Contact-Free Cardiovascular Monitoring Using AI-Driven Radar and Sensor Fusion on a Hybrid Edge-Cloud Platform

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***Abstract*—Access to essential cardiovascular parameters such as heart rate (HR), heart rate variability (HRV), and blood pressure (BP) remains limited in low-income and remote populations, particularly among older adults in developing regions. Continuous, simultaneous, and contact-free monitoring of these parameters beyond close proximity can enhance early detection, screening, and management of cardiovascular and related conditions. This study presents a real-time, contact-free health monitoring system based on millimeter-wave (mmWave) FMCW radar, phase demodulation, and digital signal processing (DSP), integrated with multimodal sensor fusion and artificial intelligence (AI)-driven inference. Sub-millimeter chest wall displacements are captured using radar in-phase and quadrature (I/Q) signals to extract beat-to-beat physiological features, including ECG-correlated waveform components, HR, and HRV, while non-invasive blood pressure is indirectly estimated using a physics-informed adaptive learning framework. A custom Long Short-Term Memory (LSTM) neural network is employed for temporal smoothing and stabilization of HRV signals, improving robustness under real-world conditions. The system is implemented within a hybrid edge–cloud architecture, enabling on-device inference for real-time monitoring and cloud-based analytics for long-term analysis and integration. Clinical-like validation conducted on over 100 adult participants demonstrates measurement accuracy comparable to clinically accepted reference devices, and statistical analysis confirms the robustness and reliability of the proposed system.**

Keywords—Wireless sensing; radar signal processing; sensor fusion; contact-free monitoring; heart rate; heart rate variability; blood pressure; deep learning

I. Introduction

Cardiovascular diseases (CVDs) remain among the leading causes of morbidity and mortality worldwide, accounting for a significant proportion of sudden cardiac deaths and long-term disability [1]. Early detection and continuous monitoring of cardiovascular function are therefore critical for preventive care, timely intervention, and effective disease management. Key physiological indicators such as heart rate (HR), heart rate variability (HRV), and blood pressure (BP) provide essential insights into cardiac health, autonomic nervous system regulation, and overall physiological resilience [2]. Abnormalities in these parameters—such as arrhythmias, reduced HRV, or sustained hypertension—are strongly associated with increased risk of stroke, heart failure, and other chronic conditions.

Despite their clinical importance, continuous and simultaneous monitoring of HR, HRV, and BP remains difficult to achieve in a practical, scalable manner, particularly in low-income, rural, and resource-constrained settings. Conventional measurement techniques, including electrocardiography (ECG), photoplethysmography (PPG) [3], and cuff-based sphygmomanometers, require physical contact with the subject and are often episodic, obtrusive, or dependent on trained personnel. These constraints limit their suitability for long-term monitoring, mass screening, and deployment in mobile or community-based healthcare programs. Additionally, contact-based systems pose challenges related to hygiene, patient comfort, and compliance, especially in elderly populations and infectious-disease scenarios.

Recent advances in contactless sensing technologies have opened new possibilities for non-invasive physiological monitoring. Radar-based systems, particularly those operating in the millimeter-wave (mmWave) spectrum, can detect sub-millimeter chest wall displacements caused by cardiac and respiratory activity, enabling remote measurement of vital signs without physical contact. Several studies have demonstrated the feasibility of using radar, cameras, or acoustic sensors to estimate heart rate and respiration. However, existing approaches remain limited in clinical applicability. Many focus on single-parameter estimation, rely on extensive subject-specific calibration, or exhibit reduced robustness under real-world conditions involving motion artifacts, environmental interference, or physiological variability. Most notably, accurate contactless estimation of blood pressure continues to be an unresolved challenge, with prior methods often depending on pulse transit time (PTT) models, multiple synchronized sensors, or regression-based techniques that may not generalize well across populations.

This disconnects between clinical requirements—namely, reliable, continuous, and multi-parameter cardiovascular monitoring and the capabilities of existing contactless systems represent a critical research gap. There is a lack of integrated, field-deployable platforms capable of simultaneously extracting HR, HRV, and BP from a single sensing modality, while maintaining medical-grade accuracy, interpretability, and scalability. Furthermore, many reported solutions remain at a proof-of-concept stage and do not address system-level considerations such as real-time processing, deployment in non-controlled environments, or integration with digital health infrastructure.

A. Research Objectives

In response to the identified limitations of existing contactless cardiovascular monitoring approaches, this study aims to investigate the feasibility of a single, contact-free radar-based sensing system combined with multimodal sensor fusion and adaptive artificial intelligence for accurate, real-time estimation of heart rate (HR), heart rate variability (HRV), and blood pressure (BP) in clinical-like and real-world environments, without reliance on physical contact or wearable sensors.

The primary objective of this research is to design, develop, and experimentally validate a contact-free cardiovascular monitoring platform that integrates millimetre-wave radar sensing, advanced digital signal processing, and AI-driven inference within a hybrid edge–cloud architecture. Specifically, the study seeks to:

- Extract beat-to-beat cardiac features from radar in-phase and quadrature (I/Q) signals using physics-guided signal processing techniques;
- Improve the stability and robustness of HR and HRV estimation through temporal modelling based on Long Short-Term Memory (LSTM) networks;
- Estimate blood pressure indirectly from radar-derived cardiac waveform features using adaptive learning methods, without the use of cuff-based measurements; and
- Evaluate system performance through comparative validation against clinically accepted reference devices under controlled and semi-controlled conditions.

B. Contribution and Significance

The proposed approach advances deployable contactless cardiovascular monitoring by translating laboratory-scale sensing into an integrated, system-level solution. By combining radar-based sensing with adaptive learning and multimodal sensor fusion, the platform supports concurrent estimation of multiple cardiovascular parameters using a single, non-intrusive device. A hybrid edge–cloud architecture enables low-latency, real-time inference at the point of care while supporting scalable cloud-based analytics for longitudinal and population-level assessment. Collectively, this work establishes a practical, scalable framework for hygienic, continuous cardiovascular monitoring in distributed, resource-constrained healthcare environments beyond conventional clinical settings and equitable access.

C. Organization of the Study

The remainder of this study is structured as follows: Section II discusses the motivation for contact-free cardiovascular monitoring. Section III reviews existing contactless monitoring techniques, identifies their limitations, and positions the proposed approach relative to prior work while highlighting its novel contributions. Section IV details the system architecture, sensing framework, and signal processing methodology. Section V presents experimental results and clinical validation. Section VI explores future research directions and potential applications. Section VII addresses data privacy and ethical considerations, and Section VIII concludes the study.

II. Motivation for Contact -Free Measurement of HR, HRV, BP, and Other Vitals in this Research

With advancements in medical devices, there is a growing demand to measure multiple vital and non-vital parameters simultaneously with a single device. However, current scientific and engineering limitations often necessitate multiple devices, complicating the process. This research aims to develop a non-invasive, hygienic, and efficient contactless method for measuring blood pressure and other vitals, enhancing patient comfort, reducing infection risk, and enabling continuous remote monitoring. To achieve this, innovative techniques are required to accurately capture vitals without altering established scientific frameworks. This study focuses on the contactless measurement of derived parameters, which can improve safety, comfort, and efficiency across various fields. The proposed method is particularly valuable in healthcare and holds promise for industrial, consumer, medical, and enterprise applications. By enabling indirect parameter measurement, this research seeks to drive innovation across multiple sectors. Specifically, it demonstrates how the radar signals can be used to measure heart rate (HR), heart rate variability (HRV), blood pressure (BP), and other dynamic vitals. Using a sensor fusion approach, the system processes data from sensors and transducers to provide accurate physiological insights through advanced digital signal processing and phase demodulation techniques.

In this research, the I (In Phase) and Q (Quadrature) components form the basis of complex signal representation, widely used in signal processing, communications, and radar systems. For orthogonal receiver radar with I/Q channels, phase information is obtained using arctangent demodulation, providing critical data for precise parameter estimation.

III. Literature Review

A. Existing Approaches

The evolution of radar-based, contactless systems for health monitoring holds transformative potential in non-invasive, patient-centered care. Building upon conventional technologies, recent research explores the unique benefits and expanded applications of radar systems, particularly in environments where physical contact with sensors may be undesirable or impractical. Zhang et al. [4] introduced "Radar-Beat", a breakthrough radar-based system capable of continuous beat-by-beat heart rate monitoring. The system leverages radar signals to measure heart rate accurately, even in dynamic settings where traditional contact-based methods might fail, marking a significant advancement for healthcare monitoring in real-life scenarios. Similarly, Maji et al. [5] explored an alternative approach using standard RGB cameras for contactless heart rate monitoring, which, while less costly and more accessible than radar, generally lacks the precision radar provides in tracking vital signs reliably in non-static environments.

The development of millimeter wave radar has been especially influential in expanding the possibilities for real-time, contactless vital sign monitoring. Gao et al. [6] demonstrated the effectiveness of millimeter wave radar for tracking both heart rate and respiratory rate simultaneously. The study highlights radar's versatility and its applications in healthcare settings, where it can offer reliable, real-time monitoring without requiring any physical contact, thereby enhancing both patient comfort and data accuracy. Deep learning integration further amplifies radar-based systems' capabilities, as explored by Ni et al. [7], who reviewed deep learning approaches to contactless heart rate measurement. By leveraging machine learning algorithms, these systems can adapt to varying signal conditions, significantly reducing noise and improving measurement accuracy, even in non-ideal conditions.

Radar-based health monitoring systems are further enriched through hybrid solutions that incorporate AI, camera, and radar technologies for a more robust measurement approach. Kolosov et al. [8] demonstrated a camera-based system enhanced by AI for monitoring heart and respiratory rates. Such multi-sensor setups, which combine data from both radar and camera sources, increase the reliability of readings, addressing potential challenges associated with either technology alone. Expanding the scope of contactless monitoring to more accessible technologies, Wang et al. [9] illustrated the use of smart speakers for heart rhythm monitoring, showcasing the flexibility of contactless technology to adapt to household devices. This expands the use of contactless systems into home environments, offering a convenient solution for ongoing monitoring outside clinical settings.

Further innovations in wearable and radar-based monitoring were presented by De Pinho Ferreira et al. [10], who reviewed non-invasive heart rate monitoring for wrist-worn devices, providing insights into the growing role of wearable applications for real-time health monitoring. Similarly, Esgalhado et al. [11] evaluated heart rate variability (HRV) derived from ECG and PPG signals, emphasizing the effectiveness of multimodal approaches that improve accuracy by drawing from multiple sources of physiological data. Zhang et al. [12] took this concept further by employing a CNN-LSTM model to detect arrhythmias in medical IoT systems, illustrating deep learning's value in enhancing diagnostic capabilities by detecting subtle patterns in heart rate data that may indicate health risks.

Radar technology has made strides in signal processing methods that enhance measurement accuracy. Park and Lubecke [13] developed a critical technique involving arctangent demodulation with DC offset compensation for Doppler radar systems, improving the precision of heart rate detection by isolating vital signals from noise and background interferences. Further refinement of signal accuracy in radar systems was achieved by Sameera et al. [14], who worked on reducing respiratory harmonics within heart signal analysis. This is crucial for radar-based systems to accurately distinguish heart rate data from respiratory noise, improving the system's overall effectiveness in diverse monitoring environments.

Nonlinear HRV analysis has also contributed to a deeper understanding of heart rate dynamics in patients with cardiovascular disease. Krstacic et al. [15] examined HRV's nonlinear dynamics in patients with coronary artery disease, illustrating how complex HRV behaviour can serve as a critical indicator of cardiovascular health and disease progression. Similarly, Kondo et al. [16] investigated laser-based monitoring of chest wall movements, presenting a promising alternative for non-contact respiratory rate tracking. This further validates radar's complementary role in continuous respiratory monitoring, especially in high-risk or critically ill patient scenarios where accurate respiratory tracking is vital.

Wearable technologies for HRV monitoring have also progressed, as evidenced by Eguchi and Aoki [17], who developed R-R interval editing techniques for single-channel ECG devices. This is essential in wearable applications, as it ensures data reliability by providing clean, precise HRV measurements even in continuous monitoring scenarios. Longitudinal studies such as Schroeder's [18] study on HRV determinants in the Atherosclerosis Risk in Communities Study provided foundational insights into how HRV changes over time can signal early indicators of cardiovascular disease, supporting the utility of continuous monitoring in preventive care.

Patented advancements have also driven innovation in radar-based health monitoring. KRS [19, 20] proposed adaptive learning-based techniques for radar signal enhancement, which enable the system to dynamically adjust and enhance input features based on rank and event-driven causes. This adaptive capability represents a major leap toward intelligent monitoring systems that can self-optimize for accuracy in real-time scenarios. Schellenberger et al. [21] contributed to this field by providing a clinically recorded radar dataset with synchronized reference sensor signals, an invaluable resource for developing, validating, and training radar-based health monitoring algorithms.

The application of ultra-wideband radar, particularly in paediatric and early childhood health monitoring, is another area of emerging interest. Arasteh et al. [22] utilized ultra-wideband radar for simultaneous monitoring of respiratory and heart rates in young children, achieving high accuracy by implementing a deep transfer learning approach. This study underscores radar's potential for non-intrusive monitoring in sensitive populations, like infants and young children, where conventional methods may not be feasible. Finally, Udupa et al. [23] investigated the applicability of HR and HRV in mental health assessments, finding that HRV can indicate autonomic dysfunction in patients with major depression. This connection between HRV and mental health broadens radar's applicability, potentially allowing healthcare providers to monitor psychological as well as physiological health indicators non-invasively.

B. Comparative Evaluation of Existing Approaches and Novel Contributions of the Present Study

Our research work represents a significant departure from prior art, introducing a clinically validated, scalable, and AI-driven contactless health monitoring system suited for low-resource and mobile healthcare settings. Existing academic and commercial efforts in radar-based vital sign monitoring often depend on pulse transit time (PTT) models or signal regression techniques requiring multiple sensors or calibration. Prior works—such as those by Mase et al. (2011), Kim & Ling (2017) [24], and Huang et al. (2016)—struggle with limited accuracy under dynamic, real-world conditions. In contrast, the presented system enables real-time blood pressure estimation using a single radar by extracting dynamic PQRS waveform segments from micro chest wall displacements. This bypasses the need for PTT calibration and enhances diagnostic precision using physics-informed modelling. A custom Long Short-Term Memory (LSTM) model, implemented in C++, ensures temporal smoothing of heart rate variability signals under fluctuating conditions. Unlike deep-learning-only prototypes such as the Smart Health mmWave Radar (UT Austin) and Convolution Neural Network (CNN) based models, Li et al. (2021), this system fuses empirical and AI-driven inference for robustness and interpretability. Patents like US11,076,522B2 (UC) and US10,995,684B2 (Google) disclose radar-based BP estimation, yet none offer a unified signal processing framework for simultaneous extraction of over 18 parameters in a validated field-deployable device. Additionally, unlike exploratory efforts like Project Soli (Google) or WO2022174460A1 (Huawei). This work has achieved Technology Readiness Level (TRL) 7 through multi-site functional validation. To the best of the authors' knowledge, it represents the first integrated platform that combines single-radar PQRS waveform generation, physics-guided modelling, hybrid AI processing (on-device and cloud), and multimodal sensor fusion. The system's industrial scalability is supported by seven patent applications, with regulatory submissions currently in progress through the US FDA 510(k) pathway under the Class B medical device category. No prior academic or commercial effort, to the authors' knowledge, demonstrates a comparable combination of parameter richness, medical-grade accuracy, model transparency, and operational readiness. These distinctions represent a significant advancement toward scalable, contact-free health monitoring platforms designed for integration into large-scale public health systems.

IV. Methodology

Although contactless monitoring of vital signs has been investigated across various research domains, the presented system represents a distinct advancement through its emphasis on clinical-grade accuracy at short-range, person-specific distances (1.25–1.75 meters). The solution combines radar-based physiological sensing with adaptive signal processing and machine learning, including a purpose-built Long Short-Term Memory (LSTM) neural network for real-time signal stabilization. Integration with a hybrid edge-cloud framework facilitates continuous, secure, and remote access to health data, enabling deployment in primary care centers, mobile clinics, and underserved healthcare environments.

In this research, a multi-sensor framework was employed that integrates multi-point temperature sensors, multimedia sensors, transducers, and millimeter-wave (mmWave) radar, all operating within the Industrial, Scientific, and Medical (ISM) radio bands. These sensors were deployed in compact integrated circuit (IC) packages, with all electronics custom-designed by Impilo Sensys and certified under CE (Conformité Européenne) and FCC (Federal Communications Commission) standards, and are lead (Pb)-free. The radar module utilizes Frequency-Modulated Continuous Wave (FMCW) technology and operates at 120 GHz (Indie Semiconductor). The study primarily focuses on three ISM-band ICs functioning at approximately 24 GHz, 61 GHz, and 120 GHz. The mmWave radar modules are responsible for non-contact measurement of human heart rate (HR), heart rate variability (HRV), and blood pressure (BP).

Due to intellectual property and regulatory considerations, detailed electronic schematics have been limited to block-level architecture, as shown in Fig. 1 and Fig. 2. Technical schematics can be made available to the editorial board under confidentiality agreements, if required.

A. Test Population

Clinical validation of the system was conducted at renowned tertiary care hospitals in Bengaluru, India, involving a diverse cohort of over 100 adult participants aged 18 to 88 years. The study included both healthy individuals and patients with known health conditions, provided they could remain still for at least two minutes. Exclusion criteria included individuals with implanted cardiac devices, movement disorders, or those undergoing beta-blocker therapies.

To ensure data privacy, only anonymized vital and non-vital parameters are shared publicly. The radar and reference signals are one-dimensional electrical signals, inherently preserving participant anonymity. Full datasets can be made available upon request under appropriate ethical data sharing agreements. Additionally, a live system demonstration with a volunteer subject can be arranged by the corresponding author for interested researchers.

B. Reference Instrument

A medical-grade pulse oximeter and stethoscope were used to measure heart rate, while a sphygmomanometer (BP cuff) was employed to measure blood pressure, serving as reference tools to validate our findings.

C. System Architecture and Sensing Framework

In alignment with the global shift toward proactive, decentralized, and digitally enabled healthcare, this research presents a contact-free, AI-powered health screening and monitoring system. Rather than a product promotion, the system serves as an illustrative example of a scalable medical device ecosystem built on artificial intelligence, sensor fusion, and hybrid edge-cloud architecture. It features a tablet-sized, portable device capable of real-time, contactless measurement of over 18 physiological parameters, including heart rate, respiratory rate, SpO_2, non-invasive blood pressure, and heart rate variability. Central to the system is a proprietary AI foundation model, HealthGPT, operating in two modes:

HealthGPT Lite for on-device inference and HealthGPT Pro for cloud-based contextual analysis. The platform is designed for standalone use or integration with external medical devices and health records, offering localized data visualization and secure cloud synchronization. Validated in clinical-like settings, the system has achieved Technology Readiness Level (TRL) 7.0, confirming its suitability for real-world healthcare deployment.

Inside the system enclosure, a tightly integrated sensor fusion framework is implemented, comprising intelligent computing hardware and analytical software modules. As illustrated in Fig. 1, this framework includes two primary subsystems: 1) a radar-based sensing unit and 2) a complementary suite of sensors contributing to multimodal data fusion. The radar subsystem operates within the Industrial, Scientific, and Medical (ISM) radio bands and is configured to initiate signal acquisition upon receiving a predefined trigger frequency. A 16-bit Analog-to-Digital Converter (ADC) samples incoming radar signals at a programmable sampling frequency, initiating processing of a defined number of data samples.

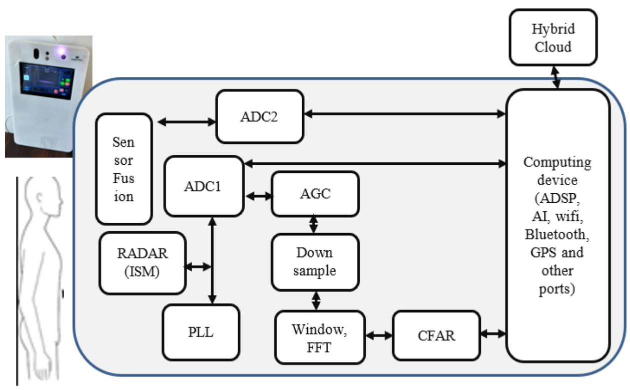

Fig. 1. Integrated sensor fusion architecture for health monitoring using radar and auxiliary sensors.

Signal strength is optimized using an Auto Gain Control (AGC) mechanism, and DC offset cancellation is performed when enabled. A Phase-Locked Loop (PLL) ensures frequency stability during operation. The acquired radar data is downsampled and processed through a Hanning window function to reduce spectral leakage, followed by a Fast Fourier Transform (FFT) with selectable lengths of 128, 256, 512, or 1024 points, depending on the sampling rate and ramp duration. From the FFT output, signal features such as magnitude and phase are extracted for target characterization. Target detection is performed using a Constant False Alarm Rate (CFAR) algorithm, which applies tuneable parameters including CFAR window size, guard bands, and threshold levels to suppress noise and false positives.

Both raw and transformed radar data are transmitted to an embedded computing device running a Linux operating system. This device also receives inputs from additional sensing modalities such as infrared sensors, camera modules, and air quality sensors via separate ADC interfaces. The aggregated multimodal data is processed using digital signal processing (DSP) algorithms and machine learning (ML) models to infer vital and non-vital health parameters through direct and indirect computational methods.

A custom web-based application is deployed locally on the device for real-time visualization and interaction. This interface also enables secure bidirectional communication with a hybrid cloud server, facilitating extended analytics, secure storage, and integration within this system platform's white-labelled device architecture.

D. MM Wave Radar Setup

The primary approach of Frequency Modulated Continuous Wave (FMCW) radar-based vital sign detection is to measure chest vibrations resulting from the mechanical effects of breathing and the cardiac cycle. The heartbeat signal typically has a fundamental frequency between 0.75 Hz and 2.5 Hz (45 to 150 beats per minute) and an amplitude of approximately 0.45 mm from the chest. In contrast, the breathing signal has a fundamental frequency between 0.1 and 0.7 Hz (6 to 42 breaths per minute) with an amplitude range of 3.5 mm to 11.5 mm. In this research, we present results obtained using a 120 GHz radar system from Indie Semiconductor FFO GmbH.

The general block diagram of the radar system is shown in Fig. 2. The antennas, labelled T(x) and R(x), correspond to the transmit and receive channels, respectively. A frequency-modulated radio frequency (RF) signal is emitted toward the subject's chest for non-contact physiological sensing.

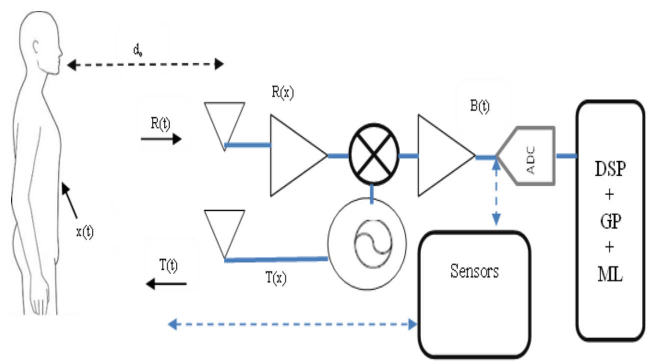

Fig. 2. Block diagram of a radar system to measure heart rate and heart rate variability wirelessly.

The received signal is first pre-processed before being sent to an analog-to-digital converter (ADC) and is then transmitted to digital signal processing (DSP) and other modules for further analysis.

The radar transmits signal T(t) via T(x) antenna to the subject at a distance of d_o :

$$T(t) = A_T COS(2\pi f\, t + \theta(t)) \tag{1}$$

where, f is the carrier frequency, A_T is the power amplitude and $\theta(\,t)$ is the phase noise from waveform generator.

Chest displacement caused by breathing and heartbeat is measured through phase modulation in the received signal, yielding a signal that encapsulates the effects of both breathing and heartbeat.

R(t) is the signal which the radar receives after it is reflected by the subject's chest displacement:

$$R(t) \cong A_R COS(2\pi f\, t - 4\pi \frac{d_0}{\lambda} - 4\pi \frac{x(t)}{\lambda} + \theta(t - 2\frac{d_0}{c})) \quad (2)$$

where, A_R is the received power, λ is the carrier wavelength, c is the speed of light in free space, $x(t)$ is the chest wall movement due to heartbeat and respiration, and $\theta\left(t - 2\, d_o / c\right)$ is the phase noise with a delay $2d_o / c$.

The same T(x) is used as local oscillator (LO) signal to down-convert R(t) to baseband B(t):

$$B(t) = \cos\,(\theta_0 + 4\pi \frac{x(t)}{\lambda} + \triangle\,\theta(t)) \qquad (3)$$

where, $\theta_0 = 4\pi d_0/\lambda + \sigma$ is the summation of phase shift from the nominal distance d_o and at the reflection surface, $\Delta\,\theta(t) = \theta(t) - \theta\left(t - 2d_o / c\right)$ is the residual phase noise.

E. Experimental Procedure

The test subject is seated between 1.25 m and 1.75 m from the radar device, with a medical-grade pulse oximeter and blood pressure monitor attached in accordance with standard clinical protocols. Data collected by the radar over a one-minute interval is processed through a series of digital signal processing (DSP) steps. These include adaptive filtering, phase demodulation, and feature extraction, followed by a Fast Fourier Transform (FFT) for frequency domain analysis.

To enhance temporal stability and reduce physiological noise, a customized Long Short-Term Memory (LSTM) neural network developed in C and C++ is employed for post-processing. Final results are transmitted securely to a hybrid cloud platform, enabling remote access to derived metrics such as heart rate (HR), heart rate variability (HRV), blood pressure (BP), and other auxiliary parameters from any connected device. Fig. 3 illustrates the overall architecture of the hybrid cloud integration.

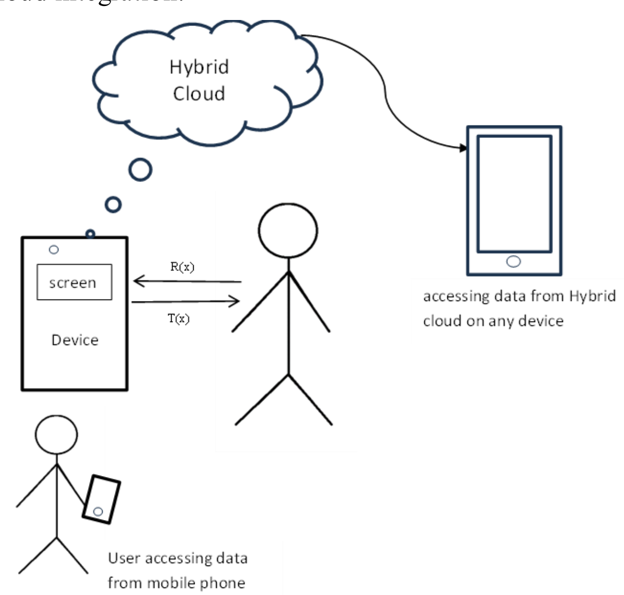

Fig. 3. Overview of device architecture and hybrid cloud integration flow.

The radar subsystem operates across widely accessible ISM frequency bands at 24 GHz, 61 GHz, and 120 GHz, capturing minute chest wall displacements associated with cardiac and respiratory activity. Signals within the 0.75–2.5 Hz range (corresponding to 45 150 BPM) are segmented into 10-second windows, producing six HR estimations per minute. These radar readings are then fused with auxiliary sensor data, including motion, temperature, and air quality, using an adaptive signal fusion framework. In future work, this multimodal sensing framework is expected to enable not only the estimation of primary vital parameters (HR, HRV, and BP) but also the inference of secondary physiological indicators, such as stress levels, brain health, mental health and fatigue states.

Preprocessing begins with phase demodulation using an arctangent-based algorithm that incorporates noise suppression mechanisms. This is followed by baseband conversion and adaptive bandpass filtering to isolate relevant physiological signals. FFT is applied to extract frequency-domain features, while template matching identifies PQRS or PQRST waveform patterns in the time domain. These extracted features are then passed to the LSTM module for signal stabilization and used in the system's indirect BP estimation module, thereby maintaining both high signal fidelity and diagnostic accuracy.

F. Temporal Smoothing Using LSTM

To address signal noise, motion artifacts, and temporal inconsistencies inherent in radar-derived HR measurements, the authors developed a C++ based LSTM neural network. Operating on 10-second radar-derived HR segments, the LSTM model was chosen over conventional smoothing techniques due to its ability to learn and retain both short- and long-term dependencies. This approach enhances the stability of HRV signals, which are further used to estimate BP and assess physiological variability under real-world conditions.

Each 10-second radar-derived reading is scaled by dividing the value by 100 to normalize it below 1 and is then fed into the LSTM model. The LSTM operates in three iterations, each using four consecutive readings: the first iteration uses readings values in a sequence 1, 2, 3, and 4; the second uses 2, 3, 4, and 5; and the third uses 3, 4, 5, and 6. Each iteration generates a predicted HR value, and the final output is calculated as the average of these three predictions. This iterative approach ensures the stabilization of the final HR value by smoothing out any inconsistencies or noise present in the raw radar data.

The internal structure of the LSTM node, as shown in Fig. 4, consists of a forget gate, input gate, and output gate, which collaboratively regulate the flow of information through the network. This architecture enables the LSTM to retain relevant patterns and discard noise, ensuring robust and accurate heart rate predictions. The LSTM's role in refining and stabilizing the HR output is integral to the system's ability to provide reliable and medically accurate real-time monitoring.

In this LSTM model, the Long-Term Memory (LTM) and Short-Term Memory (STM) values generated from the first iteration are passed forward to the next iteration, along with a new set of four HR readings. This allows the model to build upon the prior memory states, incorporating information from previous HR data to enhance accuracy and stability in the output. Specifically, the LTM and STM values calculated from readings 1, 2, 3, and 4 in the first iteration serve as the initial memory states for the next set of inputs (readings 2, 3, 4, and 5) in the second iteration. This process is repeated across iterations, with each successive iteration updating and carrying forward the LTM and STM values, thereby reinforcing the model's understanding of temporal patterns in the data. Fig. 5 provides a visual of this iterative process, illustrating how the memory states are updated and propagated, ultimately ensuring a stabilized output across multiple LSTM iterations.

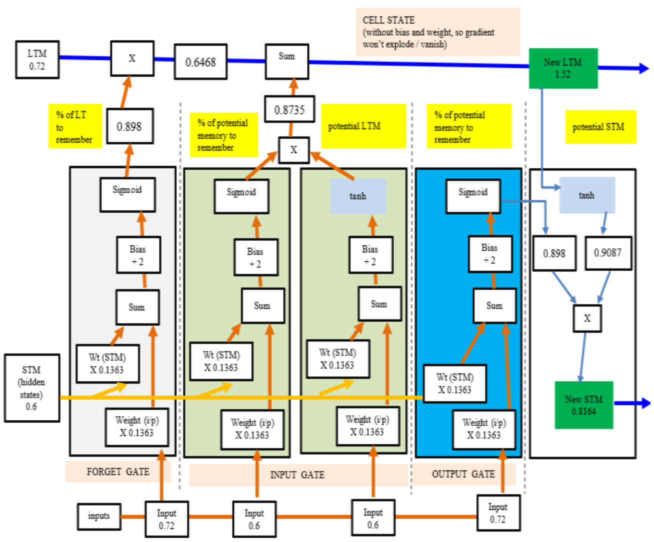

Fig. 4. Single LSTM node showing the flow of data.

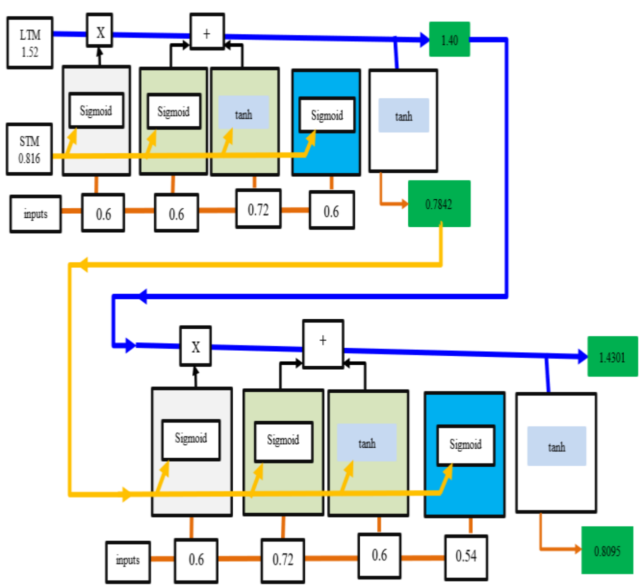

Fig. 5. Multiple iteration of the LSTM model.

G. Blood Pressure Estimation: A Physics-Informed AI Approach

A systematic approach was presented for estimating blood pressure (BP) parameters from reflected radar signals, enabling fully contactless monitoring. This methodology integrates fundamental scientific principles with adaptive artificial intelligence and advanced digital signal processing (DSP) techniques. As illustrated in Fig. 6, the process involves a series of signal transformations and algorithmic steps designed to extract vital cardiovascular information without the use of physical probes or direct contact with the subject.

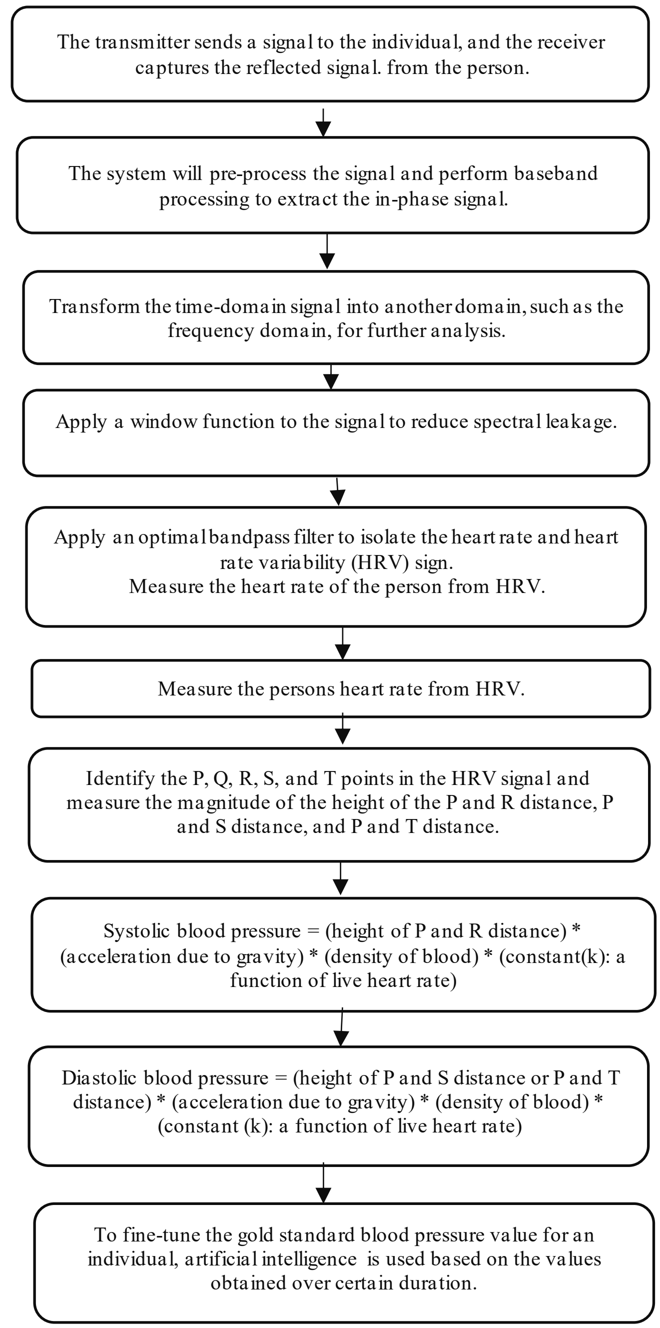

Fig. 6. Step-by-step method and data flow for measuring blood pressure wirelessly without any contact.

The radar system continuously tracks heart rate variability (HRV) signals to identify PQRST intervals, which are then analysed using adaptive learning DSP algorithms. From these features, systolic and diastolic pressures are estimated using the following equations:

Systolic blood pressure = (height of P and R distance($\boldsymbol{h}$)) * (acceleration due to gravity($\boldsymbol{g}$)) * (density of blood($\boldsymbol{\rho}$)) * (constant($\boldsymbol{k}$): a function of live heart rate) (4)

Diastolic blood pressure = (height of P and S distance or P and T distance ($\boldsymbol{h}$)) * (acceleration due to gravity($\boldsymbol{g}$)) * (density of blood ($\boldsymbol{\rho}$)) * (constant($\boldsymbol{k}$): a function of live heart rate) (5)

Here, h denotes the amplitude difference between specific cardiac waveform peaks, g is the gravitational acceleration, ρ is the blood density, and k is a constant dynamically derived from an adaptive learning AI model, which depends on the live heart rate value. This indirect estimation technique has been validated against a conventional sphygmomanometer, achieving measurement accuracy in the 90 to 98% range, as detailed in Table II.

H. User Experience and Operational Simplicity

Although supported by advanced AI and digital signal processing backends, the system is designed to offer a straightforward, hygienic, and contactless user experience. Users interact with the system via an integrated touchscreen interface or a mobile application, with measurements obtained while the individual remains seated within the operational range—without the need for physical contact or wearable sensors. This user-centric, non-intrusive design makes the system particularly suitable for deployment in eldercare facilities, infectious disease control scenarios, primary care centers, and community health programs.

The actual device, as shown in Fig. 7, is compact—approximately the size of a traditional tablet—making it both portable and unobtrusive.

Fig. 7. Contactless health screening product.

For each measurement session, the reference person (RP) or subject follows a simple and repeatable protocol to ensure accurate and consistent readings:

- The RP is seated in front of the radar and sensor-enabled device, as illustrated in Fig. 8.
- Prior to starting, the RP should ensure their bladder is nearly empty and relax for at least 5 minutes to stabilize physiological parameters.
- The RP should sit upright on a chair, facing the device at a distance of 1.1 to 1.75 meters, with both feet flat on the floor and legs uncrossed.
- The RP is encouraged to take a few deep breaths, then continue with normal, relaxed breathing throughout the measurement period.
- Measurements are recorded for a minimum of 2 minutes, extendable to 5, 10, or 15 minutes based on the use case.
- The recorded values are displayed in real time via the user interface (UI), as shown in Fig. 9, and are also transmitted to the RP's mobile device and uploaded to the cloud for secure, remote access and further analysis.
- To ensure consistency and long-term reliability, the procedure should be repeated daily at approximately the same time.

Fig. 8 shows the live demonstration of the device. The device includes a screen that displays the data. Additionally, any other device can access the same data via the hybrid cloud, ensuring flexibility and remote monitoring capabilities.

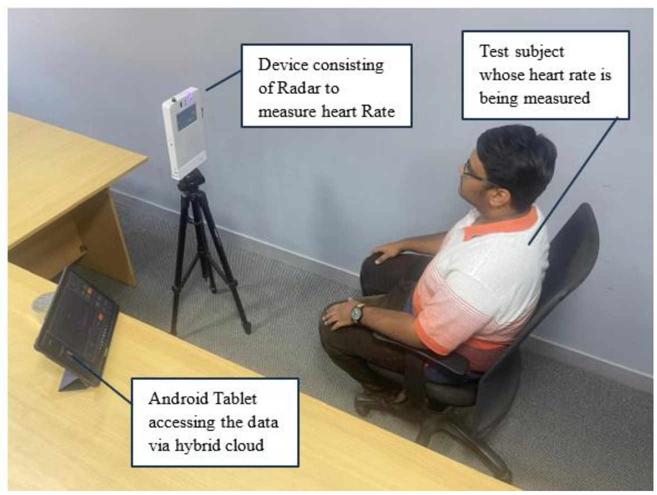

Fig. 8. Live demo of the device. (Subject is the co-author, journal is free to use their image and associated data in publication).

The device screen, as shown in Fig. 9, displays the heart rate, BP and other vitals

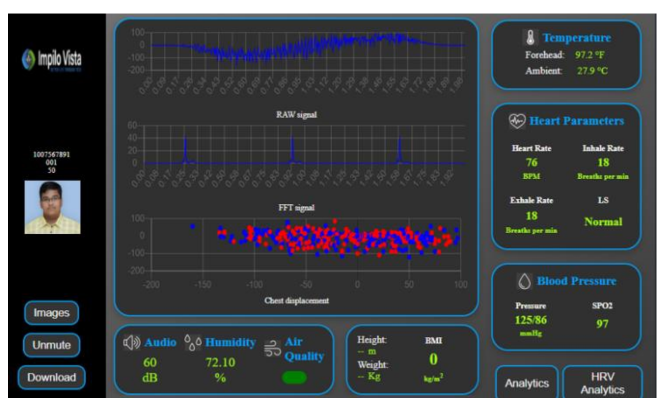

Fig. 9. Device screen showing heart rate, BP and other vitals.

I. Heart Rate Variability

The number of beats per minute is referred to as the heart rate, measured in beats per minute (BPM). Heart rate variability (HRV) represents the variation in the time intervals between consecutive heartbeats. HRV is visualized by the changes in R-R intervals over time, as shown in Fig. 10.

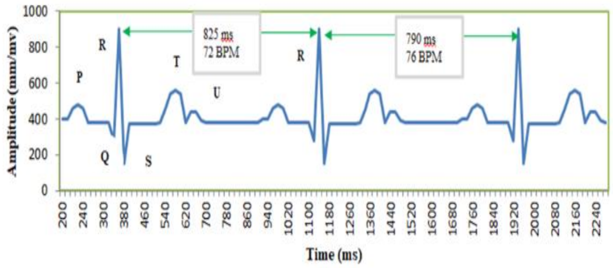

Fig. 10. Heart rate variability (HRV) visualized with R-R interval changes.

Heart rate variability (HRV) is a critical marker of autonomic nervous system function, providing valuable insights into an individual's cardiovascular fitness and stress levels. Fig. 12 illustrates a graphical representation of a heart rate variability (HRV) meter, displaying live HRV data along with the activities of the sympathetic nervous system (SNS) and the autonomic nervous system (ANS).

On the left side of the diagram, the variations and activities of the SNS are shown, highlighting its role in controlling the "fight-or-flight" response, such as reactions to fear, anxiety, or being startled. Typically, the SNS signals the adrenal glands to release adrenaline, leading to an increase in heart rate (HR) and blood pressure (BP).

On the right side, the ANS is depicted as regulating the "rest-and-digest" response, which counteracts the effects of the SNS. The diagram also outlines three conditions: rest, previous status, and live (current) status.

Low HRV is often linked to an increased risk of cardiovascular disease, as it indicates a reduced ability of the heart to adapt to changing physiological demands. Conversely, higher HRV reflects better cardiovascular health and a more flexible, responsive autonomic system. Fig. 11 illustrates human age variation as a function of heart rate variability (HRV), with the green-colored region representing the normal recommended values.

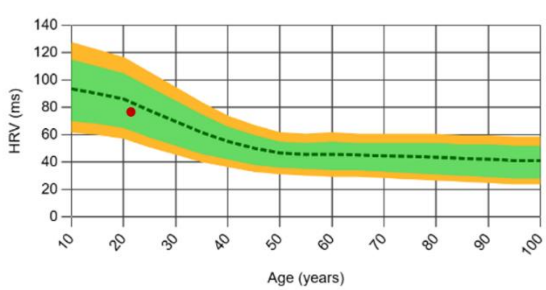

Fig. 11. Age variation as a Function of Heart Rate Variability (HRV).

V. Results

The proposed contact-free, radar-based health monitoring system demonstrates strong potential for accurate, non-intrusive estimation of key physiological parameters, including heart rate (HR), heart rate variability (HRV), and blood pressure (BP). Validation was performed on more than one hundred adult participants aged 18 to 88 years, using both the authors' vitals and those of external volunteers. Clinical-grade reference instruments—a Class B BP monitor, a manual sphygmomanometer (gold standard), a pulse oximeter, and a stethoscope—served as comparative benchmarks. The consolidated quantitative outcomes for HR and BP are summarized in Table I and Table II, respectively.

Under controlled indoor conditions (ambient temperature 18°C–32°C in an air-conditioned setting), the system achieved 90%–98% accuracy for BP estimation relative to the sphygmomanometer and 90%–95% accuracy for HR estimation compared with pulse oximeter and stethoscope readings. Each participant underwent three consecutive daily measurements to ensure statistical rigor and account for day-to-day variability.

A comprehensive quantitative analysis was performed to evaluate agreement, correlation, and precision. Bland–Altman plots demonstrated strong agreement between the contactless device and reference instruments. Pearson and Spearman correlation coefficients confirmed both linear and monotonic relationships between measured and gold-standard values. Additionally, Mean Absolute Error (MAE) with 95% confidence intervals provided insight into the system's consistency and repeatability. These findings were benchmarked against state-of-the-art radar-based literature and certified clinical devices, offering a robust comparative framework for assessing real-world applicability.

The system is implemented on a portable, tablet-sized platform integrating radar sensing, multimodal sensor fusion, signal processing, embedded AI models, and hybrid edge–cloud connectivity. This architecture enables real-time inference and supports longitudinal monitoring. The adaptive inference framework further enhances contextual interpretation of physiological signals while maintaining user simplicity and fully non-contact operation.

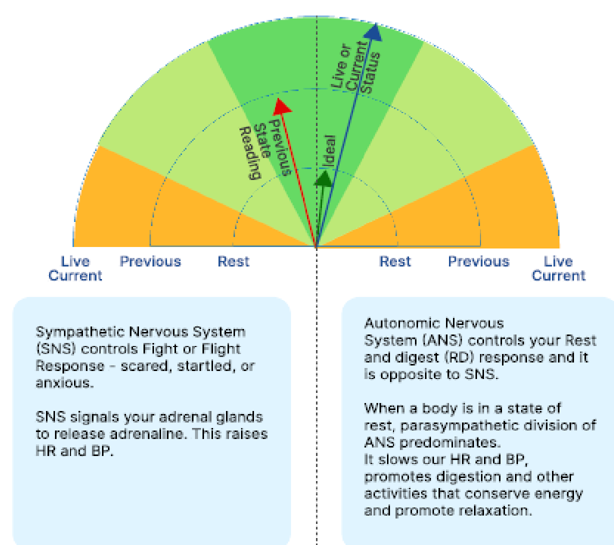

Fig. 12. Live heart rate variability (HRV) with SNS and ANS activities.

TABLE I. TEST RESULTS: COMPARISON OF HEART RATE MEASUREMENTS FROM OUR DEVICE AND REFERENCE DEVICES (BEFORE AND AFTER APPLYING LSTM MODEL): HEART RATE (HR), BEATS PER MINUTE (BPM), LONG SHORT-TERM MEMORY (LSTM)

Description Candidates/ Subjects.	HR measured using medical grade Pulse Oximeter (BPM)	HR measured using medical grade blood pressure (BP) and HR meter (BPM)	HR from our radar based contactless method. (BPM)	HR from our radar based contactless method, (BPM) with LSTM	Accuracy w.r.to medical grade pulse oximeter. (%)	Accuracy w.r.to medical grade B and HR meter. (%).
Subject 1	81	80	72	76.33	94.23	95.41
Subject 2	89	91	82	81	91.01	89.01
Subject 3	78	77	73	76	97.43	98.70
Subject 4	70	74	70	68	97.14	91.89
Subject 5	91	89	88	70	76.92	78.65
Subject 6	92	95	88	87	94.56	91.57
Subject 7	61	62	57	60	98.36	96.77
Subject 8	62	67	60	61	98.38	91.04
Subject 9	67	64	62	62	92.53	96.87
Subject 10	77	77	74	75	97.40	97.40
Subject 11	90	89	88	88	97.77	98.87
Subject 12	92	90	82	87	94.56	96.66
Subject 13	93	91	88	89	95.69	97.80
Subject 14	99	100	94	94	94.94	94.00
Subject 15	102	105	98	99	97.05	94.28
Subject 16	65	68	61	64	98.46	94.11
Subject 17	67	67	67	66	98.50	98.50
Subject 18	78	79	76	73	93.58	92.40
Subject 19	84	85	78	81	96.42	95.29
Subject 20	89	92	85	84	94.38	91.30

Note: We conducted clinical trials for this experiment at renowned hospitals in India with several test candidates. Due to data privacy concerns, we are only disclosing the data of the authors and a few selected subjects. However, researchers can contact the corresponding author for a live demo of the research work for validation.

TABLE II. TEST RESULTS: COMPARISON OF BLOOD PRESSURE (BP) MEASUREMENT FROM OUR DEVICE AND REFERENCE DEVICES BEFORE AND AFTER APPLYING THE LONG SHORT-TERM MEMORY (LSTM) TEST DURATION: 2 MINUTES

Description Candidates/ Subjects.	BP measured using medical grade BP meter. (systolic /diastolic)	BP measured using medical grade sphygmomanometer. (systolic / diastolic)	BP measured using contactless method (systolic /diastolic)	BP measured using contactless method (systolic /diastolic) with LSTM	Accuracy w.r.to BP meter. (systolic /diastolic) (%)	Accuracy w.r.to sphygmomanometer) Gold standard. (systolic /diastolic) (%).
Subject 1	120 / 84	118 / 80	116 / 82	117 / 81	97/96	99/98
Subject 2	180 / 110	170 / 105	173 / 98	168 / 95	93/86	98/90
Subject 3	130/85	140/87	122/80	123/84	94/98	87/96
Subject 4	125/84	125/90	118/87	122 /80	97/95	97/88
Subject 5	110 /75	115 / 80	102 / 75	108 /70	98/ 93	93/87
Subject 6	145 / 95	150 /100	140 /85	142 / 90	97/ 94	94/ 90
Subject 7	175 / 115	180 / 115	175 / 115	173 /113	98/98	96/98
Subject 8	125 / 85	118 / 90	116 / 82	115 / 82	92/96	97/91
Subject 9	170 / 120	180 / 105	163 / 98	165 / 95	97/ 79	91/90
Subject 10	140/95	145/ 90	122/80	133/85	95/89	91/94
Subject 11	185 / 110	175 / 105	173 / 98	168 / 100	90/90	94/98
Subject 12	135/85	140/87	122/80	123/84	91/98	87/96
Subject 13	110 /75	115 / 80	102 / 75	108 /70	98/93	93/87
Subject 14	135/85	140/87	122/80	123/84	91/98	87/96
Subject 15	120 / 84	118 / 82	116 / 82	117 / 81	97/96	97/98
Subject 16	170 / 110	170 / 105	163 / 98	168 / 95	98/86	98/90
Subject 17	115 /75	125 / 80	102 / 75	108 /70	93/93	86/87
Subject 18	165 / 110	170 / 105	155 / 98	162 / 102	98/92	95/97
Subject 9	130/85	140/87	122/80	123/84	94/98	87/96
Subject 20	120 / 88	118 / 85	116 / 82	117 / 81	97/92	99/95

Note: We conducted clinical trials for this experiment at renowned hospitals in India with several test candidates. Due to data privacy concerns, we are only disclosing the data of the authors and a few selected subjects. However, researchers can contact the corresponding author for a live demo of the research work for validation.

From a translational standpoint, the system has reached Technology Readiness Level (TRL) 7, having undergone functional validation and demonstrating readiness for controlled real-world deployment. Regulatory assessments and hospital-based evaluations are underway to advance clinical translation.

Despite its encouraging performance, certain limitations remain. The validation was restricted to adults, controlled posture, and short-range indoor operation, which may limit generalizability to dynamic or high-motion environments, paediatric populations, or broader demographic groups. Residual noise and motion artifacts, inherent to radar-based sensing, can still influence measurements. Ongoing work focuses on improving digital signal processing pipelines, minimizing internal and external artifacts, and refining real-time deep learning models to enhance robustness and statistical confidence.

Collectively, the results confirm the feasibility of contact-free estimation of cardiovascular parameters from micro chest wall displacements without wearable sensors or cuff-based methods. This represents a significant advance in remote and continuous health monitoring. Continued research and broader community validation are encouraged to further develop and expand this promising approach.

VI. Future Works

The future of medical devices is moving towards compact, portable, and contact-free systems that can securely integrate personal health data into hybrid cloud environments. This shift emphasizes the need for continuous, non-invasive monitoring solutions, adaptable across clinical, public, and home settings. Upcoming research will focus on new algorithms, multi-sensor integration, and enhanced radar signal processing to improve these devices' capabilities.

A. Advanced Algorithms for Comprehensive Monitoring

Research in advanced algorithms will be essential to capture multiple health parameters—heart rate, variability, blood pressure, glucose levels, and more, with high accuracy. These algorithms will need to account for environmental complexities, handling multiple persons, ensuring accurate, real-time, contactless readings, even in varied conditions.

B. Enhanced Accuracy with Multi-Radar Interference

Experiments with multi-radar interference techniques will boost the precision of complex measurements, such as blood pressure and respiration rates. Testing these in high-interference settings, like public areas, will provide robust, reliable radar-based monitoring and help optimize both direct and indirect measurement methods.

C. Parameter Modeling and Dependency Analysis

Studying the interdependencies between physiological parameters offers deeper insight into personalized health trends. This research will support the design of monitoring devices that adapt to individual variability, enhancing the precision and relevance of health assessments.

D. Expanding Use Cases

Contactless monitoring has wide applications, including:

- Proactive Health Monitoring for Aging Populations: Accessible devices for early health indicators could support independent living for seniors.
- Clinical and Non-Clinical Use: Psychiatry, yoga, and fitness settings can use these devices to track mental and physical well-being.
- Military and Industry Applications: Military personnel monitoring and machine health tracking (Industry 4.0/5.0) are emerging fields for this technology.
- Financial Services: Health data integration in loan and insurance processes offers new avenues for risk assessment and underwriting.

E. Miniaturization and Mobile Integration

Embedding compact monitoring modules into mobile devices will make health screening universally accessible. This requires miniaturized sensors that maintain high performance while optimizing power use, leading to future smartphones and wearables with advanced health-monitoring capabilities.

VII. Data Privacy, Ethics, Research Work Demo

1) Data privacy: This study exclusively uses the vital and non-vital parameters of the authors. Additionally, the method has been validated with data from over 100 subjects at leading hospitals in India, with all personally identifiable information removed. The radar and reference signals used are one-dimensional electrical signals, ensuring a high level of anonymity.

2) Data availability: The validated test data used for this research, obtained from ImpiloVista and other gold-standard medical devices, are available from the corresponding author upon reasonable request.

3) Ethics statement: In the initial phase, data were collected solely from the researchers themselves. All mmWave radars operate within the ISM band, and all electronic components used are CE and FCC compliant.

4) Product demo and supplementary materials: Upon request, the corresponding author can arrange a live demonstration of our research findings using the complete system with a subject for interested researchers.

5) Ethics and consent to participate declarations: We confirm that all methods were conducted in accordance with relevant guidelines and regulations, including the Declaration of Helsinki and applicable local regulatory standards. This study involved the use of medically approved international Industrial, Scientific, and Medical (ISM) band radar and medical-grade sensors, classified as a Class B medical product, without administering medication or inserting probes into the participants' bodies. All data were collected from subjects at a 1-meter distance with prior informed consent, ensuring strict privacy and confidentiality.

VIII. Conclusion

This research presents a novel, non-invasive method for accurate, real-time measurement of heart rate (HR), heart rate variability (HRV), blood pressure (BP), and other vital signs from a distance, offering dynamic and continuous monitoring without physical contact. By leveraging the same signal, HRV can be derived, providing insights into brain-heart interactions critical for optimal health and supporting real-time adjustments for well-being. Through advanced sensor fusion techniques, this study demonstrates a reliable, efficient approach to indirect measurement of both vital and non-vital parameters, positioning contactless health monitoring as a promising advancement for remote and continuous healthcare.

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