International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2480-1276
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0332

Wearable Device for Obstructive Sleep Apnea Detection and Calming Intervention Using AI

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Abstract
Obstructive Sleep Apnea (OSA) is a widespread sleep disorder marked by repeated breathing interruptions during sleep, resulting in oxygen desaturation, disturbed sleep patterns, and serious long-term health risks. Conventional diagnostic methods such as polysomnography are expensive, intrusive, and unsuitable for continuous monitoring. This paper presents a wearable device for real-time detection of Obstructive Sleep Apnea and calming intervention using Artificial Intelligence (AI). The proposed system continuously monitors physiological parameters including blood oxygen saturation (SpO_2), heart rate, respiration pattern, and body movement through wearable sensors. These signals are analyzed using AI-based algorithms to accurately detect apnea events. When abnormal breathing is identified, the system triggers a non-invasive calming intervention, such as gentle haptic or auditory feedback, to assist in restoring normal respiration without disturbing sleep. The device also enables wireless data transmission for remote monitoring and analysis for upcoming medical check-ups. The proposed solution offers a portable, and non-invasive approach for continuous sleep apnea monitoring and improved sleep quality.

Keywords *Obstructive Sleep Apnea, Wearable Device, Artificial Intelligence, Sleep Monitoring, SpO_2 Sensor, Heart Rate Monitoring, Respiration Analysis, IoT-Based Healthcare, Calming Intervention, Real-Time Detection, ESP[32] Microcontroller, Haptic Feedback.*

1. Introduction

Even while sleep is crucial for preserving both physical and mental well-being, sleep disorders like Obstructive Sleep Apnea (OSA) have a substantial impact on both general health and sleep quality [1]. Repeated episodes of partial or total upper airway blockage during sleep, which cause erratic breathing, oxygen desaturation, and frequent sleep disruptions, are the hallmark of OSA (Figure 1). If untreated, it can result in major health issues like heart disease, weariness during the day, and impaired cognitive function [2]. Polysomnography, a conventional diagnostic technique, requires monitoring multiple physiological signs in a sleep laboratory. Despite being precise, it is costly, unpleasant, and unsuitable for continuous long-term monitoring. The development of portable solutions for continuous sleep monitoring is made feasible by recent advances in wearable technology, artificial intelligence (AI), and Internet of Things (IoT) technologies. This research suggests a device that can be worn that uses artificial intelligence to identify obstructive sleep apnea and provide a relaxing solution. Using wearable sensors, the system tracks physiological data such as blood oxygen saturation (SpO_2), breathing patterns, and bodily activity. In order to identify abnormal breathing patterns, AI algorithms examine these data in real time. When an apnea episode occurs, a relaxing intervention, like soft audio feedback, is triggered to restore normal breathing. This wearable technology offers a useful substitute for conventional sleep apnea diagnostic techniques and permits ongoing home-based monitoring shown in Figure 1.

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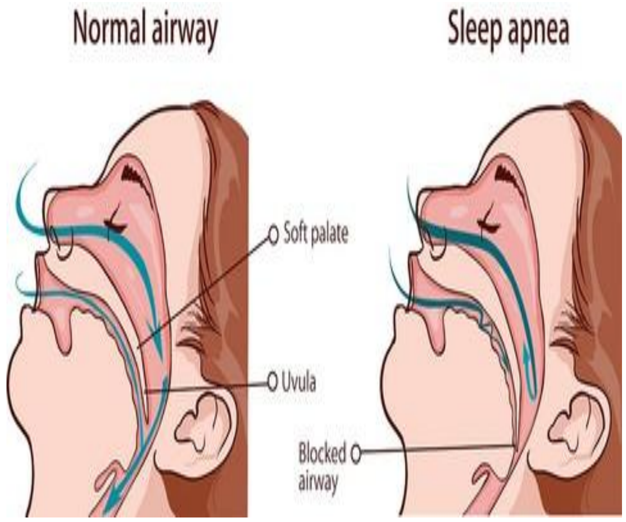

Figure 1 Normal Airway vs. Sleep Apnea Airway Obstruction

1.1. History

The understanding and diagnosis of sleep apnea have evolved from basic clinical observations to advanced physiological monitoring techniques. Early methods mainly relied on symptom reporting, which often resulted in inaccurate diagnoses. The introduction of polysomnography improved diagnostic accuracy by analyzing multiple sleep parameters, but its high cost and dependence on clinical settings limited long-term use.

1.2.Applications

The proposed wearable technology can be used to consistently monitor obstructive sleep apnea at home, allowing for enhanced sleep management and early detection. By providing long-term physiological data for medical diagnosis and treatment evaluation, it facilitates clinical decision-making [9].The technology provides immediate identification and calming intervention during apnea episodes, making it particularly helpful for elderly and high-risk individuals. Through intelligent wearable technology, it can also be coupled with telemedicine platforms for remote monitoring, supporting preventive healthcare and better sleep quality.

2. Existing Method

Existing methods for detecting Obstructive Sleep Apnea primarily rely on clinical sleep studies using polysomnography, which records multiple physiological signals such as airflow, oxygen saturation, heart rate, and brain activity in a controlled laboratory environment [10]. Although this method provides high diagnostic accuracy, it is expensive, uncomfortable, and unsuitable for continuous or long-term monitoring. Some portable monitoring devices and smartphone- based solutions have been introduced; however, most of these systems use fixed threshold-based techniques and lack intelligent analysis, leading to reduced accuracy and higher false alarm rates [4]. Additionally, existing systems focus mainly on apnea detection and do not provide real- time intervention to assist users during apnea events. These limitations highlight the need for a wearable, intelligent, and non-invasive solution capable of continuous monitoring and timely response.

3. Proposed Method

The proposed method offers a wearable device that uses artificial intelligence to determine obstructive sleep apnea in real time and provide a therapeutic solution. Vital physiological indicators associated with sleep apnea, such as blood oxygen saturation (SpO_2), heart rate, breathing rhythm, and body movement, are continuously monitored by the system. Compact, low- power wearable sensors that are integrated with a microcontroller unit are used to collect these parameters. An AI-based detection system analyses the collected sensor data after it has been preprocessed to eliminate noise and normalise signal fluctuations. The artificial intelligence model accurately detects episodes of apnea and hypopnea by analysing temporal patterns and correlations among the physiological variables [5]. The technology verifies the occurrence of a sleep apnea event when it finds aberrant breathing patterns that surpass predetermined thresholds and confidence levels. In order to urge the user to resume regular breathing without abruptly disrupting sleep, the device initiates a calming intervention mechanism upon detection, such as quiet aural stimulation.The suggested system facilitates wireless data transmission via IoT connectivity in addition to real-time detection and action, enabling remote.

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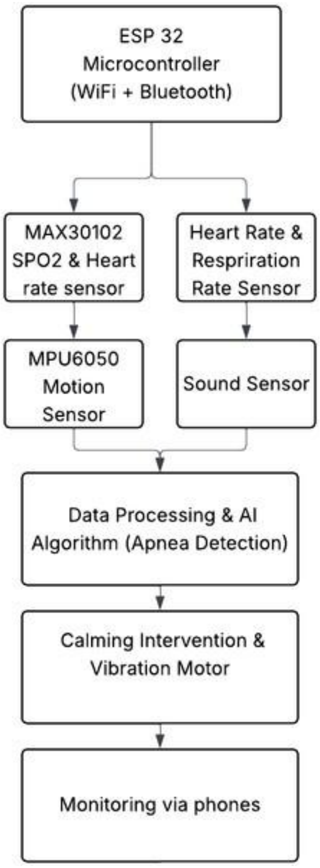

Figure 2 Architecture of the proposed method

monitoring and data visualization via a mobile or web-based platform (Figure 2). This enables consumers and medical professionals to monitor sleep quality, apnea frequency, and the efficacy of treatments over time. The suggested method's wearable, non-invasive, and intelligent characteristics make it appropriate for ongoing home-based monitoring, providing an affordable and useful substitute for traditional sleep apnea diagnostic techniques.

4. Implementation

4.1. Physiological Signal Acquisition

The implementation begins with the acquisition of physiological signals related to sleep apnea using wearable sensors. The device continuously monitors blood oxygen saturation (SpO_2), heart rate, respiration pattern, and body movement.These parameters are captured using compact, low-power sensors integrated into the wearable unit. Continuous data acquisition during sleep enables real-time monitoring of breathing irregularities while maintaining user comfort and minimal intrusion.

4.2. Signal Preprocessing And Feature Extraction

The physiological signals acquired from the earable sensors are prone to noise and motion artefacts caused by user movement and environmental interference. Therefore, preprocessing techniques such as digital filtering, smoothing, and normalisation are applied to enhance signal quality. Low-pass filtering is utilized to eliminate high- frequency disturbances in SpO_2 and heart rate signals, while motion artifacts are minimized through adaptive filtering techniques. Following preprocessing, significant features, including oxygen desaturation levels, respiration pause duration, heart rate variability, and body movement patterns, are extracted [11]. These features provide meaningful inputs for the artificial intelligence-based detection model.

4.3. AI-Based Apnea Detection

The extracted features are analyzed using an artificial intelligence algorithm designed to differentiate between normal breathing patterns and obstructive sleep apnea events. The model evaluates temporal variations in oxygen saturation, heart rate fluctuations, and irregular respiration intervals to identify abnormal breathing episodes (Figure 3). A confidence-based threshold mechanism is incorporated to ensure accurate detection while minimizing false alarms. Continuous real-time monitoring enables early identification of apnea events and improves overall reliability compared to conventional threshold-based systems.

4.4. Calming Intervention And Iot Integration

Upon detection of an apnea episode, the system activates a non-invasive calming intervention, such as a gentle vibration motor, to help restore normal breathing. The wearable prototype (Figure 4), integrates sensors, a vibration motor, and an ESP32 microcontroller for continuous monitoring during sleep. The ESP32 wirelessly transmits processed data via Wi- Fi to a mobile or web platform, enabling real-time visualisation, remote monitoring, and long-term sleep analysis. This wearable IoT-based system provides a practical

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and affordable solution for continuous home-based sleep apnea monitoring. The compact wearable design also ensures user comfort and ease of use during overnight monitoring.

A

B

Figure 3 Software output of the system showing (A) normal sleep monitoring and (B) apnea detection.

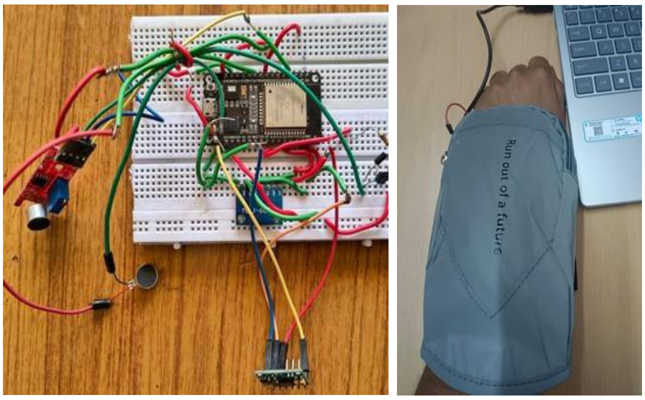

Figure 4 Prototype hardware setup of the wearable sleep apnea detection system.

5. Mathematical Modelling and Detection Algorithms

To ensure accurate physiological analysis, standard sensor-based mathematical models were implemented for heart rate estimation, oxygen saturation calculation, motion detection, and snoring analysis.

5.1. Heart Rate Estimation (MAX30102)

The MAX30102 sensor measures photoplethysmography (PPG) signals. Heart rate is calculated from the time interval between consecutive pulse peaks:

$$HR\,(bpm) = \frac{60}{TRR\,(bpm)} \tag{1}$$

Where:
TRR= time interval between two consecutive pulse peaks (seconds)
For discrete sampling:

$$HR = \frac{60 \times fs}{N} \tag{2}$$

Where:
fs= sampling frequency
N= number of samples between two detected peaks. This method is standard in PPG-based heart rate calculation.

5.2. SpO_2 Calculation (Ratio-of-Ratios Method)

SpO_2 is estimated using red and infrared light absorption.

Step 1: Compute AC/DC ratio

$$R = \frac{(ACred/DCred)}{(ACir/DCir)} \tag{3}$$

Where:
AC = pulsatile component
DC = non-pulsatile component

Step 2: Empirical SpO_2 equation

$$SpO2 = A - B \times R \tag{4}$$

Typical calibration approximation:

$$SpO2 = 110 - 25R \tag{5}$$

This formula is widely used in pulse oximetry research.

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3) Motion Detection (MPU6050)

Acceleration magnitude is calculated using:

$$Amag = \sqrt{Ax2+Ay2+Az2} \qquad (6)$$

Where:
Ax, Ay, Az = accelerometer axis readings
Abnormal movement intensity:

Abnormal movement intensity:

$$Motion = |Amag - g| \qquad (7)$$

Where:

$$g \approx 9.81\ m/s\hat{}2 \qquad (8)$$

4) Snoring Detection (Sound Sensor)

Sound intensity level is calculated as:

$$Sound\ Level = 20\log 10\ \left(\frac{Vref}{V}\right) \qquad (9)$$

Where:
V = measured voltage
Vref = reference voltage
Snore event detection using amplitude threshold:

$$Snore = \begin{cases} 1\ if\ Amplitude > Threshold \\ 0\ otherwise \end{cases} \qquad (10)$$

5) Apnea Detection Logic

Apnea events are identified using threshold-based multimodal decision logic:

$$Apnea = \begin{cases} 1,\ if\ SpO2<92\%\ AND\ HR \\ \quad variation\ present \\ 0,\ otherwise \end{cases} \qquad (11)$$

This model aligns with clinically accepted apnea indicators.

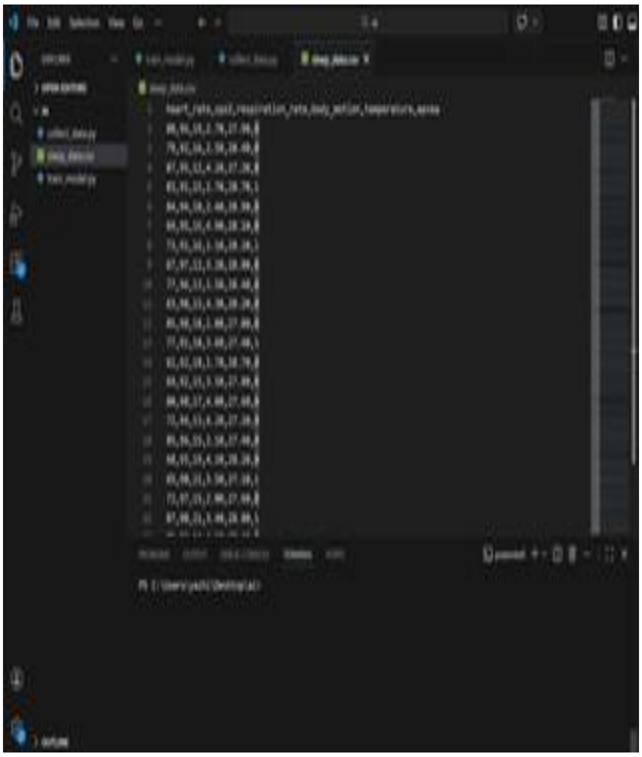

Figure 5. **Dataset showing physiological parameters used for apnea detection based on the proposed decision algorithm.**

6. Results And Discussion

6.1. Sleep Apnea Detection Output

The proposed wearable device for obstructive sleep apnea detection was tested to validate its continuous monitoring and intervention capabilities. By integrating hardware sensors with AI-based detection algorithms, the system reliably recorded physiological parameters such as SpO_2, heart rate, respiration rate, body motion index, and snoring intensity during sleepUnder normal sleep conditions, SpO_2 levels remained within the clinically accepted range of 95–100%, while heart rate was observed between 50–70 bpm, indicating reduced cardiac activity during NREM sleep. Respiration rate stayed within 12–20 breaths per minute, body motion index remained below 0.5 g during deep sleep, and snoring levels were below 40 dB, confirming stable breathing conditions and accurate baseline monitoring. During detected apnea events, noticeable deviations from normal physiological values were observed. SpO_2

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levels dropped below the clinical threshold of 90%, and breathing pauses exceeded 10 seconds, which are key indicators of apnea. Increased heart rate variability and higher snoring intensity were also recorded in some cases. The multimodal detection approach combining oxygen desaturation, respiratory interruption, and motion analysis improved detection reliability compared to single-parameter monitoring. Additionally, the vibration motor successfully provided calming stimulation during apnea episodes, helping restore normal breathing while the IoT interface logged physiological changes for further monitoring.

```
heart_rate,spo2,respiration_rate,body_motion,temperature,apnea
88,94,19,2.70,27.90,0
79,92,16,2.50,28.40,0
87,95,12,4.20,27.20,0
83,91,15,2.70,28.70,1
84,94,18,2.40,28.90,0
69,95,15,4.90,28.10,0
73,91,16,1.10,28.20,1
67,97,12,3.20,28.80,0
77,96,13,1.50,28.40,0
63,98,13,4.30,28.20,0
85,98,18,1.00,27.00,0
77,91,18,3.60,27.40,1
61,92,18,1.70,28.70,0
69,92,15,3.50,27.80,0
80,98,17,4.00,27.60,0
72,94,13,4.20,27.20,0
85,96,15,2.10,27.40,0
68,93,19,4.10,28.20,0
65,90,21,3.50,27.10,1
72,97,15,2.00,27.60,0
```

Figure 6. Dataset output showing binary classification of apnea detection

6.2. Physiological Reference Values

Clinically, respiratory deviations and prospective episodes of obstructive sleep apnea are indicated by variations from the typical physiological ranges described in Table 1. Hypoxemia is defined as a drop in SpO_2 below 90%, which indicates an inadequate oxygen supply brought on by airway blockage. One of the main markers of the severity of sleep apnea is recurrent episodes of oxygen desaturation. A sympathetic nervous system reaction brought on by breathing disruption is represented by an irregular rise or fall in heart rate as you sleep, particularly abrupt tachycardia after oxygen desaturation Clinically, an apnea event is defined as a decrease in respiratory rate or a total stoppage of airflow lasting 10 seconds or longer. On the other hand, uneven or laborious breathing patterns could be a sign of partial airway obstruction or hypopnea

Table 1 Normal Sleep Physiological Values

Parameter	Normal Range During Sleep	Units
SpO_2	95 – 100	%
Heart Rate (HR)	60 – 70	bpm
Respiration Rate (RR)	12 – 20	breaths /min
Body Motion Index	< 0.5 (low movement phase)	g
Snoring Sound Level	< 40 dB	decibels
Apnea Threshold (SpO_2)	< 90 (clinically significant)	%
Apnea Pause Duration	≥ 10	seconds
Body Temperature (Skin)	32 – 35	°C

Turbulent airflow and upper airway constriction, which are hallmarks of obstructive sleep apnea, are frequently linked to increased snoring intensity, especially above 50 dB. Clinically, deviations from the typical physiological ranges suggest the possibility of obstructive sleep apnea and respiratory instability. The two main markers of apnea episodes are a drop in SpO_2 below 90% and breathing pauses longer than 10 seconds. Airway blockage and sympathetic arousal reactions are linked to abrupt changes in heart rate and increased snoring intensity. For the purpose of detecting apnea, both upward and downward deviations from typical sleep values are clinically relevant indicators (Figure 7) (Table 2).

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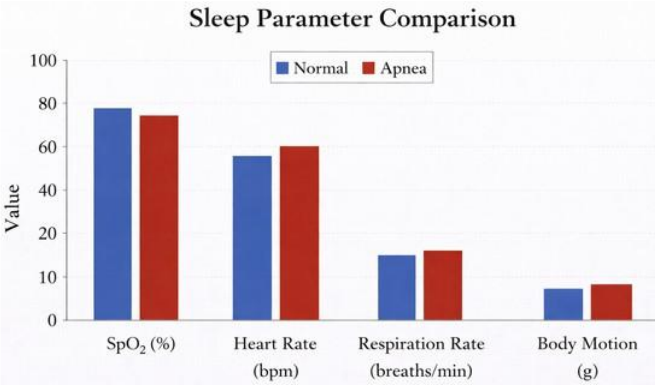

Figure 7 **Comparison of physiological parameters between normal sleep and apnea conditions based on the collected dataset**

Table 2 Normal Sleep Physiological Values

Parameter	Normal Range	Apnea Range
SpO_2(%)	98	91
Heart Rate (bpm)	78	83
Respiration Rate (breaths/min)	16	19
Body Motion (g)	1.4	1.5

Conclusion

A wearable device that uses artificial intelligence and physiological sensors to identify obstructive sleep apnea has been proposed and evaluated. In order to detect abnormal breathing patterns during sleep, the device continuously monitors vital sleep- related parameters like blood oxygen saturation, heart rate, respiration rate, body motion, and snoring intensity. Research has shown that variations in these physiological values can reliably signal apnea episodes, enabling prompt monitoring and detection. Reliability increases when multiple sensors are integrated with AI-based analysis compared with single-parameter monitoring systems. To aid in the restoration of regular breathing, the calming intervention mechanism also offers mild feedback. Every aspect is considered; the suggested wearable device provides a useful and non-invasive solution for present home-based sleep apnea monitoring. It may also help with early diagnosis and improved sleep health management.

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