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TOPICAL REVIEW

Machine Learning in RADAR-Based Physiological Signals Sensing: A Scoping Review of the Models, Datasets, and Metrics

ANTONIO NOCERA, (Graduate Student Member, IEEE),
LINDA SENIGAGLIESI, (Member, IEEE),
MICHELA RAIMONDI, (Graduate Student Member, IEEE),
GIANLUCA CIATTAGLIA, (Member, IEEE), AND ENNIO GAMBI, (Senior Member, IEEE)
Department of Information Engineering, Università Politecnica delle Marche, 60131 Ancona, Italy

Corresponding author: Linda Senigagliesi (l.senigagliesi@staff.univpm.it)

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ABSTRACT In the field of physiological signals monitoring and its applications, non-contact technology is often proposed as a possible alternative to traditional contact devices. The ability to extract information about a patient's health status in an unobtrusive way, without stressing the subject and without the need of qualified personnel, fuels research in this growing field. Among the various methodologies, RADAR-based non-contact technology is gaining great interest. This scoping review aims to summarize the main research lines concerning RADAR-based physiological sensing and machine learning applications reporting recent trends, issues and gaps with the scientific literature, best methodological practices, employed standards to be followed, challenges, and future directions. After a systematic search and screening, two hundred and seven papers were collected following the guidelines of PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses). The included records covered two macro-areas being regression of physiological signals or physiological features ($n=77$ papers) and the other a cluster of papers regarding the processing of RADAR-based physiological signals and features; the latter cluster concerns four fields of interest, being RADAR-based diagnosis ($n=77$), RADAR-based human behaviour monitoring ($n=25$), RADAR-based biometric authentication ($n=19$) and RADAR-based affective computing ($n=9$). Papers collected under the diagnosis category were further divided, on the basis of their aims: in breath pattern classification ($n=41$), infection detection ($n=10$), sleep stage classification ($n=9$), heart disease detection ($n=9$) and quality detection ($n=8$). Papers collected under the human behaviour monitoring were further divided based on their aims: fatigue detection ($n=9$), human detection ($n=7$), human localisation ($n=4$), human orientation ($n=2$), and activities classification ($n=3$).

INDEX TERMS Contactless sensing, machine learning, physiological signals, RADAR.

I. INTRODUCTION

Contactless monitoring of physiological signals is an emerging field in the domain of e-health that aims at being a viable alternative to contact monitoring techniques. Contact monitoring can be implemented with wearable devices and contact sensors. Such methods are difficult to use when dealing with particular cases, like sensitive skin of elder patients or infants, in cases of skin problems like severe burns, dermatosis or infected patients. They are ultimately inconvenient and cumbersome to be worn for long hours [1], [2]. Additionally, the medical staff must interact with the sensors and place them on the subject's body, which could be complex if patients are in frail or disabled condition [3]. The main advantage of non-contact methods is their noninvasive nature, making them a solution to the problems that can be

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encountered with contact techniques. Another advantage of non-contact techniques is the possibility of being embedded in the environment, allowing continuous monitoring without patients noticing.

This review focuses on the application of RADAR sensors, which are non-contact devices able to directly measure a target's information like the distance, the angle of arrival and velocity; this can be also classified using RADAR signals [4], [5]. Moreover, compared to RGB cameras, they pose fewer privacy concerns and are more resilient to changes in the environment, such as different lighting conditions and temperature variations [1], [2]. Other reviews in the last three years studied the topic of RADARs applied to healthcare and physiological signal sensing [1], [2], [6], [7], [8], [9], [10], [11], [12], [13]. All these reviews focused on RADAR-based vital sign extraction, mainly heart rate and breathing rate and in some cases also blood pressure or more complex physiological signal extraction. Wang et al. in 2020 [6] have reported a detailed analysis of self-injection-locked RADARs and their advantages over continuous wave technologies for vital sign extraction. Fioranelli et al. in 2021 [7] focused on recent trends in RADAR sensing in human health care, providing an overview of activity recognition and heart and respiratory rate analysis with some references to machine learning (ML) applications but is limited in the number of articles analyzed; the papers by Singh et al. in 2020 [8] and Islam et al. in 2022 [9] evaluated the issue of multi-subject sensing and the proposed solutions found in the literature to the problem. In particular, Singh et al. [8] cited only one paper regarding a machine learning application and focused more on traditional feature-based and signal processing approaches in multi-resident vital sign monitoring. In the paper by Islam et al. [9], the machine learning signal processing approach is not considered. Other traditional signal processing techniques were evaluated recently in a review regarding IQ demodulation advances by Wang et al. in 2022 [10] and in a review on spectral estimation algorithms by Hasan et al. in 2022 [11]. In the last year, only four reviews are found regarding RADAR-based physiological signal sensing [1], [2], [12], [13], [14], where a beginning interest in the machine learning applications is found. Wu et al. [12] reviewed papers dealing with vital sign estimation starting from how the signals are mathematically modelled in each of the most diffused RADAR technologies and how it can then be processed to extract the wanted information; the authors provided also the evaluation of 8 papers employing deep learning to estimate physiological parameters. Similarly, Paterniani et al. [1] published a review on the same topic starting from the available models and analysing also the recent trends, but without focusing on machine learning applications. Recently, Zhang et al. [2] published a comprehensive overview on algorithms for the extraction of cardiac features from RADAR sensing with a taxonomy that includes both features-based algorithms and deep learning alternatives (a total of 10 papers). Lastly, Shahzad Ahmed and Sung Ho Cho [13] published a review focused on machine learning applications in general healthcare RADAR sensing including both vital sign and activity recognition; nevertheless, they reviewed only 33 papers about vital sign estimation [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46] of which 25 (12% of all the reviewed papers) included also in our review.

The present review illustrates the state-of-the-art about machine learning developments in physiological signal sensing, using a systematic approach based on the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) guidelines for scoping review. From a methodological perspective, we made the effort to make the review as transparent and reproducible in the choice of the included papers. In order to have a comprehensive review, we have not limited our research to a particular vital sign [2], such as the heart rate or the breathing rate [1], or to a known issue in the RADAR sensing such as multi-subject detection [8], [9], or to a particular kind of RADAR sensor, such as portable short-range technologies [47]. In the 207 included papers, 77 works deal with RADAR-based physiological signal estimation aided by machine learning techniques, where machine learning model inputs are data extracted from RADAR, while the output is the desired vital sign or the physiological parameter or physiological waveform. The remainder of the papers applies machine learning techniques to physiological parameters extracted directly from RADARs, while the output has a specific aim which depends on the field of application. The large set of included papers give us the possibility to produce a complete taxonomy of recent trends, including RADAR-based diagnosis, RADAR-based human behaviour monitoring, RADAR-based biometric authentication and RADAR-based affective computing. Regarding the diagnosis of a disorder, current reviews of the literature are usually limited to a specific disease, such as sleep apnea [48], whereas our goal is to discuss many other recent topics, including sleep apnea and breath patterns, heart disease and arrhythmia detection, infection detection and quality detection of the physiological signals. In the field of RADAR-based human behaviour monitoring, we can see a large corpus of research and reviews, however, we have collected articles focused on the analysis of signals and physiological features that have enabled better detection, localization, and monitoring of people's actions. To the best of the authors' knowledge, this is also the first review collecting papers regarding RADAR-based affective computing, which is a rising topics in the scientific literature. Our study comprehensively reports all the machine learning techniques found in the selection process and shows trends and gaps in the existing literature. To summarise, the contributions of this review are the following:

- A detailed and systematic review of the machine learning and deep learning algorithms applied to RADAR recordings for physiological signal and parameters regression with a focus on current trends and applications.

- A taxonomy of various topics dealing with RADAR-based physiological signals given as input to machine learning to obtain other aims in the field of diagnosis, human behaviour monitoring, authentication and affective computing.
- An analysis of public and non-public datasets to understand their limitations and their strengths.
- A taxonomy of the pre-processing steps usually applied for the estimation of physiological signals and parameters before the use of machine learning and deep learning models.
- An evaluation of employed metrics in the different explored tasks and of the available standards or guidelines used to judge the performance of the proposed systems.
- A discussion providing the found gaps and issues of the reviewed literature, the good methodological practices, the challenges and future directions to explore.

The paper is organised as follows. Section II outlines the search strategy, the exclusion criteria and selection process and the data collection process. Section III describes the result of the screening process and the general trends found in the included literature. Sections IV and V show a synthesis of the included literature stratified by aims and models. Section VII provides a discussion on the issues and gaps of the literature, the good practices found, while Section VIII focuses on future directions and challenges. Finally, Section IX concludes the paper.

II. MATERIALS AND METHODS

A. INFORMATION SOURCES AND LITERATURE SEARCH STRATEGY

A literature review is conducted on six electronic databases, i.e., PubMed, Web of Science, Scopus, Science Direct, IEEExplore and ACM Digital Library on the 12th of February 2023, then updated on the 26th of October 2023 and finally updated on the 31st of December 2023. We follow the extended guidelines for scoping reviews [49]. Search terms were organized into three concepts; for each of them, the following keywords with the wildcard term '*' were used:

1) Technique: linear/logistic/regression/probabilistic model, likelihood function, linear discriminant analysis, LDA, machine/deep/*supervised/ensemble/reinforcement learning, neural networks, MLP, multiperceptron, ANN, DNN, CNN, RNN, LSTM, long short term memory, encoder, auto-encoder, SVM, support vector machine, decision tree*, random forest, cluster, clustering, k-means, knn, k-nearest neighbour.
2) Physiological parameter: heart, HR, pulse monitoring, breath*, BR, respir*, vital sign, physio*, vital parameter*.
3) Sensor: RADAR*, mmWave, mm-Wave, millimeter wave, *CW, UWB.

Search terms within each concept are combined with the Boolean operator 'OR' and then combined with the Boolean operator 'AND'. The search strategy slightly differs depending on the used database, due to the differences in the syntax to describe the query and to the limitations in the number of words. For example, in Pubmed we choose to exploit mesh terms for technique and physiological parameters. For this reason, we report the complete queries for each dataset in Table 1 of supplementary materials. The words within each concept are limited to title and abstract for the concepts related to the sensor and extended to any metadata regarding the screened article for technique and physiological parameter. The only exception is for Scopus where all the concepts were limited to title, abstract and keywords to reach a feasible number of articles to be screened. The English language is used as a limit to filter the documents. No limit is given to the publication date.

B. EXCLUSION CRITERIA AND SELECTION PROCESS

The studies are imported into the Mendeley Reference Manager system for duplicate removal. Only research papers (review papers are excluded) with titles, abstracts, and full text are considered. The following exclusion criteria are applied to screen titles, abstracts, and full text:

- RADAR employed in environment, land, hydrology, urban area, vegetation, ecology, topography, geophysics, meteorology, atmosphere, space, aerospace monitoring;
- paper with other technologies, such as laser, ultrasound, video, wearable;
- other medical applications, gait analysis, breast imaging;
- surveillance, object/target tracking, human activity, pose estimation, human movement, fall detection, gesture recognition;
- cybersecurity, wireless communications, 5G+ cellular systems;
- feature-based method or absence of machine learning for physiological sign monitoring;
- animal studies.

C. DATA COLLECTION PROCESS AND SYNTHESIS METHOD

The screened records are initially classified based on their aims and specific techniques. In this way, we recognize two macro-clusters of papers depending on their aims. The first macro-cluster contains papers proposing machine learning techniques for a better regression of physiological parameters from the RADAR acquisition, therefore their main objective is to give as output either the complete physiological signal or a relevant physiological parameter averaged across a window. For this reason and to make the discussion easier, we divide the first macro-cluster in three categories being value estimation, signal reconstruction or recovery and detection of physiological events. The second cluster contains the papers that exploit a RADAR system to make a classification or a regression taking as input the raw vital sign signal or physiological features extracted from the RADAR. In particular, we divide the second cluster in

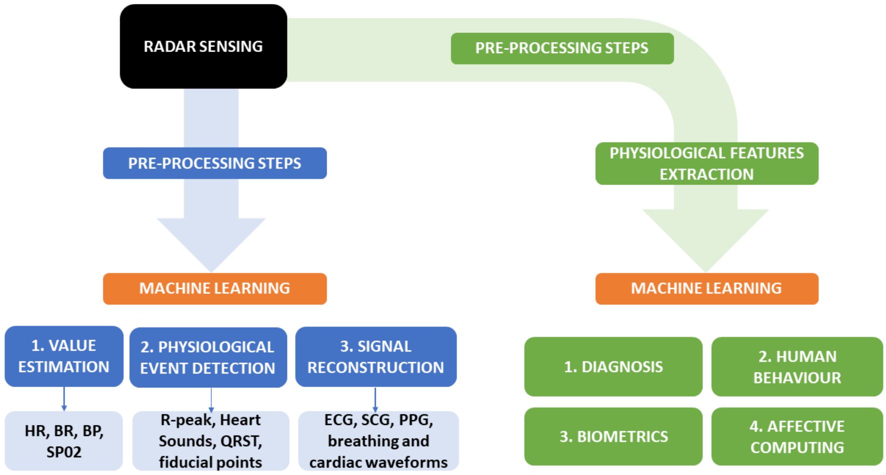


FIGURE 1. Tree chart describing how the papers are divided into each cluster.

the following four categories and relative aims, depending on what is the outcome of the classification or regression procedure (Figure 1):

- RADAR-based diagnosis: Breath patterns classification, Sleep stage classification, Heart disease detection, Infection detection, Quality evaluation.
- RADAR-based monitoring of human behaviours: Fatigue or drowsiness detection, Human detection, Human localisation regression, Human orientation regression, Human activity classification.
- RADAR-based biometric authentication.
- RADAR-based affective computing.

For each of the two macro-cluster we report the distribution of the papers across the years and the distribution of aims. The synthesis strategy is defined by collecting the following items from each included record:

- Introductory information: aim, macro-cluster.
- RADAR sensor: RADAR technology (e.g. Ultra Wide Band (UWB), Frequency Modulated Continuous Wave (FMCW), Continuous Wave (CW)), central frequency, bandwidth, other sensor technology.
- Dataset: number of subjects, demographics of the subjects, static or moving scenario, reference sensor, distance of the subjects from RADAR, number of subjects acquired simultaneously, availability of the dataset, time synchronization of RADAR and reference.
- Processing techniques: machine learning technique and how is it applied, reference sensor data processing, preprocessing of RADAR data, extracted features used for classification/regression, post-processing, other techniques used for comparisons.
- Outcomes: output of the machine learning algorithm, internal and/or external validation techniques, used metrics of accuracy, reported values for each metrics.

The items are then gathered in a single general synthesis table which includes each of the mentioned categories. We collect only the papers where the information are clearly reported, in terms of number of subjects, sex, demographic information, static or moving scenario, RADAR sensor type, reference signal, subject range and synchronisation procedure. Additionally, we synthesis the pre-processing steps employed before the application of ML or deep learning (DL) in a different table, which includes the main RADAR signal processing maps and features extracted, the filtering and target location procedure, the augmentation and the processing of the reference signal.

III. PAPER SCREENING PROCEDURE AND GENERAL TRENDS

A. STUDY SELECTION

Globally, after the update of the 31st of December 2023, 2301 studies were identified from PubMed ($n = 89$), IEEExplore ($n = 534$), Scopus ($n = 730$), Web of Science Core Collection ($n = 310$), ACM Library ($n = 336$) and Science Direct ($n = 302$). After duplicate removal and limiting the papers to English language we obtain 1527 records; the title screening procedure reduced the studies to 578; the abstract and full-text screening reduced the studies to 291 and 207, respectively. The selection procedure is summarized in Figure 2. The included records are first divided in two macro-clusters: papers obtaining as output from a machine learning model physiological signals (see Section IV) and papers giving as input to a machine learning model RADAR-based physiological signals (see Section V). The first macro-cluster includes all the papers that have RADAR data as input and a physiological waveform or physiological value (e.g. heart rate (HR), breathing rate (BR), blood pressure (BP), SpO2) or particular physiological events, such as heart sounds or other points of clinical interest (e.g. R-peak, Q-peak, S-peak, T-wave, P-wave), as output. The second macro-cluster, on the other hand, includes papers in which RADAR systems are used to extract directly physiological signals or features and use them as

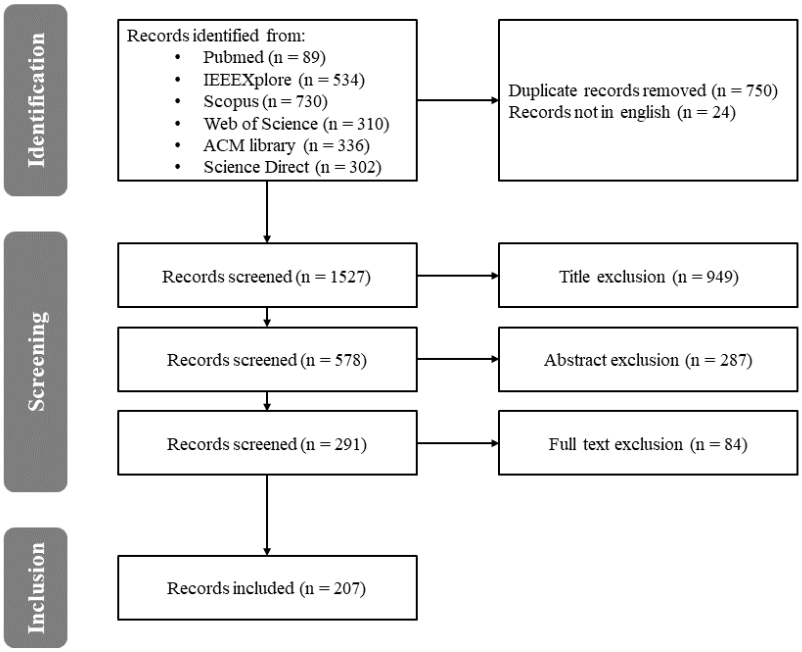


FIGURE 2. Flow chart describing the selection process (modified from [50]).

input for machine learning architectures aimed at different tasks, divided into different "RADAR-based Diagnosis". From Figure 3(a), it can be seen that these two macro-clusters of studies have developed over the years with an increasing trend of published articles, thus demonstrating the increased interest in this line of research and the importance of the research question. The first macro-cluster related to physiological parameter estimation is a slightly more recent line of research that started to grow in 2018 than the second macro-cluster on input, which also shows articles prior to 2013. For clarity, a graph of the distribution of studies in macro-cluster and purpose is shown in Figure 3(b).

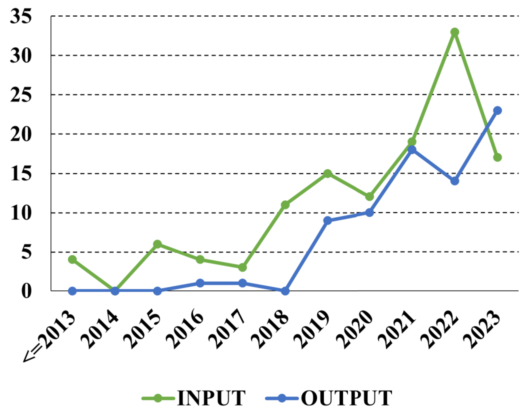
B. GENERAL TRENDS

1) MACHINE LEARNING TRENDS

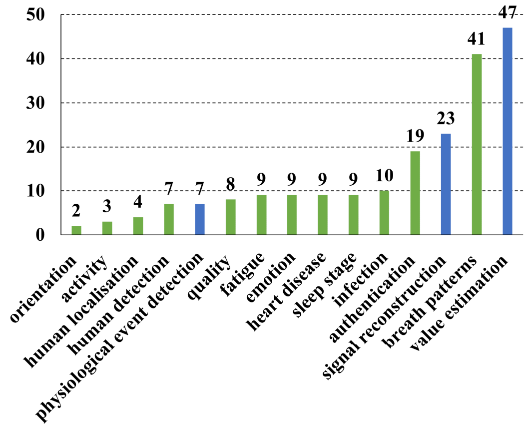
The application of machine learning and deep learning techniques to RADAR sensors has seen an increased interest during the recent years. This was a consequence of the necessity to make advancement in the automotive world in the direction of autonomous driving, and RADAR sensors offer the possibility to measure radial velocity, range, elevation and azimuth angle of object [51]. We divide the algorithms employed in traditional machine learning techniques, deep learning and hybrid architecture, which makes use of both machine learning and deep learning in cascade. In the first macro-cluster we can observe that a great percentage of the papers (78%) employs deep learning architectures to achieve their final aim of physiological parameters estimation, followed by 13% of traditional machine learning and 9% of hybrid architecture (Figure 4(a)). On the contrary, for the second macro-cluster, focusing on processing the RADAR-based physiological signals, it can be observe an inversion of the trend, with the traditional machine learning occupying the category with largest percentage (62% of papers), followed by deep learning (33%) and hybrid architectures (5%) (Figure 4(b)). The difference in the distribution of the algorithm category between the two clusters could be due to the greater complexity of estimating physiological signals in the first macro-cluster, which would justify the choice of a more complex deep learning architecture than machine learning.

2) RADAR TECHNOLOGY TRENDS

RADAR, whose expanded acronym corresponds to 'RAdio Detection And Ranging', it is a device that uses radio frequency electromagnetic waves to detect an object. RADARs are composed of one or more transmitting antennas and one or more receiving antennas. The transmitting antenna sends an electromagnetic wave that interacts with a volume measurement containing both static and moving objects or subjects and the reflected wave is received by the receiving antennas. The three major RADAR modalities found in the included papers are UWB, CW and FMCW, as shown in Figure 5(b), with a similar usage of 28% for UWB, 30% for FMCW and 24% for the CW. In a CW RADAR the transmitting antenna works continuously. The transmitted electromagnetic wave interacts with a moving object and changes its frequency due to Doppler phenomenon. The frequency change or Doppler shift can be noticed in the received wave, and it is related to the velocity of the moving object. Therefore, velocity is directly measured with a CW RADAR. On the other hand, the distance of the object

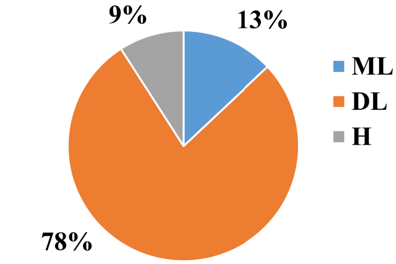


(a) Distribution of the included papers in the two macro-clusters across the years

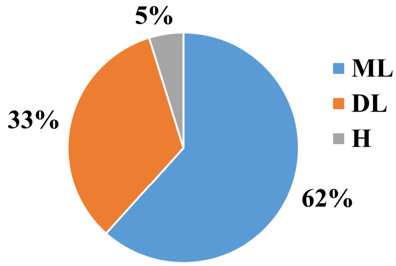


(b) Distribution of aims

FIGURE 3. **Years of paper publication and aim clusters.**



(a) Categories in the first macro-cluster



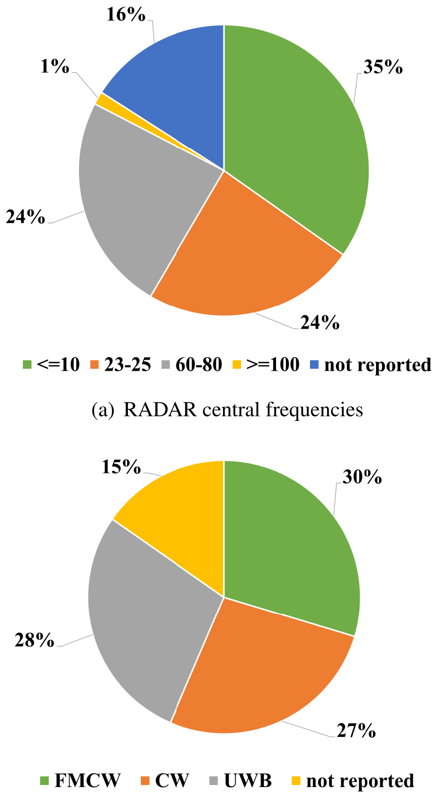
(b) Categories in the second macro-cluster

FIGURE 4. **Pie charts of the category of algorithms employed in the screened literature.**

from the RADAR can not be directly measured unless the transmitted wave is frequency modulated as in the case of FMCW RADAR. The principle by which the FMCW RADAR works is a linear modulation in time of the frequency of the transmitted wave, called 'chirp'. The starting frequency, the slope of the linear modulation, the bandwidth are all parameters that can be usually set and are known. The range of an object from the RADAR can be detected by mixing the transmitted and received waves and generating an intermediate frequency signal, whose frequency is the frequency difference between transmitted and received waves. This frequency difference, also called beat frequency, is related to the interval of time necessary to the transmitted wave to reach the object and come back, thereby from a frequency analysis of the intermediate frequency signal it is possible to obtain the range of the object. Ultra-Wide Band UWB RADAR is a technology transmitting short low-power pulses with a large bandwidth. By definition an UWB transmitter is a system that has a bandwidth of at least 0.5 Gigahertz or at least 0.2 fractional bandwidth [52]. The found frequency ranges for the employed RADAR technologies can be observed in the pie chart in Figure 5(a). We can notice a variety of different operating frequencies, with the 30% of papers working at frequencies below 10 GHz, 28% working between 60 GHz and 80 GHz, and 27% working with frequencies between 23 and 25 GHz. Only 1% of the papers use a RADAR with a central frequency greater than 100 GHz. Analysing the RADAR technology across the last 10 years, we can see a slow increase of CW RADAR usage and a more pronounced increase in the use of the other two modalities over the last 5 years (Figure 6). In 2022 and 2023, FMCW was the most employed technology, followed by UWB and CW. Thus, in the context of physiological signal sensing all the three modalities have shown an increasing trend of usage. CW RADAR is the most consolidated technology and exploiting the Doppler phenomenon can provide a way to examine the small vibrations of the human torso due to respiration or heartbeat. The main issue with CW RADAR is in the lack of subject localisation due to the impossibility of range measurement, which impairs their utilisation in multi-subject scenarios. On the contrary, the addition of a modulation scheme for FMCW RADAR enables not only to distinguish between multiple subject but also to enhance the signal quality by removing all the signal sources coming from the background.

3) TRENDS IN THE TOPICS

We analysed in detail the distribution of papers for the most relevant topics, defined as the ones with at least 5 published papers. In Table 1 we highlighted the number of papers per topic in the last 5 years summing in the first column all the papers published before 2019. We can notice that "breath



(a) RADAR central frequencies

(b) Employed RADAR technologies

FIGURE 5. Pie charts of the RADAR technologies employed in the screened literature.

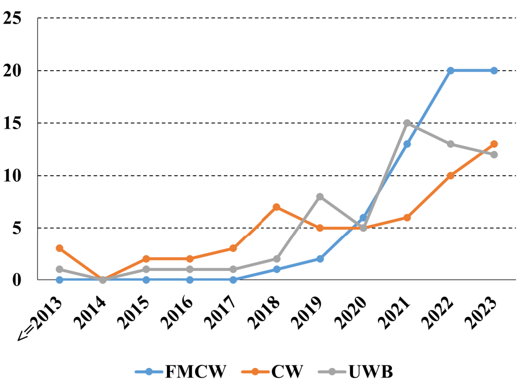


FIGURE 6. RADAR technologies distributed across the last 10 years.

patterns'' classification and ''value estimation'' not only have the highest amount of papers across all the topics but also the density of the published papers is shifted towards the last three years with a general increase of interest showed by the researchers. On the contrary, ''sleep monitoring'' and ''infection detection'' are the topics with the most papers published before 2019.

IV. PHYSIOLOGICAL SIGNALS AS OUTPUT OF MACHINE LEARNING ALGORITHMS

The first analysed macro-cluster regards papers that apply machine learning to improve the regression of physiological

TABLE 1. Most relevant topics (>5 papers) distributed across the last 5 years.

AIM	<=2018	2019	2020	2021	2022	2023
authentication	5	2	3	1	6	2
breath patterns	6	4	3	7	13	8
driver	2	1	1	2	1	2
emotion	1	0	1	3	3	1
heart disease	2	1	0	0	3	3
human detection	1	0	1	1	1	3
infection	6	2	0	1	1	0
physiological event detection	0	2	0	1	2	2
quality	0	3	0	1	2	2
signal reconstruction	1	2	3	4	6	7
sleep stage	5	1	2	2	0	0
value estimation	1	5	7	13	6	15

parameters ($n = 77$) (e.g., heart rate, respiration rate, blood pressure, electrocardiogram, photoplethismogram). The distribution of architecture is heterogeneous, and the most popular model is encoder-decoder model, which appears in 20 papers, followed by Convolutional Neural Network (CNN), appearing in 19 papers, then by MultiLayer Perceptron (MLP) in 12, Recurrent Neural Network (RNN) in 12, machine learning in 10, a combination of CNN and RNN in 7 and the use of hybrid architecture in other 7. In Table 2 we report in synthesis the references of each aforementioned algorithm, their aims, the RADAR technology and central frequency. In Table 3 we report the number of the aforementioned models for each of the sub-categories. A complete overview of each paper can be found in Tables 2 to 6 of the Supplementary materials.

A. FIRST CLUSTER TASKS

In the following, we divide the papers for a simplified analysis on the basis of the complexity of the task in value estimation ($n = 47$), signal reconstruction ($n = 23$) and physiological event detection ($n = 7$). A more detailed description of these three tasks is reported in the next subsections, while a brief summary is given in Table 4.

1) VALUE ESTIMATION

In the clinical practice, vital signs, such as HR, BR, BP and temperature, are routinely measured by clinicians to have a first overall assessment of the patient's health status. Continuous vital signs monitoring can prevent life-threatening scenarios by providing early warnings before a decline of the patient's status [115]. In this sub-category of papers on value estimation we include papers dealing with the estimation of vital signs, such as HR ($n = 20$) [17], [22], [25], [28], [29], [55], [56], [57], [67], [69], [70], [82], [83], [85], [97], [102], [104], [107], [108], [109], BR [58], [72], [98], [99], [110], [113] ($n = 6$), both HR and BR [31],

TABLE 2. Taxonomy of algorithms for the first macro-cluster. Next to the reference number we list in square brackets the year, the aim, the sensor type (FMCW, CW, UWB), if any, with the operating frequency, if any. For the row related to machine learning we add the type of algorithm.

Algorithms	Reference and general info
CNN ($n = 19$)	[53]([2023] [HR, BR estimation] [UWB 7,29]); [54]([2023] [HR, BR estimation] [UWB 7,46]); [55]([2022] [HR estimation] [FMCW 78,5]); [34]([2022] [HR, BR estimation] [FMCW]); [29]([2021] [HR estimation] [FMCW 62]), [56]([2021] [HR estimation] [UWB]); [57]([2020] [HR estimation] [FMCW 62]); [28]([2020] [HR estimation]), [58]([2019] [BR estimation] [FMCW 24]); [32]([2021] [ECG reconstruction] [FMCW 79]); [44]([2020] [SCG reconstruction] [FMCW 79]); [41]([2019] [Cardiac waveform reconstruction] [UWB 79]); [59]([2022] [Heart Sound detection] [CW 24]); [60]([2023] [Heart beat waveform reconstruction] [FMCW 60,5]); [61]([2023] [Heart beat waveform reconstruction] [FMCW 79]); [62]([2023] [Heart beat square signal reconstruction]); [63]([2023] [HR]); [64]([2023] [InterBeat interval estimation]); [65]([2023] [HR, BR estimation])
CNN + RNN ($n = 7$)	[66]([2021] [regression of spyrometric indicators and flow-volume graph] [FMCW 77,33]); [17]([2021] [HR estimation] [FMCW 76, UWB 7,29]); [56]([2021] [HR estimation] [UWB]); [28]([2020] [HR estimation]); [67]([2023] [HR estimation] [UWB 7,29]); [68]([2021] [ECG reconstruction] [FMCW 79]); [65]([2023] [HR, BR estimation])
Encoder-decoder ($n = 20$)	[69]([2019] [HR estimation] [UWB 7,29]); [66]([2021] [regression of spyrometric indicators and flow-volume graph] [FMCW 77,33]); [70]([2023] [HR estimation] [FMCW 78,5]); [71]([2022] [BP estimation] [FMCW 79]); [72]([2023] [BR estimation] [FMCW 60]); [56]([2021] [HR estimation] [UWB]); [73]([2023] [BP estimation] [FMCW 60]); [31]([2021] [HR,BR estimation] [CW 24]); [74]([2021] [Respiratory waveform reconstruction] [UWB 7,29]); [75]([2022] [PPG reconstruction] [FMCW 79]); [76]([2023] [Heart sound signal] [FMCW 78,5]); [77]([2020] [Respiratory waveform reconstruction] [24]); [78]([2022] [PPG reconstruction] [FMCW 62]); [35]([2022] [Cardiac waveform reconstruction]); [79]([2022] [Cardiac waveform reconstruction]); [23]([2019] [BR waveform reconstruction] [2,4]); [30]([2021] [Respiratory and Cardiac waveform] [FMCW 77, FMCW 24, UWB 7,29]), [80]([2023] [ECG signal reconstruction]), [81]([2023] [breathing volume parameters estimation]); [82]([2023] [HR estimation] [FMCW])
RNN ($n = 12$)	[83]([2022] [HR estimation] [CW 24]); [84]([2021] [BP estimation] [24]); [85]([2022] [HR estimation] [CW 24]); [40]([2021] [HR, BR estimation] [FMCW 79]); [86]([2020] [Future short term prediction] [CW 24]); [87]([2021] [Heart Sound detection] [CW 24]); [88]([2019] [Heart Sound detection] [24]); [89]([2023] [R-peak detection] [CW 24]); [90]([2019] [Systole-diastole detection]); [91]([2023] [R-peak detection] [CW 122]); [65]([2023] [HR, BR estimation]); [92] ([2023] [ECG signal reconstruction])
MLP ($n = 12$)	[93]([2023] [BP estimation] [FMCW 60]); [94] ([2019] [SpO2 estimation] [CW 5,8]); [95]([2023] [BP estimation] [FMCW 78,5]); [96]([2023] [HR estimation] [FMCW 78,5]); [97]([2020] [HR estimation] [CW 24]); [98]([2023] [BR estimation] [CW 5,8]); [28]([2020] [HR estimation]); [99]([2021] [BR estimation] [UWB 7,29]); [100]([2016] [Respiratory waveform reconstruction] [CW 2,4]); [30]([2021] [Respiratory and Cardiac waveform reconstruction] [FMCW 77, FMCW 24, UWB 7, 29]); [101]([2023] [Heartbeat signal reconstruction] [UWB 2.4 and 5]); [92] ([2023] [ECG signal reconstruction])
Hybrid ($n = 7$)	[102]([2021] [HR estimation] [24]); [103] ([2020] [HR, BR estimation] [CW]); [104]([2021] [HR estimation] [24]); [25]([2020] [HR estimation] [FMCW]); [105]([2022] [Respiratory waveform reconstruction] [UWB 7, 29]); [36]([2022] [ECG reconstruction] [FMCW 79]); [106]([2022] [QRSTP segments] [CW 24])
ML ($n = 10$)	[107]([2019] [HR estimation] [UWB 7,29] [Unsupervised Convolutional Sparse Coding]); [22]([2019] [HR estimation] [5,7] [supervised gamma filter]); [108]([2020] [HR estimation] [FMCW 62] [Gaussian Mixture Model + Convolutional Sparse Coding]); [109]([2021] [HR estimation] [UWB 7,29] [genetic algorithm]); [110]([2021] [BR estimation] [FMCW 79] [X-means]); [111]([2021] [BP estimation] [CW 260] [Bagging, SVM]); [112]([2022] [BP estimation] [CW 24] [decision trees, random forest]); [113]([2020] [BR estimation] [UWB] [random forest]); [114]([2017] [HR, BR estimation] [UWB 4,2] [K-means]); [92]([2023] [ECG signal reconstruction] [Logistic regression])

TABLE 3. Algorithm categories per aims in the first macro-cluster.

AIM	CNN	CNN+RNN	RNN	encoder-decoder	H	MLP	ML
values estimation	12	6	5	10	4	8	9
physiological event detection	1	0	5	0	1	0	0
signal reconstruction	6	1	2	10	2	4	1

[34], [40], [53], [54], [103], [114] ($n = 7$), BP [71], [73], [84], [93], [95], [111], [112] ($n = 7$), oxygen saturation (SpO2) [94] ($n = 1$), and spyrometric indices [66], [81] ($n = 2$) in a given windows of observation. The latter three papers differ from the other manuscripts analyzed in the particular aim of detecting indices related to respiration that the other papers overlooked. Oxygen saturation is often measured in polysomnography to distinguish forms of apnea disorders, so being able to add the ability to measure SpO2 through machine learning to RADAR systems increases their usefulness as sensors in clinical practice [94]. Several methods have been proposed for value estimation for all the previously mentioned architectures and models. Most of the employed machine learning models ($n = 9$) are applied to the value estimation task (see Table 3); nevertheless, CNN remains the most typical architecture for value estimation with 12 papers employing it. Then, 8 papers use MLP, 10 an encoder-decoder model, 6 a combination of CNN and RNN, 5 a RNN model and other 4 an hybrid architecture.

2) SIGNAL RECONSTRUCTION

In this category we include all the papers aiming at reconstructing a physiological signal from the input RADAR signal thanks to a deep learning approach. The ability to provide not only simple physiological features such as vital signs, but a proper complete waveform, gives to RADAR-based sensing the potential to be a tool of relevance in the clinical practice. In fact, it is able to provide to the medical personnel with a novel way to extract clinically relevant and interpretable features in a contactless way. We include papers regarding a fine-grained reconstruction of both a physiological signal or simplified waveform derived from a physiological signal. We find papers about the reconstruction of the electrocardiogram (ECG) ($n = 5$)

TABLE 4. Papers included for the first macro-clusters divided into aims.

Aim	Short description	References
Value estimation ($n = 47$)	Papers dealing with an accurate estimate of a physiological parameter, such as heart rate, breathing rate, blood pressure, oxygen saturation or other breathing related indices over a given interval of time. In this cases ML/DL models takes as input RADAR signals coming from the target and aims at improving the state-of-the-art techniques usually working with a frequency estimate, autocorrelation or template matching.	[17], [22], [25], [28], [29], [31], [34], [40], [53]–[58], [63]–[67], [69]–[73], [81]–[85], [93]–[99], [102]–[104], [107]–[114]
Signal reconstruction ($n = 23$)	Giving an estimate of heart rate or breathing rate is relevant to have a general view of the health status of the patients, however we lose more information regarding the overall physiological waveform. Thus, being able to unobtrusively detect fine grained physiological waveform (ECG, PPG, SCG) from a patient could give to the clinicians a better information for the diagnosis of diseases.	[23], [30], [32], [35], [36], [41], [44], [60]–[62], [68], [74]–[80], [86], [92], [100], [101], [105]
Physiological event detection ($n = 7$)	Another way to cope with vital sign estimation is to detect clinically relevant events such R-peaks, Heart Sounds or fiducial points in the physiological waveform. This gives an advantage compared to the simple value estimation task because a system being able to detect accurately physiological event can both give a quantity related to its occurrence in a given window but also the variability of its occurrence (e.g., R to R variability).	[59], [87]–[91], [106]

[32], [36], [68], [80], [92], the seismocardiogram (SCG) [44] ($n = 1$) and the photoplethismogram (PPG) ($n = 2$) [75], [78]. Reference [75], in particular, shows an example of how a RADAR sensor can be used to increase the system performance by exploiting its intrinsic privacy-preserving and fairness quality. By fusing RADAR sensing and camera, the authors were able to better reconstruct a PPG signal while increasing the fairness of the system, which is less affected by skin tone. Then we find papers dealing with respiratory waveform ($n = 4$) [74], [77], [100], [105] or simplified version of the cardiac waveform ($n = 6$) [35], [41], [60], [62], [79], [101] or both ($n = 2$) [30], [61], [86]. As it is possible to observe in Table 3, the encoder-decoder architecture is by far the most employed for this task with 10 papers, followed by 6 papers using a CNN, 4 papers for MLP, 2 papers for Hybrid architecture and RNN, 1 paper for CNN + RNN. For the hybrid architecture the deep learning model used was an encoder-decoder type in combination with extracted features from K-nearest neighbour.

3) PHYSIOLOGICAL EVENT DETECTION

In addition to extracting simple vital signs within a certain observation window, the ability to extract the onset and interval of specific events related to the physiology of breathing and heartbeats allows for a more detailed assessment of the patient's condition. With R-peak detection, for example, as proposed in [89] and [91], we can not only obtain the frequency with which an event occurs, but also its variability over time, which may provide a way to detect imbalances in the regulation of the autonomic nervous system [116], [117]. Another example of a clinically relevant task is electrocardiogram segmentation, since the ability to extract the onset and offset of the ECG major waves, as proposed in [106], opens up new possibilities for the diagnosis of short-QT and long-QT syndromes in a completely unobstrusive way. RADARs are also employed as alternatives of stethoscopes for the retrieval of heart sounds [59], [87], [88]. The SCG segmentation has also been explored with the detection of fiducial points related to known cardiac events [90].

B. DATASETS GENERAL INFORMATION

In the rest of this section we provide a summary of the papers reporting an acquisition protocol, including performance metrics, validation methodologies, pre-processing techniques and finally a comparison with the state-of-the-art. We collect information about the number of subjects, their sex, their age, height and weight (where reported), the static or moving scenario, the reference signal, the subject distance from the RADAR and how the researchers dealt with the synchronisation issues between RADAR and reference sensor. In Table 5 we report the non-public datasets with clear information about number and sex of the subjects, whereas in Table 6 we report the ones that are publicly available. The median dataset size across all the papers reporting the number of subjects is 12 (interquartile range: 5 - 24) and the median distance of the subject from the radar is 0.875 m (interquartile range: 0.55 to 1.36 m). From Table 5, we can notice that the authors made an effort to make the datasets balanced between the two sex. The synchronisation between the RADAR recording and the reference is solved by different methods, such as Precision Time Protocol [30], [74], [105], custom LABVIEW program [79], [111], post-processing manual synchronisation based on clearly defined time events [118], binary shared sequences [87], [119] or by matching of the time stamps [17], [40], [71], [72], [78], [97]. Moreover, we find two methods used to deal with synchronisation errors. The first exploits the robustness against synchronisation issues of the CNN-based parallel architectures, and it was proposed to compensate for the synchronisation issues by taking as input different delayed version of the same RADAR data [41]. Moreover, a time-invariant loss was proposed to correct for any error in the synchronization process for a PPG signal reconstruction task [78].

In the publicly available datasets there are no subjects older than 65 years of age, and they are focused on adults between 18 and 64 years, with the exception of one paper reporting data from children [43]. Three available datasets report measurements of moving subjects [17] (simple movements in a stationary position), [78] (different movements ranging from sitting to walking) and [40] (stationary jogging and walking). When considering the total amount of included papers, only 9 out of 68 papers challenged their results in moving scenarios. Among these 9, 6 consider simple movements patterns, with the subject moving mainly their limbs (e.g. performing home gym exercise, cycling, treadmill, random body movements in stationary position, sit to stand) [17], [29], [30], [68], [74], whereas the remaining 3 test their

TABLE 5. Summary of datasets reported in articles in the first macro-cluster. The table reports only articles with demographic information with datasets that are not publicly available.

Ref.	N	M/F	subjects info	static	moving	Radar	Reference	Subject range	Synchronization
[88]	30	16/14	age mean (sd) [years] : 30.7 (9.9); BMI mean (sd) [kg/m2]: 23.3(2.2)	✓	-	CW	ECG	40 to 50 cm	-
[97]	21	14/7	age mean (sd) [years]: 26.1 (5.1);height mean (sd) [m]: 179.5 (11.6); weight mean (sd) [kg]: 74.2 (16.4)	✓	-	CW	ECG	75 cm	Time stamps
[44]	21	16/5	age range [years]: 21 to 35	✓	-	FMCW	SCG	25 to 50 cm	output of reference used as ticker for mmWave data
[68]	40	20/20	age range [years]: 18 to 52 ; weight range: 45 to 84	✓	-	FMCW	ECG	1 m	Clock on data gathering laptop
[74]	12	6/6	age range [years]: 15 to 64; weight range [kg]: 50 to 80	-	✓	UWB	Respiration signal	0.5 to 2 m	Precision Time Protocol
[30]	12	6/6	age range [years]: 15 to 64; weight range [kg]: 50 to 80	-	✓	FMCW	Respiration signal	0.5 to 2m	Precision Time Protocol
[111]	8	7/1	age mean (range) [years]: 32 (25 to 49); BMI mean (sd) : 24.8 (1.7) [kg/m2]	✓	-	CW	ECG	1 m	LabVIEW program
[105]	12	6/6	age range [years]: 15 to 64; weight range [kg]: 50 to 80	✓	✓	UWB	Respiration signal	room 3 m x 7 m	Precision Time Protocol
[36]	35	22/14	age range [years]: 18 to 65	✓	-	FMCW	ECG	40 to 50 cm	-
[79]	12	6/6	age mean (sd) [years]: 24.08 (2.35)	✓	-	-	ECG	30 cm	LabVIEW program
[54]	55	32/23	mean age (range): 6.1 (10 day to 18 year);	✓	-	UWB	PSG	40cm to 1 m	-
[53]	30	14/16	mean age (sd) : 27.2 +- 4.7; mean BMI (sd): 21.9 +- 3.6	✓	-	UWB	PSG	50 cm to 2 m	-
[73]	41	30/11	age less than 40: 33; BMI less then 25: 25; BMI more than 30: 4;	✓	-	FMCW	blood pressure	12 cm to 25 cm	-
[95]	5	3/2	age range: 20 to 76;	✓	-	FMCW	blood pressure	50 cm	-
[93]	55	43/12	the majority of the subjects between 20 and 60 years; some from 70 to 90 years	✓	-	FMCW	blood pressure	3 mm	-
[94]	20	18/2	mean age: 69.05 years; mean height: 1.72 m; mean weight: 82.69 Kg; mean BMI: 28.01	✓	-	CW	PSG	50 cm	-

proposed approach in complex moving scenarios [40], [78], [105] (e.g. walking, activity of daily living).

1) PERFORMANCE METRICS

The most employed metrics for the value estimation task are Mean Absolute Error (MAE) and Accuracy (ACC), employed in 13 papers. Mean Square Error (MSE) and Root Mean Square Error (RMSE) are employed in 5 and 6 papers, respectively, followed by Mean Relative Error (MRE) and Mean Absolute Percentage Error (MAPE), used in 5 papers, and Mean Relative Percentage Error (MRPE) in 4 papers 7. Regarding the signal reconstruction papers, we note the use of some of the same metrics as a measure for judging the integrity of the physiological event and other metrics related to signal fidelity or similarity to the actual ground truth. MAE is employed in 8 papers on vital signs extracted from the reconstructed signals compared against ground truth vital signs as a metric of error for Inter-Beat Interval (IBI) [30], [32], [41], HR [36], [78], HRV [78] and BR [74], [105]. MRE ($n = 3$), MAPE ($n = 2$) and normalised absolute error based on heartbeat period (n=3) were the other metrics used for integrity of physiological events. Similarly, RMSE was applied as an error metric for HR estimation [75] and IBI estimation [41], but also as a similarity metric for sample-to-sample applied waveform reconstruction [36]. Regarding other metrics related to fidelity of signal reconstruction, we notice the diffusion of correlation [32], [36], [44], [68], also employed for HR analysis [75], and cosine similarity [30], [74], [105]. Another interesting metric related to signal fidelity is Noise, defined as difference between the ground truth signal and the reconstructed one [68], [76]. With regard to physiological event detection, two types of metrics can be distinguished: time error metrics applied to vital signs or event detection and classification metrics, such as accuracy, f1 score, recall and precision, defined on the basis of a tolerance for predicting a true positive around the event to be detected. MRE was both applied to IBI [91],

TABLE 6. Synthesis of the publicly available datasets found during the systematic search.

Ref.	N	M/F	Subject info	static	moving	Radar	Reference	Subject range	Synchronization	Availability
[87]	25	13/12	age men mean (sd) [years]: 24.3 (2.8); age women mean (sd) [years]: 23.7 (2.9)	✓	-	CW	ECG	40 cm	the two measurements are synchronised in post-processing with a binary synchronisation system	available upon request
[17]	6	4/2	age range [years]: 23 to 24; height range [m]: 1.63 to 1.86 ; weight range [kg]: 54 to 102	-	✓	FMCW UWB	pulse oximeter	2 m x 1.5 m; 2.2 m x 3.5 m; 4.3 m x 8.5 m;	Time stamps	available here
[78]	28	1) 9/9 2)5/2 3)2/1	age range [years]: 21 to 64 years; mean: 39.4 and median: 35.0	✓	✓	FMCW	PPG	1 to 4 m	Coral toolkit to simultaneously store radar and PPG data; a time-invariant loss is used in training to correct for any error in the synchronization	available here
[118]	11	7/4	age mean(sd) [years]: 34.73 (15.94); BMI mean (sd) [kg/m2]: 23.19 (3.61)	✓	-	CW	ECG , respiration signal, phonocardiogram	20 cm	manual synchronisation by tapping the shoulder of the subject with a pattern at the end of the recording	available here
[119]	30	14/16	age mean (sd) [years]: 23.1 (3.3); height mean (sd) [m]: 175.7 (14.0); weight mean (sd) [kg]: 72.2 (10.5); BMI mean (sd) [kg/m2]: 23.2 (3.3)	✓	-	CW	ECG, blood pressure signal	-	manual synchronisation using a binary sequence (gold codes) and cross-correlation of the measurements to find the amount of delay between them	available here
[85]	30	-	age range [years]: 18 to 23	✓	-	CW	PPG	-	-	available upon request
[40]	14	-	-	-	✓	FMCW	ECG, respiration signal	1 to 6 m	Synchronised through computer time stamps	available here
[120]*	9	5/4	age mean(sd) [years]: 24(5)	✓	-	CW	ECG	15 cm	LABVIEW program	available here
[43]*	50	24/26	age range [months]: 15 to 148; height range [cm]: 73.1 to 160.0; weight range [kg]: 8.7 to 54; BMI range [kg/m2]: 12.75 to 23.42;	✓	-	FMCW	HR,BR	-	-	available here
[121]*	1	1/0	height 173 cm, weight 59 kg, age 32 years old;	✓	-	UWB	respiration signal from lidar	59 cm to 78 cm	-	available here

* papers found during the screening process reporting only the dataset

whereas MAE [90], MRPE [106] and RMSE [59] where used by the authors to report metrics of distance between the detection and the true position of the event. Regarding classification metrics, based on a defined tolerance around a physiological event, we can define a true positive when the prediction is within the tolerance, a false positive when the prediction is outside the tolerance, and a false negative when there are no predictions within the tolerance. The tolerance is the maximum value allowed for the absolute difference between the predicted and the actual event. The employed tolerances change depending on the event to be detected with a tolerance of 125 ms for systolic segments classification [90], a tolerance of 70 ms [88] or 75 ms [87] in heart sound detection, a tolerance of 75 ms for R-peak detection [89] and a tolerance of 10 ms for ECG segmentation (QR, RS, ST, TQ) [106].

2) VALIDATION METHODOLOGIES

Most of the papers targeting value estimation and signal reconstruction use a simple train-test split or hold-out method, with 26 papers (61%) and 8 papers (44%), respectively. For the detection of physiological event we observe a more uniform distribution across the different classes of validation methods. Overall, K-fold CV is the second most popular alternative with 4 papers aimed at value estimation, 3 at signal reconstruction and 1 at physiological event detection. Figure 7 summarises the distribution of the validation methodology used in the three sub-categories of the first cluster.

3) PRE-PROCESSING TECHNIQUES

In this section we describe the pre-processing steps used in the included literature. In the first column of Table 8 we list

TABLE 7. Performance metrics employed in the first cluster.

Metrics	References
MAE=$\sum_i^N \frac{\lvert prediction_i - truevalue_i \rvert}{N}$	value estimation (n=13) [34], [40], [53], [54], [56], [58], [84], [96], [102]–[104], [111], [112]; signal reconstruction (n=8) [30], [32], [36], [41], [74], [75], [78], [105], normalised by heartbeat period (n=3) [36], [44], [68]
ACC=$\frac{1}{N}\sum_i^N 1 - \frac{\lvert prediction_i - truevalue_i \rvert}{truevalue_i}$	value estimation (n=13) [17], [25], [28], [29], [34], [57], [58], [67], [69], [94], [99], [112], [114]; physiological event detection (n=3) [59], [87], [88]
MSE=$\sum_i^N (prediction_i - truevalue_i)^2$	value estimation (n=5) [25], [56], [72], [94], [111]; physiological event detection (n=1) [59]
RMSE=$\sqrt{\sum_i^N \frac{(prediction_i - truevalue_i)^2}{N}}$	value estimation (n=6) [83], [85], [93], [95], [104], [110]; signal reconstruction (n=3) [36], [41], [75]
MRE=$\sum_i^N (prediction_i - truevalue_i)$	value estimation (n=5) [66], [71], [93], [108], [122]; signal reconstruction (n=3) [30], [36], [44], [105]; physiological event detection (n=1) [91]
MAPE=$\sum_i^N \frac{\lvert prediction_i - truevalue_i \rvert}{N*truevalue_i}$	value estimation (n=5) [55], [70], [83], [102], [103]; signal reconstruction (n=2) [75], [78]
MRPE=$\sum_i^N \frac{prediction_i - truevalue_i}{N*truevalue_i}$	value estimation (n=4) [22], [71], [98], [107]; physiological event detection (n=1) [106]
Correlation=$\frac{\sum_i^N (RS_i - \mu_R S)*(GD_i - \mu_G D)}{\sum_i^N (RS_i - \mu_R S)^2 \sum_i^N (GD_i - \mu_G D)^2}$	signal reconstruction (n=5) [32], [36], [44], [68], [75]
Cosine similarity $\frac{\sum_i^N GT_i * RS_i}{norm(GT)*norm(RS)}$	signal reconstruction (n=3) [30], [74], [105]
accuracy=$\frac{TP+TN}{TP+FP+TN+FN}$	physiological event detection (n=3) [59], [87], [88]
F1-score=$\frac{2\times TP}{2\times TP+FP+FN}$	physiological event detection (n=4) [87]–[89], [106]

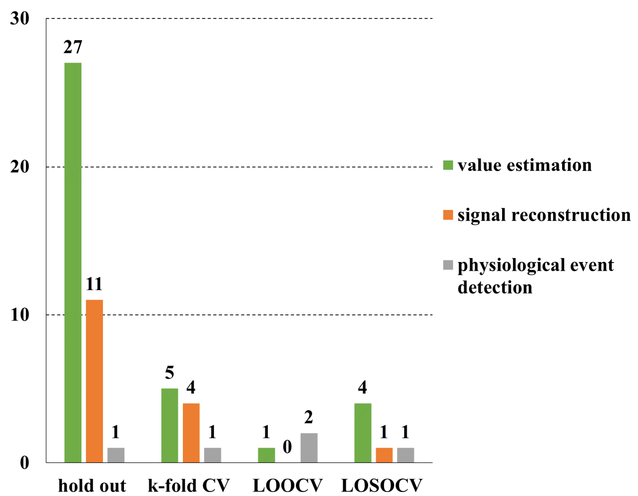


FIGURE 7. Distribution of validation methodologies in the first macro-cluster.

the traditional radar signal processing (RSP) techniques and features that are employed, including the type of radar map used among: range-time (RT), range-Doppler (RD), Doppler-time (DT), range-azimuth (RA), and whether the phase signal is extracted directly. The filtering row lists the filtering procedures adopted to remove the clutter and noise in the maps which can be further processed by locating the subject in the target location row. Filtering the radar data or locating the subject is a step that appears in 57% of the included studies; typical filters are band pass filters (often Butterworth) in the adequate cutoff frequencies for the wanted vital sign ($n = 15$) [28], [29], [40], [44], [58], [78], [83], [84], [85], [88], [90], [102], [104], [106], [110], [114] and derivative filters ($n = 4$) [36], [44], [90], [102]; typical algorithm for target location are threshold based detection ($n = 13$) [29], [30], [34], [41], [44], [55], [57], [68], [72], [74], [75], [105], [107]. The augmentation row shows the techniques to increase the dataset size in a synthetic way. Augmentation is a necessary steps when there is a lack of real data and the complexity of the algorithms used for the regression or classification task necessitate an increased number of examples. The most typical augmentation procedures include segmentation of the recordings ($n = 19$) [17], [22], [28], [29], [30], [32], [34], [35], [36], [40], [41], [44], [55], [56], [57], [59], [68], [69], [71], [72], [74], [75], [78], [79], [83], [84], [85], [87], [88], [90], [97], [99], [102], [103], [104], [105], [106], [107], [109], [110], [111], [113], [114], additive noise ($n = 3$) [29], [44], [107] and rotation of the I/Q data ($n = 2$) [75], [105]. The last row of reference processing refers to the elaboration of the reference signal needed to reduce the amount of information used in the training process. Some of the typical processing aim at simplifying the reference signal by either extracting specific cardiac events ($n = 4$), such as the R-peak [28], [87], [97] or Aortic Opening [90], or by removing some of the frequency components ($n = 2$) [78], [106] or by transforming the complex nature of the ECG signal in simple periodical shapes ($n = 4$) [22], [35], [41], [79].

4) COMPARISON WITH THE STATE-OF-THE-ART

Finally, in Table 9 we include a brief analysis of typical algorithms used to compare state-of-the-art (SoA) with proposed machine learning and deep learning approaches. By considering the taxonomy recently proposed by Zhang et al. [2], the algorithms are divided into spectrum-based, periodicity-based, agnostic source separation methods and deep learning. The taxonomy is extended to any physiological signal analyzed, although it was initially intended for cardiac feature extraction algorithms. 26 of the 77 papers (33.8%) in the first group employ other algorithms as a basis or comparison with the proposed approach; spectrum-based methods are the most popular, followed by

TABLE 8. Pre-processing steps in the first macro-cluster.

Preprocessing step	Preprocessing type	References
Radar Signal Processing and feature extraction	Range Azimuth Elevation	[36]
	Range Time	[29], [30], [34], [40], [41], [55], [60], [70], [72]–[76], [78], [82], [87], [88], [93], [95], [96], [106]–[108], [110]
	Doppler time (Spectrogram)	[31], [54], [56], [58], [68], [76], [78], [80], [102]–[104], [109]
	Continuous Wavelet Transform	[53], [92]
	Range Azimuth	[58], [71], [110]
	Range Doppler	[17], [29]
	Working with I/Q data	[74], [75], [97], [105]
	Phase extraction (e.g. arctan)	[22], [25], [28]–[30], [32], [34]–[36], [40], [41], [44], [55], [57], [59], [60], [66], [69]–[72], [76], [78], [79], [83]–[85], [87], [88], [90], [95], [96], [99], [106]–[114]
	Unwrap	[25], [60], [70], [82], [108]
	Envelope extraction	[87], [88], [91]
	Normalisation or standardisation	[23], [28], [53], [62], [79], [82], [91]
Filtering	Bandpass or highpass filter with specific cut-offs (e.g. Butterworth with cutoffs at 0.2 and 1 Hz)	[29], [40], [44], [57], [58], [62], [67], [71], [78], [80], [84]–[86], [88]–[90], [98], [102], [104], [106], [108]–[110], [112]
	1st 2nd order derivative filters	[36], [44], [86], [90], [102]
	Savitzy-Golay filter	[53], [111]
	Moving Target Indicator	[60], [72]
	Loopback filter	[67], [74]
	Threshold	[53], [82], [92], [109]
	DC removal	[67], [95]
	Moving average	[53], [105]
Target Location	Threshold-based techniques (e.g. CFAR, maximum, threshold on energy, threshold on standard deviation)	[29], [41], [55], [57], [60], [70], [72], [76], [81], [95], [107], [108]
Augmentation	Segmentation	[17], [23], [28], [29], [35], [41], [44], [56], [59], [62], [64], [65], [68], [69], [74], [79], [84], [88]–[90], [97], [103], [104], [112]
	Downsampling	[35], [65], [79], [86], [89]
	Additive Noise	[29], [44], [74], [81], [107]
	I/Q data rotation	[74], [75], [105]
	stretching/squeezing	[44], [78], [81]
Reference signal processing	Simplification of the waveform	[22], [35], [41], [79], [97]
	Filtering the signal	[78], [106]
	Mu-law processing	[36]
	DWT coefficients	[68]

TABLE 9. State-of-the-art comparisons with the included literature of the first macro-cluster.

References and proposed ML/DL model	SoA Categories [2]
[34](CNN); [78](encoder-decoder); [75](encoder-decoder); [55](CNN); [102](LSTM + K-means); [40](LSTM); [17](CNN + RNN); [57](CNN) [103] (LSTM + K-means); [22](ML, gamma filter) [70](encoder-decoder); [60](CNN)	Spectrum-based methods
[59](CNN); [83](LSTM); [87](LSTM); [57](CNN); [41](CNN); [104](CNN)	Periodicity-based methods
[102](LSTM + K-means); [17](CNN + RNN); [103] (LSTM + K-means); [67](CNN + LSTM); [70](encoder-decoder); [60](CNN)	Agnostic Source Separation Methods
[72](encoder-decoder); [106](K-means + LSTM); [40](LSTM); [30](MLP + encoder-decoder); [74](encoder-decoder); [32](CNN); [82](transformer); [70](encoder-decoder) [60](CNN)	Deep Learning

deep learning, agnostic source separation, and periodicity-based methods.

V. RADAR-BASED PHYSIOLOGICAL SIGNALS AS INPUT TO MACHINE LEARNING ALGORITHMS

The second macro-cluster analyzed aims to understand the trends in machine learning applications on RADAR vital sign extraction, with a total of 130 articles. For the second macro-cluster, traditional machine learning models are the most employed algorithms to process RADAR-based vital sign, with the Support Vector Machine (SVM) being the most popular ($n = 52$), followed by K-Nearest Neighbor (KNN) ($n = 37$), decision trees (DTs) including random forests ($n = 32$), linear models (LINEAR) ($n = 24$) including logistic regression and Linear Discriminant Analysis (LDA), ensemble techniques such XGBoost and Adaboost (n=14), and Single Layer Forward Networks (SLFNs) including Extreme Learning Machine (ELM) ($n = 4$). Among the deep learning architectures, CNN is the most widely used and appears in 26 papers, followed by MLP ($n = 13$), CNN + RNN ($n = 6$), RNN ($n = 5$) and the encoder-decoder ($n = 3$). Hybrid architecture appears in 6 papers. Tables 11 and 12 summarizes the references of each algorithm mentioned, their objectives, RADAR technology and center frequency. Table 13 shows the number of the mentioned models for each of the aims. The following summary of the results obtained can be seen as a comprehensive summary of current trends in RADAR-based physiological signal detection. A complete overview of each paper can be found in Tables 7 to 19 of the Supplementary materials.

TABLE 10. Papers included in the second macro-cluster divided by aims.

Categories	Aim	Short description	References
Diagnosis	Breath patterns classification ($n = 41$)	Breath patterns are a way to discriminate between different clinical scenarios and an early diagnosis of a specific pattern could aid the clinicians to give a proper treatment to the patient. For this reason this class of papers employs a RADAR to extract breathing waveform from a target with a traditional procedure of target location and phase extraction and then add a second step of classification of patterns with a ML/DL model.	[38], [123]–[162]
	Quality detection (n =8)	RADAR based vital sign extraction has the problem of noise and interference and to the degradation of the extracted signal quality corresponds a degradation of the vital sign estimation. Thus, ML/DL models are used to detect the occurrence of artefacts or to detect the quantity of noise in a segment of the extracted signal which can be used as a feedback to the vital sign estimator to improve the accuracy of the estimation.	[16], [46], [163]–[168]
	Infection detection ($n = 10$)	In this period of time being able to assess the physical condition of a patient and whether or not he/she has fever is relevant to prevent a further infection. RADAR-based vital signs can be provided to ML/DL models to discriminate between infected or uninfected patients without the need to touch them.	[39], [169]–[177]
	Sleep stage classification ($n = 9$)	Sleep monitoring is a topic of relevance due to the influence of sleep quality on our daily lives. The papers we find dealt with sleep staging and the extraction of sleep quality indices employing RADAR based vital signs. The us of ML/DL models was essential for a proper and accurate discriminate between all the sleep stages.	[178]–[186]
	Heart disease detection ($n = 9$)	Although the construction of RADAR-based systems that estimate vital signs or physiological signals is important to provide new methods for diagnosis, helping physicians in diagnosis with automated, contactless tools is the next step and is what the papers found want to accomplish.	[15], [187]–[194]
Human behaviour monitoring	Fatigue detection ($n = 9$)	Drivers are often dealing with situation of stress and fatigue after long hours of work, therefore systems that can unobtrusively detect this state of fatigue or drowsiness and give alert to the user are optimal to prevent accidents. RADAR based extraction of vital signs is used to detect the driver status with the aid of ML/DL models.	[195]–[203]
	Human detection ($n = 7$)	Detecting humans in complex environments, such as indoor situations, underground or in vehicles, is a field of rising interest in the RADAR community. The possibility of exploiting chest vibrations to better detect the presence or occupancy of humans is the goal of the work found in this class.	[37], [204]–[209]
	Human localisation ($n = 4$)	Human localisation is the next step after detection and it aims at giving a quantitatively accurate estimate of the position of the user. This topic is of particular relevance and complexity in indoor situations were traditional GPS system cannot aid in the localisation.	[210]–[213]
	Human orientation ($n = 2$)	Human body orientation is important in many fields, such as sleep monitoring and pedestrian intention detection; knowing the subject's orientation can be used to increase the robustness and accuracy of vital sign extraction by a RADAR. We found two articles that discuss the regression of human orientation.	[45], [214]
	Activities classification ($n = 3$)	Human activity recognition with RADAR sensors is one of the major topics in the RADAR field due to the ability of the RADAR device to detect the micro-Doppler signature of each activity. In this few papers, however, we find another perspective to the problem where RADAR based extraction of respiration features and heartbeats are used to aid in the classification of activities.	[215]–[217]
Affective computing ($n = 9$)		Emotion recognition is a rising topic in the recent years due to its connection to different fields spanning from the biomedical interest in recognizing the emotional state of a patient to the commercial interest in recognition the emotional response of a costumer to a certain product. Being able to classify what a subject feels in a contactless way gives surely an advantage and this motivates the research with RADAR sensors.	[218]–[226]
Biometric authentication ($n = 19$)		User authentication is the field trying to predict the identity of a subject for security reasons. The possibility to authenticate a user in an obtrusive way is what fuels the research on RADAR-based authentication. In the papers included in this class of aims, we find ML/DL methods that take as input vital signs extracted from RADAR sensors to predict user identity.	[24], [26], [227]–[243]

A. DATASETS GENERAL INFORMATION

For each study in which the information is present, we analysed the number of subjects involved and their range. We observe similarities with the first cluster in the small sample size, such as a median number of subjects of 12 (interquartile range: 7 - 23); the median range of subjects is slightly higher than that observed in the first cluster with 1 m (interquartile range: 0.45 - 2 m).

In the second cluster of papers reviewed, we found applications of the previously mentioned public dataset and a publicly available dataset for human presence detection, published by [206] (Dataset); the dataset consists of recordings of 20 subjects (14 males/6 females) in different positions, ranging in age from 20 to 65 years, made with a 1.3 GHz CW RADAR with a bandwidth of 60 MHz.

TABLE 11. Machine Learning algorithms in the second macro-cluster. Next to each reference number we list in square brackets the year of publication, the aim, the sensor type and its operating frequency, if present.

Algorithm	Reference and general info
CNN (n=26)	[233]([2022] [user authentication] [CW 24]); [234]([2019] [user authentication] [24]); [235]([2023] [user authentication] [FMCW 77]); [237]([2022] [user authentication] [FMCW 77]); [183]([2020] [sleep staging] [UWB 23,8]); [166]([2019] [quality detection] [24]); [207]([2023] [human detection] [UWB 7,29]) [190]([2023] [heart disease detection] [UWB 4,3]); [188]([2016] [heart disease detection] [UWB]); [219]([2022] [affective computing] [FMCW 79]); [223]([2021] [affective computing] [UWB 7,29]); [146]([2022] [breath patterns classification] [UWB 7,29]); [143]([2021] [breath patterns classification] [UWB 7,25]); [140]([2022] [breath patterns classification] [UWB 7,29]); [138]([2022] [breath patterns classification] [UWB 7,29]); [136]([2020] [breath patterns classification] [UWB 3,5]); [135]([2019] [breath patterns classification] [UWB 3,5]); [38]([2019] [breath patterns classification] [UWB 3,5]); [132]([2022] [breath patterns classification] [UWB 7,29]); [160]([2023] [breath patterns classification] [62]); [129]([2022] [breath patterns classification] [FMCW 78,5]); [124]([2022] [breath patterns classification] [UWB 7,29]); [217]([2023] [activities classification] [FMCW 78,5]); [243]([2023] [user authentication]); [203]([2023] [fatigue monitoring] [FMCW 122]); [162]([2023] [breath patterns classification] [UWB])
MLP (n=13)	[199]([2023] [fatigue monitoring] [FMCW 79]); [187]([2022] [heart disease detection] [FMCW]); [165]([2021] [quality detection] [UWB 8,75]); [228]([2022] [user authentication] [FMCW 78]); [148]([2021] [breath patterns classification] [CW 24]); [200]([2021] [fatigue monitoring] [UWB 7,29]); [240]([2016] [user authentication] [CW]); [204]([2023] [human detection] [UWB 7,25]); [223]([2021] [affective computing] [UWB 7,29]); [197]([2021] [fatigue monitoring] [FMCW 78,5]); [134]([2018] [breath patterns classification] [UWB 6,8]); [15]([2022] [heart disease detection] [FMCW 79,4]); [132]([2022] [breath patterns classification] [UWB 7,29])
CNN+RNN (n=6)	[157]([2023] [breath patterns classification] [FMCW 24]); [225]([2022] [affective computing] [FMCW 78,5]); [126]([2022] [breath patterns classification] [FMCW 60]); [243]([2023] [user authentication]); [161]([2023] [breath patterns classification] [FMCW 24])
RNN (n=5)	[147]([2023] [breath patterns classification] [UWB]); [163]([2023] [quality detection] [FMCW]); [184]([2021] [sleep staging] [UWB 7,29]); [160]([2023] [breath patterns classification] [radar 62]); [243]([2023] [user authentication]);
encoder-decoder (n=3)	[193]([2022] [heart disease detection]); [168]([2023] [quality detection] [UWB 8,75]); [194]([2023] [heart disease detection] [CW])
H (n=6)	[16]([2022] [quality detection] [UWB 8,75]); [45]([2020] [human orientation] [UWB 7,3]); [211]([2022] [human localisation] [UWB]); [192]([2019] [heart disease detection] [UWB]); [195]([2022] [fatigue monitoring] [FMCW 77]); [127]([2022] [breath patterns classification] [UWB 7,29])

1) PERFORMANCE METRICS

The performance metrics for the second cluster are more straightforward than those used in the first one, because most of the aims found are classification tasks. Therefore, the most employed metrics are classification metrics, such as accuracy, precision, recall, f1-score and ROC AUC. Only in few papers dealing with a regression task, such as localisation or orientation of the subject, we observe the use of more developed metrics, such as MAE and RMSE. A specific metric, called Equal Error Rate, is considered for user authentication, which represents the error rate obtained by adjusting the operational threshold so that the value of the false-positive and false-negative rate is identical.

2) VALIDATION METHODOLOGIES

Most articles aiming at the diagnosis of a certain disorder use a hold-out validation method ($n = 33$), followed by K-fold cross-validation (CV) ($n = 31$), Leave-One-Out CV ($n = 4$) and Leave-One-Subject-Out CV (LOSOCV) ($n = 1$). For both biometric authentication and affective computing, k-fold CV is the most popular type of validation methodology, with 7 papers in each category employing it; for behavioral monitoring, hold out and k-fold CV are used equally in 6 articles. Figure 8 summarises the distribution of the validation methodology used in the four subcategories of the second cluster.

VI. RADAR-BASED PHYSIOLOGICAL SIGNALS AS INPUT TO MACHINE LEARNING ALGORITHMS: TASKS

This section provides details of the reviewed papers belonging to the second macro-cluster, according to their task, including: diagnosis, monitoring of human behaviour, RADAR-base affected computing, and RADAR-based biometric authentication.

A. DIAGNOSIS

In many areas of medicine we notice the proposal of new systems based on deep learning or machine learning to help clinicians to make decisions and more accurate diagnosis, such as in ophthalmology [244], [245], skin cancer detection [246] or cardiovascular risk prediction [247]. RADARs having the capabilities to sense in an accurate way the periodic vibrations of the chest due to the mechanical contraction of the heart and due to the increase and decrease in the lung volume are surely a valuable tool to recognise disease from a distance.

Among the various applications explored in the literature, a significant focus lies on classifying breath patterns. While a comprehensive review on sleep apnea diagnosis was presented in 2019 [48], our efforts have centered on gathering papers that delve into discerning even more intricate patterns. This includes various manifestations of apneas and hypopneas, Biot's breathing, and Cheyne-Stokes respiration, amounting to a total of 41 papers. Another domain that underscores the inherent advantages of the contactless RADAR system is infection detection, and our exploration has led to the identification of 10 pertinent papers in this area. Then, we analysed 9 papers dealing with sleep stage classification, which is a topic of relevance due to the standard practice of sleep study, polysomnography. This conventional approach relies on highly invasive devices to furnish accurate diagnoses of disorders or assess sleep quality. The quest

TABLE 12. Machine Learning algorithms in the second macro-cluster. Next to each reference number we list in square brackets the year of publication, the aim, the sensor type and its operating frequency, if present.

Algorithm	Reference and general info
SVM (n=52)	[227]([2022] [user authentication]); [228]([2022] [user authentication] [FMCW 78]); [229]([2018] [user authentication] [CW 24]); [231]([2017] [user authentication] [CW 2,4]); [232]([2022] [user authentication] [CW 24,25]); [236]([2020] [user authentication] [2,4]); [26]([2020] [user authentication] [24; 2,4]); [24]([2019] [user authentication] [2,4]); [179]([2015] [sleep staging] [CW 24]); [180]([2021] [sleep staging] [UWB 7,29]); [46]([2022] [quality detection] [CW 24]); [165]([2021] [quality detection] [UWB 8,75]); [164]([2019] [quality detection] [CW 24]); [167]([2019] [quality detection] [24]); [202]([2018] [fatigue monitoring] [FMCW]); [201]([2019] [fatigue monitoring] [UWB 7,29]); [220]([2021] [affective computing] [CW 2,4]); [213]([2021] [human localisation] [UWB 4,3]); [215]([2022] [human detection] [CW]); [207]([2023] [human detection] [UWB 7,29]); [206]([2023] [human detection] [CW 1,3]); [37]([2018] [human detection] [UWB 4,3]); [205]([2022] [human detection] [UWB]); [187]([2022] [heart disease detection] [FMCW]); [189]([2023] [heart disease detection] [UWB 4,3]); [190]([2023] [heart disease detection] [UWB 4,3]); [173]([2015] [infection detection] [10]); [174]([2019] [infection detection] [CW 24,25]); [221]([2021] [affective computing] [FMCW 78,5]); [222]([2020] [affective computing] [CW 5,8]); [199]([2023] [fatigue monitoring] [FMCW 79]); [200]([2021] [fatigue monitoring] [UWB 7,29]); [197]([2021] [fatigue monitoring] [FMCW 78,5]); [158]([2018] [breath patterns classification] [CW 2,475]); [156]([2023] [breath patterns classification] [CW]); [155]([2021] [breath patterns classification] [FMCW 78,5]); [154]([2019] [breath patterns classification] [CW 1,6]); [153]([2023] [breath patterns classification] [UWB 8,75]); [151]([2016] [breath patterns classification]); [149]([2020] [breath patterns classification] [2,4]); [147]([2023] [breath patterns classification] [UWB]); [145]([2020] [breath patterns classification] [FMCW 79]); [144]([2018] [breath patterns classification] [24]); [139]([2017] [breath patterns classification] [CW 2,4]); [146]([2022] [breath patterns classification] [UWB 7,29]); [137]([2021] [breath patterns classification] [24]); [137]([2021] [breath patterns classification] [24]); [131]([2022] [breath patterns classification] [UWB 7,29]); [130]([2022] [breath patterns classification] [UWB 7,29]); [160]([2023] [breath patterns classification] [62]); [216]([2019] [activities classification] [UWB 3,6])
DT (n=32)	[227]([2022] [user authentication]); [228]([2022] [user authentication] [FMCW 78]); [26]([2020] [user authentication] [24; 2,4]); [230]([2022] [user authentication] [FMCW 62]); [178]([2017] [sleep staging] [CW 2,4]); [179]([2015] [sleep staging] [CW 24]); [180]([2021] [sleep staging] [UWB 7,29]); [165]([2021] [quality detection] [UWB 8,75]); [164]([2019] [quality detection] [CW 24]); [167]([2019] [quality detection] [24]); [202]([2018] [fatigue monitoring] [FMCW]); [201]([2019] [fatigue monitoring] [UWB 7,29]); [215]([2022] [human detection] [CW]); [209]([2020] [human detection] [CW 2,45]); [187]([2022] [heart disease detection] [FMCW]); [189]([2023] [heart disease] [UWB 4,3]); [190]([2023] [heart disease detection] [UWB 4,3]); [223]([2021] [affective computing] [UWB 7,29]); [222]([2020] [affective computing] [CW 5,8]); [200]([2021] [fatigue monitoring] [UWB 7,29]); [198]([2018] [fatigue monitoring] [CW 2,4]); [159]([2022] [breath patterns classification] [FMCW 24]); [157]([2023] [breath patterns classification] [FMCW 24]); [158]([2018] [breath patterns classification] [CW 2,475]); [154]([2019] [breath patterns classification] [CW 1,6]); [153]([2023] [breath patterns classification] [UWB 8,75]); [147]([2023] [breath patterns classification] [UWB]); [145]([2020] [breath patterns classification] [FMCW 79]); [146]([2022] [breath patterns classification] [UWB 7,29]); [131]([2022] [breath patterns classification] [UWB 7,29]); [160]([2023] [breath patterns classification] [62])
KNN (n=37)	[227]([2022] [user authentication]); [228]([2022] [user authentication] [FMCW 78]) [26]([2020] [user authentication] [24; 2,4]); [229]([2018] [user authentication] [CW 24]); [232]([2022] [user authentication] [CW 24,25]); [180]([2021] [sleep staging] [UWB 7,29]); [164]([2019] [quality detection] [CW 24]); [167]([2019] [quality detection] [24]); [201]([2019] [fatigue monitoring] [UWB 7,29]); [215]([2022] [human detection] [CW]); [152]([2023] [breath patterns classification] [CW 2,4; 24]); [220]([2021] [lie detection] [CW 2,4]); [187]([2022] [heart disease detection] [FMCW]); [189]([2023] [heart disease detection] [UWB 4,3]); [190]([2023] [heart disease detection] [UWB 4,3]); [212]([2006] [human localisation] [UWB]); [238]([2015] [user authentication] [2,4]) [173]([2015] [infection detection] [10]); [239]([2018] [user authentication] [CW 2,4]); [223]([2021] [affective computing] [UWB 7,29]); [222]([2020] [affective computing] [CW 5,8]); [199]([2023] [fatigue monitoring] [FMCW 79]); [197]([2021] [fatigue monitoring] [FMCW 78,5]); [155]([2021] [breath patterns classification] [FMCW 78,5]); [158]([2018] [breath patterns classification] [CW 2,475]); [241]([2020] [user authentication] [FMCW 24]); [186]([2019] [sleep staging] [2,4]); [149]([2020] [breath patterns classification] [2,4]); [154]([2019] [breath patterns classification] [CW 1,6]); [153]([2023] [breath patterns classification] [UWB 8,75]); [182]([2018] [sleep staging] [CW 2,4]) [145]([2020] [breath patterns classification] [FMCW 79]); [146]([2022] [breath patterns classification] [UWB 7,29]); [224]([2018] [affective computing] [CW 2,4]); [242]([2021] [user authentication] [7,3]); [128]([2019] [breath patterns classification] [2,4]); [130]([2022] [breath patterns classification] [UWB 7,29])
LINEAR (n=24)	[214]([2023] [human orientation] [FMCW 79]) [179]([2015] [sleep staging] [CW 24]); [39]([2019] [infection detection] [CW]); [169]([2018] [infection detection] [CW 10]); [164]([2019] [quality detection] [CW 24]); [167]([2019] [quality detection] [24]); [202]([2018] [fatigue monitoring] [FMCW]); [215]([2022] [human detection] [CW]); [172]([2011] [infection detection] [CW 10]); [208]([2021] [human detection] [FMCW 61]); [187]([2022] [heart disease detection] [FMCW]); [189]([2023] [heart disease] [UWB 4,3]); [173]([2015] [infection detection] [10]); [174]([2019] [infection detection] [CW 24,25]); [199]([2023] [fatigue monitoring] [FMCW 79]) [191]([2016] [heart disease detection] [24]); [176]([2010] [infection detection] [CW 10]) [185]([2015] [sleep staging] [CW 24]); [133]([2015] [breath patterns classification] [UWB 4,2]); [149]([2020] [breath patterns classification] [- 2,4]); [153]([2023] [breath patterns classification] [UWB 8,75]) [147]([2023] [breath patterns classification] [UWB]); [146]([2022] [breath patterns classification] [UWB 7,29]); [177]([2021] [infection detection] [CW 10])
ENSEMBLE (n=14)	[181]([2020] [sleep staging] [UWB]); [182]([2018] [sleep staging] [CW 2,4]); [165]([2021] [quality detection] [UWB 8,75]); [164]([2019] [quality detection] [CW 24]) [220]([2021] [lie detection] [CW 2,4]); [175]([2022] [infection detection] [CW]); [223]([2021] [affective computing] [UWB 7,29]) [142]([2022] [breath patterns classification] [FMCW 79]); [141]([2021] [breath patterns] [FMCW 79]); [158]([2018] [breath patterns classification] [CW 2,475]); [146]([2022] [breath patterns classification] [UWB 7,29]); [125]([2022] [breath patterns classification] [FMCW 62]); [160]([2023] [breath patterns classification] [62]); [123]([2021] [breath patterns classification] [UWB 24])
SLFN (n=4)	[170]([2015] [infection detection] [CW 10]); [171]([2013] [infection detection] [CW 10]); [210]([2022] [human localisation] [UWB 0,4])

for unobtrusive alternatives for somnologists propels this research domain, with broader reviews available on deep learning applications in sleep stage classification [248] and those involving contactless sensors [249]. Finally, we have included 9 papers focusing on heart disease detection and another 9 on quality detection, which represent two nascent

TABLE 13. Algorithm categories in the second macro-cluster per aim.

AIM	CNN	CNN + RNN	RNN	encoder-decoder	SVM	DT	KNN	LINEAR	ENSEMBLE	SLFN	MLP	H
breath patterns classification	14	3	2	0	16	10	10	5	7	0	3	1
user authentication	2	1	1	0	6	4	5	1	3	0	3	4
emotion classification	4	2	2	0	3	3	4	0	2	0	1	0
fatigue monitoring	1	0	0	0	6	4	3	2	0	1	3	1
heart disease detection	2	0	0	2	3	3	3	3	0	0	2	1
quality detection	1	0	1	1	4	3	2	2	2	0	1	1
sleep staging	1	0	1	0	2	3	3	2	2	0	0	0
infection detection	0	0	0	0	2	0	1	7	1	2	0	0
human detection	1	0	1	0	4	1	0	1	0	0	1	0
activities classification	1	0	0	0	2	1	1	1	0	0	0	0
human localisation	0	0	0	0	1	0	1	0	0	1	0	1
human orientation	0	0	0	0	0	0	0	2	0	0	0	1

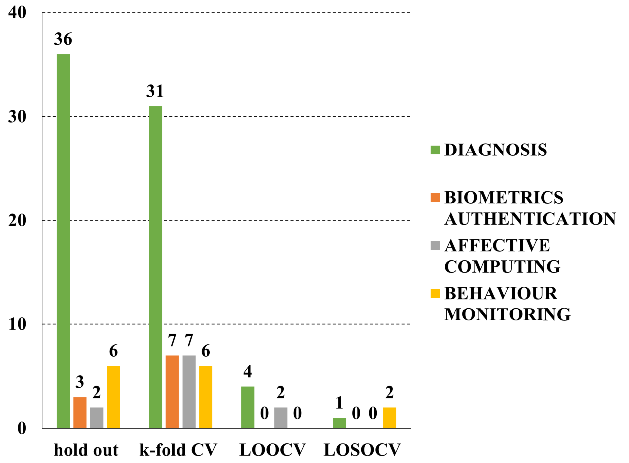


FIGURE 8. Distribution of validation methodologies in the second macro-cluster.

trends in scientific literature lacking comprehensive reviews until now.

1) BREATH PATTERNS CLASSIFICATION

Breathing pattern abnormalities are closely related to respiratory disorders, so the ability to classify them correctly is essential for identifying diseases and aiding diagnosis [250]. In addition, a patient might have a normal respiratory rate, but the respiratory signal pattern might provide different information about his or her actual clinical status [250]. Normal awake breathing consists of a quasi-periodic sequence of inspiratory and expiratory phases during which both the abdomen and thorax move synchronously. In the next paragraphs we analyse the trends in the literature regarding breathing pattern classification. We divided the included items according to the number of classes of breathing patterns evaluated, and then according to the complexity of the task. Apnea detection and abnormal breathing pattern detection include papers dealing with a binary discrimination, whereas the multi-class breathing patterns scenario is faced in the third paragraph.

a: APNEA DETECTION

Apnea is a condition happening during sleep, characterised by the absence of nasal flow and pressure [250]. The most recent definition by the American Academy of Sleep Medicine (AASM) [251] has two conditions that must be met for apnea scoring:

- A drop equal or higher than 90% of peak signal based on the baseline before the beginning of the event, measured with a recommended or alternative sensor.
- A duration of at least 10 seconds.

If, on the other hand, the percentage drop is less visible, this could be a case of hypopnea. Following the definitions of AASM, an hypopnea is scored based on the following rules:

- A drop equal or higher than 30% of peak signal based on the baseline before the beginning of the event, measured with a recommended or alternative sensor.
- A duration of at least 10 seconds.
- An increase equal or higher than 3% on the oxygen desaturation from pre-event baseline.

The occurrence of sleep apnea is related to serious health problems, including an increased risk of cardiovascular disease, stroke, and metabolic diseases, and to social problems, such as excessive daytime sleepiness, which could lead to errors in the workplace and traffic accidents [252]. Thus, the early identification of sleep apnea and the associated disorder, obstructive sleep apnea syndrome (OSAS), is important to prevent and reduce the health, social problems and the economic burden [252]. In the literature reviewed, eight papers dealt with the detection of apnea versus normal breathing [125], [130], [137], [144], [153], [156], [159], [161]. In two papers, additional classes related to subject movement or subject presence were added to the classification for more comprehensive evaluation. In two cases [130], [144], subjects involved are asked to simulate apnea, while in the remaining studies, apnea episodes are assessed with the gold standard polysomnography (PSG). Seven works [125], [130], [137], [144], [153], [156], [159] employ a simple machine learning model and feature engineering to achieve their ultimate goal, proving their validity against deep learning alternatives as well [159]. Typical performance metrics are the usual classification metrics: accuracy, precision, recall, f1-score. Also the use of kappa statistic is reported in a single paper [159].

b: ABNORMAL BREATHING DETECTION

We found eight papers [124], [132], [143], [146], [147], [151], [157], [162] dealing with the detection of abnormal versus normal breathing patterns in a binary classification scenario. From the point of view of complexity, it is a step beyond simply detecting apnea, because in the class of abnormal breathing we can find many different cases of abnormal breathing patterns, such as breathing associated with chronic obstructive pulmonary disease (COPD) [146]. In this case, we found the use of different models, where deep learning is the most diffused option (7 out of 8 papers) with solutions of complex CNN architectures, such as ResNet [124], [132], [143], [162] ang VGG16 [132]. Transfer learning is employed in one paper as a method to simplify the training process [132].

c: MULTI-CLASS BREATHING PATTERN CLASSIFICATION

We found 25 papers dealing with the classification of different respiratory waveforms [38], [123], [126], [127], [128], [129], [131], [133], [134], [135], [136], [138], [139], [140], [141], [142], [145], [148], [149], [150], [152], [154], [155], [158], [160]. The increased number of breathing patterns makes the classification task more complex, but the results are more useful from a clinical perspective. Some of the typical patterns found in the analysed papers are listed below with their references:

- Obstructive and central Apnea: the definition of apnea is given in the previous paragraph on apnea detection; obstructive apnea is characterized by the presence of inspiratory effort throughout the period of reduced airflow, whereas in central apnea inspiratory effort does not appear at all. A mixed event is characterised by the absence of inspiratory effort in the initial part, followed by a period of inspiratory effort [253].
- Obstructive and central Hypopnea: the hypopnea definition is given in the previous paragraph on apnea detection; Obstructive hypopnea is characterized by snoring during the event, increased flattening of the inspiratory portion of the nasal pressure signal, or thoraco-abdominal paradox, which is asynchronous movement of the chest and abdomen during breathing. In contrast, in central hypopnea these three characteristics do not appear [251].
- Cheyne-Stokes breathing: periodic crescendo-decrescendo curves followed by a period of apnea or hypopnea [250], [251]; it is a typical pattern in subjects suffering from stroke, brain tumor, traumatic brain injury, and carbon monoxide poisoning.
- Kussmaul's breathing: increased respiratory rate that causes patients to breathe abruptly and with difficulty. Often associated with metabolic acidosis [250].
- Biot's breathing: periods of apnea followed by bursts of high-frequency breathing [250].

A more detailed analysis of breathing patterns and sleep disorders can be found in [250]. Other simpler alternatives used in the included works are the respiratory waveform, in which only the frequency of breaths changes and one can distinguish normal breathing or eupnea (12 to 20 breaths per minute [250]), breathing at higher frequency than normal or tachypnea, breathing at lower frequency than normal or bradypnea [38], [129], [135], [136], [141], [160]. Some papers discuss breathing patterns with variations in amplitude, such as deep or heavy breathing and breath holding [127], [141], [145]. Eighteen of the twenty-five papers included evaluate their algorithm on simulated breathing patterns, asking subjects involved in the study to emulate the desired waveform [38], [127], [128], [129], [131], [134], [135], [136], [139], [140], [141], [142], [145], [148], [154], [155], [158], [160]. In one case, model training is carried out on a simulated pattern, while testing on people with a real disorder [158]. The remaining papers consider subjects with a history of sleep disorders in their studies [123], [126], [133], [138], [149], [150], [152]. Only two papers also assess the degree of severity of obstructive sleep disorders by estimating the Apnea Hypopnea Index (AHI), defined as the number of apneas and hypopneas divided by total sleep time [126], or the Respiratory Event Index (REI), defined as apnea or hypopnea events per hour of recording [150].

2) HEART DISEASE DETECTION

Cardiovascular disease is one of the leading causes of death worldwide [254], and continuous monitoring of vital signs could be one method of preventing patients' conditions from worsening. Automatic recognition of cardiovascular disease could help physicians in diagnosis with objective feedback, and the ability to obtain it in a contactless manner is essential for older patients and neonatal care. For this reason, the use of machine learning and deep learning models and RADAR sensors with their ability to extract non-contact chest vibrations could be a solution to provide an accurate and fast assessment of the patient's disorder. Nine papers [15], [187], [188], [189], [190], [191], [192], [193], [194] were found dealing with heart disease or abnormal beat prediction. In seven papers the recruited individuals have a form of heart disease [187], [189], [190], arrhythmia [193], [194] or abnormal beats [188], [192]. Iyer et al. [15] have built a deep learning system for RADAR-based arrhythmia discrimination with the help of training data from a set of ECGs, but the researchers have not tested their approach on unhealthy individuals. Yin et al. [188] use RADAR information to improve arrhythmia detection with ECG by building a CNN for sensor data fusion between RADAR and wearable sensors. In four papers [187], [189], [190], [193], authors involve subjects with cardiovascular disorders in their acquisition protocol. Zhang et al. [187] propose a framework to continuously and unobtrusively monitor 123 elder subjects across 10 different senior communities with a FMCW RADAR, achieving accuracies above 90% for cardiovascular diseases recognition using both machine learning models, such as DT, SVM KNN, and simple deep learning architecture with a multilayer perceptron. Izumi et al. [193] detect atrial fibrillation with 80% accuracy in 7 of the 10 subjects affected by the disorder with an encoder-decoder architecture. Two recent papers [189], [190], on the other hand, deal with discriminating between subjects with anterior or posterior Myocardial Infarction in a population of 868 patients with accuracies of 99% with simple KNN. An interesting application can be found in the paper by Matsui et al. [191], where a RADAR and a simple LDA model are employed to discriminate between 13 patients with major depressive disorder and 28 control subjects, based on the difference in heart rate variability due to the knowledge of autonomic dysfunction in the patients affected by this disorder. The paper obtains 85% sensitivity and 89% specificity, thus demonstrating the ability of RADAR systems to appreciate differences in the heart rate variability. Three papers [15], [187], [188] consider the use of an external dataset [255], [256], [257] to train a model of arrhythmia detection and use it directly on RADAR data, but only one paper [15] employs subjects experiencing actual arrhythmias.

3) INFECTION DETECTION

Infectious diseases require large-scale screening to prevent the possibility of outbreaks; physicians and nurses are at risk every time they approach a patient for evaluation, and this was evident during the time of the SARS-CoV-2 pandemic, during which clinical staff experienced three times the risk of infection than the general population [258]. Infectious diseases, such as dengue fever and SARS-CoV-2, are often accompanied by symptoms that can be detected by contactless devices with the help of artificial intelligence remotely and without the necessity of a medical crew. For example, Sars-Cov-2 comes with fever, fatigue, dry cough and dyspnea [259]. Thermography cameras are already used in many gathering places, but they can lose reliability due to the influence of external factors such as antifebrile intake and ambient temperature [260], [261]. Thus, RADAR sensors can be a tool to increase the reliability and accuracy of screening procedures and to limit the risks posed for health-care specialists. In this perspective, machine learning can represent the technology used to detect changes in the vital signs of patients affected by contagious diseases. Moreover, the possibility to build an automatic, unobtrusive system for symptom recognition could be helpful in the surveillance of mass gathering places, such as airports, for a quick screening and quarantine. We found 10 papers [39], [169], [170], [171], [172], [173], [174], [175], [176], [177] dealing with fever or infection detection in the context of influenza, dengue fever or Sars-Cov-2 outbreaks. In 9 papers [39], [169], [170], [171], [172], [174], [175], [176], [177] the RADAR sensor used is a CW, with one paper working at 24.25 GHz [174], 7 papers working at 10 GHz [169], [170], [171], [172], [173], [176], [177], and one papers working at 1.05 GHz [177].

In addition, the methods proposed for detection are usually simple and consider the use machine learning techniques. 7 papers exploit a linear model (LDA, QDA, Logistic regression) [39], [169], [172], [173], [174], [176], [177]. has the advantage of interpretability of results in papers that report a linear equation by which a patient's condition is judged based on only three features, i.e., heart rate (HR), breathing rate (BR), and facial temperature (T) extracted from thermal cameras [169], [172], [176], [177]. Some of the reported models f, based on these three features plus standard deviation of heartbeat interval (SDHI), are defined as follows:

$$f = 0.323 + 0.0131 * \text{HR} - 0.0096 * \text{SDHI} \text{ [176]} \quad (1)$$

$$f = 35.5 - 0.21 * \text{HR} - 0.48 * \text{RR} - 0.36 * \text{T} \text{ [177]} \quad (2)$$

$$f = 375.5 - 0.21 * \text{HR} - 0.48 * \text{RR} - 0.36 * \text{T} \text{ [172]} \quad (3)$$

$$f = 0.14 * \text{HR} + 0.19 * \text{RR} - 177.26 * \text{SDHI} \text{ [169]} \quad (4)$$

This tendency to use a relatively low frequency, a CW RADAR, and simple models could be due to the timing of publication, which was mostly before 2018. Another peculiar aspect of the included papers is that the size of the dataset is much larger than in most of the other included papers, with a median of 14 subjects (interquartile range: 7-30); the large number of subjects and the choice of simple model architectures lend greater credibility to the generalizability and reliability of the reported classification results, which were generally positive, with two papers reporting over 80% specificity and sensitivity [176], [177] and five other papers over 90% specificity and sensitivity [39], [59], [169], [171], [174]. Additionally, 5 papers [170], [171], [172], [173], [176] use more than one sensor, including in their work thermography cameras and Doppler laser to achieve better results. All of these reasons confirm the maturity of the field, which has experienced a general trend of decreasing interest in the scientific literature over the past 5 years (see Table 1).

4) SLEEP STAGE CLASSIFICATION

Sleep staging is an important process for the assessment of sleep disorders and sleep quality, but it is usually performed manually and is a tedious and time-consuming task. Automated sleep staging procedures based on electroencephalogram (EEG) or electrooculogram, typical signals in a polysomnographic study, have been proposed in the past in order to reduce the time required to classify each section and also reduce possible human error. Machine learning and deep learning methods are the tools usually employed on EEG and OCG (electrooculogram) for automatic classification, achieving accuracy ranging between 80% and 90% in the five-stage classification scenario [262]. The RADAR alternative is attractive for sleep medicine because it is completely noninvasive and is certainly much more convenient for the subject than wearable sensors. For the next summary we will use the following nomenclature of sleep stages [253]:

- Stage W: Wakefulness representing the stage from the waking state to the begin of drowsiness.

- N1 and N2: These two stages are clustered into the light sleep class in all the papers considered and are two non-rem (NREM) stages.
- N3 or deep sleep, the third NREM stage.
- REM (Rapid Eye Movement) stage.

We found 9 papers [178], [179], [180], [181], [182], [183], [184], [186], [263] dealing with sleep staging. Rahman et al. [179] built a binary classifier for sleep and wake classification, followed by another classifier for REM and NREM discrimination. Other three papers [180], [182], [185] consider the two-class scenario (W, sleep), the three-class scenario (W, REM, NREM), and the four-class scenario (W, REM, N1/N2, N3) and the remaining papers only deal with the more complex four-class scenario. Three papers [179], [181], [183] also evaluate sleep quality indices, such as total sleep time, sleep efficiency (ratio of total sleep session to total sleep time), sleep onset latency, and total wake time. We can observe that in no case was a complete sleep staging evaluated with the five standard classes.

5) QUALITY DETECTION

A key enabler in long-term continuous monitoring of vital sign with RADARs is the automatic discrimination between good quality and bad quality signals, which would increase the overall accuracy of estimation even with traditional approaches. Signal noise and artefacts are generated by a variety of causes, such as multipath, body movements, and, in vehicle applications, by seat movement and vibration. Previously cited papers in Subsection "Value Estimation" IV-A1 try to first denoise the signal with machine learning or deep learning, while in case of quality detection the goal is to understand whether a certain segment of the input physiological signal is corrupted, and then to proceed with further processing and estimation depending on the evaluation of corruption or by removing from the successive steps the signals too corrupted. We found 8 papers [16], [46], [163], [164], [165], [166], [167], [168] in which the authors perform signal quality classification to improve the performance of vital sign estimation. In two cases [164], [165] the corrupted signals are identified with the help of a clinician, and Shi et al. also report a signal quality metric based on the shape of the radar-based heart sound envelope and a threshold based on expert evaluation to provide a signal classification. The other papers consider body movements as artefacts to be recognised by means of a machine learning or deep learning detector. Regarding model choice, we can observe the use of CNN [166], hybrid structure with CNN + SVM [16], Long Short-Term Memory (LSTM) [163], LINEAR machine learning models [164], [165], [167], SVM [46], [164], [167], DT or RF [164], [165], [167], and KNN [164], [167], with accuracies of over 90% in most of the papers. A paper uses the heartbeat from a public ECG dataset to pre-train an LSTM model [163]. CW RADAR is employed in three papers, UWB RADAR in other two papers, and FMCW RADAR in the remaining two papers. A small sample size, less than or equal to ten subjects, is observed in all included articles, with the exception of two articles reporting 11 [165] and 30 involved subjects [164].

B. MONITORING OF HUMAN BEHAVIOR

Monitoring the way humans behave and act is one of most spread research lines in the RADAR sensing community, since RADARs were initially intended for target detection. In this section, we gathered papers focused on human detection ($n = 7$), localisation ($n = 4$) and orientation regression ($n = 2$), human activities classification ($n = 3$) and fatigue detection ($n = 9$). Nevertheless, our approach to the topic is slightly different from that of other reviews because in our research question, physiological sensing was a necessary aspect of the included papers; therefore, all of the included studies employ extraction of physiological signal and features as input or part of the input to a machine learning model to help achieve their final goal.

1) HUMAN DETECTION

We found 7 papers dealing with human detection aided with vital sign monitoring through radars. We can notice three main research lines across human detection papers being occupancy detection for vehicle applications [204], [208], [209], human detection underground [206], [207] and human detection in indoor environments [37], [205].

In natural disasters scenarios, such as earthquakes, floods or landslides, being able to promptly save a trapped person could make the difference between life and death. Among the included papers, two [206], [207] consider the detection of human vital signs in a simulation of a trapped victim condition aided by machine and deep learning. In this case, the choice of RADAR operating frequency is limited by the desired application, because to achieve the right penetration capabilities, RADARs need to work at low frequencies (generally less than 6 GHz). In the papers dealing with rescue systems, we notice the use of a CW RADAR at 1.3 GHz [206] and an UWB RADAR at 7.29 GHz with 1.4 GHz of available bandwidth [207]. In all these papers SVM is applied as a binary classifier to detect humans based on an input of extracted vital signs. A similar scenario for non-line-of-sight detection could be home surveillance [264], where we want to know which room a person is in. In this case, lower operating frequencies enable the necessary penetration behind the walls, as showed by Rana et al. [37], achieving an accuracy of 98.29% with a simple SVM and a UWB RADAR working at 4.3 GHz with 2.2 GHz of band-width. For general complex jamming environment detection, Liu et al. [205] propose a system based similarly on UWB and SVM to identify vital sign.

The application of occupancy detection in vehicles is another diffused topic in the research fuelled by the European New Car Assessment Program roadmap to 2025 [265], where the safety rating systems include child occupancy detection to prevent and reduce the occurrence of unattended children inside parked cars, which could lead to heat-stroke and death.

Passenger detection is relevant also for the efficiency in energy consumption and comfort of the passengers for a controlled heating in each seat [266]. Three papers implement passenger occupancy detection [204], [208], [209] with all different radar technology, being CW, FMCW and UWB, respectively. The sample size for these papers is limited to three subjects across different scenarios. The applied models are simple deep learning architectures or machine learning models, such as LDA and RF, with high reported classification metrics above 90%.

2) HUMAN LOCALISATION

Localisation of people is in a sense an extension of the detection task, where the goal is to provide a precise location of the subject with coordinates. The state-of-the-art of outdoor localisation is the Global Navigation Satellite Systems (GNSS), where the localisation performance usually ranges between 1 and 2 m of error from the subject's actual position in many commercial devices [267]. RADAR sensors in outdoor conditions can provide an increase of performance for complex environments and they do not require any receiver placed on the subject. In indoor scenarios, on the other hand, accurate positioning is more complex because of the inability to use GNSS. The state-of-the-art include many technological solutions, such as low energy Bluetooth based on Received Signal Strength (RSS) or Angle of Arrival, WiFi with channel state information, Radio Frequency Identification Device with an evaluation of Phase of Arrival, and cellular systems exploiting Reference signal-received power/quality [268]. RADAR sensors provide a further alternative which can be considered depending on the requirement of the indoor positioning system. RADAR sensors may have trouble locating a subject within a room when the subject is stationary, while showing great potential for moving subjects [269]. Therefore, detecting small vibrations in the chest due to breathing or heartbeat is often a way to mitigate the problem of a static subject [270].

Four papers [210], [211], [212], [213] deal with human localisation taking RADAR-based extracted vital sign as input. Overall, we can notice a tendency to increase the subject distance to 20 m, instead of working at the short range as in other applications. [210] employs MAE reporting an error of localisation ranging between 15 to 31 cm in outdoor conditions and 11 to 27 cm in indoor conditions; [211] employs RMSE with errors ranging from 12.3 cm to 20.7 cm; [213] uses as a metric the percentage of correct localisation within 30 cm or 10 cm error reporting a percentage from 2% to 15% with localisation based on breathing features only localisation and under 10% with localisation based on heartbeat features. All the included papers uses a UWB RADAR technology with two reported operating frequencies of 400 MHz and 4.3 GHz. The used models are KNN [212] or variants [211], SVM [213], ELM [210] and a CNN [211]. Only in the case of Liu et al. [211] subjects involved are localised while moving.

3) HUMAN ACTIVITY

Three papers [215], [216], [217] deal with activity classification taking as input vital signs. Although activity classification is a popular topic in the RADARs field, papers propose approaches based only on analysis of vital signs extracted from RADAR. Paper [215] could also have been included in the category of human detection, as it is an example of detecting human presence through the wall, to which the author also added human motion status. Another interesting example is given by [217], where five activities are analysed. The subjects performed shaking, marching, standing still, jumping, and sitting-up. Respiratory and heartbeat signals extracted by a FMCW RADAR are then given as input to a CNN-based architecture obtaining an accuracy rate of 98%.

4) HUMAN ORIENTATION

Only two papers [45], [214] were found that deal with human orientation classification by taking vital sign information as input. An interesting difference between the two papers is in the application of a simple machine learning based framework that takes breathing features as input to recognise orientation in [214], whereas a more complex deep learning alternative based on Generative Adversarial Networks is used in [45]. Both papers employed three RADARs in three distinct positions, with a slight change in their positions. In [214] the employed RADARs were perpendicular to each other and two of them were facing, whereas in [45] the RADARs were 120° apart from each other.

5) FATIGUE DETECTION

The occurrence of a fatigue or drowsiness state while driving has been described as a "silent killer" [271]. Every year 1.19 million people die as a result of traffic accidents [272], and fatigue worsens drivers' ability to respond to stimuli, their alertness and activity, increasing the probability of traffic accidents [273], [274]. The concerns with fatigue and drowsiness fuel research in advancements for driver monitoring systems [275]. For this reason the European New Car Assessment Program roadmap to 2025 [265] states that driver monitoring is a primary safety feature added to their safety rating systems. In addition to critical situations, being able to detect workers' fatigue or mental workload could be beneficial to their productivity and mental health.

We found seven papers dealing with fatigue or drowsiness detection in drivers [195], [196], [197], [198], [199], [200], [203], and two papers dealing with mental state workload [201], [202]. Six papers use a FMCW technology, two papers use UWB and one paper uses CW. The sample size of subjects involved in the studies ranges from a minimum of three to a maximum of 40, and in all papers the recordings are evaluated in simulated scenarios, with the exception of one paper that tests its approach in 6 real driving scenarios [200]. Fatigue is defined with a self-assessment of the subjects in four of the papers [195], [198], [199], [201], whereas in one paper the authors use a facial expert evaluation to assess the fatigue [196], and in another paper the drowsiness data come from drivers after a 10 hours long shift [200]. Both machine learning, such as KNN [197], [201], SVM [197], [200], [201] and ELM [196], and deep learning models with CNN + RNN [195] and MLP [199], [200] are employed. Across the included papers, the accuracy for the binary task of fatigue or drowsiness detection usually has an accuracy above 80% or AUC score above 80%. In the case of a more complex and comprehensive choice of the classes with normal, fatigue, stress and sleep, the accuracy drops to 52.88%. The only article dealing with cognitive load reports 70% accuracy for the busy and relaxed state and 83% accuracy for increasing and decreasing cognitive load [201].

C. RADAR-BASED AFFECTIVE COMPUTING

Emotions can be defined according to two main theories, i.e., the discrete emotion theory [276], and the continuous multidimensional theory, based on pleasure, arousal and dominance [277]. In the first case, emotions can be described as a set of basic and discrete categories characterised by their cognitive, physiological, and behavioural aspects. Six basic emotions were considered by Ekman [276], i.e., happiness, sadness, anger, surprise, fear and disgust. To overcome the challenges of a limited number of basic emotions, Plutchik proposed a mixture model, where more complex emotions are a composition of basic emotions [278]. On the other hand, the second theory defines emotions on a multidimensional emotional space characterized by arousal, or the level of activation; valence, or the degree of positive or negative feeling; and dominance, or the degree of control.

The interest in emotion recognition is driven by the development in human-machine interaction [279], its necessity in the field of healthcare for patients with neurological disorders [280] and for customer satisfaction prediction. There are many techniques in the scientific literature that explore emotion recognition based on physical features such as facial expressions and voice, but they lack to show a subject's inner feelings, so physiology-based features are increasingly used in the emotion recognition task with the availability of many multi-modal datasets. The use of contactless sensors offers the possibility of monitoring a subject's emotional response without having to wear cumbersome and often frustrating sensors and this motivates the research towards RADAR-based emotion classification.

We classified 9 papers in the area of RADAR-based affective computing. 7 papers [218], [219], [222], [223], [224], [225], [226] deal with emotion recognition, one paper with emotional intelligence classification [221] and one paper deals with lie detection based on the emotional response [220]. It can be noticed that all the papers dealing with emotion recognition classify only a small subset of possible emotions, with up to four classes, due to the clear complexity of the topic. The methods for building the emotion dataset in the included papers always involve a video stimulus to elicit the emotion and a questionnaire to check the emotional response. Two papers state directly the use of valence-arousal theory [219], [226]. Regarding machine learning or deep learning choice, we observe both simpler alternatives, with SVM [221], [222], KNN [222], [223], [224], Random Forest (RF) or DT [222], [223], and deeper models with MLP [223], CNN [219], [223] and CNN + RNN [225], [226]. The size of the dataset of the included papers ranges from 5 subjects [224] to 72 subjects [218], with the subjects involved in a static condition. Two interesting applications related to the field of emotion recognition are the classification of emotional intelligence into high and low in a sample of 51 subjects with labels given by a self-report [221] obtaining 85% f1-score and lie detection on a sample of 21 subjects with an accuracy better than 63.2% [220] based on heart-derived features. The overall accuracy across the emotion recognition papers ranges from 70% and to nearly 90%, but the unavailability of large public datasets and the small subset of emotions employed makes it difficult to understand the reliability of the methods and to provide benchmarks for future directions.

D. RADAR-BASED BIOMETRIC AUTHENTICATION

Biometric authentication is a field of great potential due to the fact that the biometric features that characterise each individual are intrinsic qualities of the subject's identity and thus cannot be lost as ID cards or forgotten as passwords and are really complex to fake [281]. There is growing interest in targeting people's identities with biometric features for surveillance and security purposes; contactless monitoring seems to be a solution to the problem that offers the opportunity for limited end-user interaction and continuous extraction of vital sign information. As some of the included papers state [234], [237], RADAR systems have a recognized higher reliability than facial or iris recognition systems, which are dependent on lighting conditions and do not preserve the privacy of the subject.

We found 19 papers dealing with biometric-based authentication of users. Seven papers employ a CW RADAR [229], [231], [232], [233], [239], [240], [243] and 4 papers a FMCW RADAR [228], [230], [237], [241], while the remainder do not clearly report RADAR technology. We can observe great heterogeneity in the dataset size, with 7 papers proposing methods for authenticating fewer than 7 subjects [24], [26], [229], [236], [239], [240], [241] and 6 papers proposing methods for authenticating more than 30 subjects [227], [228], [230], [231], [233], [242]. In all but one of the papers, the task is a closed-set authentication in which only users within the given dataset are classified, while Yan et al. also study the case of an open-set authentication in which a class of unknown persons in addition [233]. We also found a variety of traditional machine learning models employed, such as SVM [24], [26], [227], [228], [229], [236], KNN [26], [229], [238], [239], [241], [242], DT [227], [228], [230], and also more advanced deep learning models, such as CNN [233],

[234] and transfer learning [235], [237]. In addition, the reported accuracies in all the papers reviewed are positive in most cases, with over 90% accuracy in 12 papers [24], [26], [227], [228], [229], [231], [232], [233], [234], [236], [239], [242]; there are three examples with less than 50% accuracy [235], [237], [238] of which [235], [237] improve their classification accuracy to over 90% when both gait and heart features are included in the model. Only in two cases [230], [243], public datasets are used, and this seems to be the aspect that could be improved to provide benchmark results for future researchers in the field. In fact, when using public dataset with increased number of user the reported metrics are between 70 and 80% of accuracy. In all the papers the authentication procedure is tackled as a closed-set problem, where all the users to authenticate appear in the dataset; only in one paper [233] there is an open-set evaluation with subject external to the dataset classified as outside the authorised users. The evaluation of the system in an open-set scenario tests the its reliability against subjects on which the system has not been trained on. In fact, the model proposed in [233] achieves a 99% accuracy in a closed-set scenario, whereas in an open-set scenario the accuracy declines to 93.42%, demonstrating the more complex nature of the open-set challenge. Equal error rate (EER) is applied twice [228], [231] as a performance metric.

VII. DISCUSSION

In the recent years RADAR technologies have been extensively employed for the extraction and the classification of physiological signs. The aim of this scoping review is to report on machine learning applications in RADAR physiological signals monitoring, with emphasis on recent and current trends and possible gaps in the analysed literature. In the next sub-sections we report the main performance metrics employed for each area of interest (sub-section VII-A), the main issues found in the reviewed manuscripts (sub-section VII-B) and the good practices (sub-section VII-C).

A. STANDARDS FOR PERFORMANCE EVALUATION

The metrics used to evaluate the performance of the proposed algorithms related to the first cluster have been shown in subsection IV-B1. In the first cluster of papers and the sub-categories of value estimation, signal reconstruction and physiological event detection, we can observe a variety of metrics used to demonstrate the performance of the algorithms. In the following paragraphs we discuss the existence of standards for evaluating non-invasive devices for each of the identified objectives.

1) HR ESTIMATION

For heart rate estimation, some work uses a 2002 Association for the Advancement of Medical Instrumentation (AAMI) guideline on heart rate monitors [282], which states that the clinically acceptable absolute difference in beats per minute of a heart rate monitor compared to the reference electrocardiogram is 5 bpm. In terms of accuracy, defined in Table 7 as $\frac{1}{N}\sum_{i}^{N} 1 - \frac{|prediction_i - truevalue_i|}{truevalue_i}$, the standard reported an acceptable threshold of 90% (sometimes the threshold is referenced in terms of MAPE <10%). Thus, for heart rate measurement the metrics that should be employed are the MAE and the accuracy compared to a reliable ground truth. Even though the standard has more than 20 years now, we did not find any update available and in many other application was recently used as guideline for both contactless sensors [283], wearable sensors [284] and commercial sensors [285], confirming its relevance in the scientific literature. We note only one other standard cited in the included literature in [75]. The Consumer Technology Association released criteria for heart rate monitors with the same criteria of MAPE less than 10% [286].

2) BR AND SPO2 ESTIMATION

For the breathing rate we did not find any comparable standard available or cited by the included papers. The employed metrics for BR estimation are MAE, RMSE and accuracy. For SpO2 estimation there is only one paper that employs MSE, accuracy and Bland-Altman plots. For contactless estimation of SpO2 from RGB analysis a recent review reports the application of correlation and RMSE [283].

3) BP ESTIMATION

Regarding blood pressure estimation, we notice the application of two standards to judge the performance of non-invasive sphygmomanometers, i.e., the American Association of Medical Instrumentation (AAMI) [287] and the British Hypertension Society (BHS) standard [288]. The AAMI standard is intended for continuous cuffless monitoring in the clinical setting with a BP output every 30 seconds or less. The reference method is intra-arterial pressure, which is not used by any of the included papers. The pass requirements for the proposed method are an absolute difference of 6 mmHg and a standard deviation of 10 mmHg. The sample size can change between 30 and 120 in the standard. Instead, the BHS standard provides grades depending on the percentage of BP readings that fall within a certain absolute error of a reference auscultation method or mercury sphygmomanometer and it is intended for intermittent devices (BP output after more than 30s, usually 30 to 60 min) used across 24 hour evaluation. The sample size of subjects involved should be 85, which is not respected by any of the included papers dealing with BP estimation. A grade A is given to a device reporting 95% of the measurement within 15 mmHg error, 85% within 10 mmHg and 60% within 5 mmHg. If the percentages degrade by 5% for the 15 mmHg threshold and 10% for the other two thresholds, we have a grade B device, which is the minimum requirement for clinical use; if the percentages degrade by the same amount again we have a grade C device. Grade D is given to devices with worse performance than grade C. Another standard that can be considered, given its recent relevance, is that proposed by the European Society of Hypertension [289], which compares its recommendations with the ones of the AAMI standards and clearly explains the differences. Their guidelines are for intermittent 24-hour monitoring devices, with a reference method consisting of auscultation or oscillometry for 24 hours. The sample size ranges between 85 and 175 depending on device type, calibration-free or with demographic calibration, and provides more strictly pass requirements, with absolute difference of 5 mmHg and standard deviation of 8 mmHg taken from the Universal Standard (ISO 81060-2: 2018) [290], [291] for cuff-based methods.

4) ECG SEGMENTATION

The standard reporting performance metrics for R-peak detection and in general ECG wave recovery is the "ANSI/AAMI. Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms " [292], where a tolerance of 150 ms around a physiological event is defined for a true positive prediction. Therefore, an automatic R peak detector should produce a prediction within 150 ms of the true time position of the R peak, and all predictions outside this window are considered false positives; the absence of predictions within the window would be considered a false negative. The standard then proceeds to define Sensitivity (Se) as TP/(TP+FN) and positive predictive value (+P) as TP/(TP+FP); sensitivity is often called recall and positive predictive value is called precision. In the included papers regarding physiological event detection the researchers usually employ tolerances that are more strict than 150 ms, such as 75 ms for R-peak and heart sounds [87], [89], 70 ms for heart sounds [88] and 10 ms for ECG waveforms segmentation [106]. Moreover, some of the papers include value estimation error metrics to report the distance between estimated vital signs and ground truth vital signs, such as MAE for IBI [91], and also metrics of distance between the predicted event and the actual event such as RMSE for heart sounds prediction [59], MRE for systole/diastole segmentation [90] and MRPE on ECG waveforms [106]. Therefore, future developments should be compliant with the performances metrics reported by these papers and report at least sensitivity and positive predictive value based on the definition of a tolerance around the physiological event and also distance metrics between prediction and actual event, such as MRE, RMSE, MAE, MRPE. It is important to notice that the tolerance to 150 ms is defined for adults and it should be reduced to 50 ms when dealing with fetal ECGs [293], [294].

5) PHYSIOLOGICAL SIGNAL RECONSTRUCTION

Across the studies reporting a reconstruction of a physiological signal, such as simplified cardiac waveforms, breathing signal, PPG, SCG and even ECG, we did not find a clear cohesive set of metrics used. This may be due to the variety of signals used and the novelty of the topic. The lack of clear metrics for fine-grained reconstruction was highlighted also in a recent review regarding algorithms for heart rate estimation from RADAR sensors [2]. Nevertheless, we found some repeated metrics of interest that could delineate how to compare new approaches to previous ones. Moreover, in papers dealing with signal reconstruction, we noticed the use of performance metrics related also to the detection of physiological event and estimation of heart rate with the previously mentioned AAMI standards [282], because the output of a reconstruction algorithm must not only have high fidelity in waveform similarity, but must also be useful for detecting clinically relevant events and parameters.

The first class of metrics are the ones related to the integrity of physiological events; authors should report the error of clinically relevant parameters extracted from reconstructed signals. MAE and RMSE for IBI, HR, BR, HRV are applied in the reviewed literature [30], [36], [41], [78], [105], along with MRE and MAE normalised by heart period when dealing with automatic extraction of fiducial points [30], [44], [68], [105]. One paper by Xu et al. [68] proposes also Weighted Diagnostic Distortion, a metric usually employed in signal compression research [295] to provide a measure of clinical quality of the reconstructed signal.

The second class of metrics are related to signal fidelity and similarity, where we mainly observe the use of correlation [32], [36], [68] and cosine similarity [30], [74], [105]; two papers propose a measure of noise as difference between reconstructed signal and ground truth signal [68], [76]; RMSE is employed in [41].

B. ISSUES OF THE INCLUDED LITERATURE

1) NO CLEAR BENCHMARKS

In all the papers analysed, only a small percentage reports a comparison with traditional techniques, as reported in Subsection IV-B4. The lack of appropriate comparisons and the absence of widespread use of publicly available datasets makes it difficult to have clear benchmark results for the proposed new techniques. To achieve greater reliability, researchers should make an effort to build benchmarks on the available datasets, as has been done for human activity recognition with RADAR [296].

2) SMALL SAMPLE SIZE

We reported in Subsections IV-B and V-A the median values and the interquartile range of the dataset size for both the identified macro clusters of papers. For the first cluster, we found a median of 12 (interquartile range: 5 - 24), whereas for the second cluster we found a median of 14 (interquartile range: 6.5 - 35). There are no clear criteria in machine learning for population size, however we can notice that the median and the 75% quartile in the first and second cluster are smaller than many of the publicly available datasets 6. Moreover, if we follow the guidelines provided by the medical standards, the sample size increases to 85 subjects or more, as previously mentioned in Subsection VII-A.

3) RELIABILITY OF REFERENCE SENSORS

Regarding estimation of vital signs, having a reliable and accurate is fundamental for an adequate reporting of the results. Only 9 [22], [28], [40], [57], [97], [102], [103], [104], [114] papers of the 22 papers dealing with estimation of heart rate used an electrocardiogram (ECG) with 6 using single-lead ECG [22], [28], [40], [57], [97], [114], 1 using three-leads ECG [28] and the remaining not reporting the number of leads [102], [103], [104]. For the value estimation task an ECG is employed in one paper for breathing rate estimation [167] and in one paper for blood pressure estimation [111]. In the signal reconstruction task all the papers dealing with ECG or cardiac waveform reconstruction employ an ECG as reference sensor [32], [36], [41], [68], [79]. In the physiological event detection task 4 papers employ a public dataset with reliable ECG recordings [59], [89], [91], [106] and other 3 record data from an ECG as ground truth [87], [88], [90]. The lack of reliable reference sensor impairs the positive results of many of the reviewed literature in the context of heart rate estimation. However, it seems to be a common practice in the signal reconstruction task and physiological event detection, where the use of publicly available dataset is diffused.

4) SIMULATION OF BREATH PATTERNS

One of the largest group of papers gathered in the second cluster dealt with breath patterns classification, which is fundamental in the diagnosis of respiratory and sleep disorders. However, the majority of the papers (20 out of 39) involve subjects simulating the wanted breath patterns instead of relying on subjects experiencing a breathing disorder. Although the use of simulation can be understood in a training phase of the algorithm, it should not be used in the testing phase because the performance will be positively distorted by the simplification given by the simulation. An example of the use of simulation during training and development of the algorithm can be seen in [158], where the accuracy in validation given by simulation reached 94.7%, while in the actual deployment cases with three diseased patients the accuracies fell down below 90%. With the goal of developing contactless instruments that can be useful in clinical practice, final tests must always be performed in the scenarios in which we want the devices to work.

Nevertheless, there are situations where simulation is the only alternative, such as in the case of monitoring fatigue and drowsiness during driving. In addition, we noted an application of contactless breath patterns recognition in which subjects simulated certain breath patterns motivated by human-computer interaction rather than the diagnosis of a breathing disorder [134]; thus, in this case, the simulation was acceptable because it was the scenario in which the device was intended to be used.

C. GOOD PRACTICES

In this subsection, we aim at delineating a set of good practices that we extract from the reviewed literature that authors should maintain while building a dataset with radar sensors for vital sign sensing.

1) VALIDATION OF ML ALGORITHMS

Building a large dataset with many subjects is often a challenging task for researchers, and as can be seen from the included papers, most sample sizes are less than 30 subjects. Therefore, the first effort the authors should make is to record at least 30 subjects. When the number of subjects is small, the validation methodology employed becomes much more important. Cross validation is a statistical technique that enables to provide a measure of accuracy by taking the whole dataset in training phase and the whole dataset in the testing or validation phases. Nevertheless, researchers should be careful to divide the model development phase, which should be carried out entirely on the training data, and the model implementation phase, which should be carried out on a separate, non-overlapping validation or test set, to avoid over-fitting and biased results [297]. Thus, when dealing with small sample sizes, a nested type of k-fold cross-validation is preferred because of the demonstrated unbiased performance estimation [297]. With nested k-fold cross-validation, it is simply meant that in each fold of the validation the model development stage, starting from parameter tuning to feature selection if needed, must be performed on a training set, while the model validation must be performed on a validation set composed of a different group of subjects. The hold-out method is by far the most diffused in the analysed literature (see Figure 7), and even if is a good method in terms of positive performance bias [297] does not enable to use the whole dataset as a cross-validation procedure. Another form of cross-validation to be considered, being simply an extension of a k-fold cross-validation is the LOSOCV, where the number of folds corresponds to the number of subjects, and during each iteration a different subject is selected for validation. If there are no the computational cost issues, the LOSOCV is a good method to exploit the whole dataset and also provides unbiased estimation if the nested partition between training and validation is maintained.

2) THE PROBLEM OF SYNCHRONIZATION BETWEEN RADAR AND REFERENCE

One of the common problems encountered when building a dataset is synchronization between RADAR sensors and reference sensors. In Tables 6 and 5 different methods used in the reviewed literature are reported. The simplest one is a manual synchronisation in post-processing given by an evident mechanical event, such a shoulder tap [118]; the synchronisation in post-processing with cross-correlation study is actually a diffused method in the studied datasets thanks to the usage of binary synchronisation sequences [87], [119]. Other widespread techniques are time stamps synchronisation [40], [97], synchronisation given by a LabVIEW framework [79], [111], [120] or the Precision Time Protocol technique [30], [74], [105].

3) TESTING THE ROBUSTNESS OF THE SYSTEM

The screened literature contains different methods to check the robustness of a proposed approach and to demonstrate its reliability. One valid way to test the robustness of an approach is to measure how performance metrics change as the distance to the target from which a vital sign is extracted increases. Diraco et al. [114] test the performance of BR estimation from 0.5 m to 5 m, with accuracy dropping from 88% to 77%, and HR estimation from 0.5 m to 2 m, with accuracy dropping from 85% to 71%. Wu et al. [55] evaluate their proposed approach of HR estimation with subjects at 0.5, 0.8 and 1.2 m, with an accuracy of 97.45%, 97.12% and 97.26% in the three tested distances. Liang et al. [73] test their BP estimator with the subject arm going from 12 to 25 cm and different arm angles.

Works dealing with signal reconstruction also study the impact of distance and orientations. An interesting way to show the performance of an ECG reconstruction system is that proposed by Xu et al. [68], where a matrix of distance and subject orientation is proposed to test all the combinations between the distances of 1, 2 and 3 m and the orientations between 60 and $-60°$, with a step of 30°. The authors use the weighted diagnostic distortion value for each of the tested condition and applied a gradient to the obtained values for a simple visual check of the system performances. Zheng et al. [74] check the robustness of their approach of breathing waveform reconstruction with cosine similarity, considering subjects at a distance going from 0.5 m to 2 m. In a similar study of breathing waveform reconstruction with walking subjects [105], the performance is assessed for distances going from 1 to 6 m with a step of 1m and for different walking speeds going from 0.2 to 1.5 m/s with cosine similarity. Other external factors that can be evaluated are the clothes [74] or the accessories [68] worn by the subjects.

We also noted the use of statistical tests to check the influence of confounding factors such as age, gender, skin color, and thus the fairness of the system [68], [75].

VIII. CHALLENGES AND FUTURE DIRECTIONS

A. DEVELOPMENT IN SENSOR TECHNOLOGY

One of the most noticeable trends that we have noted throughout the literature is the spread of automotive FMCW RADARs in recent years, which are rapidly replacing CW RADARs due to their ability to provide range information and the growing interest in higher operating frequencies, which unfortunately involve higher attenuation and lower signal-to-noise ratio. Thus, it seems that the development in sensor technologies would be one of the next steps to be taken in the near future.

1) MIMO RADARs AND BEAMFORMING

In recent years there has been a growth in the use of Multiple-Input-multiple-Output (MIMO) RADARs, with an increase in the number of antennas towards what is usually called massive MIMO. Exploration of the full capabilities of these technologies is still in its early stages, and its applications in the biomedical field should be further studied. The availability of a large number of antenna arrays allows beamforming with decreasing angular resolution in azimuth and elevation. In the included literature, we have noted the application of digital beamforming to improve the performance of the proposed estimator; one example is three-dimensional digital beamforming, which allowed the authors to discriminate the phase changes of different voxels of the chest with a RADAR positioned 40-50 cm from the subject's chest [36], followed by a Dynamic Time Warping algorithm and KNN for selecting and summing similar periodic patterns, thereby achieving spatial filtering and increased signal-to-noise ratio.

We found only two papers [91], [111] dealing with RADARs working with frequencies higher than 100 GHz (0,1 THz). As operating frequencies increase and antenna sizes decrease, we obtain RADARs with more antennas for equal occupied space compared to RADARs at lower frequencies and potentially greater virtual arrays of antennas. Consequently, the ability to form narrower beams aimed at specific parts of the body has become a reality. For example, a recent application of a 122 GHz FMCW RADAR reached an angular beamwidth of 2 degrees at -3 dB of attenuation [91]. Another application of interest, where we can observe the use of TeraHertz RADAR with operating frequency at 300 GHz (0.3 THz), is in the context of driver drowsiness detection [298].

2) SENSOR FUSION

The development of techniques to merge information from multiple RADARs at different locations certainly improves estimation performance related to vital signs, as demonstrated in [45]. Nevertheless, RADAR fusion is not deeply studied in the reviewed literature and can represent a solution to deal with moving targets or multiple subjects vital sign extraction. Moreover, RADAR sensors are known for their intrinsic privacy preserving nature and for their robustness to light conditions. Thus, the fusion of information from RADAR sensors with other types of sensors could be used to improve performances, robustness, fairness and privacy of systems working with physiological signals. We have seen an example of performance improvement in the field of infection detection, where CW RADARs are used together with thermal cameras and laser Doppler sensors to achieve better results in discriminating infectious subjects [170], [171], [172], [173], [176]. Concerning fairness, we have found a study by Vilesov et al. [75] in which an automotive FMCW RADAR and RGB video were the two modalities fused together to achieve a skin tone independent estimator of the PPG signal while providing an increase in overall system performance.

3) RADAR SENSING FOR GREATER DISTANCES

From the analysed manuscripts it is possible to observe that the median distance of subjects from the radar is 0.85 meters (interquartile range 0.55 - 1.36) in the first cluster and a median distance of 1 meter (interquartile range 0.45 - 2) for the second cluster. The trend is to have the subjects at a distance of less than 3 m to have adequate performance. Increasing the distance would mean facing greater attenuation of the received signal power and thus a considerable drop in performance. This is especially relevant considering the spread of automotive RADARs working at frequencies above 60 GHz and the spread of the TeraHertz band in the near future. The ability to properly detect and localise a subject and then apply beamforming to limit the clutter given by the background would be a necessity as distances and frequencies increase.

4) RADAR SENSING FOR MOVING SUBJECTS

Scenarios in which subjects are moving pose a complex challenge for RADAR-based physiological sensing, since it is necessary to find ways to track the subject and than extract the desired physiological signal. In Tables 6 and 5 we can observe how the scenario of moving subjects is way less studied than that of static subjects; 9 out of 68 papers in the first cluster explore moving scenarios, including simple moving patters performed in a confined physical space [17], [29], [30], [68], [74], and more complex moving scenarios [40], [78], [105] (e.g. walking, activity of daily living). In the publicly available datasets there is a lack of examples in these complex conditions with the recordings of 14 walking subjects [40], the recording of 3 subjects in daily living activities [78] and the recordings of 6 subjects while performing exercises in a spatially confined space [17].

B. APPLICATION TO COMPLEX SCENARIOS

1) EXPLORING THE FEASIBILITY OF RADAR SENSORS IN THE CLINICAL CONTEXT

The contactless nature of RADAR sensing and its privacy preserving quality could make RADAR sensors a key instrument for clinical diagnosis. To achieve the goal of automatic clinical feedback or diagnosis, we must be able to extract many more features than just vital signs, which certainly remain important parameters for initial and continuous screening of a patient's health status. We have noted a few examples in the scientific literature of electrocardiogram reconstruction or segmentation of cardiac events; the ability of RADARs to not only evaluate simple vital signs but to reliably segment or reconstruct an electrocardiogram or an interpretable cardiac waveform would drastically increase their clinical utility. There are some healthcare contexts where contactless technology could be revolutionary, such as in neonatal care and elderly care, where the use of wearables causes irritation to patients' sensitive skin. However, in the reviewed literature, these two age categories have not been addressed in depth.

2) THE POTENTIAL FOR APPLICATION TO SPORT

Robust extraction of physiological signals from a moving scenario is definitely one of the biggest challenges of RADAR-based sensing, given the need to track the subject and then reconstruct the waveform. In the scientific literature, we observed the presence of approaches that generally deal with simple body movements or more complex movements such as walking. In this context, the application of ML/DL techniques can be either in the first phase of subject detection and tracking, the second phase of physiological signal reconstruction and vital sign estimation, or both. The ability to continuously monitor a subject while acting "in the wild" is certainly the ultimate goal and could have great utility in the clinical scenario. Apart from that, application to sports could be a next step. Some attempts to include contactless extraction of HR and BR from people performing quasi-static physical activity, such as jogging in place, have been identified in the literature reviewed. The possibility of applying RADAR in more complex environments, such as gyms, where RADARs could be part of the training tool and used to provide feedback and metrics on sports performance, is one of the possible other application areas in which this technology could develop.

3) EXPLORING THE EXTRACTION OF VITAL SIGNS FROM DIFFERENT BODY PARTS

Most of the studies reviewed apply RADAR as contactless extractors of chest vibrations, but we have seen some examples where small displacements given by arteries in the arm [73] or leg [57] are used to provide accurate readings of vital signs. The ability of RADAR to be focused on different parts of the body, thanks in part to the development of larger antenna arrays and beamforming capabilities, could be explored in the future. An example of application would be to distinguish chest and abdominal displacements simultaneously, giving the possibility of assessing the synchrony or asynchrony of thoraco-abdominal movement in the case of thoraco-abdominal complex, a common disorder of hypopnea patients [251]. Another possibility could be synchronous extraction of chest vibrations, directly linked to heartbeats, with arterial pulse displacement occurring in the distal parts of the body, in order to directly assess blood pressure by exploiting pulse transit time with a single device.

C. NOVELTIES IN THE EXTRACTION OF PHYSIOLOGICAL SIGNALS

1) EXPLORING THE POTENTIAL OF ABSORPTION-BASED APPROACHES

Most of the applications we have seen exploit the Doppler effect, for which changes in the phase of the transmitted signal are related to the periodic variation of the velocity of the chest or even of the arterial walls in the distal parts of the body. Nevertheless, we also found an application exploiting Received Signal Strength (RSS) for blood pressure monitoring [73], in which the authors show better performance with RSS than with the phase signal extracted from the arm for this specific application. In addition, the researchers show how the periodic variation of RSS over time is caused by the increase in blood volume absorbing more radiation, and as a result, RSS is directly proportional to the periodic variation of arterial wall diameters in the subject's arm. These absorption-based applications have not been sufficiently studied in the scientific literature and could open up the possibility of extracting other important physiological parameters, such as glucose levels [299].

D. IMPROVING THE PERFORMANCES AND RELIABILITY OF MACHINE LEARNING MODELS

1) PRE-PROCESSING NOVELTIES

In the literature reviewed, the importance given to the demodulation of In-phase and Quadrature signals is limited, with most of the papers using a standard arctan demodulation and a single paper stating the use of an extended differentiate and cross-multiply algorithm [106]. It is unclear from the literature reviewed whether changes to the demodulation algorithm can affect the performance of machine learning or a complex deep learning architecture, so this is something to be evaluated. Additionally, we found four papers [74], [75], [97], [105] dealing with raw In-phase and Quadrature signals provided directly to a deep learning architecture, thereby another alternative would be not to process the raw signals at all and to take advantage of the ability of deeper architectures to understand the high complexity of raw dynamic signals.

2) INTERPRETABILITY OF THE "BLACK-BOX" ML/DL

One step that was not performed in any of the reviewed publications is the application of interpretability analysis to the results of ML/DL approaches. Interpretability is a critical aspect to understand how the model makes a decision and how to improve its performance. For biomedical applications, having a clear view of how a model achieves a given outcome is critical to understand its adherence to physiology. In the literature reviewed, we noted a few examples in infection detection (see Subsection VI-A3) where the output of the models was easily interpretable given its simplicity and the small number of features, yet no article proposed a state-of-the-art interpretability analysis such as GRAD-CAM [300], LIME [301] and SHAP [302]. To achieve the ultimate goal of providing medical personnel with a useful tool for diagnosis and screening, we must also provide a way to interpret its results and understand the relevance of the characteristics provided as input.

3) TRANSFER LEARNING

Transfer learning, in the context of machine and deep learning, is a technique in which large datasets and validated architectures are leveraged to obtain pre-trained models, which are employed to extract feature maps from different data and for other tasks. This procedure of transferring knowledge from one task or domain to another provides a way to deal with a small sample size, as it reduces the training required and can produce better models. As a consequence, it could be a good way to address the lack of data in the field od RADAR sensing. Transfer learning was also discussed in a recent review on cardiac feature extraction algorithms as a technique to explore [2]. In some of the reviewed papers transfer learning is actually employed for the aforementioned reasons, with applications to the authentication [235], [237]. Iyer et al. [15] employed the 'MIT normal sinus and arrhythmia' dataset [255] to train a model that is directly applied to RADAR extracted heart rate. Similarly, Li et al. [163] use 'PhysioNet ECG 1D' dataset [255], [303] to train a model for HR state classification that is applied directly to signals extracted from the RADAR. Nevertheless, the two approaches do not fine-tune their developed models to improve the performance, but only applied the pre-trained models on new data. Moreover, the potential of exploiting transfer learning should also be thoroughly investigated in a hybrid framework combining deep learning and machine learning models.

IX. CONCLUSION

Contactless technology is proposed as a possible alternative to traditional contact devices in the field of monitoring and application of physiological signals. The ability to extract information about a patient's health status in an unobtrusive way, without stressing the subject and without the need for specialized personnel, fuels research in this growing field. This scoping review aims to summarize the main research lines regarding RADAR-based physiological sensing and machine learning applications, reporting recent trends, issues and gaps with the scientific literature, methodological best practices, standards employed to follow, challenges and future directions. The large number of papers found dealing with physiological sensing and machine learning confirms the importance of these research lines in the RADAR community, and the wide variety of aims lends credence to the penetration that RADAR sensors have had in many different fields of application, ranging from biomedical engineering to cyber security. In the collection of information from the included scientific literature we focus not only on the aim of application, but also on the employed RADAR technology, the employed machine learning or deep learning model, the dataset and setting of the acquisition and the reported performance. CW, FMCW, UWB RADARs were the equally employed in the reviewed manuscripts with a growing interest towards automotive RADARs in the frequency range between 60 to 80 GHz due to commercial availability and versatility. Frequency higher than 100 GHz have still limited applications.

Lack of clear benchmarks for the estimation of physiological signals and features, poor diffusion of the publicly available datasets and their limited sample size are the main issues. Moreover, even if RADAR sensors could be proposed as optimal devices in the case of the elderly care, we did not find studies dealing with the age groups of people over 65 years or even over 75 years, which means that the RADAR devices have not been tested in the actual clinical context.

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