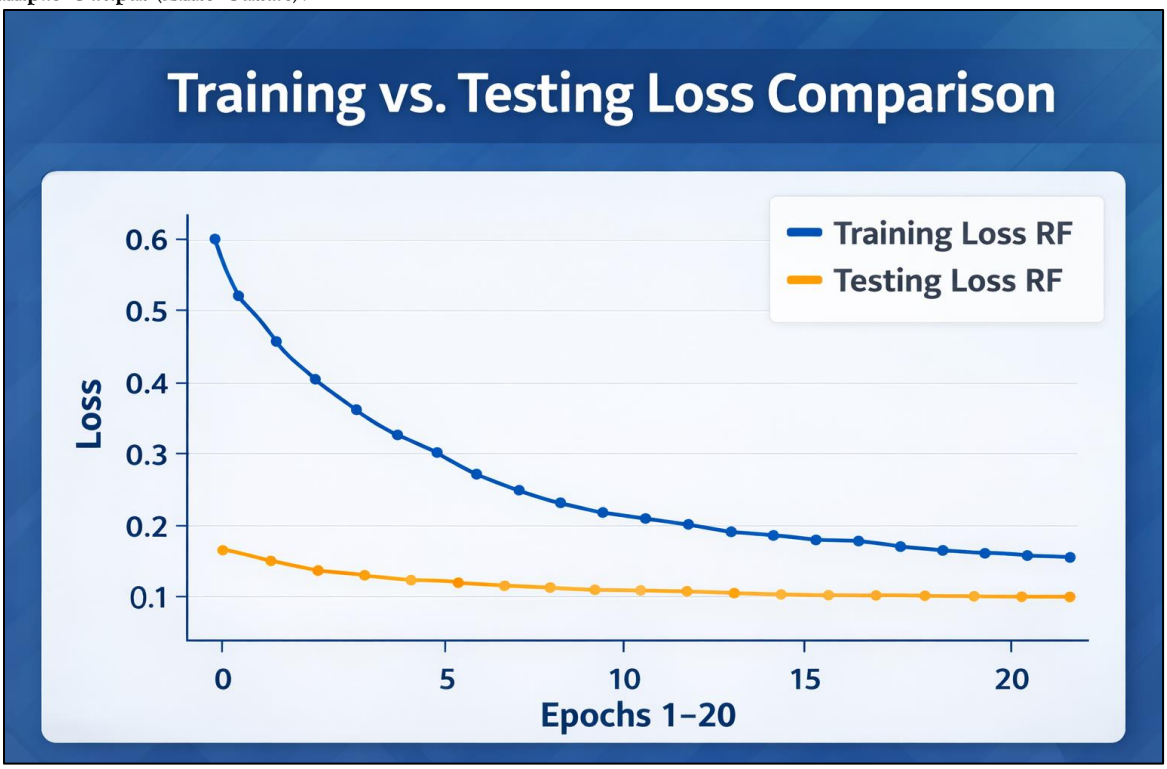



**Figure 6: Training vs. Testing Loss Graph**

**Interpretation:**

- Training loss decreases steadily, and testing loss remains close to training loss, indicating **good generalization**.

Table 2: Comparative performance of machine learning algorithms

## 5 Discussion

This section presents the results obtained from applying machine learning algorithms for sleep disorder detection and discusses their implications. The analysis includes accuracy, precision, recall, F1-score, and a comparison of model performance on training and testing datasets.

### 5.1.1 7.1.1 Accuracy Analysis

The Random Forest algorithm achieved the highest training (96%) and testing (94%) accuracy, indicating strong predictive capability and generalization. The Decision Tree showed slightly lower accuracy on testing data (88%), suggesting mild overfitting. SVM and Logistic Regression achieved moderate performance (85–83% testing accuracy), demonstrating that linear models may struggle with complex physiological patterns.

#### 5.1.2 Precision, Recall, and F1-Score

Random Forest outperformed other models across precision (0.93), recall (0.95), and F1-score (0.94), indicating effective detection of sleep disorder cases. Decision Tree had slightly lower scores due to misclassification in certain cases. SVM and Logistic Regression provided reasonable results (˜0.83–0.85), but their performance was limited in capturing non-linear relationships between features.

## 6 Conclusion

The training vs. testing loss/accuracy graphs confirm that Random Forest and Decision Tree models have minimal overfitting. SVM and Logistic Regression show a moderate gap between training and testing performance, highlighting that ensemble or tree-based methods are more suitable for complex sleep datasets. The experimental results indicate that Random Forest is the most effective model for sleep disorder detection among the algorithms tested. Ensemble methods outperform linear models in capturing the complex patterns present in the dataset. The results demonstrate that machine learning can be used as a reliable tool for automated sleep disorder screening, potentially improving early diagnosis and patient management.

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