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From pulse to pixel: artificial intelligence-enhanced pulse diagnosis for cardiovascular diseases

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Traditional Chinese medicine (TCM) pulse diagnosis is a non-invasive approach used to infer cardiovascular status, but its interpretation is relatively subjective, limiting reproducibility and diagnostic precision. This review summarizes progress in digitized radial pulse assessment using modern sensors and artificial intelligence (AI), and evaluates reported applications in cardiovascular screening and decision support. We searched PubMed, IEEE Xplore, and Web of Science Core Collection from inception through November 30, 2025, for studies that acquired wrist/radial pulse signals with electronic devices and applied quantitative analysis or machine learning/deep learning to characterize pulse patterns or assess cardiovascular conditions. Across the literature, pressure-sensor arrays, wearable photoplethysmography (PPG) surrogates, and hybrid platforms enabled more standardized pulse acquisition, while AI models reported promising performance for tasks such as blood pressure estimation, hypertension screening, coronary artery disease identification, heart failure risk stratification, and arrhythmia detection. However, methodological heterogeneity, limited sample sizes, inconsistent labeling standards, and insufficient external validation remain key barriers to clinical translation. Overall, AI-enhanced digital pulse diagnosis may improve the objectivity of TCM pulse assessment and complement conventional cardiovascular diagnostics, provided that future studies adopt rigorous protocols, transparent reporting, and clinically meaningful prospective validation.

1 Introduction

Pulse diagnosis is a cornerstone of traditional Chinese medicine (TCM), with classical texts such as the *Huangdi Neijing* (《黄帝内经》, *Inner Canon of Huangdi*) and the *Maijing* (《脉经》, *Pulse Classic*) describing how pulse features reflect internal organ health and classifying 28 distinct pulse types (e.g., floating, deep, slippery, wiry, and intermittent) [1, 2]. The heart is considered to govern the pulse in TCM theory, and changes in radial artery pulsation may provide clues to cardiovascular function and systemic health. Practitioners palpate the radial arteries at three positions [Cun (寸), Guan (关), and Chi (尺)] and multiple depths to assess a patient’s condition (Figure 1). To improve objectivity and reproducibility, engineering studies have developed multi-dimensional wrist pulse acquisition systems that quantify waveform features and spatial information that are difficult to assess manually [3]. These digital platforms can be combined with signal processing and machine learning

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models to support cardiovascular screening tasks such as blood pressure estimation and hypertension classification [3-5].

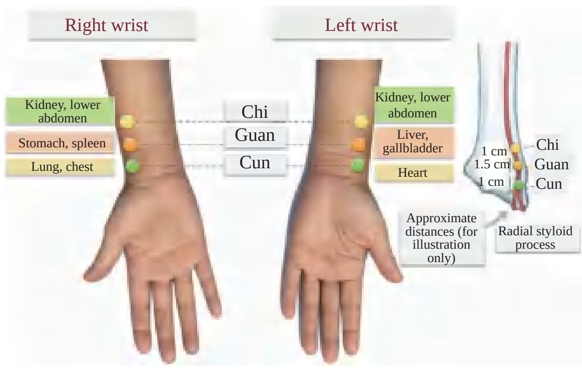

Figure 1 Standard palpation sites for TCM wrist pulse diagnosis

The schematic shows the three radial pulse-taking positions, Cun, Guan, and Chi, on both wrists. Cun is located closest to the palm/hand, Guan is located at the middle position near the radial styloid process, and Chi is located proximally toward the elbow. In the inset, the two 1 cm labels indicate the approximate distal and proximal intervals around Guan, while the 1.5 cm label indicates the approximate middle region centered near Guan. These distances are illustrative only and may vary with individual anatomy and clinical palpation practice. The adjacent labels show commonly used TCM organ-system correspondences for each pulse position.

During pulse-taking, practitioners palpate the radial artery at the Cun, Guan, and Chi positions using three fingers and evaluate multiple dimensions, including depth (superficial and deep), rate, strength, shape (e.g., slippery, wiry, choppy, and thready), and rhythm (regular vs. intermittent) [4]. For example, Huamai (滑脉, slippery pulse) is often described as smooth and flowing, whereas Semai (涩脉, choppy pulse) feels rough and uneven. Daimai (代脉, intermittent pulse) is characterized by irregular pauses and may be clinically relevant when arrhythmia is suspected. Some studies have reported associations between TCM pulse features and biomedical indices in cardiovascular disease, including coronary artery disease and hypertension [5, 6].

However, pulse diagnosis remains subjective and highly dependent on practitioner experience, and multiple pulse qualities can co-exist within the same patient. This complexity makes it difficult to quantify pulse patterns consistently, particularly in patients with complex cardiovascular diseases, where several pathological processes may occur simultaneously. To address these challenges, digital pulse-sensing systems aim to capture standardized waveform signals (e.g., amplitude, timing, and spatial distribution) and link them to clinically meaningful cardiovascular outcomes [3]. Advances in artificial intelligence (AI) may further support automated pattern recognition and classification, potentially improving reproducibility and enabling broader screening applications [7].

Despite its widespread use in TCM, manual pulse palpation is limited by subjectivity and inter-practitioner variability. Because assessment relies on tactile perception and qualitative descriptors, different practitioners (or the same practitioner at different times) may describe the same pulse differently [8, 9]. An earlier technical study also attempted to analyze pulse diagnosis quantitatively [10]. Variability can also be influenced by finger placement, applied pressure, and sensory acuity. Device-based platforms that standardize sensor placement, contact pressure, and acquisition conditions can improve comparability across recordings [11]. Manual palpation also provides only a brief snapshot and cannot be continuously monitored or objectively recorded. Digital acquisition could enable longitudinal pulse-waveform monitoring and quantification of features such as amplitude, variability, and contour as research endpoints [5]. Nevertheless, wearable optical pulse surrogates [e.g., photoplethysmography (PPG)] face challenges related to motion artifacts, skin tone, and long-term adherence [12-14]. Finally, broader clinical adoption will require device-based measurements that ground pulse descriptors in biophysical signals and support validation against clinical standards [11].

Cardiovascular diseases such as hypertension, coronary artery disease, and heart failure remain leading causes of morbidity and mortality worldwide [15, 16]. There is therefore a strong need for reliable, non-invasive approaches for early detection and longitudinal monitoring. If combined with modern sensor technologies and computational analytics, wrist pulse assessment could potentially complement conventional cardiovascular evaluation by enabling low-cost and scalable monitoring of peripheral pulse-wave dynamics. A recent review has also highlighted the broader role of AI in Chinese medicine for cardiovascular diseases, including risk prediction, diagnostic assistance, chronic disease management, and integrative clinical decision support [17].

In this article, “pulse diagnosis” refers to assessing cardiovascular conditions from pulsatile signals obtained at the wrist/radial artery in TCM practice. We primarily focus on digital tools for measuring radial pulse pressure/force (e.g., tonometry or pressure-sensor arrays aligned with the Cun, Guan, and Chi positions) and computational analysis for recognizing pulse patterns and identifying cardiovascular conditions. We discuss PPG as an optical surrogate signal widely used in wearable devices. Although PPG captures changes in blood volume rather than arterial pressure and is not equivalent to traditional pulse palpation, it can serve as a practical bridge to clinically validated workflows (e.g., rhythm monitoring and arrhythmia screening).

2 Methods of literature search

Given the breadth of wrist pulse-based sensing research across diverse clinical fields, this review focuses on cardiovascular applications of pulse diagnosis and pulse-waveform analytics. Non-cardiovascular studies were cited only when they provided broadly applicable methodological or sensor-platform insights (e.g., wearable pulse-based machine-learning pipelines developed for other diseases) [18].

2.1 Paper retrieval strategy

We searched PubMed, IEEE Xplore, and Web of Science Core Collection from inception through November 30, 2025, for studies on digital pulse diagnosis technologies and AI-driven pulse pattern recognition with cardiovascular applications.

Search terms were organized into three concept blocks: (i) pulse diagnosis/pulse waveform (e.g., "pulse diagnosis" "radial pulse" and "pulse waveform"), (ii) traditional Chinese medicine (e.g., "TCM" and "Chinese medicine"), and (iii) computational analytics (e.g., "artificial intelligence" "machine learning" and "deep learning"), combined with cardiovascular-related terms as needed.

Equivalent keyword strategies were adapted for IEEE Xplore and Web of Science Core Collection using the same concept blocks. We also manually screened reference lists in the retrieved papers for key relevant articles.

2.2 Inclusion and exclusion criteria

Inclusion criteria were: (i) studies published in English; (ii) peer-reviewed journal articles, conference papers, or clinical trials; and (iii) studies using pulse-derived signals (e.g., radial artery pressure/force signals or optical pulse surrogates such as PPG) for cardiovascular diagnosis, screening, monitoring, or risk assessment.

Exclusion criteria were: (i) purely theoretical studies without empirical pulse-wave data; (ii) studies primarily focused on non-cardiovascular conditions, unless they contributed broadly relevant methodological insights; and (iii) reviews or opinion pieces without new analysis.

2.3 Study screening

Two reviewers independently screened titles/abstracts and then full texts for eligibility. Disagreements were resolved by discussion and, when necessary, adjudication by a third reviewer.

3 Digital pulse diagnosis technologies and AI-driven analytics

To clarify the workflow from device development to clinical applications, Figure 2 summarizes a typical AI-driven

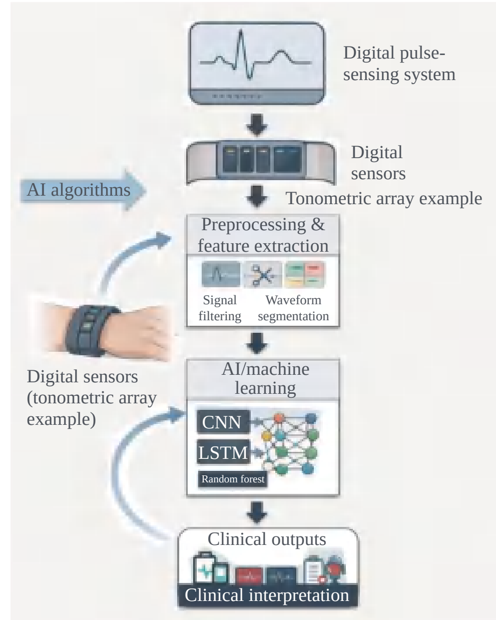

Figure 2 Conceptual workflow for AI-driven digital pulse diagnosis and cardiovascular applications

Schematic overview of a workflow in which wrist pulse signals are acquired using digital sensors, preprocessed, converted into features or representations, and analyzed using AI and machine learning models to generate clinically interpretable cardiovascular outputs. CNN, convolutional neural network; LSTM, long short-term memory.

digital pulse diagnosis pipeline: pulse signals acquired at the Cun, Guan, and Chi positions are preprocessed, transformed into features or representations, and analyzed by machine-learning models to support cardiovascular decision-making.

3.1 Sensor platforms and pulse waveform acquisition

Traditional pulse diagnosis is inherently multi-dimensional, sensing the pulse at different locations and depths simultaneously [3]. A single sensor therefore yields limited data—analogous to listening to a symphony with one earplug. Consequently, multi-point sensing platforms have been developed to better approximate the three-finger palpation approach.

As illustrated in Figure 2, AI-driven digital pulse diagnosis integrates sensor-based pulse acquisition with signal preprocessing, feature extraction, and machine learning analytics. ZHAO et al. [11] developed a flexible three-channel wrist pulse monitoring device using an array of pressure sensors aligned with the Cun, Guan, and Chi positions. The device modulated the applied contact pressure using miniature inflatable airbags to mimic the gradual pressing used in manual palpation, enabling waveform acquisition across different pressure depths. The flexible sensors showed high sensitivity and linearity and supported wireless, continuous pulse recording [11]. By analyzing how pulse amplitude changed with applied pressure, the system also estimated blood pressure non-invasively and reported performance consistent with the Association for the Advancement of Medical Instrumentation (AAMI) standard [11, 19].

Beyond pressure-sensor arrays, optoelectronic sensing with PPG provides an optical surrogate of the pulse waveform and is widely used in wearable devices. Although PPG measures blood volume changes rather than arterial wall pressure, it can support large-scale monitoring and cardiovascular screening, and in some systems it has been combined with pressure sensors to enrich the captured information [12, 13, 20]. In addition, multi-dimensional wrist pulse acquisition platforms have been proposed to capture spatial features (e.g., pulse-width distribution) in addition to temporal waveforms [3]. Such efforts, particularly active in East Asia, illustrate the diversity of sensor modalities being explored for digitizing pulse diagnosis [3].

Several commercial and research prototypes have been developed in China, reflecting strong interest in the digitization of TCM pulse diagnosis. For example, Shanghai University of Traditional Chinese Medicine has reported pulse diagnostic instruments capable of collecting detailed wrist pulse-wave data [5]. Such systems often incorporate pressure-sensor arrays to capture pulses at the Cun, Guan, and Chi positions simultaneously and integrate software for signal processing. CHEN et al. [3] developed a three-dimensional (3D) wrist pulse signal acquisition system to obtain width information from wrist pulse waves. While high-density arrays can increase cost and system complexity (e.g., reliance on external computing) [3], they represent an important step toward quantifying pulse characteristics such as amplitude, width, and rhythm in high-resolution representations [21].

In parallel, wearable electronics and flexible sensors have made pulse capture less obtrusive. Flexible piezoresistive or piezoelectric sensors printed on soft substrates can conform to the skin and maintain stable contact during motion [11], thereby improving signal fidelity and reducing motion artifacts [22]. For example, WANG et al. [23] reported a flexible pressure sensor integrated into a wristband for high-precision measurement of arterial pulse waveforms. Other flexible sensing designs can improve pressure sensitivity and enable detection of subtle pulse features [11]. These advances support unobtrusive and potentially continuous pulse monitoring, which could be leveraged for longitudinal tracking of cardiovascular status.

High-density flexible sensor arrays further extend traditional multi-site pulse palpation by capturing the spatial-temporal distribution of pulse signals [24]. For example, a multichannel flexible pulse perception array integrating a 27-channel (3 × 9) pressure-sensor matrix was reported to support pulse-signal feature extraction and automated pulse recognition, illustrating the feasibility of wearable, remotely deployable pulse-sensing devices for health assessment [24].

In summary, the hardware to digitize the pulse has matured rapidly. From single-sensor to multi-sensor arrays, from bench-top instruments to wearable platforms, today's technology can capture pulse waveforms with fidelity far beyond what a human finger can perceive. The stage is set for intelligent algorithms to interpret this wealth of data—connecting the "pixels" of pulse waveforms to meaningful diagnoses in cardiology. Representative studies of digital pulse acquisition and AI-driven analyses are summarized in Table 1.

After capturing pulse waveforms, most studies follow a common signal-processing pathway: signals are acquired at the Cun, Guan, and Chi positions; then preprocessed (e.g., filtering, baseline correction, and denoising), segmented into beats, and converted into features in the time and/or frequency domain. Many pipelines also incorporate quality-control steps to reject motion artifacts and low-quality segments, which is particularly important for wearable recordings.

3.2 AI and machine learning for pulse feature recognition

Following acquisition and preprocessing (Figure 2), transforming raw pulse wave data into clinically or diagnostically useful information is a complex task. Traditional pulse diagnosis primarily relies on practitioners' subjective classification of pulses (e.g., deciding whether a pulse is "slippery" or "wiry") based on perceived qualities. Machine learning and AI tools may make this process more reproducible and scalable. AI therefore aims to automate and standardize this recognition process by learning from data. A focused review on AI and sphygmopalpation has similarly emphasized that AI can help standardize and digitize TCM pulse diagnosis by linking pulse-pattern recognition with machine-learning approaches [29]. Two broad application areas have emerged: (i) classification of TCM pulse features (the classical descriptors), and (ii) detection or prediction of specific diseases (e.g., identifying whether a patient has hypertension or coronary disease from the pulse). These applications often overlap, since certain pulse patterns correlate with certain diseases.

Early attempts at computerized pulse analysis used hand-crafted features and classical machine learning classifiers. Researchers extracted parameters like pulse waveform peaks, troughs, rising and falling slopes, pulse period, and related parameters from the digitized signals. For example, features could include the relative heights of the first and second pulse wave peaks (h1, h2), the widths at certain fractions of amplitude, or timing intervals between inflection points. LUO et al. [5] leveraged such features in combination with patient metadata (e.g., age and sex) to train multiple machine learning models

Table 1 Representative studies of digital pulse acquisition and AI-based analysis for pulse diagnosis

Study	Acquisition/platform	Task/target	AI/analysis method	Dataset/validation	Key outcome
LAN et al. [4]	PPG + GSR (smartphone-based); 2 channels (PPG at wrist Guan, GSR at acupoints); portable	TCM pulse pattern classification (binary: wiry vs. non-wiry pulse)	Neural network (fully-connected ANN); Hand-crafted features (18 PPG + 24 GSR features)	n = 80 (40 wiry, 40 non-wiry); 5-fold CV + 10-subject external test	91% accuracy in classifying wiry vs. non-wiry pulse (fully connected NN model)
LUO et al. [5]	Pressure sensor array (PDA-1); 3 positions (Cun, Guan, and Chi); bench-top clinical device	Disease classification (hypertension vs. normal)	Classical machine learning (SVM, AdaBoost, random forest tested); hand-crafted pulse wave indices + patient info	n = 929 (450 HTN, 479 healthy); evaluated before/after k-means de-noising	85% – 86% accuracy; AUC 0.85 for hypertension classification (AdaBoost/RF models)
WU et al. [7]	Multi-point pressure pulse sensor; 3 channels (left wrist Cun, Guan, and Chi); bench-top (hospital)	Multi-class classification (cardiac function in CHD via BNP level)	Random forest (vs. decision tree baseline); hand-crafted features (time-domain waveform metrics + multiscale entropy)	n = 419; three BNP-level groups (balanced); trained/tested on combined features	90.9% accuracy; 90% precision/recall in classifying three heart-failure risk groups (random forest model)
ZHAO et al. [11]	Flexible 3-channel pressure sensor array; Cun, Guan, and Chi; wearable wristband (multi-pressure acquisition)	Cuffless blood pressure prediction (regression)	Back-propagation neural network; hand-crafted features (pulse amplitude changes under 9 pressure levels)	Volunteer data; tested on 21 held-out measurements (9 pressure levels)	SBP error: – 0.8 ± 9.0 mmHg; DBP error: – 3.2 ± 9.7 mmHg; achieved AAMI-standard accuracy for BP
KIM et al. [25]	Tonometric pressure sensor (variable pressure); single radial site; bench-top prototype	Pulse depth analysis (TCM "floating" vs. "sunken" pulse quality)	Dynamic pressure coefficient algorithm (rule-based)	Clinical pilot; sample size not reported	70% classification accuracy for distinguishing floating vs sunken pulses; 73% agreement with expert labeling (improved consistency)
LYU et al. [26]	Piezoelectric pulse sensor (SmartTCM-1); 1 channel (left radial artery, Guan); bench-top clinic device	Disease classification (CAD vs. hypertension vs. healthy)	Ensemble trees (ExtraTrees; compared with SVM, KNN, DT, RF); hand-crafted features (augmented pulse morphology parameters)	n = 608 (226 CAD, 186 HTN, 196 healthy); 10-fold CV + independent test set	85.8% accuracy; AUC 0.93 – 0.94 for identifying CAD (extra trees classifier on test set)
CHANG et al. [27]	Pulse waveform dataset (raw wrist pulse signals)	Data augmentation (pulse waveform generation)	WGAN (1D Wasserstein GAN with GP); raw pulse wave signals (unlabeled)	Unsupervised training on available pulse dataset	Successfully generated realistic wrist pulse waveforms, improving diversity of training data for deep learning (mitigates data scarcity in pulse diagnosis)
TANG et al. [28]	Expert-labeled pulse qualities/pulse indices (clinical dataset)	Hybrid TCM/biomedical diagnosis (essential hypertension vs. normal via pulse)	ANN (backpropagation and PNN models); expert-labeled pulse qualities (TCM doctor's ratings on 8 pulse attributes)	n = 260; cross-validation	80% accuracy attained in distinguishing hypertensive vs. normotensive patients using ANN; specificity/sensitivity ranged 70% – 90%

GSR, galvanic skin response. ANN, artificial neural network. CV, cross-validation. NN, neural network. PDA-1, Pulse Diagnostic Apparatus-1. SVM, support vector machine. HTN, hypertension. AUC, area under the receiver operating characteristic curve. RF, random forest. CHD, coronary heart disease. BNP, B-type natriuretic peptide. SBP, systolic blood pressure. DBP, diastolic blood pressure. BP, blood pressure. CAD, coronary artery disease. KNN, k-nearest neighbors. DT, decision tree. WGAN, Wasserstein generative adversarial network. GP, gradient penalty. PNN, probabilistic neural network.

distinguishing hypertensive patients from healthy controls. They experimented with algorithms like support vector machines, AdaBoost, and random forests, achieving accuracy in the mid-80% range for hypertension classification. Interestingly, they found that certain pulse features (e.g., the ratio of pulse height to timing, denoted h1/t1) were consistently important in both the machine learning models and traditional statistical analysis, suggesting these features could capture physiologically meaningful differences. This study, which analyzed data from nearly 929 subjects, showed that AI could objectively detect hypertension by "reading" the pulse, providing an objective reference for TCM pulse diagnosis in a modern context [5].

Most AI models for digital pulse diagnosis require labeled training data. In TCM, pulse qualities such as wiry, slippery, floating, and deep are defined by tactile descriptors rather than quantitative thresholds, which introduces labeling subjectivity and limits inter-study comparability [30]. For instance, Xianmai (弦脉, wiry pulse) is often described as taut and long, whereas Huamai (滑脉, slippery pulse) is smooth and rolling; Fumai (浮脉, floating pulse) and Chenmai (沉脉, deep pulse) refer to the depth at which the pulse is most prominent. Because these labels are qualitative, models trained on expert annotations can be difficult to validate against biomedical ground truth. As a result, many studies have focused on mapping digitized pulse waveforms to measurable cardiovascular outcomes—such as arterial stiffness, coronary artery disease, and blood pressure—rather than directly classifying traditional pulse types [31]. Despite encouraging results, external validation and standardized datasets remain limited, highlighting the need for rigorous benchmarking and harmonized labeling frameworks [5, 27, 28, 32, 33].

From the perspective of TCM pulse pattern recognition, a major challenge is the large number of pulse types (commonly described as 28 types) and the resulting multi-class, imbalanced classification problem. Therefore, many studies start with simpler sub-tasks such as pulse depth classification (e.g., floating and deep) or binary recognition of a single distinctive pulse pattern. Feature-engineering approaches have been proposed to distinguish floating from deep pulses using signal-entropy metrics [34] and waveform-difference metrics [25]. For patterns such as wiry and slippery pulses, models can leverage differences in waveform contour and spectral content when training data are labeled by experienced practitioners [4]. Although reported performance can be high in small proof-of-concept datasets, generalizability across populations and devices requires further validation.

In recent years, deep learning particularly CNNs has been applied to pulse waveform analysis, enabling automatic feature learning from raw or minimally processed signals [32]. Deep architectures have been used to classify TCM pulse patterns [32, 35] and to detect cardiovascular conditions such as coronary artery disease directly from pulse waveforms [26]. However, deep models typically require large and diverse datasets, and many published studies remain limited to cohorts of a few hundred recordings, raising concerns about overfitting and limited generalizability [32]. To mitigate data scarcity, investigators have explored data augmentation and synthetic waveform generation (e.g., generative adversarial networks, GANs) [27, 32, 36]. Community benchmark datasets and evaluation frameworks have also been proposed to facilitate standardized comparison across methods and improve reproducibility [32].

To translate these approaches into real-world use, models must also handle variability introduced by posture, respiration, motion, and changes in contact pressure. Active pressure-control mechanisms (e.g., inflatable cuffs or adaptive feedback) can improve repeatability, as demonstrated by ZHAO et al.'s multi-pressure wrist device [11]. In addition, integrating pulse-derived features with contextual information (e.g., activity level and wearable sensor metadata) may improve robustness and enable personalized baselines for longitudinal monitoring [37-40]. Ultimately, validation in prospective cohorts and deployment studies will be required to determine whether wearable pulse analytics can reliably support tasks such as hypertension management or arrhythmia screening in community settings [39, 40].

In summary, AI models can provide the “brain” to interpret the digital pulse. Whether it is through feature-based machine learning or data-hungry deep learning, these algorithms are bridging the gap between traditional pulse features and concrete clinical diagnoses. The synergy of sensor data with pattern recognition is unlocking new possibilities: from identifying a wiry pulse that signals liver-Yang hypertension tendencies to predicting a hypertensive patient’s risk of complications by analyzing pulse variability. As the field evolves, one key focus is ensuring that these models are transparent and interpretable, so that TCM and modern medical practitioners can trust and understand the basis of the AI’s conclusions—an aspect that will be discussed further in the context of clinical validation. Representative AI methods, datasets, and performance metrics are summarized in Table 1.

3.3 Methodological limitations of current studies on digital pulse diagnosis

Despite promising results, current studies on digital pulse diagnosis face several methodological weaknesses that temper their reported successes. Sample sizes are typically small, often only on the order of a few hundred subjects, and are drawn from single-center cohorts, limiting the diversity of datasets and statistical power of the findings [41, 42]. External validation on independent cohorts is generally lacking; many studies rely solely on internal cross-validation or single-center training/test splits, without confirming performance in a truly separate population [41, 42]. These limitations raise concerns such as model overfitting and inflated performance, especially for complex deep learning models trained on limited datasets [32]. Furthermore, class imbalance is common (certain pulse patterns or clinical endpoints are relatively rare), which can bias algorithms toward the more frequent classes and skew accuracy metrics upward on small datasets [41].

Another critical issue is the quality and consistency of the reference labels used to train and evaluate AI models. Although TCM pulse categories are classically defined, manual identification of these categories can be subjective. Therefore, expert-derived reference labels for AI models may be noisy or inconsistent [9]. In addition, many investigations use convenience samples (e.g. volunteers or patients from a single hospital) rather than broad population-based cohorts, introducing selection bias and limiting generalizability. A publication bias in the literature is also possible—positive results tend to be reported, whereas negative or inconclusive findings may go unpublished, skewing the apparent success rate of AI approaches [42]. Consequently, some reported accuracy figures in this domain (often around 85% – 91% for classifying certain pulse types or diagnosing conditions) may be overoptimistic [5, 28]. Without rigorous validation in larger, multi-center studies—ideally prospective trials—and direct comparison to established clinical diagnostic methods, these high accuracies may not translate to real-world performance [42-44]. Strengthening study design and validation (through larger sample sizes, external and multisite testing, and the use of strong clinical benchmarks) is essential to ensure the generalizability of AI-driven pulse diagnosis and enable these tools to provide reliable value in clinical practice.

4 Integrating pulse wave data into cardiovascular diagnostics

For digital pulse palpation tools to be clinically useful, their outputs must map to actionable cardiovascular endpoints and fit within a clear workflow (screening, confirmation, and longitudinal monitoring). In this context, AI-enhanced pulse analysis should be positioned as decision support that complements, rather than replaces, established test results.

Hypertension and blood pressure monitoring are among the most immediately translatable use cases because arterial stiffness and waveform morphology change with blood pressure status [5]. Pulse-based AI outputs are best framed as low-burden screening or trend-monitoring signals (e.g., risk score or abnormal-trend flag) that prompt confirmatory cuff measurements and clinical evaluation. Prospective and external validation across devices and populations remain essential before routine deployment.

Beyond blood pressure, pulse-derived morphology and complexity metrics (including time-domain indices and entropy measures) have been explored for coronary disease phenotyping and for stratifying cardiac function using biomarker-anchored risk groups [7]. Related work suggests that radial pulse signals may also support heart failure classification and monitoring when interpreted alongside conventional biomarkers and imaging [45].

Pulse-wave morphology has also been used in multiclass classification settings to distinguish CAD from hypertension and healthy controls, illustrating a possible adjunct for triage or screening when combined with standard risk assessment [26].

Arrhythmia screening is another practical integration route because rhythm irregularity is directly reflected in pulse intervals and waveform stability. Large-scale wearable studies show that PPG-based smartwatch algorithms can alert users to possible atrial fibrillation with meaningful positive predictive value on subsequent electrocardiogram (ECG) confirmation [40], and deep learning models trained on consumer smartwatch signals can detect atrial fibrillation with high sensitivity and specificity in clinical cohorts [39]. Smaller validation studies support feasibility for ambulatory detection of paroxysmal atrial fibrillation [46]. Nevertheless, motion artifacts, skin tone variability, and the need for confirmatory ECG mean that pulse-based arrhythmia detection should currently be implemented as a screening/triage tool rather than a stand-alone diagnostic replacement [13].

Across these applications, successful clinical integration requires standardized acquisition protocols (sensor placement, contact pressure, calibration), automated quality control and artifact handling, and reporting formats that clinicians can interpret and act upon (e.g., blood pressure trend alerts or arrhythmia screening flags). In addition, shared evaluation frameworks and benchmarking can reduce heterogeneity across studies and enable meaningful comparison between devices and algorithms [32]. Finally, because these AI-driven tools function as decision-support tools, regulatory and clinical governance considerations should be addressed early during validation and implementation.

5 Discussion

The convergence of TCM diagnostics with AI and sensor technology offers a potential pathway toward more quantitative and reproducible integrative healthcare [47]. Our review suggests that digital pulse diagnosis for cardiovascular diseases is progressing from concept to early clinical implementation. By digitizing TCM pulse assessment, an experience-based skill can be translated into measurable and shareable signals, which may help standardize training, support remote monitoring, and enable broader access when expert practitioners are scarce.

5.1 Clinical relevance and potential impact

In contrast to technological innovations that often lack a predefined clinical use, digital pulse diagnosis has a plausible niche in cardiovascular care. Hypertension and coronary disease are prevalent, but current monitoring tools are either intermittent (e.g., clinic blood pressure checks) or expensive/invasive (e.g., angiography for CAD). The studies reviewed here suggest that digital pulse waveform analysis can fill some of these gaps. For instance, a wearable pulse monitor could continuously gauge a patient's blood pressure trends and detect anomalies, sending early alerts for hypertension or poor

BP control—effectively functioning as an “AI doctor’s finger” on the pulse. In heart failure, such a device could non-invasively monitor cardiac function via pulse changes, potentially catching decompensation earlier than symptom onset. These scenarios highlight an important point: digital pulse diagnosis is not a competitor to biomedical diagnostics but a partner to them. It adds a layer of insight (pattern-based, holistic, and continuous) to the point-in-time and parameter-specific nature of Western diagnostics.

Early studies have demonstrated that digital pulse parameters correlate significantly with established cardiovascular indicators [7, 11], supporting the biomedical significance of TCM findings.

5.2 Linking TCM theory with AI feature learning

The alignment between AI-extracted pulse features and classical TCM pulse theory appears to be partial and evolving. Early AI models have achieved only moderate agreement with practitioner assessments, for example, predictive accuracy around 80% for certain pulse types, indicating that the features learned by CNNs do not yet capture all the nuances of TCM pulse descriptions [5, 20, 27, 28, 32]. This gap highlights the need for explainable AI tools to bridge TCM theory and scientific data. By applying saliency maps, feature attribution methods [e.g., local interpretable model-agnostic explanations (LIME) and SHapley Additive exPlanations (SHAP)], or CNN attention visualization, researchers can identify which aspects of the waveform (such as a sharp rise, oscillatory frequency, or damping pattern) influence the model’s decision for a pulse classification [48]. Such techniques make the AI’s “thinking” more transparent, helping to connect learned signal patterns with interpretable pulse characteristics (e.g. showing that a model focuses on the steep systolic spike when recognizing a wiry pulse). Ultimately, strengthening the dialogue between TCM experts and AI developers is crucial [5, 27, 28, 32]. Domain specialists can provide insight into pulse interpretation and ensure that CNN-derived features are meaningful, while engineers can refine AI models based on expert feedback—an interdisciplinary collaboration that will gradually harmonize TCM pulse theory and AI feature learning.

5.3 Evidence gaps, standardization priorities, and implementation barriers

5.3.1 Dataset diversity and external validation Despite these promising developments, this review identifies several limitations and challenges that should be addressed in future research. A foremost issue is the need for larger and more diverse datasets. Most current AI models in this domain have been trained and tested on relatively homogeneous populations, often from a single city or hospital. To improve generalizability, future studies should include data from different regions, ethnic groups, age ranges, and comorbid conditions. Multi-center collaborations could also support the development of a robust “PulseNet” database and facilitate external validation of algorithms. Standardized data collection, including consistent sensor calibration and acquisition protocols across sites, will be essential for building more reliable models.

5.3.2 Standardization of interpretation Standardized interpretation of acquired data is also critical. There is a risk that different AI models (from different vendors or research groups) might output different “pulse diagnoses” for the same patient, just as human practitioners might do. Reaching consensus on the definitions of pulse patterns in signal terms, and perhaps reducing redundancy in TCM pulse types for the digital era (e.g., digital systems may not need all 28 categories if some are very similar in waveform) could help. This is where collaboration between TCM scholars and biomedical engineers is essential for translating or essential—translating the language of TCM into signal features and vice versa. Encouragingly, the Chinese national research agenda has funded several projects in “TCM modernization” that bring together these disciplines [5, 27, 28, 32]. International forums and journals are fostering exchange of methodologies so that a cohesive approach can be developed.

5.3.3 Clinical workflow, regulation, and data governance Despite promising results, several barriers must be overcome before AI-enhanced pulse diagnosis can be used routinely in clinical practice. First, regulatory approval and rigorous validation are essential. AI-driven devices for pulse diagnosis will likely be regulated as medical software, requiring demonstration of safety and effectiveness in large, multi-center trials, similar to ECG-based algorithms. Second, integration into clinical workflow and practitioner acceptance present challenges. TCM practitioners may worry that automated systems could diminish their role, while conventional cardiologists may remain skeptical of TCM-derived metrics. These tools should therefore be introduced as decision-support aids rather than replacements for expert judgment. Third, continuous pulse monitoring generates sensitive health data, so robust privacy protection, informed consent, encryption, and interoperability with existing hospital systems will be required before broad implementation.

5.4 Future research directions

5.4.1 Multi-modal diagnostics and tongue-pulse integration Another future direction is the integration of multimodal diagnostics. Although this review focuses on pulse diagnosis, one could envision an AI that considers both pulse waveforms and tongue images (perhaps facial complexion or voice) to output a comprehensive health assessment. TCM has always valued the four diagnostics (inspection, auscultation and olfaction, inquiry, and palpation); future digital TCM systems could incorporate all four diagnostics via sensors and AI. For cardiology specifically, combining pulse and tongue may enhance diagnostic accuracy. For example, a recent study used AI on tongue photographs to detect coronary artery disease non-invasively [49]. Tongue features like color or tongue-body shape, when analyzed alongside pulse features, might improve risk stratification for CAD. Early evidence suggests that an abnormally dark or purplish tongue plus a certain pulse pattern (perhaps choppy or knotted) correlates with angiographic findings of coronary blockage [49]. In the future, a single clinic visit might include a quick tongue scan, a 60-second pulse recording, and an AI that synthesizes both modalities to give an integrative diagnostic report [50].

Moreover, integration with other AI-driven TCM diagnostics (such as tongue imaging) may enhance diagnostic accuracy and disease prevention strategies [49, 51].

5.4.2 Predictive analytics and personalization Future research should also explore predictive analytics and personalization. With sufficiently large longitudinal datasets, AI models may detect subtle pulse-wave changes that precede hypertensive crises, heart failure exacerbations, or other cardiovascular events. This would align with the TCM concept of prevention before overt illness. Another direction is personalization: each individual may have a unique baseline pulse profile, and deviations from that baseline may be more informative than universal thresholds. Although this review focuses on cardiovascular diseases, similar principles may eventually be extended to other conditions in which pulse-based AI has been explored, such as other conditions beyond cardiovascular disease [23].

5.4.3 Prospective multi-center validation studies A key priority is to validate AI models for pulse diagnosis using multi-center clinical studies and rigorous research designs. These studies should include appropriate control groups, predefined endpoints, and comparison against established clinical standards. A related multimodal TCM-AI study illustrates the importance of benchmarking model outputs against conventional clinical indicators and cardiovascular endpoints [52]. For pulse diagnosis models, such validation is essential for regulatory approval and for building clinician trust and adoption [53].

5.4.4 Ethical and regulatory pathway Future research must also address the ethical and regulatory concerns of pulse diagnosis-based AI models. Continuous physiologic monitoring raises concerns about data privacy and informed consent—patients should explicitly agree to the collection and use of sensitive health data over long periods. Developers need to mitigate algorithmic bias, especially since current pulse AI datasets are predominantly from Chinese/Asian cohorts; models should be tested and calibrated in other ethnic groups to avoid bias issues in diagnosis or treatment recommendations. Additionally, these AI-driven pulse diagnosis tools would likely be classified as "Software as a Medical Device (SaMD)" by regulatory agencies. Investigators should therefore plan regulatory approval pathways, including compliance with safety/effectiveness standards and evidence requirements for algorithms that learn from real-world data. Post-market surveillance mechanisms are necessary to monitor performance and update algorithms if biases or safety concerns emerge during widespread use [54, 55]. Engaging with regulators early and adhering to emerging AI medical device guidelines will ensure that innovative AI-based approaches for pulse diagnosis translate into clinically approved and ethically responsible tools [54].

5.4.5 Open datasets and benchmarks To accelerate clinical translation of AI models for pulse diagnosis, the field would benefit from open, anonymized repositories of pulse waveform data (potentially coupled with tongue images and outcomes) and common benchmark tasks. Shared datasets curated with proper de-identification would enable researchers worldwide to train and evaluate AI models on larger, more diverse samples than any single group could assemble. Equally important is establishing standard evaluation metrics and challenge competitions for tasks like disease classification or risk prediction from pulse signals. By agreeing on benchmark tasks (e.g., detecting specific cardiac conditions from pulse waves) and testing algorithms on the same public datasets, the community can fairly compare the performance of AI models and identify best practices. Recent initiatives in related domains demonstrate the value of this approach: for instance, an open repository for photoplethysmography and oximetry waveforms was launched to support consistent assessment of algorithms across diverse populations [56]. Building similar shared resources for pulse diagnosis, including multimodal TCM datasets will foster collaboration, reproducibility, and rapid innovation in this emerging interdisciplinary field [56].

6 Conclusion

The journey "from pulse to pixel" illustrates how modern sensors and AI models can transform TCM pulse diagnosis into a reproducible and quantitative tool for identifying cardiovascular diseases. Overall, digital acquisition of pulse features and machine learning analytics show promise for non-invasive screening, monitoring, and risk stratification of cardiovascular conditions. Future studies should focus on standardized acquisition protocols, larger multi-center datasets, transparent model reporting, and clinical validation against accepted reference standards. If these requirements are met, AI-enhanced pulse diagnosis could become a useful tool that bridges TCM theory with modern cardiovascular care.

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Author contributions

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Competing interests

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(Editor-in-Charge Jie Deng)

从脉搏到像素：人工智能增强的脉诊用于心血管疾病评估

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【摘要】中医脉诊是一种用于评估心血管健康的无创方法，但其解读相对主观，限制了可重复性与诊断精确性。本综述总结了利用现代传感器与人工智能（AI）对桡动脉脉诊进行数字化的研究进展，并评估了其在心血管筛查与临床决策支持中的应用。我们检索 PubMed、IEEE Xplore 和 Web of Science Core Collection 从建库起至 2025 年 11 月 30 日的文献，纳入使用电子设备采集桡动脉脉搏信号并采用定量分析或机器学习/深度学习识别脉象特征或评估心血管疾病相关结局的研究。现有文献显示，压力传感阵列、可穿戴设备常用的光电容积描记（PPG）以及混合平台可促进更标准化的脉搏采集；同时，AI 模型在血压估计、高血压筛查、冠状动脉疾病识别、心力衰竭风险分层和心律失常检测等任务中报告了有前景的性能。然而，方法学异质性、样本量有限、标注标准不一致以及外部验证不足仍是临床转化的关键障碍。总体而言，AI 增强的数字脉诊可提高脉诊评估的客观性，并可能与常规心血管诊断形成互补，但仍需在严格研究设计、透明报告和具有临床意义的前瞻性验证基础上推进。

【关键词】脉诊；中医；人工智能；心血管疾病；机器学习