Photoplethysmography and Biosensors in Non-Invasive Cardiovascular Monitoring: A Survey

www.surveyx.cn

Abstract

Photoplethysmography (PPG) and biosensors represent a transformative advancement in non-invasive cardiovascular monitoring, enabling continuous assessment of vital signs such as heart rate and blood oxygen levels. This survey paper delves into the multidisciplinary nature of PPG, integrating biomedical engineering, signal processing, and physiological monitoring to address the increasing prevalence of cardiovascular diseases. PPG's integration into wearable devices and the development of remote photoplethysmography (rPPG) techniques exemplify its utility in both clinical and everyday settings. The survey highlights innovations in hardware, signal processing algorithms, and machine learning applications that enhance the accuracy and reliability of PPG measurements. Challenges such as variability in measurements, technological limitations, and the need for standardization and validation are addressed, emphasizing the importance of inclusive approaches for diverse populations. Future directions include the integration of multimodal data sources, advancements in wearable technologies, and exploration of novel applications, paving the way for more personalized and accessible healthcare solutions. Through continuous research and technological innovation, PPG and biosensors are poised to play an increasingly vital role in modern healthcare, offering significant improvements in patient care and outcomes.

1 Introduction

1.1 Significance of Non-Invasive Cardiovascular Monitoring

Non-invasive cardiovascular monitoring is a significant advancement in healthcare, offering essential tools for accurate and user-friendly diagnostics. The rising incidence of cardiovascular diseases (CVDs), a leading global mortality factor, highlights the urgent need for innovative monitoring solutions [1]. Traditional methods like electrocardiograms (ECGs) and sphygmomanometers, while effective, are often cumbersome and unsuitable for continuous monitoring, necessitating the exploration of alternative non-invasive techniques [2]. Photoplethysmography (PPG) and its integration into wearable devices exemplify these innovations, enabling continuous monitoring through lightweight and portable technologies [3].

The advantages of non-invasive methods extend beyond convenience; they provide objective assessments that reduce the risks of misdiagnosis associated with subjective evaluations [4]. The use of smartphone cameras for continuous blood pressure monitoring represents a cost-effective, widely accessible approach, although challenges in accuracy and interpretability persist [5]. Continuous physiological monitoring is crucial for early detection and intervention, offering valuable feedback to clinicians and potentially preventing adverse health outcomes [6].

Integrating PPG with laser Doppler flowmetry (LDF) enhances our understanding of peripheral vascular dynamics, underscoring the significance of microvascular blood filtration studies [7]. These advancements not only facilitate early diagnosis and management of cardiovascular conditions but also improve patient comfort and compliance. As healthcare systems increasingly adopt remote

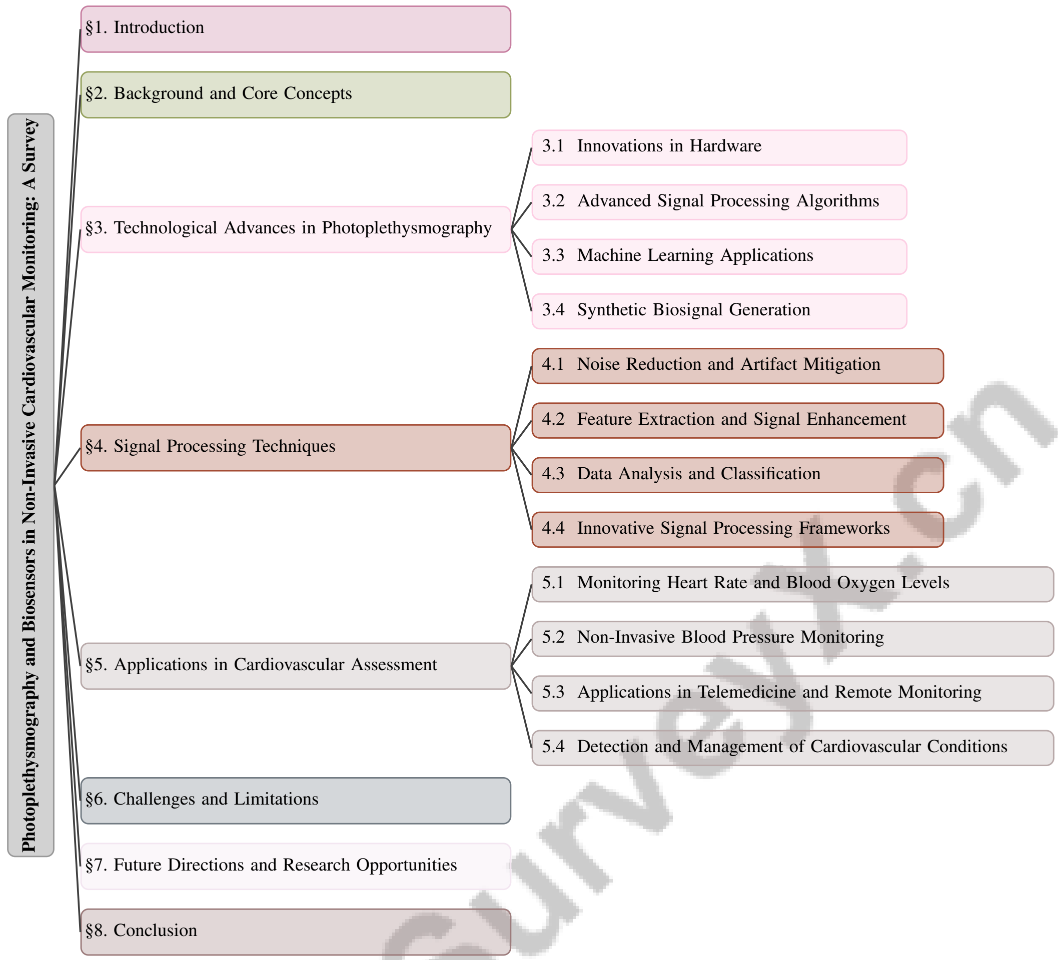


Figure 1: chapter structure

monitoring tools, the importance of non-invasive methods in cardiovascular monitoring grows, addressing the global burden of heart disease and advancing personalized medicine [8].

1.2 Role of Photoplethysmography (PPG) and Biosensors

Photoplethysmography (PPG) and biosensors are instrumental in non-invasive cardiovascular monitoring, enabling continuous assessment of physiological parameters with minimal patient discomfort. PPG detects blood volume changes through optical techniques, offering a versatile and cost-effective solution for both clinical and everyday use. The incorporation of PPG into wearable devices, such as smartwatches, has expanded its utility, allowing for continuous monitoring of heart rhythm and vital signs, thereby enhancing heart rate estimation accuracy through post-calibration methods [3].

The advent of remote photoplethysmography (rPPG) techniques, which allow for non-contact monitoring, marks a significant advancement in this field. rPPG extracts physiological features from facial videos, facilitating non-invasive monitoring without direct sensor contact [4]. These methods utilize camera measurement techniques to capture vital signs, thus enhancing scalability and reducing infection risks associated with traditional contact-based methods [8].

Despite ongoing debates regarding its accuracy, PPG's potential for blood pressure estimation underscores its importance in non-invasive cardiovascular assessments [2]. The synergy of PPG with biosensors in wearable devices continues to revolutionize healthcare by providing tools for continuous and precise patient monitoring, addressing challenges in precision and user comfort. Furthermore, the integration of these technologies into IoT-driven systems illustrates their potential for enhanced monitoring capabilities, especially in post-operative heart disease patients, highlighting the transformative impact of PPG and biosensors in modern healthcare [3].

AI-generated, for reference only.

1.3 Multidisciplinary Nature of the Field

The field of non-invasive cardiovascular monitoring through PPG and biosensors is inherently multidisciplinary, amalgamating expertise from biomedical engineering, signal processing, and physiological monitoring. This convergence is vital for developing advanced technologies that enable continuous and accurate vital sign monitoring [9]. The interdisciplinary nature of this research encompasses sensing techniques, communication modalities, and powering methods essential for the functionality of wearable and implantable devices [10].

Beyond engineering, this field includes data annotation techniques and physiological signal processing, crucial for accurate biosignal interpretation. The integration of multimodal fusion methods enhances the ability to extract meaningful insights from diverse data sources [11]. Developing biosensors necessitates a collaborative approach, requiring knowledge in mechanics, optics, biology, chemistry, and microelectronics, underscoring the complexity and interdisciplinary nature of biosensor technology [12].

PPG technology applications span various healthcare domains, including diagnosis, monitoring, screening, and fitness, each requiring distinct methodological approaches and interdisciplinary collaboration [13]. Integrating psychology, physiology, and technology is particularly critical for advancing stress detection methods, exemplifying the breadth of interdisciplinary research in this domain [14].

The shift towards non-contact monitoring techniques, prompted by the limitations of conventional methods that necessitate body contact, highlights the need for innovations in imaging technology and physiological monitoring. Additionally, analyzing heart rate variability (HRV) involves sensor technology, signal processing, and clinical applications, further illustrating the multidisciplinary framework essential for advancing cardiovascular monitoring technologies [15].

1.4 Structure of the Survey

This survey is systematically organized to provide a comprehensive overview of the role of PPG and biosensors in non-invasive cardiovascular monitoring. It begins with an introduction that emphasizes the significance of non-invasive monitoring techniques and the pivotal role of PPG and biosensors in modern healthcare, while also outlining the multidisciplinary nature of the field, integrating insights from biomedical engineering, signal processing, and physiological monitoring.

Following the introduction, the survey explores the background and core concepts, detailing the principles and applications of PPG, remote photoplethysmography (rPPG), and other non-contact techniques. This section lays the groundwork for understanding technological advances in PPG, which are subsequently examined in the context of hardware innovations, advanced signal processing algorithms, machine learning applications, and synthetic biosignal generation.

A comprehensive analysis of signal processing techniques tailored for PPG signals follows, emphasizing critical areas such as advanced noise reduction methods to alleviate motion artifacts, sophisticated feature extraction techniques for improved physiological parameter assessment, and robust data analysis approaches aimed at enhancing PPG signal quality and accuracy. Innovative frameworks leveraging machine learning and cutting-edge technologies are also explored to optimize PPG signal processing, facilitating reliable applications in clinical and everyday health monitoring environments [15, 16, 17, 18]. This is succeeded by a discussion of PPG and biosensor applications in cardiovascular assessment, including heart rate and blood oxygen level monitoring, non-invasive blood pressure monitoring, telemedicine, and cardiovascular condition management.

The subsequent section addresses challenges and limitations in pervasive healthcare, specifically focusing on the need for inclusive approaches for diverse patient populations, variability in measurement accuracy due to motion artifacts, technological constraints, standardization of protocols and devices, and ethical considerations regarding patient privacy and data security [19, 18]. The survey concludes by examining future directions and research opportunities, emphasizing the potential for integrating multimodal data sources, advancements in wearable and telemedicine technologies, clinical validation efforts, and novel applications that could drive innovations in PPG technology.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Photoplethysmography (PPG): Principles and Applications

Photoplethysmography (PPG) is a non-invasive optical technique used to monitor physiological parameters by detecting blood volume changes in the microvascular bed of tissue. It operates based on light absorption and reflection principles, where a light source illuminates the skin, and a photodetector measures variations in light intensity corresponding to blood volume fluctuations. PPG functions in two modes: transmission, where light passes through the tissue, and reflectance, where light is reflected back to the sensor, both essential for cardiovascular assessment [2].

PPG has broad clinical applications, including continuous monitoring of heart rate (HR), heart rate variability (HRV), and blood oxygen saturation (SpO2), which are critical for cardiovascular health assessment and can be tracked using wearable devices [3]. However, motion artifacts during physical activities often affect HR estimation accuracy in consumer-grade wrist-worn devices, necessitating advanced signal processing techniques to enhance measurement reliability [3].

The potential of PPG extends to blood pressure estimation, though challenges regarding accuracy and reliability compared to invasive methods remain a research focus [2]. The integration of PPG into wearable technology exemplifies its utility for continuous and real-time vital sign monitoring, significantly benefiting early disease detection and management.

Recent advancements in PPG technology include deep learning models to improve feature extraction and precision in physiological measurements. Non-contact monitoring techniques using advanced camera technologies—such as RGB, near-infrared (NIR), and far-infrared (FIR)—have broadened PPG's utility in telemedicine and remote health monitoring. These methods facilitate the assessment of vital signals like heart rate and respiratory rate without direct sensor contact, making them valuable in various settings, including hospitals and personal health tracking via mobile devices. Innovations like the DistancePPG algorithm enhance measurement accuracy by addressing challenges like skin tone variability and motion artifacts, while transmittance photoplethysmographic imaging (PPGI) allows for long-distance cardiovascular monitoring. Additionally, research into remote photoplethysmography (rPPG) has demonstrated the feasibility of capturing blood volume changes from various body regions, thereby expanding the scope of non-contact physiological monitoring. Collectively, these advancements enhance the reliability and applicability of non-contact PPG techniques, paving the way for more comprehensive and user-friendly health monitoring solutions [20, 21, 22, 23, 24].

2.2 Remote Photoplethysmography (rPPG) and Non-Contact Techniques

Remote Photoplethysmography (rPPG) is a transformative non-invasive physiological monitoring approach that derives cardiovascular parameters such as heart rate and blood volume changes from facial videos without direct contact [4]. This technique detects subtle color variations in the skin captured by standard cameras to infer vital signs, offering a practical solution in settings where traditional contact-based methods may be impractical or undesirable [8]. The underlying principle of rPPG involves the relationship between the distance to the subject and the received light power, where periodic physiological movements produce detectable signal variations [25].

Despite its promise, rPPG faces accuracy challenges due to motion artifacts that can disrupt heart rate and blood oxygen saturation readings during physical activities [25]. Advanced methodologies like DL-rPPG, employing deep learning techniques for video data analysis, have been developed to enhance the accuracy of contactless monitoring [26]. Furthermore, innovative applications of rPPG, such as using facial videos to detect emotional states, highlight the broader potential of this technology in non-contact health monitoring [27].

The integration of supervised learning approaches utilizing facial recognition to predict health attributes like pulse rate from video footage underscores the accessibility and applicability of rPPG in remote health monitoring [26]. Additionally, research into novel technologies, including mmWave radar, presents promising avenues for advancing non-contact physiological monitoring [8].

As rPPG technology rapidly evolves, it holds the potential to revolutionize remote health monitoring by enabling non-contact cardiovascular health assessments through standard cameras. This innovative approach measures blood volume changes by analyzing hemoglobin's light absorption characteristics, facilitating the extraction of vital physiological signals such as heart rate, blood pressure, and stress levels. The convenience of utilizing everyday devices, combined with ongoing research to address challenges like lighting conditions and skin color variability, positions rPPG as a promising solution for telemedicine and early cardiovascular disease detection. The development of comprehensive benchmarking frameworks and datasets will further enhance the reliability and accuracy of rPPG applications, making cardiovascular health assessment more accessible and efficient for diverse populations. The continuous refinement of existing techniques and the introduction of new methodologies promise to enhance non-contact monitoring capabilities, establishing it as an indispensable tool in telemedicine and remote healthcare applications [20, 28, 29, 30, 31].

2.3 Vital Signs Monitoring: Key Concepts and Techniques

Vital signs monitoring through photoplethysmography (PPG) and biosensors is crucial for non-invasive cardiovascular health assessment, enabling continuous tracking of parameters such as heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO2), and respiratory rate (RR). PPG detects blood volume changes using optical techniques, providing an efficient method for capturing these vital signs [32]. However, motion artifacts pose significant challenges, as they can mimic arrhythmic characteristics like atrial fibrillation (AF), necessitating sophisticated algorithms to differentiate AF from other cardiac rhythms.

Datasets for evaluating PPG performance often comprise recordings from patients with sinus rhythm and AF, providing a robust foundation for assessing PPG efficacy in diverse clinical conditions [33]. The importance of efficient evaluation of long-term PPG recordings has grown due to their widespread application in clinical assessments and consumer products [34]. Techniques such as HeartBEAT enhance heart rate tracking accuracy from wrist-type PPG signals by improving signal processing methods to address motion artifacts [35].

Advanced statistical analysis, machine learning, and deep learning approaches are integral to vital signs monitoring using PPG, providing sophisticated methods for AF detection and cardiovascular assessments [36]. The Mobile-Efficient, Deep Learning-Based Vital Sign Estimation (MEDVSE) method exemplifies the potential of smartphone cameras to estimate vital signs, including heart rate, oxygen saturation levels, and respiratory rate [37]. This method analyzes pulse waveforms captured by smartphone cameras to estimate blood pressure through data processing and predictive modeling [5].

Innovative deep learning architectures like SQUWA incorporate attention mechanisms to prioritize high-quality signal segments, enhancing AF detection from PPG signals [38]. Furthermore, models like P A P A G EI provide benchmarks for evaluating cardiovascular health, sleep disorders, pregnancy monitoring, and overall wellbeing, showcasing the broad applicability of PPG technologies [39].

Ongoing advancements in PPG and biosensor technologies, driven by interdisciplinary research and innovative signal processing techniques, enable precise and real-time monitoring of vital signs such as heart rate, oxygen saturation, and blood pressure. This progress enhances the accuracy of cardiovascular assessments and supports early detection of various health conditions, ultimately improving healthcare outcomes and facilitating chronic disease management through continuous, non-invasive monitoring [15, 13, 40, 41, 9].

3 Technological Advances in Photoplethysmography

The exploration of technological advances in photoplethysmography (PPG) reveals a spectrum of innovations enhancing non-invasive cardiovascular monitoring. Recent hardware developments have improved PPG device precision and accessibility, opening new avenues for health monitoring applications. Figure 2 illustrates the hierarchical categorization of these technological advances, highlighting innovations in hardware, signal processing algorithms, machine learning applications, and synthetic biosignal generation. Each category is further divided into key areas, showcasing the integration of advanced technologies to enhance non-invasive cardiovascular monitoring and improve health data analysis. The following subsection delves into these hardware innovations, showcasing transformative technologies in PPG and biosensor systems.

AI-generated, for reference only.

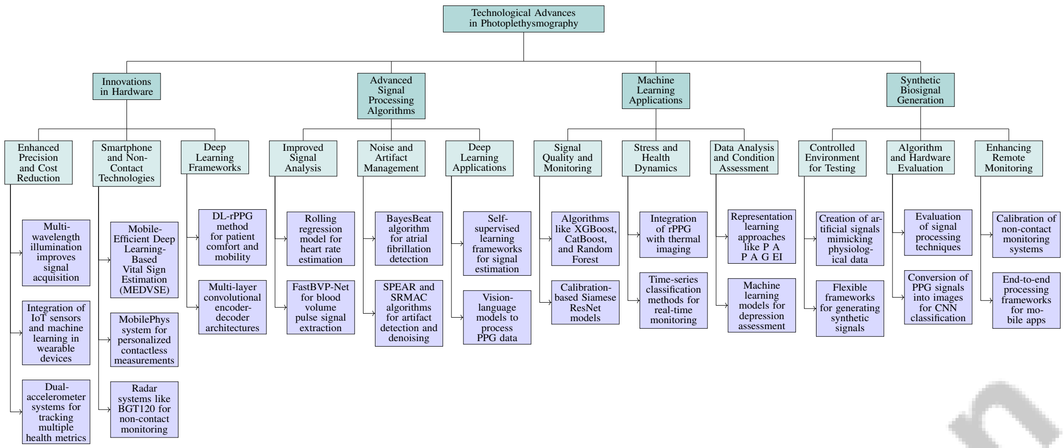


Figure 2: This figure illustrates the hierarchical categorization of technological advances in photoplethysmography (PPG), highlighting innovations in hardware, signal processing algorithms, machine learning applications, and synthetic biosignal generation. Each category is further divided into key areas, showcasing the integration of advanced technologies to enhance non-invasive cardiovascular monitoring and improve health data analysis.

3.1 Innovations in Hardware

Recent hardware advancements in PPG and biosensors have significantly enhanced non-invasive cardiovascular monitoring by increasing precision and reducing costs. As illustrated in Figure 3, these innovations can be categorized into three main areas: PPG and biosensors, smartphone technology, and non-contact monitoring methods. Multi-wavelength illumination improves signal acquisition and minimizes motion artifacts, thus enhancing measurement accuracy [7]. The integration of IoT sensors and machine learning in wearable health devices, such as iCardiaX, facilitates early detection and intervention, offering continuous monitoring capabilities that enhance patient care [5]. Dual-accelerometer systems further enrich cardiovascular health monitoring by simultaneously tracking heart rate, blood pressure, and respiratory rate [8].

Smartphone technology has been leveraged for health monitoring, with systems like Mobile-Efficient Deep Learning-Based Vital Sign Estimation (MEDVSE) reducing computational complexity through advanced architectures [25]. The MobilePhys system exemplifies personalized contactless measurements by generating self-supervised PPG labels, enhancing adaptability and accuracy [8].

Non-contact monitoring technologies, including radar systems like BGT120, have shown promise in estimating heart and respiratory rates, highlighting radar's potential in non-invasive monitoring [8]. The DL-rPPG method further advances non-contact monitoring by improving patient comfort and mobility [25]. The integration of deep learning frameworks, utilizing multi-layer convolutional encoder-decoder architectures, exemplifies significant innovation, facilitating rapid extraction of respiratory waveforms and vital signs [5].

3.2 Advanced Signal Processing Algorithms

Advancements in signal processing algorithms have greatly improved PPG signal analysis, focusing on accuracy and reliability amid noise and motion artifacts. A rolling regression model, incorporating physical activity data and personal information, refines heart rate estimation [3]. Machine learning techniques, such as FastBVP-Net, enhance blood volume pulse signal extraction, improving PPG measurement reliability in dynamic environments [17, 18]. The BayesBeat algorithm integrates Bayesian deep learning for atrial fibrillation detection amidst noise, while DeepBeat combines signal quality assessment with AF detection for enhanced accuracy.

Innovative methods like SPEAR decouple artifact detection and signal reconstruction for targeted denoising. The SRMAC algorithm improves PPG peak detection accuracy through smoother recursive moving averages, optimizing real-time applications on embedded devices [42, 43]. The HeartBEAT

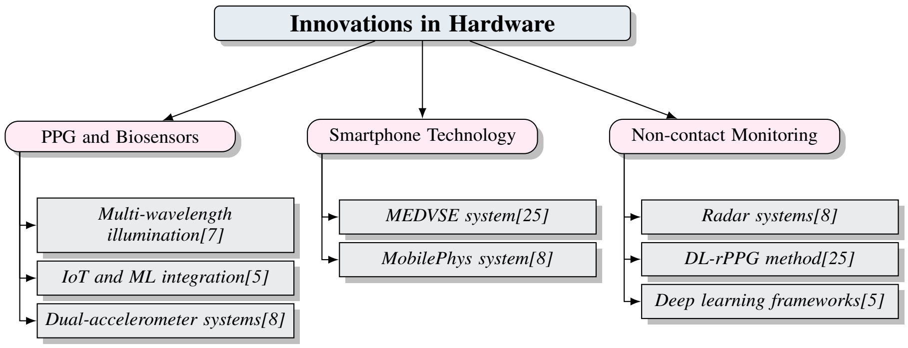


Figure 3: This figure illustrates recent advancements in hardware for cardiovascular monitoring, categorizing them into PPG and biosensors, smartphone technology, and non-contact monitoring methods.

method sets a new standard for PPG peak detection by employing advanced signal processing techniques to mitigate motion artifacts.

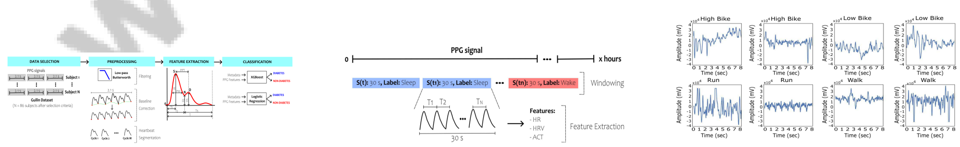
Deep learning applications in PPG signal processing utilize self-supervised learning frameworks, enhancing physiological signal estimation accuracy. These frameworks leverage advanced vision-language models to process PPG data, improving vital sign estimation [44, 45, 46]. Practical strategies in remote PPG systems address challenges and enhance reliability, exemplifying ongoing advancements in PPG signal processing technologies.

3.3 Machine Learning Applications

Machine learning integration into PPG and biosensor technologies has significantly advanced non-invasive cardiovascular monitoring, enhancing diagnostic accuracy and efficiency. Algorithms like XGBoost, CatBoost, and Random Forest ensure PPG signal quality, refining signal processing for accurate assessments [40]. Calibration-based Siamese ResNet models and ARMA models exemplify machine learning's role in improving non-invasive blood pressure monitoring [2, 47].

Machine learning aids in classifying perceived human stress and enhances prediction performance by integrating rPPG with thermal imaging [48, 27]. Time-series classification methods facilitate real-time cardiovascular monitoring, offering insights into patient health dynamics [49]. Representation learning approaches like P A P A G EI enrich PPG data analysis, while machine learning models enhance condition assessments like depression [39, 4].

Machine learning advancements in PPG technologies enhance wearable device accuracy for continuous health assessment, paving the way for sophisticated, user-friendly, and cost-effective health monitoring systems [50, 17, 51, 40].



(a) Data Selection, Preprocessing, Feature Extraction, and Classification in a Diabetes Detection System[52]

(b) Sleep and wake state detection using PPG signal[53]

(c) Comparison of Heart Rate Variability (HRV) during Different Activities[54]

Figure 4: Examples of Machine Learning Applications

As illustrated in Figure 4, machine learning has significantly expanded PPG's applications in health domains. The diabetes detection system employs a comprehensive approach for accurate diagnosis, emphasizing data quality and feature extraction. PPG signals distinguish sleep states, aiding sleep health improvement. HRV comparisons across activities highlight PPG's utility in cardiovascular monitoring, illustrating machine learning's transformative impact on PPG applications [52, 53, 54].

AI-generated, for reference only.

3.4 Synthetic Biosignal Generation

Synthetic biosignal generation is crucial for advancing PPG and biosensor technologies by providing a controlled environment for device testing. This involves creating artificial signals mimicking real physiological data, enhancing device accuracy and reliability. Flexible frameworks generate synthetic signals across physiological conditions, simulating real-world scenarios [55].

Synthetic biosignals are particularly valuable in early device development, serving as benchmarks for testing algorithms and hardware. They allow for rigorous evaluation of signal processing techniques, such as those estimating SpO2 levels and heart rate amid motion artifacts, facilitating algorithm refinement without extensive clinical trials [56, 18]. The conversion of PPG signals into images for CNN classification exemplifies synthetic signals' role in improving signal quality assessment [57].

Synthetic biosignals also aid in calibrating non-contact monitoring systems. An end-to-end processing framework combining landmark extraction, noise reduction, and vital signs calculation within a mobile app demonstrates synthetic signals' potential in enhancing remote monitoring technologies [58].

Overall, synthetic biosignal generation is key in PPG and biosensor evolution, offering a platform for testing and optimizing device performance. By simulating diverse physiological conditions, synthetic biosignals enhance non-invasive monitoring devices' development, increasing health data diversity for machine learning model training and improving applications like HRV assessment and signal segmentation. Comprehensive synthetic datasets, like SCAMPS, provide high-quality data supporting scalable, cost-effective physiological monitoring solutions, ultimately enhancing patient care [55, 59, 60].

4 Signal Processing Techniques

4.1 Noise Reduction and Artifact Mitigation

Extracting physiological parameters from photoplethysmography (PPG) signals is often hindered by noise and motion artifacts, necessitating sophisticated noise reduction and artifact mitigation techniques. Traditional methods frequently struggle with computational inefficiencies and inaccuracies, especially in high-noise environments [34]. The Automated MNA Detection Method (AMDA) enhances heart rate monitoring by identifying PPG segments affected by motion and noise artifacts [61].

Innovative approaches like deppG use nonlinear data-adaptive masks to refine PPG signal spectrograms, significantly improving signal clarity [62]. Similarly, the MEDVSE method facilitates real-time vital sign estimation from raw data, bypassing extensive preprocessing [37]. These methods highlight the importance of advanced signal processing in improving physiological assessment accuracy.

Deep learning methods have proven effective in mitigating noise and artifacts in PPG signals. The DL-rPPG method employs deep learning to extract complex patterns from video data, enhancing physiological signal extraction amid motion and lighting variations [26]. Davies et al.'s framework focuses on learning compressed representations from PPG, crucial for noise reduction and artifact mitigation [63].

Quality assessment techniques are vital in minimizing noise impact on PPG signals. Methods described by Dias et al. enhance the reliability of physiological parameter extraction by reducing noise interference [40]. However, challenges remain, particularly concerning noise in remote PPG (rPPG) data and thermal imaging region of interest (ROI) identification [27].

Despite advancements, PPG signals still provide limited information for accurate blood pressure estimation compared to invasive arterial blood pressure (IABP) measurements [2]. Continued research in noise reduction and artifact mitigation is essential for enhancing the reliability of PPG-based non-invasive cardiovascular monitoring. Advanced signal processing methods and personalized approaches are crucial for more effective healthcare solutions, with methods like those described by Chen et al. addressing noise and motion artifacts in respiratory rate estimation [25].

4.2 Feature Extraction and Signal Enhancement

Feature extraction and signal enhancement are crucial for accurately interpreting physiological parameters from PPG signals, such as heart rate (HR) and heart rate variability (HRV). These processes extract significant features while reducing noise and artifact influence, essential for the growing use of PPG in monitoring cardiovascular conditions [17, 18, 40].

Advanced methodologies improve PPG signal quality. DeepBeat, for example, uses convolutional denoising autoencoders for feature extraction, significantly enhancing atrial fibrillation detection [64]. The Integrate and Fire Converter (IFC) enhances signal processing by emphasizing precise pulse timing [65]. SPEAR, a self-supervised algorithm, denoises PPG signals by reconstructing corrupted segments while preserving clean parts [46].

Addressing motion artifacts is crucial for signal enhancement; methods like a two-step filtering and refining process yield high-quality PPG signals for vital sign estimation [16]. Supervised learning techniques analyze facial pixel intensity changes to infer physiological changes related to heart activity [66]. Classification of PPG segments as clean or containing motion and noise artifacts (MNA) using a Least Squares Support Vector Machine (LS-SVM) classifier is vital for ensuring high-quality data [61].

4.3 Data Analysis and Classification

Data analysis and classification are essential for accurately interpreting PPG signals. Evaluating performance metrics such as precision, recall, F1-score, accuracy, and the area under the curve (AUC) ensures reliable PPG signal processing results. Subject-wise cross-validation is often used to validate the robustness of proposed methods, ensuring they are not overly tailored to specific datasets [67].

Metrics like sensitivity and specificity are crucial for evaluating PPG signals' effectiveness in detecting conditions such as sepsis [68]. Classification accuracy is assessed using a confusion matrix, providing a detailed breakdown of true positives, false positives, true negatives, and false negatives [54]. Dimensionality-Optimized Analysis (DOA) uses dimensionality reduction to streamline large dataset processing while preserving essential information [69].

Performance metrics in signal processing include peak signal-to-noise ratio (PSNR) and correlation coefficients, assessing output pulse trains' accuracy against desired outputs [65]. Mean absolute error (MAE) metrics evaluate algorithms like SPEAR, ensuring processed data accuracy and reliability [46].

Real-time data analysis, exemplified by Temporal Convolutional Networks (TCNs) predicting sepsis onset, showcases advanced machine learning techniques' potential to enhance PPG-based monitoring systems' predictive capabilities [6].

To illustrate these concepts, Figure 5 presents a figure that illustrates the hierarchical structure of data analysis and classification in PPG signal processing, emphasizing performance metrics, dimensionality reduction, and real-time analysis techniques. This figure highlights the use of specific metrics and methods to enhance the accuracy and applicability of PPG-based monitoring systems in healthcare. By integrating sophisticated data analysis and classification methods, researchers continue to improve PPG signal accuracy and applicability in healthcare.

4.4 Innovative Signal Processing Frameworks

Innovative signal processing frameworks have significantly improved PPG signal analysis and interpretation, enhancing non-invasive cardiovascular monitoring accuracy and reliability. These advancements integrate PPG with technologies like artificial intelligence and biosensors, enabling personalized health monitoring. PPG is increasingly recognized as a valuable tool for assessing heart rate variability (HRV) and diagnosing cardiovascular diseases [15, 17].

Flexible synthetic biosignal models provide controlled environments for testing and validating signal processing techniques. By simulating beat intervals, signal waveforms, and noise characteristics, these models generate synthetic ECG and PPG signals for evaluating new algorithms' performance [55]. Advanced time-frequency analysis techniques, like the Sawtooth Artifact Identification and Mitigation (SAIM) framework, improve cardiovascular assessment accuracy by identifying and quantifying sawtooth artifacts [70].

AI-generated, for reference only.

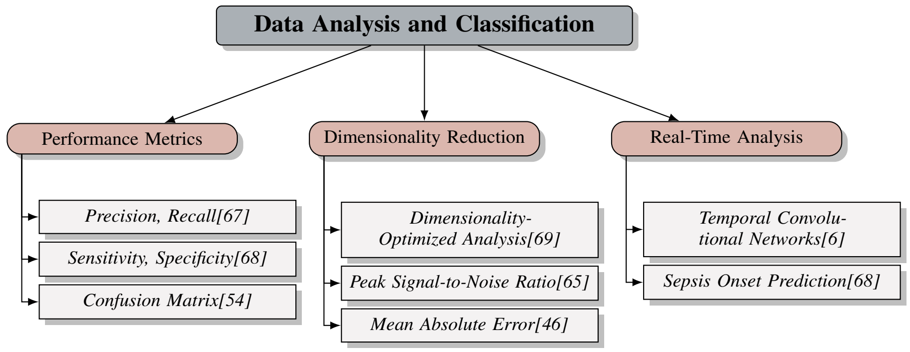
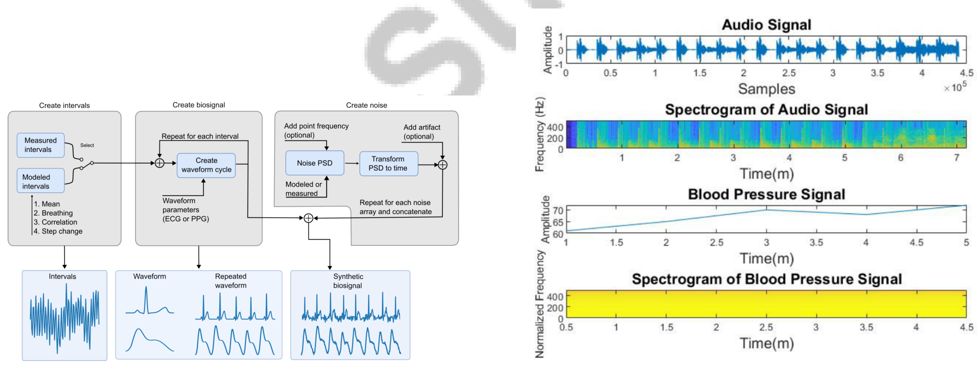


Figure 5: This figure illustrates the hierarchical structure of data analysis and classification in PPG signal processing, emphasizing performance metrics, dimensionality reduction, and real-time analysis techniques. It highlights the use of specific metrics and methods to enhance the accuracy and applicability of PPG-based monitoring systems in healthcare.

Recent research highlights the critical role of merging advanced analytical techniques with synthetic signal generation, significantly improving PPG signal processing and analysis. These approaches enhance the extraction of vital physiological parameters while addressing challenges posed by motion artifacts. By integrating machine learning and cutting-edge technologies, these frameworks aim to establish robust methodologies for PPG signal processing, expanding applications in clinical and mobile health settings [15, 16, 17, 18]. By tackling noise interference and artifact distortion, these frameworks contribute to developing accurate and reliable non-invasive monitoring technologies, ultimately improving patient care and health outcomes.



(a) Creating a Synthetic BioSignal[55]

(b) Audio and Blood Pressure Signal Spectrograms[67]

Figure 6: Examples of Innovative Signal Processing Frameworks

As shown in Figure 6, innovative signal processing frameworks include generating synthetic biosignals and analyzing audio and blood pressure signal spectrograms. The first example illustrates generating signals that mimic real-life bioelectric signal characteristics, crucial for testing and validating biomedical devices and algorithms. The second example delves into spectrograms for analyzing audio and blood pressure signals, providing a time-frequency representation revealing frequency content over time and insights into dynamic changes in both audio and physiological signals. These frameworks highlight innovative techniques in signal processing that enhance our ability to analyze complex datasets, paving the way for advancements in biomedical engineering and audio signal processing [55, 67].

AI-generated, for reference only.

5 Applications in Cardiovascular Assessment

5.1 Monitoring Heart Rate and Blood Oxygen Levels

Photoplethysmography (PPG) is crucial for non-invasive monitoring of heart rate and blood oxygen levels, providing continuous and accessible vital sign assessment. Its integration into wearable devices and smartphones has transformed real-time health monitoring. Advanced algorithms, such as those proposed by Gudi et al., achieve high accuracy in heart rate and variability estimation on datasets like VicarPPG and PURE [71], underscoring the efficacy of sophisticated methods in precise physiological assessments.

Enhancements in PPG signal processing and hardware have improved heart rate estimation accuracy. Choksatchawathi et al. introduced a post-calibration method that significantly reduces mean absolute error in heart rate estimation [3]. Additionally, frameworks by Davies et al. demonstrate accuracy in respiratory rate estimation, reinforcing PPG's role in monitoring vital signs [63].

PPG's ability to track blood oxygen levels (SpO2) across various activities enhances its utility in dynamic environments, expanding its application in cardiovascular health monitoring and telemedicine [72, 40, 22]. These advancements improve patient care by enabling continuous monitoring through wearable devices, facilitating timely interventions for chronic conditions and supporting personalized healthcare solutions [73, 74, 19, 75, 5].

5.2 Non-Invasive Blood Pressure Monitoring

Non-invasive blood pressure monitoring using PPG offers significant advantages over traditional methods. Machine learning and signal processing advancements have enhanced blood pressure estimation accuracy from PPG signals. Calibration-based models predict blood pressure from normalized PPG and intra-arterial blood pressure signals, with N-IABP signals outperforming N-PPG in accuracy [2].

Deep learning models, such as LSTM networks, estimate nocturnal systolic blood pressure dips with high accuracy, offering a non-intrusive alternative to cuff-based measurements. The TransfoRhythm model, utilizing transformer architectures, significantly improves systolic and diastolic blood pressure estimates from PPG signals, achieving RMSEs of 2.21 mmHg and 1.84 mmHg, respectively [76, 77, 78, 79, 5].

Despite progress, PPG-based blood pressure monitoring remains sensitive to external factors such as touch force and motion artifacts, necessitating robust system designs [80, 81, 22]. Machine learning models enhance system reliability by effectively classifying blood pressure changes.

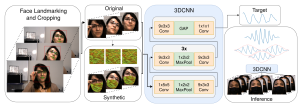
Innovations in PPG technology, including smartphone-based estimation and deep learning models, promise to improve cardiovascular health monitoring accuracy and accessibility, supporting personalized healthcare solutions [19, 51, 82, 79, 5].

5.3 Applications in Telemedicine and Remote Monitoring

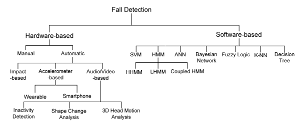
PPG is integral to telemedicine and remote monitoring, offering continuous, non-invasive vital sign assessment. Advances in hardware and signal processing enhance signal quality for telemedicine applications [83]. The MTTS-CAN framework maintains high accuracy and real-time processing on mobile devices, enhancing telehealth services [84]. MobilePhys provides personalized, contactless physiological sensing, adapting to individual and environmental variations [85].

Real-time rPPG pipelines, such as those by Gudi et al., accurately estimate heart rate and variability, crucial for telemedicine [31]. Non-contact PPG acquisition offers potential for continuous remote monitoring [86]. Frameworks like Contrast-Phys and SiNC enable vital sign estimation from unlabelled video data, enhancing telemedicine by utilizing rPPG [87, 73, 19, 58, 84].

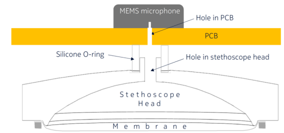
Nguyen et al.'s work on rPPG accuracy in challenging environments supports PPG's role in telemedicine, ensuring reliable remote monitoring [30]. These advancements underscore PPG's transformative impact on telemedicine, offering scalable, accurate remote health monitoring solutions.



(a) 3D Convolutional Neural Network for Face Landmarking and Cropping[88]



(b) Fall Detection Systems[19]



(c) The image depicts a schematic of a MEMS (Micro-Electro-Mechanical Systems) microphone integrated into a stethoscope head.[89]

Figure 7: Examples of Applications in Telemedicine and Remote Monitoring

As depicted in Figure 7, technological advancements are revolutionizing telemedicine and remote monitoring. 3D Convolutional Neural Networks enhance facial recognition for applications like remote pulse estimation [88]. Fall detection systems, utilizing accelerometers and machine learning, improve patient safety [19]. MEMS microphones integrated into stethoscopes exemplify the fusion of traditional tools with modern electronics for remote auscultation [89]. These innovations enhance cardiovascular assessment and telemedicine capabilities.

5.4 Detection and Management of Cardiovascular Conditions

PPG and biosensors are vital in detecting and managing cardiovascular conditions, offering non-invasive, continuous monitoring. Advanced algorithms, such as the deppG algorithm, excel in extracting instantaneous heart rate and interbeat intervals from PPG signals, crucial for real-time monitoring [62]. PPG's role in detecting atrial fibrillation highlights its diagnostic capabilities [36].

PPG signal morphology variability provides insights comparable to invasive measurements, enhancing cardiovascular health assessments [90]. IoT-based systems enable continuous vital sign tracking, improving post-operative care [91]. Models like P A P A G EI and the Performer architecture set new standards in PPG analysis and CVD detection [39, 79].

The i-CardiAx system exemplifies PPG's application in high-risk populations, aiding sepsis diagnosis and management [6]. Integration with laser Doppler flowmetry enhances peripheral vascular dynamics understanding [7]. Remote monitoring frameworks measure respiratory rates from face videos, demonstrating PPG's remote potential [25]. Advancements in PPG and biosensors, supported by interdisciplinary research, significantly improve cardiovascular condition detection and management, enhancing patient outcomes.

6 Challenges and Limitations

Examining the challenges and limitations of photoplethysmography (PPG) and biosensor technologies highlights the complexities in measurement accuracy and their implications across diverse populations. This section delves into the specific obstacles and innovations necessary to enhance these technologies' applicability and effectiveness, ensuring equitable healthcare outcomes for all demographic groups.

6.1 Challenges and Innovations in Diverse Populations

PPG and biosensors face significant challenges in monitoring diverse populations, particularly regarding measurement accuracy and reliability. A critical issue is the lack of data diversity in existing benchmarks, which affects the efficacy of remote photoplethysmography (rPPG) for individuals with darker skin tones [92]. This gap necessitates the development of algorithms that can process physiological signals across varied skin tones and conditions.

Traditional sensing technologies also struggle in adverse environments, requiring enhanced signal processing and multimodal integration to improve detection accuracy [93]. Additionally, biases in measurement accuracy across demographics and motion artifacts complicate current methodologies [8]. Innovative solutions, such as portable, low-cost monitoring devices, are crucial for extending PPG applicability in non-clinical settings and low-income countries, improving accessibility [27, 29, 94].

User compliance with data labeling and management is another challenge, especially in monitoring diverse populations, including the elderly and those with chronic conditions [19, 8, 18]. Continued research and development can substantially enhance PPG and biosensor technologies' effectiveness, improving healthcare outcomes across various demographics.

6.2 Variability in Measurements

Variability in PPG measurements presents a significant challenge to the reliability of non-invasive cardiovascular monitoring systems. Noise and artifacts exacerbate this variability, compromising the quality of physiological data [40]. Motion and noise artifact detection techniques, particularly in wrist-based recordings, often fail to distinguish between clean and artifact-laden segments, leading to data interpretation inconsistencies [61].

Challenges in accurately identifying waveform features due to low signal quality and physiological variations further complicate PPG signal analysis [5]. Non-invasive blood pressure monitoring methods also face difficulties in providing precise beat-to-beat readings, limiting their effectiveness [49]. Addressing this variability requires robust algorithms to enhance data analysis and improve the reliability of PPG-based monitoring systems [15].

Certain heart rate estimation methods falter during high-intensity activities, where errors persist despite advanced signal processing [3]. Additionally, PPG methods are sensitive to poor signal quality from voluntary movements and illumination changes, impacting signal extraction accuracy [25]. Research advancements in PPG technology must prioritize signal quality and incorporate multimodal approaches to enhance monitoring accuracy and reliability, particularly in wearable devices [16, 40].

6.3 Technological and Methodological Limitations

PPG technologies face several technological and methodological limitations affecting their non-invasive cardiovascular monitoring effectiveness. A significant challenge is the dependency on input data quality, impacting signal processing accuracy. For instance, rPPG signal extraction relies heavily on video quality, which can compromise monitoring accuracy [4]. High costs and lack of portability of traditional heart rate detection tools also hinder widespread application [27].

Methodologically, PPG systems often struggle with computational complexity and real-time processing challenges, limiting real-time applications on edge devices [1]. Hardware limitations, such as sensor accuracy and connectivity issues, further impact PPG system performance, emphasizing the need for complementary clinical assessments [91]. Addressing these limitations is crucial for enhancing PPG technologies' effectiveness and reliability, particularly in real-time cardiovascular health monitoring through wearable devices [80, 17, 40, 22].

6.4 Standardization and Validation Challenges

Benchmark	Size	Domain	Task Format	Metric
rPPG-Bench[28]	900	Remote Physiological Signal Sensing	Heart Rate Estimation	MAE, RMSE
RePSS[95]	2,498	Physiological Signal Sensing	Heart Rate Estimation	MAE, RMSE
ISV-ASC[96]	1,000	Psychophysiology	Classification	Accuracy, ROC Area
HR-BCG[97]	4,500	Cardiovascular Monitoring	Heart Rate Detection	MAE, MAPE
DCC[98]	19	Cardio-respiratory Monitoring	Vital Sign Measurement	MAE, SNR
V4V[99]	1,358	Physiological Signal Estimation	Heart Rate And Respiration Rate Estimation	cMAE, cRMSE
MSPM[100]	1,480	Physiological Monitoring	Multi-site Vital Signs Estimation	MAE, RMSE
DEAP[101]	861	Physiological Signal Processing	Pulse Rate Estimation	Mean Absolute Error, Root Mean Square Error

Table 1: This table presents a comprehensive overview of representative benchmarks used for evaluating remote photoplethysmography (rPPG) techniques. It includes details on benchmark names, dataset sizes, domains, task formats, and the metrics employed for performance assessment. The information is crucial for understanding the current landscape of standardization and validation in the field of physiological signal sensing.

Advancing PPG technologies requires rigorous standardization and validation to ensure device reliability across applications and environments. The lack of standardized protocols and validation frameworks impedes widespread adoption and clinical integration. Variability in device specifications and measurement techniques leads to inconsistent data interpretation and clinical outcomes. PPG devices must address noise sources, including individual patient variations and environmental influences, complicating health monitoring [17, 22].

Table 1 provides a detailed overview of the representative benchmarks essential for the standardization and validation of remote photoplethysmography (rPPG) technologies, highlighting the diversity in dataset sizes, domains, task formats, and evaluation metrics. A universal benchmarking framework for evaluating rPPG techniques is critical for systematic performance assessment and promoting standardized protocols [28]. Comprehensive clinical testing is necessary to validate PPG devices' accuracy and reliability across diverse demographics and environments, ensuring effective real-world monitoring [13, 16, 40, 17, 22]. Developing standardized metrics for evaluating PPG signal quality and device performance is essential for enhancing clinical utility and patient outcomes [19, 17, 18].

6.5 Ethical and Practical Considerations

The deployment of PPG and biosensors in healthcare raises ethical and practical considerations. The non-invasive nature of PPG methods enhances patient comfort and compliance, essential for long-term monitoring [102]. Ethical oversight is crucial to protect patient rights and ensure research integrity, as demonstrated by studies adhering to ethical guidelines [48, 103].

Practical challenges include generalizability across diverse populations, often limited by small sample sizes in studies [104]. Integrating PPG technologies into clinical practice requires assessing data privacy and security, particularly regarding rPPG systems' vulnerabilities to spoofing attacks. Implementing robust security measures is vital to protect sensitive physiological data and ensure safe application in healthcare settings [105, 106, 18, 40, 17]. Compliance with regulatory standards for data collection and storage is essential to protect patient confidentiality and ensure reliable clinical decision-making.

7 Future Directions and Research Opportunities

7.1 Integration of Multimodal and Diverse Data Sources

Integrating multimodal and diverse data sources is crucial for advancing photoplethysmography (PPG) in non-invasive cardiovascular monitoring. Future research should refine signal processing and explore novel data fusion methods to enhance remote PPG (rPPG) applications across various conditions [25]. Expanding datasets to include diverse demographics is vital for improving PPG technology's generalizability and reliability. Existing studies reveal performance biases in PPG models, particularly for individuals with darker skin tones. Initiatives like the VITAL dataset, which includes 432 videos from subjects of varying skin tones, and the PaPaGei model, trained on over 57,000 hours of diverse PPG data, aim to address these biases [72, 39, 92]. The VitalVideo dataset further supports this by offering a large-scale real-world rPPG dataset with diverse subjects. These efforts contribute to developing standardized protocols and leveraging AI advancements for real-time monitoring, enhancing PPG application accuracy and sensitivity. Combining PPG with other physiological signals, such as ECG, can improve health metrics precision, aiding in atrial fibrillation detection and stress monitoring [36, 107]. Machine learning advancements, like attention-based deep state-space modeling, show promise in translating PPG signals into ECG waveforms with high accuracy. Future research should refine algorithms to reduce noise and improve calibration, enhancing blood pressure estimation accuracy and signal acquisition techniques [40, 81]. Integrating diverse data sources into healthcare monitoring systems can significantly enhance capabilities by leveraging camera technologies, such as rPPG, for non-contact vital sign measurement. Addressing accuracy gaps and overcoming accessibility challenges can lead to more effective AI-driven healthcare solutions [8, 29].

7.2 Advancements in Wearable and Telemedicine Technologies

Advancements in wearable and telemedicine technologies are pivotal for enhancing PPG and biosensor systems, enabling continuous and accurate vital sign assessment. Future research should focus on improving methods to recover accurate heart rate waveforms during interfering activities, crucial for wearable device reliability in dynamic environments [108]. Machine learning algorithms can enhance data interpretation and health assessment accuracy [109]. In telemedicine, enhancing method robustness through further clinical validations is essential, ensuring PPG-based monitoring reliability across various conditions and exploring additional applications in telemedicine and biometric security [110]. Continuous innovation in wearable and telemedicine technologies can significantly improve PPG systems' accuracy and reliability, enhancing monitoring capabilities for cardiovascular health and expanding clinical applications. These advancements can lead to better patient care and health outcomes, particularly through wearable devices that facilitate continuous, non-invasive health monitoring in clinical and everyday environments [13, 17, 41, 40].

7.3 Clinical Validation and Standardization Efforts

Clinical validation and standardization of PPG technologies are crucial for ensuring reliability and accuracy across diverse clinical settings. Future research should enhance PPG algorithms for improved pulse detection and explore additional features from PPG data that offer insights into various health applications, including sleep health and stress level predictions [111]. Robustness against movement artifacts is vital in settings like surgical monitoring or sleep studies [21]. Personalized PPG normalization processes can enhance intra-subject analysis over time, offering tailored patient monitoring [112]. Expanding data collection in various environments and enhancing signal quality support comprehensive health monitoring, integrating additional physiological parameters into PPG systems [113]. Future research should focus on expanding datasets and exploring hyperparameter tuning to improve classification accuracy and robustness [54]. Validating tools like the pyPPG toolbox across diverse datasets and enhancing algorithms like HeartBEAT for performance across different signal types is vital for ensuring versatility and applicability [114, 35]. Addressing these aspects will help establish comprehensive validation and standardization protocols, facilitating the widespread adoption and clinical integration of PPG technologies, ultimately improving patient care and health outcomes.

7.4 Exploration of Novel Applications and Innovations

Exploring novel applications and innovations in PPG can significantly advance non-invasive cardiovascular monitoring. Future research should expand the range of physiological modalities captured by PPG technologies, enhancing applicability in diverse clinical settings. Developing flexible frameworks for dynamic parameter adjustments could improve arrhythmia representation, providing more accurate monitoring solutions [55]. Refining template matching approaches can improve ballistocardiography (BCG) signal detection and analysis, leading to more reliable heart rate detection and cardiovascular dynamics understanding [97]. Integrating PPG with near-infrared (NIR) video technology offers exciting possibilities for camera-based blood pressure estimation and pupillometry, providing new insights into physiological responses [100]. Further research should investigate skin properties' influence on volumetric photoplethysmography (vPPG) signals to enhance clinical applicability [115]. Enhancing algorithms like distancePPG for high-motion scenarios and real-time mobile applications could expand PPG utility in dynamic environments [24]. Innovations in machine learning, such as the VGTL-net model, should be explored for integrating additional physiological signals and optimizing model architecture for improved accuracy and performance [116]. By exploring innovative PPG applications, researchers can enhance non-invasive cardiovascular monitoring, improving vital sign assessment accuracy and expanding health metrics derived from PPG signals. Recent findings suggest analyzing the second derivative of the PPG waveform can provide insights into cardiovascular conditions like atherosclerosis and arterial stiffness, enabling early detection and continuous monitoring [41, 40].

8 Conclusion

This survey highlights the crucial role of photoplethysmography (PPG) and biosensors in non-invasive cardiovascular monitoring, emphasizing their potential in enhancing healthcare technologies. PPG's early detection capabilities for cardiovascular diseases position it as a vital tool in modern diagnostics [41]. The integration of multimodal fusion techniques and customized data preprocessing is imperative for improving the accuracy of physiological signal analysis, particularly in emotion recognition and stress assessment. Furthermore, advancements in PPG-based atrial fibrillation

AI-generated, for reference only.

detection underscore the importance of addressing signal quality and developing extensive labeled datasets to boost diagnostic precision [36].

The findings call for ongoing research and technological advancements to enhance PPG signal processing and device functionality, thereby ensuring reliable and precise monitoring solutions. By employing advanced algorithms and machine learning techniques, significant improvements in the accuracy and applicability of PPG technologies can be realized. As these innovations progress, PPG and biosensors are set to become increasingly essential in non-invasive cardiovascular monitoring, facilitating more personalized and accessible healthcare solutions that can markedly improve patient outcomes.

References

[1] Ali Tazarv and Marco Levorato. A deep learning approach to predict blood pressure from ppg signals, 2021.

[2] Felipe M. Dias, Diego A. C. Cardenas, Marcelo A. F. Toledo, Filipe A. C. Oliveira, Estela Ribeiro, Jose E. Krieger, and Marco A. Gutierrez. Exploring the limitations of blood pressure estimation using the photoplethysmography signal, 2024.

[3] Tanut Choksatchawathi, Puntawat Ponglertnapakorn, Apiwat Ditthapron, Pitshaporn Leelaarporn, Thayakorn Wisutthisen, Maytus Piriyajitakonkij, and Theerawit Wilaiprasitporn. Improving heart rate estimation on consumer grade wrist-worn device using post-calibration approach, 2020.

[4] Constantino Álvarez Casado, Manuel Lage Cañellas, and Miguel Bordallo López. Depression recognition using remote photoplethysmography from facial videos, 2022.

[5] Ivan Liu, Fangyuan Liu, Qi Zhong, and Shiguang Ni. A finger on the pulse of cardiovascular health: Estimating blood pressure with smartphone photoplethysmography-based pulse waveform analysis, 2024.

[6] Kanika Dheman, Marco Giordano, Cyriac Thomas, Philipp Schilk, and Michele Magno. i-cardiax: Wearable iot-driven system for early sepsis detection through long-term vital sign monitoring, 2024.

[7] Denis S Goldobin and Irina A Mizeva. Conjecture on reflectionlessness of blood-vascular system as a wave-conducting medium, 2017.

[8] Daniel McDuff. Camera measurement of physiological vital signs, 2021.

[9] Toshiyo Tamura. Current progress of photoplethysmography and spo2 for health monitoring. *Biomedical engineering letters*, 9(1):21–36, 2019.

[10] Baibhab Chatterjee, Pedram Mohseni, and Shreyas Sen. Bioelectronic sensor nodes for internet of bodies, 2023.

[11] Zeeshan Ahmad and Naimul Khan. A survey on physiological signal based emotion recognition, 2022.

[12] Vinayak Pachkawade. N/mems biosensors: An introduction, 2023.

[13] Malak Abdullah Almarshad, Md Saiful Islam, Saad Al-Ahmadi, and Ahmed S BaHammam. Diagnostic features and potential applications of ppg signal in healthcare: A systematic review. In *Healthcare*, volume 10, page 547. MDPI, 2022.

[14] Aamir Arsalan, Muhammad Majid, Imran Fareed Nizami, Waleed Manzoor, Syed Muhammad Anwar, and Jihyoung Ryu. Human stress assessment: A comprehensive review of methods using wearable sensors and non-wearable techniques, 2023.

[15] Jermana L Moraes, Matheus X Rocha, Glauber G Vasconcelos, José E Vasconcelos Filho, Victor Hugo C De Albuquerque, and Auzuir R Alexandria. Advances in photopletysmography signal analysis for biomedical applications. *Sensors*, 18(6):1894, 2018.

[16] Runyu Mao, Mackenzie Tweardy, Stephan W. Wegerich, Craig J. Goergen, George R. Wodicka, and Fengqing Zhu. Motion artifact reduction in photoplethysmography for reliable signal selection, 2021.

[17] Junyung Park, Hyeon Seok Seok, Sang-Su Kim, and Hangsik Shin. Photoplethysmogram analysis and applications: an integrative review. *Frontiers in physiology*, 12:808451, 2022.

[18] Chizhong Wang. *Estimation of SPO2 Levels and Heart Rate from PPG Signals in the Presence of Motion Artifacts*. PhD thesis, New Jersey Institute of Technology, 2024.

[19] Deepak Uniyal and Vaskar Raychoudhury. Pervasive healthcare-a comprehensive survey of tools and techniques, 2014.

[20] Lu Niu, Jeremy Speth, Nathan Vance, Benjamin Sporrer, Adam Czajka, and Patrick Flynn. Full-body cardiovascular sensing with remote photoplethysmography, 2023.

[21] Robert Amelard, Christian Scharfenberger, Farnoud Kazemzadeh, Kaylen J. Pfisterer, Bill S. Lin, Alexander Wong, and David A. Clausi. Non-contact transmittance photoplethysmographic imaging (ppgi) for long-distance cardiovascular monitoring, 2015.

[22] Jesse Fine, Kimberly L Branan, Andres J Rodriguez, Tananant Boonya-Ananta, Ajmal, Jessica C Ramella-Roman, Michael J McShane, and Gerard L Coté. Sources of inaccuracy in photoplethysmography for continuous cardiovascular monitoring. *Biosensors*, 11(4):126, 2021.

[23] Nhi Nguyen, Le Nguyen, Constantino Álvarez Casado, Olli Silvén, and Miguel Bordallo López. Non-contact heart rate measurement from deteriorated videos, 2023.

[24] Mayank Kumar, Ashok Veeraraghavan, and Ashutosh Sabharval. Distanceppg: Robust non-contact vital signs monitoring using a camera, 2015.

[25] Mingliang Chen, Qiang Zhu, Harrison Zhang, Min Wu, and Quanzeng Wang. Respiratory rate estimation from face videos, 2019.

[26] Wei Chen, Zhe Yi, Lincoln Jian Rong Lim, Rebecca Qian Ru Lim, Aijie Zhang, Zhen Qian, Jiaxing Huang, Jia He, and Bo Liu. Deep learning and remote photoplethysmography powered advancements in contactless physiological measurement. *Frontiers in bioengineering and biotechnology*, 12:1420100, 2024.

[27] Ivan Liu, Fangyuan Liu, Qi Zhong, Fei Ma, and Shiguang Ni. Your blush gives you away: detecting hidden mental states with remote photoplethysmography and thermal imaging, 2024.

[28] Dae-Yeol Kim, Eunsu Goh, KwangKee Lee, JongEui Chae, JongHyeon Mun, Junyeong Na, Chae bong Sohn, and Do-Yup Kim. Remote bio-sensing: Open source benchmark framework for fair evaluation of rppg, 2023.

[29] Xin Liu, Shwetak Patel, and Daniel McDuff. Rgb camera-based physiological sensing: Challenges and future directions, 2022.

[30] Nhi Nguyen, Le Nguyen, Honghan Li, Miguel Bordallo López, and Constantino Álvarez Casado. Evaluation of video-based rppg in challenging environments: Artifact mitigation and network resilience, 2024.

[31] Amogh Gudi, Marian Bittner, and Jan van Gemert. Real-time webcam heart-rate and variability estimation with clean ground truth for evaluation, 2020.

[32] Tania Pereira, Nate Tran, Kais Gadhoumi, Michele M Pelter, Duc H Do, Randall J Lee, Rene Colorado, Karl Meisel, and Xiao Hu. Photoplethysmography based atrial fibrillation detection: a review. *NPJ digital medicine*, 3(1):3, 2020.

[33] Adrian Tarniceriu, Jarkko Harju, Antti Vehkaoja, Jakub Parak, Ricard Delgado-Gonzalo, Philippe Renevey, Arvi Yli-Hankala, and Ilkka Korhonen. Detection of beat-to-beat intervals from wrist photoplethysmography in patients with sinus rhythm and atrial fibrillation after surgery, 2017.

[34] Márton Á. Goda, Peter H. Charlton, and Joachim A. Behar. Robust peak detection for photoplethysmography signal analysis, 2023.

[35] Huijie Pan, Dogancan Temel, and Ghassan AlRegib. Heartbeat: Heart beat estimation through adaptive tracking, 2018.

[36] Cheng Ding, Ran Xiao, Weijia Wang, Elizabeth Holdsworth, and Xiao Hu. Photoplethysmography based atrial fibrillation detection: an updated review from july 2019, 2023.

[37] Taha Samavati, Mahdi Farvardin, and Aboozar Ghaffari. Efficient deep learning-based estimation of the vital signs on smartphones, 2024.

[38] Runze Yan, Cheng Ding, Ran Xiao, Aleksandr Fedorov, Randall J Lee, Fadi Nahab, and Xiao Hu. Squwa: Signal quality aware dnn architecture for enhanced accuracy in atrial fibrillation detection from noisy ppg signals, 2024.

[39] Arvind Pillai, Dimitris Spathis, Fahim Kawsar, and Mohammad Malekzadeh. Papagei: Open foundation models for optical physiological signals, 2025.

[40] Felipe M. Dias, Marcelo A. F. Toledo, Diego A. C. Cardenas, Douglas A. Almeida, Filipe A. C. Oliveira, Estela Ribeiro, Jose E. Krieger, and Marco A. Gutierrez. Quality assessment of photoplethysmography signals for cardiovascular biomarkers monitoring using wearable devices, 2023.

[41] Denisse Castaneda, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and Homer Nazeran. A review on wearable photoplethysmography sensors and their potential future applications in health care. *International journal of biosensors & bioelectronics*, 4(4):195, 2018.

[42] Cesar Abascal Machado, Victor O. Costa, Cesar Augusto Prior, and Cesar Ramos Rodrigues. Srmac – smoothed recursive moving average crossover for real-time systolic peak detection in photoplethysmography, 2023.

[43] Jeremy Speth, Nathan Vance, Patrick Flynn, and Adam Czajka. Sinc+: Adaptive camera-based vitals with unsupervised learning of periodic signals, 2024.

[44] Zijie Yue, Miaojing Shi, Hanli Wang, Shuai Ding, Qijun Chen, and Shanlin Yang. Bootstrapping vision-language models for self-supervised remote physiological measurement, 2025.

[45] Qi Zhan, Wenjin Wang, and Gerard de Haan. Analysis of cnn-based remote-ppg to understand limitations and sensitivities, 2020.

[46] Pranay Jain, Cheng Ding, Cynthia Rudin, and Xiao Hu. A self-supervised algorithm for denoising photoplethysmography signals for heart rate estimation from wearables, 2023.

[47] Armin Soltan Zadi, Raichel M. Alex, Rong Zhang, Donald E. Watenpaugh, and Khosrow Behbehani. Mathematical modeling of arterial blood pressure using photo-plethysmography signal in breath-hold maneuver, 2018.

[48] Aamir Arsalan, Muhammad Majid, Syed Muhammad Anwar, and Ulas Bagci. Classification of perceived human stress using physiological signals, 2019.

[49] Jingyuan Hong, Manasi Nandi, Weiwei Jin, and Jordi Alastruey. Using photoplethysmography to detect real-time blood pressure changes with a calibration-free deep learning model, 2024.

[50] Guangkun Nie, Jiabao Zhu, Gongzheng Tang, Deyun Zhang, Shijia Geng, Qinghao Zhao, and Shenda Hong. A review of deep learning methods for photoplethysmography data, 2024.

[51] Stewart Whiting, Samuel Moreland, Jason Costello, Glen Colopy, and Christopher McCann. Recognising cardiac abnormalities in wearable device photoplethysmography (ppg) with deep learning, 2018.

[52] Filipe A. C. Oliveira, Felipe M. Dias, Marcelo A. F. Toledo, Diego A. C. Cardenas, Douglas A. Almeida, Estela Ribeiro, Jose E. Krieger, and Marco A. Gutierrez. Machine learning-based diabetes detection using photoplethysmography signal features, 2023.

[53] Douglas A. Almeida, Felipe M. Dias, Marcelo A. F. Toledo, Diego A. C. Cardenas, Filipe A. C. Oliveira, Estela Ribeiro, Jose E. Krieger, and Marco A. Gutierrez. A machine-learning sleep-wake classification model using a reduced number of features derived from photoplethysmography and activity signals, 2023.

[54] Eoin Brophy, José Juan Dominguez Veiga, Zhengwei Wang, Alan F. Smeaton, and Tomas E. Ward. An interpretable machine vision approach to human activity recognition using photoplethysmograph sensor data, 2018.

[55] Katri Karhinoja, Antti Vasankari, Jukka-Pekka Sirkiä, Antti Airola, David Wong, and Matti Kaisti. Flexible framework for generating synthetic electrocardiograms and photoplethysmograms, 2024.

[56] Ilker Bayram. An exploratory method for smooth/transient decomposition, 2020.

[57] Tamaghno Chatterjee, Aayushman Ghosh, and Sayan Sarkar. Signal quality assessment of photoplethysmogram signals using quantum pattern recognition and lightweight cnn architecture, 2022.

[58] Donghao Qiao, Amtul Haq Ayesha, Farhana Zulkernine, Raihan Masroor, and Nauman Jaffar. Revise: Remote vital signs measurement using smartphone camera, 2022.

[59] Daniel McDuff, Miah Wander, Xin Liu, Brian L. Hill, Javier Hernandez, Jonathan Lester, and Tadas Baltrusaitis. Scamps: Synthetics for camera measurement of physiological signals, 2022.

[60] Yuntong Zhang, Jingye Xu, Mimi Xie, Dakai Zhu, Houbing Song, and Wei Wang. Efficient and direct inference of heart rate variability using both signal processing and machine learning, 2023.

[61] Kaat Vandecasteele, Jesús Lázaro, Evy Cleeren, Kasper Claes, Wim Van Paesschen, Sabine Van Huffel, and Borbála Hunyadi. Artifact detection of wrist photoplethysmograph signals. In *BIOSIGNALS*, pages 182–189, 2018.

[62] Antonio Cicone and Hau-Tieng Wu. How nonlinear-type time-frequency analysis can help in sensing instantaneous heart rate and instantaneous respiratory rate from photoplethysmography in a reliable way, 2017.

[63] Harry J. Davies and Danilo P. Mandic. Rapid extraction of respiratory waveforms from photoplethysmography: A deep encoder approach, 2022.

[64] Jessica Torres Soto and Euan Ashley. Deepbeat: A multi-task deep learning approach to assess signal quality and arrhythmia detection in wearable devices, 2020.

[65] Gabriel Nallathambi and Jose C. Principe. Theory and algorithms for pulse signal processing, 2018.

[66] Mayank Gupta, Lingjun Chen, Denny Yu, and Vaneet Aggarwal. A supervised learning approach for robust health monitoring using face videos, 2021.

[67] Sidharth Srivatsav Sribhashyam, Md Sirajus Salekin, Dmitry Goldgof, Ghada Zamzmi, Mark Last, and Yu Sun. Pattern recognition in vital signs using spectrograms, 2021.

[68] Marco Giordano, Kanika Dheman, and Michele Magno. Sepal: Sepsis alerts on low power wearables with digital biomarkers and on-device tiny machine learning, 2024.

[69] Muhammad Saran Khalid, Ikramah Shahid Quraishi, Hadia Sajjad, Hira Yaseen, Ahsan Mehmood, Muhammad Mahboob Ur Rahman, and Qammer H. Abbasi. A low-cost ppg sensor-based empirical study on healthy aging based on changes in ppg morphology, 2023.

[70] Yu-Ting Lin, Yu-Lun Lo, Chen-Yun Lin, Hau-Tieng Wu, and Martin G. Frasch. Unexpected sawtooth artifact in beat-to-beat pulse transit time measured from patient monitor data, 2019.

[71] Amogh Gudi, Marian Bittner, Roelof Lochmans, and Jan van Gemert. Efficient real-time camera based estimation of heart rate and its variability, 2019.

[72] Pradyumna Chari, Krish Kabra, Doruk Karinca, Soumyarup Lahiri, Diplav Srivastava, Kimaya Kulkarni, Tianyuan Chen, Maxime Cannesson, Laleh Jalilian, and Achuta Kadambi. Diverse r-ppg: Camera-based heart rate estimation for diverse subject skin-tones and scenes, 2020.

[73] Atul Sharma, Mihaela Badea, Swapnil Tiwari, and Jean Louis Marty. Wearable biosensors: an alternative and practical approach in healthcare and disease monitoring. *Molecules*, 26(3):748, 2021.

[74] Duarte Dias and João Paulo Silva Cunha. Wearable health devices—vital sign monitoring, systems and technologies. *Sensors*, 18(8):2414, 2018.

[75] Ahsan Mehmood, Asma Sarauji, M. Mahboob Ur Rahman, and Tareq Y. Al-Naffouri. Your smartphone could act as a pulse-oximeter and as a single-lead ecg, 2023.

[76] Amir Arjomand, Amin Boudesh, Farnoush Bayatmakou, Kenneth B. Kent, and Arash Mohammadi. Transforhythm: A transformer architecture conductive to blood pressure estimation via solo ppg signal capturing, 2025.

[77] Lei Zhao, Cunman Liang, Yan Huang, Guodong Zhou, Yiqun Xiao, Nan Ji, Yuan-Ting Zhang, and Ni Zhao. Emerging sensing and modeling technologies for wearable and cuffless blood pressure monitoring. *npj Digital Medicine*, 6(1):93, 2023.

[78] Mustafa Radha, Koen de Groot, Nikita Rajani, Cybele CP Wong, Nadja Kobold, Valentina Vos, Pedro Fonseca, Nikolaos Mastellos, Petra A Wark, Nathalie Velthoven, Reinder Haakma, and Ronald M Aarts. Estimating blood pressure trends and the nocturnal dip from photoplethysmograph, 2018.

[79] Performer: A novel ppg-to-ecg reconstruction transformer for a digital biomarker of cardiovascular disease detection.

[80] Irene Pi, Isleen Pi, and Wei Wu. External factors that affect the photoplethysmography waveforms, 2021.

[81] Kaylie Welykholowa, Manish Hosanee, Gabriel Chan, Rachel Cooper, Panayiotis A Kyriacou, Dingchang Zheng, John Allen, Derek Abbott, Carlo Menon, Nigel H Lovell, et al. Multimodal photoplethysmography-based approaches for improved detection of hypertension. *Journal of Clinical Medicine*, 9(4):1203, 2020.

[82] Yongyang Tang, Zhe Chen, Ang Li, Tianyue Zheng, Zheng Lin, Jia Xu, Pin Lv, Zhe Sun, and Yue Gao. Merit: Multimodal wearable vital sign waveform monitoring, 2024.

[83] Tamas Nagy and Zoltan Gingl. Low-cost photoplethysmograph solutions using the raspberry pi, 2013.

[84] Xin Liu, Josh Fromm, Shwetak Patel, and Daniel McDuff. Multi-task temporal shift attention networks for on-device contactless vitals measurement, 2021.

[85] Xin Liu, Yuntao Wang, Sinan Xie, Xiaoyu Zhang, Zixian Ma, Daniel McDuff, and Shwetak Patel. Mobilephys: Personalized mobile camera-based contactless physiological sensing, 2022.

[86] Israel Jesus Santos Filho, Muhammad Mahboob Ur Rahman, Taous-Meriem Laleg-Kirati, and Tareq Al-Naffouri. Non-contact acquisition of ppg signal using chest movement-modulated radio signals, 2024.

[87] Amtul Haq Ayesha, Donghao Qiao, and Farhana Zulkernine. A web application for experimenting and validating remote measurement of vital signs, 2022.

[88] Jeremy Speth, Nathan Vance, Patrick Flynn, Kevin Bowyer, and Adam Czajka. Remote pulse estimation in the presence of face masks, 2021.

[89] Hongwei Li, Zoran Radivojevic, Maja Hedlund, Anton Fahlgren, and Michael S. Eggleston. The patchkeeper: An integrated wearable electronic stethoscope with multiple sensors, 2024.

[90] Yu-Chieh Ho, Te-Sheng Lin, She-Chih Wang, Chen-Shi Chang, and Yu-Ting Lin. Variability of morphology in beat-to-beat photoplethysmographic waveform quantified with unsupervised wave-shape manifold learning for clinical assessment, 2023.

[91] Jayed Bin Harez, Shapla Akter, Rayhanul Islam Sony, M T Hasan Amin, Meratun Junnut Anee, and Amzad Hossain. Iot-driven system for continuous monitoring of heart disease patients post-surgery, 2024.

[92] Jiankai Tang, Xinyi Li, Jiacheng Liu, Xiyuxing Zhang, Zeyu Wang, and Yuntao Wang. Camera-based remote physiology sensing for hundreds of subjects across skin tones, 2024.

[93] Yu Rong, Richard M. Gutierrez, Kumar Vijay Mishra, and Daniel W. Bliss. Non-contact vital signs detection with uav-borne radars, 2020.

[94] Jeremy Speth, Nathan Vance, Patrick Flynn, Kevin W. Bowyer, and Adam Czajka. Digital and physical-world attacks on remote pulse detection, 2021.

[95] Mikhail Kopeliovich, Konstantin Kalinin, Yuriy Mironenko, and Mikhail Petrushan. On indirect assessment of heart rate in video, 2020.

[96] Zachary Dair, Samantha Dockray, and Ruairi O'Reilly. Inter and intra signal variance in feature extraction and classification of affective state, 2022.

[97] Ibrahim Sadek and Bessam Abdulrazak. A comparison of three heart rate detection algorithms over ballistocardiogram signals, 2021.

[98] Yingen Zhu, Jia Huang, Hongzhou Lu, and Wenjin Wang. Privacy protected contactless cardio-respiratory monitoring using defocused cameras during sleep, 2024.

[99] Ambareesh Revanur, Zhihua Li, Umur A. Ciftci, Lijun Yin, and Laszlo A. Jeni. The first vision for vitals (v4v) challenge for non-contact video-based physiological estimation, 2021.

[100] Jeremy Speth, Nathan Vance, Benjamin Sporrer, Lu Niu, Patrick Flynn, and Adam Czajka. Mspm: A multi-site physiological monitoring dataset for remote pulse, respiration, and blood pressure estimation, 2024.

[101] Anton M. Unakafov. Pulse rate estimation using imaging photoplethysmography: generic framework and comparison of methods on a publicly available dataset, 2017.

[102] Mrinmoy Sarker Turja, Tae Ho Kwon, Hyoungkeun Kim, and Ki Doo Kim. Noninvasive in vivo estimation of hba1c based on beer lambert model from photoplethysmogram using only two wavelengths, 2024.

[103] Naimahmed Nesaragi, Lars Øivind Høiseth, Hemin Ali Qadir, Leiv Arne Rosseland, Per Steinar Halvorsen, and Ilangko Balasingham. Non-invasive waveform analysis for emergency triage via simulated hemorrhage: An experimental study using novel dynamic lower body negative pressure model, 2023.

[104] Steven Marty, Federico Pantanella, Andrea Ronco, Kanika Dheman, and Michele Magno. Investigation of mmwave radar technology for non-contact vital sign monitoring, 2023.

[105] Lin Li, Chao Chen, Lei Pan, Yonghang Tai, Jun Zhang, and Yang Xiang. Hiding your signals: A security analysis of ppg-based biometric authentication, 2022.

[106] Xue Xian Zheng, M. M. Ur Rahma, Bilal Taha, Mudassir Masood, Dimitrios Hatzinakos, and Tareq Al-Naffouri. Multimodal biometric authentication using camera-based ppg and fingerprint fusion, 2024.

[107] Khuong Vo, Mostafa El-Khamy, and Yoojin Choi. Ppg-to-ecg signal translation for continuous atrial fibrillation detection via attention-based deep state-space modeling, 2024.

[108] Xiang Zhang, Yu Gu, Huan Yan, Yantong Wang, Mianxiong Dong, Kaoru Ota, Fuji Ren, and Yusheng Ji. Wital: A cots wifi devices based vital signs monitoring system using nlos sensing model, 2023.

[109] Elena Javidi da Costa. Array signal processing applications on biomedical engineering. 2024.

[110] Benjamin Kossack, Eric Wisotzky, Peter Eisert, Sebastian P. Schraven, Brigitta Globke, and Anna Hilsmann. Perfusion assessment via local remote photoplethysmography (rppg), 2022.

[111] Pigv^2: Monitoring pig vital signs through ground vibrations induced by heartbeat and respiration.

[112] Francesca Gasparini, Alessandra Grossi, Marta Giltri, and Stefania Bandini. Personalized ppg normalization based on subject heartbeat in resting state condition, 2022.

AI-generated, for reference only.

[113] Haimiao Mo, Shuai Ding, Shanlin Yang, Athanasios V. Vasilakos, and Xi Zheng. Collaborative three-tier architecture non-contact respiratory rate monitoring using target tracking and false peaks eliminating algorithms, 2022.

[114] Marton A. Goda, Peter H. Charlton, and Joachim A. Behar. pyppg: A python toolbox for comprehensive photoplethysmography signal analysis, 2023.

[115] Matheus Bigatão Martinelli, Christian Tolentino Dominguez, Luciano Bachmann, and George C. Cardoso. Skin optical attenuation coefficient modulation with arterial pulsation, 2018.

[116] Yuyang Miao, Harry J. Davies, and Danilo P. Mandic. Amplitude-independent machine learning for ppg through visibility graphs and transfer learning, 2024.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.