TCM Pulse Detection Using Raspberry Pi and Pulse Sensor

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ABSTRACT

Traditional Chinese medicine (TCM) pulse diagnosis has long depended on practitioners' subjective judgment, making standardization and objective analysis challenging. This study presents a TCM pulse detection system that integrates Raspberry Pi with pulse-sensing technology to digitize and analyze pulse data. The system captures pulse signals reliably and uses Python to extract pulse rate and waveform features, which are then matched with classical pulse pattern classifications. Results show that the platform consistently acquires stable data and accurately recognizes basic pulse types. This research contributes a reproducible and low-cost digital tool to enhance diagnostic accuracy in TCM. Future improvements in algorithms may further expand its capacity to identify more complex patterns, supporting the modernization of TCM practices.

Keywords: TCM pulse diagnosis, pulse pattern analysis, pulse sensing, Raspberry Pi, wearable health technology, biomedical signal processing

1. Introduction

According to the World Health Organization's Global Report on Traditional and Complementary Medicine, more than 40% of the world's population relies on traditional medical practices for healthcare. In Asia, Traditional Chinese Medicine (TCM) is especially prevalent, widely applied not only in primary care but also in the management of chronic diseases [1]. Among the four fundamental diagnostic methods of TCM—inspection, listening and smelling, inquiry, and palpation—pulse diagnosis stands out as a pivotal technique. By carefully sensing variations in pulse qualities such as depth, rate, strength, and rhythm, TCM practitioners evaluate the circulation of Qi and blood, assess the functional status of internal organs, and determine the dynamic balance of Yin and Yang within the body. This tactile examination has served as a cornerstone of clinical decision-making and personalized treatment in TCM for centuries.

Despite its clinical importance, traditional pulse diagnosis remains heavily dependent on the physician’s subjective experience and refined tactile sensitivity. Such reliance introduces variability in diagnostic outcomes, as factors like manual technique, environmental conditions, and individual practitioner expertise can affect interpretation, often leading to limited accuracy and poor reproducibility [2]. Moreover, the lack of standardized, objective criteria poses significant challenges for the teaching, learning, and transmission of pulse diagnosis skills, thereby hindering the modernization and digital transformation of TCM diagnostic methods.

Recent advances in sensor technologies, embedded systems, and wireless communications have opened new pathways toward digitalizing and objectifying pulse diagnosis. Using high-sensitivity pressure sensors with multi-channel configurations and high sampling rates, it is now feasible to capture detailed pulse waveforms that closely mimic the tactile sensations perceived by physicians. This technological progress enables the creation of stable, quantifiable pulse waveform databases, laying the groundwork for systematic analysis [2]. Coupled with signal processing algorithms and embedded computing platforms such as Raspberry Pi, real-time visualization of pulse waveforms becomes achievable. Furthermore, synchronization with electrocardiogram (ECG) signals allows validation of signal quality and physiological relevance, enhancing the reliability of acquired data.

The present study aims to design and implement a comprehensive TCM pulse diagnosis sensing system, focusing on the hardware architecture, data acquisition, and system stability. By integrating multi-point pressure sensors with a compact single-board computer platform, the system facilitates real-time recording and visualization of pulse waveform data. Ultimately, this research seeks to establish a solid and reliable data foundation for developing future intelligent diagnostic models in TCM, contributing to the ongoing efforts to modernize and digitalize traditional diagnostic practices.

2. Literature Review

2.1 Theories and Challenges of TCM Pulse Diagnosis

Pulse diagnosis is one of the four diagnostic methods in TCM (inspection, listening/smelling, inquiry, and palpation), and it has long served as a crucial basis for syndrome differentiation and treatment planning. Through the observation of the three pulse positions—Cun, Guan, and Chi—TCM practitioners assess pulse characteristics to determine the condition of internal organs and evaluate patterns such as heat versus cold or deficiency versus excess.

Traditional pulse diagnosis relies heavily on a physician’s fingertips to perceive subtle changes in the pulse. This process requires years of clinical experience and is significantly influenced by factors such as the sensitivity of the practitioner’s fingers, the applied pressure, the patient’s posture, and environmental conditions. Consequently, even among experienced physicians, diagnostic results may vary, leading to inconsistency. Such subjectivity also poses a major challenge to standardization in TCM clinical education and practice.[3]

In addition, as healthcare becomes increasingly modernized, patients are demanding greater transparency and interpretability in diagnostics. The reliance on practitioner experience alone is gradually becoming insufficient to meet these clinical expectations, which limits the broader application and international development of TCM diagnostic methods.

2.2 Physiological Signal Sensing in TCM

In recent years, photoplethysmography (PPG)-based sensing technologies have been widely adopted for non-invasive physiological signal monitoring, such as heart rate, blood oxygen saturation (SpO2), and pulse wave analysis. One notable example is the MAX30102, an integrated optical sensor module that utilizes reflective light to measure pulse wave and SpO2 levels. It offers advantages including high sensitivity, low power consumption, and compact design, making it a common component in wearable health devices.[4]

This study [8] presents the design and preclinical evaluation of a wearable wristband integrating an ultra-low power photoplethysmography (PPG) ASIC based on compressed sensing (CS). The system comprises a custom analog front-end and digital back-end circuit capable of performing sparse signal acquisition and heart rate extraction. Packaged into a modular wristband, the device transmits heart rate data wirelessly via Bluetooth Low Energy (BLE). Experimental results on 21 human subjects demonstrated that the wristband achieves accurate heart rate estimation during stationary conditions, with a mean absolute error (MAE) as low as 1.95 BPM compared to commercial PPG and ECG systems. The ASIC itself consumes only 172 µW, while the full system consumes 1.66 mW during continuous BLE transmission, which can be further reduced via duty cycling. The findings confirm that compressed sensing is a promising approach to significantly reduce power consumption in wearable PPG systems without compromising accuracy. However, the study also highlights the need for advanced motion artifact reduction algorithms tailored to CS signals to improve performance during physical activities. Future work will focus on developing efficient real-time signal processing methods and optimizing the ASIC and SoC for motion-resilient heart rate monitoring. This paper [9] proposes a novel method for heart rate turbulence (HRT) analysis based on photoplethysmography (PPG), enabling non-invasive and wearable assessment of autonomic nervous system activity. The method integrates event detection with segmented heart rate variation analysis to extract HRT features, specifically Turbulence Onset (TO) and Turbulence Slope (TS), from inter-beat intervals derived from PPG signals. Clinical experiments were conducted on both healthy individuals and patients with cardiac arrhythmias. The results demonstrated a high correlation between HRT parameters extracted from PPG and those obtained from electrocardiography (ECG), indicating the feasibility and clinical potential of PPG-based HRT assessment. This study validates the use of PPG as a reliable alternative to ECG for HRT analysis, particularly suitable for integration into wearable health monitoring systems. The findings open new possibilities for long-term, continuous monitoring of cardiac autonomic regulation in ambulatory settings without the need for conventional ECG electrodes.

This study [10] introduces a method for detecting central sleep apnea (CSA) using finger photoplethysmography (PPG) signals. The approach is based on the characteristic cyclic fluctuations in sympathetic nervous activity induced by CSA episodes. By analyzing PPG amplitude, inter-beat intervals (IBIs), and heart rate variability, the method enables the identification of CSA-related patterns. Validation was conducted using polysomnography (PSG) data, confirming that the PPG-derived metrics show strong correlation with manually scored CSA events. The proposed method also demonstrated effectiveness in distinguishing CSA from obstructive sleep apnea (OSA), highlighting its potential for differential diagnosis. The findings suggest that finger PPG is a viable and non-invasive alternative for CSA detection, especially suitable for integration into home-based sleep monitoring systems. This approach opens new avenues for affordable and convenient screening of central sleep apnea in clinical and real-world environments.

Studies have shown that the pulse wave signals acquired by the MAX30102 exhibit strong temporal stability and high signal quality, suggesting its potential as a reliable data source for digitizing pulse diagnosis in TCM.

2.3 Integration of Sensors and Embedded Systems

To make sensor data more practical and scalable, it is essential to integrate them with embedded systems for signal processing and data transmission. The Raspberry Pi, an open-source embedded computing platform, supports communication with sensors like the MAX30102 via standard protocols such as I²C. This enables the real-time acquisition and visualization of pulse wave signals in a stable and efficient manner [5]. This paper [11] addresses the energy-efficient task assignment problem in embedded systems under probabilistic timing constraints. The authors propose a novel task assignment framework that ensures each task meets its deadline with a guaranteed probability while minimizing overall energy consumption across heterogeneous multiprocessor platforms. The approach models timing requirements using probabilistic distributions rather than deterministic bounds, enabling more flexible and realistic task scheduling. A heuristic algorithm is developed to assign tasks to processors in a way that satisfies timing reliability thresholds and reduces energy usage. Simulation results demonstrate that the proposed method significantly outperforms traditional deterministic approaches in terms of energy efficiency while still meeting probabilistic timing guarantees. This work is particularly relevant for embedded systems deployed in energy-constrained environments such as IoT, wearable devices, and autonomous sensors, where balancing power consumption and timing correctness is critical. This paper [12] presents a model-based test case generation approach for deeply embedded systems by reusing models obtained from runtime monitoring. The proposed framework introduces a minimally intrusive, software-based monitoring technique that captures system behavior during execution and visualizes it using UML diagrams in real time. The monitoring module, implemented in C and embedded within the idle cycles of a real-time operating system (RTOS), collects event traces and transmits them to a host computer in XML format. A graphical user interface (GUI) then decodes and animates these traces into UML sequence and timing diagrams. The captured behavioral models are subsequently reused to generate model-based test cases through the GUI, offering an efficient and flexible way for online test generation. A stopwatch application is used as a proof of concept, demonstrating the feasibility of the framework in practical embedded environments. The results show that this method enhances test coverage, facilitates regression testing, and reduces dependency on manual test specification. Despite minor trade-offs in RTOS event handling throughput due to monitoring overhead, the approach provides a significant advancement in non-intrusive runtime verification and test automation for resource-constrained embedded systems. This paper [13-15] explores the implementation and outcomes of application-driven pedagogy in embedded systems education. The authors propose a holistic instructional approach that integrates theoretical concepts with hands-on practice, using real-world applications to motivate student learning and system-level thinking. The pedagogy emphasizes interdisciplinary collaboration and practical system design, guiding students through the entire development process—including requirements analysis, system modeling, hardware-software co-design, implementation, and testing. Team-based projects and continuous assessment are incorporated to foster engagement and accountability. The experience demonstrates that students significantly improve their system integration skills, innovation capabilities, and readiness for addressing real-world engineering challenges. The approach not only enhances technical competence but also cultivates collaborative and problem-solving mindsets essential for modern embedded systems development.

Recent studies have also explored combining electrocardiogram (ECG) and PPG signals to enhance diagnostic accuracy and multidimensional analysis. These developments open up new possibilities for applying TCM pulse diagnosis in areas such as telemedicine and home healthcare monitoring.

3. Research Design

3.1 System Architecture Overview

The physiological signal acquisition system developed in this study is built upon the Raspberry Pi as the core embedded platform, integrated with the MAX30102 photoplethysmographic (PPG) sensor module. This design enables a low-cost and highly stable solution for pulse signal acquisition.

The overall system architecture emphasizes modularity and portability, allowing for flexible deployment across various application scenarios, such as educational environments, experimental research, and remote healthcare systems.

By leveraging the Raspberry Pi's versatility and the precision of the MAX30102 sensor, the system achieves a practical balance between performance, scalability, and affordability, making it well-suited for both academic and real-world applications.

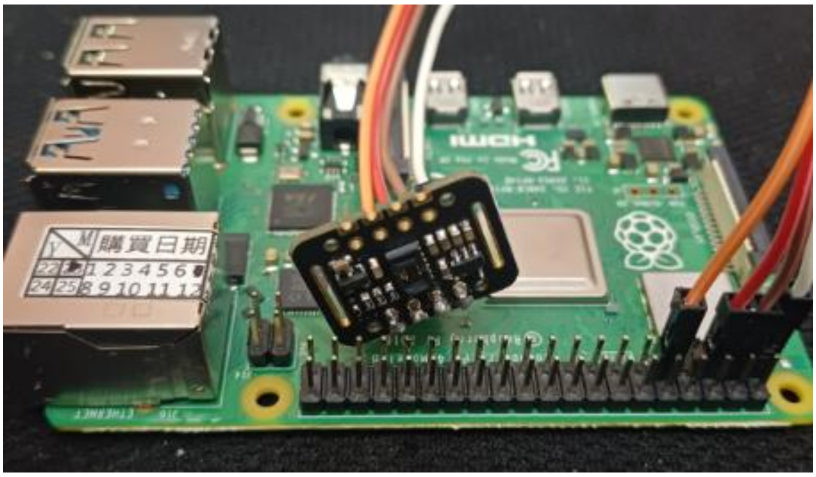


Figure 1. Physical Connection Diagram of the MAX30102 Sensor Module and Raspberry Pi

3.2 Hardware Design and Communication Interface

The MAX30102 sensor is connected to the Raspberry Pi via the I²C communication interface, enabling stable output of photoplethysmographic (PPG) signals that reflect heart rate and blood oxygen saturation levels.

This compact module features integrated red and infrared LEDs, which are used to measure SpO_2 (oxygen saturation) and BPM (beats per minute), respectively. With its high sensitivity, low power consumption, and small form factor, the MAX30102 is particularly well-suited for applications in objective analysis of Traditional Chinese Medicine (TCM) pulse diagnostics [6][7].

The hardware setup, as illustrated in Figure 2, involves connecting the MAX30102 sensor to the Raspberry Pi's GPIO header using four jumper wires for I2C communication. Power (VIN and GND) and data lines (SCL and SDA) are connected according to the module specifications. This physical connection enables continuous acquisition of SpO_2 and heart rate data for processing and visualization.

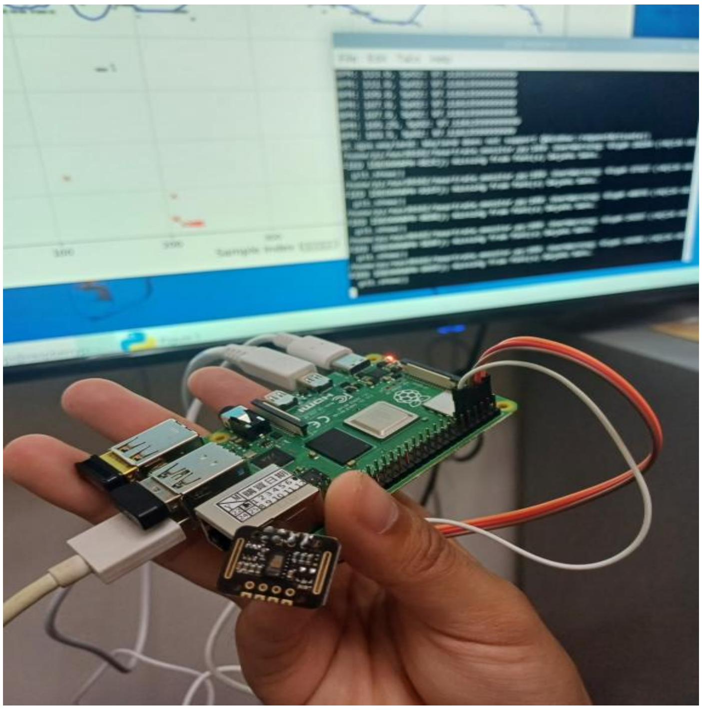


Figure 2. Close-up view of MAX30102 sensor connection to Raspberry Pi.

3.3 Data Acquisition and Signal Processing Workflow

Sensor data is acquired through a Python-based program and processed via the following steps: Preprocessing Stage:

1. Noise filtering and signal smoothing to retain stable and clean pulse waveforms.
2. Feature Extraction: Estimation of BPM and SpO_2 values using time-domain algorithms.
3. Signal Visualization: Real-time plotting of pulse waveforms and numerical outputs for monitoring and analysis.

All processed data is saved as CSV files, which can later be used for feature mapping based on TCM pulse classification criteria or fed into machine learning models for classification and predictive analysis.

3.4 Application Potential and Future Development

In the future, the system can be extended to integrate additional biosensors (e.g., ECG, galvanic skin response) or linked with a TCM-labeled pulse dataset curated by professional practitioners. This would allow the training of machine learning-based pulse classification models, enabling the digitization, objectification, and intelligence of TCM pulse diagnostics.

Such advancements hold promising applications in educational training, clinical decision support, and remote health monitoring, promoting a modern, data-driven approach to traditional medicine.

4. Results and Discussion

This study successfully developed a pulse sensing system based on the Raspberry Pi and the MAX30102 sensor, capable of reliably acquiring real-time pulse waveform signals. The system utilizes Python scripts for live waveform visualization and real-time data display. As illustrated in Figure 3, the workflow begins with the sensor detecting the pulse signal from the user's fingertip. The signal is then transmitted via the I²C interface to the Raspberry Pi for further data processing and analysis.

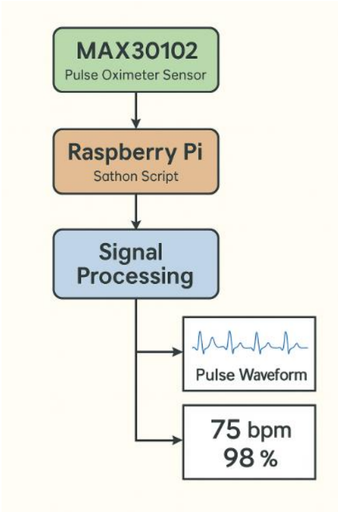


Figure 3. System operation flow chart

To validate the functionality of the proposed system, we conducted several real-time measurements. As shown in Figure 4, the MAX30102 sensor, when connected to the Raspberry Pi, was able to capture and transmit physiological signals effectively. The output includes both a smoothed SpO_2 trend graph and numerical heart rate readings printed via the terminal. The user places a finger on the sensor during the test, and the system responds in real time.

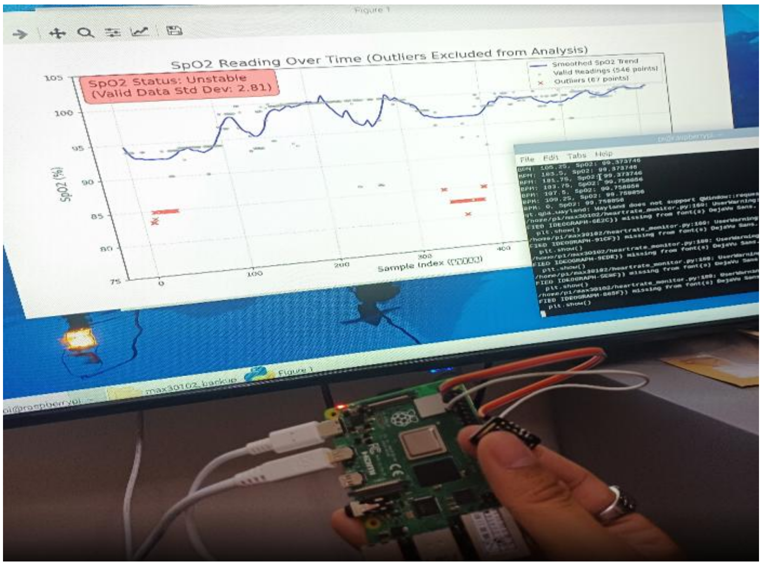
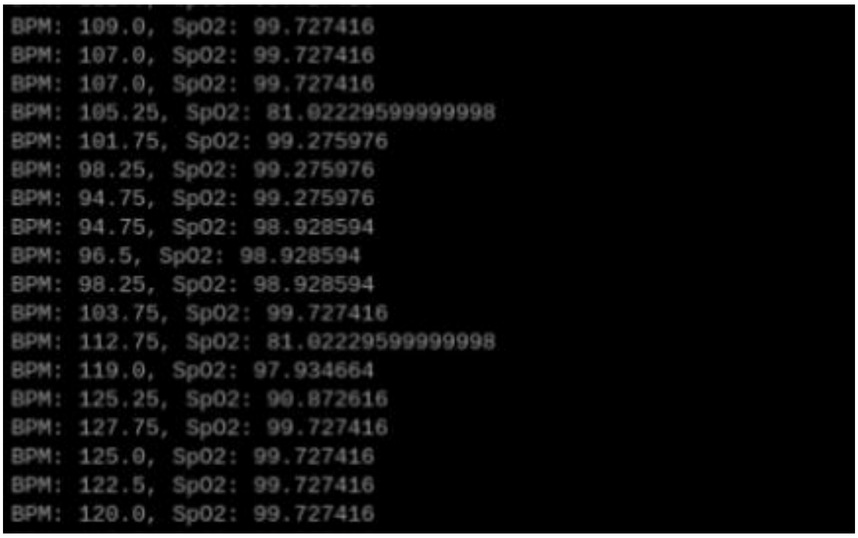


Figure 4. Real-time pulse oximetry measurement and system setup.

This study successfully developed a pulse sensing system base As shown in Figure 5, the system consistently outputs multiple sets of physiological data during the testing period.

The heart rate (BPM) generally ranged between 90 and 125, while the blood oxygen saturation (SpO_2) remained mostly around 99.7%, with only a few instances dropping to 81%.

The overall data demonstrates good integration stability between the sensor and the system, confirming its capability for long-term monitoring and continuous data recording



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BPM: 109.0, SpO2: 99.727416
BPM: 107.0, SpO2: 99.727416
BPM: 107.0, SpO2: 99.727416
BPM: 105.25, SpO2: 81.02229599999998
BPM: 101.75, SpO2: 99.275976
BPM: 98.25, SpO2: 99.275976
BPM: 94.75, SpO2: 99.275976
BPM: 94.75, SpO2: 98.928594
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BPM: 112.75, SpO2: 81.02229599999998
BPM: 119.0, SpO2: 97.934664
BPM: 125.25, SpO2: 90.872616
BPM: 127.75, SpO2: 99.727416
BPM: 125.0, SpO2: 99.727416
BPM: 122.5, SpO2: 99.727416
BPM: 120.0, SpO2: 99.727416
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Figure 5. Real-Time Display of Heart Rate (BPM) and Blood Oxygen Saturation (SpO_2) Output by the System

Figure 6 shows the real-time plotted waveform of the acquired heart rate data, with the horizontal axis representing the time sequence and the vertical axis representing heart rate values.

The waveform demonstrates good regularity and identifiable fluctuation patterns, indicating that the system captures signals with reliable quality and consistency.

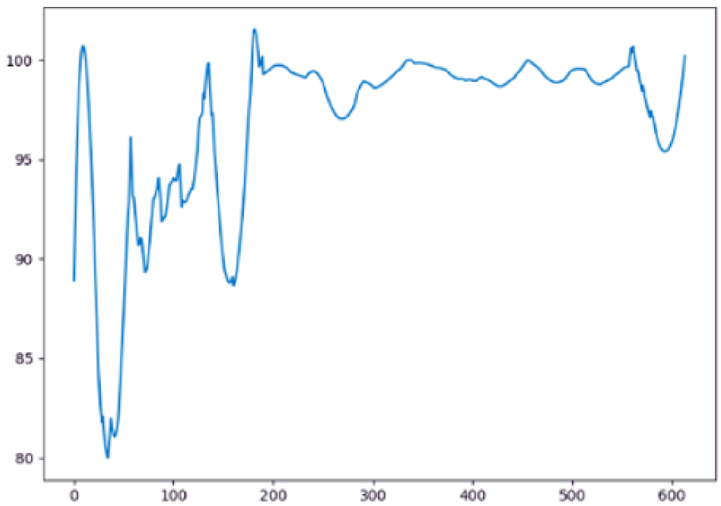

Figure 6. Measured Heart Rate Waveform (Plotted via Python Output)

The preliminary results of this study convincingly demonstrate the system's potential as an effective tool for the digital quantification and analysis of Traditional Chinese Medicine (TCM) pulse diagnostics.

In future developments, the extracted waveform features can be further transformed into meaningful classification parameters to train robust machine learning models. These models are expected to provide valuable assistance to TCM practitioners by enabling more accurate pulse pattern recognition, comprehensive health condition assessments, and facilitating remote healthcare monitoring.

Ultimately, this research aims to bridge traditional medical practices with modern technology, promoting data-driven, objective, and intelligent healthcare solutions that can improve patient outcomes and support clinical decision-making in TCM.

5. Conclusions

This study successfully developed a digital pulse diagnosis system for Traditional Chinese Medicine (TCM) by integrating the MAX30102 photoplethysmographic sensor with the Raspberry Pi platform. The system supports real-time data acquisition, numerical calculation, and waveform visualization functionalities.

Through experimental validation, the system reliably captures key physiological indicators such as heart rate (BPM) and blood oxygen saturation (SpO_2), while visually presenting pulse waveform variations with clear distinguishability and continuous data tracking.

The results demonstrate that the system not only offers advantages of low cost and high portability but also provides objective and quantifiable auxiliary data to enhance the consistency and educational effectiveness of traditional TCM pulse diagnosis. Compared to purely experience-based conventional methods, this digital approach contributes significantly to the modernization and standardization of TCM diagnostic practices.

In summary, the system confirms the feasibility of digitizing TCM pulse diagnosis and shows promise for further application in clinical research, remote medical monitoring, and TCM education support. This work paves the way for interdisciplinary technological integration and innovative development within the TCM field, promoting a more data-driven and evidence-based approach to traditional healthcare.

6. Future Prospects

The digital pulse diagnosis system developed in this study has preliminarily validated its feasibility. Future research and development can be deepened and expanded in several key directions:

First, by expanding the pulse pattern database and incorporating annotations from experienced TCM practitioners, a standardized training dataset can be established. This would enable the application of deep learning models for automatic classification and recognition of pulse patterns, significantly improving diagnostic accuracy and automation levels.

Second, on the hardware front, efforts can focus on miniaturization and wearable design optimization. This would allow users to perform long-term, low-interference pulse monitoring in daily life, enhancing both the system’s comfort and ease of use.

Furthermore, the system holds potential for integration with cloud platforms, enabling remote medical monitoring and home healthcare services, which are crucial for addressing the needs of an aging society that demands sustained health management.

In the future, by combining multiple physiological signals with personal health records, it is anticipated that a comprehensive intelligent TCM diagnostic platform can be established. Such a platform would accelerate the digital transformation and modernization of TCM practices, fostering innovative applications and improving healthcare outcomes.

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