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REVIEW

Combining Artificial Intelligence with Ayurveda and Siddha Medicine: An Examination of Pulse-Based Disease Diagnosis Systems

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Abstract: Advancements in the fields of Ayurveda and Siddha worldwide have led to an increasing need for objective, noninvasive, technology-based diagnostic methods. Therefore, traditional pulse diagnosis has become a pivotal field in computational research to enhance diagnostic consistency. With the emergence of new biomedical sensing techniques and computational intelligence, automatic pulse diagnosis systems have been developed for pulse signal acquisition and analysis. This review paper introduces the technologies of pulse acquisition, signal preprocessing, feature extraction, machine learning, and deep learning-based methods to diagnose the disease by pulse in an automated system and also analyzed paradigms using sensors such as strain-gauge sensors, piezoelectric sensors, microelectromechanical systems, multichannel pulse sensors, photoplethysmography, piezoelectric wafer active sensors, Internet of Things-enabled devices, and artificial intelligence (AI)-assisted platforms. The preprocessing techniques, such as Butterworth, Chebyshev, Bessel, and Savitsky–Golay filters for enhancement of pulse waveform quality and feature reliability and assessment of the pulse parameters related to arterial stiffness and vascular function, along with K-Nearest Neighbors, support vector machines, Decision Trees, Random Forests, and artificial neural networks, were utilized for dosha classification and disease prediction. The review results show remarkable advances in sensing technology, signal analysis, and intelligent diagnostics algorithms. But there are hurdles, such as nonuniform datasets, explainability gaps, and clinical validation. For future studies, explainable AI, integration with wearables, standardized datasets, and widespread clinical testing are areas of interest to improve health assessment and early disease screening.

Keywords: pulse diagnosis, machine learning, deep learning, biomedical sensors, computational intelligence

1. Introduction

Analyzation of pulse is requisite in traditional medicine to find three doshas—(i) Vata, (ii) Pitta, and (iii) Kapha—to determine the equilibrium in order to diagnose various illnesses such as nervous, musculoskeletal, circulatory, digestive, inflammatory, metabolic, cardiological, respiratory, and psychological disorders. Generally, the Vata dosha directs the nerves, circulation, muscles, movements, and joints, and Pitta dosha directs the hormones, inflammation, digestion, heat, and metabolism, and Kapha dosha directs fluid balance, immunity, and structure. This three doshas of pulses are combined to identify the imbalances: (a) Vata–Pitta, which causes migraine, hyperacidity, ulcerative colitis, and nervous inflammation, (b) Pitta–Kapha, which causes inflammation, obesity, sinusitis, and diabetes; (c) Vata–Kapha, which causes respiratory obstruction, hypothyroidism with anxiety, and asthma; and (d) Vata–Pitta–Kapha, which causes autoimmune conditions, systemic illnesses, and chronic disorders, as illustrated in Figure 1 [1–3].

The evolution of pulse diagnosis starts by acquiring pulse waves utilizing piezoelectric, microelectromechanical system (MEMS), multichannel, photoplethysmography (PPG), and piezoelectric wafer active (PWA) sensors. After that, the acquired pulses are recorded; cleansed utilizing Bessel, Butterworth, Chebyshev, artifact reduction, and noise removal filters; processed to extract information such as amplitude, pulse depth, rhythm, peak positions, energy distribution, pulse types, and digital features mapping of imbalances; and classified to predict diseases utilizing many automated and semiautomated approaches.

Numerous machine learning (ML) and deep learning (DL) paradigms aided in the accurate prediction and classification of the pulse diagnosis system, for example. K-Nearest Neighbor (KNN) is a simple and powerful supervised learning technique, which works with the intuition of comparing an unknown sample with the closest samples from the training set and classifying the sample into the class. The classification is done based on the

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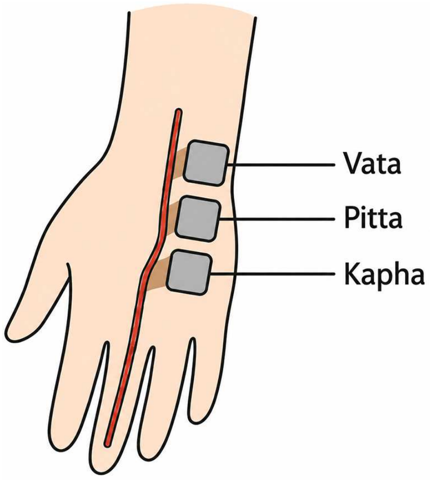
Figure 1
Vata, Pitta, and Kapha sites on the radial artery



maximum voting of the closest neighbors, which makes KNN best suited for pulse data having well-defined patterns. Another popular supervised learning algorithm is support vector machine (SVM), which forms an optimum decision boundary, called a hyperplane, to separate the various classes of pulse signals. SVM is able to classify even high-dimensional and complex datasets well, as it maximizes the separation between the classes. Because of its kernel functions, SVM can represent the nonlinear relationship between the biomedical signals and current diagnosis, and thus, SVM is widely used in biomedical signal analysis and disease diagnosis. DL is a specialized form of ML that involves several layers of artificial neural networks (ANNs) to learn complex representations of features directly from raw or only slightly processed data. DL models can identify complex relationships and patterns in pulse data that are not apparent in traditional ML approaches, which rely on manually designed features, potentially enhancing diagnostic accuracy. The capabilities of convolutional neural networks (CNNs), recurrent neural networks, and other deep neural networks in processing physiological signals and identifying diseases have been proven to be very promising.

Apart from KNN, SVM, and DL models, various other ML methods such as Random Forest (RF) and ANNs are also used in the study of pulse diagnosis. Models such as RF can increase the rate of classification and even minimize the overfitting problem, and models based on neural networks can detect complex nonlinear relationships between the characteristics of the pulses. Together, these smart algorithms enable automatic processing of pulse signals and aid in accurate disease prediction, which helps to establish new computer-aided diagnostic systems [4–6].

In spite of these enhancements, challenges remain, including the standard acquisition paradigm, largely labeled datasets, and clinically substantiated models that can correlate the traditional subjective and computational feature interpretations for diagnosis. This review paper aims to address these research gaps by scrutinizing the automated pulse analysis progression and its proposed methodologies [7, 8].

2. Research Synthesis

This research review has been divided into five areas: (i) sensor-based paradigms, (ii) methodical signal recording, (iii) biomedical platforms integration, (iv) commencement of artificial intelligence (AI), and (v) comprehensive digital platforms. Even though the progression of the above areas shows enhancement, this field still lacks benchmark datasets, robust validation, and paradigms that need to be consistently improved in an automated way. Table 1 describes the evolution of different sensors, signal processing, and AI techniques from early to recent years.

In the early years, pulse analysis was done purely in a theoretical way with the help of medical practitioners. O'Rourke and Gallagher [9] reviewed arterial stiffness by utilizing contour analysis on the data given by medical practitioners. It established the foundation and parameters for analyzation. Following that, Duprez et al. [10] reviewed the physiological conditions affecting radial waveform indices in the data provided by medical practitioners. It identified various key features influencing the pulse morphology. However, the theoretical review and the lack of sensor-based work have become the limitations that motivated researchers to introduce many sensor-based paradigms and measurement systems [11].

After that, one of the most innovative paradigms for pulse diagnosis was developed utilizing a piezoelectric sensor-based paradigm for acquiring the radial pulse, which illustrated feasibility in pulse acquisition, but it has low signal stability, which caused irregularities during disease analyzation. To overcome this limitation, an advanced pulse transit time estimation paradigm was developed utilizing the same piezoelectric sensor. It provided better resolution in time and reduced the irregularities but developed artifacts, which led the direction of research to develop multi-sensor-based systems for acquisition and analyzation. Then the Naadi Tarangini paradigm was introduced, utilizing strain gauges based on Vata, Pitta, and Kapha pulse acquisition and digitization, named Cun-Guan-Chi [12, 13]. First, it was structured based on the traditional pulse acquisition technique, which provided high precision in the diagnosis of various diseases, but challenges persisted, such as complex architecture due to immense sensors and calibration. To overcome calibration, an amplitude distribution analysis system was developed to statistically analyze the arterial pulse amplitude to measure tridosha imbalance, which quantified waveform features. However, some difficulties emerged to interpret clinically, so it paved the way to introduce ML techniques for interpretation. Later, pulse variation at different sites was overcome by reviewing and comparing the morphology of the radial pulse waveform across various wrist positions. It provided and proved the sensor positional sensitivity, which affects the precision of diagnosis [14–18]. Subsequently, the study was established by Palakurthi et al. [19] to set reliability benchmarks to reduce artifacts in pulse analysis by introducing a PWA-based paradigm. But it is only applicable for diseased adults, not for healthy adults [17–19]. In order to elaborate the PWA study, the pulse analyzation technique was introduced based on PWA for pregnant women, which evaluated PWA changes during pregnancy and also illustrated diagnostic probability in obstetrics, but was limited to general diagnosis. After that, a review study on PWA and pulse wave velocity (PWV) was introduced, where the perspectives to overcome the problems of feature analyzation and diagnosis precision through sensor prototypes and ML techniques emerged [20, 21].

Later, a transfer function-based technique was developed to estimate the blood pressure (BP) from the radial pulse acquired by a sensor prototype. But it heavily depends on modeling assumptions for classification of waveforms in order to distinguish the aortic pulse for BP, which affects the prediction. To overcome the classification limitation, the first ML technique, SVM, was developed, where the pulse signal was classified for

Table 1
Timeline table for the evolution of automated pulse diagnosis

Time period	Sensor evolution	Computational evolution	Application scenario	Diagnostic target
2001–2005 (Early Experiments)	Piezoelectric sensors	Peak detection, amplitude tracking, and basic waveform analysis	Initial digital acquisition of radial pulse signals	Pulse waveform characterization and preliminary dosha assessment
2006–2010 (Structured Acquisition and Feature Extraction)	Multi-point pressure sensors	Wavelet transforms, frequency-domain analysis, noise removal, feature extraction, and baseline correction	Standardized pulse recording and extraction of pulse characteristics	Identification of Vata, Pitta, and Kapha pulse features
2011–2015 (Biomedical Integration)	Pressure, temperature, and PPG sensors	KNN, SVM, and Decision Tree-based classification	Automated pulse analysis and classification	Dosha classification and disease-related pulse abnormalities
2016–2020 (ML Growth and Commercial Devices)	Wearable PPG, MEMS, and strain-gauge sensors	SVM, Random Forest, and artificial neural networks	Portable and wearable pulse monitoring systems	Hypertension, diabetes, cardiovascular disorders, and dosha imbalance detection
2021–2023 (Deep Learning and Real-Time Monitoring)	Wearable piezoelectric sensors and IoT-enabled devices	CNN, Long Short-Term Memory (LSTM), multimodal fusion, and real-time analytics	Continuous health monitoring and smart diagnostic platforms	Automated tridosha assessment and disease prediction
2024–2025 (Fully Digital Naadi Platforms)	Thin-film and flexible sensors	Cloud-integrated intelligent systems and decision-support frameworks	Digital Naadi diagnosis and remote healthcare applications	Personalized tridosha evaluation and clinical decision support

many diseases with the help of an elastic metric, but it has dataset limitations. Jin et al. [22] conducted a wave intensity analysis for wave classifiers developed by ML techniques to advance the wave propagation model, which increased the accuracy, but too difficult for clinical routine [22, 23]. To analyze continuous BP, a combined paradigm of Electrocardiogram (ECG), pulse sensor, and ML model was developed, which improves BP accuracy through multimodal sensing, classification, and analyzation. However, to combine modern and traditional technology, a piezoelectric sensor-based ML model aligned with Ayurvedic Vata, Pitta, and Kapha signals is used. It enhanced the matching among modern and traditional techniques, but validation has not been done, and it is not a wearable prototype [24, 25].

Subsequently, based on matching technique, Nie et al. [26] developed a paradigm which combined piezoelectric and approximation entropy model were healthy and unhealthy pulse waves, has been diagnosed. It provided high sensitivity even to subtle changes in the pulse waveforms. However, it has heavy computational complexity due to matching traditional and modern techniques for entropy estimation. The analysis of the piezoelectric and approximation technique was done in pregnant women. It helped to analyze the pulse waveform shifts and validated variations in physiology too [26, 27]. To help the ML model for validation, Palakurthi et al. [19] conducted clinical testing on Maharishi Nadi-Vigyan to establish the robustness of AI models, and it motivated the researcher to develop the fully automated pulse analysis paradigm. Later, PWV estimated through ML was developed by Jin et al. [22], which helped the model to estimate arterial stiffness, but the dataset limitations were there [18, 19]. So, to overcome the limitations of PWV estimation through an ML model, modified piezoelectric physiological pulse acquisition was demonstrated, and it appears to be a compact and high-sensitivity-based system, but it is not a wearable prototype. One of the most innovative paradigms for pulse diagnosis was initially developed utilizing a piezoelectric sensor-based paradigm to apprehend Vata, Pitta, and Kapha signals with enhanced reliability. It differentiated the age, gender, and diabetic conditions by analyzing the tridosha imbalance, and it showed enhanced precision across all conditions, indicating prominent consistency. However, the paradigm lacked samples, labeled datasets, analyzation across larger populations, extra feature extraction, specific disease validation, and measurement variability due to sensor placement and pressure [28, 29].

Later, many ML classification techniques for pulse quality have been developed, especially after Ouyoung et al.'s [27] ML classifier to analyze high- and low-quality pulses, which increased the dataset reliability, but it is not focused on disease diagnosis. Then Liu et al. [28] developed a wearable pulse sensor prototype with an SVM model for basic diseases such as BP and heart rate. To advance that prototype, Deng et al. [29] developed a smart wearable device combining pulse acquisition through sensors and continuous analyzation through an Internet of Things (IoT)-enabled health monitoring system [30]. Then, the pulse wave analysis of the prototype was enhanced by Jin et al. [22] by developing an algorithm named waveform recognition utilizing an ML technique, which provided high precision, especially for cardiovascular monitoring with slight sensor complexity. To overcome this, many flexible wearable sensors have been developed in recent days, as illustrated in Table 2, by year of implementation, methodology used, and their advantages and disadvantages, paving the way for further future design implementations, which still lack

Table 2
Summary of literature on sensor AI-based pulse diagnosis

Year	Method	Application scenario	Diagnostic target	Advantages	Limitations	Research motivation	Database source
2001	Review of Pulse-Wave Mechanics	Fundamental pulse waveform studies	Pulse waveform characterization	Established terminology and theoretical foundation	No experimental implementation	Encouraged engineering-based pulse research	Scopus, Web of Science, PubMed
2004	Physiological Factors Affecting Radial Waveform	Radial pulse assessment	Identification of pulse-influencing factors	Identified key variables affecting pulse characteristics	No sensor innovation	Supported controlled pulse acquisition studies	PubMed, Scopus
2004	Piezoelectric Transducer for Radial Pulse	Sensor-based pulse acquisition	Dosha-related pulse measurement	Demonstrated feasibility of piezoelectric sensing	Limited stability and signal quality	Initiated sensor-assisted Ayurvedic pulse diagnosis	IEEE Xplore, Scopus
2006	Pulse Transit Time Estimation Using PZT Sensors	Time-domain pulse analysis	Arterial pulse timing estimation	Improved temporal measurement accuracy	Sensitive to motion artifacts	Supported development of multi-sensor systems	IEEE Xplore, Scopus
2007	Strain-Gauge Diaphragm System for Cun-Guan-Chi	Digital Naadi assessment	Vata, Pitta, and Kapha evaluation	First structured Ayurvedic pulse digitization system	Bulky design and calibration requirements	Became a reference model for later systems	IEEE Xplore, Scopus
2007	Probability Distribution of Waveform Amplitudes	Mathematical pulse analysis	Pulse variability assessment	Quantified pulse variations mathematically	Difficult clinical interpretation	Inspired entropy-based and probabilistic models	Scopus, Web of Science
2008	Waveform Analysis at Multiple Radial Positions	Multi-location pulse acquisition	Dosha localization studies	Demonstrated positional sensitivity of pulse signals	Standardization challenges	Motivated multi-sensor array development	Scopus, PubMed
2008	PWA Repeatability Studies	Pulse waveform validation	Consistency assessment	Established benchmark validation methods	Limited subject diversity	Improved reliability evaluation techniques	PubMed, Scopus
2009	Pregnancy Waveform Analysis	Obstetric monitoring	Pregnancy-related physiological changes	Identified diagnostic potential in pregnancy	Limited generalizability	Encouraged disease-specific pulse applications	PubMed, Scopus
2011	Pulse Mechanics and PWV Analysis	Biomedical pulse assessment	Arterial stiffness evaluation	Unified engineering and medical perspectives	Lack of experimental validation	Assisted future device and algorithm selection	Scopus, Web of Science

(*Continued*)

Table 2
(*Continued*)

Year	Method	Application scenario	Diagnostic target	Advantages	Limitations	Research motivation	Database source
2013	Transfer-Function-Based Estimation	Blood pressure monitoring	Central blood pressure estimation	Clinically meaningful BP prediction	Model dependency	Motivated ML-based blood pressure estimation	PubMed, IEEE Xplore, Scopus
2014	SVM with Elastic Distance Metrics	Automated pulse classification	Dosha and disease classification	First successful ML application in pulse diagnosis	Small dataset	Opened pathway for advanced AI models	IEEE Xplore, Scopus
2014	Wave Propagation and Intensity Modeling	Physiological pulse analysis	Hemodynamic assessment	Improved physiological interpretation	Computational complexity	Supported advanced pulse feature development	Scopus, Web of Science
2017	Cun-Guan-Chi Pulse Sensor	Ayurvedic pulse assessment	Dosha classification	Strong agreement with traditional diagnosis	Limited clinical validation	Basis for wearable pulse diagnosis systems	IEEE Xplore, Scopus
2018	ECG and Pulse Integration	Multimodal health monitoring	Continuous blood pressure estimation	Improved monitoring accuracy	Complex hardware design	Inspired multimodal diagnostic systems	IEEE Xplore, PubMed, Scopus
2018	Gestational Pulse Variation Study	Maternal health assessment	Physiological changes during pregnancy	Validated pulse variations across gestation	Small-scale study	Strengthened constitution-based analysis	PubMed, Scopus
2019	ApEn and Piezo-Electret Sensor Integration	Automated health monitoring	Health status detection	Detected subtle waveform variations	High computational cost	Motivated feature-engineering approaches	IEEE Xplore, Scopus
2021	Ayurvedic Pulse Assessment	Traditional diagnosis support	Disease identification	Demonstrated practical diagnostic use	Practitioner-dependent interpretation	Encouraged automation efforts	Scopus, PubMed
2021	PWV Estimation from Radial Pulse	Cardiovascular assessment	Arterial stiffness measurement	Noninvasive evaluation method	Device-specific datasets	Influenced cardiovascular ML applications	PubMed, Scopus
2022	PZT-Based Physiological Monitoring	Wearable health monitoring	Pulse and physiological parameter tracking	High sensitivity and compact design	Noise susceptibility	Foundation for next-generation wearable sensors	IEEE Xplore, Scopus
2022	Pulse Quality Assessment Using ML	Signal quality evaluation	Reliable pulse signal selection	Improved dataset reliability	Not disease-focused	Supported robust preprocessing strategies	IEEE Xplore, Scopus
2023	Cun-Guan-Chi Simulation Using PZT	Digital Naadi simulation	Dosha pattern analysis	Correlated with traditional pulse diagnosis	Early-stage validation	Basis for flexible pulse sensing systems	IEEE Xplore, Scopus

(*Continued*)

Table 2
(*Continued*)

Year	Method	Application scenario	Diagnostic target	Advantages	Limitations	Research motivation	Database source
2023	IoT-Enabled Health Monitoring	Remote healthcare monitoring	Continuous health assessment	Mapped recent digitization trends	Limited experimental validation	Motivated smart Naadi monitoring platforms	IEEE Xplore, Scopus
2023	Waveform Recognition with Cardiovascular Monitoring	Intelligent pulse diagnosis	Cardiovascular abnormality detection	High diagnostic precision	Requires high-quality sensors	Supported advanced sensing technologies	IEEE Xplore, Scopus
2025	Thin-Film PZT Radial Pulse Sensor	Wearable pulse diagnosis	Dosha and disease assessment	High precision with wearable design	Expensive fabrication process	Represents current state-of-the-art development	IEEE Xplore, Scopus, Web of Science

in data acquisition, classification, and various disease prediction through analyzation.

The present work is a review of pulse diagnosis technologies and does not focus on diagnosing a single disease. Instead, it examines the sensing methods, signal processing techniques, feature extraction approaches, and ML models that have been reported in previous studies. The literature shows that pulse-based diagnostic systems have been applied to the assessment of several health conditions. Among the most commonly investigated conditions are hypertension, cardiovascular diseases, diabetes, arrhythmia, arteriosclerosis, and other circulatory disorders. Researchers have analyzed variations in pulse waveform characteristics such as amplitude, rhythm, pulse width, and energy distribution to distinguish between healthy individuals and patients with specific medical conditions. By combining pulse signal analysis with ML techniques, these studies have demonstrated the potential of pulse diagnosis as a supportive tool for early disease detection and health monitoring. Therefore, rather than concentrating on a particular disease, this review highlights the broad range of medical applications in which pulse diagnosis has been explored.

3. Research Methodology

This research review highlights the consistent advancements in acquisition and analysis of dosha signals, which are widely driven by various biomedical sensing technologies, enhanced processing methods, and automated models. Early generations have proven that pulse waves can be collected consistently and reliably. Based on this groundwork, many advanced systems have been introduced based on sensors, AI, and IoT-enabled prototypes, which allow continuous monitoring and classification [31]. Despite several enhancements, various significant challenges still exist, such as large-scale validated datasets, metrics, and developing a fully automated system for routine healthcare monitoring and diagnosis. This extensive clinical use of pulse analysis is nevertheless constrained because of these persistent problems [32].

3.1. Data acquisition and dataset limitations

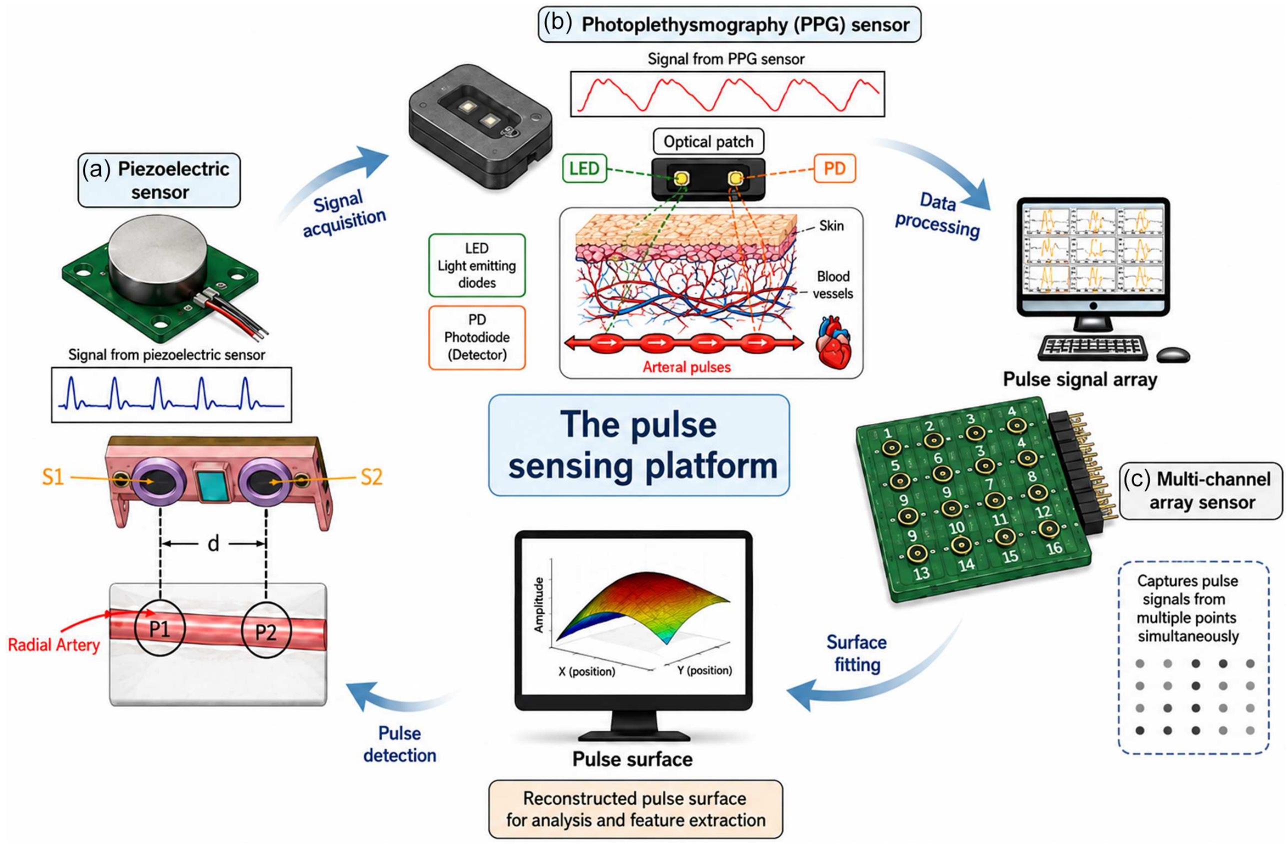
Acquiring a pulse signal plays a significant role in analysis. The features of acquiring data can be varied based on a person's diet, the position of the sensor probes, and the pressure sensitivity of the area. Only a few studies have used large datasets, but the majority of the paradigms used small-scale datasets. While tremendous sensor-based researches do not completely adhere to these conditions, the need for conventional practice in acquisition can produce large-scale datasets for analyzation. Additionally, the statistics generated by these studies are typically private and inaccessible to the public, which restricts the ability to compare different approaches or create consistent performance standards. The advancement of pulse diagnosis systems has been stimulated by the advancement of sensing technology for accurately and noninvasively measuring the pulse waveform. The most common techniques in the literature for capturing pulse signals are piezoelectric sensors, PPG sensors, and multichannel array sensors, as shown in Figure 2.

The piezoelectric sensor is used to detect the blood vessel pressure produced by the pulsation of the blood vessels. These sensors, when placed over the radial artery, are able to measure very small changes in pressure and generate an electrical signal, which can be recorded with a high degree of sensitivity. The sensor's direct response to arterial pressure variations makes it possible to gain information on the strength of the pulse, its rhythm, and the shape of the pulse wave [33].

PPG sensors are based on the optical principle. The skin is illuminated with a light source, and a photodetector is used to detect the light that is reflected or transmitted. The level of light detected by the photodiode fluctuates with blood volume changes in each heartbeat, creating a blood volume waveform or blood volume pulse signal. As PPG sensors are noninvasive, compact, and easy to use, they are commonly used in wearable, healthcare-related devices and continuous monitoring applications [34, 35].

Multichannel array sensors are sensors that are a matrix of various sensing elements. These sensors are not only located at a single site but also obtain data from multiple positions throughout

Figure 2
Common sensors used for pulse signal acquisition: (a) piezoelectric sensor, (b) photoplethysmography (PPG) sensor and (c) multichannel array sensor



the arterial area. This approach provides a more complete picture of the pulse characteristics, such as pressure distribution and spatial variations, which tends to be more reliable for assessing the pulse [36, 37].

When and after the signals are acquired, the recorded pulse waveforms are preprocessed to enhance the quality of the signals. Filtering techniques such as Butterworth, Bessel, and Chebyshev filters are used to eliminate unwanted noise, baseline drift, and motion artifacts. After the signals are cleaned, the physiological information of the signals is extracted from the waveform. Typical features extracted are pulse amplitude, peak locations, pulse width, heart rate, pulse rhythm, waveform morphology, and energy-related features. These features are then compiled into structured data and fed to ML and DL models for disease classification and prediction. With the fusion of advanced sensing technologies and feature extraction technology, the capacity of pulse diagnosis systems based on computers is greatly enhanced, and the assessment of human health conditions is more accurate and objective [38].

3.2. Signal preprocessing and denoising

After dataset preparation, various preprocessing techniques have been utilized by various research studies, such as Chebyshev, Butterworth, Bessel, and Savitzky–Golay filters, to denoise the signals to increase the precision. The variability in datasets due to noise can cause artifacts to affect the model's robustness. This variability makes cross-study comparison challenging and can have a substantial impact on diagnostic results because the shape and characteristics of the pulse waveform are very sensitive to these decisions. So, the determination of employing the exact preprocessing techniques will preserve the pivotal characteristics of pulse signals and enhance benchmark evaluations during analyzation [39, 40].

The Butterworth filters are, for example, used when high-frequency noise has to be reduced without affecting the response of the signal. The Bessel filters are used when it is important to maintain the temporal properties of the waveform since they cause little distortion to the waveform. The Chebyshev filters have a sharper transition band between the passband and stopband and can offer good noise suppression. Likewise, Savitzky–Golay filters are often used to smooth out pulse signals while preserving significant features of the signal, such as the morphology, peaks, and valleys [41].

The quality of the pulse features extracted in the preprocessing stage directly affects the quality of the features obtained. There can be residual noise or artifacts that can affect the characteristics of the waveform and, therefore, the results of the analysis [42]. Additionally, direct comparisons are often hard to make due to differences in the preprocessing techniques employed in studies. The type of preprocessing technique used to generate pulse waveforms is critical, as the waveforms are very sensitive to the process by which they are created, so careful selection of preprocessing is required to maintain meaningful physiological information. The improvement of the reliability of the feature extraction is just one of the benefits that can be achieved by effective preprocessing, which can also help to make diagnostic evaluation and performance evaluation more accurate.

3.3. AI model validation and interpretability

The comprehensive study on AI-based automated pulse diagnosis paradigms is generally focused on differentiating the normal and abnormal pulses, but its findings contributed little to real-time clinical decisions, and these implementations illustrated and proved that pulse analyzation can be done completely through computation, and it shows that various AI studies have been explored and evaluated for specific diseases such as diabetes, pregnancy pulse observation, and cardiac issues. Some of the significant ML techniques, such as KNN, RF, and SVM, achieved higher precision. They established and analyzed the correlation between extracted features through AI and traditional pulse analysis, such as normal stiffness, movement, and stiffness. But the limited interpretability due to small-scale datasets in ML paradigms is another crucial problem. Despite enhanced progress, there are still some gaps that persist including inadequate disease-specific validation, inconsistent preprocessing techniques, a lack of standardized data gathering protocols, restricted public dataset accessibility, and inadequate model transparency. To address these problems, engineers, data scientists, and Ayurvedic specialists must work together to create reliable datasets and comprehensible AI systems that connect contemporary analytics with conventional diagnostic knowledge [43, 44].

3.4. Conceptual framework and illustrations

The automated pulse analysis conceptual framework combines contemporary engineering and computational methods with conventional diagnostic concepts. It describes how AI is used to convert biological pulse signals obtained from the radial artery into useful diagnostic findings. Sensor-based pulse acquisition, data preprocessing and conditioning, feature extraction and classification, and AI-enabled disease prediction are the four main parts of this approach, as illustrated in detail in Figure 3. First, capturing the mechanical pulse variations generated by the cardiovascular system is the primary goal of the first component, the sensor-based prototype design. In accordance with Ayurvedic diagnostic sites, a multichannel sensing unit is positioned at the wrist's Vata, Pitta, and Kapha places. Small artery movements are converted into electrical impulses using piezoelectric, pressure, or optical sensors. A data acquisition module that interfaces with these sensors digitizes the pulse waveforms for collecting in real time. Software platforms such as LabVIEW or MATLAB assist the hardware, making it possible to continuously monitor, visualize, and save pulse data from patients of a variety of ages and health problems [45, 46].

Second, signal preparation ensures that raw data are clean, consistent, and analysis-ready. Motion noise, baseline drift, sensor movement, and ambient interference can all affect pulse signals. So, to overcome that, various filtering techniques such as denoising and noise cancelation were utilized, and correlating pulse replication and removing artifacts through normalization and segmentation enhances the signal's quality. These results provide a stable waveform that observes each individual's unique physiological features. Piezoelectric, PPG, and multichannel array sensors only obtain the pulse signals as continuous waveforms. These waveforms have useful information about cardiovascular activity. These data are used for computational analysis to represent numerically. The parameters that are commonly extracted are pulse amplitude, heart rate, pulse width, peak-to-peak interval, and signal energy. The numerical characteristics are used to give a quantitative description of the pulse and will serve as input to the models for disease classification.

The values in Table 3 depict how the pulse waveforms are converted into measurable parameters. For instance, the amplitude of a pulse is the energy of the pulse signal, and the width of a pulse is the length of a pulse cycle. Heart rate variability is estimated by the peak-to-peak interval, and the energy index gives information on the overall intensity of the pulse form. The data obtained by these methods can be used to systematically analyze for the prediction of disease and health assessment using ML and DL techniques.

Third, cleaned waveforms are transformed into quantitative descriptors in the third component, feature extraction and classification. Amplitude, slope, pulse width, and interbeat intervals are examples of time-domain characteristics. While morphological parameters describe rigidity, rhythm, and waveform shape, frequency-domain aspects capture harmonic content and energy

Figure 3
Illustration of conceptual framework and stages of pulse diagnosis

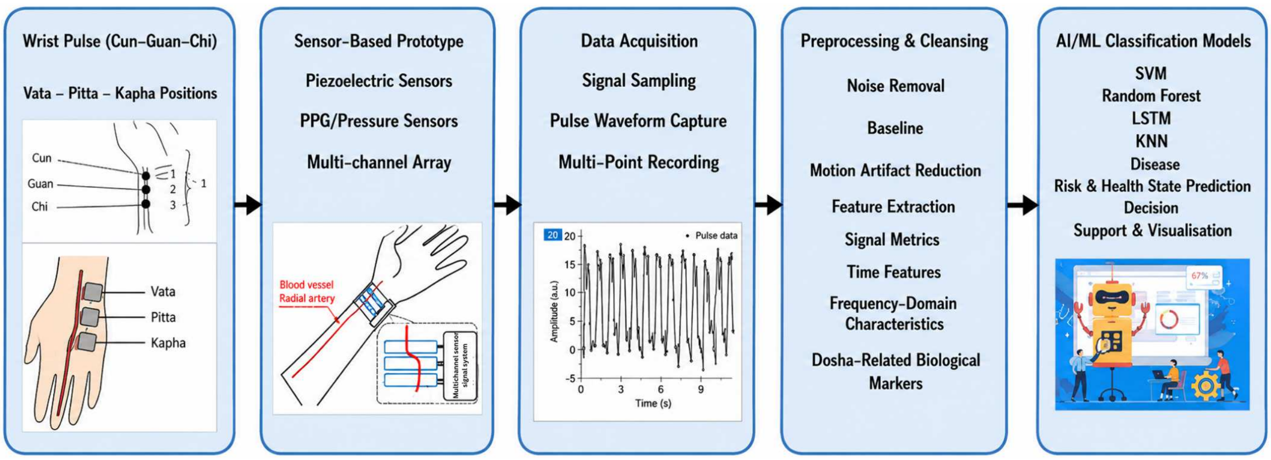


Table 3
Samples of numerical features extracted from pulse sensor measurements

Sample ID	Sensor type	Pulse amplitude (mV)	Heart rate (BPM)	Pulse width (ms)	Peak-to-peak interval (ms)	Energy index
S1	Piezoelectric	1.24	72	145	833	0.84
S2	Piezoelectric	1.37	76	141	789	0.89
S3	PPG	0.95	71	150	845	0.80
S4	PPG	1.08	82	132	732	0.93
S5	Multichannel Array	1.42	74	143	811	0.88
S6	Multichannel Array	1.56	87	128	690	1.01

distribution. ML techniques such as SVM, RF, KNN, and Decision Trees are used to analyze these features. Subjects are categorized by the models according to demographic parameters, including age and gender, dominant dosha patterns, or pulse characteristics.

Finally, the last part connects clinical results with quantified pulse properties through AI-driven illness prediction. To detect early indicators of metabolic, cardiovascular, and stress-related disorders, predictive models are trained. AI algorithms create risk evaluations and likelihood scores by identifying minute waveform abnormalities linked to conditions such as diabetes, hypertension, or vascular stiffness. This process turns conventional pulse interpretation into a diagnostic tool with a solid scientific foundation. When combined, these elements provide a methodical approach that combines conventional wisdom with cutting-edge technology to produce a dependable system for objective, noninvasive pulse-based diagnosis.

However, the advent of ML and DL techniques has brought new possibilities for automatic pulse diagnosis in Ayurvedic tradition, as represented in Table 4. Pulse examination in Ayurvedic medicine is an approach that assesses the equilibrium between Vata, Pitta, and Kapha by observing characteristics such as strength, rhythm, speed, depth, and regularity of the pulse. Many of the parameters that are extracted from the digital pulse signals, such as amplitude, pulse width, peak characteristics, energy-related parameters, etc., are measured representations of the traditional observations [47, 48]. Thus, computational techniques are adjunctive tools to enhance the uniformity and objectivity in the assessment of the pulse, while maintaining important principles of Ayurvedic diagnosis [49, 50].

As people start to use wearable pulse monitoring systems, data privacy and ethical use have become an issue of great concern. The devices continuously record physiological data; therefore, suitable protective measures must be taken to ensure that the physiological data are not accessed or used by another party. Data storage, transmission, and sharing should be done in a proper way to ensure data confidentiality and compliance with the relevant data sharing rules. It is also vital that the users be told what information is being collected and how it is being used. Finally, more transparency in automated decision-making can boost the confidence of the users and help foster responsible use of wearable pulse monitoring technology in healthcare practice [51].

Table 4
Comparison of machine learning and deep learning models used in automated pulse diagnosis

Model	Typical dataset size	Application	Strengths	Limitations
KNN	Small to medium datasets	Dosha classification and Pattern recognition of pulses	Easy implementation and easy to understand	Performance decreases with large datasets and noisy data
SVM	Small to medium datasets	Disease classification and pulse categorization	Effective for high-dimensional data and limited samples	Sensitive to parameter selection and kernel choice
Decision Tree	Small datasets	Rule-based pulse classification	Easy to understand and visualize	Prone to overfitting
Random Forest	Medium to large datasets	Disease prediction and pulse feature classification	Improved robustness and reduced overfitting	Increased computational complexity
ANN	Medium datasets	Pulse pattern learning and disease detection	Captures nonlinear relationships	Requires parameter tuning and sufficient training data
CNN	Large datasets	Automated pulse waveform analysis	Learns features directly from raw signals	Requires large labeled datasets and computational resources
LSTM	Sequential pulse datasets	Temporal pulse signal analysis	Effective for time-series data	Training complexity and longer processing time

4. Conclusion

This review explored and analyzed the evolution of various basic and semiautomated pulse diagnosis paradigms from the initial stage to the final stage, which is from signal acquisition to AI-based disease diagnosis paradigms. The replacement of disease diagnosis through physical palpation has been precisely done by sensor models for data acquisition, waveform variation analysis, and classification through advanced computational models. However, existing researchers have analyzed tridosha imbalances digitally, but still, there are some limitations that persist in data collection, feasible preprocessing selection for denoising, a fully automated model, experts' direction, and clinical validation. The majority of these research studies were employed, explored, and utilized as experimental tools rather than as clinically diagnostic solutions.

The results show that there is a great advancement in the field of sensor technology, signal preprocessing, feature extraction, and ML-based diagnostic techniques. Recent advances have helped to increase the objectivity of the pulse assessment and decreased the need to rely on subjective interpretations. Despite these gains, however, differences in data collection techniques and the fact that these systems have not been widely tested in clinical settings remain to impact the reliability and widespread use of these systems.

5. Future Work

The development of well-defined techniques for positioning sensors, applying the pressure, and the settings for sampling will be beneficial to future research, providing continuously enhanced results in real time. In the future, the process of understanding the diagnostic judgment by an automated model requires the integration of explainable AI into the computational aspects and traditional Ayurvedic concepts. The future of wearable sensors, multimodal data fusion technologies, and cloud-based analytics will further aid continuous monitoring and remote health evaluations. The ultimate goal of future research ought to be to create something fully validated, understandable, and clinically applicable that incorporates modern biomedical technology and traditional pulse diagnostics.

Recommendations

Developing and creating large-scale datasets with consistent placement in sensor, frequency, and diversity in real time and allowing that to be utilized by researchers can increase the validation accuracy of the datasets. Using multimodal sensors to acquire and detect slight variations in the pulse and then incorporating denoising can enhance accuracy and reliability. After that, correlating and integrating the modern and traditional metrics can provide several hybrid features for analyzation. Utilizing an advanced AI model for interpretation can produce classification of doshas, imbalances, and disease predictions. However, after developing a fully automated analysis paradigm, it is recommended to test the paradigm with a real-time clinical trial, especially for hypertension, nervous disorders, diabetes, and cardiac disorders, and this fully automated paradigm needs to be deployed into a single system. It needs to ensure compliance with medical regulations and the patient's privacy guidelines. After that, exploration and expansion should be done for collaboration with AI experts to develop more paradigms.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Priyadharshini K: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Saravanan K:** Conceptualization, Validation, Writing – review & editing, Supervision, Project administration.

References

[1] Lee, D., Park, S., Kim, G., Baek, Y., & Park, Y.-C. (2025). Effect of contralateral acupuncture (Geoja technique) in musculoskeletal disorders stratified by pulse strength differences: A retrospective study [Response to Letter]. *Journal of Pain Research*, *2025*(18), 6849–6852. https://doi.org/10.2147/JPR.S584837

[2] Jonnalagadda, P., & Biswas, A. (2025). A review on radial artery pulse diagnosis training simulators: Challenges and future scope. In *Responsible and Resilient Design for Society, Proceedings of ICoRD 2025*, 75–85. https://doi.org/10.1007/978-981-96-5507-6_7

[3] Sheikhlarabadi, J., Arabzadeh, M., & Esfahani Khaleghi, A. (2025). Diagnosing anxiety with the Ayurvedic pulse reading method. *International Journal of Social Sciences and Management Review*, *8*(5), 10–20.

[4] Bawankar, B. U., Dharmik, R. C., & Telrandhe, S. (2021). Nadi pariksha: IOT-based patient monitoring and disease prediction system. *Journal of Physics: Conference Series*, *1913*(1), 012124. https://doi.org/10.1088/1742-6596/1913/1/012124

[5] Kumar, S., Tayade, A., Shrivastava, A., & Bhallamudi, R. (2026). Non-invasive cardiovascular risk stratification in type 2 diabetes: A pulse wave and pulse rate variability analysis with machine learning. *Biomedical Signal Processing and Control*, *112*, 108938. https://doi.org/10.1016/j.bspc.2025.108938

[6] Travers, C. P., Nakhmani, A., Armstead, K. M., Benz, R. L., Foshee, K. M., & Carlo, W. A. (2026). Diagnostic accuracy of an over-the-counter infant pulse oximeter for cardiorespiratory events. *Archives of Disease in Childhood - Fetal and Neonatal Edition*, *111*(1), F13–F19. https://doi.org/10.1136/archdischild-2025-328540

[7] Ko, S. Y., Ghotb Razmjou, S., Haagsma, J. A., & Verdonschot, R. J. C. G. (2026). Point-of-care ultrasound vs. manual palpation for pulse check in cardiac arrest patients: A systematic review. *The Journal of Emergency Medicine*, *80*, 112–118. https://doi.org/10.1016/j.jemermed.2025.09.019

[8] Huang, L., Šmíd, M., Yang, L., Humphries, O., Hagemann, J., Engler, T., . . . , & Cowan, T. E. (2026). Demonstration of

full-scale spatiotemporal diagnostics of solid-density plasmas driven by an ultra-short relativistic laser pulse using an X-ray free-electron laser. *Matter and Radiation at Extremes*, *11*(1), 017201. https://doi.org/10.1063/5.0279974

[9] O'Rourke, M. F., & Gallagher, D. E. (1996). Pulse wave analysis. *Journal of Hypertension. Supplement: Official Journal of the International Society of Hypertension*, *14*(5), S147–S157.

[10] Duprez, D. A., Kaiser, D. R., Whitwam, W., Finkelstein, S., Belalcazar, A., Patterson, R., . . . , & Cohn, J. N. (2004). Determinants of radial artery pulse wave analysis in asymptomatic individuals. *American Journal of Hypertension*, *17*(8), 647–653. https://doi.org/10.1016/j.amjhyper.2004.03.671

[11] Guo, C., Dai, S., Zhang, C., Jiang, Z., Wu, B., & Zhang, D. (2026). Data-driven study on why wrist pulse can assess health conditions. *IEEE Journal of Biomedical and Health Informatics*, *30*(1), 138–148. https://doi.org/10.1109/JBHI.2025.3598165

[12] Dai, S., Zhang, C., Guo, C., Wu, B., & Zhang, D. (2025). Hierarchical fuzzy stochastic configuration network based on canonical correlation analysis for multiview pulse signal fusion. *IEEE Transactions on Fuzzy Systems*, *33*(8), 2779–2791. https://doi.org/10.1109/TFUZZ.2025.3576112

[13] Fan, L., Chen, T., He, L., Wang, Z., & Zhang, R. (2025). GADM: Data augmentation using Generative Adversarial Diffusion Model for pulse-based disease identification. *Biomedical Signal Processing and Control*, *100*, 107005. https://doi.org/10.1016/j.bspc.2024.107005

[14] Zhao, X., Song, Y., Shi, B., & Fan, Y. (2025). Continuous dynamic microforce reconstruction using electrical stimulation for remote pulse diagnosis. *Fundamental Research*, *5*(6), 2453–2462. https://doi.org/10.1016/j.fmre.2025.09.002

[15] Ali, F., Rehman, S., Ayaz, A., & Ahmad, A. M. (2025). Disease detection using wrist pulse analysis. *International Journal of Innovations in Science & Technology*, *7*(7), 50–61. https://doi.org/10.33411/IJIST/1329

[16] Fatangare, M., & Bhingarkar, S. (2024). A comprehensive review on technological advancements for sensor-based Nadi Pariksha: An ancient Indian science for human health diagnosis. *Journal of Ayurveda and Integrative Medicine*, *15*(3), 100958. https://doi.org/10.1016/j.jaim.2024.100958

[17] Jia, H., Gao, Y., Zhou, J., Li, J., Yiu, C. K., Park, W., . . . , & Yu, X. (2024). A deep learning-assisted skin-integrated pulse sensing system for reliable pulse monitoring and cardiac function assessment. *Nano Energy*, *127*, 109796. https://doi.org/10.1016/j.nanoen.2024.109796

[18] Manjunatha, Y. C., Raghu, B., & Pavan Kumar, Y. C. (2023). Nadifit: A novel single position pulse based diagnostic system. *International Journal of Community Medicine and Public Health*, *10*(11), 4512–4519. https://doi.org/10.18203/2394-6040.ijcmph20233503

[19] Palakurthi, M., Fergusson, L., Dornala, S. N., & Schneider, R. H. (2021). Diagnostic validity of Āyurvedic pulse assessment: Maharishi Nādi-Vigyān in cardiovascular health. *Journal of Maharishi Vedic Research Institute*, *17*, 33–73.

[20] Fan, L., Zhang, J. C., Wang, Z., Zhang, X., Yao, R., & Li, Y. (2022). Application research of pulse signal physiology and pathology feature mining in the field of disease diagnosis. *Computer Methods in Biomechanics and Biomedical Engineering*, *25*(10), 1111–1124. https://doi.org/10.1080/10255842.2021.2002306

[21] Dubey, S., Chinnaiah, M. C., Pasha, I. A., Prasanna, K. S., Kumar, V. P., & Abhilash, R. (2022). An IoT based Ayurvedic approach for real time healthcare monitoring. *AIMS Electronics and Electrical Engineering*, *6*(3), 329–344. https://doi.org/10.3934/electreng.2022020

[22] Jin, W., Chowienczyk, P., & Alastruey, J. (2021). Estimating pulse wave velocity from the radial pressure wave using machine learning algorithms. *PLOS One*, *16*(6), e0245026. https://doi.org/10.1371/journal.pone.0245026

[23] Yazhini, A., & Saravanan, K. (2023). IoT based Siddha diagnosis for human health monitoring. *Indian Journal of Traditional Knowledge*, *22*(4), 717–726. https://doi.org/10.56042/ijtk.v22i4.7195

[24] Sanu, U. S., Prasad, B. S., Hiremath, R. R., & Vernekar, S. S. (2023). Repeatability of arterial pulse-based diagnosis (*Naadi pariksha*) by test–retest method: An observation study. *Indian Journal of Health Sciences and Biomedical Research KLEU*, *16*(1), 41–47. https://doi.org/10.4103/kleuhsj.kleuhsj_398_21

[25] Sanu, U., Vernekar, S. S., & Patil, S. (2025). The ultrasound Doppler study of distal radial arterial pulse (Naadi) for various pulse characteristics in Vataja Naadi, Pittaja Naadi, Kaphaja Naadi and Sama Naadi– A cross-sectional pilot study. *Journal of Ayurveda and Holistic Medicine*, *13*(8), 12–24. https://doi.org/10.70066/jahm.v13i8.2092

[26] Nie, J., Zhang, L., Liu, J., & Wang, Y. (2022). Pulse taking by a piezoelectric film sensor via mode energy ratio analysis helps identify pregnancy status. *IEEE Journal of Biomedical and Health Informatics*, *26*(5), 2116–2123. https://doi.org/10.1109/JBHI.2021.3125707

[27] Ouyoung, T., Weng, W.-L., Hu, T.-Y., Lee, C.-C., Wu, L.-W., & Hsiu, H. (2022). Machine-learning classification of pulse waveform quality. *Sensors*, *22*(22), 8607. https://doi.org/10.3390/s22228607

[28] Liu, Y.-Y., Lv, Y.-X., & Xue, H.-B. (2023). Intelligent wearable wrist pulse detection system based on piezoelectric sensor array. *Sensors*, *23*(2), 835. https://doi.org/10.3390/s23020835

[29] Deng, Z., Guo, L., Chen, X., & Wu, W. (2023). Smart wearable systems for health monitoring. *Sensors*, *23*(5), 2479. https://doi.org/10.3390/s23052479

[30] Kumar, S., Singh, D. N., & Mahato, D. K. (2025). PZT-based piezoelectric materials: From synthesis to functional properties and diverse applications. In N. B. Singh & D. K. Mahato (Eds.), *Piezoelectric materials: Design and applications* (pp. 47–73). Jenny Stanford Publishing. https://doi.org/10.1201/9781003598978-3

[31] Gabrielli, D., Prenkaj, B., Velardi, P., & Faralli, S. (2025). AI on the pulse: Real-time health anomaly detection with wearable and ambient intelligence. In *Proceedings of the 34th ACM International Conference on Information and Knowledge Management*, 4717–4721. https://doi.org/10.1145/3746252.3760799

[32] Zheng, Y. (2025). *A review of wearable sweat monitoring platforms: From biomarker detection to signal processing systems*. arXiv. https://doi.org/10.48550/ARXIV.2512.01320

[33] Saha, M., Xu, M. A., Mao, W., Neupane, S., Rehg, J. M., & Kumar, S. (2025). Pulse-PPG: An open-source field-trained PPG foundation model for wearable applications across lab and field settings. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *9*(3), 126. https://doi.org/10.1145/3749494

[34] Zheng, Y., Wu, C., Cai, P., Zhong, Z., Huang, H., & Jiang, Y. (2024). Tiny-PPG: A lightweight deep neural network for real-time detection of motion artifacts in photoplethysmogram

signals on edge devices. *Internet of Things*, *25*, 101007. https://doi.org/10.1016/j.iot.2023.101007

[35] Rubin, I. M., & Volynsky, M. A. (2026). Obzor metodov glubokogo obucheniya dlya obrabotki videodannykh v fotopletizmografii [Review of deep learning methods for imaging photoplethysmography data processing]. *Scientific and Technical Journal of Information Technologies, Mechanics and Optics*, *26*(2), 236–249. https://doi.org/10.17586/2226-1494-2026-26-2-236-249

[36] Liu, T., Gou, G., Gao, F., Yao, P., Wu, H., Guo, Y., . . . , & Xue, N. (2023). Multichannel flexible pulse perception array for intelligent disease diagnosis system. *ACS Nano*, *17*(6), 5673–5685. https://doi.org/10.1021/acsnano.2c11897

[37] Kang, X., Huang, L., Zhang, Y., Yun, S., Jiao, B., Liu, X., . . . , & Zhang, H. (2023). Wearable multi-channel pulse signal acquisition system based on flexible MEMS sensor arrays with TSV structure. *Biomimetics*, *8*(2), 207. https://doi.org/10.3390/biomimetics8020207

[38] Xie, H., Yang, L., Jiang, B., Huang, Z., & Lin, Y. (2025). State-of-the-art wearable sensors for cardiovascular health: A review. *npj Cardiovascular Health*, *2*(1), 53. https://doi.org/10.1038/s44325-025-00090-6

[39] Liao, S., Liu, H., Lin, W.-H., Zheng, D., & Chen, F. (2023). Filtering-induced changes of pulse transmit time across different ages: A neglected concern in photoplethysmography-based cuffless blood pressure measurement. *Frontiers in Physiology*, *14*, 1172150. https://doi.org/10.3389/fphys.2023.1172150

[40] Fromberg, L., Das, S., & Clemmensen, L. K. H. (2023). *Pre-processing blood-volume-pulse for in-the-wild applications*. arXiv. https://doi.org/10.48550/ARXIV.2304.14186

[41] Watanabe, Y., Yamane, N., Sathyanarayana, A., Mishra, V., & Goodwin, M. S. (2026). Beyond motion artifacts: Optimizing PPG preprocessing for accurate pulse rate variability estimation. In *Companion of the 2025 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 1176–1182*. https://doi.org/10.1145/3714394.3756241

[42] Hibbing, P. R., & Khan, M. M. (2024). Raw photoplethysmography as an enhancement for research-grade wearable activity monitors. *JMIR mHealth and uHealth*, *12*, e57158. https://doi.org/10.2196/57158

[43] Lapitan, D. G., Rogatkin, D. A., Molchanova, E. A., & Tarasov, A. P. (2024). Estimation of phase distortions of the photoplethysmographic signal in digital IIR filtering. *Scientific Reports*, *14*(1), 6546. https://doi.org/10.1038/s41598-024-57297-3

[44] Kao, Y.-H., Shahmirzadi, D., Hsieh, S.-T., & Wang, W.-F. (2025). Filter and sampling rate optimization for PPG-based detection of autonomic dysfunction: An ECG-guided approach. *Measurement Science Review*, *25*(4), 200–211. https://doi.org/10.2478/msr-2025-0024

[45] Cao, Y., Li, P., Zhu, Y., Wang, Z., Tang, N., Li, Z., . . . , & Sun, L. (2025). Artificial intelligence-enabled novel atrial fibrillation diagnosis system using 3D pulse perception flexible pressure sensor array. *ACS Sensors*, *10*(1), 272–282. https://doi.org/10.1021/acssensors.4c02395

[46] Zhu, J., Yuan, K., Prabhakara, A., Li, Y., Wang, G., Michaelsen, K., . . . , & Kumar, S. (2026). Measuring multi-site pulse transit time with an AI-enabled mmWave radar. *Nature Communications*, *17*(1), 4554. https://doi.org/10.1038/s41467-026-73453-x

[47] Jain, P., Ding, C., Rudin, C., & Hu, X. (2024). A self-supervised algorithm for denoising photoplethysmography signals for heart rate estimation from wearables. *Harvard Data Science Review*, *6*(3), 1–45. https://doi.org/10.1162/99608f92.8636cb81

[48] Chen, W., Yi, Z., Lim, L. J. R., Lim, R. Q. R., Zhang, A., Qian, Z., . . . , & Liu, B. (2024). Deep learning and remote photoplethysmography powered advancements in contactless physiological measurement. *Frontiers in Bioengineering and Biotechnology*, *12*, 1420100. https://doi.org/10.3389/fbioe.2024.1420100

[49] Kechris, C., Dan, J., Miranda, J., & Atienza, D. (2025). KID-PPG: Knowledge informed deep learning for extracting heart rate from a smartwatch. *IEEE Transactions on Biomedical Engineering*, *72*(3), 870–877. https://doi.org/10.1109/TBME.2024.3477275

[50] Jiang, H., Yao, T., & Ding, C. (2025). PPG-based glucose sensors: A review. *Artificial Intelligence Review*, *58*(12), 391. https://doi.org/10.1007/s10462-025-11379-4

[51] Castrejón-Peralta, C., Montiel-Pérez, J. Y., Gante-Díaz, S. A., Cruz-Vazquez, J. A., Rubín-Alvarado, A. A., Reyes-Vera, Z., . . . , & Cruz-Sánchez, V. G. (2026). Artificial intelligence and deep learning-based methods and devices for measuring vital signs: A systematic review. *Applied Sciences*, *16*(2), 1126. https://doi.org/10.3390/app16021126

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