International Journal of Engineering Science Technologies
March-April 2026 10(2)
www.ijoest.com

Review Article

ENGINEERING APPROACHES IN THE DIAGNOSIS OF SLEEP APNEA

Hatice Bilgili [1*], Elif Kucuktag [2]
[1] Assistant Professor Dr., Engineering Faculty, Biomedical Engineering Department, Inönü University, Malatya, Turkey
[2] MSc Student, Engineering Faculty, Biomedical Engineering Department, Inönü University, Malatya, Turkey

ABSTRACT

Sleep apnea is a sleep disorder that significantly affects human life and occurs as a result of repeated obstructions in the respiratory system lasting at least 10 seconds during sleep. The most common type, Obstructive Sleep Apnea (OSA), affects the upper respiratory tract, whereas Central Sleep Apnea (CSA) occurs due to dysfunction in the respiratory control center in the brain. Sleep apnea manifests with symptoms such as fatigue upon awakening, snoring, and daytime sleepiness. If left untreated, it may lead to serious health complications including stroke, cardiovascular diseases, and hypertension. Polysomnography (PSG) is the most widely used diagnostic method for sleep apnea. However, this test involves several limitations in terms of time consumption, patient comfort, and financial cost. Therefore, there is an increasing need for alternative engineering-based diagnostic support methods to complement polysomnography. Recent advancements in Biomedical Engineering, Electrical and Electronics Engineering, and Software Engineering have enabled the development of portable, cost-effective, and highly compatible systems for sleep apnea detection. Sleep apnea can be detected through physiological measurements, including electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), and oxygen saturation levels. Biomedical signal analysis of the obtained data is enabled by artificial intelligence methods and machine learning algorithms. Moreover, integrating wearable devices with the Internet of Things (IoT)-based telehealth enables continuous monitoring of patients in their homes. This study highlights the significance of engineering-based solutions in sleep apnea diagnosis and highlights their contributions to modern healthcare technologies.

Keywords: Sleep Apnea, Artificial Intelligence, Polysomnography, PSG, Wearable Devices

INTRODUCTION

Sleep is a complex biological process that plays a crucial role in human life by affecting both physical and mental health. It constitutes approximately one-third of human life and is essential for maintaining overall health and well-being. Sleep disorders are generally associated with an increased risk of mental disturbances and various physiological symptoms in the human body. Among sleep disorders, sleep apnea is one of the most frequently encountered conditions. Sleep apnea is characterized by a reduction or complete cessation of airflow due to obstruction in the respiratory tract during sleep Altun (2015). In general, this disorder is diagnosed using polysomnography (PSG), which is a time-consuming and costly procedure typically conducted in sleep laboratories Mendonca et al. (2018). Polysomnography involves the recording of multiple physiological signals, including brain activity, respiratory parameters, and cardiovascular events, through a variety of sensors. During the polysomnography procedure, electrodes

*Corresponding Author:
Email address: Hatice Bilgili (hatice.bilgili@inonu.edu.tr), Elif Kucuktag (elfkucuktag23@gmail.com)

Received: 05 January 2026; **Accepted:** 11 February 2026; **Published** 09 March 2026
DOI: 10.29121/IJOEST.v10.i2.2026.743
Page Number: 1-12
Journal Title: International Journal of Engineering Science Technologies
Journal Abbreviation: Int. J. Eng. Sci. Tech
Online ISSN: 2456-8651
Publisher: Granthaalayah Publications and Printers, India
Conflict of Interests: The authors declare that they have no competing interests.
Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
Authors' Contributions: Each author made an equal contribution to the conception and design of the study. All authors have reviewed and approved the final version of the manuscript for publication.
Transparency: The authors affirm that this manuscript presents an honest, accurate, and transparent account of the study. All essential aspects have been included, and any deviations from the original study plan have been clearly explained. The writing process strictly adhered to established ethical standards.

are attached to several parts of the body, such as the mouth, nose, head, chest, and abdomen, to record physiological signals throughout the sleep period. By analyzing the physiological responses and body movements occurring during sleep, clinicians obtain information regarding apnea events Koçak et al. (2016). The recorded signals generally include electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), oxygen saturation (SpO_2), and electrocardiography (ECG) data Altun (2015). Due to factors such as unhealthy lifestyle conditions, obesity, and stress, the prevalence of sleep apnea has been increasing worldwide, which has attracted growing attention from researchers and accelerated the number of related studies over the years Figure 1.

Figure 1

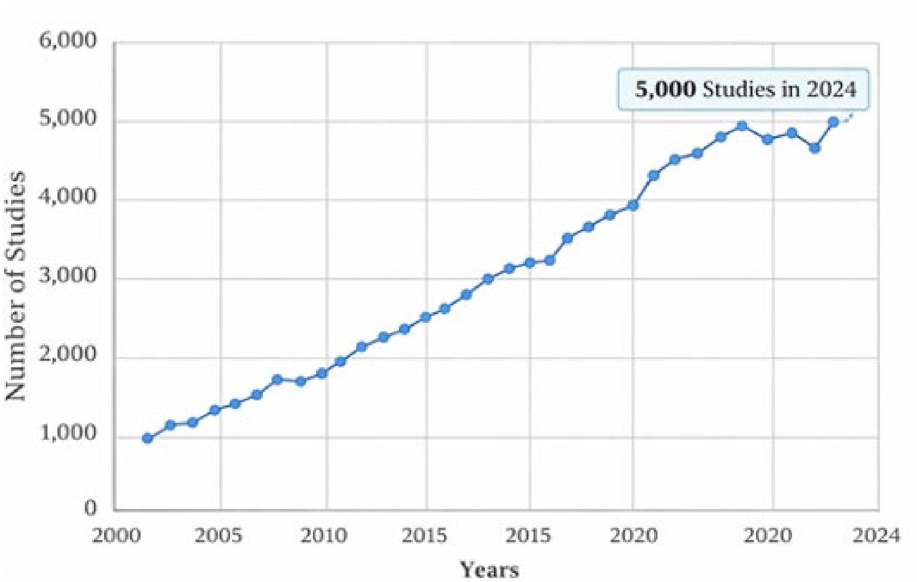

Figure 1 The Annual Number of Scientific Studies Related to Sleep Apnea from 2000

The signals obtained from polysomnography are evaluated by sleep specialists to diagnose apnea events. But doing this can be a tedious, slow process. To overcome these barriers, diagnostic methods aided by computer software have been increasingly developed in recent years Altun (2015).

TYPES OF SLEEP APNEA

Sleep apnea is generally classified into two main types--obstructive sleep apnea (OSA) and central sleep apnea (CSA). A complex form of sleep apnea (including both OSA and CSA) may also occur.

1) **Obstructive Sleep Apnea (OSA):** OSA is a condition in which breathing during sleep is interrupted because the upper respiratory tract becomes blocked or collapsed. These respiratory breaks usually occur during recurrent episodes lasting at least 10 seconds, during which blood oxygen saturation decreases by more than 4% Şener and Güner (2024). OSA is often accompanied by frequent awakenings and the formation of fragmented sleep, excessive daytime tiredness, and several symptoms. If left untreated, OSA may increase the risk of serious and potentially life-threatening complications.
2) Central Sleep Apnea (CSA) : Central Sleep Apnea (CSA) occurs when the brain fails to transmit appropriate signals to the respiratory muscles responsible for breathing. This condition may arise from various factors that impair the ability of the brainstem, which connects the brain to the spinal cord and regulates essential physiological functions such as heart rate and respiration. In central sleep apnea, breathing stops for at least 10 seconds during sleep, and unlike obstructive sleep apnea, the individual also lacks respiratory effort during these episodes Köktük and Tu (2003). This type of apnea accounts for approximately 5–10% of sleep apnea cases Evlice (2012).
3) **Mixed Sleep Apnea:** Mixed sleep apnea is a form of apnea that initially begins as central apnea and subsequently continues as obstructive apnea. In central apnea, respiratory effort ceases simultaneously with the apnea event. However, in mixed apnea, respiratory effort initially stops and then resumes before the apnea episode completely ends. These events result in a reduction in airflow of approximately 30% Yıldız (2021).

OVERVIEW OF POLYSOMNOGRAPHY (PSG) TESTS

Polysomnography (PSG), considered the gold standard in the diagnosis of sleep disorders, enables the simultaneous recording of physiological parameters occurring in the human body during sleep. Through this test, the biological processes of an individual are examined in detail, providing valuable information about sleep stages and wakefulness patterns. In this method, the sleep process is first divided into epochs, which are subsequently scored for analysis. These stages are typically identified through the analysis of electroencephalography (EEG), electrooculography (EOG), and electromyography (EMG) signals, as illustrated in Figure 2, Köktürk (2013).

Figure 2

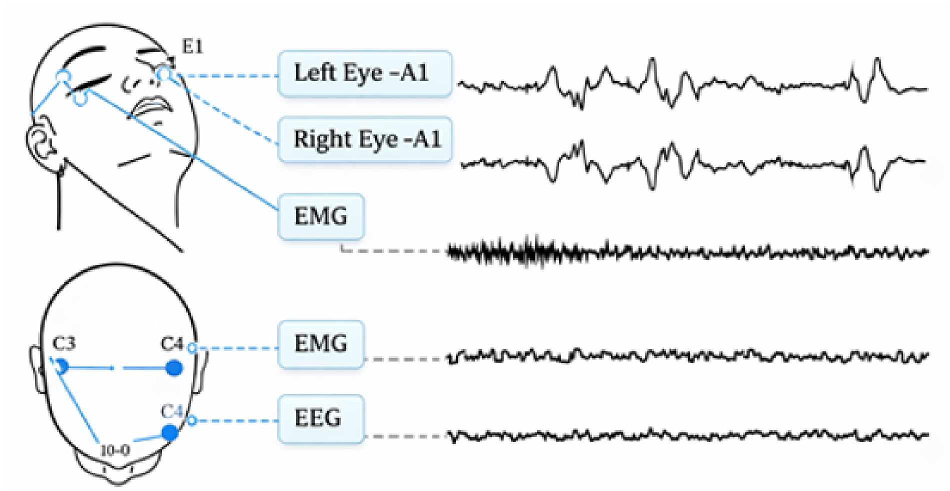

Figure 2 Signals Recorded During Polysomnography Köktürk (2013)

Polysomnography allows the detection of abnormalities in respiration and other vital physiological functions during sleep. However, an important consideration is that interpreting polysomnography results requires significant effort, as well as specialized expertise and clinical experience in sleep medicine Haghighat et al. (2025). Furthermore, the characteristics and comparison of the recordings obtained from polysomnography are presented in Table 1.

Table 1

Modality	Recording	Physiological Variable	Clinical Significance
EEG		Brain activity	Determination of sleep stages (N1, N2, N3, REM) and detection of arousals
EOG		Eye movements	Identification of REM sleep and sleep stage transitions
Chin EMG		Muscle tone	Evaluation of REM atonia and detection of bruxism
Leg EMG		Limb muscle activity	Detection of periodic limb movements during sleep (PLMS)
ECG		Cardiac rhythm and heart rate	Identification of arrhythmias and cardiac responses to respiratory events
Nasal Airflow Sensor		Cardiac rhythm and heart rate	Identification of arhythmias and cardiac responses to respiratory evensts
Nasal Airflow Sensor		Airflow	Detection and classification of apnea and hypopnea events
Thoracic & Abdominal Effort Belts		Respiratory effort	Differentiation between obstructive and central respiratory events

Table 1 Physiological Signals Recorded During Polysomnography and Their Clinical Significance

Polysomnography, as mentioned previously, is performed in hospital sleep laboratories under the supervision of trained specialists. During the polysomnography test, several electrodes and sensors (e.g., EEG, ECG, EOG, EMG) are attached to the patient in the sleep laboratory. Instead of sleeping in their own bed, patients are required to sleep in the sleep center while connected to these electrodes and monitoring devices. This situation may cause discomfort for many patients, and a considerable number of individuals experience difficulty falling asleep in such an unfamiliar environment. Since patients struggle to go back to normal sleep in a new environment, this could contribute to inaccurate and unreliable data. Moreover, PSG devices are not portable and cannot be used in home environments. Furthermore, the availability of such devices in hospitals is limited to the laboratories of specially designated sleep centers, so in most medical institutions, there are few or none. Consequently, patients spend a long time waiting for their appointments, which may seriously affect their health. In private hospitals, the cost of PSG assessments would also impose a significant financial burden on patients. These limitations have contributed to a call for alternative diagnostic methods. Recent work has therefore emphasized implementing fewer sensors, computer-embedded systems, and home-based surveillance for sleep apnea diagnosis Uçar et al. (n.d.).

ARTIFICIAL INTELLIGENCE IN SLEEP APNEA DIAGNOSIS

The practice of diagnosing and treating diseases is an interconnected process within healthcare systems. Early diagnosis and treatment not only help improve understanding of health issues and provide better outcomes for the public but also lower healthcare costs. They also enhance both healthcare efficiency and effectiveness. At this point, the role of Artificial Intelligence (AI) systems in improving healthcare services is becoming increasingly significant. AI technologies assist physicians in the diagnostic process, greatly easing it and enabling treatment to start sooner, making success more achievable Akalın and Veranyurt (2022). Since its foundation in the mid-20th century Figure 3, artificial intelligence has been highly successful and is now widely used across many fields, including medicine, defense, and economics. AI capabilities have become accessible to individual users in recent years. AI refers to computer programs that mimic human intelligence (i.e., learning, reasoning, and analyzing) Akalın and Veranyurt (2022). AI research involves multidisciplinary work including computer engineering, philosophy, cognitive science, and electronics. Artificial intelligence covers broad areas such as artificial neural networks, expert systems, fuzzy logic, and genetic algorithms Pirim (2006). AI algorithms can analyze large datasets to predict and make decisions, and these models are known as flexible computational models. These computational methods have expanded alongside recent technological advancements. Included among these are machine learning and deep learning, advanced techniques that have become key components of modern AI technologies Metlek and Kayaalp (2020).

Figure 3

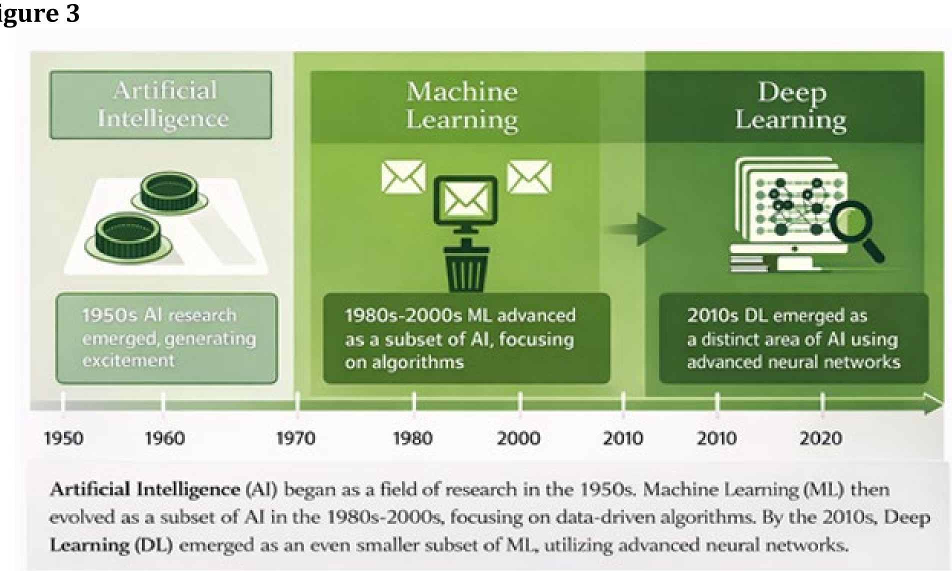

Figure 3 The Historical Development of Artificial Intelligence Metlek and Kayaalp (2020)

These approaches can even learn complex patterns directly from data in contrast to classical rule-based approaches Belk et al. (2023). AI models in healthcare have significantly improved the analysis of complex medical data and have provided substantial support in both diagnostic and treatment processes. Apart from helping doctors diagnose, artificial intelligence systems also contribute to telemedicine applications by providing treatment recommendations that physicians can evaluate more quickly. Digital interaction between healthcare providers and patients is also quicker. In otolaryngology, machine learning and deep learning predictive models have been increasingly used to improve the accuracy and sensitivity of sleep apnea diagnostic methods. These models are good for analyzing large datasets and perform quite well for screening and diagnosis Giorgi et al. (2025).

MACHINE LEARNING

A fundamental technique for achieving artificial intelligence, in which systems learn automatically from experience and adapt accordingly, making AI applications more effective and intelligent. Machine learning is a subfield of AI concerned with building systems that learn and improve as they process more data, typically at a larger scale. Artificial intelligence is the umbrella term for systems or machines that mimic human intelligence. Thus, in the scientific literature, machine learning and artificial intelligence are often combined. With rapidly advancing technology and development trends, concepts such as big data, cybersecurity, artificial intelligence, and machine learning have become increasingly widespread. As the volume of information created in modern digital environments continues to grow exponentially, analyzing and deriving meaning from these large datasets has become a major challenge. In recent years, patterns and relationships have emerged from the analysis of large datasets and predictive modeling of future outcomes. Humans also have predictive skills based on experience and prior observations. However, human decision-making is often influenced by emotional factors, and limited ability to manage vast amounts of data can hinder accuracy and efficiency. Unlike human decision-making, machine learning models can analyze such datasets rapidly and systematically, yielding more reliable and objective decision-making. The main objective of machine learning is to model human cognitive processes through computational algorithms. Several algorithms are used in this case to build predictive models from available data. In some applications, the data volume is extremely large, which may result in computational speed and processing time issues. However, these challenges can be mitigated with data classification and preprocessing methods Tosunoğlu et al. (2021). Machine learning has also become widely used in medicine, assisting physicians in diagnosing diseases. By training algorithms on patient health data, machine learning systems can identify trends and provide predictions that aid clinicians in diagnosis. These systems have been called clinical decision support systems (CDSS) Karakoyun and Hacıbeyoğlu (2014). Data plays a critical role in machine learning applications, where algorithms use data-driven insights to identify disease features. Datasets are divided broadly into labeled and unlabeled data. The former type is used during the training stage of an algorithm, while the latter is used during testing to determine model performance Bilgin (2017). The choice of the algorithm depends on the characteristics of the data. Machine learning algorithms are typically used to perform tasks such as clustering, classification, and prediction. These algorithms are generally classified into three main learning paradigms: supervised learning, unsupervised learning, or reinforcement learning. The main machine learnings are illustrated in Figure 4. Both input and output data are fed to the system under supervised learning, whereas only input data are provided under unsupervised learning. Reinforcement learning, on the other hand, aims to train a system to take the best actions by analyzing feedback signals of the input.

Figure 4

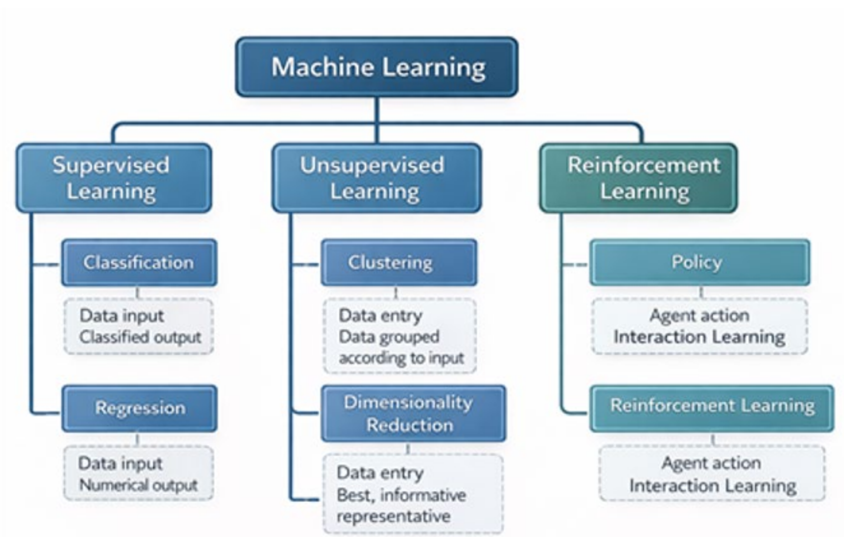

Figure 4 Conceptual Overview of Machine Learning Paradigms, Illustrating the three Primary Approaches—Supervised Learning, Unsupervised Learning, and Reinforcement Learning—and their Representative tasks Tosunoğlu et al. (2021)

Choosing the optimal algorithm is an important challenge for practitioners and researchers, as the model can only perform its best if it is compatible with the dataset. Popular machine learning algorithms include k-Nearest Neighbors (kNN), Naïve Bayes classifiers, decision trees, logistic regression, support vector machines (SVM), and artificial neural networks (ANN) Tosunoğlu et al. (2021). In supervised learning, the system is trained on labeled data, where each training example contains both an input and a corresponding output value. This process involves evaluating the trained model on a test dataset to measure its accuracy. The trained algorithm assigns predicted outputs to previously unseen test data using the patterns in the training dataset. Often, the problem is solved in the context of classification tasks, where the model tries to assign instances to predefined categories. Different classification techniques may be used depending on the problem and the dataset. Thus, the number of labeled samples needed for training may vary by application. In unsupervised learning, the model is trained on unlabeled data, unlike supervised learning. No classification can be performed directly, as the data's output labels are unknown Bilgin (2017). Unsupervised learning, by contrast, seeks to identify hidden patterns or structures in data. The most popular form of unsupervised learning is clustering, in which data samples are grouped by similarity in their features. To minimize dataset complexity, clustering techniques are often used alongside feature extraction and dimensionality reduction methods to capture relationships among variables. These analyses generate input features for supervised learning models Bilgin (2017).

WEARABLE TECHNOLOGY AND SLEEP DISORDERS

Wearable devices are components of wearable technology that monitor health, activity, security, and communication, among other functions. These devices include smartwatches, fitness bands, smart glasses, and sensor-based health-monitoring systems, all of which can aggregate and analyze physiological information Yıldız (2025).

Figure 5

Figure 5 Overview of Wearable Technology Devices by Body Placement and their Associated Applications Kılıç (2017).

A major benefit of wearable devices deployed in health care is that they can be worn throughout the day, collecting continuous, real-time data. The rapidly escalating costs of healthcare services, as well as limited access to healthcare in underdeveloped regions and shortages of healthcare personnel, have also motivated the use of wearable technologies in the healthcare sector. The data captured by these devices Figure 5 can be used to monitor an individual's health in real-time, reducing healthcare costs and inefficiencies in healthcare utilization, and is therefore valuable for patients, healthcare professionals, and society as a whole Gün and Bayzan (2024). Recently, novel wearable devices have been developed that can detect physiological signals through body contact and send the acquired information to physicians. With the advent of wearable technologies, the traditional patient-physician relationship has changed. Through wearables, a number of sensors contribute to the diagnostic procedure by enabling individuals to continuously monitor their health conditions. Such devices facilitate the identification of suitable therapeutic measures for patients and enable doctors to gather patient information remotely. Most hospitals have medical records related to patients' health conditions. Incorporation of these records, together with physiological and sensor data collected from wearable devices, could yield richer, more complete data to aid the treatment process Aydın (2019).

Figure 6

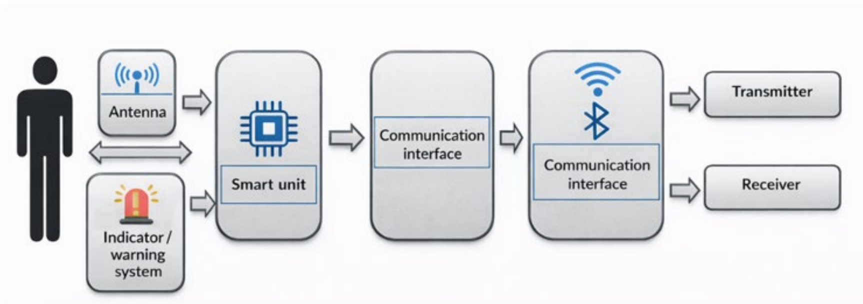

Figure 6 Wearable Healthcare Monitoring System with Data Acquisition, Processing, and Wireless Transmission Modules Özcan (2025)

Figure 6 shows the general architecture of the wearable monitoring system. Sensors turn an individual's physiological signals into electrical signals. Digital signals are sent straight to the smart processing unit, while analog signals are converted through an analog-to-digital converter to digital before being sent to the smart unit. Then the acquired data is subsequently transmitted to the evaluation center for further analysis and interpretation Özcan (2025). In recent years, the growing prevalence of the Internet of Things (IoT) has enabled both healthcare professionals and patients to benefit from improved monitoring capabilities. Wearable devices, such as cardiac monitoring bands, enable patients to track their heart activity without visiting a hospital. Physiological data derived from these devices allows physicians to perform clinical assessments without extensive diagnostic testing. As a result, patients can monitor their health status despite of location. Furthermore, wearable technologies allow patients to monitor their health conditions without requiring prolonged hospital stays or occurring often visits to healthcare facilities. This approach mahe less unnecessary healthcare costs and patient stress while decreasing the burden on healthcare systems Aydın (2019).

Figure 7

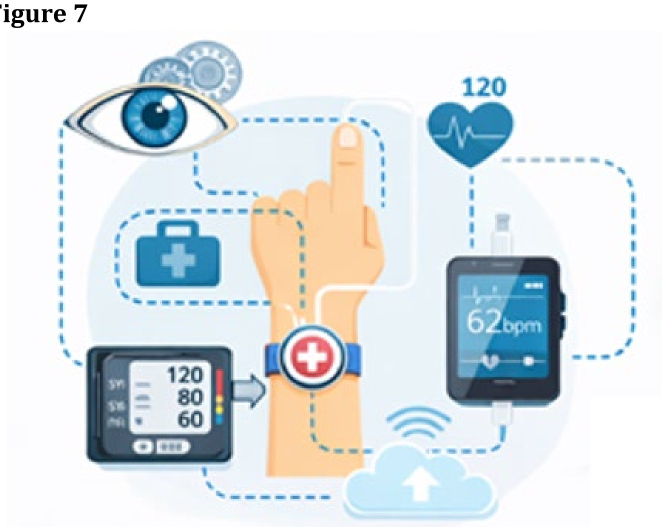

Figure 7 A Wearable Sleep-Monitoring Device for Sent to Hysiological Signals and Remote Medical Analysis Çakır et al. (2018)

Sleep disorders can lead to numerous adverse effects in daily life, as well as attention deficits, memory problems, problems in concentration, mood changes, anxiety, and many neurological complications. These complications may cause stress, cardiovascular diseases, and even diabetes, which can also be sources of this kind. Among sleep disorders, sleep apnea is thought to be one of the most serious conditions, and if left untreated, it can have life-threatening consequences. Thus, precise diagnosis of sleep disorders and adequate interpretation of psychophysiological data are indispensable for supporting physicians in reaching a correct conclusion about the patient's disease condition. Compared with the classical diagnostic approach, wearables have been increasingly adopted for assessing sleep processes in recent years, such as WatchPAT in Figure 7 Serçe and Ovayolu (2024).

SIGNAL PROCESSING METHODS USED IN SLEEP APNEA DIAGNOSIS

Examining studies on sleep apnea, it is evident that the research process comprises three major parts. The first stage involves obtaining biosignals directly from PSG or portable monitoring devices and applying filtering to remove noise. In the second stage, the obtained signals are preprocessed, and relevant features are extracted. The extracted features are analysed in the last step by software tools, producing diagnostic results. Several feature extraction techniques have been developed in the literature. Some of the most commonly used techniques include power spectral density (PSD), wavelet transform, and time–frequency analysis Uçar et al. (n.d.). Extracting meaningful features from acquired signals is one of the most critical steps in signal processing. There are many techniquesin the literature for analyzing features in both the time and frequency domains Balcı et al. (2021). A signal can be defined as a numerical function that represents physical changes over time; mathematically, a signal can be expressed as a function g(t) of t Öner et al. (2017). In time-series analysis, spectral analysis methods such as the Fourier transform and the the wavelet transform are frequently used to study signal characteristics Abrak and Yerci (2012).

1) **Fourier Transform:** The Fourier Transform is one of the most widely used techniques in signal processing, transforming signals from the time domain into the frequency domain Ersöz and Özşen (2011). It indicates both the amplitude and phase of a signal. Because of the Fourier transform's analytical power, it has become important in many scientific fields, such as engineering, medicine, and chemistry Bracewell (1989). A Fourier Transform is one of the most important methods for analyzing signals, independent of translation and scaling. The Fourier analysis of the signal data yields frequency-domain representations, enabling the identification and analysis of its frequency components. Typically, in various studies, Fourier Transform-based frequency spectra are employed to analyze information extracted from signals Hanbay (2021).

On the other hand, stationary signals usually perform better with Fourier analysis. Fourier-based approaches may not be sufficient for non-stationary signals, such as EEG signals with transient spikes and complex waveform patterns Ersöz and Özşen (2011). In the latter case, wavelet analysis is an ideal alternative, as it permits the study of localized signal characteristics in both the time and frequency domains Walker (1997).

2) **Wavelet Analysis:** The wavelet transform is the standard method for time–frequency signal analysis. One reason for the popularity of this approach is that the window size can vary with the analysis scale. At a broader window scale, the mother wavelet captures low-frequency components of the signal. In contrast, lowering the window scale narrows the window, making its higher-frequency components detectable. Thus, both the low-frequency and high-frequency characteristics of the signal are available for simultaneous analysis Walker (1997). Wavelets are finite-time oscillatory functions with a characteristic start and ending approaching zero. Due to their short duration and variable shape, wavelets are very useful to detect transient changes in signals. The two key approaches in wavelet analysis are widely adopted. One such method is the Discrete Wavelet Transform (DWT), which is specifically capable of detecting sharp transformations in the signals. The second application requires continuous wavelet analysis to obtain a time–frequency description of the signal and detect changes in frequency over time Sak and Beyen (2019).

3) **Power Spectral Density:** The Power Spectral Density (PSD) is a signal analysis technique that characterizes the distribution of signal power across different frequency components. This approach defines the power of a signal as a function of frequency and facilitates the analysis of the distribution of the signal energy in varying frequency ranges. In fact, PSD analysis is a technique that can tell us whether a particular frequency component is present in a signal and calculate the power associated with those frequencies İkizler and Ekim (2025).

SELECTED STUDIES ON SLEEP APNEA

Sleep apnea syndrome may lead to serious health complications if left untreated that quality of life. For an accurate and effective diagnosis of this illness, several methods and technological approaches have been proposed in the literature. Generally, these approaches focus on facilitating the diagnostic process and providing decision-support tools for physicians.

In a study, Sharma et al. (2022) developed an automated apnea detection method to determine oxygen saturation and pulse rate signals using a pulse oximeter. In that study, some sleep-related occurrences were labeled using the Sleep Heart Health Study dataset, which included a variety of patient cohorts (n = 8068, age ≥ 40 years). In this study, which used two independent test groups and 30-second periods, a deep learning model was trained to detect sleep apnea.

The proposed algorithm demonstrated high performance in apnea detection, achieving an area under the receiver operating characteristic curve (AUC-ROC) of 90.4% and an area under the precision–recall curve of 58.9%. The model achieved the highest sensitivity for obstructive apnea detection at 93.4%, followed by 90.5% for central apnea detection Sharma et al. (2022).

Pépin et al. (2009) conducted a study involving 34 patients suspected of having sleep apnea. In their research, polysomnography was performed simultaneously with nasal pressure (NP) and Holter ECG recordings. A healthcare specialist who was blinded to the polysomnography results analyzed the Holter ECG and nasal pressure recordings. The apnea–hypopnea index (AHI) obtained from polysomnography was compared with the AHI values derived from the visual and automated analysis of Holter ECG and nasal pressure signals. Using a randomly selected group of 10 participants as the development set, the optimal threshold value for detecting sleep apnea (AHI > 20 events/hour in PSG) was determined to be 35 events/hour using receiver operating characteristic (ROC) analysis. The prospective evaluation of this threshold was then performed on 19 participants in the test set. For visually scored Holter ECG plus NP recordings, the negative predictive value (NPV) for sleep apnea was 80%, while the positive predictive value (PPV) reached 100%. The area under the ROC curve was found to be 0.97. For automated analysis, the NPV was 86%, the PPV was 100%, and the area under the ROC curve was 0.85. The authors concluded that nasal pressure recordings obtained via a Holter system could serve as an effective screening tool for sleep-related breathing disorders in routine cardiology practice Pépin et al. (2009).

Li et al. (2017) investigated the reliability of a pulse oximeter system capable of automated analysis based on photoplethysmography (PPG) signals for the diagnosis of sleep apnea. The authors compared measurements obtained from PPG signals with those obtained through polysomnography. In their study, PPG monitoring was performed simultaneously with overnight polysomnography in a sleep laboratory. A total of 49 patients with suspected sleep apnea (38 males; mean age: 43.5 ± 16.9 years; BMI: 26.9 ± 0.5 kg/m^2) were included in the study. Automated analysis was performed using only PPG and oximeter signals. The respiratory event index derived from PPG showed a strong correlation with the apnea–hypopnea index obtained from PSG ($r = 0.935$, $P < 0.001$). In addition, significant correlations were observed between PPG- and PSG-derived total sleep time and oxygen desaturation index values ($r = 0.418$, $P = 0.003$; $r = 0.933$, $P < 0.001$, respectively). Bland–Altman analysis demonstrated good agreement between PPG and PSG measurements. The authors concluded that pulse oximeter systems based on PPG recordings could provide acceptable results for the diagnosis and screening of moderate and severe OSA patients Li et al. (2017).

Nazli (2021) analyzed electrocardiography (ECG) signals by dividing them into one-minute segments and extracting heart rate variability (HRV) signals using the information obtained from R-peaks. Time-domain and frequency-domain features were derived from HRV signals, and apnea classification was performed using five different machine learning algorithms. The highest classification accuracy (85.26%) was achieved using the Random Forest algorithm. The highest sensitivity (78.08%) was obtained using the k-Nearest Neighbor (kNN) algorithm, while the highest specificity (91.4%) was achieved with the Random Forest classifier Nazli (2021).

Babur et al. (2018) proposed an apnea prediction method using signals recorded by polysomnography during sleep. In their study, ECG signals obtained from sleep laboratory recordings were processed using MATLAB to predict apnea events. The analysis was based on the RR interval variations of ECG signals. Various parameters derived from these RR intervals were used in the analysis. As a result, by determining the power spectral density of ECG signals, the authors achieved an apnea detection accuracy of 88.57% for obstructive apnea and hypopnea events Babur et al. (2018).

Karamustafaoğlu et al. (2014) used electrocardiography (ECG), electroencephalography (EEG), and electromyography (EMG) signals obtained from sleep laboratory recordings. The aim of the study was to predict apnea events by applying different signal processing techniques to these signals. Signals recorded during obstructive apnea, hypopnea, and normal breathing periods were processed in the MATLAB environment. The results obtained from the proposed methods were compared with diagnoses made by healthcare professionals to determine accuracy rates. The authors applied Yule–Walker, Welch, and Periodogram methods to estimate the power spectral density of the signals. The results indicated that determining the power density of ECG signals provided an apnea detection accuracy of 88.3% in obstructive apnea and hypopnea cases Karamustafaoğlu et al. (2014).

Yıldız et al. (2017) investigated whether apnea events could be automatically detected from heart sounds by training classifiers using time-domain and frequency-domain features characterizing changes in heart sounds during apnea events. Polysomnography recordings were obtained from 17 individuals, and heart sounds were recorded simultaneously. Machine learning classification methods, including kNN and SVM, were applied to heart sound features. The results indicated that the kNN classifier reached 48% accuracy and 100% specificity, while the SVM classifier reacded 82% accuracy and 42% specificity. The authors concluded that apnea detection based only on heart sound signals was not sufficiently reliable Yıldız et al. (2017).

In a separate study, Yıldız et al. (2017) developed an automatic recognition system to detect apnea from single-channel ECG recordings. The 8-hour ECG recordings in the study comprise 20 healthy individuals and 40 patients with apnea. A wavelet-based algorithm was used to detect changes in RR intervals, which represent heart rate variability. SVM and ANN algorithms were used to classify apnea and non-apnea recordings. Here, the accuracy of the SVM classifier was 98.3%, and the ANN classifier achieved 96.7% Yıldız (2017).

Table 2 shows a summary of some studies focusing on sleep apnea detection using physiological signals and machine learning techniques is presented.

Table 2

Table 2 Summary of Some Studies on Sleep Apnea.

Study	Data Type / Signals	Method / Algorithm	Participants	Key Results
Pulse Oximetry (SpO_2 and Pulse Rate)	SpO_2 and Pulse Rate	Deep Learning Model	8068 Participants	AUC-ROC: 90.4%, Sensitivity: 93.4% OSA / 90.5% CSA
Holter ECG and Nasal Pressure	ROC-Threshold Analysis	ROC-Threshold Analysis	34 Patients	NPV: 80–86%, PPV: 100%, AUC: 0.97
PPG and Pulse Oximetry	Automated Signal Analysis	Automated Signal Analysis	49 Patients	Correlation with PSG AHI, r = 0.935
ECG-Derived HRV	Random Forest, kNN	1-Minute Segments	1-Minute Segments	Accuracy: 85.26%, Sensitivity: 78.08%, Specificity: 91.4%
ECG (RR Intervals)	Power Spectral Analysis	Sleep Lab Data	Sleep Lab Data	Accuracy: 88.57%
ECG, EEG, EMG	Yule-Walker, Welch PSD	Sleep Lab Datasets	Sleep Lab Datasets	Accuracy: 88.3%
Heart Sound Recordings	kNN and SVM Classifiers	—	17 Subjects	kNN: 48%, SVM: 82%
Single-Channel ECG	SVM and ANN Classifiers	8-Hour Recordings	8-Hour Recordings	SVM: 98.3%, ANN: 96.7%

DISCUSSION AND CONCLUSION

The prospects of artificial intelligence, machine learning, and wearable technologies for diagnosing sleep apnea have been discussed, highlighting the essential role of engineering disciplines in these areas. The results suggest that the diagnosis of advanced sleep disorders such as sleep apnea cannot be made solely through medical methods but also requires multidisciplinary engineering. In this regard, biomedical engineering leads to the development of sensors for physiological signal detection and state monitoring; electrical and electronics engineering supports data acquisition, transmission, and hardware system design; and software engineering aids AI–based data analysis and decision support systems. The cooperation between these engineering disciplines accelerates diagnostic methods, making them faster, more accessible, and more efficient while surmounting many constraints of conventional diagnostics. Additionally, the integration of wearable and intelligent data analysis methodologies has established the ability of continuous evaluation and early diagnosis of sleep disorders. These technological advances may minimize reliance on conventional lab-based diagnostic systems and realize a more individualized approach in patient-centered healthcare. Ultimately, different engineering fields involved in sleep apnea diagnosis not only improve the results of the existing diagnosis, the work of these engineering fields could also push future advancements of medical electronics as well as healthcare technologies. For these innovations to progress sustainably, interdisciplinary collaboration is essential, along with engineering solutions that address clinical needs while prioritizing patient comfort and accessibility.

ACKNOWLEDGMENTS

None.

REFERENCES

Abrak, R. A., and Yerci, M. (2012). En Küçük Karelerle Spektral Analiz ve Fourier Tekniğinin Karşılaştırılması. Selcuk University Journal of Engineering Sciences, 11(1), 32–47.

Akalın, B., and Veranyurt, Ü. (2022). Sağlık 4.0 ve Sağlıkta Yapay Zekâ. Sağlık Profesyonelleri Araştırma Dergisi, 4(1), 57–64.

Altun, S. (2015). Derin Öğrenme ve Makine Öğrenmesi Yöntemleriyle Polisomnografi Sinyallerinden Uyku Evrelerinin Sınıflandırılması. Karadeniz Fen Bilimleri Dergisi, 13(2), 583–600. https://doi.org/10.31466/kfbd.1246482

Aydın, N. (2019). Giyilebilir Sağlık Teknolojisinin Geleceği. In XI. International Balkan and Near Eastern Social Sciences Congress Series.

Babur, S., Bektaş, B., and Turhal, U. (2018). EKG Kayıtlarından Uyku Apnesi Hastalığının Destek Vektör Makineleri Yöntemi Kullanılarak Tespiti.

Balcı, M., Gölcük, A., Küççüktürk, S., Tasdemır, S., Vatansev, H., and Vatansev, H. (2021). Wavelet Dalgacık Dönüşümü ile Tıkayıcı Uyku Apnesi Tahmini ve Epok Sürelerinin Etkisi. Avrupa Bilim ve Teknoloji Dergisi, 26, 276–283. https://doi.org/10.31590/ejosat.954003

Belk, R. W., Belanche, D., and Flavián, C. (2023). Key Concepts in Artificial Intelligence and Technologies 4.0 in Services. Service Business, 17(1), 1–9. https://doi.org/10.1007/s11628-023-00528-w

Bilgin, M. (2017). Gerçek Veri Setlerinde Klasik Makine Öğrenmesi Yöntemlerinin Performans Analizi. Breast, 2(9), 683.

Bracewell, R. N. (1989). The Fourier Transform. Scientific American, 260(6), 86–95. https://doi.org/10.1038/scientificamerican0689-86

Çakır, F. S., Aytekin, A., and Tüminçin, F. (2018). Nesnelerin İnterneti ve Giyilebilir Teknolojiler. Sosyal Araştırmalar ve Davranış Bilimleri Dergisi, 4(5), 84–95.

Ersöz, A., and Özşen, S. (2011). Uyku EEG Sinyalinin Yapay Sinir Ağ Modeli ile Sınıflandırılması.

Evlice, A. T. (2012). Obstrüktif Uyku Apne Sendromu. Arşiv Kaynak Tarama Dergisi, 21(2), 134–150.

Giorgi, L., Nardelli, D., Moffa, A., Iafrati, F., Di Giovanni, S., Olszewska, E., ... and Casale, M. (2025, January). Advancements in Obstructive Sleep Apnea Diagnosis and Screening Through Artificial Intelligence: A Systematic Review. In Healthcare (Vol. 13, No. 2, 181). MDPI. https://doi.org/10.3390/healthcare13020181

Gün, A., and Bayzan, Ş. (2024). Dijitalleşmenin Teknolojik Boyutu.

Haghighat, S., Joghatayi, M., Issa, J., Azimian, S., Brinz, J., Ashkan, A., ... and Sangalli, L. (2025). Diagnostic Accuracy of Artificial Intelligence for Obstructive Sleep Apnea Detection: A Systematic Review. BMC Medical Informatics and Decision Making, 25(1), 278. https://doi.org/10.1186/s12911-025-03129-x

Hanbay, K. (2021). Görüntü Bölütleme İçin Fourier Dönüşümü, Hessian Matris ve Özdeğerler Kullanılarak Yeni Bir Aktif Kontur Modeli. Türk Doğa ve Fen Dergisi, 10(2), 242–247. https://doi.org/10.46810/tdfd.977786

İkizler, N., and Ekim, G. (2025). Epileptik Nöbet Tespiti İçin Yüksek Çözünürlüklü Güç Spektral Yoğunluk Yaklaşımları. Politeknik Dergisi, 1–1. https://doi.org/10.2339/politeknik.1605362

Karakoyun, M., and Hacıbeyoğlu, M. (2014). Biyomedikal Veri Kümeleri İle Makine Öğrenmesi Sınıflandırma Algoritmalarının İstatistiksel Olarak Karşılaştırılması. Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi, 16(48), 30–42.

Karamustafaoğlu, G., Akan, A., and Saatçi, E. (2014). Polisomnografi Sinyallerinin İşlenmesi ile Uyku Apnesinin Otomatik Teşhisi / Polisomnografi Sinyallerinin İşlenmesiyle Uyku Apnesinin Otomatik Tespiti.

Kılıç, H. Ö. (2017). Giyilebilir Teknoloji Ürünleri Pazarı ve Kullanım Alanları. Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 9(4), 99–112.

Koçak, O., Beytar, F., Fırat, H., Telatar, Z., and Eroğul, O. (2016, October). Comparison of Non-Parametric PSD Detection Methods in the Anaylsis of EEG Signals in Sleep Apnea. In 2016 Medical Technologies National Congress (TIPTEKNO) (1–4). IEEE. https://doi.org/10.1109/TIPTEKNO.2016.7863133

Köktük, O., and Tu, Ç. (2003). Santral Uyku Apne Sendromu. Tuber ve Toraks Derg, 51(3), 349–360.

Köktürk, O. (2013). Uyku Kayıtlarının Skorlanması. Solunum, 15(2), 14–29. https://doi.org/10.5152/solunum.2013.027

Li, Y., Gao, H., and Ma, Y. (2017). Evaluation of Pulse Oximeter Derived Photoplethysmographic Signals for Obstructive Sleep Apnea Diagnosis. Medicine, 96(18), e6755. https://doi.org/10.1097/MD.0000000000006755

Mendonca, F., Mostafa, S. S., Ravelo-Garcia, A. G., Morgado-Dias, F., and Penzel, T. (2018). Obstrüktif Uyku Apnesi Tespit Yaklaşımlarının Bir İncelemesi. IEEE Journal of Biomedical and Health Informatics, 23(2), 825–837. https://doi.org/10.1109/JBHI.2018.2823265

Metlek, S., and Kayaalp, K. (2020). Makine Öğrenmesinde, Teoriden Örnek MATLAB Uygulamalarına Kadar Destek Vektör Makineleri (100). İksad Yayınevi.

Nazli, B. (2021, June). Evaluation of Different Machine Learning Algorithms for Classification of Sleep Apnea. In 2021 29th Signal Processing and Communications Applications Conference (SIU) (1–4). IEEE. https://doi.org/10.1109/SIU53274.2021.9477705

Öner, İ. V., Yeşilyurt, M. K., and Yılmaz, E. Ç. (2017). Wavelet Analiz Tekniği ve Uygulama Alanları. Ordu Üniversitesi Bilim ve Teknoloji Dergisi, 7(1), 42–56.

Özcan, F. (2025). Giyilebilir Teknolojiler ve Hasta İzleme. In Sağlık Bilimlerinde Tüm Yönleriyle Hemşirelik (39).

Pépin, J. L., Defaye, P., Vincent, E., Christophle-Boulard, S., Tamisier, R., and Lévy, P. (2009). Sleep Apnea Diagnosis Using an ECG Holter Device Including a Nasal Pressure (NP) Recording: Validation of Visual and Automatic Analysis of Nasal Pressure Versus Full Polysomnography. Sleep Medicine, 10(6), 651–656. https://doi.org/10.1016/j.sleep.2008.07.002

Pirim, A. G. H. (2006). Yapay Zeka. Yaşar Üniversitesi E-Dergisi, 1(1), 81–93.

Sak, Ö., and Beyen, K. (2019). Yapıların Zaman-Frekans Ortamında Dalgacık Dönüşümü Metoduyla Hasar Analizleri. Teknik Dergi, 30(1), 8835–8860. https://doi.org/10.18400/tekderg.300366

Şener, E., and Güner, P. (2024). Obstrüktif Uyku Apne Sendromu: Diş Hekimliği Yönünden Risk Faktörlerinin Değerlendirilmesi. Journal of Turkish Sleep Medicine, 11(2), 69–77. https://doi.org/10.4274/jtsm.galenos.2023.49091

Serçe, S., and Ovayolu, Ö. (2024). Obstrüktif Uyku Apne Sendromunda Giyilebilir Teknolojinin Yorgunluk ve Gündüz Uykululuğuna Etkisi: Literatür İncelemesi. Sağlık Bilimlerinde Değer, 14(1), 163–167. https://doi.org/10.33631/sabd.1271348

Sharma, P., Jalali, A., Majmudar, M., Rajput, K. S., and Selvaraj, N. (2022, July). Deep-Learning Based Sleep Apnea Detection Using SpO2 and Pulse Rate. In 2022 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2611–2614). IEEE. https://doi.org/10.1109/EMBC48229.2022.9871295

Toraman, S., and Türkoğlu, İ. (2019). Dalgacık Dönüşümü ve Makine Öğrenme Teknikleri Kullanılarak FTIR Sinyallerinden Kolon Kanseri Hastaları ve Sağlıklı Kişileri Sınıflandırmak İçin Yeni Bir Yöntem. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi, 35(2), 933–942. https://doi.org/10.17341/gazimmfd.564803

Tosunoğlu, E., et al. (2021). Eğitimde Makine Öğrenmesi: Araştırmalardaki Güncel Eğilimler Üzerine İnceleme. Ahmet Keleşoğlu Eğitim Fakültesi Dergisi, 3(2), 178–199.

Uçar, M. K., et al. (n.d.). Uyku EEG ve EOG Sinyallerinin Sınıflandırılmasında Zaman ve Frekans Domeni Özelliklerinin Etkisi / Effect of Time and Frequency Domain Features in Sleep EEG and EOG Signals Classification. Delta, 1, 0.5–2.5.

Walker, J. S. (1997). Fourier Analizi ve Dalgacık Analizi. AMS Bildirileri, 44(6), 658–670.

Yıldız, A. (2017). Tek Kanallı EKG Kayıtları Analizinden Uyku Apne Tespiti. Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi, 8(1), 111–122.

Yıldız, M. (2021). Uyku Apnesi Tespitinde Yenilikler. Natural and Applied Sciences Journal, 3(Special Issue: Full Papers of 2nd International Congress of Updates in Biomedical Engineering), 32–39.

Yıldız, M. E. (2025). Giyilebilir Akıllı Cihazların Mobil Sağlık (mHealth) Ekosistemindeki Yükselişi. In Spor Bilimlerinde Güncel Kavramlar ve Yenilikçi Araştırmalar (34).

Yıldız, M., Tabak, Z., and Yetkin, S. (2017). Kalp Seslerinden Uyku Apnesi Tespit Edilebilir mi? Journal of Turkish Sleep Medicine, 4(1). https://doi.org/10.4274/jtsm.07108