A Comprehensive Study on Heart Rate and Blood Pressure Measurement Techniques

Suneetha Irala[1]
Department of Electronics and Communication Engineering
Annamacharya Institute of Technology and Sciences
Tirupati,India
iralasuneetha.aits@gmail.com

Neha Sai Velpula[2]
Department of Electronics and Communication Engineering
Annamacharya Institute of Technology and Sciences
Tirupati,India
nehasaivelpula2198@gmail.com

Moula Kothapalli[3]
Department of Electronics and Communication Engineering
Annamacharya Institute of Technology and Sciences
Tirupati,India
kothapallimoula@gmail.com

Pujith Kommindala[4]
Department of Electronics and Communication Engineering
Annamacharya Institute of Technology and Sciences
Tirupati,India
Kommindalapujith@gmail.com

Mukunda Yarla[5]
Department of Electronics and Communication Engineering
Annamacharya Institute of Technology and Sciences
Tirupati,India
monstarmukunda041@gmail.com

Abstract**—** The synthesis explores diverse methodologies for the non-contact estimation of heart rate (HR), breathing rate (BR), and apnea detection. Recent advancements leverage three primary technological pillars: Wireless Sensing (Wi-Fi/Radar): Systems like "PulseFi" utilize Wi-Fi Channel State Information (CSI) and custom Long Short-Term Memory (LSTM) models to achieve high accuracy without complex multi-antenna setups. Similarly, radar-based studies demonstrate that vital sign measurement is increasingly feasible with maximum deviations often falling within 5% to 10%. Remote Photoplethysmography (rPPG): Camera-based rPPG analyzes subtle skin color changes. Research indicates that optimizing Regions of Interest (ROI), particularly the forehead and cheeks, significantly improves HR estimation accuracy. Optical Fiber Sensing: Mattress-integrated sensors using ballistocardiogram (BCG) signals and adaptive spectrum analysis offer a discrete way to monitor vital signs during sleep, effectively managing individual differences such as weight and posture.

Keywords—Contactless monitoring, Heart rate measurement , Breathing rate detection, WiFi signal analysis , Radar sensing, Camera-based pulse detection, Wireless health monitoring , Real-time monitoring.

I. INTRODUCTION

The global rise in aging populations and chronic diseases has created an urgent need for continuous health monitoring. Cardiopulmonary metrics like HR and BR are critical indicators of cardiovascular health, infections, and acute conditions like pneumonia. Furthermore, detecting sleep apnea—temporary pauses in breathing—is vital due to its high global prevalence and potential for serious complications. While clinical standards like ECG and polysomnography (PSG) remain the "gold standard" for diagnosis, their intrusiveness limits their role in proactive, long-term monitoring. This has spurred innovation in non-contact sensing.

Wireless signals (e.g., Wi-Fi and Radar) are advantageous because they can penetrate obstructions, function in low light, and preserve user privacy. Camera-based rPPG provides a transformative solution for clinical and at-home settings by utilizing standard RGB cameras, though it remains sensitive to lighting and motion. Optical fiber-based mattresses offer high reliability and durability for unconstrained monitoring, providing a promising alternative for specialized medical environments and home use.

II. LITERATURE SURVEY

[1]. Estimation of Breathing Rate and Heart Rate from Photoplethysmogram

Rosmina Jaafar, Mohd Aliff Azroy Rozali have explored estimating HR and BR from physiological signals, particularly electrocardiogram (ECG) and photoplethysmogram (PPG) signals. PPG has gained significant attention due to its non-invasive nature, low cost, and ease of implementation, and previous studies have demonstrated that PPG signals contain not only cardiac information but also respiratory-induced modulations. Various signal processing techniques have been applied to extract these components, including peak detection, frequency analysis, principal component analysis (PCA), and empirical mode decomposition (EMD).

[2]. Remote PPG (rPPG) via Deep Learning

Mehrjouseresht, P. et al. (2021) , Remote PPG (rPPG) via Deep Learning .This seminal work focuses on Remote Photoplethysmography (rPPG). The core principle is that with every heartbeat, the blood volume in facial vessels changes, slightly altering the light absorption of the skin. While these changes are invisible to the naked eye, Mehrjouseresht and colleagues used deep learning to extract these signals from standard RGB camera feeds.
The project's strength lies in its "contactless" philosophy. It eliminates the need for any wearable hardware. The researchers developed a pipeline that involves face tracking, Region of Interest (ROI) selection (usually the forehead or cheeks), and signal filtering. By applying deep learning filters, they successfully separated the pulse signal from ambient light noise, making it a pioneer for telehealth applications during the post-pandemic era. Motion Artifacts: This is the "Achilles' heel" of rPPG. If the subject moves their head significantly, the ROI is lost, and the signal-to-noise ratio drops to unusable levels. Skin Tone Bias: Light absorption varies significantly across different Fitzpatrick skin types. Many rPPG models historically struggle with darker skin tones because the signal strength (AC component) is much weaker compared to the background light (DC component). Environmental Sensitivity: Fluorescent lights or "flicker" from electronic screens can mimic heart rate frequencies, leading to false positives.

[3]. Heart Rate and Respiratory Rate Measurement by Means of Radar Technology

Magdalena Liebetruth , Kai Kehe , Dirk Steinritz, Stefan Sammito, radar-based sensing has emerged as a promising alternative, enabling remote and non-invasive measurement of physiological parameters by detecting minute chest wall movements caused by cardiac activity and respiration .Early studies on radar-based vital sign monitoring date back to the 1970s, but significant advancements have been achieved in recent years due to improvements in signal processing, hardware miniaturization, and algorithm development.

[4]. 3D CNN for Heart and Respiratory Rate Prediction

Ibne Farabi Shihab (2025) , 3D CNN for Heart and Respiratory Rate Prediction . Shihab's 2025 research represents the cutting edge of deep learning applications in healthcare. The paper addresses the fundamental flaw in traditional 2D video analysis: the loss of temporal (time-based) depth. By utilizing 3D Convolutional Neural Networks (3D CNNs), the system doesn't just look at individual frames; it analyzes "spatial-temporal" volumes of video data. This allows the model to capture the subtle rhythmic changes in skin color (photoplethysmography) and chest movements simultaneously. The project is designed specifically for noisy, real-world smartphone environments. Unlike clinical settings where lighting is controlled, Shihab's model employs advanced preprocessing to normalize varying light conditions. The author posits that by training on diverse datasets, the 3D CNN can learn to ignore "distractor" movements (like a user blinking or shifting slightly) while focusing on the micro-oscillations associated with heart and lung activity. Computational Intensity: 3D CNNs are notoriously "heavy." Running these models on a standard smartphone in real-time requires significant GPU optimization, which limits the accessibility for older hardware.

[5]. PulseFi: Wi-Fi CSI for Cardiopulmonary Monitoring

Kocheta, P. et al. (2025) , PulseFi: Wi-Fi CSI for Cardiopulmonary Monitoring , PulseFi is perhaps the most "invisible" of all the projects. It utilizes Wi-Fi Channel State Information (CSI). Essentially, it treats the Wi-Fi signals already present in your home as a sensor. When a person breathes or their heart beats, it causes minute disturbances in the Wi-Fi waves reflecting off their body. Kocheta et al. developed a custom LSTM (Long Short-Term Memory) neural network to analyze these disturbances over time. LSTMs are perfect for this because they are designed to remember patterns in sequences. The model filters out the "static" of the room (furniture, walls) and isolates the

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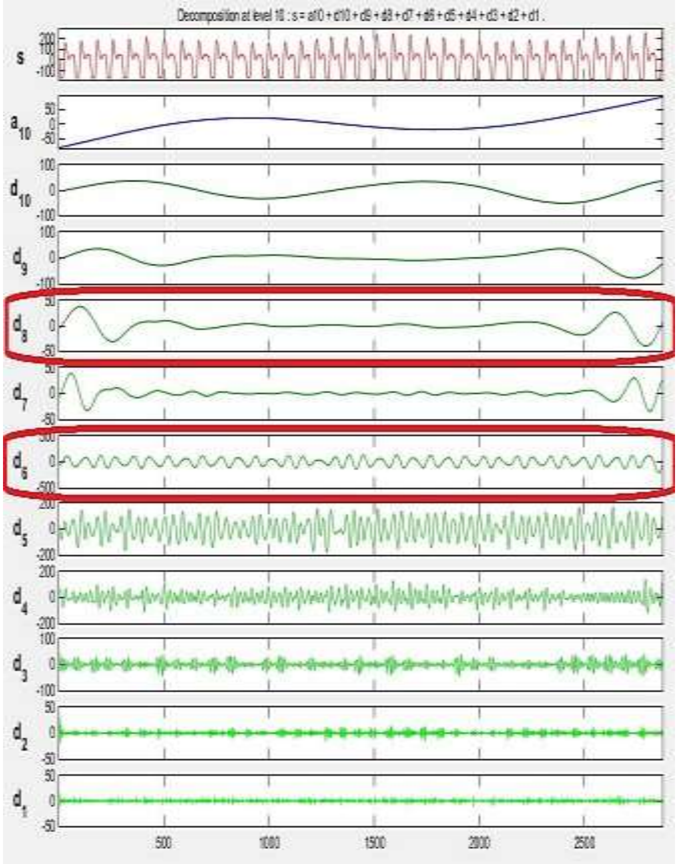
rhythmic patterns of the human chest. This project is revolutionary because it requires zero new hardware—just a router and a receiver (like a phone or laptop). Early Prototype Stage: As noted in your table, this is still a preprint. The real-world validation is limited to controlled environments with few obstructions. Multi-Person Interference: If two people are in the same room, the Wi-Fi signals bounce off both, making it extremely difficult to isolate the heart rate of just one person (the "multi-user separation" problem). Sensitivity to Environment: Moving a piece of furniture or opening a door can change the CSI patterns significantly, requiring the system to be re-calibrated.

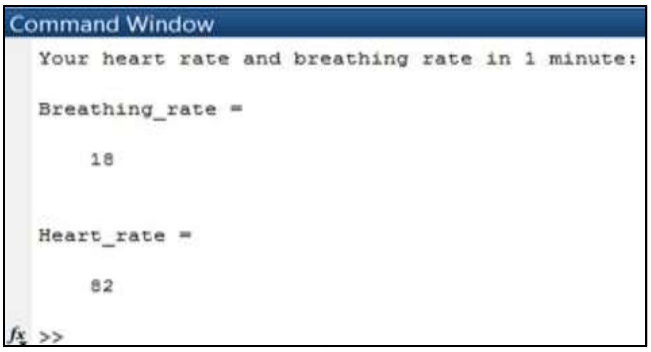
[6]. The role of face regions in remote photoplethysmography for contactless heart rate monitoring

MaksymBondarenko ,CarloMenon, MohamedElgendi, Remote photoplethysmography (rPPG) has emerged as a promising contactless solution by estimating heart rate from subtle skin color variations captured using standard RGB cameras. Unlike traditional PPG, rPPG eliminates the need for direct contact and enables heart rate monitoring in both clinical and home environments. Prior research has demonstrated that facial regions with high blood perfusion, particularly the forehead and cheeks, are most effective for capturing rPPG signals.

III.METHODOLOGY

[1].A PPG sensor works by using an infrared LED and a photodetector to measure changes in blood volume in the fingertip, which occur due to heartbeats and respiratory activity. In this study, the PPG signal is acquired through a custom-built circuit integrated with an Arduino Uno, which collects analog signals and transfers them to a computer for processing in MATLAB. The recorded signals are first filtered to remove noise and then processed using wavelet decomposition to separate heart and respiratory components at different frequency levels. Specifically, detail coefficient D6 corresponds to heart rate (around 1 Hz or 60 beats per minute), while D8 corresponds to breathing rate (0.2–0.35 Hz or 12–21 breaths per minute). Power Spectral Density (PSD) analysis is then applied to identify the dominant frequencies, and a peak detection algorithm is used to calculate HR and BR per minute. The system was tested on seven subjects, and the estimated values were compared with manually measured clinical values. Results showed small percentage errors, ranging from 0–9.5% for breathing rate and 2.1–5.7% for heart rate, indicating good accuracy. The study concludes that estimating HR and BR from PPG signals is reliable and more comfortable compared to bulky clinical equipment like spirometers, making it suitable for continuous and non-invasive health monitoring applications.





Sample no.	Clinical method	System development	Percent error (%)
1	19	20	5.3
2	18	18	0.0
3	20	21	5.0
4	21	23	9.5
5	24	26	8.3
6	22	23	4.5
7	21	22	4.8

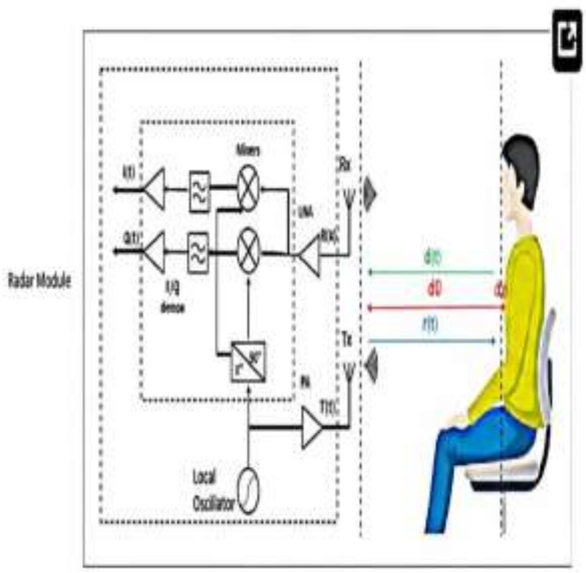
[2].The project workflow describes a vision-based non-invasive health monitoring system that transforms a standard camera into a medical-grade diagnostic tool. The process begins with Video Data Acquisition, where a

webcam or smartphone camera captures a video stream of the subject's face. Unlike radar or WiFi, this relies on visible light reflecting off the skin. The system immediately applies Face Detection and ROI (Region of Interest) Tracking to locate the face and specifically isolate areas rich in blood flow, such as the forehead and cheeks, while stabilizing these regions to account for head movements.

Once the facial regions are locked, the system performs Raw Signal Extraction. It analyzes the subtle color variations in the skin pixels (Red, Green, and Blue channels) that occur with every heartbeat due to blood volume changes. However, these signals are often polluted by lighting changes and movement. Therefore, the data undergoes Signal Pre-Processing and Normalization, using techniques like detrending or bandpass filtering to remove lighting flicker and environmental noise. In modern 2025-era systems, this step often involves generating Spatial-Temporal Maps (STMaps)—a way of representing the video data that highlights physiological pulses while suppressing non-physiological noise, preparing it for deep learning analysis.

The core of the intelligence lies in the Deep Learning Model (e.g., CNN, LSTM, or Transformer). Instead of manual mathematical formulas, the pre-processed data (or STMap) is fed into a neural network trained on vast datasets of physiological signals. The model learns to extract the clean Blood Volume Pulse (BVP) waveform from the noisy video data, effectively separating the true pulse from artifacts. This clean signal is then used for Physiological Parameter Estimation, calculating metrics such as Heart Rate (HR), Respiration Rate (RR), Heart Rate Variability (HRV), and even Oxygen Saturation (SpO2). Finally, the system performs Output Visualization, displaying real-time graphs and vital sign values on a monitor for user or clinical review.

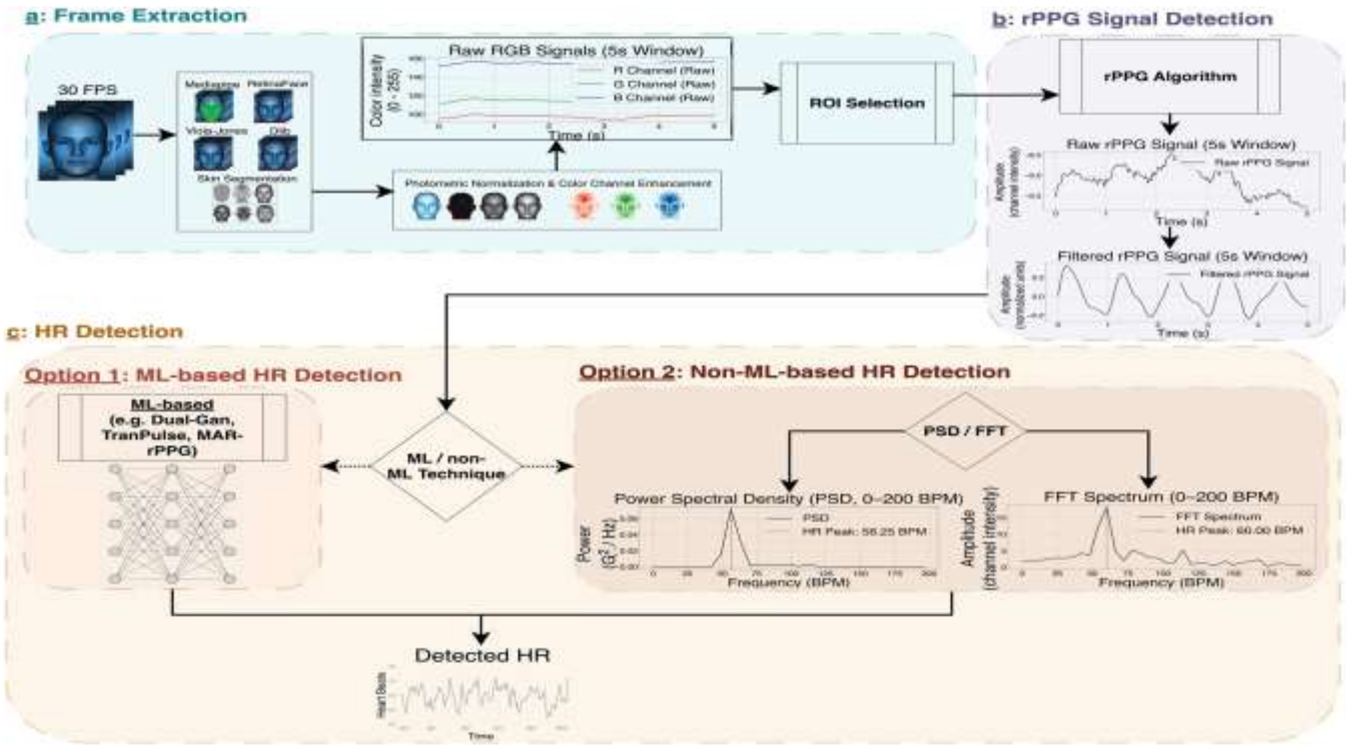
[3]. Vital signs such as heart rate and respiratory rate are essential indicators of health. Traditional measurement methods like ECG electrodes, respiratory belts, and pulse



technology offers a non-contact alternative by detecting tiny chest movements caused by breathing and heartbeat. The authors conducted their review following PRISMA guidelines and screened 1122 publications, ultimately including 131 studies, of which 114 contained experimental data. The radar types analyzed included Continuous Wave (CW), Frequency-Modulated Continuous Wave (FMCW), and Ultra-Wideband (UWB) systems. Most studies measured both heart rate and respiratory rate, and there has been a clear increase in publications over recent years, showing growing research interest.In terms of accuracy, 37% of respiratory rate studies and 48% of heart rate studies reported a maximum deviation of 5% from reference measurements. When a 10% deviation was accepted, accuracy increased to 85% for respiratory rate and 87% for heart rate. Correlation values However, the review highlights major limitations. Study conditions varied widely in distance, subject position, radar frequency, and algorithms, making quantitative comparisons difficult. Many studies focused heavily on signal-processing algorithms.

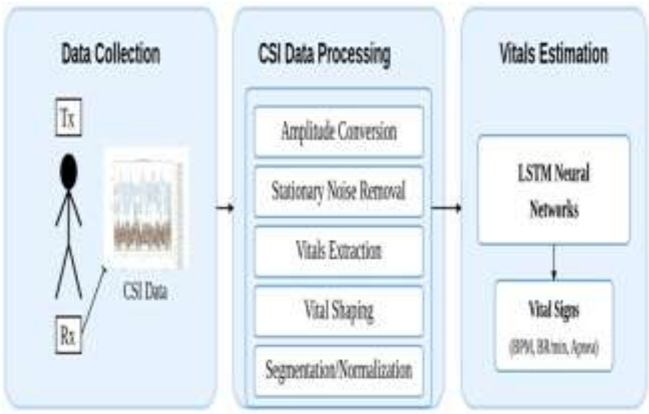
[4].A Review of Deep Learning-Based Contactless Heart Rate Measurement Methods" by Aoxin Ni, Arian Azarang, and Nasser Kehtarnavaz explains how heart rate can be measured without touching the body, using only a normal RGB camera and deep learning techniques. It first describes how traditional photoplethysmography (PPG) works by detecting blood volume changes under the skin, and then explains that contactless PPG (rPPG) replaces the light sensor with a camera that captures tiny color changes on the face caused by blood flow . The paper explains the general rPPG process: selecting a face region (ROI), filtering the signal, reducing noise using methods like ICA or PCA, and

then estimating heart rate using frequency or peak detection



methods . It also discusses common challenges such as motion and lighting variations, which affect accuracy . The main focus of the paper is on deep learning-based approaches, which are divided into two categories: combinations of conventional signal processing with deep learning, and fully end-to-end deep learning models . The authors compared four publicly available deep learning models—rPPGNet, 3D-CNN, PhysNet, and Meta-rPPG—using the same dataset to ensure fair evaluation . Among them, PhysNet achieved the best overall performance with the lowest average error (MAE = 2.57 bpm and MSE = 7.56 bpm), meaning it measured heart rate more accurately than the others . The paper also compared computation time, showing that 3D-CNN was fastest (0.74 seconds), while Meta-rPPG was slowest (1.7 seconds) . Finally, the authors conclude that deep learning significantly improves contactless heart rate measurement accuracy, and among the tested methods, PhysNet performs best on average

[5]. The system performs Feature Extraction, distilling the signals into time-domain, frequency-domain, and statistical features that characterize the rhythm and health of the pulses. These features are then fed into a Machine Learning Model. During the Training Phase, the model learns to associate specific signal patterns with known medical data; during the Testing/Inference Phase, it applies this logic to new, unseen WiFi data. This leads to Cardiopulmonary Parameter Estimation, where the system calculates the actual Breathing Rate (BR) and Heart Rate (HR). Finally, the results undergo Post-Processing & Validation—applying smoothing filters to prevent sudden spikes in data—before being sent to an Output Display, such as a mobile app or medical dashboard, for real-time monitoring.



[6].“The Role of Face Regions in Remote Photoplethysmography for Contactless Heart Rate Monitoring” explains how heart rate can be measured without physical contact using a camera-based technique called remote photoplethysmography (rPPG). This method works by analyzing subtle color changes in the human face that occur due to blood circulation with each heartbeat. When the heart pumps blood, tiny variations in skin color appear, especially in areas rich in blood vessels. The study mainly focuses on identifying which regions of the face provide the most accurate heart rate signals. Different facial areas such as the forehead, cheeks, nose, and full face were analyzed to compare signal quality. The researchers used video recordings and applied signal processing techniques to extract pulse signals from these regions. They evaluated performance based on signal strength, noise levels, and

estimation accuracy compared to ground truth heart rate measurements. The findings show that the forehead and cheek regions generally provide stronger and more stable rPPG signals because they have less motion interference and relatively uniform skin texture. In contrast, areas around the mouth and eyes are more affected by facial movements like talking and blinking, which introduce noise into the signal. The paper concludes that selecting the correct facial region significantly improves the reliability and accuracy of contactless heart rate monitoring systems. This research is important for developing non-invasive health monitoring technologies that can be used in telemedicine, driver monitoring systems, smart surveillance, and home healthcare. Overall, the study highlights that proper region selection and signal processing methods are key factors in improving remote heart rate estimation performance.

IV. COMPARISION

Title	Methods	Year	Advantages	Limitations
Estimation of Breathing Rate and Heart Rate from PhotoPlethysmogram	It uses the photoplethysmogram sensor to measure Heart rate	2017	It is contact based sensor , It also provides accurate values	Sensor captures all the unwanted signals and it causes skin problems
Remote PPG(rPPG) via Deep Learning	It uses rPPG with Deep Learning to estimate data	2021	It uses Deep Learning , it gives accurate output , it is slightly cheaper than CNN	Large trained data is required
Heart and Respiratory rate by means of Radar Technology	It uses Radar Technology	2024	It calculates values by projecting beams on the person, Video capturing not required	Radar is high cost , High beam antennas are required
3D CNN for Heart and Respiratory Rate Prediction	It uses Convolutional Neural Networks (CNN) for Estimating Heart Rate	2025	It uses contactless method with CNN , it gives accurate output	Huge data is required . storage cost is higher
PulseFi - Wi-Fi SCI for cardiopulmonary Monitoring	It uses PulseFi Wi-Fi Module	2025	Low cost and Highly sensitive	It requires lab like environment
Role of face regions in Photoplethysmography for Contactless Heart rate Monitoring	It uses rPPG with Machine Learning	2025	It is Contactless method , it uses signal processing	It is sensitive to environment and lighting variations

V. CONCLUSION

Based on the identified limitations such as the requirement of huge datasets, high storage costs, dependence on large-scale trained models, expensive radar systems with high-beam antennas, laboratory-like environmental constraints, sensor-induced skin irritation, and sensitivity to environmental noise and illumination variations, conventional physiological monitoring approaches present significant practical challenges for real-world deployment. Radar-based systems are cost-intensive and infrastructure-dependent, while contact-based sensors are prone to motion artifacts, user discomfort, hygiene concerns, and long-term dermatological effects. Additionally, multimodal sensor systems often capture unwanted physiological and environmental signals, reducing signal-to-noise ratio (SNR) and overall accuracy.

Therefore, the proposed contactless heart and breathing rate estimation using phase-based video motion processing is justified as a cost-effective, non-invasive, and scalable alternative. By leveraging subtle phase variations in video frames to amplify imperceptible physiological motions, the system minimizes dependency on specialized hardware and eliminates direct skin contact, thereby improving patient comfort and safety. Unlike radar or wearable sensors, camera-based monitoring can operate using standard imaging devices, making it suitable for telemedicine, home healthcare, neonatal monitoring, and remote patient supervision. Although sensitivity to illumination and environmental variation exists, advanced signal processing techniques and adaptive filtering can enhance robustness. Hence, the phase-based video motion processing framework provides a practical balance between accuracy, affordability, and real-world applicability, making it a promising solution for next-generation non-contact vital sign monitoring systems.

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