



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14

Issue: IX

Month of publication:

September 2026

DOI: <https://doi.org/10.22214/ijraset.2026.84844>

www.ijraset.com

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IoT-Based Sleep Apnea Prevention, Detection, and Emergency Alert System

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Abstract: Obstructive Sleep Apnea (OSA) is a common sleep disorder that often goes undiagnosed. It causes breathing to stop and restart repeatedly during sleep, which can increase long-term risks for heart and metabolic health. Polysomnography is the standard method for diagnosing OSA. However, it relies on lab equipment, overnight supervision, and trained technicians, making it expensive and mostly impractical for use at home. This work proposes an IoT-based system for preventing, detecting, and alerting about sleep apnea. The goal is to allow affordable, continuous monitoring at home. The design uses an ESP32 microcontroller connected to a MAX30102 pulse oximetry sensor, an INMP441 digital MEMS microphone, and an MPU6050 motion sensor. Together, these devices capture data on SpO₂ levels, heart rate, snoring, body posture, breathing movement, and respiratory rate. The system filters and normalizes these signals, converting them into Mel-Frequency Cepstral Coefficients (MFCC) and Short-Time Fourier Transform (STFT) features. This data goes to a hybrid CNN-BiLSTM-XGBoost model, which evaluates sleep quality and the severity of apnea, categorizing it as Normal, Mild, Moderate, or Severe. If a Severe episode is detected, the system uploads the information to Firebase Cloud, retrieves the patient's location from a NEO-6M GPS module, and sends an emergency SMS to registered caregivers via a SIM800L GSM module. It also gently wakes the patient using a micro speaker that plays a softly rising tone and activates a relay-controlled mini air pump for additional support.

A thematic review of related IoT, wearable technology, deep learning, contactless systems, and cloud-based monitoring supports the proposed design and explains the integrated sensing- to-response process. Since this paper discusses a proposed system instead of one that has been built and tested, it emphasizes design intent and expected functionality, rather than actual results.

Keywords: Internet of Things (IoT), Embedded Healthcare, Artificial Intelligence, Cloud Monitoring, Obstructive Sleep Apnea, ESP32, GSM/GPS Emergency Alert

I. INTRODUCTION

Sleep apnea is a breathing disorder characterized by repeated, involuntary pauses in breathing during sleep. Each pause reduces the oxygen levels in the body. Over months or years, this can lead to heart problems, high blood pressure, daytime tiredness, and lower cognitive performance. The most common type, Obstructive Sleep Apnea (OSA), happens when the upper airway partially or completely collapses during sleep. This causes irregular breathing and lowers blood-oxygen levels.

Polysomnography (PSG) remains the standard test for diagnosing OSA. However, it relies on specialized lab equipment, overnight staff, and trained technicians, making it expensive and mostly available in major hospitals. Because of this, many people with OSA remain undiagnosed until they face complications. Advances in the Internet of Things (IoT), embedded sensing, and Artificial Intelligence (AI) have created a viable path for continuous, low- cost, home-based alternatives that do not need clinical supervision.

This paper suggests an IoT-Based Sleep Apnea Prevention, Detection, and Emergency Alert System designed to make overnight monitoring feasible outside of a clinical setting. The design combines an ESP32 microcontroller with a MAX30102 pulse-oximetry sensor, an INMP441 digital MEMS microphone, and an MPU6050 motion sensor. This setup continuously monitors SpO₂, heart rate, snoring, body position, breathing movements, and respiratory rate. The data goes through an AI process, with MFCC and STFT feature extraction leading into CNN, BiLSTM, and XGBoost stages. This process assesses sleep quality and classifies the severity of apnea. When a severe episode occurs, the system saves the record to Firebase Cloud, identifies the patient's location using GPS, sends a GSM-based SMS alert to registered caregivers, gently wakes the patient with a softly rising tone from a micro speaker, and activates a mini air pump as a supportive response. This works without relying on local buzzers, alarms, or voice calls.

The rest of this paper is organized as follows: Section II reviews current sleep-monitoring methods. Section III groups related research by theme and compares the studies. Section V identifies the resulting research gap. Section VI outlines the proposed system architecture and methodology. Section VII wraps up the paper and discusses future work.

II. BACKGROUND

Methods for monitoring sleep disorders generally fall into four categories: clinical, wearable, therapeutic, and manual. Each category balances diagnostic accuracy with cost and accessibility differently.

- 1) **Polysomnography (Sleep Study):** This test is conducted in a sleep lab under medical supervision. PSG records EEG, EOG, EMG, ECG, oxygen saturation, airflow, and respiratory effort. It provides a complete diagnostic picture. Its accuracy is well known. However, the cost, equipment, and unfamiliar sleep environment make it impractical for routine or continuous use.
- 2) **Wearable Devices:** Smartwatches, fitness bands, and dedicated sleep trackers estimate sleep duration, stage, and quality using actigraphy and, in some models, optical SpO₂ sensing. They are convenient and non-invasive. However, their indirect, algorithm-based estimates are not reliable enough to detect clinically significant apnea events.
- 3) **CPAP Therapy:** Continuous Positive Airway Pressure (CPAP) machines treat OSA by keeping the airway open with steady airflow through a mask. It is effective as a treatment, but CPAP is not designed to detect or classify apnea events. It also lacks emergency alerts and often faces compliance issues due to user discomfort.
- 4) **Manual Observation:** At home, caregivers sometimes monitor for breathing irregularities and distress without dedicated equipment. This method is unreliable over long periods of unattended sleep. It is prone to fatigue and human error, and it leaves no record for later review.

These gaps highlight the need for an integrated, low-cost home-monitoring solution that can still trigger timely responses during emergencies. This is the goal of this paper.

III. LITERATURE REVIEW

Rather than treating each study separately, the discussion below groups related work by research theme. This highlights recurring design patterns, trade-offs, and open challenges that relate to the system proposed in this paper.

A. IoT-Based and Cloud-Assisted Monitoring Systems

One common direction in the literature pairs low-cost physiological sensors with an IoT microcontroller and a cloud backend for remote viewing [1], [19]. These systems typically combine SpO₂, respiration, and acoustic sensing on an ESP32-class board. They stream data to a cloud dashboard, allowing caregivers to check trends remotely. Their strengths include low cost and constant connectivity. However, most implementations stop at monitoring and visualization, with no defined step from detecting an anomaly to triggering an automatic real-world response, such as location sharing or an SMS alert. Another shared limitation is that they rely on stable internet; a dropped connection can disrupt monitoring.

B. Wearable Healthcare Devices

A second group of studies examines consumer wearables like wristbands, smartwatches, and phone-linked sensors as a convenient, non-clinical monitoring option [5], [10], [11], [12], [15]. This research shows that low-cost accelerometer, PPG, and ECG sensors on the wrist can approximate sleep-stage and apnea-related patterns reasonably well. A meta-analysis of wearable AI systems confirms their increasing use in screening [12]. Still, wearable systems often lack the accuracy of purpose-built clinical sensors. Their performance can vary across datasets and based on how the device is worn, making it difficult to pinpoint the exact beginning and end of individual apnea events [15]. Since these devices are not intended to be constant bedside monitors, they depend on the wearer keeping them on all night, which does not always occur.

C. Artificial Intelligence and Deep Learning Approaches

Other studies focus less on sensing hardware and more on the classification stage. They apply machine-learning and deep-learning models to physiological signals to detect apnea and estimate its severity [3], [6], [17], [20]. Neural networks trained on ECG and respiratory effort signals closely match PSG-derived severity scores [6]. Lightweight object-detection models used on ECG spectrograms, along with entropy-based EEG features, have also been tested for faster, edge-deployable inference [17], [20]. This suggests that the classification layer of a monitoring system can perform well regardless of which

sensors feed it. However, most models are trained and tested on limited datasets. Questions remain about how well they generalize to different populations and home settings [3].

D. Contactless and Radar-Based Monitoring Systems

To avoid the discomfort of worn sensors, another line of work employs contactless sensing based on Wi-Fi Channel State Information (CSI) and radar. Attention-based deep-learning models applied to Wi-Fi CSI have detected apnea and limb movement without any body-worn device [4]. K-band and continuous-wave radar, combined with signal processing and SVM classifiers, have accurately detected respiratory motion from a distance [9], [18]. The advantage here is comfort and no compliance issues. The downside is sensitivity to patient movement and ambient interference, which can undermine reliability in an uncontrolled home environment.

E. Sleep Staging and EEG-Based Techniques

Another group of studies focuses on detailed sleep-stage classification using EEG. This is often a step before or alongside apnea detection [7], [14]. In-home EEG devices paired with deep learning have improved automatic sleep-stage classification compared to earlier methods. However, accuracy still drops during deep (N3) sleep, which is often when apnea-related events are clinically important. This indicates that EEG-centric pipelines are informative but not yet a full substitute for multi-modal sensing at home.

F. Home-Based and Edge-Deployable Monitoring

Closer to the focus of this paper, several studies examine home deployment and on-device inference directly. TinyML models running on ESP32-class hardware show that useful apnea-related inference is possible on limited embedded platforms, reducing the need for continuous cloud processing [8]. A Random-Forest system using SpO₂, heart rate, snoring, and posture has also shown that early detection and alerting can work with modest computing power [13]. A review of non-invasive ultrasonography suggests that low-cost screening tools can achieve useful sensitivity for OSA indicators without full PSG [2]. Separate modeling of airway narrowing and respiratory mechanics [16] helps explain sensor- derived breathing signals physiologically, even if those models are not deployable monitoring systems themselves.

Across these six themes, progress has been made in various aspects of the sleep-apnea monitoring problem—sensing, classification, contactless operation, sleep staging, and edge deployment. However, few efforts have come together into a single low-cost platform that can handle a detected event through to an automated, location-aware emergency response. That gap is the specific direction this paper pursues.

Table I lists the twenty studies surveyed above, along with the technique used, its main advantage, and its main limitation. Across the themes, IoT and wearable methods prioritize affordability and continuous use, contactless radar/Wi-Fi methods favor comfort at the expense of motion sensitivity, and EEG and ECG deep-learning methods focus on classification accuracy while adding preprocessing overhead. Together, these findings support the idea of combining different sensing methods rather than relying on just one.

TABLE I. COMPARISON OF EXISTING STUDIES

Sl.	Author / Year	Technique Used	Advantage(s)	Disadvantage(s) / Limitation(s)
1	Jennifer [1] (2023)	IoT monitoring: ESP32, MAX30100, cloud	Real-time monitoring achieved	No GPS/GSM emergency response
2	Terawatpothong et al. [2] (2026)	Systematic review of upper-airway ultrasonography (6 studies)	High sensitivity for OSA screening	No standardized thresholds; cannot replace PSG
3	Sabarish & Vishnu [3] (2023)	Machine learning + GUI	User-friendly interface	Limited training dataset; poor generalization
4	Chang et al. [4] (2023)	Wi-Fi CSI + attention-based deep learning	Non-contact detection	Sensitive to environmental interference
5	Sumona & Aurthy [5] (2023)	ECG, PPG, accelerometer sensors	Low-cost solution	Lower accuracy than clinical PSG

6	Fonseca et al. [6] (2024)	ECG + respiratory effort + neural networks	Close agreement with PSG severity	Extensive signal preprocessing required
7	Tsumoto et al. [7] (2024)	EEG + machine learning sleep staging	Improved sleep-stage analysis	Reduced accuracy in deep (N3) sleep
8	Duan & Jin [8] (2024)	TinyML on ESP32	On-device edge inference	Requires fixed-length signal input
9	Dong et al. [9] (2024)	K-band biomedical radar	Contactless detection	Affected by body motion
10	Olsen et al. [10] (2024)	Deep transfer learning, wrist wearables	High detection accuracy	Dependent on continuous wearable use
11	Multi-modal phone/smartwatch [11] (2024)	Smartphone + smartwatch multimodal signals	Feasible home monitoring	Depends heavily on user/device behaviour
12	Abd-alrazaq et al. [12] (2024)	Meta-analysis of wearable AI systems	Comprehensive evidence synthesis	Dataset variability across studies
13	Aniyan et al. [13] (2024)	SpO ₂ , HR, snoring, posture + Random Forest	Early detection and alerting	Limited large-scale clinical validation
14	Gao et al. [14] (2025)	Single-channel EEG, Bi-GRU + SVM	Efficient combined screening	Reduced accuracy in deep sleep
15	Luszczynski et al. [15] (2025)	Mamba deep learning, wearable multimodal	High agreement with PSG	Difficulty resolving exact event boundaries
16	Aftab et al. [16] (2025)	Computational airway/respiratory modelling	Physiological insight into airway narrowing	Not a deployable monitoring system
17	Aqueel et al. [17] (2025)	EEG entropy features + weighted KNN	High classification accuracy	Sensitive to EEG noise
18	Yen et al. [18] (2025)	Continuous-wave radar + SVM	Non-contact monitoring	Affected by patient motion
19	Adlino et al. [19] (2025)	AI + IoT non-invasive monitoring	Improved detection accuracy	Depends on continuous internet; no GPS alert
20	Nipattanon & Lin [20] (2025)	YOLOv8-Nano on ECG spectrograms	Lightweight, edge-deployable	Requires high-quality ECG input signal

IV. RESEARCH GAPS

The thematic review in Section III highlights several limitations shared by current sleep-apnea monitoring systems. Many still rely on costly polysomnography equipment or clinical-grade EEG and radar hardware, which makes them less affordable and accessible for everyday use. Among the cheaper options, most only provide isolated physiological sensing, such as SpO₂ alone or motion alone. This approach does not combine oxygen saturation, heart rate, snoring, posture, and respiratory rate into one platform. As a result, there is less confidence in any single-parameter detection decision.

Home monitoring often faces challenges due to a need for continuous internet access or issues with wearables. Even when cloud connectivity is available, it usually serves only for passive data storage and not as an active channel for emergency response. Emergency notifications are mostly absent. Very few systems actually retrieve a patient's location or send an automatic alert to a caregiver when a serious event occurs. None of the reviewed systems combine GPS-based location sharing with GSM SMS alerts and a physical device that can intervene automatically. When severity classification does exist, it is often binary (normal or abnormal), which limits its usefulness for prioritizing responses.

These issues—fragmented AI-IoT integration, limited home accessibility, a weak link between cloud data and response, and a lack of GPS-assisted emergency handling—highlight the need for a platform that treats sensing, classification, cloud synchronization, and emergency intervention as a single, continuous pipeline instead of separate, loosely connected components. This is the specific focus of Section VI.

V. PROPOSED SYSTEM OVERVIEW

A. System Architecture

The system that has been proposed is made up of four functional layers—the Sensor, the Processing, the Communication, and the Application—by means of which a physiological reading is taken and then passed on to an emergency response that is capable of being taken.

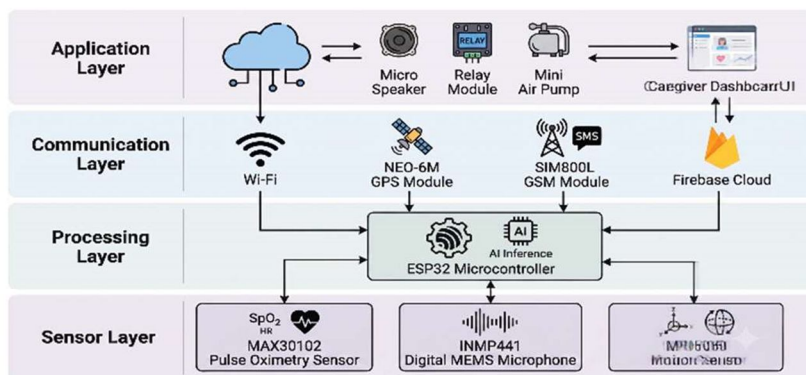


Figure 1. A diagram showing the overall system architecture of the proposed IoT-based sleep apnea monitoring system.

The Sensor Layer consists of the MAX30102 sensor used for acquiring SpO₂ and heart rate, the INMP441 digital MEMS microphone for detecting snoring, and the MPU6050 motion sensor for tracking posture and breathing movements. These sensors are connected to an ESP32 microcontroller, which in turn supports the Processing Layer and forms the on-board/edge part of the AI pipeline. The Communication Layer makes use of Wi-Fi to connect to Firebase Cloud, a NEO-6M GPS module to obtain location data, and a SIM800L GSM module to send emergency alerts by means of SMS. The Application Layer offers the Firebase-based cloud dashboard for remote monitoring, together with the micro speaker, relay module, and mini air pump which constitute the system's physical response in the case of a detected severe event.

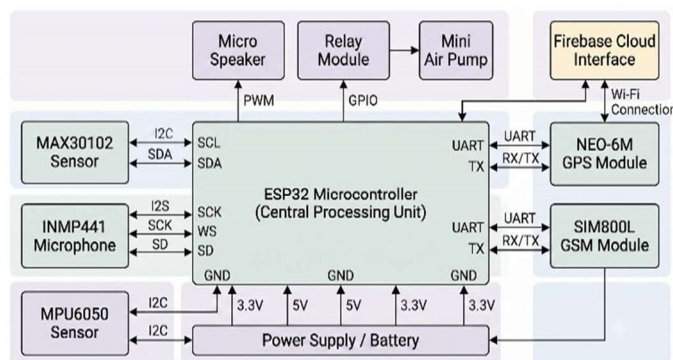


Fig. 2. Hardware block diagram showing sensor, processing, communication, and intervention components.

TABLE II. HARDWARE COMPONENTS AND THEIR FUNCTIONS

Hardware / Cloud Component	Function
ESP32 Development Board	Central controller; acquires sensor data and coordinates processing, cloud, and communication modules
MAX30102 Sensor	Measures blood oxygen saturation (SpO ₂) and heart rate via reflective photoplethysmography
INMP441 Digital MEMS Microphone	Captures audio for snoring-pattern detection
MPU6050 Motion Sensor	Monitors body posture and breathing/chest movement for respiratory-rate estimation
NEO-6M GPS Module	Retrieves the patient's live location for emergency alerts
SIM800L GSM Module	Sends emergency SMS notifications to registered caregivers

Mini Speaker	Gently wakes the patient using soft, gradually rising audio during a severe apnea event
Relay Module	Switches the mini air pump on/off under microcontroller control during a severe event
Mini Air Pump	Provides relay-activated supportive intervention during a detected severe apnea event
Firebase Cloud	Cloud platform for data synchronization, storage, and remote dashboard monitoring
Power Supply / Battery	Provides continuous power for overnight operation

TABLE III. SENSOR FEATURES EXTRACTED

Signal	Sensor	Extracted Features	Purpose
SpO ₂ / Heart Rate	MAX30102	Blood-oxygen percentage, pulse rate, inter-beat interval	Detects hypoxia events and abnormal heart-rate patterns associated with apnea
Snoring Audio	INMP441 Microphone	MFCC coefficients, STFT time-frequency spectrum, sound-intensity envelope	Identifies snoring episodes and airway-obstruction acoustic signatures
Body Posture / Movement	MPU6050	Tri-axial acceleration, orientation angle, movement variance	Determines sleeping posture and estimates breathing/respiratory rate
Location	NEO-6M GPS	Latitude, longitude coordinates	Enables location sharing during a severe emergency event

B. Methodology and AI Pipeline

STFT analysis monitors how the frequency content of breathing and snoring changes over short time windows—thus producing a time-frequency feature set which is appropriate for distinguishing normal breathing from apnea-related acoustic events.

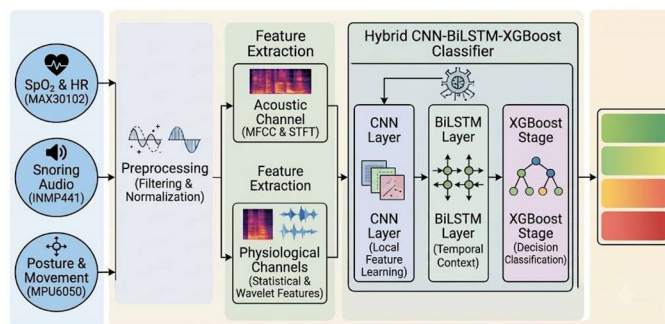


Fig. 3. Signal filtering and MFCC/STFT feature-extraction stage.

The process starts with the continuous collection of SpO₂ levels, heart rate, snoring audio, posture, and motion data from the Sensor Layer. The raw readings are filtered and normalized in order to eliminate sensor noise and compensate for baseline drift before feature extraction takes place. For the acoustic channel, MFCCs are used to capture the spectral envelope of the snoring sounds, while

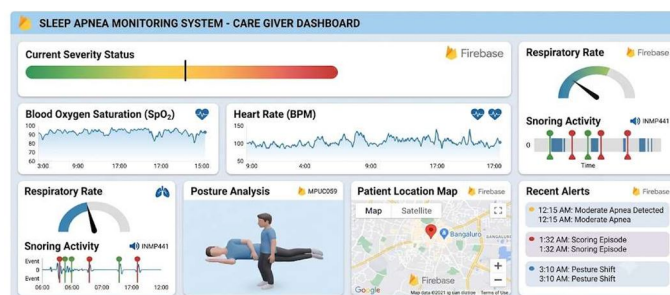


Figure 4. A conceptual arrangement of the cloud monitoring dashboard based on Firebase.

Together with the SpO₂, heart-rate, and motion data streams, these features are used in a hybrid classification process. In this process, a Convolutional Neural Network (CNN) section learns the local patterns present in the extracted features, a Bidirectional Long

Short-Term Memory (BiLSTM) section captures the temporal dependencies over a breathing cycle in both directions, and an XGBoost stage carries out the final classification by assigning one of the severity labels—Normal, Mild, Moderate, or Severe—based on the combined feature representation. The fact that the approach is divided into stages allows each part to take responsibility for a different aspect of the problem: the learning of local features, the modelling of temporal context, and the decision-level classification, rather than depending on a single large model. The classification results together with the relevant sensor summaries are sent to Firebase Cloud so that they can be viewed on the caregiver-facing dashboard and allow trends to be reviewed over multiple nights rather than just during a single session.

C. Communication and the handling of emergencies

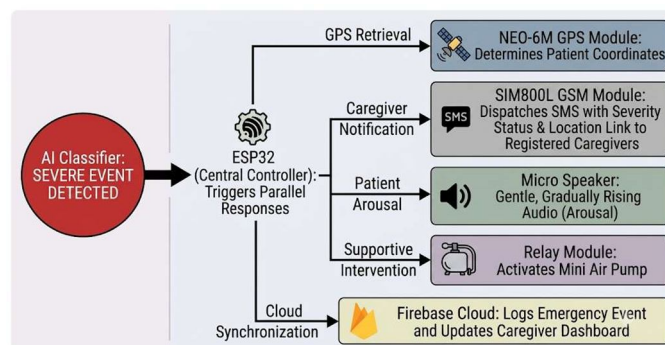


Fig. 5. Workflow from severe-event detection to GPS retrieval, GSM SMS alert, gentle micro-speaker wake-up, and relay-controlled mini air pump activation.

If the classification pipeline assigns a Severe label, the Communication Layer is automatically activated. The NEO-6M GPS module then obtains the patient's present position and the SIM800L GSM module sends an SMS with the severity status and a link to the location to one or more registered caregiver numbers. Meanwhile, the micro speaker gently wakes the patient using a soft tone that rises gradually instead of sounding like a harsh alarm, and the relay module turns on the mini air pump as a supportive measure. The event is recorded in Firebase Cloud so that the caregiver dashboard can show the emergency in real time. This design does not make use of a local buzzer, a loud alarm, or an automated voice call; the complete emergency-response pathway is made up of location sharing, SMS alerting, gentle wake-up, cloud logging, and relay-controlled intervention.

D. Proposed Algorithm

In step 1 The first step is to initialise the ESP32 and the sensors connected to it.

In step 2 obtain data on SpO₂, heart rate, snoring, posture, and movement.

In step 3, the sensor readings obtained should be filtered and normalized.

From the acoustic channel, extract the MFCC and STFT features. In step 5, use the CNN-BiLSTM-XGBoost pipeline to evaluate sleep quality and to classify the severity.

In step 6, the result should be classified as Normal, Mild, Moderate, or Severe.

Step 7: Sync the classification result and the sensor summary with Firebase Cloud.

In step 8, if the result is classified as Severe, the GPS position should be retrieved, a GSM SMS alert should be sent to the registered caregivers, the patient should be gently woken up using the micro speaker, and the relay-controlled mini air pump should be activated.

In Step 9: Continue monitoring.

The design intended to achieve a practical balance between classification accuracy and the computing capabilities of embedded, battery-operated hardware, with the aim of keeping the route from detection to notification to the caregiver short and automatic.

Table IV presents a summary of how the proposed system is expected to compare to polysomnography, consumer wearables, CPAP therapy, and generic IoT dashboards with respect to cost, emergency-response capability, cloud connectivity, AI-based analysis, GPS location sharing, GSM SMS alerting, sleep-quality assessment, and severity classification.

TABLE IV. COMPARISON BETWEEN EXISTING SYSTEMS AND PROPOSED SYSTEM

Existing Systems	Cost	Emergency Alert	Cloud	AI	GPS	SMS	Sleep Quality	Severity Classification
PSG / Hospital Sleep Study	High	No	No	No	No	No	Limited	Detailed (clinical only)
Consumer Wearables	Moderate	Limited	Sometimes	Limited	No	No	Limited	Basic / None
CPAP (treatment only)	High	No	No	No	No	No	No	No
Generic IoT Monitor (dashboard only)	Low	Limited	Yes	Limited	No	No	Limited	Basic
Proposed System (this work)	Low	Yes	Yes	Yes	Yes	Yes	Yes	Normal/Mild/Moderate/Severe

VI. CONCLUSION

This paper describes the design of an IoT-Based Sleep Apnea Prevention, Detection, and Emergency Alert System. It combines low-cost embedded sensing, AI-based severity classification, cloud synchronization, and an automated emergency response pathway into a single platform that can be used at home. The system uses the MAX30102, INMP441, and MPU6050 sensors, all connected to an ESP32 microcontroller. It routes severe event detections through Firebase Cloud, shares GPS locations, sends GSM SMS alerts, gently wakes users with a micro-speaker, and controls a mini air pump via a relay. This design addresses the gaps in AI-IoT integration and emergency response capabilities found in existing studies. Since this paper presents a proposed system rather than a tested one, it does not include figures for accuracy, precision, or performance. Future work will focus on integrating and calibrating hardware, collecting controlled data to train and evaluate the CNN-BiLSTM- XGBoost pipeline, measuring GPS/GSM response delays, and testing the usability of the Firebase-based dashboard for caregivers.

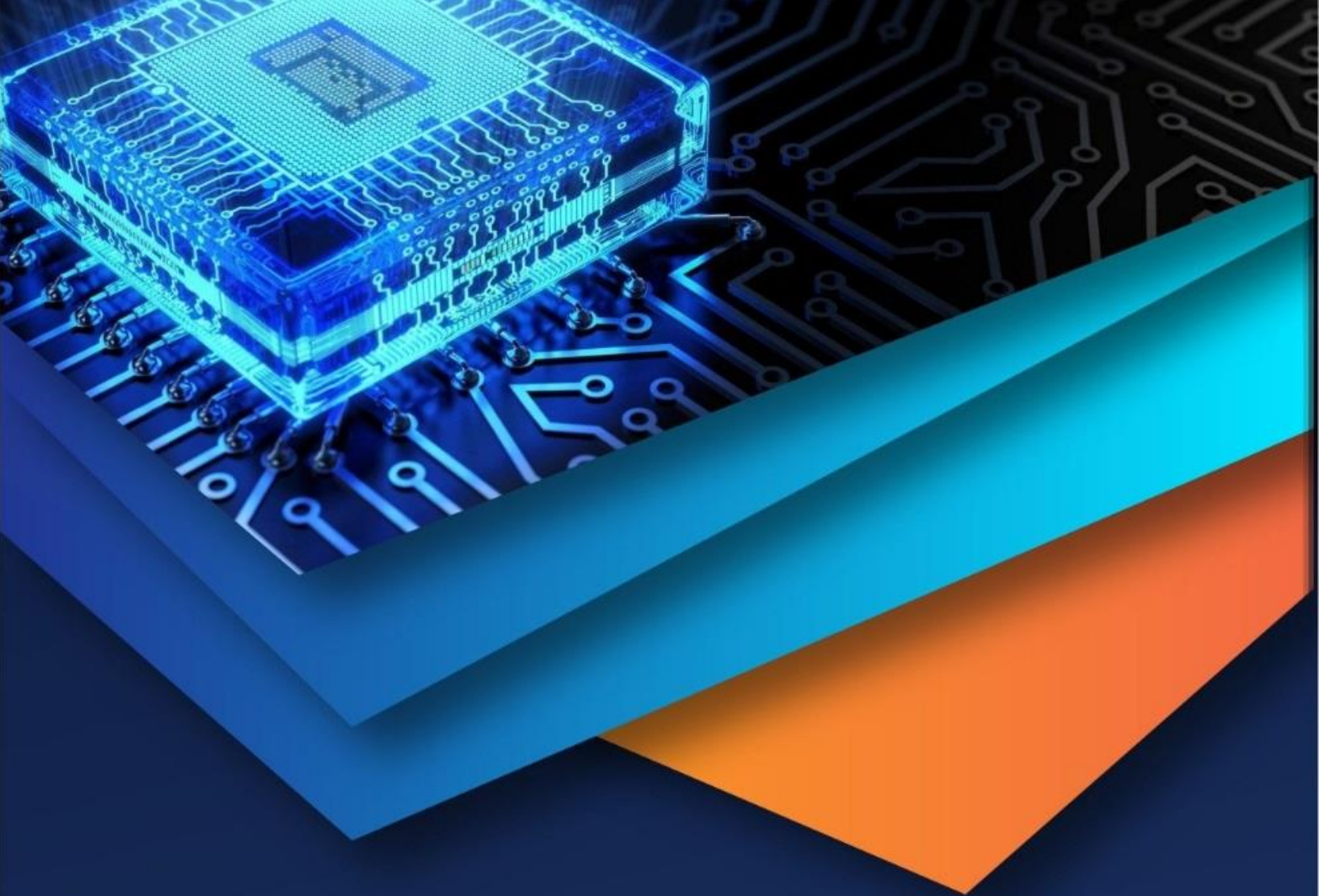
The proposed system could provide better access to ongoing, affordable sleep apnea monitoring. The design aims to ensure timely notifications for caregivers during severe events, subject to the validation mentioned above.

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