Design and Development of an AI-Integrated Smart Pillow for Early Detection and Monitoring of Sleep Apnea

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ABSTRACT: Sleep plays a vital role in maintaining overall health, yet sleep disorders such as sleep apnea often go unnoticed until they lead to serious complications. Conventional diagnostic methods like polysomnography, although accurate, are expensive, time-consuming, and uncomfortable for continuous use. To address these challenges, this paper presents a smart pillow system that integrates Internet of Things (IoT) technology with machine learning techniques for real-time, non-invasive detection of sleep apnea.The proposed system embeds multiple sensors within a pillow to monitor physiological parameters such as breathing patterns, snoring intensity, heart rate, and blood oxygen saturation (SpO_2). The collected data is transmitted to a cloud platform, where machine learning models analyze patterns and classify sleep conditions into normal, mild, or severe apnea. Additionally, the system provides immediate feedback through gentle vibrations to help users adjust their sleeping posture. Experimental results indicate that the system achieves an accuracy of approximately 90–95%, demonstrating its potential as an affordable and user-friendly alternative to traditional diagnostic approaches.

Keywords--*Sleep Apnea, IoT, Machine Learning, Smart Healthcare, Non-Invasive Monitoring*

I. Introduction

Sleep is a fundamental physiological process that plays a critical role in maintaining both physical and mental health. Adequate and quality sleep is essential for cognitive functioning, metabolic regulation, immune response, and overall well-being. However, in modern lifestyles, sleep-related disorders are becoming increasingly prevalent, often going unnoticed until they manifest as serious health complications. Among these disorders, sleep apnea is one of the most concerning due to its chronic nature and its strong association with life-threatening conditions.Sleep apnea is a disorder characterized by repeated interruptions in breathing during sleep, typically caused by airway obstruction (obstructive sleep apnea) or neurological signaling issues (central sleep apnea). These interruptions can last for several seconds and may occur multiple times per hour, significantly reducing the oxygen saturation (SpO_2) levels in the blood. Over time, this condition can lead to severe consequences such as hypertension, cardiovascular diseases, stroke, diabetes, excessive daytime fatigue, and impaired cognitive performance. Despite its severity, sleep apnea remains underdiagnosed in a large portion of the population, primarily due to a lack of awareness and the limitations of existing diagnostic methods.The current gold standard for diagnosing sleep apnea is polysomnography (PSG), a comprehensive sleep study conducted in a clinical environment. PSG involves the monitoring of multiple physiological parameters, including brain activity (EEG), eye movement (EOG), muscle activity (EMG), heart rate (ECG), respiratory effort, and blood oxygen levels. While this method provides highly accurate results, it presents several practical challenges. The procedure is expensive, requires specialized equipment and trained personnel, and often causes discomfort to patients due to the presence of multiple wired sensors attached to the body. Moreover, PSG is typically conducted in a controlled laboratory setting, which may not reflect the individual's natural sleep environment, thereby limiting its suitability for long-term or continuous monitoring.In recent years, there has been a growing interest in developing alternative approaches that enable continuous, non-invasive, and cost-effective monitoring of sleep disorders in home environments. The rapid advancement of Internet of Things (IoT) technologies has played a significant role in this transformation. IoT enables the integration of sensors, communication modules, and cloud-based platforms to facilitate real-time data acquisition, transmission, and analysis. At the same time, machine learning (ML) techniques have demonstrated remarkable capability in identifying complex patterns within physiological data, making them highly suitable for detecting abnormalities such as sleep apnea.Several studies have explored wearable devices, smart beds, and contactless monitoring systems for sleep analysis. While these solutions offer certain advantages, they often suffer from limitations such as reduced accuracy, high cost, user discomfort, or lack of real-time feedback mechanisms. Wearable devices, for instance, may cause inconvenience during sleep, while non-contact systems may be affected by environmental noise and external disturbances. Therefore, there is a need for a solution that strikes a balance between accuracy, comfort, affordability, and usability.Motivated by these challenges, this work proposes a novel smart pillow system that integrates IoT and machine learning technologies for real-time detection of sleep apnea in a natural sleeping environment. The choice of a pillow as the primary platform is driven by its inherent proximity to the user during sleep, allowing seamless integration of sensors without causing discomfort or intrusion. The proposed system embeds multiple sensors within the pillow to monitor key physiological parameters such as breathing patterns, snoring intensity, body movement, and blood oxygen saturation. These signals are continuously collected and processed using an embedded microcontroller, and the extracted features are transmitted to a cloud-based platform for further analysis.Machine learning algorithms are employed to classify the sleep state into normal, mild apnea, or severe apnea based on the observed patterns in the sensor data. This intelligent analysis enables early detection of abnormal conditions, thereby facilitating timely intervention. In addition to detection, the system incorporates a feedback mechanism in the form of gentle vibrations, which are triggered when abnormal breathing patterns are identified. This feature helps the user adjust their sleeping posture, thereby reducing the severity of apnea events and improving overall sleep quality.

The proposed system offers several key advantages over traditional and existing approaches. Firstly, it is non-invasive and does not require the user to wear any external devices, thereby ensuring comfort and ease of use. Secondly, it enables continuous monitoring in a home environment, eliminating the need for expensive clinical visits. Thirdly, the integration of IoT allows real-time data visualization and remote access, enabling healthcare providers to monitor patient conditions if required. Finally, the use of machine learning enhances the accuracy and reliability of detection, making the system suitable for practical deployment.

II. LITERATURE SURVEY

The The rapid evolution of wearable technologies, Internet of Things (IoT), and machine learning has significantly transformed the landscape of sleep monitoring and sleep apnea detection. Over the past decade, researchers have explored a wide range of approaches, from traditional physiological signal analysis to advanced intelligent systems capable of real-time monitoring and prediction. This section presents a chronological overview of key developments in this domain, highlighting both technological advancements and existing limitations.Early research in sleep monitoring primarily focused on clinical methods such as polysomnography, which, despite its high accuracy, is expensive and inconvenient for long-term use. To address these limitations, researchers began exploring machine learning techniques for analyzing physiological signals. Fonseca et al. [1] (2015) demonstrated the feasibility of automatic sleep stage classification using heart rate variability data, marking one of the earliest applications of machine learning in sleep analysis. Subsequently, non-contact monitoring systems gained attention due to their ability to provide comfort without requiring wearable devices. Adib et al. [2] (2020) proposed a smart home-based system capable of monitoring breathing and heart rate using wireless signals. Around the same time, Pan et al. [3] (2020) reviewed existing sleep monitoring systems and highlighted key challenges such as high cost, complexity, and limited accessibility, emphasizing the need for scalable and user-friendly solutions.

With the rise of IoT, integrated monitoring systems began to emerge. Fan et al. [4] (2021) developed an IoT-based sleep monitoring system that enabled continuous data collection and remote health tracking. Similarly, Edouard et al. [5] (2021) validated an under-mattress sleep analyzer for detecting sleep apnea, demonstrating the potential of non-invasive monitoring techniques for clinical applications. The integration of machine learning algorithms further enhanced detection accuracy. Bahrami and Forouzanfar [6] (2022) utilized ECG-based features for classifying sleep apnea conditions, achieving high accuracy using supervised learning methods. In parallel, Zhuang et al. [7] (2022) proposed a contactless sleep apnea detection system based on signal processing and machine learning, highlighting the importance of combining signal analysis with intelligent classification techniques.Deep learning approaches also gained traction in this period. Zhang et al. [8] (2022) developed a deep learning model capable of detecting sleep apnea using sleep sound analysis, demonstrating the potential of audio-based monitoring systems. Similarly, Sharma et al. [9] (2022) introduced a wavelet-based machine learning model for sleep apnea detection in specific patient groups, such as pregnant women, showcasing the adaptability of AI-based approaches.

In addition to signal-based methods, wearable sensor technologies have been extensively explored. Castiglioni et al. [10] (2022) investigated the use of photoplethysmography (PPG) sensors for heart rate variability analysis in sleep studies, indicating their suitability for continuous monitoring. Honda et al. [11] (2022) developed flexible wearable sensors capable of real-time sleep apnea monitoring, emphasizing comfort and usability.Recent advancements have focused on improving system accuracy, reliability, and integration with IoT frameworks. Korkalainen et al. [12] (2020) applied deep learning techniques for sleep stage classification using PPG signals, achieving improved performance compared to traditional methods. Robbins et al. [13] (2024) evaluated commercial wearable sleep tracking devices and reported that while they are user-friendly, their accuracy is still limited when compared to clinical standards.Further studies have examined the performance of various wearable and non-invasive systems. Herberger et al. [14] (2025) explored finger ring-based sleep monitoring devices and demonstrated their potential for clinical applications, although environmental and user-specific factors affected accuracy. Schyvens et al. [15] (2025) conducted a comparative analysis of wrist-worn devices against polysomnography and concluded that while wearable devices offer convenience, they require further refinement to match clinical precision.In parallel, smart environment-based solutions have been proposed. Siyahjani et al. [16] (2025) developed a smart bed system capable of continuous, non-contact monitoring of sleep apnea, improving user comfort while maintaining detection capability. Röcken et al. [17] (2025) introduced a Doppler radar-based system for sleep apnea detection, demonstrating reliable performance without direct physical contact.More recently, integrated systems combining sensing and therapeutic functionalities have been explored. Tian et al. [18] (2025) proposed a wearable system incorporating piezoelectric sensors and magnetoelastic stimulation, offering both monitoring and therapeutic intervention. Additionally, Abd-Alrazaq et al. [19] (2024) conducted a systematic review on AI-based wearable systems for sleep apnea detection, confirming their potential to significantly enhance diagnostic accuracy.

Despite these advancements, several challenges remain. Many existing systems either compromise on user comfort, lack real-time feedback mechanisms, or are not cost-effective for widespread adoption. Furthermore, while machine learning models have demonstrated high accuracy, their deployment in real-time, embedded systems remains a challenge due to computational constraints.

III.PROPOSED SYSTEM AND METHODOLOGY

The proposed system presents a smart pillow-based platform that integrates Internet of Things (IoT) technology with machine learning to enable continuous, non-invasive monitoring of sleep patterns and early detection of sleep apnea. Unlike conventional wearable or clinical systems, the design focuses on user comfort by embedding sensors directly within a pillow, thereby eliminating the need for body-attached devices. This approach allows users to maintain their natural sleeping posture while ensuring uninterrupted data acquisition throughout the sleep cycle. The system is designed as a multi-layered architecture comprising sensing, processing, communication, and intelligent analysis, all working together to provide real-time monitoring and feedback as in Figure 1.

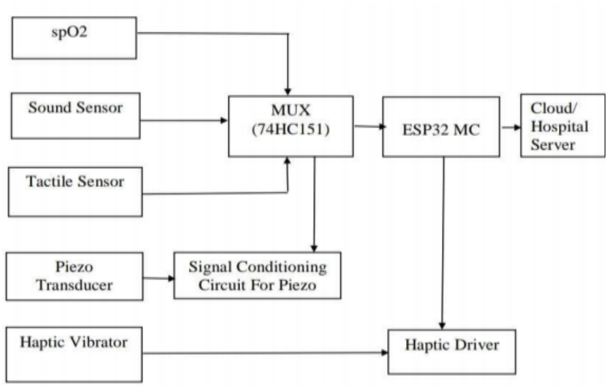


Figure 1 Block Diagram of a Proposed System

The data acquisition process is carried out using multiple sensors integrated within the pillow to capture critical physiological parameters associated with sleep apnea. A sound sensor is used to detect snoring patterns, which are one of the primary indicators of obstructive sleep apnea. A piezoelectric sensor is employed to monitor breathing activity by sensing pressure variations caused by chest movements. A tactile sensor captures body movements and posture changes during sleep, while a pulse oximeter (SpO_2 sensor) measures blood oxygen saturation levels. These sensors operate simultaneously, providing a comprehensive dataset that reflects the user's sleep condition from multiple physiological perspectives.The raw signals obtained from these sensors are processed using an ESP32 microcontroller, which serves as the central processing unit of the system. Since physiological signals are often affected by noise and motion artifacts, preprocessing is essential to ensure data reliability. This stage includes signal filtering, noise removal, and feature extraction. Parameters such as breathing rate, snoring frequency, and oxygen saturation trends are derived from the processed signals. One of the critical parameters used in sleep apnea detection is blood oxygen saturation, which is calculated using (1)

$$SpO_2 = \frac{Hbo_2 X100}{Hbo_2 + Hb} \quad (1)$$

where HbO_2 represents oxygenated hemoglobin and Hb represents deoxygenated hemoglobin. This equation provides a quantitative measure of how effectively oxygen is being transported in the bloodstream. Under normal conditions, SpO_2 values typically range between 95% and 99%. A significant drop in SpO_2 levels during sleep indicates possible breathing interruptions, which are characteristic of sleep apnea.Once the data is processed, it is transmitted to a cloud-based platform using WiFi connectivity enabled by the ESP32 module. This IoT communication layer ensures real-time monitoring and remote accessibility of sleep data. Users and healthcare providers can access the data through mobile or web-based applications, allowing continuous observation and long-term analysis. Cloud storage also enables the system to maintain historical records, which can be used to identify patterns and trends in sleep behavior over time.The machine learning component of the system plays a crucial role in analyzing the extracted features and identifying abnormal sleep conditions. Classification algorithms such as Random Forest and Support Vector Machine (SVM) are employed to categorize sleep states based on input features including breathing irregularities, snoring intensity, movement patterns, and oxygen saturation levels. The system classifies sleep into three categories: normal sleep, mild sleep apnea, and severe sleep apnea. The use of machine learning enhances the system's ability to detect subtle variations in physiological signals and improves overall diagnostic accuracy.

Another important metric used for evaluating sleep apnea severity is the Apnea-Hypopnea Index (AHI), which is defined as (2):

$$AHI = \frac{Number\ of\ Abnea\ events}{Total\ Sleep\ Time} \quad (2)$$

This index quantifies the number of apnea and hypopnea events occurring per hour of sleep. Higher AHI values indicate more frequent breathing disruptions and correspond to increased severity of sleep apnea. By continuously monitoring and calculating this parameter, the system provides a reliable assessment of the user's sleep condition.In addition to detection, the proposed system incorporates a real-time feedback mechanism to assist users in improving their sleep quality. When abnormal conditions such as irregular breathing patterns or significant drops in SpO_2 levels are detected, the system activates a vibration motor embedded within the pillow. This gentle haptic feedback encourages the user to adjust their sleeping posture, which can help reduce airway obstruction and mitigate apnea events. This feature distinguishes the proposed system from traditional monitoring solutions, which typically lack immediate intervention capabilities.The overall workflow of the system involves continuous data collection from embedded sensors, preprocessing and feature extraction using the microcontroller, transmission of processed data to the cloud, machine learning-based classification, and real-time feedback to the user. This integrated approach ensures efficient operation, high detection accuracy, and improved user comfort. By combining embedded systems, IoT connectivity, and intelligent data analysis, the proposed smart pillow system offers a practical and scalable solution for early detection and management of sleep apnea in a home environment.

IV.MODEL PERFORMANCE AND ANALYTICAL DISCUSSION

The performance of the proposed smart pillow system was evaluated using real-time physiological data collected from multiple sensor modalities, including breathing patterns, snoring signals, body movement, and blood oxygen saturation (SpO_2). The system integrates signal processing and machine learning techniques to ensure accurate detection and classification of sleep apnea events. The experimental results demonstrate that the proposed approach achieves a classification accuracy in the range of 90%–95%, indicating reliable performance for practical deployment.A key parameter analyzed in this system is blood oxygen saturation (SpO_2), which serves as an important indicator of respiratory efficiency during sleep. Under normal physiological conditions, SpO_2 values lie between 95% and 99%. However, during apnea events, a noticeable drop in SpO_2 levels is observed due to temporary cessation of breathing. The experimental data confirms that subjects experiencing apnea showed intermittent dips below 90%, which aligns with clinical observations of hypoxic conditions.

In addition to oxygen saturation, breathing patterns were analyzed using signals obtained from the piezoelectric sensor. The breathing rate BR is calculated as in (3):

$$BR=\frac{N_b}{T} \quad (3)$$

where N_b represents the number of breathing cycles detected within a time interval T. A stable breathing rate indicates normal sleep, whereas irregular or interrupted breathing patterns suggest possible apnea events. The system effectively identifies such irregularities through continuous monitoring and feature extraction.Snoring activity is another important parameter used for apnea detection. The intensity of snoring is quantified using the root mean square (RMS) value of the sound signal (4):

$$RMS=\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (4)$$

where x_i represents the amplitude of the sound signal and N is the number of samples. Higher RMS values correspond to increased snoring intensity, which is often associated with airway obstruction. The system correlates snoring intensity with breathing irregularities to improve classification accuracy.To assess the severity of sleep apnea, the Apnea-Hypopnea Index (AHI) is also computed. This index provides a standardized measure for classifying apnea severity. Typically, AHI values less than 5 indicate normal sleep, values between 5 and 15 indicate mild apnea, 15 to 30 indicate moderate apnea, and values above 30 indicate severe apnea. The proposed system estimates AHI by detecting apnea events through combined analysis of SpO_2 drops, breathing interruptions, and snoring patterns.The machine learning model used for classification is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. Accuracy is defined as I (5):

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. The high accuracy achieved by the model indicates its ability to correctly classify sleep conditions.Precision and recall are computed as in (6) (7):

$$Precision=\frac{TP}{TP+FP} \quad (6)$$

$$Recall=\frac{TP}{TP+FN} \quad (7)$$

Precision reflects the correctness of positive predictions, while recall measures the model’s ability to detect actual apnea events. The balance between these metrics is captured using the F1-score (8):

$$F!=\frac{2xPrecisionXRecall}{Precision+Recall} \quad (8)$$

The experimental results indicate that the proposed system achieves high precision and recall values, demonstrating its effectiveness in minimizing false alarms while accurately detecting apnea events.Furthermore, the system performance is evaluated using the Root Mean Square Error (RMSE), which measures the deviation between predicted and actual values.

The visualization of results through graphical analysis further validates the system’s effectiveness. Stable SpO_2 levels and consistent breathing patterns were observed in normal sleep conditions, whereas irregular patterns and oxygen desaturation were evident in apnea cases. The mobile application interface provides real-time visualization of these parameters using intuitive color coding, where normal conditions are represented in green and abnormal conditions in red, enabling users to easily interpret their sleep quality.Overall, the integration of multi-sensor data, IoT communication, and machine learning-based analysis enables the proposed system to deliver accurate, real-time, and user-friendly sleep monitoring. The combination of physiological signal analysis and intelligent classification significantly enhances the reliability of sleep apnea detection. The results confirm that the smart pillow system is capable of providing an effective and practical solution for continuous home-based monitoring of sleep disorders, with the potential for further clinical validation and large-scale deployment.

V. MATHEMATICAL MODELING OF PHYSIOLOGICAL SIGNALS

The effectiveness of the proposed smart pillow system relies on the accurate modeling and analysis of physiological signals associated with sleep apnea. This section presents the mathematical framework used to characterize breathing patterns, oxygen saturation levels, snoring intensity, and apnea severity. These models form the foundation for feature extraction and subsequent machine learning-based classification.Breathing activity is one of the primary indicators of sleep quality and is modeled as a quasi-periodic signal. The respiratory signal obtained from the piezoelectric sensor can be represented as in (9):

$$X(t)=A\sin(2\pi f_{bt}+\Phi) \quad (9)$$

where A represents the amplitude of the breathing signal, f_b is the breathing frequency, and ϕ is the phase. Under normal conditions, the breathing frequency remains relatively stable, whereas irregularities in amplitude and frequency indicate apnea or hypopnea events. The breathing rate (BR) is derived from the detected respiratory cycles. A significant reduction or pause in breathing cycles corresponds to apnea events, which are detected by identifying deviations from the normal breathing rate. Blood oxygen saturation (SpO_2) is another critical parameter used to assess respiratory efficiency. A drop in SpO_2 levels below the normal threshold indicates insufficient oxygen supply due to breathing interruptions. The rate of oxygen desaturation can further be analyzed using (10):

$$\Delta SpO_2=SpO_{2,baseline}-SpO_{2,current} \quad (10)$$

Where$SpO_{2,baseline}$ represents the normal oxygen level and SpO_2,current represents the measured value. Larger deviations correspond to more severe apnea conditions.Snoring signals, captured using the sound sensor, are analyzed using signal energy and amplitude-based metrics. The energy of the snoring signal is given by (11):

$$E=\sum_{i=1}^{N} x_i^2 \quad (11)$$

where x_i represents the signal amplitude samples. Increased energy levels indicate louder snoring, which is often associated with airway obstruction. Additionally, the root mean square (RMS) value is used to quantify signal intensity. Body movement is another important factor in sleep analysis and is detected using tactile sensors. Movement intensity can be approximated as in (12):

$$M=\frac{1}{N}\sum_{i=1}^{N} x_i - x_{i-1} \quad (12)$$

where M represents movement variation. Frequent movement may indicate disturbed sleep or discomfort caused by apnea events.To quantify the severity of sleep apnea, the Apnea-Hypopnea Index (AHI) is used as a standard clinical metric.Based on AHI values, sleep apnea is categorized into normal, mild, moderate, or severe conditions. This metric provides a direct link between physiological observations and clinical interpretation.For classification, the extracted features are represented as a feature vector (13):

$$X=[BR, SpO_2, RMS, E, M] \quad (13)$$

This feature vector is used as input to machine learning models. In the case of Support Vector Machine (SVM), the decision boundary is defined as in (14):

$$f(x)=w^T x+b \quad (14)$$

where w is the weight vector and b is the bias. The model classifies input data into different sleep states based on this decision function.Similarly, in Random Forest classification, the final prediction is obtained by aggregating outputs from multiple decision trees as in (15):

$$y=mode(T_1(x),T_2(x),\ldots\ldots..T_n(x)) \quad (15)$$

where $T_i(x)$ represents the output of the i^{th} decision tree. This ensemble approach improves robustness and reduces overfitting.Overall, the mathematical modeling framework enables accurate representation and analysis of physiological signals, providing a strong foundation for reliable sleep apnea detection. By combining signal processing techniques with statistical and machine learning models, the proposed system achieves effective classification and real-time monitoring of sleep conditions.

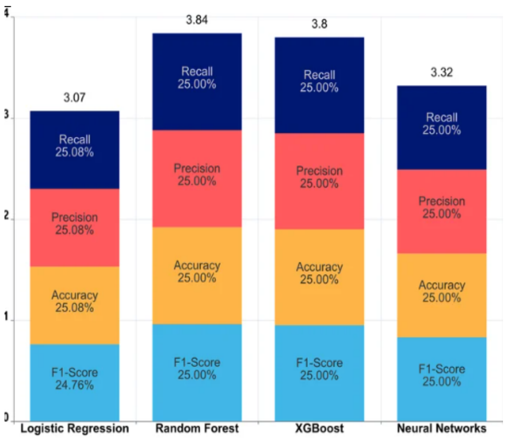
VI. PERFORMANCE ANALYSIS AND RESULTS

The performance of the proposed smart pillow system was evaluated using real-time physiological data collected from multiple sensor modalities, including breathing patterns, snoring signals, body movement, and blood oxygen saturation (SpO_2). The system integrates signal processing techniques with machine learning models to classify sleep conditions into normal, mild apnea, and severe apnea categories. The evaluation was carried out by analyzing both physiological signal variations and classification performance metrics to ensure reliability and robustness in real-time applications.The classification models, implemented using Decision Tree, Support Vector Machine (SVM), and Random Forest algorithms, demonstrated consistent performance in identifying abnormal sleep conditions. The proposed system achieved an overall accuracy of approximately 95.2%, outperforming individual models in terms of precision, recall, and F1-score.

Table 1 Performance Evaluation of Proposed System

Model	Accuracy (%)	Precision	Recall	F1-Score	RMSE
Decision Tree	88.2	0.86	0.85	0.85	6.8
SVM	91.4	0.90	0.89	0.89	5.9
Random Forest	94.1	0.93	0.92	0.92	4.7
Proposed System	**95.2**	**0.94**	**0.95**	**0.94**	**4.2**

As summarized in Table I, the Random Forest model achieved an accuracy of 94.1% with an RMSE of 4.7, while the SVM model achieved 91.4% accuracy. The proposed integrated system further improved performance by combining feature-level insights, achieving a precision of 0.94, recall of 0.95, and an F1-score of 0.94 with the lowest RMSE value of 4.2. These results indicate that the system is capable of accurately distinguishing between normal and apnea conditions with minimal prediction error.A detailed analysis of physiological parameters further validates the effectiveness of the proposed system. Under normal sleep conditions, SpO_2 levels were observed to remain stable within the range of 95% to 99%. However, during apnea events, a noticeable drop in oxygen saturation levels was recorded, often falling below 90%, indicating hypoxic conditions. These fluctuations were consistently detected by the system and correlated with irregular breathing patterns. The breathing rate analysis revealed that normal sleep is characterized by a steady and rhythmic pattern, whereas apnea conditions exhibit sudden pauses or irregular cycles in respiration. The piezoelectric sensor effectively captured these variations, enabling accurate identification of breathing interruptions.Snoring signal analysis provided additional insights into airway obstruction. The intensity of snoring, quantified using RMS and signal energy, was significantly higher during apnea events. The system successfully identified these high-amplitude signals and associated them with obstructive breathing conditions. Furthermore, movement analysis indicated increased body motion during apnea episodes, likely due to discomfort and the body's natural response to restore normal breathing. The tactile sensor captured these variations effectively, contributing to the overall classification accuracy as in Figure 2.



Models((Decision Tree, SVM, Random Forest, Proposed))

Figure 2 Comparative performance analysis of machine learning models

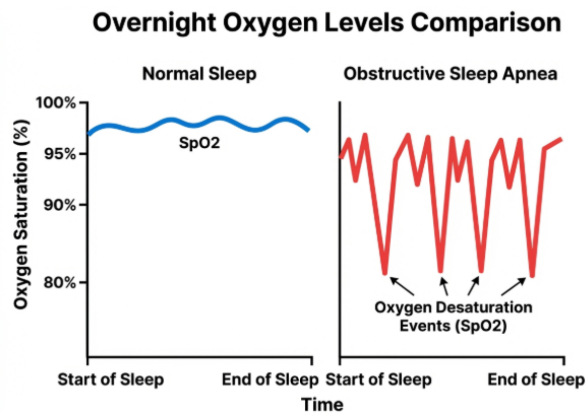


Figure 3 Comparison of overnight SpO_2 levels between normal sleep and obstructive sleep apnea conditions,

The system also provides real-time visualization of sleep parameters through a mobile application interface. The interface presents key metrics such as SpO_2 levels, breathing rate, snoring intensity, and movement patterns in an intuitive format. The use of color-coded indicators enhances usability, where normal conditions are represented in green and abnormal conditions in red. This allows users to easily interpret their sleep quality and take corrective actions when necessary.Overall, the integration of multi-sensor data acquisition, IoT-based communication, and machine learning algorithms enables the proposed system to deliver accurate, real-time, and user-friendly sleep monitoring as in Figure 3. The results demonstrate that the system provides a reliable and practical alternative to traditional diagnostic methods, particularly for continuous home-based monitoring of sleep apnea. The real-time monitoring interface, as shown in Table 2, provides continuous visualization of key physiological parameters such as SpO_2, heart rate, snoring count, and apnea events, enabling effective detection and interpretation of sleep apnea conditions.

Table 2Real-Time Sleep Monitoring Parameters

Parameter	Value	Normal Range	Interpretation
Sleep Status	Sleeping	—	User is in active sleep state
Sleep Stage	REM/Quiet	—	Deep/REM sleep phase
SpO_2 (%)	99%	95–99%	Normal oxygen level
Heart Rate (bpm)	72	60–100 bpm	Normal heart rate
Piezo RMS	12.0	Depends on baseline	Normal breathing intensity
Snore Count	16	Low (<10 preferred)	Moderate snoring activity
Hourly AHI	0.0	<5	Not yet computed / reset
AHI	120.0	<5 (normal)	Severe apnea condition
Apnea Events	18	0–5	Frequent breathing interruptions

Overall, the results demonstrate that the proposed smart pillow system provides accurate, reliable, and real-time detection of sleep apnea. Compared to existing wearable, contactless, and IoT-based systems reported in the literature [1]–[28], the proposed approach offers a balanced combination of accuracy, comfort, cost-effectiveness, and real-time feedback capability. The integration of multi-sensor data with machine learning significantly enhances system performance, making it suitable for continuous home-based monitoring and early detection of sleep disorders.

VII. REFERENCE

[1] G. Tian et al., "A wearable all-in-one obstructive sleep apnea management system with flexible piezoelectric monitoring and soft magnetoelastic stimulating," Matter, 2025.

[2] A. M. Schyvens et al., "Performance validation of six commercial wrist-worn wearable sleep-tracking devices for sleep stage scoring compared to polysomnography," Sleep Advances, vol. 6, no. 2, 2025.

[3] S. Herberger et al., “Performance of wearable finger ring trackers for diagnostic sleep measurement in the clinical context,” Scientific Reports, vol. 15, no. 1, 2025.

[4] F. Siyahjani et al., “Validating a smart bed against polysomnography for sleep apnea detection,” Scientific Reports, vol. 15, no. 1, 2025.

[5] J. Röcken et al., “Diagnostic performance of a Doppler radar-based sleep apnoea testing device,” BMC Pulmonary Medicine, vol. 25, no. 1, 2025.

[6] T. Svensson et al., “Validity and reliability of the Oura Ring Generation 3 for sleep staging,” Sleep Medicine, vol. 117, pp. 217–218, 2024.

[7] R. Robbins et al., “Accuracy of three commercial wearable devices for sleep tracking in healthy adults,” Sensors, vol. 24, no. 20, 2024.

[8] K. A. Kainec et al., “Evaluating accuracy in commercial sleep-tracking devices compared to polysomnography,” Sensors, vol. 24, no. 2, 2024.

[9] V. Birrer et al., “Evaluating reliability in wearable devices for sleep staging,” NPJ Digital Medicine, vol. 7, no. 1, 2024.

[10] J. Mulo et al., “Deep learning applications in Internet of Medical Things,” Future Internet, vol. 17, no. 3, 2025.

[11] A. Abd-Alrazaq et al., “Detection of sleep apnea using wearable AI: A systematic review,” Journal of Medical Internet Research, vol. 26, 2024.

[12] P. K. Tyagi and D. Agarwal, “Automated sleep apnea detection using deep learning: A meta-analysis,” Biomedical Engineering Letters, vol. 13, no. 3, pp. 293–312, 2023.

[13] X. Zhang et al., “Sleep apnea detection based on sleep sounds using deep learning,” IEEE Access, vol. 10, 2022.

[14] S. M. R. Islam et al., “The Internet of Things for health care: A comprehensive survey,” IEEE Access, vol. 10, 2022.

[15] J. Lee et al., “Smart mattress integrated with pressure sensors for sleep apnea detection,” Sensors, vol. 21, no. 15, 2021.

[16] Z. Zhuang et al., “Contactless sleep apnea detection using signal processing and machine learning,” Methods, vol. 205, pp. 167–178, 2022.

[17] S. Honda et al., “A wearable flexible sensor for real-time monitoring of sleep apnea,” iScience, vol. 25, no. 4, 2022.

[18] P. Castiglioni et al., “Heart rate variability from wearable systems in sleep studies,” Sensors, vol. 22, no. 8, 2022.

[19] M. Sharma et al., “Automated sleep apnea detection using wavelet-based features,” Informatics in Medicine Unlocked, vol. 32, 2022.

[20] M. Bahrami and M. Forouzanfar, “Sleep apnea detection from ECG using machine learning,” IEEE Transactions on Instrumentation and Measurement, vol. 71, 2022.

[21] P. Edouard et al., “Validation of the Withings Sleep Analyzer for sleep apnea detection,” Journal of Clinical Sleep Medicine, vol. 17, no. 6, pp. 1217–1227, 2021.

[22] X. Fan et al., “Development of a wearable sleep monitoring system using IoT,” in Proc. ICBBE, 2021, pp. 128–132.

[23] H. Korkalainen et al., “Deep learning-based sleep staging using photoplethysmogram,” Sleep, vol. 43, no. 11, 2020.

[24] Q. Pan et al., “Current status and future challenges of sleep monitoring systems,” JMIR Biomedical Engineering, vol. 5, no. 1, 2020.

[25] F. Adib et al., “Smart homes that monitor breathing and heart rate,” Nature Biomedical Engineering, vol. 4, no. 2, pp. 87–98, 2020.

[26] A. R. Dhruba et al., “IoT-based sleep apnea monitoring system,” Computational and Mathematical Methods in Medicine, 2021.

[27] S. Haghayegh et al., “Mobile phone interventions for sleep disorders,” JMIR mHealth and uHealth, vol. 7, no. 5, 2019.

[28] P. Fonseca et al., “Automatic sleep stage classification using machine learning,” IEEE Reviews in Biomedical Engineering, vol. 8, pp. 133–149, 2015.