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Article

Sleep Scan: Sleep Disorder Detection in Real Time Using Smart Machine Learning Models

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Abstract: Sleep disorders such as insomnia, sleep apnea, and restless leg syndrome significantly impact an individual's physical health, cognitive performance, and overall quality of life. However, early diagnosis remains a major challenge due to the limited availability of sleep laboratories, high costs, and lack of continuous monitoring solutions. To address these limitations, this work proposes Sleep Scan Smart, a real-time machine learning-based system designed for early identification of sleep disorders in a non-invasive and cost-effective manner. The system continuously collects physiological signals including heart rate, oxygen saturation (SpO_2), respiration rate, body movement, and electroencephalogram (EEG) data using wearable or sensor-based devices. These signals undergo real-time preprocessing and feature extraction to remove noise and enhance data quality. Advanced machine learning and deep learning models such as Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) are employed to analyze patterns and detect abnormalities associated with various sleep disorders. Sleep Scan Smart performs real-time anomaly detection and generates instant alerts, enabling timely intervention. The system also provides comprehensive sleep health insights through a user-friendly interface, helping users and healthcare professionals make informed decisions. By achieving high accuracy with reduced false alarms, the proposed solution ensures reliable monitoring. Overall, the system enables continuous, home-based sleep assessment and contributes to the advancement of smart, AI-driven preventive healthcare by facilitating early diagnosis and improving long-term health outcomes.

Keywords: Sleep disorder identification, Neural network model, Neural network, Real-time monitoring, Sleep apnea, EEG analysis, Wearable sensors, Health monitoring system, Predictive healthcare, LSTM, CNN, SVM, Random forest, Random forest.

1. Introduction

Sleep is a a important physiological characteristic required for the preservation of bodily well being, mental acuity, and properly-being, and regular acceptable of existence. Modern way of life pressures, heightened tension ranges, and severe biological ailments have pushed a sharp increase in therapeutic sleeping pathologies, most thoroughly obstructive sleep apnea, stressed legs syndrome, and insomnia. To the left uncontrolled, these situations precipitate intensive structural consequences, including cardiovascular morbidity, cognitive deficits, reduced place of business efficiency, and multiplied mortality. However, a large element of these rest abnormalities remains unchecked till advanced levels, a deficit in large part stemming from a lack of flexible, non-stop monitoring frameworks.

The traditional diagnostic gold well known, polysomnography (PSG), mandates overnight patient evaluation inside specialised scientific units to tune concurrent physiological metrics. Although particularly expensive, strenuous, and counterproductive to everyday human practice, laboratory-based holistic assessments are still relatively expensive, limiting their potential for clinical use. In particular, those subject to horizontal, household-primarily based data may not observe actual sleep patterns during the day. To bridge this gap, computing cleverness and automated learning algorithms today provide opportunity pathways for real-time, computational class of sleep problems. Thus, cutting-edge literature carefully explores statistical studying fashions to refine medical precision and automate earlier threat prediction.

For example, AI-based entirely customer interface structures for rest disorder prediction had been proposed to brighten usability and accessibility[1]. Comprehensive scientific techniques based entirely on quantitative getting to know methodologies have exhibited significant skill in the effectiveness of predicted models in identifying sleep-associated problems[2], yet as deep gaining knowledge of procedures have proven encouraging effects in taking pictures complicated sleep styles[3].

Current systems have deployed computerized computational frameworks aimed toward rest disorder prediction with superior performance and scalability]4]. Hybrid deep learning models along with CNN-LSTM had been used to forecast sleep troubles and fine by examining physiological and way of life variables .]5]. Earlier works on algorithmic sleep architecture categorization via deep neural networks]6] and sleep apnea detection the usage of ECG alerts]7] have laid the inspiration for contemporary sensible sleep monitoring systems. Moreover, wearable device-based approaches have been used to identify insomnia and other problems in real-world environments]8].

Different Prediction accuracy and clarity had been more enhanced by means of device gaining knowledge of techniques consisting of SVM[9], cross deep gaining knowledge of models]10], and knowable AI methodologies[11]. Research specializing in sleep enjoyable prediction[12] and heavy getting to know-based completely tracking structures[13] have established the potential of non-stop health checking. Furthermore, ensemble learning techniques[14] and AI-based mobile programming[15] have contributed to the enhancement of sleep fitness tests, which are additionally accurate, scalable, and customer-pleasant .

In this approach, Sleep Scan Smart is proposed as a revolutionary real-time sleep-disturbance monitoring and detection tool. This machine uses advanced technology to organize and read multimodal physiological data, with random forest, SVM, long short-term memory (LSTM), and convolutional neural networks (CNN). plays

The proposed application is intended to provide a low-cost, non-invasive, and customer-friendly solution for non-preventative home drinking monitoring. By generating real-time indicators and providing critical insights into sleep health, Rest Scan Smart First View facilitates perfectly timed interventions. As a tool, it continuously optimizes customized fitness tracking while managing workout improvement, but additionally completes the extensive brainstorming of an intelligent, AI-powered precautionary health tool.

2. LITERATURE SURVEY

M.Sc. M.Sc. Islam and so on. [4], 2025, developed a tool that uses an analytics-first based sleep disorder prediction engine using fitness-related data. The system dreams of increasing the accuracy of the initial survey. The strategy includes monitoring strategies for operations and refinement via ML algorithms. This shows the effectiveness of good forecasting. Disadvantages: The limited record period affects the normalization.

C. V. Stephen et al. [5], 2025, proposed a CNN-LSTM cross-version for anticipated dangerous tuned sleep disorders. The research integrates lifestyle and herbal statistics for better accuracy. The technique combines conventional analysis strategies with sequential analysis strategies. It effectively captures both temporal and spatial features. Limitations: Requires high computational costs and large datasets.

B. Anupama and so on. [1], 2024, proposed an AI-based total sleep disturbance estimation engine along with a personalized and pleasant software application for clean communication. The study is about increasing the supply of sleep assessment tools. The operational design includes clients that capture image detail streams and use programmatic test information in system commands. The gadget enhances the features through a graphical interface. Limitations: Limited information dimensions and no constant real-time monitoring.

N. Malik et al. [2], 2024, presents the overall predictive validity of the evaluation of somnographic positioning systems through a numerical exploratory paradigm approach. A study that compares specific models to determine typical performance and accuracy. The techniques include info preprocessing and design of classifiers such as SVM and Random Forest. It produces a few numerical end results. Limitations: Does not help real-time testing and lacks multidimensional adjustments.

S. Gupta et al. [14], 2023, proposes a cluster-based approach to obtain absolutely complete knowledge about the process of relaxation problem education. The study combines a number of different sets of policy regimes for greater accuracy. The strategy includes boosting and bagging methods. Increases agility. Cons: Increased complexity, and longer training times.

S.S. Kumar is the name. [15], 2023, develops a full battery life based primarily on AI for sleep and exercise assessment. The tool presents pure to use experience and insights. The approach involves ML-based prediction embedded in cellular systems. This can increase comfort. Limitations: Limited accuracy due to preference of main sensor input.

R. Sharma et al. [11], 2022, will focus on intelligent AI to predict slack problems to strengthen transparency. The results allow version selection within enjoy. The approach includes intelligent ML fashion and modeling strategies. This increases the evaluation in the predictions. Limitations: Less accuracy in the estimation of dark field styles.

D. Hepsiba et al. [3], 2021, explores vast learning methods for sleep's disturbing reputation and classification. The results demonstrate the popularity of neural networks in the study of sophisticated sleep patterns. The method evaluates CNN, RNN, and hybrid models. This makes the update much appreciated. Disadvantages: Lack of empirical deployment and real-time verification.

M. Hassan et al. [12], 2021, The structural learning paradigms introduced herein are designed for predicting sleep quality using physiological data. The system supports health monitoring applications. Methodology includes preprocessing and classification using ML algorithms. It shows correct forecast accuracy. Restriction: Limited actual-time applicability.

Y. Fan et cetera.]Tretten], 2021, developed a understanding-load-slack monitoring device for non-forestall tracking. This technique makes use of neural networks for empirical forecast. The method involves edition evaluation on resting datasets. This improves get performance. Limitations: Big computational resources are required.

J. Jiang et cetera.]10], 2020, created a strong know-how platform designed for sleep apnea assessment. This software system integrates many neural community configurations. The approach combines CNN and RNN techniques for day efficiency. This improves therapy accuracy. Limitations: It is mathematically costly and calls for large datasets.

K. Beatty et cetera.]8], 2019, advanced a complete wearable-based entirely system for sleeplessness detection the use of structure reading. This approach lets in actual-time monitoring in natural environments. Strategies with brilliant sensors, ML. This improves ease. Limitations: Accuracy depends on detector dependency and defensive behavior.

T. Penzel et cetera.]7], 2018, provided an evaluation of Sleep Apnea to benefit perception into the use and framework strategies of ECG indicators. The results decreased the personal belief in different PSG agencies. The strategy consists of work extraction and group from ECG facts. This produces fascinating identity results. Restrictions: Just uses ECG statistics, ignoring some biological parameters.

S. Akara et al. [6], 2017, Introduced automated sleep macro-architecture categorization via deep neural networks. The system focuses on identifying sleep stages from EEG data. Methodology includes training deep learning models on physiological signals.

It improves classification accuracy. Limitation: Requires labeled datasets and lacks real-time implementation. Almazaydeh et al. [9], 2012, Proposed Identification of sleep disorders using SVM. The study demonstrates early use of ML in sleep analysis. Methodology includes feature extraction and SVM classification. It achieves moderate accuracy. Limitation: Limited scalability and lower performance compared to modern models

3. PROPOSED METHODOLOGY

The proposed Sleep Scan Smart system is designed to detect sleep disorders in real-time by integrating physiological data-acquisition transducers driven by high-capacity algorithmic frameworks models. The following steps make up the methodology:

1. Data Acquisition using Sensors

Physiological data is continuously collected using non-invasive wearable and IoT-based senses:

- Sensor of Heart Rate(e.g., Pulse Sensor / PPG) – measures heart rate variability
- SpO_2 Sensor (e.g., MAX30100/MAX30102) – measures oxygen saturation
- Respiration Sensor (e.g., Piezo belt / airflow sensor) – monitors breathing rate
- Accelerometer (MEMS) – detects body movement and sleep posture
- EEG Sensor (optional, e.g., Muse headband) – captures brain activity for sleep stages

These sensors provide real-time information toa processing unit (Arduino/Raspberry Pi).

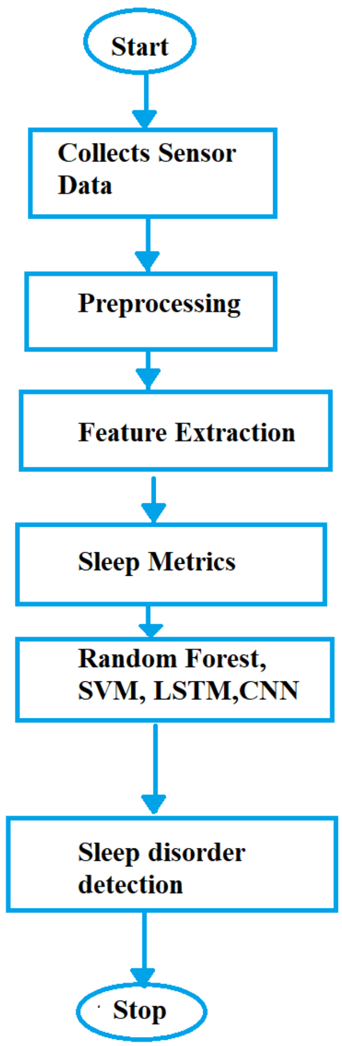


Figure 1: Proposed flow diagram

HeartRate	SpO2	Movement	Temperatur	SleepStatus
100	95	7	37.5	Insomnia
102	89	3	36.5	Apnea
109	82	4	37.5	Apnea
94	82	2	37.1	Apnea
88	83	3	37.1	Apnea
95	94	5	37.4	Insomnia
96	97	7	37.1	Insomnia
78	96	1	36.2	Normal
72	98	10	36.7	Restless
85	99	9	36.9	Restless
63	96	3	36.2	Normal
76	94	7	36.7	Insomnia
94	87	2	36.4	Apnea
75	97	7	37.2	Restless
99	87	2	36.3	Apnea

Figure 1: Sample dataset

2. Data Transmission

- Data from sensors is sent through Bluetooth/Wi-Fi (IoT module like ESP8266/ESP32)
- Data is sent to a local system or cloud server for processing
- Ensures continuous and real-time monitoring

Data Preprocessing

- Noise removal using filtering techniques (e.g., low-pass filter)
- Handling missing or inconsistent data
- Signal normalization and smoothing
- Segmentation of time-series data into sleep windows

Feature Extraction

Highly discriminative feature subsets are mathematically distilled from physiological signals:

- Heart Rate Variability (HRV)
- Oxygen desaturation levels
- Breathing irregularities
- Movement frequency and intensity
- EEG frequency bands (alpha, beta, delta, theta)

Models for Deep Learning and Machine Learning

the distilled predictive attributes are channeled directly to models like:

- Random Forest – for classification and feature importance
- SVM (Support Vector Machine) – for binary/multi-class classification
- Time-series sleep patterns are analyzed using Long Short-Term Memory, or LSTM.
- CNN (Convolutional Neural Network) – for extracting features from the signal data patterns

Algorithm 1: Random Forest for Sleep Disorder Classification

Input: Sensor feature dataset D={(xi,yi)}i=1

Output: Predicted sleep disorder class y^

Steps:

1. Draw BBB bootstrap samples from D dataset.

2. For each sample, grow A tree of decisions Tb:

1. Select a random subset of features at each split.

2. Using the best feature based on impurity (Gini index), split the node.

3. Repeat until all trees are constructed.

4. Get forecasts for a fresh input x. from all trees.

5. Aggregate predictions utilizing a majority decision:

y^=mode{T1(x),T2(x),...,TB(x)}

7. Output final predicted class.

Algorithm 2: Support Vector Machine (SVM)

Input: Training data (xi,yi), where yi∈ {−1,+1}
Output: Optimal hyperplane for classification

Steps:

1. Normalize input feature vectors.

2. Data is mapped to a higher dimensional space using the kernel function K(xi,xj).

3. Solve optimization problem:

$$\min_{w,b} \frac{1}{2}||w||^2 \quad \text{subject to } y_i(w \cdot x_i + b) \geq 1$$

4. Identify support vectors closest to hyperplane.

5. Construct decision function:

$$f(x) = \text{sign}(w \cdot x + b)$$

6. Classify new input data based on decision boundary.

Algorithm 3: LSTM for Time-Series Sleep Analysis

Input: Sequential data X={x1,x2,...,xt}

Output: Predicted sleep disorder

Steps:

1. Set the cell state values c0 and the hidden state h0 to their initial values. .

2. At every time step t , compute:

ft=σ(Wf· [ht−1,xt]+bf)]

it=σ(Wi· [ht−1,xt]+bi)

ct=ft∗ ct−1+it∗ ct~

1. Update hidden state ht.

2. Pass final output to dense layer.

3. Predict sleep disorder class.

Algorithm 4: Convolutional Neural Network (CNN)

Input: Structured signal data XXX
Output: Predicted sleep disorder class

Steps:

1. Apply convolution operation:

$$(X * W)(i,j) = \sum_m \sum_n X(i+m, j+n) W(m,n)$$

Apply activation function:

$$f(x) = \max(0, x)$$

1. Perform pooling to reduce dimensions.

2. Vectorized features that are flat.

3. Traverse levels that are completely connected.

4. Use Softmax for categorization:

$$P(y=i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

5. Sleeping disorder was predicted by result.

Sleep Disorder Detection

The structure breaks down sleep disorders into categories:

- Normal Sleep
- Insomnia
- Sleep Apnea
- Restless Leg Syndrome

To identify irregular patterns, anomaly detection is carried out.

Real-Time Alert System

- Alerts issued for peculiar circumstances(such as low SpO2 levels and abnormal respiration)
- SMS notifications sent via a GUI screen or a mobile app
- Emergency warnings for severe weather

Visualization & User Interface

- Real-time guidelines are displayed on a graphic screen.
- Sleeping patterns and tendencies are created
- Simple program for doctors and patients

Data Storage & Analysis

- Data stored locally or in cloud database
- Helps in long-term health monitoring

Outcome

- Early diagnosis of sleep disorders

- Continuous home-based monitoring
- Less time spent on hospital-based rest studies
- Improved healthcare decision-making

System Architecture

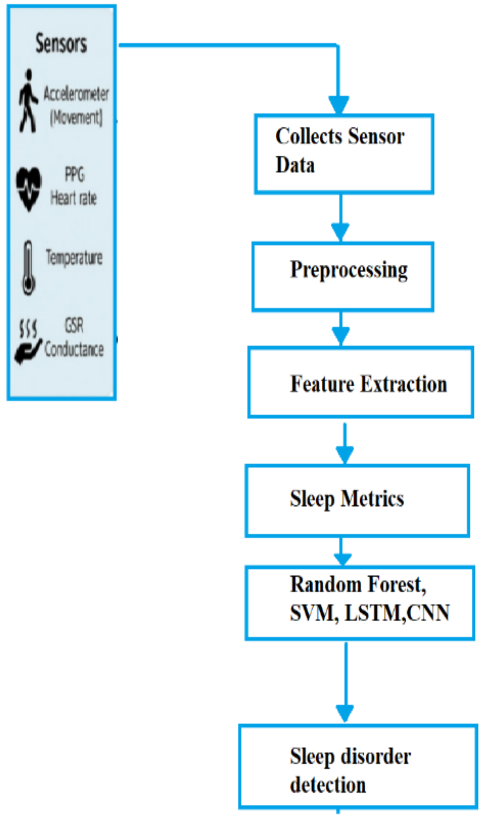


Figure 2: System Architecture

The structure describes the process by which data moves through a dependant pipeline, from sensors to final decision-making and user alerts.

Sensing Layer

The system's primary location is this.

- Sensors like Heart Rate (PPG), SpO_2, Respiration Sensor, Accelerometer, and EEG collect physiological data during sleep.
- These sensors continuously monitor body signals in real time.

 Output: Raw physiological data

Edge Device (Hardware Layer)

- Devices like the ESP32, Raspberry Pi, and Arduino collect data from sensors.
- Performs basic processing like filtering and formatting.
- Acts as an interface between sensors and network.

 Output: Cleaned sensor data

IoT Communication Layer

- Data is transmitted using Wi-Fi or Bluetooth.
- Can also be sent to cloud platforms (AWS / Firebase).
- Ensures continuous and real-time data transfer.

 Output: Data sent to processing system

Data Processing Layer

- Performs:
  - Preprocessing (noise removal, normalization)
  - Feature Extraction (HRV, breathing pattern, movement)
- Converts raw signals into meaningful features.

 Output: Feature data

Machine Learning Layer

- Uses models like:
  - Random Forest
  - SVM
  - LSTM
  - CNN
- Performs:
  - Classification
  - Pattern recognition
  - Anomaly detection

 Output: Sleep disorder prediction

Real-Time Analysis & Detection

- Combines processed data and ML outputs

  Detects conditions like:
  - Sleep apnea, insomnia, and restless legs

 Output: Diagnosis result

Application Layer

- Displays results through:
  - Mobile App
  - Dashboard
- Shows:
  - Graphs (heart rate, oxygen levels)
  - Sleep patterns
  - Health insights

 Output: User-friendly visualization

Alert & Notification System

- Generates alerts for abnormal conditions:
  - Low SpO_2
  - Irregular breathing
- Sends:
  - Notifications
  - Alarms

- Output: Immediate warnings

Data Storage

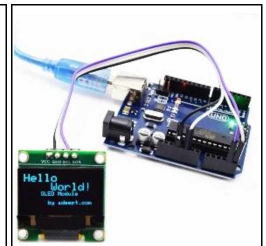
- Stores data in:
  - Cloud (Firebase, AWS)
  - Local database
- Used for:
  - History tracking
  - Long-term analysis

Doctor Recommendation Layer

- Provides:
  - Health insights
  - Recommendations
- Helps doctors make decisions based on data

Table 1: Components List

Component Name	**Uses**	**Image**
MAX30100 Sensor for Pulse Oximetry	measures blood oxygen levels and heart rate. (SpO_2) levels for sleep monitoring and apnea detection.	
AD8232 ECG Sensor Module	Captures ECG and heartbeat signals for cardiac monitoring during sleep analysis.	
Arduino Uno	Acts as the main controller to collect sensor data and process sleep monitoring tasks.	

Component Name	Uses	Image
OLED Display	Displays live heart rate, SpO_2, and sleep status readings in real time.	

4. RESULTS AND DISCUSSION

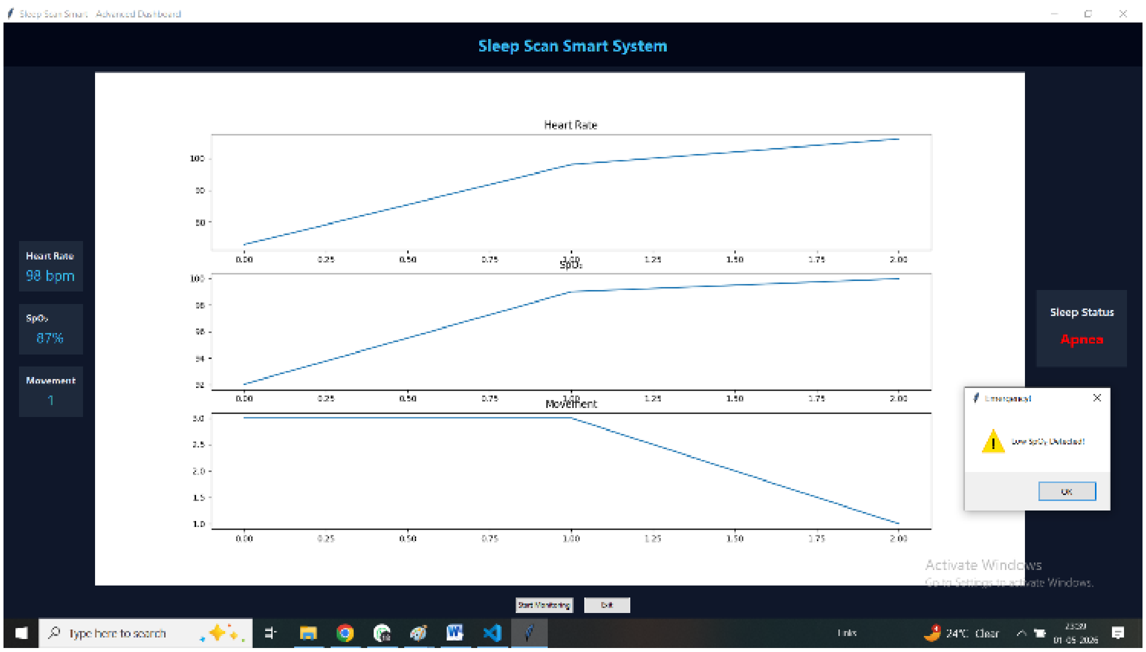


Figure 3: Sleep scan smart system

The Sleep Scan Smart System dashboard monitors vital sleep-related parameters such as heart rate, SpO_2 level, and movement in real time using sensors and statistical modeling protocols. This deployed architecture analyzes these signals continuously to identify possible sleep disorders early and generates alerts when abnormal sleep conditions like apnea are detected

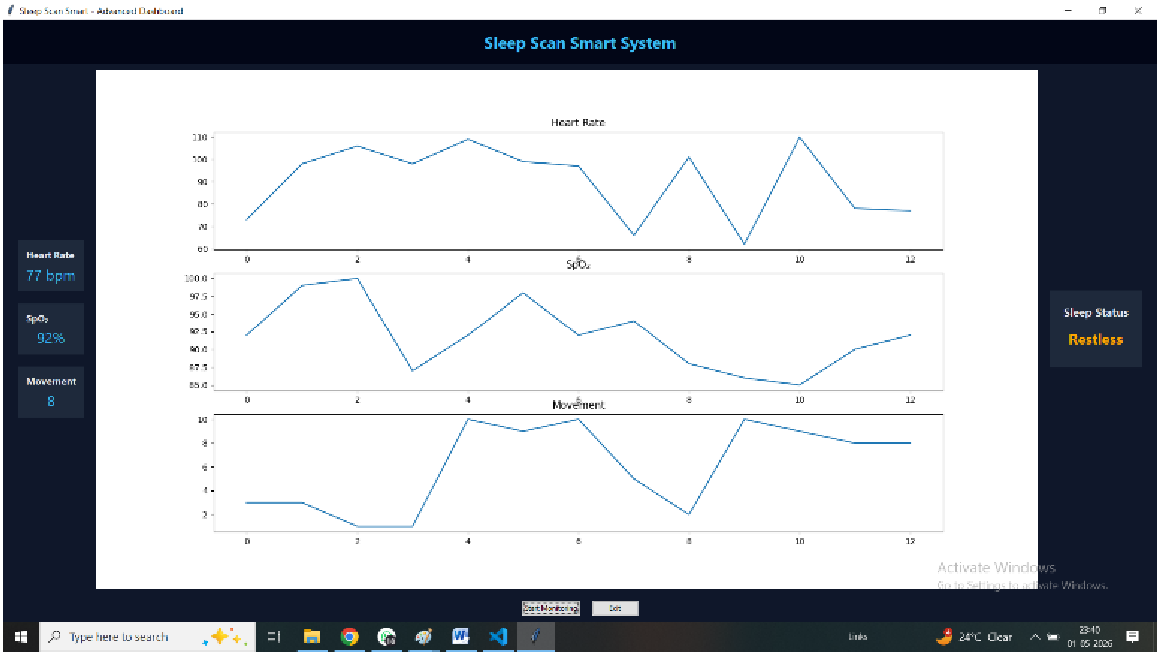


Figure 4: Sleep scan smart system Sleep status

This dashboard displays real-time sleep monitoring information gathered via wearable sensors, including blood oxygen level (SpO_2), heart rate, and bodily activity. This sleep-related machine recognition tool examines these styles and detects incorrect sleep habits, helping you save diseases that grow earlier than signs of sleep disorders and abnormal sleep patterns.

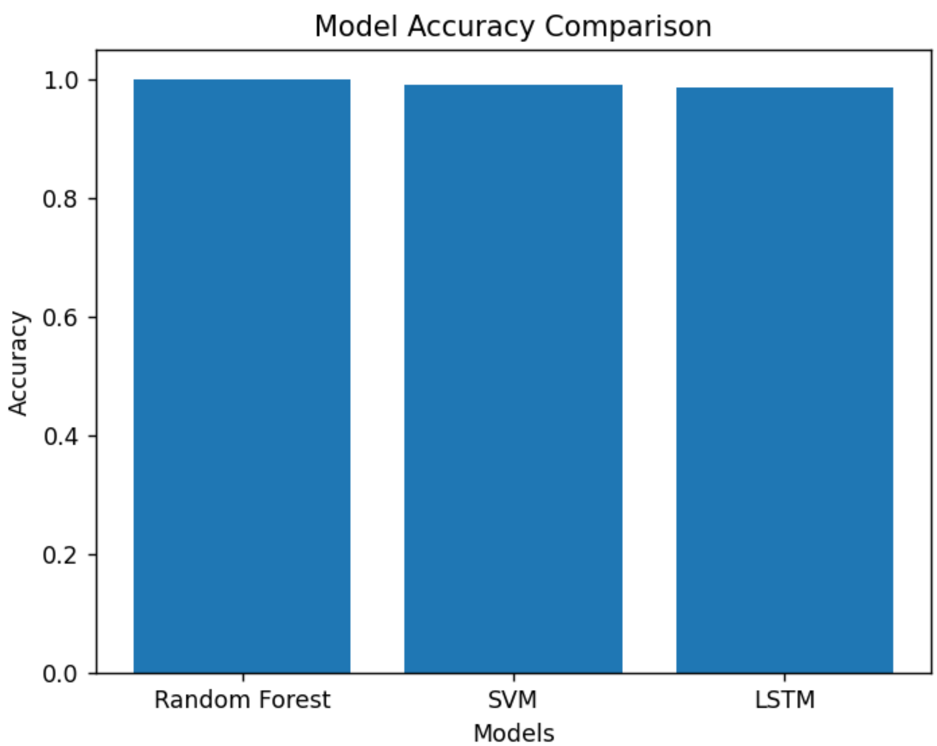


Figure 5: Model Accuracy graph

A number of machine learning models used to determine sleep disorders, including Random Forest, SVM, and LSTM, are evaluated in the graph. SVM and LSTM both produced fairly accurate results, demonstrating that each one fashions are effective for actual-time sleeping problem identity, while the Random Forest architecture also achieved the top of the line accuracy benchmark.

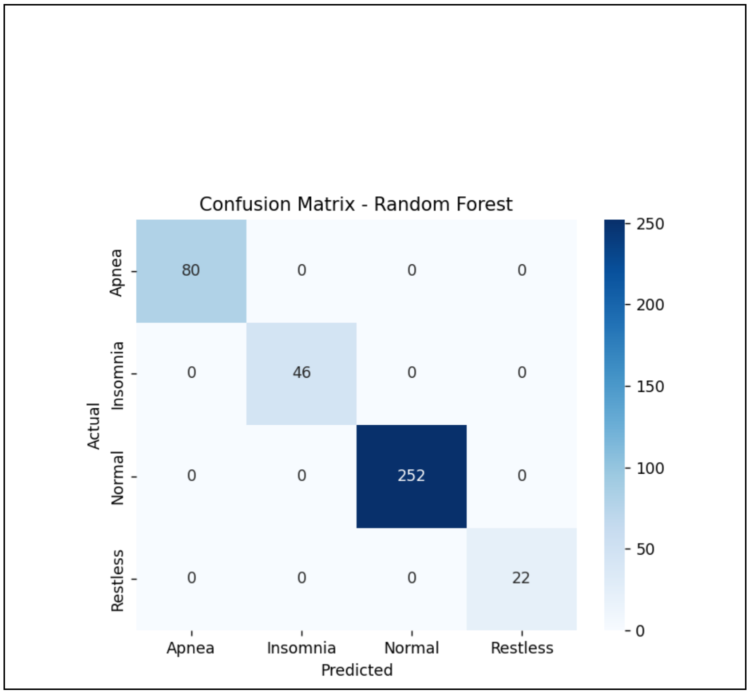


Figure 6: Confusion matrix

In defining numerous sleep issues, including insomnia, apnea, anxious sleep, and regular sleep, the resulting contingency matrix expressly maps the category error distribution across the Random Forest version. The majority of values are accurately anticipated along the horizontal, indicating that the sleeping disorder classification was classified with the least amount of misclassification possible.

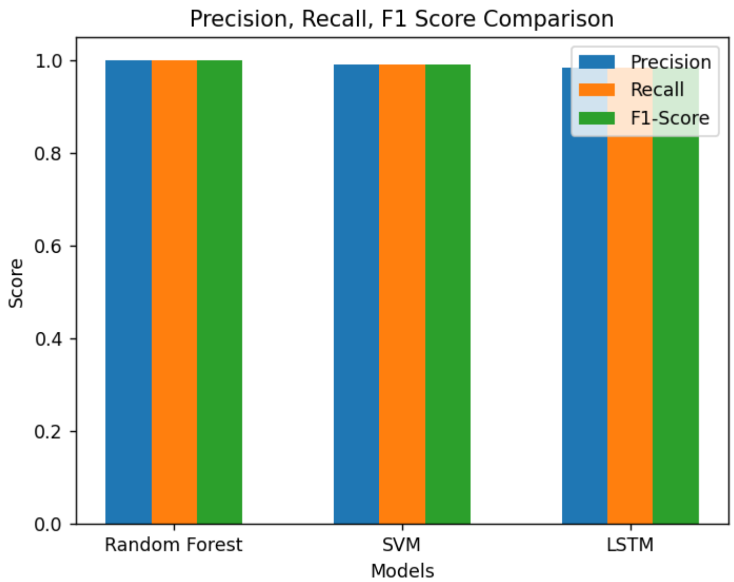


Figure 7: Performance Metrics Graph

The chart compares the accompanying wonderful predictive values, sensitivity levels, and harmonic imply rankings from the arbitrary forest, guide vector, and recurrent neural frameworks used to predict sleep pathology identification. With the exception of a few bogus predictions, all fashions produced scores close to 1.0, which demonstrates excellent overall performance in the class, high reliability, and accurate sleep disorder detection.

Formulas Used:

Precision = TP / (TP + FP)

decides how many positives were correctly predicted.

Recall (Sensitivity) = TP / (TP + FN)

determines the number of true positives that are accurately identified.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

The numerical equilibrium is determined by the combination of don't forget favorable prediction rates.

Table 1: Metrics performance Table

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.98	0.98	0.98	0.98
Random Forest	1.00	1.00	1.00	1.00
SVM	0.99	0.99	0.99	0.99

5. CONCLUSION AND FUTURE WORKS

A). Conclusion

A smart and powerful gadget-grade analysis method is provided through the proposed Nap Scan Smart gadget for early detection of sleep disorders. The device’s sensors, which include coronary artery rate, SpO2, respiration, movement, and EEG, allow for non-adversarial, non-invasive statistics within the household, as it may be able to identify problems with high accuracy when considering sleep patterns advanced Formest, SVM and Rando. LSTM, CNN and big fashion understanding. User-friendly applications, full sleep tracking, and real-time signals are available these days. The reduction depends on high-value sleep labs. Ultimately, this will improve ‘medical access, early identification and preventive care’ for sleep-related problems.

B). Potential Scope

Incorporating additional advanced functions and technology might increase the effectiveness of the software. Other possible improvements include:

- Integration with sophisticated wearable devices for more accurate and at relieve facts collection
- Explainable AI (XAI) utility to increase forecast transparency and agree with
- Large-scale sleep facts assessment the use of cloud-based completely big records analytics
- Development of mobile programs with tailored tips using AI
- Integration with smart home structures(IoT) for computerized surroundings adjustment(light, temperature, noise)
- Improvement through making use of multi-layered connectionist designs like Transformers for better time-series assessment
- Telecommunication between doctors and telemedicine guide
- Expanding to identify other illnesses like stress, anxiety, and cardiac issues.

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