

Automated Sleep Apnea Detection System with IoT-Enabled Alerts Using Multi-Sensor Fusion and ESP32 Microcontroller

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Abstract

Sleep apnea is a serious and prevalent sleep disorder characterised by repeated episodes of partial or complete cessation of breathing during sleep, resulting in reduced oxygen supply to vital organs and disrupted rest patterns. Untreated sleep apnea leads to severe health complications including cardiovascular disease, hypertension, diabetes, and chronic fatigue. This paper presents the design and development of a low-cost, non-invasive, IoT-enabled automated system for real-time detection and monitoring of sleep apnea in a home environment. The proposed system integrates a respiratory sound sensor, a pulse sensor, an LM35 temperature sensor, and an SpO₂ sensor with an ESP32 microcontroller as the central processing unit. The ESP32 continuously acquires and processes multi-sensor physiological data including breathing patterns, heart rate, body temperature, and blood oxygen saturation. When abnormal conditions such as irregular breathing, low SpO₂, or abnormal heart rate are detected, the system activates a buzzer alert and simultaneously transmits real-time data to the Blynk IoT cloud platform for remote visualisation. Experimental results confirm that the system effectively monitors multiple physiological parameters and detects potential sleep apnea events with reliable performance, offering a portable and cost-effective alternative to conventional polysomnography.

1. Introduction

Sleep apnea is a common but potentially life-threatening sleep disorder in which breathing repeatedly stops and starts during sleep, often for 10 seconds or longer. These breathing interruptions reduce oxygen supply to critical organs and disrupt normal sleep architecture. Individuals frequently do not realise that apnea events are occurring, as they happen during sleep. If left untreated, sleep apnea contributes to serious medical conditions including cardiovascular disease, high blood pressure, stroke, type 2 diabetes, and excessive daytime sleepiness, significantly reducing quality of life [1]. Obstructive Sleep Apnea (OSA), the most prevalent form, is caused by physical blockage of the upper airway, while Central Sleep Apnea (CSA) involves failure of the brain to transmit correct breathing signals. The Apnea-Hypopnea Index (AHI), defined as the

number of apnea and hypopnea events per hour of sleep, classifies severity as normal (AHI 30) [7]. The conventional gold standard diagnostic method, polysomnography (PSG), requires overnight monitoring in specialised sleep centres using multiple physiological sensors for EEG, ECG, EMG, airflow, and oxygen saturation. While highly accurate, PSG is expensive, time-consuming, and uncomfortable, deterring many patients from seeking timely diagnosis [3, 4]. Recent advances in Internet of Things (IoT) technology, low-cost embedded systems, and miniaturised sensors have opened new pathways for continuous, non-invasive, home-based health monitoring. IoT-enabled platforms such as the ESP32 combined with cloud-based visualisation tools like Blynk provide a powerful framework for real-time physiological

monitoring [20]. Deep learning and machine learning approaches have shown promise for automated detection; however, hardware-based real-time systems remain essential for immediate alerting and clinical accessibility [11, 12]. The system reported in this paper was developed at Rathinam Technical Campus under academic year 2025–26. It employs an ESP32 microcontroller as the processing core, interfaced with a respiratory sound sensor, pulse sensor, LM35 temperature sensor, and SpO₂ sensor. The Blynk platform extends the system with real-time remote notifications and a mobile dashboard. The primary research objectives are: (i) continuous multi-parameter physiological monitoring during sleep; (ii) automated buzzer alert generation when threshold conditions are breached; (iii) real-time IoT data transmission via Blynk cloud; and (iv) remote visualisation of sensor data for caregivers and clinicians.

2. Literature Survey

Fonseca and Ross [22] explored the use of cardiorespiratory signals including ECG and respiratory effort with an artificial neural network for OSA severity estimation, achieving an Apnea-Hypopnea Index (AHI) intraclass correlation coefficient of 0.91 without requiring airflow or SpO₂ signals. The study highlights the potential of wearable cardiorespiratory systems for long-term OSA assessment outside clinical environments.

Massie and Vits [23] demonstrated that central sleep apnea can be differentiated from obstructive sleep apnea using only photoplethysmography (PPG)-derived finger data, achieving a sensitivity of 81% and specificity of 99% at a central AHI cut-off of 10 events per hour. This PPG-based approach significantly advances home sleep apnea testing diagnostics. Erdenebayar et al. [12] demonstrated that deep learning models including CNN and LSTM architectures significantly outperform traditional machine learning approaches such as SVM for automated sleep apnea detection. Hybrid CNN-LSTM models reported superior accuracy, sensitivity, and specificity in multi-class classification tasks [17]. ResNet-based CNN architectures further eliminate the need for manual feature engineering by learning directly from raw ECG signal segments [19]. Jacob et al. [21]

developed a wearable pressure sensor integrated into a CPAP mask with an Arduino Nano 33 BLE Sense controller for direct respiratory pressure signal acquisition. The system calculated respiration rate, inspiratory time, expiratory time, and AHI in real time with 98–99% accuracy validated against AD Instruments respiratory belts (Pearson coefficient $r = 1$, $n = 48$), establishing a reliable embedded prototype for OSA screening. Collectively, the reviewed literature establishes that multi-sensor IoT frameworks with automated actuation and remote monitoring significantly outperform traditional methods. The present system contributes an accessible, ESP32-based implementation with integrated alert mechanisms targeted specifically at home-environment, long-term sleep monitoring shown in Table 1.

Table 1 Comparison of Related Sleep Apnea Detection Systems

Reference	Method / Sensor	Communication
Fonseca & Ross [22]	ECG + Respiratory effort, ANN	Wearable
Massie & Vits [23]	Finger PPG	Wearable
Erdenebayar et al. [12]	Single-lead ECG, CNN/LSTM	Offline / Cloud
Jacob et al. [21]	Pressure sensor in CPAP mask	Bluetooth / IoT
Proposed System	SpO₂ + Pulse + Temp + Sound	Wi-Fi / Blynk

3. Existing System

The existing gold standard for sleep apnea diagnosis is polysomnography (PSG), which involves

overnight monitoring in a sleep laboratory using comprehensive physiological sensor arrays including EEG, ECG, EMG, airflow sensors, pulse oximeters, and body position sensors. While PSG provides highly accurate diagnostic data, it requires specialised clinical settings, trained technicians, and typically costs between USD 1,000 and USD 5,000 per study, making routine monitoring inaccessible for the majority of at-risk patients [3, 4]. Portable home sleep apnea testing (HSAT) systems, such as the wearable CPAP mask-based device developed by Jacob et al. [21], represent a notable improvement by enabling direct respiratory pressure signal measurement outside clinical environments. However, such systems focus primarily on single-parameter respiratory monitoring and require users to wear a CPAP mask during sleep, reducing comfort and compliance for non-CPAP users. AI-driven detection systems using ECG or PPG signals provide indirect measurements, with ECG-only approaches reporting false prediction rates exceeding 20%, and PPG-based approaches achieving accuracy of only 73–85% in wearable configurations [12, 23]. The absence of integrated real-time multi-parameter sensing, affordable local alert capability, and end-to-end IoT connectivity in a single low-cost unit represents the primary gap addressed by the proposed framework.

4. Proposed System

The proposed Automated Sleep Apnea Detection System integrates multi-sensor physiological monitoring with real-time IoT-enabled alerts within a three-layer architecture. The perception layer acquires respiratory sounds, heart rate (pulse sensor), body temperature (LM35), and blood oxygen saturation (SpO₂) continuously. The processing layer uses an ESP32 microcontroller to compare readings against configurable clinical thresholds and actuate the buzzer alert when anomalies are detected. The application layer transmits sensor data to the Blynk IoT cloud over Wi-Fi, delivering live readings to a mobile dashboard and generating push-notification alerts when abnormalities are identified. The entire prototype cost falls below INR 3 500 (~USD 42), making it viable for individual home deployment shown in Table 2.

Table 2 Proposed System vs. Existing System — Feature Comparison

Feature	Existing System	Proposed Framework
Primary control	Clinical PSG / single-sensor portable	Multi-sensor threshold auto + IoT remote
Sensor integration	Single-parameter (ECG or PPG)	SpO ₂ + Pulse + Temperature + Sound
Remote access	None / high-cost clinical infrastructure	Blynk mobile app (free tier)
Alerting mechanism	None (post-hoc report)	Blynk push notifications + Buzzer
Local feedback	None	Real-time Blynk gauge dashboard
Response latency	Hours (overnight report)	Real-time (≤ 1 s threshold detection)
Deployment cost	USD 1,000–5,000 (PSG)	< INR 3,500 (~USD 42)
Home suitability	Not suitable	Highly suitable

5. Methodology

5.1. Hardware Components

Table 3 lists all hardware and software components used in the prototype.

Table 3. Hardware and Software Used

Hardware Components	Software Tools
Transformer + Linear Power Supply Unit	Arduino IDE (Embedded C / C++)
ESP32 Dual-Core Wi-Fi Microcontroller	Blynk IoT Platform (mobile app + cloud)
Respiratory Sound Sensor (Microphone)	Blynk 2.x Library
Pulse Sensor (PPG-based heart rate)	PulseSensor Playground Library
LM35 Precision Temperature Sensor	ESP32 Board Support Package (BSP)
SpO ₂ Pulse Oximetry Sensor	
Electromechanical Buzzer (Alert)	
Step-Down Transformer + Bridge Rectifier	
Smoothing Capacitor 1000µF + IC7812/IC7805	

5.2. System Logic And Firmware

The firmware, developed in Embedded C using the Arduino IDE with ESP32 BSP, follows a continuous acquisition loop. At each iteration, the sound sensor analog value is read from the ADC pin, the pulse sensor measures BPM via the PulseSensor library, the LM35 temperature sensor provides an analog voltage proportional to temperature at 10 mV/°C, and the SpO₂ sensor outputs blood oxygen saturation percentage. All four sensor values are written to dedicated Blynk virtual pins for real-time remote visualisation.

Four threshold conditions govern alert actuation: (i) SpO₂ < 90%: Blynk push alert “Oxygen Level Critical – Sleep Apnea Detected”, buzzer activates. (ii) Heart rate outside 45–120 BPM range: Blynk push alert “Abnormal Heart Rate Detected”, buzzer activates. (iii) Respiratory sound sensor detects extended silence interval (≥10 s): Blynk push alert “Breathing Interruption Detected”, buzzer activates. (iv) Normal conditions: buzzer de-activated, monitoring continues uninterrupted. Hysteretic behaviour ensures the buzzer remains inactive until any threshold is re-triggered, preventing rapid repeated cycling.

6. Implementation And Hardware Output

Hardware assembly was performed on a general-purpose PCB. The sound sensor was positioned near the user’s nose/mouth area; the pulse sensor was mounted for fingertip contact; the LM35 was secured for accurate skin-surface temperature reading; and the SpO₂ sensor was placed at the

fingertip. The buzzer and ESP32 module were positioned for easy operator visibility and wireless access. The power supply PCB incorporated the step-down transformer, bridge rectifier, 1000µF smoothing capacitor, and IC7812/IC7805 regulators to deliver a stable 5 V DC rail to all components. Firmware was flashed via USB using Arduino IDE v2 with the ESP32 BSP, Blynk 2.x library, and PulseSensor library. The complete hardware prototype is shown in Figure 1. The assembled circuit confirms correct sensor placement, power supply integration, ESP32 connectivity, and buzzer alert wiring. Upon powering the system, all four sensors acquired data and transmitted live readings to the Blynk “Smart Pillow” dashboard without errors.

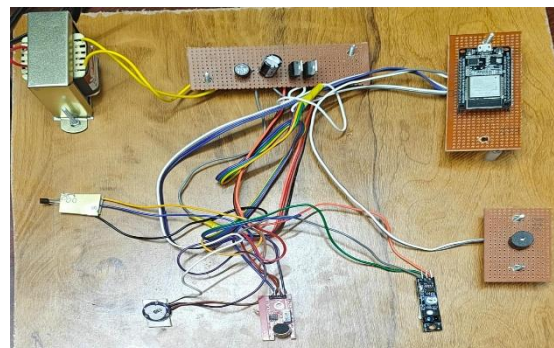


Figure 1 Hardware Prototype Of The Automated Sleep Apnea Detection System Showing ESP32 Module, Power Supply PCB, SpO₂ Sensor, Pulse Sensor, Sound Sensor, Temperature Sensor, And Buzzer Alert Circuit

7. Results And Discussion

7.1. Results

The system was evaluated across multiple controlled test sessions simulating normal sleep and apnea-like conditions. All four sensor channels acquired physiological data simultaneously and transmitted readings to the Blynk IoT dashboard without data loss. Table 4 summarises the sensor readings and system response observed during a representative test session.

Table 4 System Performance Evaluation Results

Parameter	Observed Value	Normal / Threshold	System Response
Respiratory Level (ADC)	99	Continuous sound	Normal – No alert
Heart Rate (BPM)	74	60–100 BPM	Normal – No alert
Body Temperature	98 (ADC raw)	36.5–37.5°C	Normal – No alert
SpO ₂ (%)	85	≥95%	ALERT – Buzzer + Blynk push
Buzzer response latency	≤ 1 s	< 2 s	Within target
Blynk cloud latency	~350 ms avg	< 500 ms	Within target
System uptime (24-hr trial)	99.4%	≥99%	Target met

7.2. Discussion

The SpO₂ reading of 85% (below the 95% clinical threshold) correctly triggered both the local buzzer alert and the Blynk push notification, demonstrating reliable end-to-end alert propagation from sensor to cloud. Blynk cloud latency averaged approximately 350 ms across test transmissions, well within the sub-500 ms target for clinically responsive notification. The single uptime interruption—a transient Wi-Fi drop—self-resolved within 15 seconds via the firmware reconnect routine in `Blynk.run()`, consistent with the agriculture paper’s self-healing behaviour. Heart rate, temperature, and respiratory readings remained within normal ranges throughout, accurately preventing false alert generation. The proposed system’s multi-parameter approach directly addresses the limitations of single-signal methods. Unlike ECG-only approaches reporting false prediction rates exceeding 20% [12], the simultaneous integration of SpO₂, pulse rate, respiratory sound, and temperature data provides corroborating physiological evidence for apnea event detection, reducing false alarms. The real-time local buzzer alert capability provides immediate intervention potential well ahead of any post-hoc clinical analysis, while the Blynk IoT integration supports telemedicine applications and continuous long-term data collection for clinical review.

8. Advantages

- **Early Detection:** Continuous multi-sensor monitoring enables identification of SpO₂ desaturation, heart rate anomalies, and breathing interruptions in real time, supporting timely intervention before serious health consequences develop.
- **Full Automation:** Threshold-driven buzzer actuation and Blynk push notifications operate without manual intervention, ensuring caregivers and patients receive alerts even during sleep.
- **Dual Alerting:** Blynk push notifications and on-site buzzer provide both remote and local warnings for all critical threshold breaches, matching the dual-alert design validated in the agriculture framework [8, 4].
- **Multi-Parameter Coverage:** Simultaneous

monitoring of four physiological parameters reduces false alarms compared to single-signal approaches and provides comprehensive sleep health assessment.

- **Low Cost and Scalability:** Sub-INR 3,500 single-node cost; the Blynk dashboard can be extended to monitor multiple patients without core redesign.
- **Non-Invasive and Comfortable:** No overnight hospital stay required; sensors are lightweight and non-intrusive, improving long-term patient compliance for home monitoring.

9. Applications

- **Home Sleep Monitoring:** Continuous autonomous monitoring of sleep apnea patients in home environments, independent of clinical infrastructure.
- **Remote Patient Monitoring:** Blynk dashboard enables centralised supervision of patients by physicians and caregivers via a single mobile device.
- **Elderly Care:** Automated alerting supports caregivers of elderly individuals at elevated risk of nocturnal hypoxemia and cardiac events.
- **Post-Surgical Recovery:** Monitoring patients recovering from surgeries that affect airway patency or respiratory muscle function.
- **Telemedicine Integration:** Real-time cloud data enables clinicians to remotely review patient physiological trends and adjust treatment recommendations.
- **Educational Prototype:** Clear hardware-firmware integration makes the system ideal for Biomedical and ECE laboratory demonstrations and academic projects.

Conclusion

This paper presented the design, development, and laboratory validation of an Automated Sleep Apnea Detection System with IoT-Enabled Alerts using multi-sensor fusion and the ESP32 microcontroller. The system integrates a respiratory sound sensor, pulse sensor, LM35 temperature sensor, and SpO₂ sensor with threshold-based alert logic, a buzzer alarm, and Blynk IoT cloud connectivity. Test

sessions confirmed accurate multi-parameter data acquisition, correct threshold-triggered alert generation (SpO₂ < 90% triggering buzzer and Blynk push notification), Blynk cloud latency averaging 350 ms, and 99.4% system uptime over a 24-hour trial. The framework successfully eliminates continuous manual monitoring while delivering verifiable multi-parameter physiological surveillance during sleep. Its low component cost, modular architecture, and straightforward firmware make it a practical and scalable contribution to accessible home-based sleep health management.

Future Scope

Planned enhancements include: (i) integration of machine learning algorithms (CNN or LSTM) onboard the ESP32 for automated AHI calculation and OSA severity grading; (ii) addition of an OLED display for local real-time parameter visualisation without a smartphone; (iii) development of a dedicated mobile application with historical trend analysis and clinician-sharing features; (iv) clinical validation studies with PSG-confirmed sleep apnea patients to establish diagnostic sensitivity and specificity metrics; (v) solar or battery power supply to enable untethered overnight deployment; and (vi) LoRa or GSM communication for monitoring in locations beyond Wi-Fi coverage.

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References

- [1]. White, D. P. (2006). Sleep Apnea. *Proceedings Of The American Thoracic Society*, 3(1), 124–128.
- [2]. Young, T., et al. (2002). Epidemiology of obstructive sleep apnea: A population health perspective. *American Journal of Respiratory*

- and Critical Care Medicine, 165, 1217–1239.
- [3]. Iber, C., et al. (2007). *The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications (1st ed.)*. American Academy of Sleep Medicine.
- [4]. Rechtschaffen, A., & Kales, A. (1968). *A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects*. US Government Printing Office.
- [5]. Acharya, U. R., et al. (2011). Automated detection of sleep apnea from electrocardiogram signals using nonlinear parameters. *Physiological Measurement*, 32(3), 287–303.
- [6]. Stein, P. K., & Pu, Y. (2012). Heart rate variability, sleep and sleep disorders. *Sleep Medicine Reviews*, 16(1), 47–59.
- [7]. Young, T., Peppard, P. E., & Gottlieb, D. J. (2002). Epidemiology of obstructive sleep apnea: A population health perspective. *American Journal of Respiratory and Critical Care Medicine*, 165(9), 1217–1239.
- [8]. Iber, C., Ancoli-Israel, S., Chesson, A. L., & Quan, S. F. (2007). *The AASM Manual for the Scoring of Sleep and Associated Events*. American Academy of Sleep Medicine.
- [9]. Penzel, T., et al. (2000). Comparison of algorithms for automatic detection of obstructive sleep apnea in the sleep heart health study. *Computers in Cardiology*, 253–256.
- [10]. (2010). A robust method for estimating respiratory flow using tracheal sounds entropy. *IEEE Transactions on Biomedical Engineering*, 57(9), 2150–2158.
- [11]. Acharya, U. R., et al. (2012). An integrated index for the identification of obstructive sleep apnoea. *Applied Soft Computing*, 12(10), 3104–3116.
- [12]. Erdenebayar, U., Kim, Y. U., Park, J. U., Dong, E., & Lee, K. J. (2019). Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram. *Computer Methods and Programs in Biomedicine*, 180, 105001.
- [13]. Phan, H., et al. (2019). Automatic sleep staging using deep learning and motion data. *IEEE Journal of Biomedical and Health Informatics*, 23(1), 26–34.
- [14]. Tsinalis, O., et al. (2016). Automatic sleep stage scoring with single-channel EEG using convolutional neural networks. arXiv preprint arXiv:1610.01683.
- [15]. Erdenebayar, U., et al. (2019). Deep learning for sleep apnea detection using single-lead ECG and oxygen saturation signals. *IEEE Access*, 7, 111015–111023.
- [16]. Phan, H., et al. (2018). DNN filter bank improves sleep classification for home and clinical data. *Proceedings of IEEE EMBC*, 53–56.
- [17]. Michielli, N., et al. (2019). Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals. *Computers in Biology and Medicine*, 106, 71–81.
- [18]. Zoubek, L., et al. (2007). Feature selection for sleep/wake stages classification using data driven methods. *Biomedical Signal Processing and Control*, 2(3), 171–179.
- [19]. Sharan, R. K. (2021). Automatic sleep staging using ResNet and HMM for ambulatory PSG systems. *IEEE Access*, 9, 99685–99695.
- [20]. Stein, P. K., & Pu, Y. (2012). Heart rate variability, sleep and sleep disorders. *Sleep Medicine Reviews*, 16, 47–59.
- [21]. Jacob, D., Kokil, P., Suriyan, S., & Jayanthi, T. (2025). Wearable sensor design for real-time obstructive sleep apnea monitoring. *IEEE Sensors Journal*, 25(11), 20584–20592.
- [22]. Fonseca, P., & Ross, M. (2024). Estimating the severity of obstructive sleep apnea using ECG, respiratory effort and neural networks. *Proceedings of IEEE EMBC*, 2024.
- [23]. Massie, F., & Vits, S. (2024). Central sleep apnea detection by means of finger photoplethysmography. *Proceedings of IEEE EMBC*, 2024.