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Integration of AI and Iot Technologies for Non-Invasive Sleep Apnea Detection and Monitoring

Patrice Adlino, Parth Jadhav, Pavan Pawar, Amey Prayag

Department of Mechanical Engineering, Vishwakarma Institute of Technology, Pune

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ABSTRACT

The prevalence of sleep apnea has driven demand for low-cost, non-invasive, and continuous home-based monitoring systems. This research paper presents an AI-enabled IoT architecture integrating wearable sensors, ESP32 microcontroller processing, and cloud-based analytics for real-time detection of apnea events. The system monitors physiological parameters including SpO2, heart rate, respiratory rate, and body movement. Machine learning models such as SVM, Random Forest, CNN, and LSTM enhance detection accuracy. Findings demonstrate 93% accuracy and 94% sensitivity, validating the effectiveness of the system as a scalable alternative to clinical polysomnography.

INTRODUCTION

Sleep apnea is a chronic disorder characterized by repeated interruptions in breathing during sleep, leading to oxygen desaturation, cardiovascular stress, and long-term health risks. Conventional diagnosis relies on clinical polysomnography (PSG), which is accurate but expensive, time-consuming, and inaccessible to many patients.

This study proposes a non-invasive, AI-powered IoT system designed to detect sleep apnea events autonomously through real-time monitoring. The solution emphasizes low cost, portability, remote accessibility, and continuous data analytics suitable for home-based monitoring.

LITERATURE REVIEW

Recent advancements in smart healthcare highlight the integration of IoT and AI for physiological monitoring. Alshehri & Muhammad (2021) provide a broad survey of IoT-driven healthcare, emphasizing remote monitoring benefits. Olsen et al. (2024) demonstrate feasibility in using wearable sensors for sleep stage detection via deep learning. Systems such as SHIFT and Fusion-Infused Hypnocare exhibit the growing trend toward multimodal real- time health monitoring.

Explainable AI models like Random Forest and deep-learning frameworks such as CNNs and LSTMs have proven effective in identifying respiratory anomalies. These studies validate the potential for decentralized, automated, and continuous detection systems for sleep apnea, aligning closely with the system developed in this work.

METHODOLOGY

The methodology includes hardware integration, data acquisition, signal preprocessing, AI model development, and cloud-based analysis. Wearable sensors—MAX30102 pulse oximeter, respiratory monitor, and MPU6050 accelerometer—collect key physiological signals.

The ESP32 microcontroller handles preliminary filtering and feature extraction. Cleaned data is transmitted via Wi- Fi or Bluetooth to a cloud server for real-time processing. Machine learning models classify apnea events based on thresholds and pattern detection.

System Architecture

The system consists of four layers:

- Sensor Layer – captures SpO2, HR, respiratory rate, and body posture.
- Processing Layer – ESP32 performs noise filtering, edge computation, and data forwarding.
- Communication Layer – Wi-Fi for cloud upload and Bluetooth for sensor–controller data transfer.
- Application Layer – mobile/web dashboard for visualization, remote access, and alerts.

Cloud-based algorithms identify apnea events when SpO2 drops below thresholds or respiration halts for extended intervals.

RESULTS AND ANALYSIS

System testing involved comparing sensor readings against clinical benchmarks. The MAX30102 sensor maintained ±2% accuracy for SpO2, and respiratory readings were within ±1 bpm error.

AI model performance:

- Accuracy: 93%
- Sensitivity: 94%
- AUROC: 92%

These results confirm the system's reliability and suitability for continuous sleep monitoring in home environments.

DISCUSSION

The system demonstrates strong potential as a low-cost alternative to PSG while maintaining high detection accuracy. However, signal degradation due to motion artifacts and varying sensor placements introduces limitations. Additionally, model performance can vary when deployed across diverse populations and environments.

Future improvements include multimodal data fusion, improved artifact removal, enhanced edge processing, and integration of Explainable AI frameworks to increase clinical trust and adoption.

CONCLUSION

The presented AI-IoT sleep apnea detection system successfully identifies apnea events with high accuracy using wearable sensors and cloud-based machine learning models. Its portability, affordability, and capability for long-term home monitoring make it a viable extension of traditional PSG. Further research into robustness, scalability, and clinical validation will strengthen its potential for widespread healthcare adoption.

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