Science Archives (ISSN:2582-6697)

Journal homepage: www.sciencearchives.org

DOI: https://doi.org/10.47587/SA.2026.7206

Review Article

AI-Powered Biomedical Signal Processing Applications in Diagnosis and Remote Patient Monitoring

Micheal Abimbola Oladosu[1]✉, Moses Adondua Abah[2], Loveth Agbo[3] and Olaide Ayokunmi Oladosu[4]

[1]Department of Chemical Sciences, Faculty of Science, Anchor University Lagos, Ayobo-Ipaja, Lagos, Nigeria.
[2]Department of Biochemistry, Faculty of Pure and Applied Sciences, Federal University of Wukari, Wukari, Taraba State, Nigeria.
3Department of Pharmacy, Faculty of Pharmaceutical Sciences, University of Porth Harcourt, River State, Nigeria

[4]Department of Computer Science, Faculty of Science and Technology, Babcock University, Ilishan, Nigeria.

(✉) Corresponding Author

Received: April 26, 2026/ Revised: May 28, 2026/Accepted: June 3, 2026

Abstract

Air-powered biomedical technologies represent an emerging paradigm in healthcare monitoring, combining pneumatic sensing mechanisms with advanced signal processing techniques for non-invasive diagnostic applications. This review examines the integration of air-powered sensors, including pneumatic tactile sensors, respiratory monitoring devices, and soft robotic systems, with biomedical signal processing algorithms for real-time patient monitoring and disease diagnosis. The synthesis of pneumatic sensing technology with machine learning algorithms, edge computing, and Internet of Things (IoT) infrastructures has enabled continuous, wireless monitoring of vital physiological parameters, including respiratory patterns, cardiovascular signals, and biomechanical activities. Key applications discussed include respiratory disease monitoring, cardiac signal analysis, tumour detection through robotic palpation, and remote patient monitoring systems. Signal processing methodologies encompassing wavelet transforms, entropy-based analysis, and deep learning architectures are critically evaluated for their efficacy in extracting clinically relevant features from air-powered sensor data. Current challenges, including sensor drift, environmental interference, data privacy, and standardisation, are addressed alongside emerging solutions through adaptive filtering and federated learning frameworks. This review underscores the transformative potential of air-powered biomedical signal processing in advancing personalised, accessible, and efficient healthcare delivery systems.

Keywords: Air-powered sensors, pneumatic sensing, biomedical signal processing, remote patient monitoring, respiratory monitoring, machine learning, soft robotics, wearable sensors

1. Introduction

The healthcare sector is witnessing a paradigm shift toward personalised, continuous, and remote patient monitoring systems driven by the convergence of sensor technologies, advanced signal processing, and wireless communication infrastructures. Traditional diagnostic approaches relying on episodic clinical visits and invasive procedures are progressively being complemented by wearable and non-invasive monitoring technologies that enable real-time assessment of physiological parameters in naturalistic settings.[1,2] Among emerging sensing modalities, air-powered or pneumatic sensors have garnered significant attention due to their unique advantages, including electrical safety, mechanical compliance, temperature immunity, and optical transparency, which collectively enhance their suitability for biomedical applications. [3]

Air-powered biomedical sensors operate on pneumatic principles, utilising air pressure variations, flow dynamics, and mechanical deformations to transduce physiological signals into quantifiable measurements.[4] These sensors find applications across diverse clinical domains, including respiratory monitoring, where they detect airflow, temperature, and humidity changes in exhaled breath; cardiovascular assessment through mechanically-induced pressure variations; and robotic surgery, where transparent pneumatic tactile sensors enable simultaneous mechanical sensing and visual feedback. [5,6] The integration of pneumatic sensing mechanisms with sophisticated biomedical signal processing algorithms has facilitated the extraction of clinically actionable information from complex, multimodal physiological data streams.[7]

Biomedical signal processing encompasses a suite of computational techniques designed to enhance signal quality, extract relevant features, and enable pattern recognition from physiological measurements such as electrocardiograms (ECG), electroencephalograms (EEG), electromyograms (EMG), and respiratory signals.(8) Contemporary signal processing methodologies leverage wavelet transforms for multi-resolution analysis, entropy-based metrics for complexity quantification, and machine learning algorithms for automated classification and prediction.[9] When applied to air-powered sensor data, these techniques enable robust respiratory rate estimation, breathing pattern classification, disease biomarker detection, and anomaly identification critical for timely clinical intervention.[10]

The synergistic integration of air-powered sensors with Internet of Things (IoT) architectures and edge computing platforms has revolutionised remote patient monitoring capabilities.[11] These connected health ecosystems facilitate continuous data acquisition, real-time signal processing at the network edge to minimise latency and bandwidth consumption, secure wireless transmission, and cloud-based analytics for long-term trend analysis and predictive modelling.[12] Such systems are particularly valuable for managing chronic respiratory conditions, including asthma, chronic obstructive pulmonary disease (COPD), and sleep apnea, where continuous monitoring enables early detection of exacerbations and optimization of therapeutic interventions.[13]

This review provides a comprehensive analysis of air-powered biomedical signal processing applications in diagnosis and remote patient monitoring. The manuscript is structured to first examine the fundamental principles and types of air-powered sensors utilized in healthcare contexts, followed by detailed exploration of signal processing methodologies tailored for pneumatic sensor data. Subsequently, we discuss clinical applications across respiratory monitoring, cardiovascular assessment, and surgical robotics, before addressing integration strategies with IoT platforms and machine learning frameworks. The review concludes with critical evaluation of current challenges and future research directions in this rapidly evolving field.

2. Air-Powered Sensor Technologies in Biomedical Applications

2.1 Pneumatic Tactile Sensors for Robotic Surgery

Pneumatic tactile sensors represent a sophisticated class of air-powered devices that combine mechanical sensing capabilities with optical transparency, enabling simultaneous tissue palpation and visual examination during minimally invasive procedures. [3] These sensors typically employ polydimethylsiloxane (PDMS) chambers filled with air, where mechanical deformation induces pressure changes that are transduced into electrical signals via integrated pressure transducers. The transparent nature of PDMS allows optical pathways for visualization while maintaining high sensitivity to mechanical stimuli. [14]

Recent innovations in transparent pneumatic tactile sensors have demonstrated exceptional performance in tumor detection through robotic palpation. [3] These miniaturised sensors, with diameters as small as 10 mm, exhibit sensitivity of 1.25 mbar and negligible hysteresis, enabling differentiation of tissue stiffness ranging from 0 to 2.5 MPa. [14]

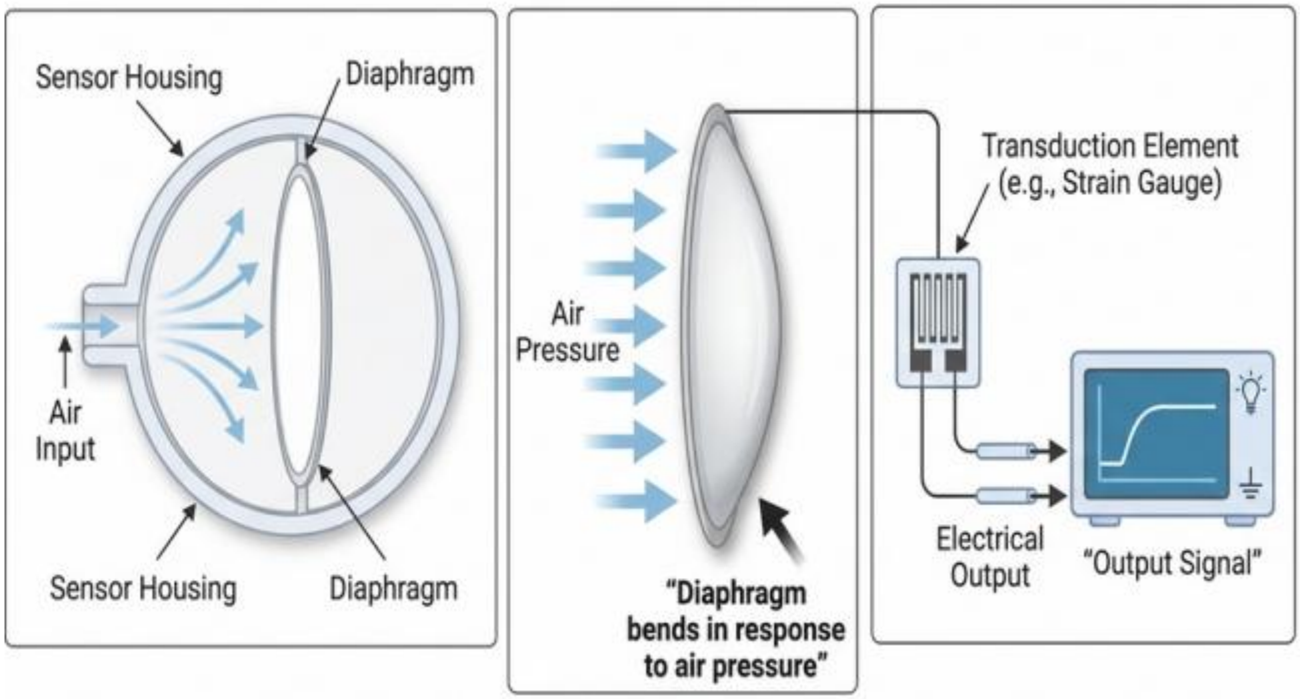

FIGURE 1: Schematic Illustration of Air-Powered Sensor Operating Principles
Source: Authors illustrations adapted from [3, 14, 17]

Such capabilities are particularly valuable for early cancer detection, where solid tumors typically exhibit altered mechanical properties compared to surrounding healthy tissues. The integration of these sensors with soft robotic manipulators driven by hydraulic artificial muscles creates all-in-one surgical systems capable of simultaneous diagnosis and therapy. [3]

The pneumatic sensing mechanism offers distinct advantages over electrical tactile sensors, including elimination of electrical wiring at the end-effector, enhanced patient safety through intrinsic electrical isolation, and immunity to electromagnetic interference prevalent in operating room environments.[14] However, challenges remain regarding temperature compensation, as pneumatic systems can be sensitive to ambient temperature variations that may introduce measurement drift during prolonged surgical procedures.

2.2 Respiratory Monitoring Sensors

Air-powered respiratory sensors constitute the most extensively developed category of pneumatic biomedical devices, encompassing diverse sensing modalities for capturing breathing parameters.[15] These sensors detect various aspects of respiration including airflow rate, respiratory volume, breathing frequency, breath temperature, humidity, and volatile organic compounds (VOCs) in exhaled breath.[16]

Airflow and Pressure Sensors:

Pressure-based pneumatic sensors monitor chest wall expansion and airflow through direct measurement of pressure variations.[17] These sensors can be integrated into chest belts, smart textiles, or face masks to capture respiratory mechanics during rest and physical activity. Soft pressure sensors utilizing gradient spherical crown microstructures demonstrate high sensitivity to weak dynamic pressure signals even under substantial static loading, enabling accurate capture of subtle respiratory patterns when mounted on seats or beds.[18]

Thermal Pneumatic Sensors:

Pyroelectric and thermochromic sensors detect respiratory cycles through temperature changes in exhaled breath compared to ambient air.[19] Wearable pyroelectric sensors based on zinc oxide (ZnO) or polyvinylidene fluoride (PVDF) nanofibers can be integrated into face masks for continuous respiratory monitoring with self-powered operation.[20] These thermal sensors offer advantages in terms of rapid response times and minimal power consumption.

Humidity-Sensitive Sensors

Pneumatic humidity sensors exploit the water vapor content difference between inhaled and exhaled air to detect respiratory events.[21] These sensors typically employ hygroscopic materials whose electrical or optical properties change in response to moisture variations, providing complementary information to airflow and temperature measurements.

2.3 Wearable Pneumatic Sensors for Cardiovascular Monitoring

Pneumatic sensing principles have been adapted for cardiovascular signal acquisition through measurement of mechanical vibrations and pressure variations associated with cardiac activity.[22] Ballistocardiogram (BCG) sensors utilizing flexible pressure-sensitive materials can capture cardiac-induced body movements when integrated into chairs, beds, or wearable devices.[23] These sensors offer unobtrusive monitoring capabilities suitable for continuous health tracking without direct skin contact.

Flexible pressure sensors featuring gradient microstructures demonstrate exceptional sensitivity to weak dynamic pressures, enabling BCG and respiratory signal acquisition from seated individuals. [18] The wireless integration of these sensors with edge computing systems facilitates real-time analysis of heart rate variability and breathing patterns, supporting applications in stress assessment, sleep quality monitoring, and early detection of cardiovascular abnormalities. Table 1 highlights the different types of Air

Table 1. Types of Air-Powered Sensors for Biomedical Applications

Sensor Type	Sensing Mechanism	Key Applications	Advantages	Limitations	References
Pneumatic Tactile Sensors	Pressure changes in air-filled chambers due to mechanical deformation	Robotic surgery, tumor detection, tissue palpation	Optical transparency, electrical isolation, high sensitivity (1.25 mbar)	Temperature sensitivity, complex fabrication	(3,14)
Thermal Respiratory Sensors	Temperature difference between exhaled and ambient air	Respiratory rate monitoring, breathing pattern analysis	Fast response, self-powered capability, low power consumption	Environmental temperature effects, limited specificity	(19,20)
Pressure-Based Respiratory Sensors	Chest wall expansion detection, airflow pressure changes	COPD monitoring, asthma management, sleep apnea detection	Direct measurement, textile integration, long-term wearability	Motion artifacts, sensor placement sensitivity	(17,45)

Source: Authors illustrations adapted from [3, 14, 17, 18, 19, 20, 21, 23, 45]

2. Biomedical Signal Processing Methodologies

3.1 Signal Preprocessing and Artifact Removal

Biomedical signals acquired from air-powered sensors are inherently susceptible to various artifacts including motion-induced noise, environmental interference, sensor drift, and physiological confounds.[24] Robust preprocessing is essential to enhance signal quality prior to feature extraction and classification. Wavelet-based denoising has emerged as a particularly effective approach for biomedical signals due to its ability to decompose signals into multiple frequency bands and selectively attenuate noise components while preserving signal morphology.[25] Digital filtering techniques including bandpass filters, notch filters for power line interference, and adaptive filters for motion artifact reduction are routinely employed.[26]

3.2 Feature Extraction and Selection

Extraction of discriminative features from pre-processed signals constitutes a critical step in enabling automated diagnostic algorithms and pattern recognition systems.[28] Feature engineering for air-powered sensor data spans multiple domains including time, frequency, and time-frequency representations. Time-domain features such as mean, standard deviation, skewness, and kurtosis capture amplitude distributions and variability patterns.[29]. Figure 2 Presents the Signal Processing pipeline for Air-Powered Biomedical Sensors.

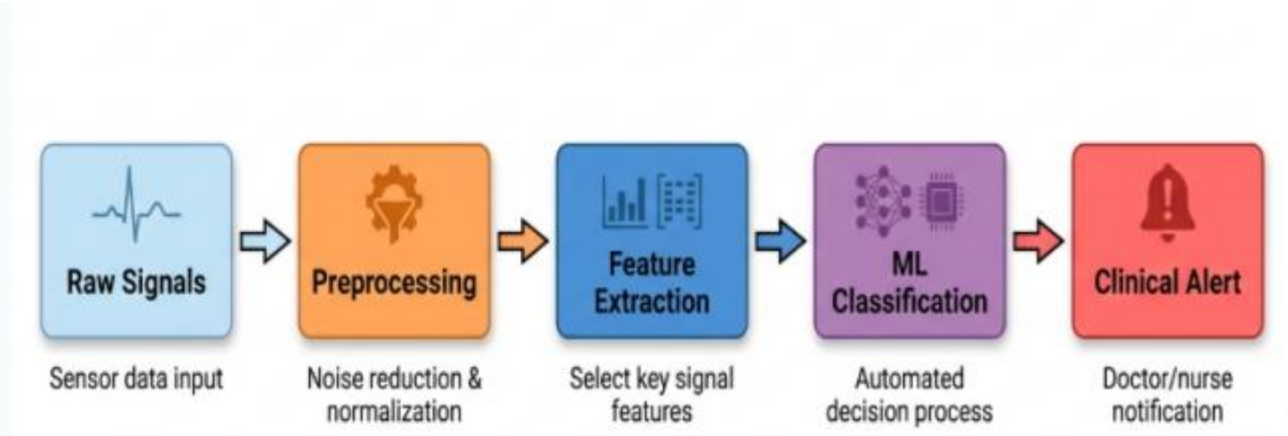

FIGURE 2: Signal Processing Pipeline for Air-Powered Biomedical Sensors
Source: [25, 31, 32, 36, 37, 38]

Frequency-domain features through power spectral density (PSD) estimation quantify the distribution of signal energy across frequency bands.[30] Entropy and complexity measures including approximate entropy (ApEn), sample entropy (SampEn), and permutation entropy (PerEn) quantify signal regularity and complexity.[32]

3.3 Machine Learning Algorithms for Pattern Recognition

Contemporary biomedical signal analysis increasingly relies on machine learning algorithms to automate classification, prediction, and anomaly detection tasks.[35] Support Vector Machines (SVM) with various kernel functions excel at binary and multiclass classification tasks involving respiratory pattern recognition and disease detection.[36] Deep learning architectures including Convolutional Neural Networks (CNNs) automatically learn hierarchical feature representations from raw or minimally processed signals.[37] Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants, excel at modelling long-term temporal dependencies in sequential data.[38]

3.4 Real-Time Signal Processing at the Edge

Edge computing strategies enable processing of biomedical signals directly on or near the sensor platform, reducing latency, conserving bandwidth, and enhancing privacy.[40] For air-powered sensor systems, edge processing involves implementation of lightweight algorithms optimized for resource-constrained microcontrollers. Real-time computation of critical features such as respiratory rate and breathing regularity can be performed locally, with only processed features transmitted wirelessly.[41]. Table 2 shows the Signal Processing Techniques for Air-Powered biomedical Sensors.

4. Clinical Applications in Diagnosis and Monitoring

4.1 Respiratory Disease Monitoring

Continuous respiratory monitoring using air-powered sensors has transformed the management of chronic pulmonary conditions.[43] Wearable respiratory sensors enable long-term tracking of breathing patterns, detection of disease exacerbations, and assessment of treatment efficacy. COPD patients exhibit characteristic respiratory patterns including increased breathing frequency, reduced tidal volume, and prolonged expiratory phases.[44] Pneumatic chest belts equipped with pressure sensors can continuously monitor these parameters, with machine learning algorithms detecting early signs of acute exacerbations. Studies have demonstrated correlation coefficients exceeding 0.83 between pneumatic sensor measurements and gold-standard spirometry.[45]

Air-powered flow sensors track breathing patterns that precede asthmatic attacks, enabling pre-emptive medication use.[46] Pneumatic sensors detect obstructive sleep apnea (OSA) events through identification of absent or reduced airflow despite continued respiratory effort.[47] Signal processing algorithms employing wavelet energy, permutation entropy, and spectral analysis achieve diagnostic accuracy comparable to polysomnography for OSA screening.[48] The COVID-19 pandemic accelerated development of wearable respiratory sensors for early symptom detection and disease progression monitoring.[49,50]

Table 2. Signal Processing Techniques for Air-Powered Biomedical Sensors

Processing Technique	Application Domain	Key Features	Computational Complexity	Clinical Utility	References
Wavelet Transform (DWT/CWT)	Respiratory signals, ECG, multimodal fusion	Multi-resolution analysis, time-frequency localization	Moderate to High	Artifact removal, feature extraction, pattern detection	(25,31)
Entropy Methods (ApEn, SampEn, PerEn)	Breathing patterns, cardiovascular signals	Complexity quantification, regularity assessment	Low to Moderate	Disease detection, anomaly identification, sleep staging	(32,48)
Support Vector Machine (SVM)	Pattern classification, disease diagnosis	Robust to overfitting, kernel-based non-linearity	Moderate	Respiratory pattern classification, tumor detection	(36)
Convolutional Neural Networks (CNN)	Raw signal processing, automated feature learning	Hierarchical feature extraction, end-to-end learning	High	Real-time classification, disease prediction	(37)

Source: Adapted from [25, 30, 31, 32, 36, 37, 38, 39, 40, 41, 48]

4.2 Cardiovascular Assessment

Air-powered sensors provide non-invasive approaches to cardiovascular monitoring through detection of mechanical signals associated with cardiac activity.[51] Ballistocardiogram (BCG) sensors capture cardiac-induced body vibrations resulting from blood ejection and vascular movements during each heartbeat.[23] Signal processing algorithms extract heart rate, heart rate variability, and BCG waveform morphology. Machine learning models trained on BCG features have demonstrated capability for detecting heart failure decompensation and predicting hospitalizations.[52] Pulse wave velocity and pulse transit time extracted from synchronized pneumatic pressure sensors enable cuffless blood pressure estimation.[53]

4.3 Surgical Robotics and Tumor Detection

Transparent pneumatic tactile sensors integrated with soft robotic surgical systems enable real-time tissue characterization during minimally invasive procedures.[3] Pneumatic tactile sensors mounted on robotic end-effectors can systematically scan tissue surfaces, acquiring spatial maps of mechanical properties.[14] Signal processing algorithms convert pressure-deformation relationships into stiffness values, with classification algorithms distinguishing between normal tissue and malignant lesions. Preliminary studies have demonstrated detection of phantom tumors with stiffness differences as small as 0.5 MPa, suggesting potential for early cancer detection.[3]

4.4 Multimodal Physiological Monitoring

Integration of air-powered sensors with complementary sensing modalities enables comprehensive physiological assessment.[55] Multimodal systems combining pneumatic respiratory sensors, electrocardiography, photoplethysmography (PPG), and inertial measurement units (IMUs) provide holistic views of cardiovascular and respiratory function. Signal processing techniques including Kalman filtering and deep learning-based fusion architectures integrate data from multiple sensors to enhance measurement accuracy.[56] Multimodal systems can differentiate between various physical activities and body positions through pattern recognition algorithms.[57]. Table 3 Presents the Clinical Applications and performance Metrics of Air-Powered Monitoring Systems.

Table 3. Clinical Applications and Performance Metrics of Air-Powered Monitoring Systems

Clinical Application	Monitored Parameters	Sensor Configuration	Performance Metrics	Clinical Outcomes	References
COPD Monitoring	Respiratory rate, tidal volume, breathing pattern	Wearable chest belts, smart textiles	Correlation with spirometry: r=0.836; Sensitivity: 89%; Specificity: 92%	Early exacerbation detection, reduced hospitalizations	(44,45)
Sleep Apnea Detection	Apnea-hypopnea events, respiratory effort	Mattress sensors, wearable patches	Diagnostic accuracy: 85-91%; AHI correlation: r>0.80	Home-based screening, improved treatment adherence	(47,48)
Cardiovascular Monitoring (BCG)	Heart rate, HRV, cardiac timing	Seat sensors, wearable devices, smart mattresses	Heart rate accuracy: ±2 bpm; HRV correlation: r=0.75	Heart failure monitoring, stress assessment	(18,23,52)
COVID-19 Symptom Monitoring	Respiratory rate, cough events, breathing difficulty	Face mask-integrated sensors, chest patches	Early symptom detection: 3-5 days before clinical diagnosis	Remote triage, reduced hospital burden	(49,50)
Robotic Tumor Detection	Tissue stiffness, mechanical properties	Transparent pneumatic tactile sensors on robotic arms	Stiffness resolution: 0.5 MPa; Detection sensitivity: >90% for tumors >5mm	Minimally invasive diagnosis, surgical guidance	(3,14)

Sources: Adapted from [3, 14, 18, 23, 44, 45, 47, 48, 49, 50, 52]

5. IoT Integration and Remote Patient Monitoring Systems

5.1 Connected Health Ecosystems

The Internet of Things paradigm has revolutionized patient monitoring through interconnected networks of sensors, edge computing devices, communication gateways, and cloud-based analytics platforms.[11] Air-powered biomedical sensors seamlessly integrate into these ecosystems, enabling continuous data acquisition, transmission, storage, and analysis. Typical IoT-enabled systems comprise sensor nodes with embedded microcontrollers, local processing units, wireless communication modules (Bluetooth Low Energy, Wi-Fi, cellular), cloud infrastructure, and end-user interfaces.[58]. Figure 3 illustrates the IoT-Enabled Patient Monitoring System Architecture.

Selection of wireless protocols depends on range, bandwidth, power consumption, and reliability requirements.[59]

Remote monitoring systems must implement robust security measures to protect sensitive health information.[60] Encryption during transmission, secure authentication, role-based access control, and compliance with regulations such as HIPAA and GDPR are essential. Edge computing enhances privacy by processing sensitive data locally and transmitting only anonymized or aggregated information to cloud servers.

5.2 Cloud-Based Analytics and Predictive Modelling

Cloud computing platforms provide computational resources for advanced analytics that exceed the capabilities of local devices.[61] Large-scale data storage enables longitudinal analysis of individual patient trends. Cloud-based systems track physiological parameters over extended periods, identifying gradual deteriorations, circadian variations, and responses to therapeutic interventions.[62] Machine learning models trained on historical data can predict adverse events such as COPD exacerbations, heart failure decompensations, or sleep apnea complications hours to days before clinical manifestation.[63] Aggregated data from distributed sensor networks enable public health surveillance and disease outbreak detection.[64]

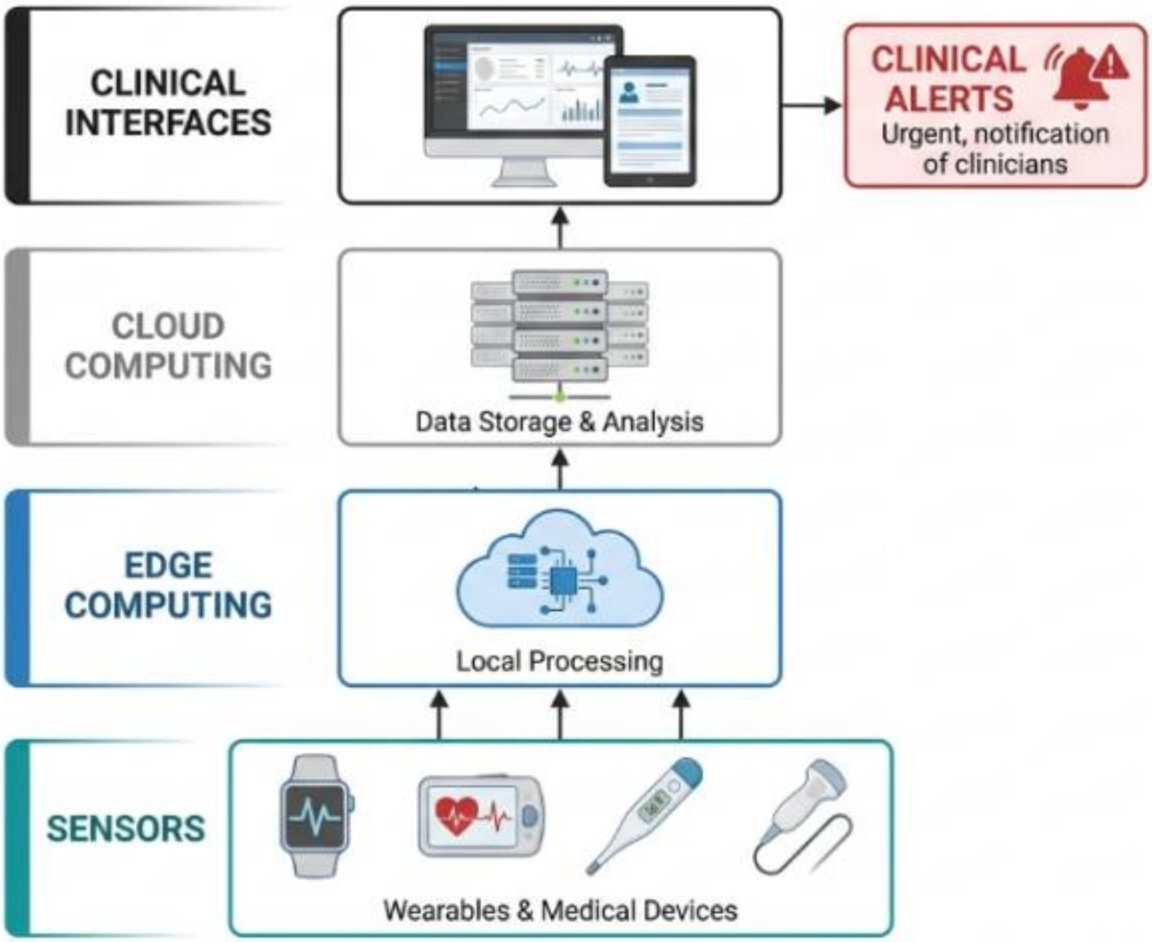

FIGURE 3: IoT-Enabled Remote Patient Monitoring System Architecture
Source: Authors Illustrations adapted from [11, 12, 58, 59, 61]

5.3 Clinical Integration and Workflow Considerations

Successful implementation requires thoughtful integration into clinical workflows.[65] Electronic health record (EHR) interoperability, clinician decision support tools, and patient engagement strategies are critical components. Seamless data flow between remote monitoring platforms and EHR systems enables clinicians to access sensor data alongside other clinical information.[66] Intelligent algorithms analyse incoming sensor data and present actionable insights through prioritized alerts, trend visualizations, and risk stratification.[67]

6. Challenges and Future Directions

6.1 Technical Challenges

Long-term stability remains a concern for pneumatic sensors, as material properties and environmental conditions can induce gradual measurement drift.[68] Development of self-calibrating sensors and drift compensation algorithms using machine learning represents an active research area. Temperature variations, humidity changes, and atmospheric pressure fluctuations can affect pneumatic sensor performance.[69] Continuous wireless operation requires efficient power management, with innovations in energy harvesting from body heat, motion, or respiration enabling self-powered devices.[70] Absence of standardized testing protocols and regulatory frameworks hinders clinical adoption.[71]

6.2 Clinical and Regulatory Challenges

Rigorous clinical trials demonstrating diagnostic accuracy, clinical utility, and patient outcomes are required for widespread adoption. [72] Validation studies must encompass diverse patient populations, comorbidities, and real-world usage conditions. Air-powered biomedical devices require regulatory approval from agencies such as the FDA and EMA.[73] Healthcare reimbursement systems must evolve to incentivize remote monitoring services.[74] Value-based payment models that reward improved patient outcomes could accelerate adoption.

6.3 Data Science and AI Challenges

Deep learning models offer superior performance but lack transparency regarding decision-making processes.[75] Development of explainable AI methods that provide clinically meaningful insights is essential for building clinician trust and regulatory acceptance. Federated learning frameworks enable collaborative model development without centralizing sensitive data.[76] Ensuring algorithmic fairness and equitable performance across age, gender, ethnicity, and socioeconomic groups requires diverse training datasets and rigorous validation.[77]

6.4 Future Research Directions

Next-generation air-powered sensors will leverage advanced materials including liquid metals, self-healing polymers, and bio-integrated electronics to enhance sensitivity, durability, and biocompatibility.[78] Additive manufacturing techniques enable rapid prototyping and customization. Continued advances in AI, particularly in transfer learning, few-shot learning, and continual learning, will enable sensor systems to adapt to individual patients with minimal labelled data.[79] Future systems will integrate air-powered sensors with molecular diagnostics, genomic information, and social determinants of health.[80] Air-powered monitoring will enable truly personalized healthcare through continuous phenotyping, individualized reference ranges, and treatment optimization based on real-time physiological responses.[81]

7. Conclusion

Air-powered biomedical signal processing technologies represent a transformative approach to continuous, non-invasive patient monitoring and disease diagnosis. The unique characteristics of pneumatic sensors including electrical safety, mechanical compliance, temperature immunity, and optical transparency complement traditional biomedical sensors and enable novel clinical applications. Integration with sophisticated signal processing algorithms encompassing wavelet analysis, entropy metrics, and machine learning architectures facilitates extraction of clinically actionable information from pneumatic sensor data. Applications span respiratory disease monitoring, cardiovascular assessment, surgical robotics, and comprehensive remote patient monitoring through IoT-enabled ecosystems. Despite challenges related to sensor stability, environmental interference, standardization, and regulatory approval, ongoing innovations in materials science, artificial intelligence, and systems integration promise to advance air-powered technologies toward widespread clinical adoption. As healthcare continues its evolution toward personalized, predictive, and preventive paradigms, air-powered biomedical signal processing will play an increasingly vital role in delivering accessible, continuous, and high-quality patient care across diverse clinical and home settings. Future research should prioritize rigorous clinical validation, algorithm interpretability, equitable performance across populations, and seamless integration into clinical workflows to realize the full potential of these promising technologies in improving global health outcomes.

ACKNOWLEDGEMENTS

The authors acknowledge valuable Contributions from colleagues in the field of Biomedical Engineering and Public health research.

Author Contributions

The author has significantly contributed to the study's conception, design, data collection, analysis, and interpretation. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accept full responsibility for the content and integrity of the work.

Financial Support

The authors declare that no external funding was received for this study.

Conflicts of Interest

The authors state that there are no financial, personal, or professional conflicts of interest associated with this research.

Ethical Approvals

This research did not involve the use of human participants or animal subjects and therefore did not require ethical clearance

Publisher's Note

The Journal stays neutral about jurisdictional claims in published maps and institutional affiliations

References

1. Abdulmalek S, Nasir A, Jabbar WA, Almuhaya MAM, Bairagi AK, Khan MAM, et al. IoT-based healthcare-monitoring system towards improving quality of life: a review. Healthcare (Basel). 2022;10(10):1993. https://doi.org/10.3390/healthcare10101993
2. Krishnan S, Athavale Y. Trends in biomedical signal feature extraction. Biomed Signal Process Control. 2018;43:41-63. https://doi.org/10.1016/j.bspc.2018.02.008
3. Zhao S, Nguyen CC, Hoang TT, Do TN, Phan HP. Transparent pneumatic tactile sensors for soft biomedical robotics. Sensors (Basel). 2023;23(12):5671. https://doi.org/10.3390/s23125671

4. Massaroni C, Nicolò A, Lo Presti D, Sacchetti M, Silvestri S, Schena E. Contact-based methods for measuring respiratory rate. Sensors (Basel). 2019;19(4):908. https://doi.org/10.3390/s19040908
5. Yin Z, Yang Y, Hu C, Li J, Qin B, Yang X. Wearable respiratory sensors for health monitoring. NPG Asia Mater. 2024;16. https://doi.org/10.1038/s41427-023-00513-9
6. Lee K, Ni X, Lee JY, Arafa H, Pe DJ, Xu S, et al. Mechano-acoustic sensing of physiological processes and body motions via a soft wireless device placed at the suprasternal notch. Nat Biomed Eng. 2020;4(2):148-158. https://doi.org/10.1038/s41551-019-0480-6
7. Guo X, Zhou Y, Yang D, Wang Z, Wang C, Jiang S, et al. Artificial intelligence on biomedical signals: technologies, applications, and future directions. Med-X. 2024;2:20. https://doi.org/10.1007/s44258-024-00043-1
8. Mporas I, Tsirka V, Zacharaki EI, Koutsouris D, Golemati S. Bridging signal intelligence and clinical insight: a comprehensive review of feature engineering, model interpretability, and machine learning in biomedical signal analysis. Appl Sci. 2025;15(22):12036. https://doi.org/10.3390/app152212036
9. Massaroni C, Romano C, Lo Presti D, Zaltieri M, Innocenti L, Sacchetti M, et al. Advances in respiratory monitoring: a comprehensive review of wearable and remote technologies. Biosensors (Basel). 2024;14(2):90. https://doi.org/10.3390/bios14020090
10. Khan F, Ghaffar A, Khan N, Cho SH. Recent developments in wearable breath sensors for healthcare monitoring. Commun Mater. 2024;5:17. https://doi.org/10.1038/s43246-024-00480-w
11. Kumar M, Chopra V. Biomedical devices for remote diagnosis and monitoring based on IoT. In: Role of science and technology for sustainable future: Applied sciences and technologies. Singapore: Springer Nature Singapore; 2025. p. 141-168. https://doi.org/10.1007/978-981-97-5177-8_8
12. Silva CD, Gonçalves B, Biduski D, Rodrigues CR, Silva LT, Lima L, et al. Enhancing connected health ecosystems through IoT-enabled monitoring technologies: a case study of the Monit4Healthy system. Sensors (Basel). 2025;25(8):2378. https://doi.org/10.3390/s25082378
13. Hayward N, Shaban M, Badger J, Jones I, Wei Y, Spencer D, et al. A capacitflector provides continuous and accurate respiratory rate monitoring for patients at rest and during exercise. J Clin Monit Comput. 2022;36(5):1535-1546. https://doi.org/10.1007/s10877-021-00798-7
14. Thai MT, Phan PT, Tran HA, Nguyen CC, Hoang TT, Davies J, et al. Advanced soft robotic system for in situ 3D bioprinting and endoscopic surgery. Adv Sci. 2023;10(15):2205656. https://doi.org/10.1002/advs.202205656
15. Gunawardana U, Sarmas E, Wanniarachchi WKM, Liyanage Y. State of the art review of wearable devices for respiratory monitoring. IEEE Access. 2025;13:8462-8484. https://doi.org/10.1109/ACCESS.2025.3525947
16. Romano C, Nicolò A, Innocenti L, Sacchetti M, Schena E, Massaroni C. Design and testing of a smart facemask for respiratory monitoring during cycling exercise. Biosensors (Basel). 2023;13(3):369. https://doi.org/10.3390/bios13030369
17. Zheng Z, Zhu R, Peng I, Xu Z, Jiang Y. Wearable and implantable biosensors: mechanisms and applications in closed-loop therapeutic systems. J Mater Chem B. 2024;12:8577-8604. https://doi.org/10.1039/D4TB00782D
18. Zhang J, Xu H, Liu S, Wang Y, Wang D. Smart wireless flexible sensing system for unconstrained monitoring of ballistocardiogram and respiration. NPJ Flex Electron. 2025;9:2. https://doi.org/10.1038/s41528-025-00388-6
19. Xue H, Yang Q, Wang D, Luo W, Wang W, Lin M, et al. A wearable pyroelectric nanogenerator and self-powered breathing sensor. Nano Energy. 2017;38:147-154. https://doi.org/10.1016/j.nanoen.2017.05.056
20. Kim MJ, Khan MU, Lee J, Kim J, Woo SH, Bange A, et al. Breathing-driven self-powered pyroelectric ZnO integrated face mask for bioprotection. Small. 2023;19(10):2200712. https://doi.org/10.1002/smll.202200712
21. Kim DH, Lu N, Ma R, Kim YS, Kim RH, Wang S, et al. Epidermal electronics. Science. 2011;333(6044):838-843. https://doi.org/10.1126/science.1206157
22. Meng K, Zhao S, Zhou Y, Wu Y, Zhang S, He Q, et al. Wearable pressure sensors for pulse wave monitoring. Adv Mater. 2022;34(21):2109357. https://doi.org/10.1002/adma.202109357
23. Kim CS, Ober SL, McMurtry MS, Finegan BA, Inan OT, Mukkamala R, et al. Ballistocardiogram: mechanism and potential for unobtrusive cardiovascular health monitoring. Sci Rep. 2016;6:31297. https://doi.org/10.1038/srep31297
24. Kubicek J, Fiedorova K, Vilimek D, Cerny M, Penhaker M, Janura M, et al. Recent trends, construction challenges and future directions of wearable devices for sport activities monitoring. Proceedings. 2020;49(1):127. https://doi.org/10.3390/proceedings2020049127
25. Stanke L, Kubicek J, Vilimek D, Penhaker M, Cerny M, Augustynek M, et al. Towards optimal wavelet denoising scheme—a novel spatial and volumetric mapping of wavelet-based biomedical data smoothing. Sensors (Basel). 2020;20(18):5301. https://doi.org/10.3390/s20185301
26. Rogers B, Schaffarczyk M, Gronwald T. Estimation of respiratory frequency in women and men by Kubios HRV software using the Polar H10 or Movesense medical ECG sensor during an exercise ramp. Sensors (Basel). 2022;22(19):7156. https://doi.org/10.3390/s22197156
27. Cay G, Solanki D, Al Rumon MA, Ravichandran V, Fapohunda KO, Mankodiya K. SolunumWear: a smart textile system for dynamic respiration monitoring across various postures. iScience. 2024;27(7):110223. https://doi.org/10.1016/j.isci.2024.110223
28. Vo K, Le T, Rahmani AM, Dutt N, Cao H. An efficient and robust deep learning method with 1-D octave convolution to extract fetal electrocardiogram. Sensors (Basel). 2020;20(13):3757. https://doi.org/10.3390/s20133757
29. Pankaj, Kumar A, Komaragiri R, Kumar M. A novel method for the diagnosis of epileptic seizure using multi-domain features of EEG signals. Comput Biol Med. 2022;141:105081. https://doi.org/10.1016/j.compbiomed.2021.105081
30. Becerra-Sánchez P, Reyes-Munoz A, Guerrero-Ibañez A. Feature selection model based on EEG signals for assessing the cognitive workload in drivers. Sensors (Basel). 2020;20(20):5881. https://doi.org/10.3390/s20205881
31. Addison PS, Walker J, Guido RC. Time-frequency analysis of biosignals. IEEE Eng Med Biol Mag. 2009;28(5):14-29. https://doi.org/10.1109/MEMB.2009.934244
32. Kumar M, Ganesh B, Thiyagarajan D, Vamsee T. Automatic identification of obstructive sleep apnea using multimodal features. Biomed Signal Process Control. 2025;105:107572. https://doi.org/10.1016/j.bspc.2025.107572

33. Khare SK, Gadre VM, Acharya R. ECGPsychNet: an optimized hybrid ensemble model for automatic detection of psychiatric disorders using ECG signals. Physiol Meas. 2023;44(11):115004. https://doi.org/10.1088/1361-6579/ad00ff
34. Feng B, Yu T, Wang H, Liu K, Wu W, Long W. Editorial: machine learning and deep learning in biomedical signal analysis. Front Hum Neurosci. 2023;17:1183840. https://doi.org/10.3389/fnhum.2023.1183840
35. Singh A, Majumder S. Self-supervised learning for biomedical signal processing: a systematic review on ECG and PPG signals. medRxiv. 2024. https://doi.org/10.1101/2024.09.30.24314588
36. Siuly S, Li Y, Zhang Y. EEG signal analysis and classification: techniques and applications. Cham: Springer International Publishing; 2020. https://doi.org/10.1007/978-3-030-49000-1
37. Park J, Mah AJ, Nguyen T, Park S, Ghazi Zadeh L, Shadgan B, et al. Modification of a conventional deep learning model to classify simulated breathing patterns: a step toward real-time monitoring of patients with respiratory infectious diseases. Sensors (Basel). 2023;23(12):5592. https://doi.org/10.3390/s23125592
38. Petmezas G, Haris K, Stefanopoulos L, Kilintzis V, Tzavelis A, Rogers JA, et al. Automated atrial fibrillation detection using a hybrid CNN-LSTM network on imbalanced ECG datasets. Biomed Signal Process Control. 2021;63:102194. https://doi.org/10.1016/j.bspc.2020.102194
39. Del Pup M, Atzori M. Applications of self-supervised learning to biomedical signals: a survey. IEEE Access. 2024;12:1884-1902. https://doi.org/10.1109/ACCESS.2023.3344531
40. Alshamrani M. IoT and artificial intelligence implementations for remote healthcare monitoring systems: a survey. J King Saud Univ Comput Inf Sci. 2022;34(8):4687-4701. https://doi.org/10.1016/j.jksuci.2021.06.005
41. Moon KS, Lee SQ. A wearable multimodal wireless sensing system for respiratory monitoring and analysis. Sensors (Basel). 2023;23(15):6790. https://doi.org/10.3390/s23156790
42. Prigent G, Aminian K, Rodrigues T, Vesin JM, Millet GP, Falbriard M, et al. Indirect estimation of breathing rate from heart rate monitoring system during running. Sensors (Basel). 2021;21(16):5651. https://doi.org/10.3390/s21165651
43. Javaid M, Haleem A, Singh RP, Rab S, Haq MIU, Raina A. Internet of Things in the global healthcare sector: significance, applications, and barriers. Int J Intell Netw. 2022;3:165-175. https://doi.org/10.1016/j.ijin.2022.10.002
44. Kaminsky DA, Bates JH, Irvin CG. Effects of continuous positive airway pressure on the breathing pattern of healthy subjects. Respir Physiol Neurobiol. 2020;261:103547. https://doi.org/10.1016/j.resp.2019.103547
45. Harbour E, Lasshofer M, Genitrini M, Schwameder H. Validation of a textile-based wearable sensor for respiratory rate monitoring. Sensors (Basel). 2021;21(15):5036. https://doi.org/10.3390/s21155036
46. Menagadevi M, Madian N, Thiyagarajan D, Rajendran R. Smart medical devices: making healthcare more intelligent. In: Tripathi SL, Balas VE, Mahmud M, Banerjee S, editors. Machine learning models and architectures for biomedical signal processing. London: Academic Press; 2025. p. 487-501. https://doi.org/10.1016/B978-0-443-22158-3.00020-X
47. Niu J, Shi Y, Cai M, Cao Z, Wang D, Zhang Z, et al. Detection of sputum by interpreting the time-frequency distribution of respiratory sound signal using image processing techniques. Biomed Signal Process Control. 2021;64:102408. https://doi.org/10.1016/j.bspc.2020.102408
48. Kumar P, Sharma A, Goel N. Machine learning based obstructive sleep apnea detection using single-lead ECG features. IEEE Trans Instrum Meas. 2023;72:2516811. https://doi.org/10.1109/TIM.2023.3293246
49. Chen G, Shen S, Tat T, Zhao X, Zhou Y, Fang Y, et al. Wearable respiratory sensors for COVID-19 monitoring. View (Beijing). 2022;3(5):20220024. https://doi.org/10.1002/VIW.20220024
50. Faezipour M, Abuzneid A. Smartphone-based self-testing of COVID-19 using breathing sounds. Telemed e-Health. 2020;26(10):1202-1205. https://doi.org/10.1089/tmj.2020.0114
51. Li J, Lin Q, Miao J, Sun C, Jiang C, Xu Y, et al. Thin, soft, wearable system for continuous wireless monitoring of artery blood pressure. Nat Commun. 2023;14:5009. https://doi.org/10.1038/s41467-023-40877-3
52. Stehlik J, Schmalfuss C, Bozkurt B, Nativi-Nicolau J, Wohlfahrt P, Wegerich S, et al. Continuous wearable monitoring analytics predict heart failure hospitalization: the LINK-HF multicenter study. Circ Heart Fail. 2020;13(3):e006513. https://doi.org/10.1161/CIRCHEARTFAILURE.119.006513
53. Tang Z, Tamura T, Sekine M, Huang M, Chen W, Yoshida M, et al. A chair-based unobtrusive cuffless blood pressure monitoring system based on pulse arrival time. IEEE J Biomed Health Inform. 2021;25(5):1603-1614. https://doi.org/10.1109/JBHI.2020.3021481
54. Rus D, Tolley MT. Design, fabrication and control of soft robots. Nature. 2015;521(7553):467-475. https://doi.org/10.1038/nature14543
55. Gao H, Huang J, He Y, Zhao K, Ding W, Fang J, et al. Graphene-integrated mesh electronics with converged multifunctionality for tracking multimodal excitation-contraction dynamics in cardiac microtissues. Nat Commun. 2024;15:2321. https://doi.org/10.1038/s41467-024-46635-4
56. Zhou Y, Zheng H, Huang K, Xia J, Wu K, Cao L. Multi-modal fusion framework for EEG and fNIRS based motor imagery tasks classification. Biomed Signal Process Control. 2023;82:104560. https://doi.org/10.1016/j.bspc.2022.104560
57. Degtyarenko I, Slyusarenko K, Omelchenko A, Riabov V, Chyzhyk S. Device for automatic measuring of human respiratory parameters. Sensors (Basel). 2022;22(5):1857. https://doi.org/10.3390/s22051857
58. Qadri YA, Nauman A, Zikria YB, Vasilakos AV, Kim SW. The future of healthcare internet of things: a survey of emerging technologies. IEEE Commun Surv Tutor. 2020;22(2):1121-1167. https://doi.org/10.1109/COMST.2020.2973314
59. Petroni A, Cuomo F, Schepis L, Biagi M, Listanti M, Scarano G. Adaptive data synchronization algorithm for IoT-oriented low-power wide-area networks. Sensors (Basel). 2018;18(11):4053. https://doi.org/10.3390/s18114053
60. Sadek I, Codjo J, Rehman SU, Abdulrazak B. Security and privacy in the internet of things healthcare systems: toward a robust solution in real-life deployment. Comput Methods Programs Biomed Update. 2022;2:100071. https://doi.org/10.1016/j.cmpbup.2022.100071
61. Kelly JT, Campbell KL, Gong E, Scuffham P. The internet of things: impact and implications for health care delivery. J

Med Internet Res. 2020;22(11):e20135. https://doi.org/10.2196/20135
62. Pradhan B, Bhattacharyya S, Pal K. IoT-based applications in healthcare devices. J Healthcare Eng. 2021;2021:6632599. https://doi.org/10.1155/2021/6632599
63. Manickam P, Mariappan SA, Murugesan SM, Hansda S, Kaushik A, Shinde R, et al. Artificial intelligence (AI) and internet of medical things (IoMT) assisted biomedical systems for intelligent healthcare. Biosensors (Basel). 2022;12(8):562. https://doi.org/10.3390/bios12080562
64. Al-Kahtani MS, Khan F, Taekeun W. Application of internet of things and sensors in healthcare. Sensors (Basel). 2022;22(15):5738. https://doi.org/10.3390/s22155738
65. Wei JCJ, van den Broek TJ, van Baardewijk JU, van Stokkum R, Kamstra RJM, Rikken L, et al. Validation and user experience of a dry electrode-based health patch for heart rate and respiration rate monitoring. Sci Rep. 2024;14:23098. https://doi.org/10.1038/s41598-024-73557-8
66. Islam MM, Nooruddin S, Karray F, Muhammad G. Internet of Things: device capabilities, architectures, protocols, and smart applications in healthcare domain. IEEE Internet Things J. 2023;10(4):3611-3624. https://doi.org/10.1109/JIOT.2022.3228795
67. Charfare RH, Desai AU, Keni NN, Nambiar AS, Cherian MM. IoT-AI in healthcare: a comprehensive survey of current applications and innovations. Int J Robot Control Syst. 2024;4(3):1446-1472. https://doi.org/10.31763/ijrcs.v4i3.1526
68. Liu Z, Cascioli V, McCarthy PW. A single subject feasibility study of using a non-contact measurement to visualize temperature at body-seat interface. Sensors (Basel). 2022;22(10):3941. https://doi.org/10.3390/s22103941
69. Bibbo D, Klinkovsky T, Penhaker M, Kudrna P, Peter L, Augustynek M, et al. A new approach for testing fetal heart rate monitors. Sensors (Basel). 2020;20(15):4139. https://doi.org/10.3390/s20154139
70. Roy K, Sarkar S, Ghosh D, Padmanaban B, Goswami P. A self-powered wearable pressure sensor and pyroelectric breathing sensor based on GO interfaced PVDF nanofibers. ACS Appl Nano Mater. 2019;2(4):2013-2025. https://doi.org/10.1021/acsanm.9b00033
71. Raghavendra U, Gudigar A, Paul A, Goutham TS, Inamdar MA, Hegde A, et al. Brain tumor detection and screening using artificial intelligence techniques: current trends and future perspectives. Comput Biol Med. 2023;163:107063. https://doi.org/10.1016/j.compbiomed.2023.107063
72. Chien JC, Lee JD, Su E, Li SH. A bronchoscope localization method using an augmented reality co-display of real bronchoscopy images with a virtual 3D bronchial tree model. Sensors (Basel). 2020;20(23):6997. https://doi.org/10.3390/s20236997
73. U.S. Food and Drug Administration. Digital health technologies for remote data acquisition in clinical investigations. Guidance for industry, investigators, and other stakeholders. 2023. Available from: https://www.fda.gov/regulatory-information/search-fda-guidance-documents/digital-health-technologies-remote-data-acquisition-clinical-investigations
74. Mehta N, Venkataraman R. Digital health reimbursement landscape. Digit Health. 2023;9:20552076231164505. https://doi.org/10.1177/20552076231164505
75. De Campos Souza PV, Lughofer E. Identification of heart sounds with an interpretable evolving fuzzy neural network. Sensors (Basel). 2021;21(19):6477. https://doi.org/10.3390/s21196477
76. Khare SK, Gaikwad NB, Bajaj V. VHERS: a novel variational mode decomposition and Hilbert transform-based EEG rhythm separation for automatic ADHD detection. IEEE Trans Instrum Meas. 2022;71:2516611. https://doi.org/10.1109/TIM.2022.3204076
77. Khare SK, March S, Barua PD, Gadre VM, Acharya UR. Application of data fusion for automated detection of children with developmental and mental disorders: a systematic review of the last decade. Inform Fusion. 2023;99:101898. https://doi.org/10.1016/j.inffus.2023.101898
78. He R, Hua Q, Hao W, Zhao Q, Zhang L, Dong S. Flexible miniaturized sensor technologies for long-term physiological monitoring. NPJ Flex Electron. 2022;6:20. https://doi.org/10.1038/s41528-022-00146-y
79. Rong G, Mendez A, Assi EB, Zhao B, Sawan M. Artificial intelligence in healthcare: review and prediction case studies. Engineering. 2020;6(3):291-301. https://doi.org/10.1016/j.eng.2019.08.015
80. Aldabbas H, Albashish D, Khatatneh K, Amin R. An architecture of IoT-aware healthcare smart system by leveraging machine learning. Int Arab J Inf Technol. 2022;19(2):160-169. https://doi.org/10.34028/iajit/19/2/3
81. Jarchi D, Salvi D, Tarasenko L, Clifton DA. Validation of instantaneous respiratory rate using reflectance PPG from different body positions. Sensors (Basel). 2018;18(11):3705. https://doi.org/10.3390/s18113705

How to cite this article

Oladosu, M. A., Abah, M. A., Agbo, L., & Oladosu, O. A. (2026). *AI-powered biomedical signal processing applications in diagnosis and remote patient monitoring*. *Science Archives, 7*(2), 74–85. https://doi.org/10.47587/SA.2026.7206

This work is licensed under a Creative Commons Attribution 4.0 International License