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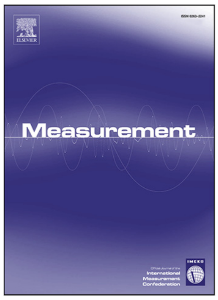

A survey on machine learning approaches for vital sign monitoring using radar

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PII: S0263-2241(25)01066-8
DOI: https://doi.org/10.1016/j.measurement.2025.117707
Reference: MEASUR 117707

To appear in: *Measurement*

Received date : 7 January 2025
Revised date : 23 April 2025
Accepted date : 26 April 2025

Please cite this article as: M.H. Shirazi, S. Yongchareon, A. Singh et al., A survey on machine learning approaches for vital sign monitoring using radar, *Measurement* (2025), doi: https://doi.org/10.1016/j.measurement.2025.117707.

Graphical Abstract

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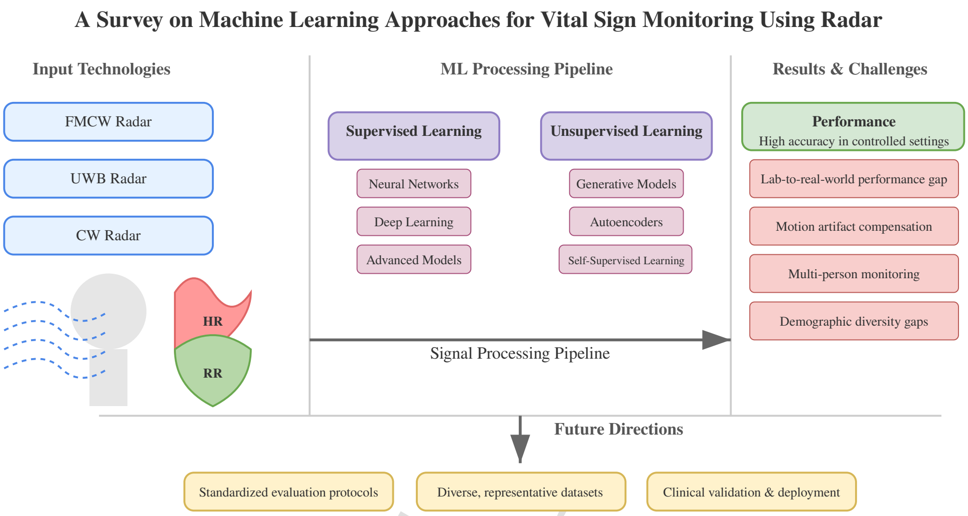

Highlights

A Survey on Machine Learning Approaches for Vital Sign Monitoring Using Radar

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- Systematic analysis of machine learning architectures for radar-based vital sign monitoring from 2020-2025.
- Quantitative assessment of laboratory-to-real-world performance gaps across monitoring paradigms.
- Demographic impact analysis revealing how subject diversity affects algorithm generalizability.
- Comparative evaluation of supervised versus unsupervised learning approaches for different monitoring scenarios.
- Standardized evaluation protocols for consistent cross-study comparisons in vital sign monitoring.

A Survey on Machine Learning Approaches for Vital Sign Monitoring Using Radar

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Abstract

The integration of machine learning methodologies with radar-based vital sign monitoring represents a significant advancement in non-contact healthcare surveillance systems. This systematic literature review synthesizes and critically analyzes research from 2020 to 2025, addressing substantive theoretical and methodological gaps in extant literature. Our comprehensive taxonomic classification of machine learning paradigms employed in this domain elucidates the progressive refinement from conventional algorithmic approaches to sophisticated deep learning architectures, with particular emphasis on hybrid neural network configurations optimized for physiological signal extraction in non-stationary environments. Methodologically, this survey contributes a rigorous evaluation framework comprising standardized assessment protocols, quantifiable performance metrics, and cross-validation methodologies—elements conspicuously absent in previous reviews. Empirical analysis demonstrates substantial correlations between dataset demographic characteristics and algorithmic generalizability, with heterogeneous participant cohorts yielding markedly enhanced performance across cardiac, respiratory, and hemodynamic parameter estimation tasks. The review delineates four distinct developmental phases in the field's chronological evolution and provides analytical insight into persistent technical challenges: motion artifact compensation, multi-subject disambiguation, and the translation of laboratory efficacy to clinical utility. This comprehensive examination of computational approaches for radar-based vital sign monitoring establishes a theoretical foundation and methodological framework to guide future research toward physiologically robust and clinically viable implementations.

Keywords: Non-intrusive Vital Sign Monitoring, Machine Learning, Radar

1. Introduction

Global population forecasts predict a rise to 9.687 billion by 2050 from 7.942 billion in 2022, exacerbating the necessity to tackle increasing chronic diseases [1]. This demographic transition necessitates innovative healthcare solutions, particularly for continuously monitoring activities such as driving, independent living, and patient care. This is especially crucial due to the shortage of healthcare professionals in developed countries [2, 3]. The advancement of non-invasive sensor technology, augmented by machine learning and affordable commercial sensors, facilitates efficient contactless monitoring [4, 5].

Vital signs, which indicate physiological aspects of physical and mental condition, primarily encompass Heart Rate (HR), Respiratory Rate (RR), and Blood Pressure (BP) [6]. These measurements are essential for heart rate variability evaluation, sleep apnea identification, and security authentication procedures. Current monitoring technologies encompass electrocardiography (ECG) [7], photoplethysmography (PPG)[8], thermal imaging, RGB imaging, laser Doppler vibrometer (LDV) [9], and radar, each presenting unique operational principles and challenges in both contact-based and remote sensing applications. These measurement techniques can be broadly categorized into contact-based methods requiring direct sensor attachment (ECG, PPG) and contactless methods (radar, thermal imaging)[10] that can measure vital signs without physical contact.

Radar sensors facilitate the acquisition of physiological signals while preserving privacy and minimizing environmental disturbances such as lighting, rendering them essential for ambient intelligence [11]. The technology operates by emitting intermittent signals that bounce off objects within the radar cross-section, disclosing the target's health status. This provides benefits compared to conventional ECG sensors, which may be uncomfortable during activities such as driving or for individuals with dermatological conditions [12].

The radar market is projected to grow from 21.03 billion in 2024 to 45.42 billion by 2029, reflecting a compound annual growth rate (CAGR) of 16.65%, as reported by Mordor Intelligence Corporation [13]. North America constitutes the largest market, while Asia Pacific exhibits the highest growth. The 77 GHz automotive radar band has been widely employed in healthcare research. Radar-based healthcare technology is deemed essential in the fourth industrial revolution, highlighting the integration of AI [14, 15]. Research

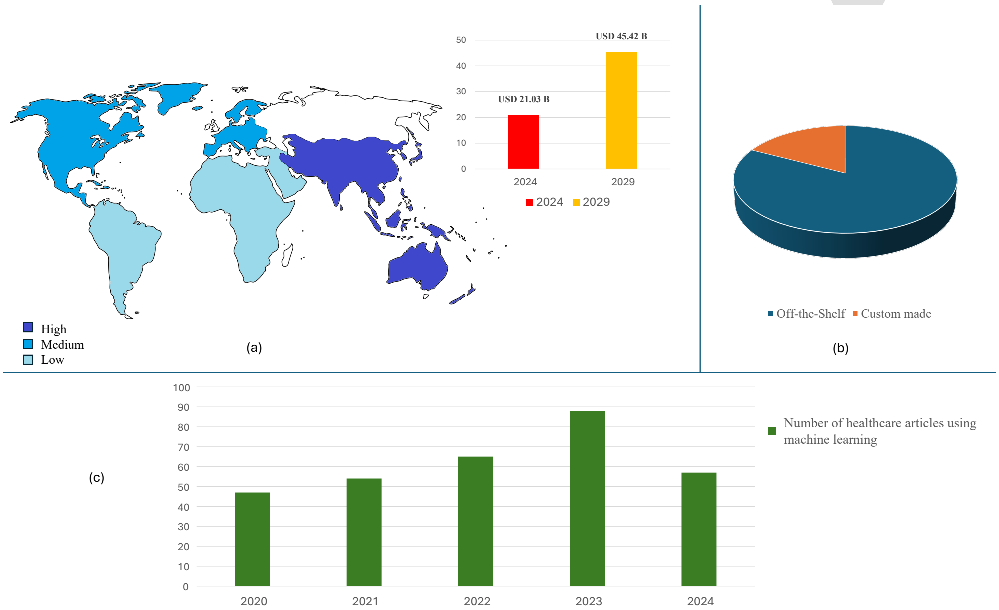

Figure 1: (a) Radar market growth rate, (b) Radars used for health monitoring, (c) Yearly studies using ML

trends indicate a growing utilization of commercial radar and machine learning applications for vital sign monitoring and activity recognition, emphasizing algorithmic development over hardware design [16, 17]. As illustrated in Figure 1, (a) the radar market shows substantial growth potential from 2024 to 2029, (b) off-the-shelf radar solutions are increasingly preferred over custom-made options for health monitoring, and (c) there is a steady rise in healthcare articles utilizing machine learning from 2020 to 2024.

Traditional radar research focused on signal processing techniques [18, 19, 20, 21]; however, the integration of radar with machine learning and deep learning has transformed signal analysis, enhancing the accuracy of vital sign acquisition [22, 23, 24, 25, 26, 27]. This intricate domain demonstrates increasing academic interest and varied healthcare applications. The technology facilitates an accurate assessment of heart rate variability, which is essential for the early identification of heart disease and myocardial infarction [28]. This advancement represents progress in the early detection and management of chronic conditions while preserving technical sophistication in monitoring systems.

Recent reviews in radar-based vital sign monitoring (2020-2023) have primarily focused on hardware and signal processing rather than machine learning. Cardillo and Caddemi [16] explored MIMO radar systems without addressing machine learning, Kebe et al. [29] examined technical challenges with minimal classification algorithm discussion, Singh et al. [30] analyzed hardware specifications focusing on conventional processing techniques, and Paterniani et al. [31] contributed to signal processing while overlooking machine learning integration. These reviews reflect the field's emphasis on hardware over computational intelligence.

Wu et al. [32] reviewed mmWave sensing but lacked systematic categorization of machine learning architectures, demographic dataset analysis, standardized evaluation protocols, advanced technique treatment, quantification of real-world performance gaps, and blood pressure monitoring comparison. Similarly, Ahmed and Cho [33] examined vital sign monitoring without comparative analysis of frequency-dependent capabilities, demographic representation impact, real-world performance degradation assessment, technical comparisons of mmWave/UWB approaches for blood pressure monitoring, and standardized cross-study evaluation frameworks.

With the advancement in radar technology, there remains a critical need for a comprehensive review focusing specifically on the intersection of ML and radar-based vital sign monitoring. Our systematic review addresses these technical gaps through the following key contributions:

- **Machine Learning Architecture Analysis**: Classifying approaches from traditional to hybrid architectures, demonstrating evolution from signal processing to AI-driven solutions with performance metrics showing superior accuracy in both controlled and movement conditions.

- **Demographic Representation Impact**: Analyzing how dataset characteristics affect algorithm generalizability, revealing better performance with larger participant pools (>30 subjects) compared to limited subjects (<15).

- **Real-world Performance Assessment**: Quantifying laboratory-to-real-world performance gaps, with validation across multiple monitoring scenarios (sitting, lying, driving) against ECG, PPG, and accelerometer measurements.

- **Learning Paradigm Comparison**: Comparing supervised and unsupervised paradigms while proposing standardized evaluation protocols for consistent cross-study comparisons.

- **Advanced Monitoring Techniques**: Analyzing blood pressure monitoring across mmWave/UWB approaches and examining multi-resolution signal processing for interference management, providing practical implementation assessments.

This survey analyzes machine learning approaches for radar-based vital sign monitoring published between January 2020 and March 2025. We conducted a systematic literature search across DBLP, IEEE Xplore, ACM Digital Library, and Google Scholar, combining radar technology terms (radar, mmWave, FMCW, UWB, CW), machine learning terminology (machine learning, artificial intelligence, deep learning, neural networks), and vital sign monitoring keywords. From 87 initial papers, we selected 34 studies meeting our inclusion criteria: direct application of radar technology for vital sign monitoring, implementation of machine learning beyond traditional signal processing, quantifiable performance metrics, and peer-reviewed publication status.

After applying these criteria, 34 studies were selected for detailed analysis in this survey. These papers represent diverse applications of machine learning in radar-based vital sign monitoring, including both classification approaches (e.g., abnormality detection, signal quality assessment) and regression tasks (e.g., waveform reconstruction, vital parameter estimation). The distribution of radar technologies and learning paradigms across these studies is visualized in Figure 9 and discussed in Section 5.

Table 1 presents a systematic analysis of current research gaps in radar-based vital sign monitoring, highlighting the significant disparity between existing capabilities and the requirements for real-world clinical applications.

The rest of this article is organized as follows. In Section II, we discuss radars and their taxonomy, their applications for vital sign monitoring, and technical details. This section also explains cardio-respiratory activity simulation and introduces databases used in other studies, including both public and private datasets, with more information provided for public datasets. Section III presents the signal processing chain, detailing the methods used in most studies and explaining each step in technical detail. Section IV describes the ML methods reviewed in this article, categorizing them into supervised learning and unsupervised learning. Each subsection highlights the drawbacks and challenges that require further research or improvement and compares the different approaches. In Section V, the survey discusses various approaches for evaluating studies regarding hardware and learning styles and addresses open challenges and future directions. Finally, Section VI presents the conclusions of these discussions.

2. RADARS: OVERVIEW AND TAXONOMIES

Radar systems for vital sign monitoring comprise transmit/receive, radio frequency, analog, and digital components as shown in Figure 2. The signal originates from a voltage-controlled oscillator, with part directed to the transmitting antenna and another part connected to the mixer. [34] Received signals undergo Low Noise Amplification before mixing with transmitted signals to produce Intermediate Frequency signals [35, 36]. Systems can generate either complex I/Q signals through quadrature mixing or real signals through single-channel mixing [37, 38].

Radar systems are categorized based on waveform generation: Continuous Wave (CW) radars transmit signals continuously, while pulsed radars transmit over short periods. Both can utilize modulated or unmodulated signals [31, 39]. For vital sign monitoring applications, researchers employ various hardware including FMCW and UWB technologies [40, 32, 41], though some studies propose custom antenna arrays that limit reproducibility [42, 43]. Each radar technology offers distinct capabilities: CW radar provides simplicity but cannot measure frontal distance and suffers from signal leakage [38].

UWB (Ultra-Wideband) radar [44] is technically defined by its fractional bandwidth exceeding 20% of the center frequency or absolute bandwidth greater than 500 MHz. Operating in the 3.1-10.6 GHz frequency range, UWB systems transmit ultra-short pulses with durations of 0.2-1.5 nanoseconds. The range resolution (ΔR) of UWB radar is directly related to its bandwidth (B) through the equation $\Delta R = c/2B$, where c is the speed of light, yielding a typical resolution of 1-3 cm. The radar cross-section (RCS) in UWB systems varies with frequency, requiring frequency-domain analysis techniques. UWB signal processing typically involves matched filtering in the time domain or frequency domain correlation. For vital sign detection, UWB systems extract phase variations from pulse-to-pulse correlation, with displacement sensitivity approximately $\lambda/4\pi$. The signal-to-noise ra-

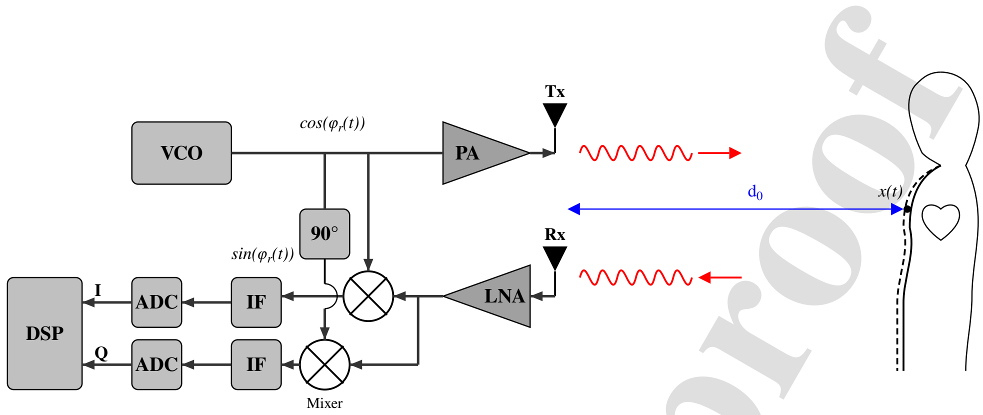

Figure 2: The block diagram of radar systems for non-contact vital sign measurement

tio in UWB systems is proportional to transmitted energy and processing gain, defined as TBP (time-bandwidth product)[45]. UWB radar employs specialized clutter rejection algorithms including background subtraction, singular value decomposition (SVD), or wavelet-based approaches for stationary target detection[46]. It's important to note that UWB is defined by its bandwidth characteristics rather than by a specific implementation approach. Multiple radar technologies can be designed to fulfill UWB criteria. IR (Impulse Radio) UWB is the most common implementation, using extremely short duration pulses that inherently occupy a wide bandwidth. Alternatively, SFCW (Stepped-Frequency Continuous Wave) [47, 48] radars can also achieve UWB characteristics by transmitting a sequence of narrowband signals stepped across a wide frequency range, synthesizing an effective wideband response. While each SFCW transmission is narrowband, the composite frequency coverage can meet UWB definitions.

FMCW (Frequency-Modulated Continuous Wave) radar operates by transmitting a continuous signal with frequency varying linearly over time, typically in the 24-81 GHz range for vital sign applications. The transmitted signal is mathematically represented as $S_{Tx}(t) = \exp[j \cdot (2\pi f_c t + \pi\beta t^2 + \theta)]$, where $\beta = B/T$ is the chirp rate, B is the bandwidth, and T is the chirp duration. Range measurement in FMCW is determined by the beat frequency (f_b) between transmitted and received signals: $R = c \cdot f_b/2\beta$. The phase shift analysis for displacement detection follows the relationship $\Delta\phi = \frac{4\pi d}{\lambda}$, where d is the displacement and λ is the wavelength. [49, 50, 51] FMCW systems typically achieve phase noise of -80 to -110 dBc/Hz at 100 kHz offset. Signal processing in FMCW radar involves range-FFT, Doppler-FFT, and

CFAR (Constant False Alarm Rate) detection algorithms. For vital sign extraction, FMCW radar employs complex demodulation techniques including arctangent demodulation and linear phase demodulation. The intermediate frequency (IF) signal in FMCW systems is processed through quadrature sampling at rates of 2-10 MHz with a typical ADC resolution of 12-16 bits.

The technical differences between these systems are summarized in Table 2. FMCW radars process phase/frequency relationships for target detection, while UWB systems analyze reflected pulse characteristics. Both technologies require specific signal processing approaches to extract vital sign information from complex radar returns in realistic environments [52, 53, 54].

2.1. Datasets

The field of radar-based vital sign monitoring has been advanced by numerous datasets released by researchers worldwide. Despite their relative scarcity, these publicly available datasets, as cataloged in Table 3, provide invaluable resources for algorithm development and validation. It is important to note that among the datasets listed, only four are publicly available for research community use: Sadeghi et al. [55], Yoo et al. [56], Schellenberger et al. [57], and Shi et al. [58]. The remaining datasets are private, developed for specific research projects but not openly accessible. This limited availability of public datasets represents a significant challenge for reproducible research in this field. These datasets exhibit significant heterogeneity across multiple dimensions that merit detailed analysis. To address the heterogeneity in evaluation methodologies across studies, we propose a standardized evaluation protocol in Table 4 that encompasses comprehensive metrics, test scenarios, reference standards, and reporting requirements.

Dataset Distribution and Demographic Coverage: Subject population sizes vary considerably, revealing three distinct categories: small-scale studies (2-10 subjects) representing 38% of datasets, medium-scale studies (11-25 subjects) constituting 43%, and large-scale studies (>25 subjects) comprising 19%. This distribution reflects the challenges in acquiring large-scale physiological datasets while highlighting opportunities for more extensive data collection efforts. Notably, datasets Schellenberger et al. [57], Yoo et al. [56], and Iyer et al. [68] stand out with 30, 50, and 33 subjects respectively, while Wang et al. [81] further extends this range with 70 participants, enabling more robust algorithm validation across diverse demographics.

The demographic composition across datasets reveals important patterns and limitations. While most datasets include healthy adults, specific populations receive targeted attention: Yoo et al. [56] uniquely focuses on children under 13 years, critical for pediatric applications, while Hu et al. [83] specifically includes subjects with various blood pressure profiles. Recent datasets show increasing demographic documentation detail, with Wang et al. [81] reporting a wide age range (25-80 years) with balanced gender distribution (40 females, 30 males) and inclusion of 13 subjects diagnosed with hypertension. Similarly, Shi et al. [73] document not only gender balance (11 females, 14 males) but also weight distribution (48-91kg) and age stratification (23-61 years). Despite these improvements, a significant limitation across datasets persists, with only a minority providing detailed age distributions, gender balance information, and health status details beyond "healthy participants." This gap in demographic documentation presents challenges for assessing algorithm generalizability across diverse populations.

Technological Diversity and Measurement Capabilities: Radar technology distribution reveals clear preferences and evolution trends. FMCW radar dominates at 66% of datasets, followed by UWB (19%) and CW (16%). Within FMCW implementations, we observe a marked industry standardization around Texas Instruments hardware platforms, with the IWR6843, AWR1642, and IWR1443 series appearing across multiple studies. This standardization facilitates cross-study comparison while potentially limiting the exploration of alternative hardware configurations. Notably, blood pressure monitoring studies show divergent technological approaches, with Wang et al. [81] leveraging ultra-wideband technology for its superior material penetration capabilities, while Shi et al. [73] utilizes millimeter-wave radar positioned just 5cm above the subject's wrist, a significantly closer monitoring distance than most other studies.

Frequency band analysis shows clustering in two primary ranges: 24 GHz (datasets [57, 70, 72]) and 77-81 GHz (datasets [63, 67, 76, 79]). The higher frequency range offers improved precision in detecting minute chest wall movements but exhibits reduced penetration capabilities. Dataset [56] uniquely employs 60 GHz with 4 GHz bandwidth, balancing these trade-offs for child monitoring in automotive settings.

Measurement capabilities vary substantially, with 39% of datasets focusing exclusively on heart rate (HR), 54% covering both HR and respiratory rate (RR), and 7% dedicated to blood pressure (BP) monitoring. This distribution highlights the progression from single-parameter to multi-parameter monitoring, reflecting the field's increasing sophistication. The emergence of dedicated BP monitoring datasets [81, 73, 83] represents a significant advancement, extending radar-based vital sign monitoring beyond cardiorespiratory parameters to cardiovascular hemodynamics. This expansion is particularly noteworthy given that continuous BP monitoring has traditionally required invasive arterial catheters or uncomfortable cuff-based methods, making non-contact alternatives exceptionally valuable for longitudinal health monitoring.

Validation Methodologies and Reference Standards: Ground truth validation approaches exhibit structured diversity. Medical-grade ECG systems are employed in 28% of datasets [58, 57, 63, 72, 79, 80], offering the highest-fidelity validation with typically ±1-2ms temporal accuracy. Consumer-grade wearables appear in 24% of datasets, including Polar devices [59, 65, 74, 55], and Heal Force monitors [67, 75], balancing accuracy with practicality. For blood pressure validation, FDA-approved devices predominate, with Wang et al. [81] using the Omron HEM-7132 and Shi et al. [73] employing the Omron HEM-7121 arm-cuff device, establishing a de facto standard for non-invasive BP ground truth. The remaining datasets employ specialized sensors including accelerometers [60], respiration belts [64, 78], and multi-parameter devices [70, 56].

Synchronization methodologies between radar measurements and ground truth receive inconsistent reporting across datasets. Approximately 35% provide detailed synchronization protocols, while others leave this critical aspect unspecified. The most rigorous approaches include datasets [57] and [79], which employ dedicated synchronization hardware, while others rely on software-based time alignment with varying precision levels.

Experimental Scenarios and Environmental Contexts: The experimental scenarios documented in 3 reveal three principal categories with varying prevalence and complexity. Stationary scenarios dominate, with sitting (40%), lying (22%), and unspecified stationary positions (12%) collectively representing 74% of datasets. This prevalence indicates the field's primary focus on establishing baseline performance under controlled conditions. Blood pressure monitoring studies exhibit particularly controlled protocols, with Shi et al.[73] specifying precise posture requirements (subjects seated with back support, making a fist with purlicue facing up) and even controlling ambient temperature (20-22°C).

Dynamic scenarios appear in 26% of datasets, encompassing controlled movements [65], daily activities [62, 64], specific exercises [82], and driving conditions [56, 67]. This category shows marked evolution from early datasets with limited movement to more recent collections featuring complex activity patterns, reflecting growing algorithm robustness.

Environmental diversity is gradually expanding, though laboratory settings remain predominant, followed by automotive environments, office environments, and naturalistic home settings. The Wang et al.[81] dataset notably incorporates office environment testing, marking a step toward real-world validation. Nevertheless, this distribution still highlights a significant gap between controlled validation environments and intended real-world deployment contexts, raising questions about ecological validity and algorithm transferability.

Temporal Characteristics and Quantity Metrics: The dataset scale varies dramatically both in duration and sample count. Total recording durations range from minutes [59, 71] to 60+ hours [81], while sample counts span from hundreds to hundreds of thousands. The most comprehensive datasets include [57] with 24 hours of continuous monitoring, [76] with nearly 73 hours of sleep data, [78] with 316,800 respiratory samples, and Wang et al.[81] with 60 hours of signal data. Blood pressure dataset Shi et al. [73] takes a different approach, prioritizing measurement diversity over duration with 100 samples per subject collected across different days and times, enabling evaluation of diurnal variations in cardiovascular parameters.

Sampling rate documentation reveals inconsistent reporting practices across datasets. While 65% specify frame rates or sampling frequencies, these vary considerably from 20 Hz (common in heartbeat monitoring) to 1000 Hz (necessary for capturing rapid movements). This variation impacts the temporal resolution of physiological signals, with higher rates enabling a more detailed waveform.

This section presents a concise summary of the historical background and evolution of radars and their diverse categorizations, accompanied by an exploration of the constraints linked to each model category. Given the prevalence of frequency-modulated continuous waves in the scrutinized literature, a more intricate analysis of these models is integrated. The methodologies employed for data collection and the array of datasets utilized in the scrutinized literature, encompassing openly accessible datasets, are also expounded upon. This discussion is of considerable importance, as the initial stage of the signal processing sequence revolves around data acquisition. The following section will examine the computational steps for extracting essential information through signal processing. The focus is on the subsequent application of Machine Learning techniques after completing the initial signal processing calculations.

3. SIGNAL PROCESSING CHAIN FOR RADAR-BASED VITAL SIGN SENSING

The vital signals derived from chest vibration present in the wireless signal received are of very low strength. Therefore, extracting vital signals from these wireless signals poses a significant challenge due to various technical obstacles such as motion artifacts, random body movements, and DC offset [87, 88]. In this segment, an overview of a general signal processing sequence for radar-based vital sign sensing, sourced from a wide array of literature, is provided [89]. As depicted in Figure 3, the signal processing pipeline consists of five main sequential components: signal acquisition, preprocessing, phase processing, signal separation, and vital sign estimation.

Initially, the received signal undergoes acquisition using various radar technologies, including FMCW (76.7%), UWB, and CW operating at different frequency ranges (24-81 GHz for FMCW, 3.1-10.6 GHz for UWB), followed by I/Q sampling and Range-Doppler processing. As shown in Figure 3, the preprocessing phase involves noise suppression, target localization using Range-FFT and CFAR [90], and DC removal. Subsequently, the phase processing stage handles demodulation techniques (using arctangent phase extraction $\Phi = \tan^{-1}(Q/I)$) and phase unwrapping. The signal separation stage employs band-pass filters (0.1-0.9 Hz for respiration, 0.6-4.2 Hz for cardiac signals) and advanced decomposition techniques like EMD/VMD. Finally, these processed signals feed into the vital sign estimation stage using both time domain (peak detection) and frequency domain (FFT, CWT, AR) approaches to derive heart rate and respiratory rate parameters.

3.1. Preprocessing

The preprocessing phase encompasses noise suppression, target localization, and DC removal as shown in Figure 3. For noise suppression, techniques range from traditional linear filters (low-pass, high-pass, band-pass) to advanced approaches [91]. These include frequency-domain Wiener filters, non-linear filters (median, morphological) for impulsive noise removal, and adaptive filtering methods like LMS, NLMS, and RLS algorithms that dynamically adjust filter coefficients [92]. For colored noise, transform domain adaptive filters (DCT-LMS, DFT-LMS) are employed, while multi-channel systems implement MVDR and LCMV for spatial noise reduction. Statistical approaches include Kalman filtering for Gaussian noise and particle filters for

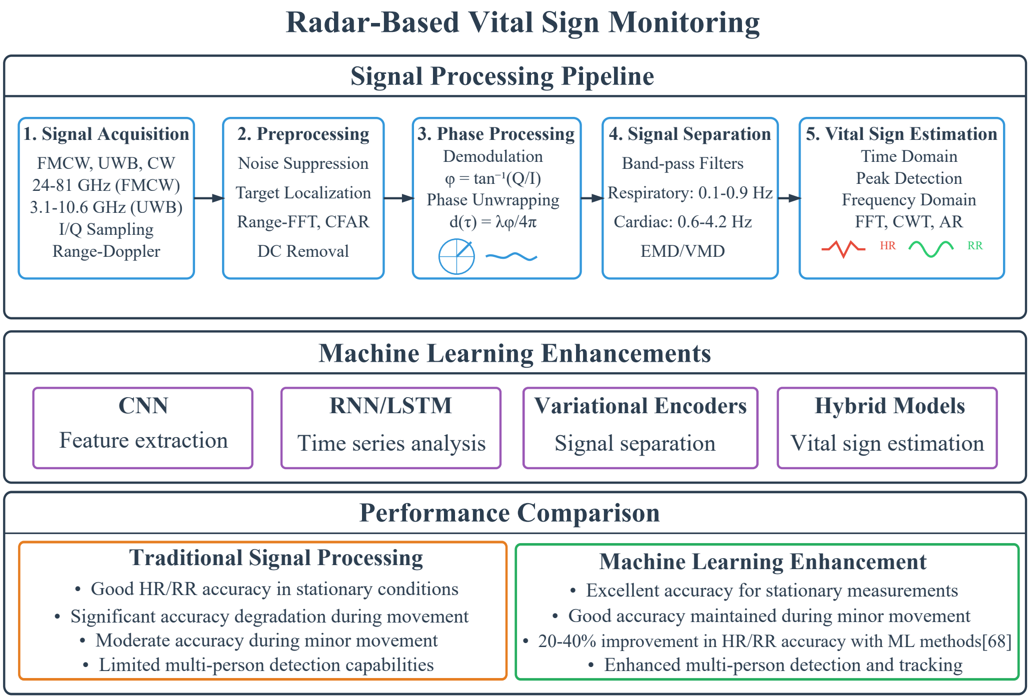

Figure 3: Signal processing pipeline and machine learning enhancements for radar-based vital sign monitoring

non-linear scenarios [93, 94]. Various techniques demonstrate different trade-offs between signal quality improvement, computational requirements, and real-time processing capabilities.

Recent studies have provided rigorous experimental validation of various noise reduction techniques under different conditions. Thibault et al. [95] conducted a comprehensive comparison of signal processing methods including Kalman filter (KF), Exponential Weighted Moving Average (EWMA), Short-Time Fourier Transform (STFT), and Wavelet Transform (WT), using synthetic signals in heat exchanger network simulations. Their comparative analysis showed that the Wavelet Transform consistently outperformed other methods across different noise levels, achieving the highest RMSE reduction (average of 24.91% compared to 15.67% for KF and 13.66% for EWMA) and SNR improvement (6.97% compared to 4.19% for KF and 3.60% for EWMA). Similarly, Zhang et al. [96] experimentally compared Multi-Resolution Singular Value Decomposition (MRSVD) against EMD, EEMD, VMD, SVD, and Wavelet Decomposition using both synthetic signals and real-world bearing fault data. Their results demonstrated that MRSVD consistently achieved the highest SNR values (12.62 dB for simulated signals at 1 dB initial SNR compared to 11.84 dB for SVD and 8.38 dB for EEMD) and lowest MSE values across different noise powers. In 2024, Zhang et al.[97] further extended these comparisons by evaluating Wavelet Packet Decomposition (WPD) in chaotic communication systems, which showed superior performance over Variational Modal Decomposition (VMD). Unlike traditional wavelet transforms that only decompose low-frequency components, WPD comprehensively decomposes signals across both low and high-frequency bands, providing more detailed time-frequency analysis. In direct comparison tests, WPD required approximately 2.4 dB lower signal-to-noise ratio than VMD to achieve the same bit error rate performance in chaotic systems. These experimental validations highlight the importance of parameter optimization in noise reduction performance and provide evidence that multi-resolution approaches generally outperform single-scale methods in processing complex sensor signals, as summarized in Table 5.

For target detection and localization [98], range information extraction utilizes RangeFFT for FMCW and time-domain range profiles for SFCW systems [99]. The CFAR (Constant False Alarm Rate) technique is often employed to detect targets in varying noise conditions adaptively. Angle estimation employs various algorithms, including AngleFFT and digital beamforming methods [100] such as Bartlett [101], Capon [102], LCMV [103], MUSIC [104], MVDR [105], and ESPRIT [106]. The MUSIC algorithm leverages signal-noise subspace orthogonality for enhanced DOA estimation, while ESPRIT utilizes rotational invariance properties for computational efficiency [107]. Technical challenges addressed include multipath propagation (using Time Reversal MUSIC) [108], non-line-of-sight situations (through UWB radar), and micro-Doppler effects (via time-frequency analysis and machine learning) [109].

3.2. Phase Processing, Signal Separation, and Vital Sign Estimation

As shown in Figure 3, the signal processing pipeline continues with phase processing, signal separation, and vital sign estimation stages. Phase processing extracts vital signs by analyzing how physiological activities alter wireless signals, calculating the phase information using arctangent demodulation (Φ

$= \tan^{-1}(Q/I)$) followed by phase unwrapping to recover the true displacement ($d(t) = \lambda\phi/4\pi$). Arctangent demodulation, though simple, compresses the true phase to $[-\pi/2, \pi/2]$, potentially causing phase discontinuities that require unwrapping algorithms [110]. Linear demodulation, based on signal subspace concepts, addresses these limitations and works effectively with short arc lengths, low SNR conditions, or when using alternating current coupling [111]. The DACM algorithm provides improved stability by utilizing differentiation and cross-multiplication instead of arctangent.

Signal separation is essential as extracted phase signals contain multiple physiological components. The challenge lies in separating respiratory signals (with greater amplitude and harmonics close to the heartbeat frequency) from heartbeat signals. As shown in the pipeline, methods include Band Pass Filtering (BPF) at specific frequency ranges (0.6–4.2 Hz for cardiac signals, 0.1–0.9 Hz for respiration) [53], dual-parameter Least Mean Squares filtering [112], and Wavelet Transform [113]. Advanced techniques such as Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) address mode-mixing and endpoint-effect issues [114], demonstrating robustness against noise interference. Recent advances in signal separation have demonstrated the potential of leveraging higher-order harmonics rather than suppressing them. [115] introduced a novel approach that identifies previously undiscovered frequency ranges (beyond 10-order heartbeat harmonics) where heartbeat information predominates over respiratory motion. Their key insight is that respiratory harmonics decay more rapidly than heartbeat harmonics, enabling clean heartbeat signal extraction from higher frequency bands. By exploiting the "beat frequency effect" - where superimposed adjacent heartbeat harmonics generate distinctive patterns with a frequency precisely equal to the heart rate - their system achieved clinical-grade accuracy without requiring machine learning models. When evaluated with 6,222 participants, their method demonstrated a median real-time inter-beat interval (IBI) error of 26.1 ms, representing a tenfold improvement over conventional methods that extract signals solely from the heart rate frequency band. Vital sign estimation employs both time-domain and frequency-domain approaches as illustrated in the final stage of the pipeline. In time-domain analysis, peak detection serves as the fundamental approach, with advancements including amplitude threshold-based peak filtration [53], Viterbi algorithm for accounting heartbeat phase variations [116], and Kalman filtering for enhanced accuracy [117]. This facilitates critical Heart Rate Variability metrics computation. Frequency-domain approaches primarily use Fast Fourier

Transform (FFT) [118], Continuous Wavelet Transform (CWT) [119], and Auto-Regressive (AR) modeling, though these methods may degrade in low SNR environments. Hybrid methodologies combine initial time-domain HR estimation with spectral refinement [120], while alternatives include cross-correlation analysis [121].

3.3. Machine Learning Aided Processing

As depicted in Figure 3, machine learning approaches have significantly enhanced radar-based vital sign monitoring capabilities. Traditional signal processing techniques achieve moderate to high accuracy in controlled settings but suffer substantial accuracy drops during movement and have limited multi-person monitoring capabilities. In contrast, machine learning enhancements provide consistently high accuracy (using regression-based methods), with less accuracy degradation compared to signal processing approaches during movement and improved multi-person monitoring.

Various machine learning architectures have been employed for different aspects of vital sign monitoring. Convolutional Neural Networks (CNNs) excel at feature extraction, with systems like HeRe achieving 97.5% accuracy. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks perform well in time series analysis, with CardiacWave achieving 0.91% error rates. Variational encoders are particularly effective for signal separation tasks, with Variational Encoder-Decoder (VED) architectures achieving 0.92 correlation with ground truth measurements. Hybrid models combining CNN and Transformer architectures provide advanced capabilities for complex monitoring scenarios. Table 6 summarizes the specific limitations of traditional signal processing approaches and how deep learning solutions address these challenges across different problem domains.

In this section, a comprehensive examination is carried out on the signal processing techniques utilized in obtaining appropriate signals for vital sign estimation. The elucidation encompasses a range of methodologies for diminishing noise, segregating signals, and extracting relevant features. The subsequent section will delve into the utilization of ML techniques for vital signs computation, emphasizing its advantages, including enhanced precision and efficacy, along with its application in categorization assignments.

4. MACHINE LEARNING METHODS FOR VITAL SIGN MONITORING

This paper presents a comprehensive analysis of the integration between radar technology and vital sign monitoring systems, emphasizing the crucial role of artificial intelligence and machine learning methodologies. The convergence demonstrates significant advancements in real-time physiological monitoring across diverse environmental conditions, with particular emphasis on signal processing optimization and noise reduction techniques. The implementation of AI-driven algorithms has shown remarkable effectiveness in enhancing measurement accuracy and data fidelity, particularly in challenging environmental contexts [122, 123, 15]. The research methodology incorporates a systematic classification framework that bifurcates machine learning approaches into two fundamental paradigms: supervised learning, which utilizes labeled data for model training and prediction, and unsupervised learning, which focuses on pattern discovery and structural analysis within unlabeled datasets [124, 125]. This classification, as visualized in Figures 4 and 5 of the original text, establishes a foundational framework for analyzing the application of machine learning in radar-based vital sign monitoring systems [17]. The integration of these technologies represents a significant advancement in non-invasive physiological monitoring capabilities, with potential applications across medical, safety, and surveillance domains.

4.1. Supervised Learning

Supervised Learning involves a systematic training methodology in which the algorithm iteratively enhances its predicting abilities by identifying connections between input features and their respective output labels. This learning process functions via parameter optimization, wherein the model modifies its internal variables to reduce prediction error concerning ground truth values [126]. The application range of supervised learning spans various fields, notably in healthcare monitoring systems, particularly for non-contact vital sign monitoring via radar technology integration. The collaboration of supervised learning algorithms and radar-based monitoring systems has led to notable improvements in healthcare surveillance, allowing for enhanced accuracy and reliability in physiological parameter identification. This integration signifies a vital advancement in non-invasive medical monitoring technology, illustrating the practical application of supervised learning in tackling intricate healthcare monitoring issues [126].

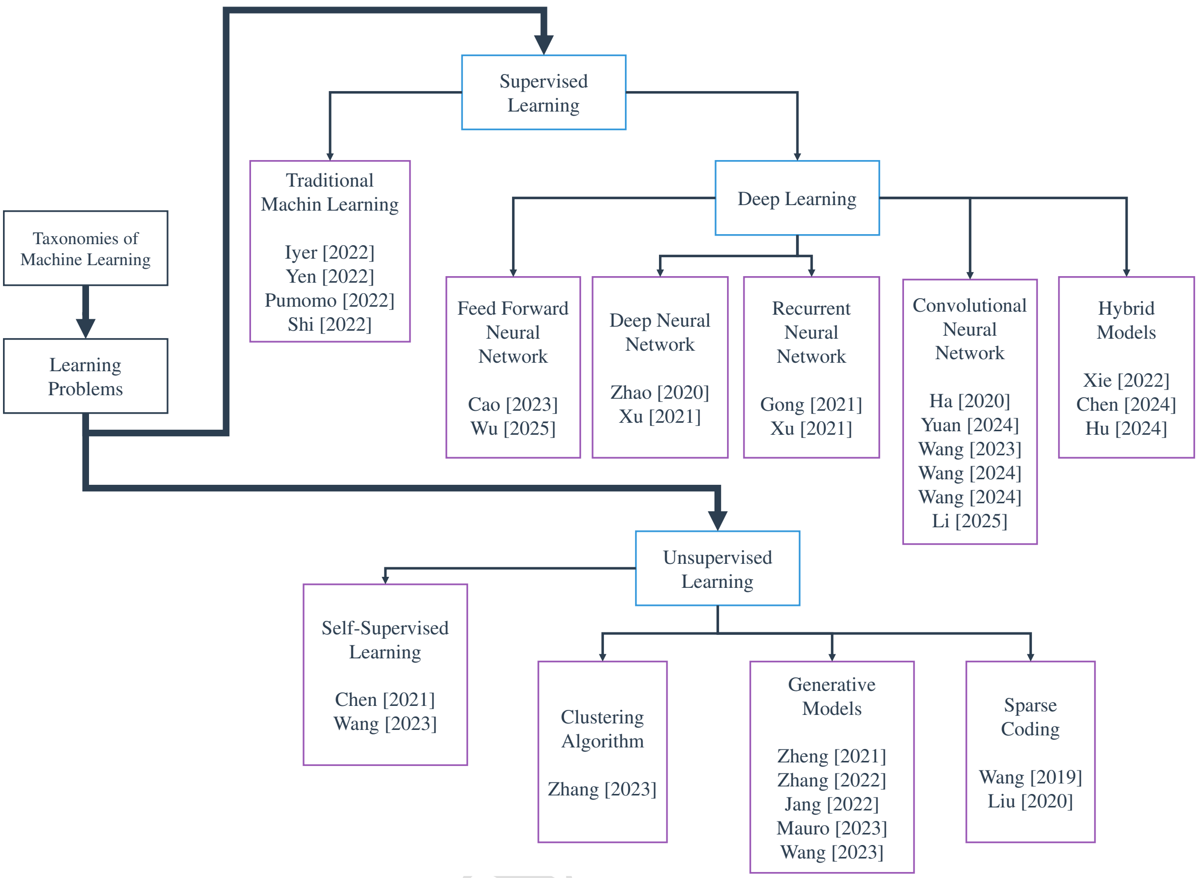

Figure 4: Different ML Methods for Vital Sign Monitoring

Traditional ML: In [67], the mmECG system showcases the application of traditional ML techniques for regression tasks. Employing hierarchical VMD alongside a trained Support Vector Machine (SVM), this system effectively extracts phase changes from mmWave signals, enabling the automatic determination of parameters for heart movement estimation. The achieved performance metrics demonstrate the system's reliability, with an average HR estimation error of 0.37 beats per minute and a cardiac cycle estimation error of 6.8 milliseconds. On the other hand, [68, 70, 71], employs traditional ML for classification. In [68], Utilizing a three-layer Artificial Neural Network, this approach focuses on arrhythmia prediction by analyzing statistical features extracted from radar signals. Despite achieving an average testing accuracy of 75% and a coefficient of determination of 0.876 for the trained dataset, it highlights the challenges and nuances inherent in classification tasks compared to regression. The [70] focuses on signal quality assessment, particularly in non-contact monitoring amidst the COVID-19 pandemic. This study delved into the realm of signal quality assessment, pitting SVM against other formidable contenders like Decision Trees, Logistic Regression, and K-nearest neighbors. It highlights SVM's exceptional performance, achieving a validation accuracy of 99.1% during model training. This precision significantly enhances vital sign monitoring and optimizes signal processing workflows, with SVM outperforming other algorithms. The system's robustness in detecting vital sign irregularities is evident from notable reductions in RR and HR deviations, ranging from 0 to 1 bpm and 0 to 4 bpm, respectively. In [84], the study focuses on the critical need for non-contact monitoring of COVID-19 patients' breathing to minimize transmission risks and ensure accurate monitoring during isolation. This research uses real-time detection of respiratory signals, where various ML algorithms are applied. These include Multivariate Linear Regression, Decision Trees, Random Forests, SVM, XGBoost, LightGBM, CatBoost, and Multilayer Perceptron. Additionally, stacked ensemble models like Stacked Ensemble Classifiers, Bagged Trees with Subsampling and Column Subsampling, and Neural Stacked Ensemble Models are utilized. The comparison reveals that the Neural Stacked Ensemble Model emerges as the top performer, achieving an average accuracy of 97.1% in identifying breathing patterns. This outcome underscores the significance of leveraging advanced ML techniques, particularly ensemble methods, for real-time respiratory signal detection and classification tasks.

Convolutional Neural Network: The mBeats [59] system integrates advanced learning-based methods for feature extraction in HR monitoring, offering a non-intrusive solution unaffected by user orientation and position by employing a domestic service robot equipped with a mmWave radar for vital sensing. Overcoming the challenge of low robot height, mBeats measures HR on the user's leg, utilizing a biquad cascade IIR filter to accurately extract heartbeat waveforms amidst noise from skin micro displacements. Treating HR estimation as a regression task, a custom deep neural network (DNN) predictor is employed. Experimental results demonstrate mBeats achieving a high HR estimation accuracy of 95.26% across diverse user poses, while the system's mmWave sensing capabilities extend to detecting subtle chest displacements from combined heartbeat and respiration signals, prompting further research into vital waveform recovery using mmWave sensing for comprehensive vital signal analysis.

The RF-SCG [60] method and the DeepVS [66] framework both utilize ML for RF-based vital sign monitoring but differ in their approaches and results. RF-SCG reconstructs the seismocardiogram waveform using mmWave radar signals, employing a 4D Cardiac Beamformer for heart localization and CNN-assisted template matching for HR estimation. It also uses a CNN-based translator and Unet architecture for Seismocardiography (SCG) waveform reconstruction and automatic labeling of fiducial points, achieving a correlation coefficient over 0.72 and accurate event timestamping with a median error of 0.26% to 1.29%. Also, DeepVS tackles RF signal modulation and body movement interference by integrating a 1D CNN for local feature extraction, an attention module for capturing temporal correlations, and a multi-head regression module for unified HR and RR estimation. The inclusion of the attention module in DeepVS enhances its ability to manage temporal dependencies and improve estimation accuracy, resulting in superior performance with 80-percentile HR/RR errors of 7.4/4.9 beats/breaths per minute. RF-SCG focuses on detailed cardiovascular event detection and accurate waveform reconstruction using CNNs and beamforming, while DeepVS emphasizes overcoming signal modulation and movement interference with an advanced deep learning architecture that includes an attention module, leading to more accurate vital sign estimation. Additionally, [80] in 2024 attempted to reduce computation time using CNN and by constructing a new architecture. This study introduces a novel deep-learning network for HR and HRV monitoring using FMCW. The proposed network integrates a frequency representation module and a residual-in-residual module, transforming radar signals from the time domain to the frequency domain, thereby achieving high-resolution spectrum representation within specified frequency intervals. Experimental results demonstrate that the algorithm maintains an average heart rate measurement accuracy above 95% with data lengths as short as 4 seconds, significantly reducing latency and improving HRV estimation accuracy. They also tested their proposed model on the dataset [57] and compared their model with HeRe [74], showing about a 2% improvement in final performance.

The HeRe [74] and the contactless ECG monitoring system [79] both utilize CNNs primarily for classification. HeRe introduces a remote HR estimation method composed of data preprocessing, heartbeat signal reconstruction, and HR estimation. Radar signals undergo preprocessing to isolate micro-movement signals, which are then decomposed using the VMD algorithm into a 2-D feature matrix. This matrix is sampled with a sliding window technique to create a dataset for a detector network, allowing precise heartbeat signal identification. HR estimation employs frequency-domain analysis and historical data correction, resulting in an impressive average accuracy of 97.5% during long-term tracking using the BGT60TR13C radar [127]. The contactless ECG monitoring system [79] addresses the discomfort of traditional electrode-based ECG methods using millimeter-wave radar technology. It consists of two modules: Cardiac Motion Measurements in Radar and DNN for Domain Transformation. The former uses signal processing algorithms like 3D beamforming and spatial filtering to extract cardiac motions, while the latter employs an encoder-decoder network with a hybrid CNN-Transformer-based encoder and a TCN-based decoder to convert cardiac mechanical signals into ECG waveforms to achieve precise peak timing and morphology correlation. This system achieves median errors of 14ms, 3ms, 8ms, and 10ms for Q, R, S, and T peak timing accuracy, a median Pearson-Correlation of 90% for waveform morphology, and a median RMSE of 0.081mv against ground truth ECG data. Its consistent performance across different age groups highlights its potential for accurate and continuous contactless ECG monitoring.

In recent developments, Li et al. [86] in 2025 presents a CNN-based approach with an encoder-decoder architecture for reconstructing high-resolution vital signs from RF signals. The system combines advanced beamforming using double phase shifter (DPS) antenna arrays with a 1D CNN that processes segmented phase signals to extract temporal features and reconstruct vital sign waveforms. The authors deliberately chose this CNN approach over traditional signal processing methods to better handle complex relationships between RF signals and physiological measurements in practical scenarios where breathing/heartbeat periodicity varies. The system demonstrates remarkable performance, achieving breathing rate estimation errors of only 0.3 BPM and heart rate estimation errors of 2.7 BPM, representing 93% and 78% reductions respectively compared to non-ML approaches. This work demonstrates the significant advantage of deep learning in extracting fine-grained vital sign information from radar signals.

Recurrent Neural Network: The CardiacWave system [63] and the self-calibrated Long Short-Term Memory (LSTM) based framework [65] for RF vital sign sensing represent significant advancements in the field of non-contact vital sign monitoring, leveraging deep learning approaches to enhance accuracy and robustness in dynamic environments. The CardiacWave system employs a DNN with a recurrent architecture to monitor cardiac electrical activity using mmWave technology. The methodology focuses on analyzing the cardiac-mmWave scattering effect (CaSE) to extract detailed cardiac activity information. Key steps include feature extraction with learnable masks and noise suppression using the Constant False Alarm Rate (CFAR) method [128]. This system also incorporates a wavelet-based error function to ensure precise signal reconstruction. In experiments with 40 subjects, CardiacWave achieved normalized error rates below 0.91% for key cardiac parameters and correlation coefficients around 0.9 between the reconstructed ECG-like signals and the actual ECG baseline. These results underscore the system's high fidelity and accuracy in non-contact cardiac monitoring, demonstrating its resilience to varying body conditions and the presence of wearable accessories. Similarly, the self-calibrated LSTM-based framework for RF vital sign sensing tackles the challenge of motion artifacts during body movement by correlating HR and RR with motion intensity. The researchers developed a movement power detection module that integrates radar signals and analytical models with LSTM-based [129] approaches to estimate motion intensity accurately. A notable innovation is the self-calibrated LSTM model, which generalizes across different subjects without requiring explicit data labeling, thereby adapting to varying vital sign patterns. This system is particularly adept at functioning under unrestricted body movement, a significant challenge for traditional RF sensing systems. It demonstrated an average estimation error of 5.57 bpm for HR and 3.32 bpm for RR, surpassing existing systems and proving its effectiveness in dynamic and everyday environments. This makes it highly suitable for applications such as home-based metabolism tracking and fitness monitoring during exercise. Both systems utilize sophisticated ML methodologies to enhance the precision and resilience of monitoring essential vital signs. The CardiacWave system excels in high-definition cardiac monitoring with a focus on signal fidelity and non-contact measurement, while the self-calibrated LSTM-based framework addresses the challenges of motion artifacts and generalization in RF vital sign sensing, making it highly effective for real-world, dynamic scenarios.

Feed Forward Networks: In [74], the main issue addressed in the paper is the accuracy and efficiency of vital sign monitoring using radar in real-time scenarios, particularly with limited data volumes. Traditional methods of spectrum analysis frequently necessitate lengthy time series data, a practice that may present challenges in conducting real-time calculations.

This method utilizes an advanced birth-death strategy and the M-Rife algorithm [130] for frequency interpolation. The birth-death strategy detects new frequencies and monitors changes within frames per second, enhancing the algorithm's effectiveness in vital sign monitoring. The selection of the longest link, closest to the frequency of the preceding second, accurately represents the vital sign rate. Simulations on a publicly available dataset validate the method's feasibility and accuracy, with experimental results demonstrating an impressive 98% accuracy in real-time heartbeat rate estimation. The technique also reduces interference from clutter and respiratory harmonics. This frequency-tracking algorithm offers significant advantages over traditional spectrum analysis approaches, providing real-time estimation capabilities with potential market applications. The outcomes of simulations and experimental trials illustrate that the suggested algorithm surpasses alternative approaches like TVF-EMD and FFT [131] in terms of precision. The algorithm shows high measurement accuracy in calculating respiration and heartbeat rates, even with limited data. It is also more responsive to variations in respiratory and heartbeat rates. The authors used ML, specifically a neural net fitting method, to enhance the accuracy of real-time vital sign monitoring by estimating respiration and heartbeat rates from radar data. This method is employed for regression tasks, as it involves predicting continuous values of physiological signals rather than discrete classes. The neural network is trained to fit the interpolation points and output the appropriate respiration or heartbeat frequency, which are continuous variables. This approach allows for capturing intricate patterns in the data, which is essential for accurate real-time monitoring of vital signs.

In 2025, Wu et al. [85] introduced a two-layer feed-forward neural network for apnea detection during sleep. The neural network, characterized as a "pattern net," processes five key features extracted from radar signals: variance, maximum value, minimum value, integral of absolute value, and maximum magnitude distance. This model achieves a remarkable accuracy of 93.6% in identifying apnea events in real-time, successfully detecting episodes lasting 12-21 seconds. The researchers selected this simple architecture based on its computational efficiency, suitability for binary classification, and effectiveness with the statistical features extracted. The system also incorporates a Template Matching Estimation (TME) algorithm for heart rate detection, which achieves 90.25% accuracy within ± 2 bpm, significantly outperforming traditional FFT and Peak Spacing methods. This approach demonstrates the effectiveness of even relatively simple neural network architectures when properly applied to focused detection tasks in non-contact vital sign monitoring.

Hybrid Models: Recent advancements have emerged1 sophisticated hybrid architectures that combine multiple neural network paradigms to achieve superior performance in complex monitoring scenarios. The Wang et al. [82] system introduced in 2024 implements a hybrid CNN-Transformer architecture specifically designed for respiratory monitoring during physical exercise—a particularly challenging environment due to complex motion artifacts. This system employs a CNN encoder with 5 consecutive 1D CNN layers to extract temporal patterns from 49 radar signal channels, followed by a 4-block transformer decoder with 8 attention heads to model relationships between channels. The architecture is implemented within a teacher-student knowledge distillation framework, where the student network (CNN-Transformer) learns to predict demixing weights from a teacher component (ridge regression solver). This approach achieves a median respiratory waveform cosine similarity of 0.75 and respiratory rate error of only 0.5 RPM across various exercise types, significantly outperforming previous methods in dynamic environments. The system was validated with 13 participants across 9 different exercise types, demonstrating robust performance even during intensive activities like running.

In 2024, Hu et al. [83] presented a groundbreaking hybrid Transformer model called mmFormer for continuous arterial blood pressure waveform monitoring. This architecture features a UNet-like encoder-decoder structure with 5 resolution levels, incorporating convolutional layers with LeakyReLU activation for local feature extraction, a 12-layer transformer with 8 attention heads in the bottleneck, and spatially-aware attention shortcuts between encoder and decoder. The system achieves a remarkable waveform correlation of 0.903 (basic version) and 0.935 (personalized version) with medical-grade reference equipment, with mean absolute errors as low as 4.99 mmHg for continuous blood pressure measurements. This represents the first contactless system capable of generating continuous arterial blood pressure waveforms (125 Hz) rather than just discrete values, demonstrating the power of hybrid architectures in extracting complex physiological information from radar signals.

These hybrid architectures represent the cutting edge of radar-based vital sign monitoring, effectively combining the spatial feature extraction capabilities of CNNs with the temporal modeling strengths of transformers and recurrent networks to address increasingly complex monitoring scenarios.

An extensive examination of radar-based vital sign detection techniques from 2020 to 2025, Table 7, indicates notable advancements in both methodologies and performance metrics. The approaches are classified into two principal learning paradigms: Deep Learning (73.69% of studies) and Traditional Machine Learning (26.31% of studies). Deep Learning methodologies mostly employ regression techniques, with architectures advancing from fundamental 1D-DNN and 1D-CNN frameworks to more complex implementations that integrate LSTM, attention mechanisms, and hybrid CNN-transformer models. The architectural evolution exhibits a distinct trend towards heightened complexity, with initial systems such as [59] utilizing a simple 1D-DNN, whereas subsequent implementations like [63] integrate dual DNN-LSTM architectures for more detailed signal analysis.

From the perspective of radar technology, FMCW radar dominates, being utilized in 66% of research studies, while UWB and CW radar systems see less use on their own. The predominance of FMCW is due to its optimal balance between range resolution and system complexity. The measurement scope has expanded considerably, with early studies focused primarily on heart rate (HR) monitoring, while recent research has diversified to include respiratory rate (RR), apnea detection, and even continuous blood pressure (BP) waveforms, reflecting a trend towards comprehensive physiological assessment.

Performance measures show a significant upward trend, with regression-based methods yielding especially remarkable outcomes. Initial implementations established rigorous standards, exemplified by [60] mean error range of 0.26-1.29% in heart rate monitoring. This foundation was expanded upon by further studies, culminating in advanced systems such as study [74], which attained 98% accuracy using neural network fitting techniques. The newest studies in 2024-2025 have pushed boundaries further, with Li et al. [86] achieving breathing rate errors of just 0.3 BPM, Wang et al. [82] maintaining accurate respiratory monitoring even during intense physical activity, and Hu et al. [83] pioneering the first contactless continuous arterial blood pressure waveform monitoring.

The complexity of architecture exhibits a distinct relationship with measurement capabilities and environmental challenges. Recent studies reveal a clear trend toward hybrid architectures, particularly CNN-Transformer combinations that effectively leverage both spatial and temporal features of radar signals. This architectural sophistication enhances system robustness in challenging real-world environments while expanding monitoring capabilities beyond basic vital signs. The progression from single-task systems to comprehensive monitoring platforms capable of detecting multiple physiological parameters simultaneously represents a significant advancement toward practical clinical applications.

The field exhibits four distinct developmental phases: initial establishment (2020-2021) concentrating on foundational architectures and baseline performance metrics; diversification (2021-2022) distinguished by the investigation of alternative radar technologies and machine learning methodologies; refinement (2022-2023) defined by architectural sophistication and improved real-world applicability; and expansion (2024-2025) characterized by application to new vital signs (blood pressure), challenging environments (exercise), and finer measurement granularity. This evolution signifies a maturing discipline where the research emphasis has transitioned from mere performance enhancements to system resilience, practical utility in diverse environments, and comprehensive physiological monitoring capabilities. As illustrated in Table 8, machine learning approaches consistently outperform traditional signal processing techniques across various monitoring scenarios, though this performance advantage comes with increased computational demands.

Blood Pressure Monitoring: Blood pressure monitoring technology has evolved from traditional cuff-based techniques toward non-invasive contactless approaches, each with distinct technical implementations and limitations. Recent radar-based sensing methods have emerged as promising solutions for continuous monitoring without requiring physical contact.

Shi et al. [73] utilize 77 GHz mmWave radar with 4 GHz bandwidth for contactless BP measurement. Its core technique, delay-Doppler domain feature transformation (DDFT), performs the Wigner transform followed by the symplectic finite Fourier transform (SFFT):

$$\Lambda[k,l] = \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} R[n,m] e^{-j2\pi(\frac{kn}{N}-\frac{lm}{M})} \tag{1}$$

This approach separates pulse signals from noise based on their different delay-Doppler responses, yielding higher SNR than conventional methods. While technically sound, its machine learning component employs standard regression models (Random Forest, SVM, Decision Tree), revealing a reliance on established techniques rather than algorithmic innovation. Its performance (0.87 mmHg/1.55 mmHg mean errors for SBP/DBP) is notable but was validated on a limited dataset (25 subjects).

Wang et al. [81] operate at lower frequencies (7.3 GHz with 1.4 GHz bandwidth), implementing algorithmic processing rather than novel sensing principles. Its Automated Multiscale-based Peak Detection (AMPD) algorithm identifies peaks through subsequence decomposition and cost function optimization, while its deformed signal detection uses basic cosine similarity thresholding (threshold=0.8). The deep learning architecture employs standard convolutional operations with varying kernel sizes and a conventional channel attention mechanism combining average and max pooling. Results (6.5 mmHg/4.7 mmHg MAE for SBP/DBP) demonstrate lower accuracy than mmBP despite using more complex signal processing, suggesting potential shortcomings in lower-frequency UWB sensing for BP applications.

Hu et al. [83] target continuous waveform reconstruction rather than discrete values, employing a 77 GHz/4 GHz bandwidth configuration. Its architectural complexity exceeds previous approaches, implementing a hybrid Transformer with UNet-inspired multi-resolution design and spatially-aware attention shortcuts:

$$F_{out} = FC(CV) \text{ where } C = \text{Softmax}(\frac{QK^T}{\sqrt{D}}) \tag{2}$$

The beamforming-based data augmentation operates as a specialized form of signal mixing:

$$\tilde{X}(\theta) = W^H(\theta)X, \text{ where } W_c(\theta) = \exp[-j2\pi d_c \sin(\theta)/\lambda] \tag{3}$$

While achieving a high waveform correlation (0.903), the system's complexity introduces computational demands that may limit real-world deployment. The personalization requirement (requiring 20 minutes of calibration data for optimal performance) presents a practical limitation for casual users, and the evaluation lacks specificity regarding performance on subjects with cardiovascular conditions.

Direct comparison reveals a technical progression toward increasingly complex machine learning approaches, with a corresponding trend toward higher frequency radar sensing. However, no approach has fully resolved the tension between accuracy, generalizability, and deployability. The lower-complexity Shi et al. system paradoxically achieves better accuracy metrics than the more algorithmically sophisticated Wang et al. This suggests that operating frequency and bandwidth may be more deterministic of performance than algorithmic complexity. Meanwhile, Hu et al.'s [83] focus on

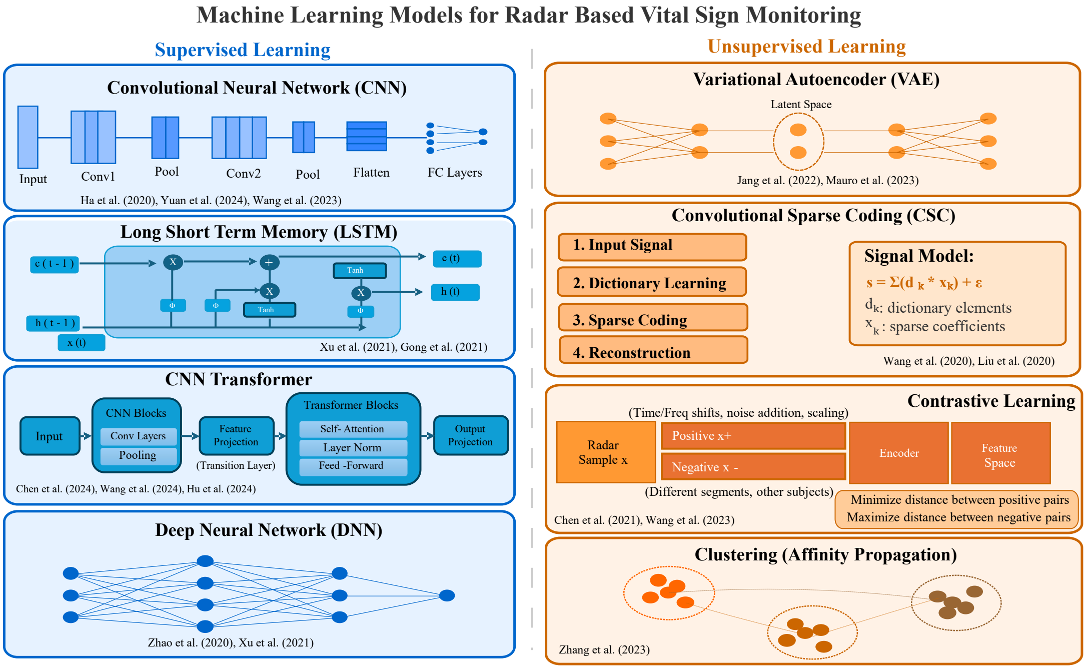

Figure 5: A graphical representation of the key models employed in supervised learning and unsupervised learning

continuous waveform measurement represents a distinct technical approach that addresses different clinical requirements than discrete value estimation.

4.2. Unsupervised Learning

Unsupervised learning is an ML approach in which algorithms analyze unlabeled data to uncover patterns or structures without relying on explicit instructions or predefined outputs. Instead of being guided by labeled examples, the algorithm autonomously explores the data to identify similarities, differences, or underlying relationships among the data points. Unsupervised learning techniques encompass various methods, including clustering, dimensionality reduction, and density estimation. Clustering algorithms group similar data points into clusters, while dimensionality reduction techniques aim to simplify the data by capturing its essential features. Density estimation methods estimate the probability distribution of the data. Unsupervised learning finds applications in numerous domains, including data mining, anomaly detection, and exploratory data analysis, where understanding the data's inherent structure is essential for making informed decisions or extracting valuable insights [132]. Table 9 presents a comprehensive overview of recent studies employing unsupervised learning approaches for vital sign monitoring using radar technology.

Sparse Coding Approaches: Early advancements in radar-based vital sign monitoring employed sparse coding techniques to separate physiological signals effectively. In 2020, Wang et al. [133] pioneered the application of Convolutional Sparse Coding (CSC) for extracting vital signs from UWB radar signals. Operating directly in the time domain, this approach modeled signals as convolutions of multiple bases with sparse coefficients, enabling accurate separation of respiratory and cardiac components with minimal data (just 5 seconds). The methodology achieved impressive precision with heartbeat rate errors of only 0.04 Hz (2.6%) and respiratory rate errors of 0.008 Hz (4%), demonstrating CSC's effectiveness for limited-data scenarios. Building upon this foundation, Liu et al. [61] introduced an enhanced approach combining CSC with Gaussian Mixture Models (GMM-CSC) to better handle complex noise environments in FMCW radar signals. By modeling noise as a mixture of Gaussian distributions rather than a single distribution, this hybrid method achieved approximately 35% improvement over standard CSC, with a correct detection rate of $\sim$0.88 in experimental validation. The GMM-CSC approach proved particularly effective in capturing the statistical characteristics of mixed noise sources from body movements, environmental factors, and device limitations. Figure 6 presents the overall schematic and sequential stages of CSC.

Generative Models: From 2021 to 2023, variational encoder-decoder approaches have seen notable advancements in non-contact health monitoring, addressing various challenges in respiration and cardiac signal recovery. In 2021, the MoRe-Fi [64] system introduced an innovative variational encoder-decoder network (IQ-VED) for respiration monitoring, capable of recovering fine-grained respiratory waveforms from complex radar signals despite full-scale body movements. By processing radar signals in the complex IQ domain, utilizing a CNN-based encoder and a decoder for accurate waveform reconstruction, and employing variational inference and bivariate analysis, MoRe-Fi maintained a cosine similarity above 0.95 for most cases and above 0.85 for over 75% of cases. It demonstrated significantly better performance than the BreathListener [134] baseline in waveform recovery, respiratory rate estimation, and peak-valley time accuracy, though movements like

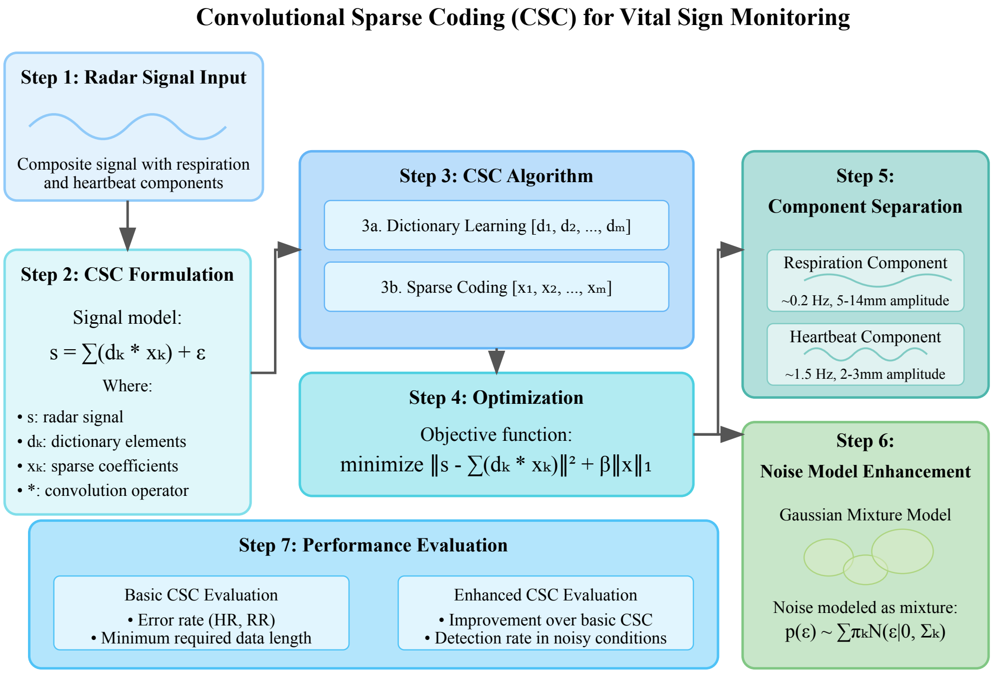

Figure 6: Convolutional Sparse coding

walking and sit-stand caused notable errors. In 2022, researchers employed a deep generative model known as the VED to extract detailed heartbeat waveforms from RF sensor data, successfully addressing the challenges posed by nonlinear signal mixing. This innovative model demonstrated superior performance compared to the traditional EEMD method, achieving higher cosine similarity scores and lower mean errors in heartbeat estimation and interval measurement. Additionally, the VED model attained a Correlation Score of 0.9 for UWB sensors and 0.92 for FMCW sensors, highlighting its effectiveness [69]. Another study in 2022 implemented a variational autoencoder (VAE) to reconstruct Doppler Cardiogram (DCG) signals into synthetic ECG signals, enhancing the consistency of HR variability metrics by 75.5% and proving superior in accuracy and reliability for remote cardiovascular disease diagnoses compared to traditional methods. The system required preprocessing steps and specialized filtering post-VAE to improve clarity and accuracy [72]. In 2023, a sophisticated user-adaptable radar system for precise respiratory signal estimation in office settings was developed, integrating episodic

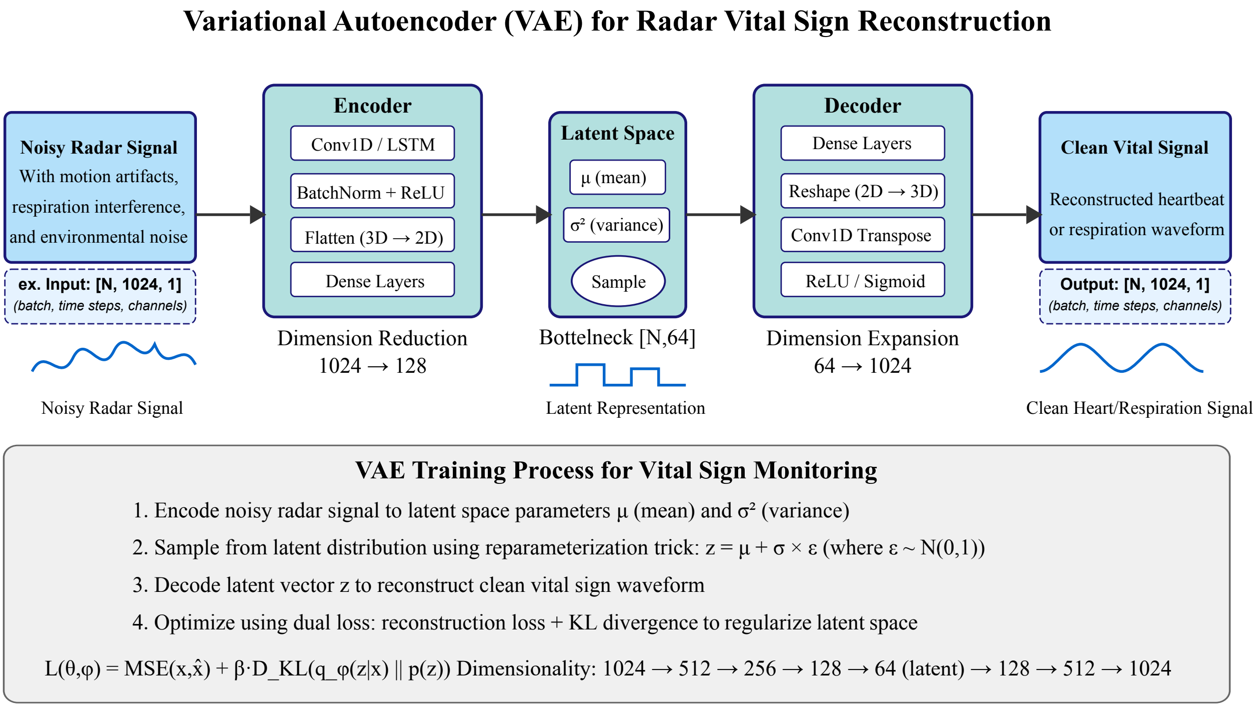

Figure 7: VAE model

learning and a variational autoencoder to rapidly adapt to new users. This system estimated respiratory rates with an average accuracy of 92.5% for users within the standard range and reduced signal distortion by 15% compared to traditional methods [78]. However, it faced challenges with individuals having non-standard respiratory rates, motion artifacts, and the need to discard corrupted data. Despite these challenges, the continuous evolution of variational encoder-decoder techniques underscores their potential for robust, non-contact health monitoring, demonstrating superior performance over traditional methods while highlighting areas for further optimization, particularly in handling motion artifacts, non-standard data adaptation, and signal clarity. Figure 7 presents the overall schematic and sequential stages of the VAE model.

Contrastive Learning: The MoVi-Fi system [62] is designed for motion-robust vital signs monitoring using radio-frequency (RF) sensing technology.

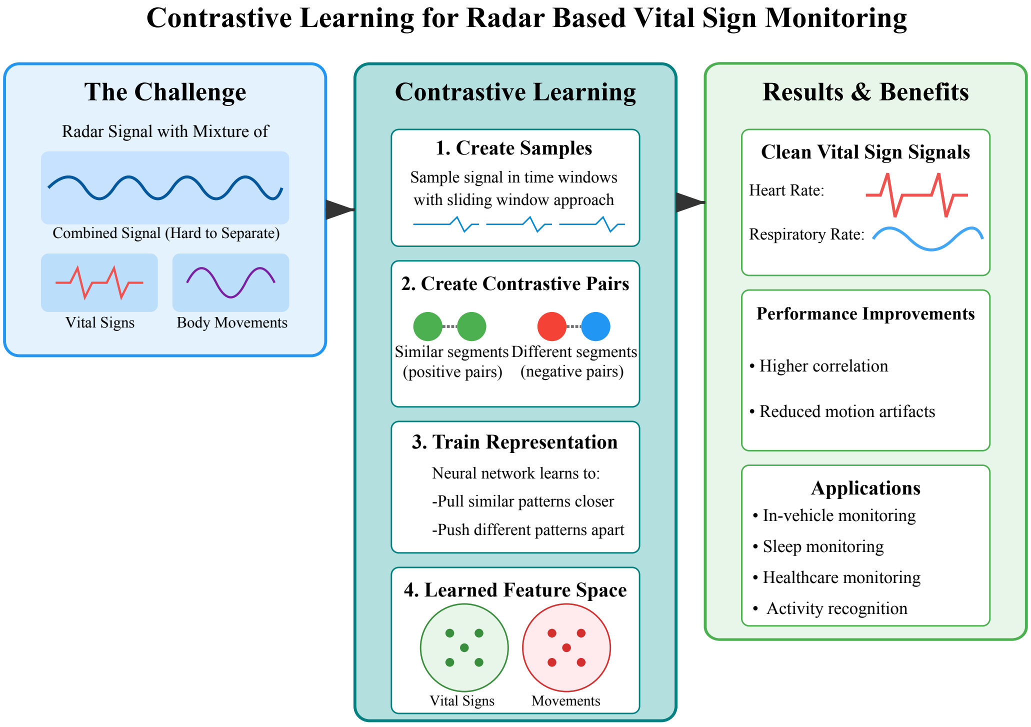

Figure 8: Contrastive Learning

It synchronizes clocks with Precision Time Protocol and employs a unified RF-sensing model to capture motion-induced reflection signals represented by RF Channel Impulse Responses (CIRs). MoVi-Fi categorizes body movements into stationary, cyclostationary, and non-stationary types, utilizing a self-supervised contrastive learning algorithm to separate interference from vital signs. By sampling data streams with a sliding window approach, the system distinguishes between stationary and non-stationary movements, extracting vital signs waveforms and refining them with VS-Net. The results demonstrate accurate extraction of vital signs waveforms under severe body movements, showcasing MoVi-Fi's effectiveness in motion-robust vital signs monitoring. Figure 8 presents the overall schematic and sequential stages of Contrastive Learning for vital sign monitoring.

Clustering Algorithm: Radar-Beat [76] adopts a comprehensive approach, integrating innovative methodologies and algorithms to achieve its objectives. At the core of its functionality lie two crucial components: a highly sensitive body motion detection algorithm and an optimal Range-bin selection algorithm. These components collaborate seamlessly to automatically identify and adapt to body motion, ensuring optimal utilization of heartbeat signal channels for precise monitoring. A pivotal aspect of Radar-Beat's methodology involves integrating a Body Motion (BM) index [135] and a corresponding mask (m) to detect instances of body motion during monitoring. The BM index measures the amplitude of body motions based on radar signals, with adjustments made to enhance sensitivity. If the accumulated BM index within a specific time window exceeds a predefined threshold, the method identifies body motion occurrences within that window. The mask (m) is then utilized to indicate whether body motions occur at each time point; if detected, m[t] is set to 1, otherwise, it remains at 0. This mask acts as a crucial indicator for subsequent monitoring stages, enabling Radar-Beat to adapt its strategy dynamically in response to detected body motions, thereby ensuring monitoring accuracy and reliability. Furthermore, Radar-Beat employs advanced similarity functions to enhance monitoring accuracy further. By analyzing heartbeat signals within specific time windows, Radar-Beat assesses the degree of resemblance to a predefined template. Notably, when the heartbeat signal closely resembles the template, a positive peak consistently appears. This capability enables Radar-Beat to effectively identify and differentiate genuine heartbeat signals from noise or artifacts, thereby significantly improving the overall reliability of the monitoring process.

Statistical Approaches: Recent advancements have demonstrated the effectiveness of statistical methods for radar-based vital sign monitoring. In 2024, Yao et al. [84] introduced a sophisticated approach using Maximum Likelihood Estimation (MLE) for extracting heart rate and breathing rate from FMCW radar signals. Rather than employing traditional deep learning architectures, this method models vital sign signals as a sum of sinusoids with harmonics and applies Newton's method to optimize the likelihood function. The key innovation addresses a critical challenge in the field: separating heartbeat signals from respiratory harmonics that often cause interference. This statistical approach achieved remarkable precision with RMSE < 1 bpm for breathing rate and < 1.5 bpm for heart rate estimation, demonstrating comparable or superior performance to machine learning methods in specific scenarios. The implementation is particularly suitable for IoT applications due to its computational efficiency while maintaining high accuracy. This development highlights how classical statistical methods can complement modern machine learning approaches in the vital sign monitoring domain.

From 2020 to 2024, advanced techniques in radar-based vital sign detection exhibit an evolving landscape of methodological approaches. Initial developments in 2020 established foundational sparse coding techniques with wang et al. [82] utilizing CSC for time-domain analysis of UWB signals and Liu et al. [61] enhancing noise robustness through GMM-CSC integration with FMCW radar. The field progressed in 2021 with MoVi-Fi [62] employing self-supervised contrastive learning alongside multi-radar technology, attaining correlation values ranging from 0.8 to 0.9. Simultaneously, MoRe-Fi [64] implemented generative modeling via VED architecture, achieving exceptional accuracy despite body movements.

The field saw substantial progress in 2022 with the deployment of prominent generative models. Study [69] enhanced VED architecture by employing both FMCW and UWB radar technologies, resulting in superior correlation scores of 0.9 for UWB and 0.92 for FMCW in heart rate monitoring. Study [72] presented a VAE architecture utilizing CW radar, emphasizing consistency enhancement with a 75.5% improvement.

In 2023, methodological diversity expanded considerably. Radar-Beat [76] implemented clustering methods via affinity propagation, attaining accurate heart rate measurements with an error margin of merely 0.65 bpm. Study [78] integrated Conditional VAE with MAML, exhibiting reliable respiratory rate detection with MSE below 100. The most significant advancement came from study [75], which combined cGANs and contrastive learning, achieving remarkable correlation scores and minimal RMSE in heart rate monitoring.

Recent developments in 2024 continue to advance the field with novel approaches. Yao et al. [84] introduced a statistical approach using Maximum Likelihood Estimation (MLE) that specifically addresses the challenge of respiratory harmonics interfering with heartbeat detection, achieving impressive precision with RMSE below 1 bpm for breathing rate and below 1.5 bpm for heart rate. This demonstrates that statistical approaches can rival machine learning methods in specific vital sign monitoring applications.

Key technical observations encompass:

- Methodological progression from sparse coding to generative models and finally to hybrid architectures
- A gradual transition from single-radar to multi-radar methodologies

- Evolution from simplified noise models to sophisticated approaches handling complex interference patterns
- Steady enhancement in performance indicators across vital signs with progressively shorter required measurement windows
- Enhanced resilience to motion artifacts and environmental fluctuations
- Shift towards more advanced evaluation methods that integrate correlation coefficients with error assessments

The chronological evolution indicates a distinct tendency towards increasingly sophisticated, hybrid methodologies that maintain or enhance performance measures, especially in addressing real-world challenges such as movement artifacts, signal consistency, and efficient operation with minimal data collection periods.

Table 10, offers a summarized comparison of supervised and unsupervised learning methods in vital sign monitoring. It thoroughly delineates their definitions, data types, advantages, disadvantages, and prevalent models/networks. The table indicates that although supervised learning provides more accurate results and utilizes labeled data with prominent networks such as CNN and LSTM, it encounters difficulties due to the labor-intensive nature of data labeling. In contrast, unsupervised learning, which employs unlabeled data and models such as VED and VAE, is proficient in trend identification but may exhibit reduced accuracy and increased time consumption. This comparison aids researchers in comprehending the trade-offs associated with selecting between these learning methodologies for vital sign monitoring applications.

5. Discussion

The integration of machine learning with radar technology for vital sign monitoring represents a significant advancement in non-contact healthcare solutions. Through a comprehensive analysis of the studies presented in Tables 9 and 10, we observe distinct patterns in methodological approaches, technological implementations, and performance metrics. As shown in Figure 9, FMCW radar systems demonstrate considerable dominance, including over 66% of the examined studies, mostly owing to the widespread use of standardized modules like Texas Instruments' IWR6843 and AWR1642. This popularity arises not only from availability but also from FMCW's greater range resolution capabilities and increased resistance to multipath effects relative to conventional CW systems. This section provides a detailed examination of current achievements, limitations, and future directions in this rapidly evolving field, structured through multiple analytical lenses, including hardware configurations, learning paradigms, and practical implementation challenges. The standardization of these platforms has markedly expedited research advancement by facilitating direct comparison and validation of procedures across various studies.

In the realm of machine learning architectures, our analysis reveals a clear dichotomy between regression and classification approaches:

- Regression-based vital sign estimation has evolved through three distinct generations. First-generation methods, which relied on conventional neural networks, achieved limited success and suffered significant performance declines in real-world scenarios. The second generation, exemplified by devices like RF-SCG [60], utilized sophisticated convolutional neural network (CNN) designs, achieving mean errors as low as 0.26% in controlled environments; however, these methods required near-perfect subject immobility. The current third generation, as demonstrated in works such as [80], has delivered exceptional performance, with an RMSE of 21.83 ms despite analyzing data segments in as little as 4 seconds, marking a substantial advancement in real-time monitoring capabilities. Nevertheless, these systems consistently show reduced accuracy during significant body movement, highlighting an ongoing challenge in mitigating motion artifacts.

- Classification methodologies have exhibited significant advancements in precision and resilience. Conventional machine learning classifiers, especially Support Vector Machines (SVMs), have demonstrated remarkable efficacy in particular tasks, attaining classification accuracies beyond 99% in research such as [70]. Nonetheless, deep learning methodologies, particularly convolutional neural networks and hybrid architectures have surfaced as optimal solutions for intricate situations. The HeRe system [77] typifies this improvement, with 97.5% accuracy in heartbeat detection via ResNet architecture, while hybrid methodologies such as [79]'s CNN-Transformer integration has further advanced the field, obtaining median errors as low as 14ms for cardiac timing parameters.

An in-depth examination of fundamental data attributes uncovers alarming trends. Research utilizing extensive datasets (>30 individuals) consistently exhibits enhanced generalization ability, whereas studies with restricted subjects (<15) demonstrate a significant drop in performance when tested on unseen subjects. This pattern indicates a significant issue in the field: most current research depends on very small, homogeneous datasets that may not sufficiently reflect real-world population variety. Performance measures under varying operational situations illustrate a sobering reality: whereas systems attain remarkable accuracy in controlled settings (± 2 bpm for heart rate, ± 1 breath/min for respiratory rate), real-world performance frequently deteriorates considerably. Minor movement can lead to a slight decrease in accuracy, while significant movement may result in a substantial decline. The disparity in performance between laboratory and real-world situations constitutes a major challenge for the field.

Current developments indicate a growing emphasis on unsupervised and semi-supervised methodologies, especially via generative models such as VAE or VED architectures. These methods exhibit encouraging outcomes in managing unlabeled data and adjusting to novel situations. However, based on Figure 9, they now fall short of supervised techniques in absolute performance metrics. The development of hybrid architectures that integrate various learning paradigms indicates a viable avenue for future study, likely providing more resilient solutions for practical applications.

This comprehensive examination demonstrates notable advancements and ongoing difficulties in the subject. Despite achieving remarkable precision in controlled settings, the shift to dependable real-world applications continues to pose challenges. Future studies must rectify these shortcomings by enhancing motion compensation algorithms, employing more advanced data processing methods, and, importantly, creating more extensive and varied datasets.

6. Open Challenges and Future Directions

The employment of ML for radar-based vital sign monitoring is a recent advancement that is still in its early phases, showing considerable potential for further exploration in new research initiatives. The challenges related to vital signs monitoring, previously mentioned, present open avenues for investigation and innovation. It is crucial to stress the importance of early detection of abnormalities in cardiac and respiratory functions in future stud-

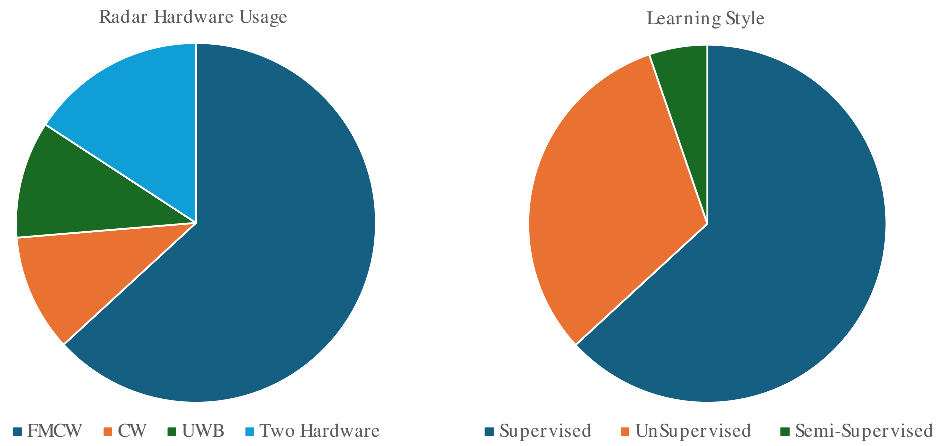

Figure 9: Distribution of radar hardware technologies and learning approaches across the 26 studies analyzed in this survey (2020-2024). This analysis reveals a clear preference for FMCW radar (66%) and supervised learning methods (65.5%) in vital sign monitoring applications.

ies. Both cardiac and respiratory vital signs can act as foundational components for various systems aimed at detecting anomalies and implementing preventive measures.

However, the application of ML and DL in this field faces several specific limitations and challenges. One key issue is the tuning of parameters, which requires significant expertise and can greatly impact the performance of the algorithms. The computational power needed for training and running these models is substantial, making real-time processing a difficult goal. Additionally, the requirement for large, high-quality datasets is a significant hurdle, as acquiring such data can be resource-intensive. The power consumption of these algorithms is also a concern, particularly for continuous monitoring applications. Training time is another critical factor, as it can be lengthy and computationally expensive, especially for deep learning models. Furthermore, generalized ML performance metrics, such as accuracy, precision, recall, and F1-score, need to be carefully considered and reported in studies to provide a comprehensive evaluation of the models' effectiveness.

The field of Vital Sign measurements lacks thorough examinations of generative ML concepts for model training and testing purposes. The only existing study on the use of generative ML techniques combines data from multiple radar sources using Generative Adversarial Networks (GANs) to determine the human body's orientation while simultaneously recording vital signs. A suggested approach is to utilize GAN methodologies to generate additional signals representing heart and respiration waveforms obtained from radar sensors. In continuation, an evaluation of some of the most significant among these challenges has been conducted. Table 11 provides a critical assessment of the theoretical, practical, and domain-specific limitations of various machine learning approaches in vital sign monitoring, offering valuable insights for researchers in selecting appropriate methodologies based on application requirements.

6.1. Accuracy Improvement

While mmWave radar technology shows promise for non-contact vital sign monitoring, several critical challenges persist. This section examines these challenges and evaluates the current ML approaches, highlighting both their potential and limitations.

1. Large Body Movement: Large-scale body movements remain a significant obstacle in achieving accurate vital sign monitoring in dynamic environments. While studies like MoVi-Fi [62] and MoRe-Fi [64] have made progress, several critical issues remain:
    - Limited Scope: The focus on respiratory rate (RR) over heart rate (HR) reveals a significant gap in current research. This bias towards easier-to-detect vital signs may be slowing overall progress in the field.
    - Controlled Environments: The reliance on controlled environments raises serious questions about the real-world applicability of these techniques. There's a risk of developing solutions that work well in labs but fail in practical scenarios.
    - Computational Complexity: The computational complexity of current approaches is concerning. In a field where edge computing and real-time processing are crucial, resource-intensive algorithms may prove impractical for widespread adoption.

   Although ML approaches demonstrate potential in addressing motion artifacts, they frequently fall short in real-world scenarios with unpredictable movements. The field needs to move beyond controlled experiments to validate these techniques in diverse, uncontrolled environments.

2. Breathing Harmonics Distorting Heart-rate Harmonics [78]:
   - Supervised Learning Limitations: Current supervised learning methods struggle when harmonics are closely spaced or fused.
   - Data Dependency: The effectiveness of deep learning architectures heavily depends on the quality and quantity of training data, which may not always be available or representative of all scenarios.

   Although ML approaches demonstrate potential in addressing motion artifacts, they frequently fall short in real-world scenarios with unpredictable movements. The field needs to move beyond controlled experiments to validate these techniques in diverse, uncontrolled environments.
3. Accurate Human Detection (Range Point Selection) [67], [136]:
   - Environmental Complexity: Current algorithms often struggle in complex environments with multiple reflective surfaces or multiple human targets.
   - Privacy Concerns: Advanced human detection techniques raise important privacy issues that need to be addressed.

   Despite showing promise in improving human detection, current ML approaches often lack the robustness needed for real-world deployment. Additionally, the ethical implications of increasingly accurate human detection technologies need careful consideration.
4. Low SNR of Extracted Vital Sign Signal [67]:
   - Overfitting Risk: Advanced deep learning models like denoising autoencoders and GANs risk overfitting to specific noise patterns, potentially failing in novel environments.
   - Real-time Processing Challenges: Many advanced denoising techniques are computationally intensive, making real-time processing challenging on resource-constrained devices.

   Although machine learning techniques have shown improvements in SNR, their real-world performance and generalizability remain questionable. More research is needed to develop lightweight, adaptive algorithms that can handle diverse noise environments.
5. Reconstruction of Heartbeat Waveform Similar to ECG Sensor [67], [75], [77]:

- Physiological Variability: Current approaches often fail to account for the wide range of physiological variability among individuals.
- Validation Gaps: Most studies validate their results against traditional ECG in controlled settings, leaving questions about performance in real-world scenarios.

Machine learning methods show potential for waveform reconstruction, yet the field is still far from achieving reliable ECG-like measurements. The focus on supervised learning may be limiting; unsupervised or semi-supervised approaches might offer more robust solutions but remain underexplored.

6.2. Multi-Person Vital Sign Monitoring

The monitoring of vital signs for multiple individuals utilizing mmWave radar technology poses distinct issues that require new solutions. The main technical challenge is the precise identification and simultaneous monitoring of many subjects inside the radar's range of vision.

1. Signal Separation: Radar reflections frequently overlap and interfere in circumstances involving multiple individuals. Current algorithms inadequately differentiate these interwoven signals, resulting in possible misattribution of critical indications among participants [137].
2. Spatial Resolution: Conventional mmWave radar systems may be deficient in the precise spatial resolution required to distinguish between individuals close, especially in congested settings such as hospital wards or public areas [137], [138].
3. Motion Artifacts: Numerous individuals might generate intricate motion artifacts, complicating the proper extraction of vital sign data [139].
4. Variable Radar Cross Sections: Diverse body proportions, orientations, and garment materials among various subjects can result in substantial fluctuations in radar cross-sections, influencing signal strength and quality.
5. Dynamic Positioning: In practical situations, individuals enter and exit the radar's range of vision, necessitating algorithms capable of adjusting to fluctuating quantities of subjects and their locations [139].

Future investigations in multi-person vital sign monitoring utilizing mmWave radar must focus on several critical domains to surmount existing constraints.

Exploring advanced MIMO approaches [140, 109, 141], particularly tailored for multi-person contexts, may substantially improve spatial resolution and subject distinction. This methodology should be enhanced by the creation of advanced machine learning models, specifically deep neural networks, proficient in the real-time separation and categorization of radar data from various sources. The integration of mmWave radar with computer vision technology offers a promising opportunity to enhance subject tracking and vital sign attribution in intricate situations. Researchers ought to explore the utilization of distributed sensing networks, utilizing numerous spatially distributed mmWave radar devices to improve coverage and resolution in multi-person environments. Adaptive waveform design may be essential, facilitating dynamic modifications according to the quantity and location of subjects to enhance vital sign acquisition. Creating resilient, real-time subject-tracking algorithms is crucial for ensuring continuous observation despite variations in subject placements or orientations. Ultimately, executing thorough validation tests in varied, real-world settings is essential to evaluate and enhance the efficacy of these systems under different scenarios. By exploring these interrelated research avenues, the field can progress towards more dependable and precise multi-person vital sign monitoring, facilitating new opportunities in healthcare, public safety, and smart environment applications where concurrent monitoring of multiple individuals is essential.

6.3. Real-Time Vital Sign Monitoring

During health crises like the ongoing COVID-19 pandemic [3, 71], maintaining uninterrupted surveillance is imperative for effective patient care management. The mm-wave radar allows early identification of health deterioration because of real-time monitoring, facilitating prompt intervention by healthcare professionals to mitigate adverse outcomes [142]. Moreover, it reduces the need for in-person assessments, easing the strain on healthcare resources and minimizing risks of exposure for patients and medical personnel. Thus, continuous monitoring [143, 144], especially during crises, highlights the transformative potential of mmWave radar technology in enhancing patient care standards. They excel in identifying irregularities in vital signs, such as arrhythmias, Apnea [145], and respiratory distress. Additionally, mmWave radar technology enables continuous measurement of stress levels [146], adding an important dimension to patient monitoring. This continuous monitoring of stress levels, along with other vital signs, provides comprehensive insights into patients' health status. Furthermore, personalized monitoring is facilitated by adapting to individual physiological characteristics and preferences, enhancing vital sign monitoring accuracy while minimizing false alarms. Accurately detecting and isolating vital signs from radar signals requires sophisticated algorithms to handle the noise and interference inherent in non-contact methods. Additionally, the system must be capable of processing and analyzing data in real-time, demanding efficient, high-performance computational models. The CNN models applied must be optimized to work with the unique characteristics of the radar signals, such as the 1D and 2D signals transformed by CWT, to ensure accurate and timely vital sign estimation. Real-time monitoring using radar technology involves significant hardware challenges. The design and implementation of the radar system require careful consideration of factors such as the sensitivity and specificity of the radar sensors, the power consumption for long-term operation, and the miniaturization of the hardware for non-intrusive monitoring. Additionally, the hardware must support the high-speed data acquisition and processing needed for real-time analysis. Ensuring robust and reliable signal transmission and reception in various environmental conditions without compromising the accuracy of vital sign detection adds another layer of complexity. These challenges highlight the need for advanced hardware solutions that can effectively support the sophisticated algorithms used in real-time monitoring systems. These challenges remain significant obstacles for real-time monitoring. Implementing machine learning solutions requires more powerful processors and storage alongside traditional signal processing systems.

6.4. Challenges in Blood Pressure Monitoring

Continuous non-invasive blood pressure monitoring remains a key challenge in ubiquitous healthcare. Early work by Poon and Zhang [147] utilized pulse transit time between ECG and PPG, yielding errors of 0.6±9.8 mmHg (SBP) and 0.9±5.6 mmHg (DBP), though it required skin contact and calibration. Recent developments have shifted toward non-contact radar-based methods. For instance, Shi et al.'s mmBP [73] uses millimeter-wave radar with delay-Doppler feature transformation and Random Forest regression to achieve mean errors of 0.87 mmHg for SBP and 1.55 mmHg for DBP. Wang et al. [81] employ UWB signals, PCA for motion artifact reduction, and a deep learning model with multi-scale feature extraction and attention mechanisms, achieving MAEs of 6.5 mmHg for SBP and 4.7 mmHg for DBP. The latest advancement, Hu et al.[83], leverages mmWave radar with a hybrid Transformer model, beamforming-based data augmentation, and cross-modality knowledge transfer from cardiac signals, reaching a waveform correlation of 0.903. Despite these advances, significant challenges remain that future research must address. Motion artifacts continue to plague radar-based methods, requiring increasingly sophisticated compensation techniques like temporal referential functional link adaptive filters (TR-FLAF) in mmBP or beamforming-based data augmentation in Hu et al. [83] The generalizability across diverse populations remains problematic, with most systems requiring some degree of personalization or calibration— Wang et al. [81] offer two schemes with different calibration requirements, but completely calibration-free solutions are still elusive. The physiological relationship between radar-captured signals and actual blood pressure mechanisms needs further validation through larger clinical studies. Additional challenges include measurement distance limitations (though Wang et al. [81] operate effectively up to 70cm), sensitivity to environmental factors, and the need for more robust algorithms for subjects with cardiovascular conditions. Future research directions should explore multi-sensor fusion approaches combining complementary sensing modalities, more robust motion compensation algorithms, personalization strategies requiring minimal calibration data, and extensive clinical validation studies across diverse populations and health conditions.

6.5. Emerging Applications: Beyond Vital Sign Monitoring

Recent research has expanded radar-based monitoring beyond traditional vital signs, exploring novel physiological parameters with high clinical relevance. A 2025 study employing coupled and radiated UWB microwave sensors (1.5-10 GHz) demonstrated capability for non-invasive lung water level monitoring [148]. These sensors, fabricated on flexible Roger substrate (170 μ m thickness, $\epsilon r = 3.5$, tan$\delta = 0.0002$) and textile substrates, detected water content variations of 0-20% with phase measurements exhibiting significantly higher sensitivity than amplitude variations. Notably, this study implemented machine learning in signal processing, developing a deep learning-based denoising scheme to filter Base Line Wander (BLW) noise. The deep filter model consisted of 4 layers with different filter modules, trained on the QT Database and MIT-BIH Noise Stress Test Database, achieving Sum of Squared Distance (SSD) of 3.678 and Maximum Absolute Distance (MAD) of 0.11 with a balance term $\lambda = 50$.

Another pioneering study investigated dielectric property alterations in blood across 10-67 GHz for non-invasive glucose monitoring [149]. Using open-ended coaxial probe measurements, researchers quantified how medications affect blood's electromagnetic signature: Aspirin (0.4 mg/ml) reduced the dielectric constant (ϵ') by 6.2% and increased loss tangent (tanδ) by 6.64% at 60 GHz, while Ibuprofen (0.07 mg/ml) caused a 0.94% decrease in ϵ' and 2.22% increase in tanδ. Near-field sensing using FMCW radar with 7 GHz bandwidth (57-64 GHz) corroborated these findings through distinct scattering signature shifts. These medication-induced alterations were found comparable to glucose variations, emphasizing the need for calibration methods that can account for such confounding factors.

A significant advancement in affective state monitoring was demonstrated through mmNS, a learning-based end-to-end framework for contactless nighttime stress monitoring using mmWave radar [150]. Operating at 60-64 GHz with 2.56 GHz bandwidth, this system incorporated radar signal processing with a self-supervised physiological feature separation strategy specifically designed for periodic patterns. The framework employed Temporal Convolutional Networks (12 layers) combined with Spatial Transformer Blocks (4 attention heads) to extract and encode physiological features from radar data. The novel periodicity-based contrastive learning approach achieved approximately 76% accuracy in classifying low, medium, and high-stress levels from 2098 hours of nighttime monitoring data across 9 subjects.

While these applications use conventional signal processing, machine learning integration could enhance capabilities by addressing nonlinear relationships between radar signals and physiological parameters. Various neural architectures could extract spatial and temporal features from radar data, while providing adaptive calibration to compensate for individual variations and confounding factors. The convergence of radar technology with machine learning presents significant potential for expanding non-invasive physiological monitoring beyond traditional vital signs.

7. Conclusion

The healthcare industry has benefited greatly from the recent expansion in the use of radar technology in non-military sectors, which has been fueled by the greater accessibility of commercially accessible radars. Radar-based healthcare is now a more viable and dependable choice thanks to the incorporation of machine learning algorithms, which have changed healthcare applications by overcoming old limits. The main objective of this article is to present an in-depth review of healthcare organizations' use of machine learning to measure vital signs.

It is evident from our analysis that within the realm of vital sign measurement, researchers effectively utilize machine learning as an additional tool to augment the precision and resilience of conventional algorithms. Machine learning classifiers are frequently deployed to identify vital signs anomalies, which can be disregarded or rectified. The application of regression techniques utilizing both shallow and deep learning models has proven to be advantageous in restoring distorted vital signs. Autoencoders have also proven effective when used for denoising. Critical sign measurement has also been made easier using machine learning, even in non-stationary states of the human subject. With the use of radar technology, vital signs may also be retrieved. This allows for the training of machine learning systems to create novel applications, like robust HRV and BP extraction and non-intrusive user authentication grounded in breathing patterns. To be sure, there is a research deficit that must be filled, but it's also important to recognize that the field is still in its early stages of study.

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Table 1: Gap Analysis in Radar-Based Vital Sign Monitoring with Machine Learning

Research Area	Current State	Research Gap
Motion Artifacts	Moderate accuracy reduction during movement, significant drop in the presence of substantial motion	Lack of robust algorithms that maintain minimal accuracy degradation during natural movements
Multi-person Monitoring	Limited to a small number of stationary subjects with spatial separation	Unable to track and monitor multiple closely positioned subjects with similar vital rates
Real-time Processing	Processing windows in the range of a few seconds with high computational cost	Need for low-latency, near-instantaneous algorithms suitable for edge computing with limited resources
Dataset Diversity	Predominantly lab-based, with demographically homogeneous data (mostly healthy adults)	Insufficient data from diverse populations, including elderly individuals, children, and patients with cardiovascular conditions in varied environments
Blood Pressure Monitoring	Requires personalization, accuracy decreases with increased distance	No calibration-free solution with medical-grade accuracy at practical monitoring distances
Generalizability	Noticeable performance decline when evaluating new subjects	Models failing to generalize across different demographic groups and environmental conditions
Non-standard Physiological States	Reduced performance with irregular heart rhythms, rapid heart rates, and respiratory distress	Limited capability to detect and accurately monitor abnormal vital signs

Table 2: Different Radar Technologies for Vital Sign Monitoring

Characteristics	**CW**	**FMCW**	**UWB**
Frequency Range	2.4 GHz - 77 GHz	24 GHz - 81 GHz	3.1 GHz - 10.6 GHz
Bandwidth	Narrow	Moderate to Wide (0.5-4 GHz)	>500 MHz or >20% of center frequency
Range Resolution	None	High (1-5 cm)	Very High (1-3 cm)
Implemented As	Single frequency	Linear chirp	IR (Impulse Radio) or SFCW (Stepped-Frequency)
Multi-target Detection	Poor	Good	Excellent
System Complexity	Low	Medium	High
Signal Processing	Doppler analysis	Range-FFT, Doppler-FFT	Matched filtering, correlation
Phase Wrapping Issues	Less prone	Can be an issue at higher frequencies	Not applicable to IR implementation
Displacement Detection	Phase analysis $\frac{4\pi d}{\lambda}$	Phase shift analysis $\frac{4\pi d(\tau)}{\lambda}$	Pulse timing and correlation
Power Consumption	Low	Moderate	Varies by implementation
Vital Sign Extraction	Doppler shift	Phase/frequency variation	Pulse timing variation

Table 3: Available Radar Datasets for Vital Signs Monitoring

Ref	Year	#Sub	Ground Truth	Type	Measure	Scenarios
[59]	2020	2	Polar H10	FMCW	HR	Sitting/lying
[58]	2020	11	ECG	CW	HR, RR	Post-exercise
[57]	2020	30	ECG, PCG	CW	HR, RR	Multiple
[60]	2020	21	Accelerometer	FMCW	HR	Sitting
[61]	2020	5	PPG	FMCW	HR	Multiple distances
[62]	2021	12	PPG	UWB	HR, RR	Activities
[63]	2021	40	ECG	FMCW	HR	Sitting
[64]	2021	12	NeuLog	UWB	RR	Daily
[65]	2021	14	Polar H10	FMCW	HR, RR	Moving
[56]	2021	50	BSM6501K	FMCW	HR, RR	Car
[66]	2022	8	Pulse Oxi.	UWB	HR, RR	Sleep
[67]	2022	25	Heal Force	FMCW	HR	Driving
[68]	2022	33	Omron	FMCW	HR	Normal
[69]	2022	12	PPG, ECG	FMCW	HR	Sitting
[70]	2022	10	BIOPAC	CW	HR, RR	Lying
[71]	2022	4	–	FMCW	HR	Distance/angles
[72]	2022	12	ECG	CW	HR	Lying
[73]	2022	25	Omron HEM-7121	FMCW	BP	Sitting
[74]	2023	10	Polar H9	FMCW	HR, RR	Sitting
[75]	2023	11	Heal Force	UWB	HR	Lying
[76]	2023	11	SOMNO	FMCW	HR	Sleep
[77]	2023	3	PPG sensor	FMCW	HR, RR	Sitting
[78]	2023	24	Go Direct	FMCW	RR	Multiple
[79]	2024	35	ECG+ADS1292	FMCW	HR	Multiple
[55]	2024	10	Polar H10	FMCW	HR	Multiple
[80]	2024	3	ECG	FMCW	HR	Lying
[81]	2024	70	Omron HEM-7132	UWB	BP	Office
[82]	2024	13	EQ02+ belt	FMCW	RR	9 exercise types
[83]	2024	43	CNAP Monitor	FMCW	BP, HR	Sitting
[84]	2024	10	Piezo/Pulse	FMCW	HR, RR	Multiple
[85]	2024	10	PPG	FMCW	HR, RR	Sleep
[86]	2025	7	NeuLog PPG	CW	HR, RR	Sitting

Table 4: Proposed Standards for Evaluating Radar Vital Sign Monitoring Performance

Required Metrics	• MAE, RMSE (bpm for HR, breaths/min for RR) • Pearson correlation with reference device • Beat/Breath interval accuracy, F1-Score (if applicable)
Test Scenarios	• **S1**: Sitting (5+ min) • **S2**: Lying (5+ min) • **S3**: Periodic movements • **S4**: Natural activities • **S5**: Multi-person • **S6**: Post-exercise
Reference Setup	• Medical ECG (HR), RIP bands (RR) or FDA-approved monitors • Sync accuracy: $\leq$10ms, Sample rate: $\geq$250Hz (ECG), $\geq$50Hz (RR)
Subject Diversity	• Min. 30 subjects; 3+ age groups (18-35, 36-55, 56+) • Gender balance (min. 40% underrepresented); varied BMI
Reporting	• Algorithm details, hardware specs, computational metrics • Per-subject metrics, failure case analysis (bottom 10%)

Table 5: Comparative Performance of Noise Reduction Methods

Method	SNR Improvement	Error Reduction	Comput. Efficiency	Optimal Application Context
Wavelet Transform	Highest (6.97% avg) [95]	Highest (24.91% avg RMSE reduction) [95]	Moderate	Non-stationary signals with multi-scale features
MRSVD	Superior at high noise levels (9.18 dB at -5 dB initial SNR) [96]	Lowest MSE (0.071 at 1 dB noise) [96]	High	Bearing fault detection, signals with periodic components
Kalman Filter	Good (4.19% avg) [95]	Good (15.67% avg RMSE reduction) [95]	High for real-time	Signals with known state-space model
EWMA	Moderate (3.60% avg) [95]	Moderate (13.66% avg RMSE reduction) [95]	Very low	Simple implementation for online monitoring
EMD EEMD	Variable (1.75-8.38 dB at 1 dB noise) [96]	Inconsistent across noise levels [96]	High	Non-linear and non-stationary signals
STFT	Lowest (1.88% avg) [95]	Lowest (9.07% avg RMSE reduction) [95]	Moderate	Stationary signals with fixed time-frequency resolution
Wavelet Packet Decomposition	Superior at moderate to high SNR (2.4 dB advantage over VMD) [97]	Comprehensive time-frequency analysis	Moderate	Complex signals requiring both high and low-frequency band analysis

Table 6: Technical Analysis of Signal Processing Limitations and Deep Learning Solutions

Challenge Area	Signal Processing Limitations	Deep Learning Solutions
Noise Handling	Struggles with non-Gaussian noise, Limited to predefined noise models, Poor performance with unknown noise distributions	Denoising autoencoders learn arbitrary noise patterns, Blind source separation without prior models, End-to-end noise removal
Feature Extraction	Requires manual basis selection, Fixed dictionary limitations, Suboptimal for unknown pattern types	CNNs automatically learn hierarchical features, Transfer learning adapts to new domains, Self-supervised feature discovery
Temporal Analysis	Fixed window size trade-offs, Difficulty with variable-length patterns, Limited memory depth in traditional filters	LSTM/GRU captures long-term dependencies, Transformers handle variable sequences, Attention spans unlimited temporal range
Adaptability	Slow convergence in adaptive filters, High computational cost for fast adaptation, Limited by filter order selection	Online adaptation through backpropagation, Meta-learning for fast adaptation, Dynamic architecture adjustment
Pattern Recognition	Limit to predefined pattern templates, Poor generalization to pattern variations, Sensitive to transformations	Deep networks learn invariant representations, Handle pattern variations naturally, Robust to transformations

Table 7: Summary of Supervised Learning approach aided to vital sign monitoring

Ref	Learning Style	Usage	Method	Radar	Measure	Performance
[59]	DL	Reg.	1D - DNN	FMCW	HR, RR	Acc. 95.26%
[60]	DL	Reg.	1D - CNN	FMCW	HR	ME 0.26% - 1.29%
[63]	DL	Reg.	DNN, LSTM	FMCW	HR	P Err: 0.67%, T: 0.71%, QRS: 0.49%
[65]	DL	Reg.	self-calibrated LSTM	FMCW	HR, RR	Abs. Err: 4.22, 2.91 beats/br.
[66]	DL	Reg.	1D-CNN, Attention	UWB	HR, RR	Err. 7.4, 4.9 beats/br.
[67]	Trad. ML	Reg.	SVM	FMCW	HR	Abs. Err: 0.37 Abn. HB Det: 88.9%
[68]	Trad. ML	Class.	ANN	FMCW	HR	Acc. 75%
[70]	Trad. ML	Class.	SVM, DT, LR, KNN	CW	HR, RR	Acc. 99.1%
[71]	Trad. ML	Class.	MLR, DT, RF, SVM, XGB	FMCW	HR	97.1% br. patterns (NSEM)
[74]	DL	Reg.	Neural net fitting	FMCW	HR, RR	RMSE 2.52, Acc. 97.5%
[77]	DL	Class.	ResNet	FMCW	HR, RR	Acc. 97.5%
[79]	DL	Class.	hybrid CNN Transformer	FMCW	HR	90-perc. err: 9ms
[80]	DL	Reg.	CNN	FMCW	HR	RMSE: 21.83ms, Acc. 95.4%
[73]	Trad. ML	Reg.	RF, SVM, DT	FMCW	BP	ME 0.87/1.55 mmHg (SBP/DBP)
[81]	DL	Reg.	CNN with Attention	UWB	BP	MAE 6.5/4.7 mmHg (SBP/DBP)
[83]	DL	Reg.	Hybrid CNN-Transformer	FMCW	BP	Waveform Corr. 0.903, MAE 5.7 mmHg
[82]	DL	Reg.	CNN-Transformer	FMCW	RR	Cos. Sim. 0.75, RR Err. 0.5 RPM
[85]	DL	Class.	Feed-forward Neural Net	FMCW	HR, RR	Acc. Apnea 93.6%
[86]	DL	Reg.	1D CNN Encoder-Decoder	CW	HR, RR	BR Err. 0.3 BPM, HR Err. 2.7 BPM

Table 8: Comparative Analysis: Traditional Signal Processing vs. Machine Learning Approaches

Scenario	Metric	Traditional Signal Processing	Machine Learning
Stationary	Heart Rate Accuracy	Good	Excellent
	Respiratory Rate Accuracy	Good	Excellent
	Processing Time	Faster	Slower
Minor Movement	Heart Rate Accuracy	Moderate	Good
	Respiratory Rate Accuracy	Moderate	Good
	Processing Time	Faster	Slower
Major Movement	Heart Rate Accuracy	Poor	Moderate to Good
	Respiratory Rate Accuracy	Poor to Moderate	Good
	Processing Time	Faster	Slower
Multi-Person	Target Separation	Limited capability	Enhanced capability
	Cross-subject Interference	High	Moderate
	Accuracy Degradation	Significant	Moderate
Hardware	Memory Requirements	Lower	Higher
	Power Consumption	Lower	Higher

Table 9: Unsupervised Learning Aided Vital Sign Measurement Studies Using Radar

Ref	Learning Style	Usage	Method	Radar	Measure	Performance
[133]	Trad. ML	Reg.	Convolutional Sparse Coding (CSC)	UWB	HR, RR	HR Err: 0.04 Hz (2.6%), RR Err: 0.008 Hz (4%)
[61]	Trad. ML	Reg.	GMM-CSC	FMCW	HR	∼35% improvement over standard CSC, Det. rate: ∼0.88
[62]	DL	Class.	Contrastive learning	UWB, FMCW	HR, RR	Corr. Score 0.8 to 0.9
[64]	DL	Reg.	VED	UWB	RR	below 0.1 bpm, with PP and SL movements
[69]	DL	Reg.	VED	FMCW, UWB	HR	Corr. Score 0.9 (UWB), 0.92 (FMCW)
[72]	DL	Reg.	VAE	CW	HR	Impr. in consistency 75.5%
[76]	Trad. ML	Class.	Affinity propagation clustering	FMCW	HR	Err. 0.65 bpm
[78]	DL	Reg.	C-VAE+ MAML	FMCW	RR	MSE under 100
[75]	DL	Reg., Class.	cGAN's, Contrastive Learning	UWB	HR	Corr. Score 0.917 and 0.958, RMSE 0.04 and 0.1
[84]	Trad. ML	Reg.	Maximum Likelihood Estimation	FMCW	HR, RR	RMSE < 1 bpm (BR), < 1.5 bpm (HR)

Table 10: Classifications of ML Based on Learning Types

	Definition	Data Type	Advantages	Disadvantages
Sup. Learning	Model learns from labeled input-output pairs	Labeled	High accuracy; Explicit prediction targets	Time-consuming labeling; Potential overfitting
Unsup. Learning	Model extracts patterns without labeled examples	Unlabeled	Discovers hidden patterns; No labeling needed	Less accurate; Difficult to evaluate results

Table 11: Key Limitations of ML Approaches for Vital Sign Monitoring

ML Approach	Theoretical Limitations	Practical Limitations	VS Monitoring Specific
CNN	Limited temporal modeling; Fixed receptive field	High data requirements; Computational intensity	Orientation sensitivity; Poor signal separation
RNN/LSTM	Vanishing gradients; Limited context window	Sequential computation; Slow training/inference	Noise sensitivity; Motion artifact vulnerability
VAE	Mode/posterior collapse; Gaussian assumptions	Complex KL-balancing; High training cost	Feature smoothing; Poor multi-person handling
Contrastive Learning	Representation collapse; Projection head design	Sample selection challenges; Memory requirements	Pattern definition issues; Weak abnormality detection
Hybrid Models	Integration complexity; Overfitting risk	Hyperparameter explosion; Resource requirements	Signal quality dependency; Limited interpretability

Title Page Template

Title:

A Survey on Machine Learning Approaches for Vital Sign Monitoring Using Radar

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We would like to express our sincere gratitude to all colleagues and researchers who contributed their valuable insights and expertise to this survey paper, particularly our academic mentors whose guidance significantly enhanced the quality of this work. We extend our appreciation to the anonymous reviewers for their thorough evaluation and helpful feedback, which greatly improved both the content and presentation of this survey. We also acknowledge the technical and administrative support provided by our institution throughout the research process, as well as fellow researchers in the field who shared their perspectives during various academic discussions and conferences. Finally, we are grateful to our families and friends for their understanding, encouragement, and unwavering support during the preparation of this manuscript.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: