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# Machine Learning for Healthcare Radars: Recent Progresses in Human Vital Sign Measurement and Activity Recognition

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***Abstract*—The unprecedented non-contact, non-invasive, and privacy-preserving nature of radar sensors has enabled various healthcare applications, including vital sign monitoring, fall detection, gait analysis, activity recognition, fitness evaluation, and sleep monitoring. Machine learning (ML) is revolutionizing every domain, with radar-based healthcare being no exception. Progress in the field of healthcare radars and ML is complementing the existing radar-based healthcare industry. This article provides an overview of ML usage for two major healthcare applications: vital sign monitoring and activity recognition. Vital sign monitoring is the most promising healthcare application of radar, as it can predict several chronic cardiac and respiratory diseases. Activity recognition is also a prominent application since the inability to perform activities may result in critical suffering. The article presents an overview of commercial radars, radar hardware, and historical progress of healthcare radars, followed by the usage of ML for healthcare radars. Subsequently, the paper discusses how ML can overcome the limitations of conventional radar data processing chains for healthcare radars. The article also touches upon recent generative ML concepts used in healthcare radars. Among several interesting findings, it was discovered that ML does not completely replace existing vital sign monitoring algorithms; rather, ML is deployed to overcome the limitations of traditional algorithms. On the other hand, activity recognition always relies on ML approaches. The most widely used algorithms for both applications are Convolutional Neural Network (CNN) followed by Support Vector Machine (SVM). Generative AI has the capability to augment data and is expected to have a significant impact soon. Recent trends, lessons learned from these trends, and future directions for both healthcare applications are presented in detail. Finally, the future work section discusses a wide range of healthcare topics for humans, ranging from neonates to elderly individuals.**

***Index Terms*—Healthcare Radars, deep-learning, vital sign measurement, activity recognition.**

## I. Introduction

DUE to a rapid increase in the life expectancy, population aged 65 years or above is expected to reach nearly 1.5 billion in 2050 which previously was 524 million in 2010 [1]. Consequently, age-related chronic diseases are also increasing and the need for having detective and persuasive healthcare solutions is more than it was ever. Elderly person either living at home or old-care facility, should not be left unattended for a long period of time. Additionally, at a healthcare facility, everyone regardless of age requires a continuous health monitoring to prevent chronic sufferings such as cardiac arrest and fall, and the hospitals in the developed countries are already facing under-staff issue [2]. In addition to the usage at healthcare facilities, ambient intelligence offered in non-contact and non-invasive fashion can be used in the daily living spaces since humans spends a sizeable amount of time at home. For such scenarios requiring continuous or at least frequent monitoring, a non-contact and non-invasive sensor can provide a detective and persuasive system. Perhaps, progresses in Machine Learning (ML) and low-cost off-the-shelf (OTS) sensors can collectively complement the existing detective and persuasive healthcare system.

Physiological and bio-medical signals measurement in non-contact and non-invasive fashion can be accomplished with several sensors such as a vision-based (camera) sensor, or a radio sensor such as radar. Unlike vision-based sensors, radars have no associated privacy issue, and the radar-acquired data is not highly vulnerable to lightning and other environmental factors [3].

Radar sensors embedded in the surroundings of a patient can provide an ambient intelligence platform, capable of extracting several health-related physical and physiological signals. In radio detection (Radar), a transmitter sends a periodic signal which is reflected by the target present within the radar-cross-section (RCS). The signals reflected from the target are collected at the receiver to extract the information related to the target under consideration [4]. With human subjects as a target in the RCS area, the radar returns can be analyzed to extract information related to the health and well-being of human subject under consideration. Fig. I (a) shows all the physiological signals that can be measured using radar sensor.

While designing a healthcare solution with radar, radar-extracted bio signal must be compared with a medically proven gold standard technology. Hence, the signals from both the sensors are extracted simultaneously to measure the correlation between radar and the reference gold standard device. Fig. I (b) outlines a few gold standard sensors being used alongside the radar sensor. For instance, respiration belt, End-tidal Co2 mask and Electrocardiogram (ECG) sensor are considered as a reference devices to measure the Breathing-Rate (BR) as shown in Fig. I (b). Similarly, Electrocardiogram (ECG) sensor is used as a reference sensor to measure the Heart Rate (HR). Measuring BR and HR from the chest displacement is one of the most promising applications being offered by radar

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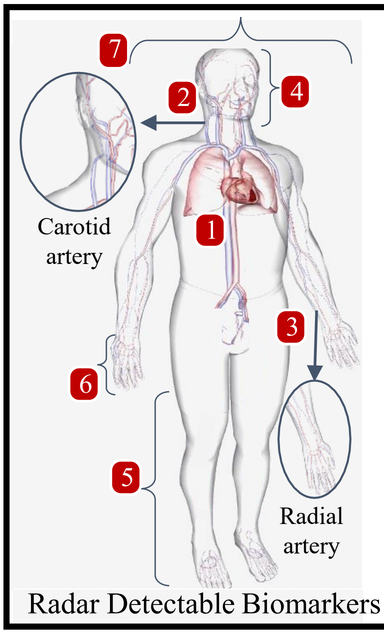
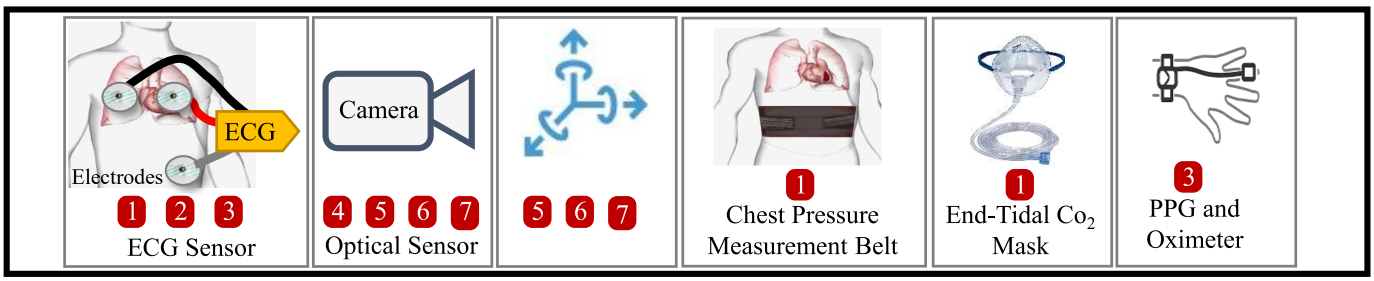


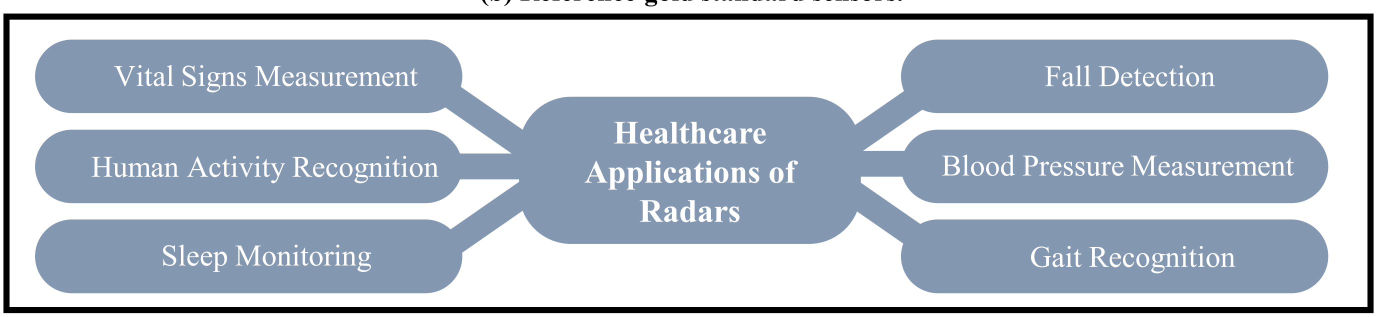

**Biomedical signal measurement through radar**

| No | Movement | Measurable bio-signal | Movement Type | Gold-standard Sensor |
|---|---|---|---|---|
| 1 | Chest & lungs | Heart Rate and Breathing Rate measurement | Periodic | ECG, oximeter, pressure belt |
| 2 | Carotid pulse | Heart rate measurement and ECG signal construction | Periodic | ECG sensor |
| 3 | Radial Pulse | Heart rate and blood pressure measurement | Periodic | PPG, ECG sensors |
| 4 | Head | Assisted living | Aperiodic | Camera |
| 5 | Gait (leg) | Fall prediction & Neural disorder detection | Aperiodic | IMU, Camera, warble markers |
| 6 | Hand | Assisted living | Aperiodic | Camera |
| 7 | Full body | Fall and activity recognition | Aperiodic | Camera, IMU |

**(a) Summary of biomarkers and the corresponding biomedical signal measurement through radar.**




**(b) Reference gold standard sensors.**




**(c) Popular radar-based healthcare applications.**

Fig. 1. (a) Healthcare-related physiological signals measurable with radar sensor, (b) the gold standard sensors for performance evaluation and (c) list of few popular healthcare applications

[5]. Other than chest vibrations, the vibrations created by carotid pulse around neck area are also used to extract the Electrocardiogram (ECG) signal [6], as expressed in the Fig. I (a). Radar sensor has also shown its effectiveness in the radial pulse measurement [7], and the synchronized extraction of carotid pulse signal and the radial pulse signal has enabled radar to measure human blood pressure [7].

The prominent healthcare applications of radar enabled by utilizing these biomarkers are listed in Fig. I (c). Each application has independently been studied by several researchers. At present, each of the applications has emerged as an independent research domain.

Artificial Intelligence (AI) has widely been considered to process radar-recorded physiological signals. Similar to any other domain, AI is also revolutionizing the radar based digital healthcare industry. Use of AI or more precisely, ML has made it possible for radars to detect several chronic diseases such as Arrhythmia [8], Alzheimer [9] and Apathy [10]. Perhaps the ML has shown its footprints in every radar-based health related applications discussed in Fig. I (c). Additionally, ML equipped radar solutions are overcoming the existing limitations in the healthcare industry. For instance, the radar-based Vital Sign (VS) measurements are easily altered even with a slight body

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movement. ML approaches such as Support vector machine (SVM) are deployed to detect and the body movement and discard the measured VS containing body movement [11].

### A. Motivation, Scope and Methodology of Our Review

Radar based healthcare systems are emerging at a rapid pace and a considerable amount of work is underway currently. The motivations of considering vital sign measurement and activity recognition concurrently are as follow:

- Current research trend discussing these two topics together [12]–[18].
- Broad range of applications offered by healthcare radars, posing challenges in comprehensive coverage of several applications within a single paper.
- Vital sign and activity recognition are the most prominent healthcare applications.

Recently, several papers have begun to discuss vital sign measurement and activity recognition together [12], [13], [15], [18]. It provides a holistic approach for health monitoring by observing vital signs and activity recognition in living environment, and the medical experts can obtain a detailed overview of an individual's health. The integration of data from various sources into a unified view has emerged as a prominent trend, with the utilization of recent Internet of Things (IoT) advancements.

Each of the healthcare applications of radar shown in Fig. I (c) has emerged as an independent research domain and a considerable amount of work has been done. Simultaneously reviewing all these fields will expand the scope of the article. On that account, this article provides an overview of healthcare radars followed by in-depth review of two of the most prominent applications which are human vital sign monitoring and activity recognition.

VS monitoring is the most prominent and important radar-based healthcare application which can provide early detection for several chronic diseases. Human activity recognition on the other hand, is always deciphered using ML system in literature. Moreover, activity recognition in context of healthcare is of great importance since the inability to perform daily living activities has greatly been associated with mortality of elderly persons [1]. Specifically, aging societies require continuous activity monitoring since aging brings several undesired impairments to perform activities of daily life. Consequently, these two examples are discussed in this paper.

The yearly breakdown of the vital sign and activity recognition studies considered in this work is presented in Fig. 2. These studies are mentioned in Table I for reference. According to our data scrapping, ML for these topics was introduced around the year 2008. Consequently, the review covers the studies between the years 2008-present, mainly from the years 2017-2022. During the years 2008-present, only studies related discussing VS and activity recognition with ML are mainly considered. Topics other than ML based VS Measurement and activity recognition are excluded due to the richness of those topics. We tried to collect articles from reputed publishers such as IEEE, Springer, Taylor and Francis, Elsevier, MDPI, ACM, Nature, Optica, and Frontiers. The considered keywords are:

TABLE I
SUMMARY OF ARTICLES CONSIDERED IN THIS REVIEW

| Topic | Count | References |
|---|---|---|
| Related Reviews | 21 | [2], [15], [19]–[37] |
| Vital Signs | 33 | [8], [11], [12], [38]–[67] |
| Activity recognition | 92 | [10], [68]–[158] |
| Total | 143 | - |

- 'Radar vital signs' and 'machine learning'
- 'Radar vital signs' and 'deep learning'
- 'Radar vital signs' and 'SVM/ CNN/ RNN'
- 'Radar vital body movement' and 'Machine learning'
- 'Radar vital body movement' and 'Machine learning'
- 'Radar human activity' and 'Machine learning'
- 'Radar human activity' and 'CNN/ SVM/ kNN/ Encoder/ Neural Network'
- 'Radar human activity' and 'supervised/ unsupervised/ semi-supervised'.
- 'Radar vital body movement' and 'Machine learning'
- 'Human activity/vital' and 'reinforcement learning'

Next, we explain the existing reviews work related to healthcare with radar.

### B. Existing Reviews and Surveys

Few studies have previously reviewed the radar-based digital healthcare applications (see Table II). The first review summarizing the use of radar in healthcare industry was presented by Lin in 1992 [19]. The author reviewed the studies related to the non-invasive physiological measurements presented between 1960 to 1992. Later in 2002, Staderini [20] provided a short review on UWB radar applications in medicine. The pervasive health care applications were reviewed by Li and Lin [21]. Non-contact healthcare applications based on the Doppler radar were reviewed by Li et al. [22]. Gu [23] summarized the non-contact VS applications with radar. Ferreras and co-workers [24] studied the progresses on multimodal, short range, Continuous Wave (CW) radars for VS extraction. Another work by Li et al [25] reviewed portable radar-based applications such as human VS extraction, animal veterinary monitoring and activity recognition. In these aforementioned researched [19]–[21], [23]–[25], the use of DL in radar-based healthcare industry was not discussed instead, the core focus was centered around the detection and estimation of human VS based on signal manipulation.

Radar-based healthcare applications specifically assisted living, in context of Internet of things (IoT) were discussed by Le and co-workers [26]. Persuasive healthcare applications based on ML algorithms driven by the micro-Doppler spectrum were briefly discussed. However, the discussion on ML was too brief in their review. Shah et al. [28] reviewed assisted living technologies such as radar, RFID, Wi-Fi. However, only a few articles regarding radar-based activity recognition

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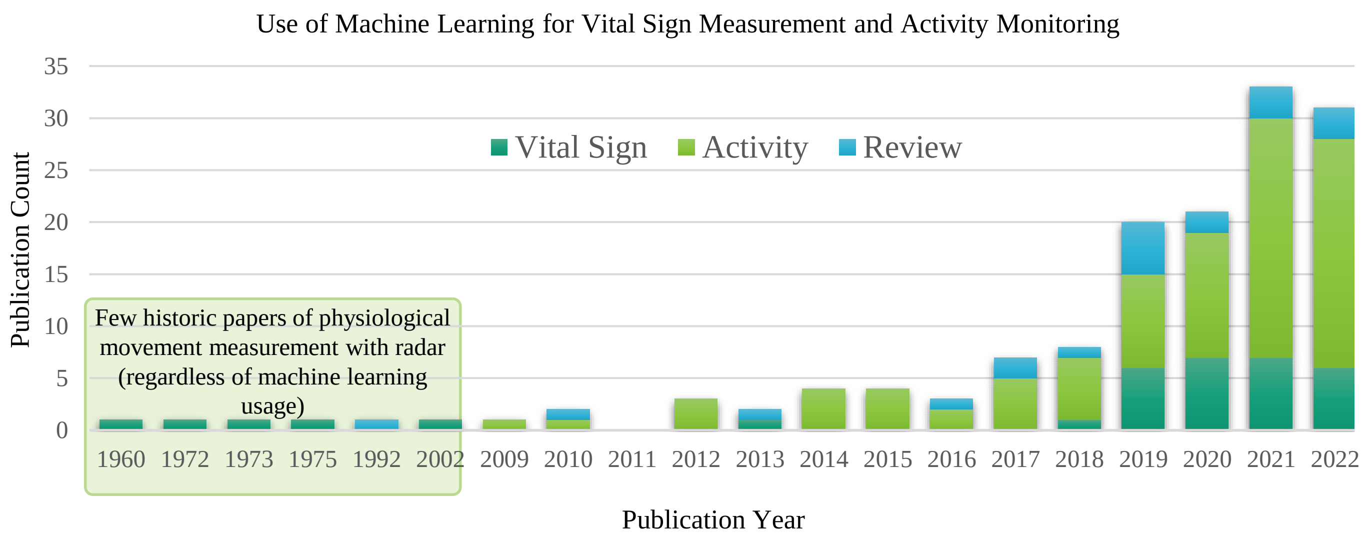


Fig. 2. Yearly breakdown of vital sign measurement and Activity recognition articles discussed in this work.

are considered since radar was not the main focus of this study. Two studies presented by Fioranelli, et al. [15] and Li et al. [27] summarized the usage of radar for activity monitoring purpose only. In addition to that, the two studies [15], [27] does not provide a radar-based activity recognition tutorial and studies until 2018 were covered. Recent years have shown frantic development for the related topic in recent years. Recently, several researches are aiming to review a specific topic of healthcare in context of radar sensor such as sleep monitoring [32]. Another paper reviewed the signal processing aspects of multi-human VS extraction approaches [5]. The use of ML with wireless sensors was reviewed by Saeed and co-workers [35]. However, the discussion on radar was limited since the paper reviewed several different wireless sensing technologies altogether. Similarly, activity recognition with radar was briefly introduced in a tutorial published by shastri et al. [161]. Additionally, their work focused mainly on mm-Wave sensing and activity recognition was not discussed in detail. Remainder of the details, strength and weaknesses of existing reviews are summarized in Table II.

The shortcomings of the current review articles for both topics can independently be summarized as:

1) Vital sign monitoring: To our knowledge, the existing reviews and surveys only cover the conventional signal processing methods for vital sign recognition [5], [19]–[24], [29], [30], [159], [160]. A detailed survey and tutorial for ML based vital sign studies is yet to be discussed.
2) Activity Recognition: Table II suggests that few authors have reviewed sensing technologies for activity recognition in general, while quoting a few radar related examples [162]. The existing dedicated reviews [27] for activity recognition are not up to date since over forty new articles have been published recently. In addition to that, previous articles lack the discussion on the current AI trends such as generative AI (in context of radar-based activity recognition). Currently, generative AI such as Generative Pre-Transformers (GPT) and Generative Adversarial Networks (GAN) are gaining huge attention and in fact, GANs have already begun to show their footprints in the radar-based healthcare applications. Another limitation of the previous articles is the lack of a comprehensive summary regarding the utilization of OTS commercial radar for activity recognition (and healthcare industry in general). To our knowledge, availability of OTS radars is one of the main driving factors of radar-sensors adaptability in non-military applications (See Section I-D).
3) Recent review covering both the activity and vital sign simultaneously consists of less than fifty articles [163].

### C. Our Review: Novelty and Organization

The research on the applicability of AI for activity-recognition and VS measurement is progressing at a significant pace. A considerable amount of work has been done in recent years. A dedicated review is required for ML based VS measurement and activity recognition which must cover the most recent research work. Consequently, in contrast to the previous reviews, this study aims to provide a detailed analysis of the recent usage of ML in radar-based healthcare applications. Main focus is exerted on the topic of VS measurement and activity recognition. This article aims to familiarize the readers with the basics and taxonomic details of ML, and how to use them for radar-based VS monitoring and activity recognition. The multi-fold contributions of this work are as follow:

- This review attempts to provide a detailed answer to the question that how the integration of AI with radar is overcoming the existing limitations for radar-based healthcare applications.
- This article also aims to provide an answer to the question that how ML is being used for the radar-based healthcare industry, and what are the current challenges to be solved for the two of the most widely discussed

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TABLE II
EXISTING SURVEY AND REVIEWS FOR RADAR BASED HEALTHCARE

| Study | Scope | Limitation |
|---|---|---|
| Lin (1992) [19] | Physiological signals measurement based on microwaves. | Only pioneer studies were discussed since at that time, ML was not yet developed. |
| Staderini (2002) [20] | UWB radar based vital sign measurement and few microwave radar prototypes. | Only UWB radars and signal processing based works are presented. Machine learnig is not discussed at all. |
| Li and Lin (2010) [21] | Vital sign extraction. | Only legacy techniques were discussed. No discussion of ML for vital sign or activity recognition is presented. |
| Li et al. (2013) [22] | Review of different architectures, and radar systems for vital sign extraction. | Only vital sign extraction is discussed. No discussion on ML is presented at all for any of the topic. |
| Gu C. (2016) [23] | Doppler radar-based vital sign extraction. | Other radars were not discussed and discussion is limited to vital signs only. No discussion of ML for vital sign or activity recognition is presented. |
| Ferreras et al. (2017) [24] | Radar-based human vital sign extraction and localization. | No discussion of ML for vital sign or activity recognition is presented. |
| Li et al. (2017) [25] | Applications of short range radars. | No discussion of ML based vital sign or activity recognition is presented. Additionally, the healthcare related applications are discussed too briefly. |
| Le et al. (2018) [26] | Radar for assisted living. | Brief (3 pages) discussion is proved for the topic of assisted living. |
| Shah et al. (2019) [28] | Assisted living based on RF technologies. | Several sensors were discussed altogether and radar-based activity recognition is briefly introduced only. |
| Fioranelli et al. (2019) [15] | Dedicated article for vital sign extraction and activity recognition. | Paper provides an overview consisting of twelve articles only. historic progresses and current trends are not discussed. |
| Li et al. (2019) [27] | DL for activity recognition. | Vital sign was not discussed. In addition, the field has progressed a lot in 2019 onward which are not present in this survey. |
| Zhu et al. (2019) [159] | Review on random body movements cancellation while measuring vital signs. | Discussed a single challenge related to vital signs in a brief fashion. No discussion of ML for vital sign or activity recognition is presented. |
| Peng and Li (2019) [29] | Brief review on radar-based localization and life tracking applications. | Only vital signs for life detection purposes are reviewed. No discussion of ML for vital sign or activity recognition is presented. |
| Gouveia et al. (2019) [30] | Vital sign measurement and motion detection. | Only reviewed studies related to movement detection and compensation. Machine learning was not discussed at all. |
| Meng et al. (2020) [31] | Activity recognition using non-contact sensors. | Several sensors are discussed and as a result, the radar-based activity recognition part is too brief. |
| Singh et al. (2020) [5] | Multiple-subjects vital sign sensing with traditional signal processing approaches. | Activity recognition and ML approaches are not discussed. |
| Khan et al. (2020) [160] | Signal processing based vital sign sensing. | No discussion on ML was preseted at all. |
| Walid et al. (2021) [32] | Sleep monitoring based on radars. | Only sleep related studies were discussed. |
| Abdul et al. (2022) [34] | DL for mm-wave radars. | Several applications are reviewed the main focus is not on vital sign and activity recognition. |
| Saeed et al. (2022) [35] | Several different non-contact sensors were discussed such as camera radar and other RF sensors. | Discussion on radar sensor is too brief since focus was divided on several fields. |
| Shastri et al. (2022) [161] | Sensing and localization using mm-Wave devices. | The main focus of review was localization and activity sensing were discussed as a use-case scenario only. |
| Hernandez et al. (2022) [162] | Non-contact sensing through Wi-Fi Devices. | Wireless sensing and activity recognition with Wi-Fi devices is discussed. |
| Fioranelli et al. (2023) [163] | Activity recognition and vital sign monitoring. | Only few papers are discussed since the total count of papers is less than 40. |

healthcare applications which are VS monitoring and activity recognition. Visualization of current trends and learned lessons based on these trends are also presented for these two applications.
- Based on literature survey, few open issues are presented at the end. In addition to that, a few issues which are not yet explored by healthcare radar research community are also suggested.
- While the existing articles only discuss the discriminative ML approaches, this article also provides a comprehensive note on the usage of generative ML approaches for healthcare-radars. A comprehensive note on generative networks is also included in this article.
- Unlike the existing reviews, details regarding the current usage of OTS radars along with the brief market statistics are also included in this article. The availability of low-

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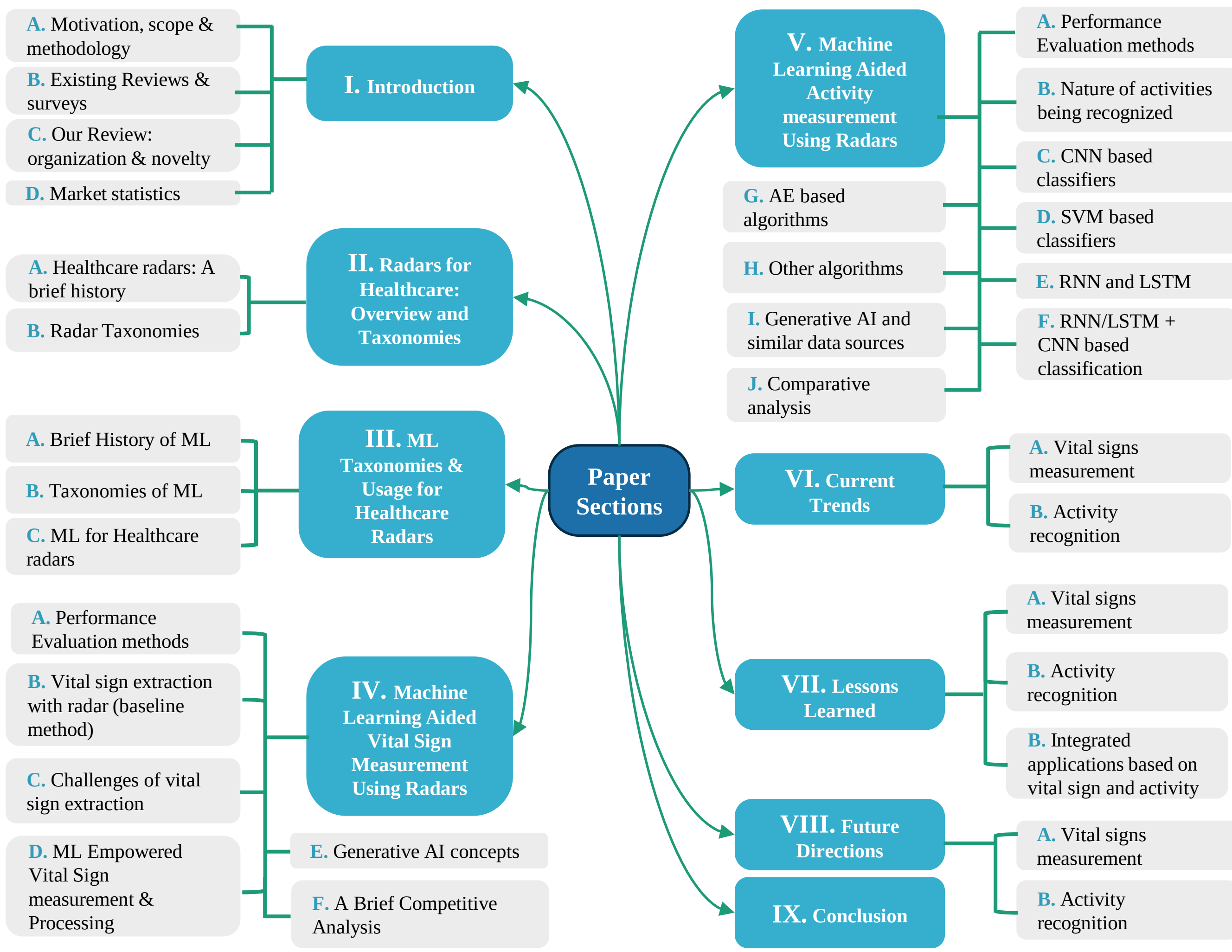


Fig. 3. Organization of this review article.

cost commercial radar sensors is one of the driving factors contributing to the adoption of radars for non-military applications.

The article is organized as explained in Fig. 3. The overview of the topic, motivation, existing reviews, novelty of this review, and the market statistics are covered in Section I. Section II deals with the background of radar sensors from hardware perspective. Details regarding available radar technologies and their strengths and weaknesses are discussed. Afterwards, Section III explains the taxonomies, popular ML algorithms and their usage for healthcare radars. ML aided VS recognition and activity recognition are discussed in section IV section V respectively. Section VI and VII present the current trends and lessons learned respectively. Finally, Section IX concludes the paper.

### D. Market Statistics and OTS radars

During the period of 2020-2027, (military and non-military) radars market is expected to register an overall Compound annual growth rate (CAGR) of 17.8% [164]. The applications of short and medium-range radars have become more diverse, and the commercialization of short-range radar is already on the go. In the year 2022, estimated radar market is of US 34.2 Bn with automotive radar being the biggest (non-military) shareholder. In the healthcare industry, several studies have used radar which were originally fabricated for automotive applications at 77 Ghz band [141], [147]. Additionally, it is expected that in the industrial revolution 4.0, which already enforces the importance of AI, radar-based healthcare will also play a critical role [165]. While the exact market trends and future predictions related to the healthcare radar are yet to be explored, Fig. 4(a) shows the trend of overall radar sensor market in terms of CAGR. Fig. 4(b) shows the type of radar being used in the reviewed articles. It can be seen that most of the works are based on OTS radar. Instead of focusing on designing radar hardware, ML based VS and activity recognition research works are mainly algorithm-based works. A Few biggest OTS radar vendors for the topic in consideration are additionally shown in Fig. 4(c). The rest of the popular OTS radars being in use for VS measurement and activity recognition are listed in Table III, which includes the radar model and operating frequency.

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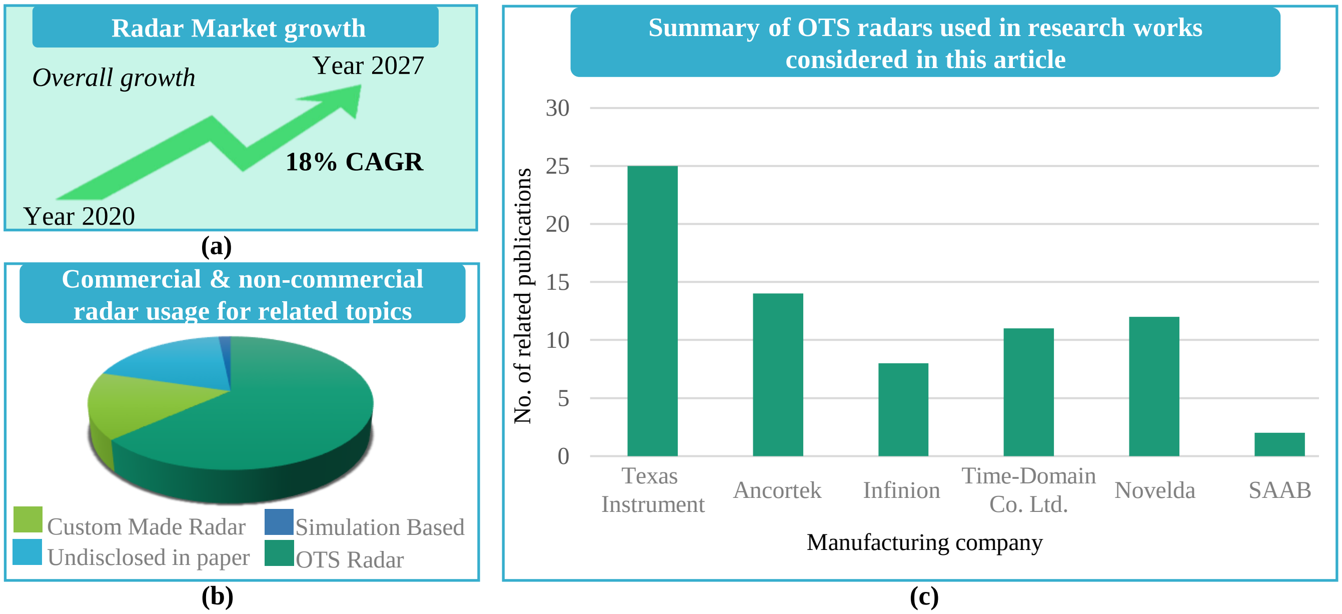


Fig. 4. (a) Radar market growth rate (including all the applications), (b) usage of commercial (OTS) and non-commercial radars for DL based VS measurement and activity monitoring tasks, and (c) OTS radars being used for vital sign monitoring and activity recognition purposes.

## II. Radars for Healthcare: Overview and Taxonomies

### A. Healthcare Radars: A Brief History

The use of radar for healthcare industry dates to 1960 when microwaves were used by Moskalenko [38] to quantity the volumetric change caused by the movement of biological objects. Later, Johnson and Guy in 1972 [39] confirmed the capability of radar to measure the change in ventricular volume of human heart by observing the transmission loss of 915 Mega Hertz (MHz) radar. This groundbreaking finding laid the foundation of research related to VS measurement using microwaves. Lung's abnormalities detection [40] and measurement of respiration rate [41] were the initial healthcare related applications of radar.

Human motion and behavior monitoring studies gained attention in 2000s where several authors used shallow ML algorithm such as Multi-class SVM [126] to classify human activities. For instance, shallow ML algorithms were also used to classify fall and non-fall activity [166]. The reason behind the popularity of shallow models was the fact that DL models were not easy to train at that time. However, later CNN based model gained huge attention in 2012. Afterwards, DL based healthcare applications using radar gained most of the attention. Nevertheless, shallow learning models are still in practice for applications based on VS measurement [47] and activity recognition [122].

### B. Radar Taxonomy

Several taxonomies of radar-based hardware exist. In this article we adopt the taxonomy based on the transmitted signal shape which are [3]:

- Frequency Modulated Continuous Wave (FMCW) radar.
- Single Frequency Continuous wave (SFCW) radar.
- Pulsed radar.

As the name suggests, SFCW and FMCW transmit a continuous signal whereas pulsed radar transmits the impulse like, discrete signal. SFCW radar can be considered as a mono-pulse radar having a fixed carrier frequency whereas FMCW radar increases the frequency linearly with time for a fixed bandwidth. One such modulated signal transmission is known as chirp [50], [53]. A single FMCW frame consists of several chirps. The frame of pulsed radar on the other hand consists of several narrow time-domain pulses which have a wide frequency spectrum. Consequently, these radars are often termed as Impulse Radio-Ultra wide Band (IR-UWB) radars [160]. Table IV shows the comparative summary of these radar technologies.

In SFCW radar, the peaks in the frequency domain resolve the Doppler velocity of the target. On the other hand, for the case of UWB radar, the peaks in time domain of the received signal resolves the range of the target. In contrast to SFCW and UWB radars, FMCW radar can provide both the distance as well as velocity of the target simultaneously. The transmitted SFCW radar waveform can be expressed as:

$$x_{SFCW}(t) = \cos(2\pi f t + \phi), \tag{1}$$

where $x_{SFCW}(t)$ represents the transmitted signal, $f$ represents the center frequency of radar, and $\phi$ represents the phase of the transmitted signal.

UWB radar on the other hand transmits a discrete signal which can be expressed as:

$$x_{UWB}[n] = \sum_{n=1}^{N} s[n - nN], \tag{2}$$

where $x_{UWB}(t)$ represents the transmitted discrete signal, $n$ represents the delay between the two consecutive pulses within a frame, and $s$ represents the shape of transmitted signal.

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TABLE III
OTS RADARS USED IN RESEARCH WORKS SUMMARIZED IN THIS REVIEW.

| Model | Frequency | Example studies |
|---|---|---|
| TI - xWR12xx | 76 GHz | [61] |
| TI - xWR14xx | 76 GHz | [8], [46], [65], [75], [83], [86], [105], [114], [125] |
| TI - xWR16xx | 77 GHz | [135], [141], [147]–[149] |
| TI - xWR18xx | 77 GHz | [12], [57] |
| TI - xWR68xx | 60 Ghz | [50], [64], [73], [85], [121], [154], [155] |
| TI - Unknown Model | - | [55], [63] |
| SAAB - SIRS 77TD | 77 GHz | [102] |
| SAAB - SIRS 6100TD | 77 GHz | [138] |
| Infinion - BGT24xx | 24 GHz | [68], [91], [94]–[96] |
| Infinion - BGT60xx | 60 GHz | [69], [77], [117] |
| Ancortek - SDR 2500 | 25 GHz | [108], [120], [158] |
| Ancortek - SDR 580 | 5.8 GHz | [70], [81], [87], [98], [103], [106], [123], [142], [143], [145], [146] |
| BumbleBee Radar | 5.8 GHz | [112] |
| Timedomain Co. - Puls ON P220 | 3.2 GHz | [129], [131] |
| Timedomain Co. - PulsON P4xx | 4.8 GHz | [58], [82], [90], [100], [101], [104], [107], [136] |
| Novelda Xethru | 7 GHz | [11], [48], [54], [66], [71], [80], [99], [113], [122], [124] |
| Novelda - NVA 6100 | 6 GHz | [74], [139] |
| TI - AWR 1243 | 77 Ghz | [61] |
| WalaBot | 3.3 – 10.3 GHz | [144] |
| RF Beam Swiss K-MC1 | 24 GHz | [47] |
| New-JRC, Tokyo, Japan | - | [60] |
| Imec Heverlee, Belgium | 79 GHz | [62] |
| Multiple OTS | - | [12], [51] |

TABLE IV
COMPARISON OF DIFFERENT RADARS.

| | SFCW | FMCW | Pulsed |
|---|---|---|---|
| **Transmission** | Continuous | Continuous | Discrete |
| **Signal** | Single tone | Modulating frequency | Pulsed |
| **Spectrum** | Narrow | Wide/narrow | Wide |
| **Data-Domain** | Frequency | Frequency | Time |
| **Range Res.** | - | $C$ / $2B$ | $C.\tau$ / 2 |
| **Information** | Doppler/ radial velocity | Range and velocity | Fine Range. |

C: Speed of light, B: bandwidth, $\tau$: Pulse width.

Similarly, signal transmitted by FMCW radar can be expressed as:

$$x_{FMCW}(t) = \cos(2\pi ft + \frac{B}{T}t^2), \quad (3)$$

where $x_{FMCW}(t)$ represents the transmitted FMCW signal having modulation bandwidth $B$ and time-period $T$. The remainder of the similarities and differences of these radars are summarized in Table IV. It can be seen in Table IV that both FMCW and UWB radar have same bandwidth-dependent range resolution which is $c/2B$.

## III. ML TAXONOMIES AND USAGE FOR HEALTHCARE RADARS

In this section, a brief history of AI is presented which is followed by a brief introduction of commonly used machine learning algorithms for activity recognition and VS measurement.

### A. Brief History of ML

The term AI was first proposed by McCarty in 1956 and the term ML was first introduced by Arthur Samuel in 1952 [167]. The first 2D learning network named Neocognitron [168] was proposed in 1980 which is a bit similar to today's convolutional networks. Multi-class SVM was first introduced in 1992. Deep Learning (DL) which is the subset of ML, has gained attention recently after 2010. There were several training related issues which hindered the applicability of DL in early 2000. In 2006 several research works (such as [169]) provided solutions to these training related issues which shifted the trends towards DL and resulted in several DL models based on learning characteristics such as AlexNet, ResNet and GoogleNet.

ML algorithms without considering DL approach requires features engineering and one must be aware of the detailed characteristics of input data. On the other hand, DL algorithms can learn data characteristics by themselves. Next, we summarize a few taxonomies of ML algorithms with examples related to the considered topic.

### B. Taxonomies of ML

ML based on the learning style and labeling strategy are classified mainly into three classes which are:

- Supervised Learning
- Unsupervised Learning
- Semi-supervised Learning

Table V summarizes the definitions, strengths, and weaknesses of each learning type separately. Healthcare radar examples are also included in Table V. Other than these aforementioned classes, another class exists in between the semi-supervised and unsupervised learning called as reinforcement learning. Reinforcement Learning operates on the game theory of positive or negative reward system. Reinforcement learning has currently been used for several radar applications such as scene adaptive target tracking of multiple targets [170] automotive radar and spectrum allocation [171]. However, the use of reinforcement learning for healthcare radar has not yet been considered so far. The reminder of details which include advantages, disadvantages and popular ML networks are summarized in Table V. In addition to that, a radar-based healthcare application is also included.

Considering the task-based taxonomies, the system can be sub divided as:

- Classification
- Regression

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TABLE V
TAXONOMIES OF ML (BASED ON LEARNING TYPES)

| Detail | Supervised | Unsupervised | Semi-supervised |
|---|---|---|---|
| Definition | During training, input data types are known to the model | During training, input data types are completely unknown to the model | Few samples are known to the model, and most of the samples are unknown |
| Data Type | Labeled data | Unlabeled data | Labeled and unlabeled both |
| Advantages | Produce data output from previous experiences | Helpful in finding patterns in data. Perfect tool for data scientists | Minimize the amount of labeled data needed |
| Disadvantages | Requires data labeling which is time consuming and tedious task | Less accurate, time-consuming process, Not feasible for known tasks | Irrelevant input feature present training data could furnish incorrect decisions |
| Popular models & networks | CNNs, DNNs, RNN, LSTM | Boltzmann Machines, Auto-Encoders and GANs (Generative Adversarial Network), RNN, and CNN | GANs, RNNs which include GRUs and LSTMs, are used for semi-supervised learning. Multi-view training, graph methods, and generative models |
| Radar Data Example | CNN based activity recognition [147] | Markov chain based unsupervised activity recognition [127] | Auto-encoder based activity recognition with labeled and unlabeled samples [76] |

- Clustering

Classification deals with dividing data into a few groups based on features. In literature, with particular interest in VS monitoring and activity recognition through radar, the classification task is mostly dealt as a supervised ML problem. For instance, human activity classification using radar presented by Noori et al. [124] presents classification of five human activities in supervised fashion. Regression on the other hand deals with predicting a quantity or quantities based on one or more variables. For radar-based healthcare issues, missing data in the VS measured using radar can be filled up using a linear regression approach as demonstrated by Xie and co-workers [54]. Clustering deals with grouping objects of similar properties together. Unlike classification, the number of groups in clustering can vary. Clustering is often achieved with an unsupervised ML approach. In healthcare applications, clustering has enabled several applications such as activity recognition [127] and fall detection [172].

Based on the complexity of network, the ML systems can be divided into two categories which are:

- **Shallow Network:** A single layer of non-linear features transformation
- **Deep network:** Multiple layers of features transformation

In shallow network, all the learning and decision is made on that single layer. A Neural network with a single hidden layer will be a shallow network. Shallow architectures have shown their usefulness in solving several well-constrained, simple problems. However, since the complexity and modeling is limited, dealing with complex real-world generalized problems is difficult for a shallow network. On the other hand, DL models operate on the principle of the human brain where the information is processed in layered architecture. For instance, human retina and camera sensor respectively act as an input to the human brain and a ML model. This information is passed through several layers in systems to make final decision.

Another (recent) type of taxonomy can be considered as follow:

- **Discriminative AI:** Constitute the decision boundaries between two or more classes of data.
- **Generative AI:** As the name implies, generative AI is used to create new data points.

While detection and recognition are widely discussed previously in literature, generative AI is lately getting huge attention as well. Generative adversarial networks (GAN) are a famous DL based data augmentation approach introduced in 2014. Current trend is showing a huge usefulness of AI in the field of data generation such as Generative Pre-training Transformer (GPT). The popular AI models and their use-cases example in the field of radar based healthcare applications are shown in Fig. 5.

### C. ML for Healthcare Radars

Fig. 6 shows the standard steps to be carried out in radar data processing chain. For each step, in context of healthcare applications of radar, a few traditional and the ML based approaches are also mentioned. It must be noted that all or any one of the step can be carried out with ML approaches discussed in Fig. 6.

Researchers have reported that ML based approaches can overcome several limitations being imposed by the conventional approaches. For instance, data scarcity [173] and imbalanced nature of dataset [174] poses a huge challenge for radar-based healthcare applications. Data augmentation is often performed to overcome this issue. To generate new samples from existing data, data transformation approaches often rely on adding noise [174] or performing geometric and spatial transformations [73]. Huang et al. [174] used Gaussian noise to balance radar-based sleep monitoring dataset and Yu et al. [73] used spatial transformation for activity recognition dataset. However, these approaches may not generate statistically independent samples for training [108]. As a result, Generative AI is getting huge attention lately. Recently, GAN (shown in Fig. 5) has emerged as a candidate solution for several activity recognition works using radar. For example, by using GAN data to train the radar-based activity recognition algorithm, 14 % increase in accuracy was reported in reference [108].

The second step shown in Fig. 6 deals with pre-processing the radar data (fabricated with or without augmentation).

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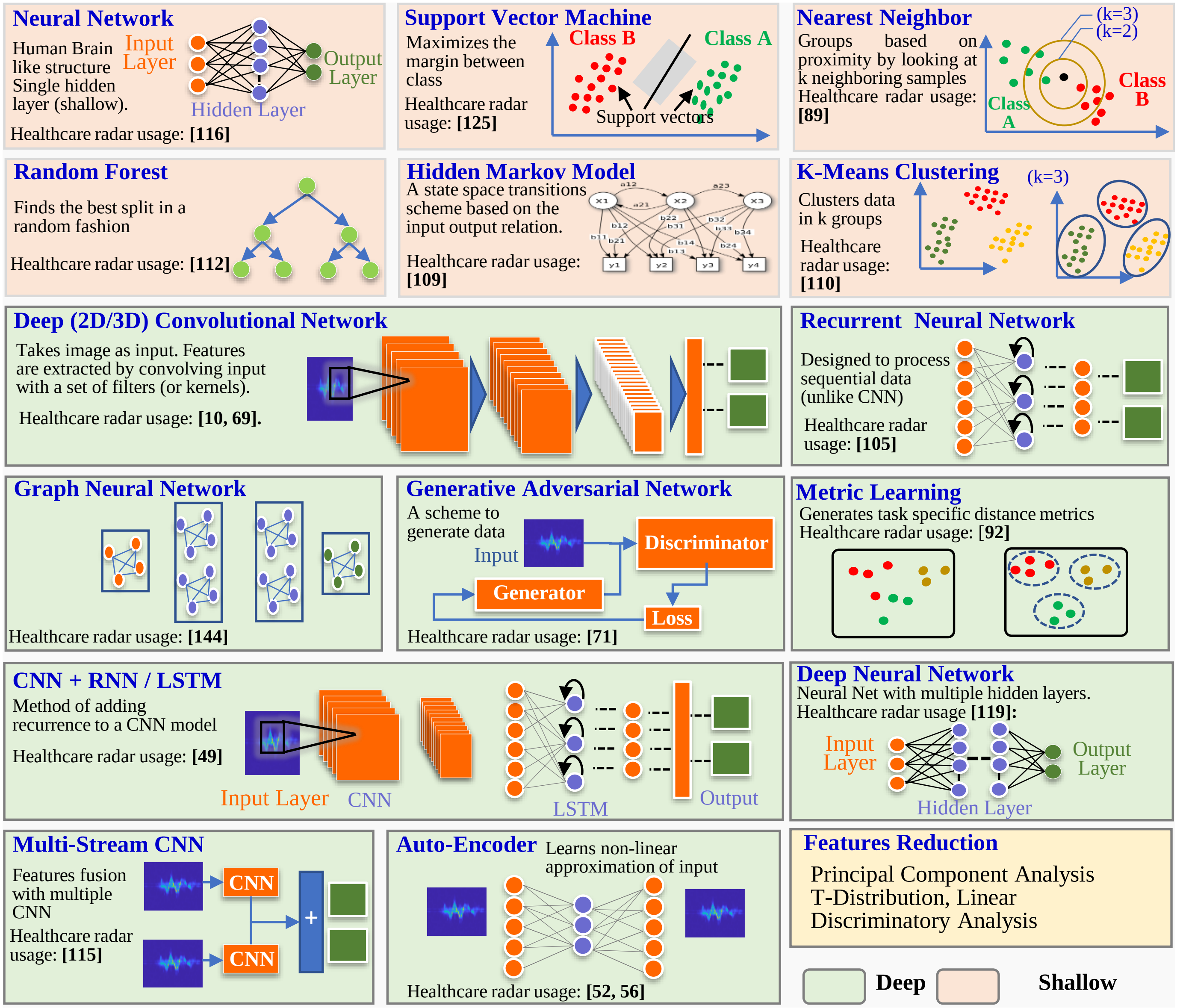


Fig. 5. Basic architectures of well known shallow and deep learning models being used for heatlhcare radars.

Simple iterative low pass filters are extensively being used to filter the static unwanted reflections, known as clutter [11], [173], [175]. However, researches show that simple sources separation fails when the unwanted signal to be segregated becomes complex [51]. For instance, removal of body movement while measuring vital signs was demonstrated in reference [51] where Auto-Encoder (AE) was used for source separation. Similarly, [44] used DNN for similar research problems.

For features extraction, a vast number of studies have demonstrated the dominance of DL techniques over the hand crafted features [176]. In addition to that, we may not be required to perform features engineering while using DL techniques. In a similar way, unsupervised features reduction methods are a common practice to efficiently reduce features space. PCA has widely been considered for this purpose.

Fig. 6 shows the comparison of both the conventional approaches as well as the machine learning approaches for different radar data processing tasks. Their strengths and weaknesses are also summarized as well. It must be noted that DL can be opted at any or all of these steps. For instance, if we have enough dataset, we may not require augmenting the data.

After a brief introduction of ML techniques and their current usage trend for radar-based healthcare applications, further section presents detailed review of two of the most prominent healthcare applications individually.

## IV. ML Aided Vital Sign Measurement

VS measurement is the most promising healthcare application offered by radar. Decades long research for VS measurement through radar has enabled the simultaneous measurement of HR and BR in non-contact and non-invasive fashion [160]. As stated earlier, VS measurement through radar dates back to 1960s [19] and the field has evolved sufficiently.

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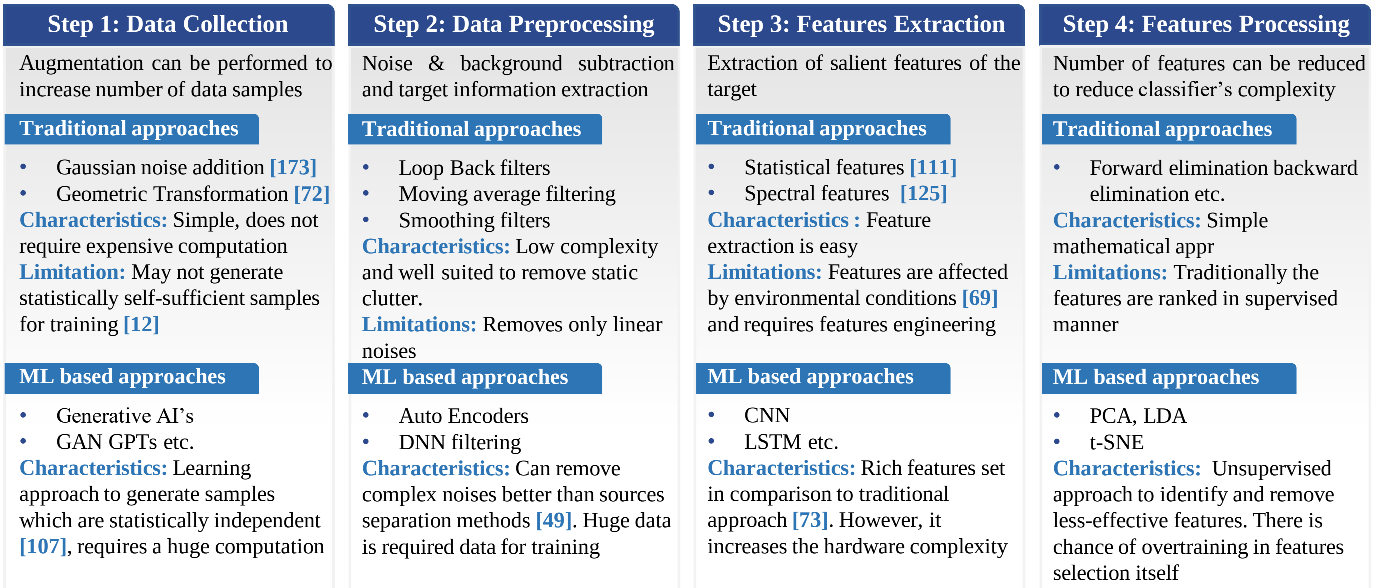


Fig. 6. Radar data processing steps using traditional and ML based approaches (Quoting references form healthcare applications of radar).

Currently, several researches are being carried out to make radar measurement more robust against the environmental factors.

During breathing, the air enters and leaves the lungs which causes contraction and relaxation of diaphragm. This diaphragm movement repeats at a rate of 8 to 25 times per minute for a young healthy adult. The heart rate on the other hand expands and contracts with a rate of 55-110 beats per minute to ensure blood circulation in the body. Due to these movement of lungs and heart, the chest also vibrates periodically. Radar sensor, being sensitive to fine movements, can effectively measure and quantify these movements to extract the heart rate and breathing rate. However, since both movements are superimposed on each other, a set of signal processing techniques is required to extract the two quantities.

### A. Performance Evaluation Methods of VS Measurement

As shown earlier in Fig. I, the data from radar and clinical heart and breathing measurement sensor is captured in simultaneous fashion. Several matrices exist to find correlation between the two sensors. Mean absolute error (MAE), mean error (ME) and mean-square error (MSE) are extensively used to show the difference of beats captured through radar and clinical sensors [55].

The difference between radar and reference sensor sometimes may not show the capability of radar to follow the heart variations. Consequently, statistical plots such as correlation plots and Bland-Altman plots are also being considered as well [64]. These plots additionally show the correlation factors and confidence range. The higher the Correlation factor, the higher is the accuracy. Research works often use correlation factor with based approach and conventional approach to quantify the overall improvement of system [65].

### B. Vital Signs Extraction with Radar (Baseline Method)

In order to demonstrate the VS extraction process, we established an exemplary VS extraction setup using Pulsed and CW (FMCW) radar as shown in Fig. 7(a). A human participant wearing a respiration belt and ECG electrodes was sitting in front of radar at a distance of 0.5 meters. We used Xethru X4 Pulsed radar designed by Novelda, Norway and IWR-6843 FMCW Radar designed by Texas, Instruments, USA. For BR reference, GDX-RB respiration belt designed by Vernier, Beaverton, USA was used, and for ECG measurement, PSL-iECG2 ECG module developed by PhysioLab, Ltd., Korea was used. As shown on the right side of Fig. 7(a), the breathing and respiration movement scatter points are superimposed on each other [177].

Fig. 7(b) shows the signal processing chain to extract VS using both the pulsed and CW radars. For the case of pulsed radar, the signal is processed in time-domain where the first step is to remove the unwanted static reflections from the received signal since received signal contains reflections from the chest as well as surroundings. A clutter removal filter is often deployed to reduce the background reflections [175]. Afterwards, the distance showing the maximum variance is selected and FFT analysis is performed at the values observed at that point to extract VS. The process for CW radars is also similar however, the processing is being performed in frequency domain. At the beginning, FFT of received raw data is performed followed by clutter removal and human detection blocks. Finally, the phase is unwrapped to extract the VS signal.

While the initial processing in both radars differ slightly, Fig. 7(b) suggests that the final stage of the extracting VS are similar for both technologies. From the extracted and the processed data of both radars, two separate band-pass filters (BPF) ranging between 0.1 to 0.9 Hz and 1 to 2.5 Hz are used to extract the breathing and heart signal respectively.

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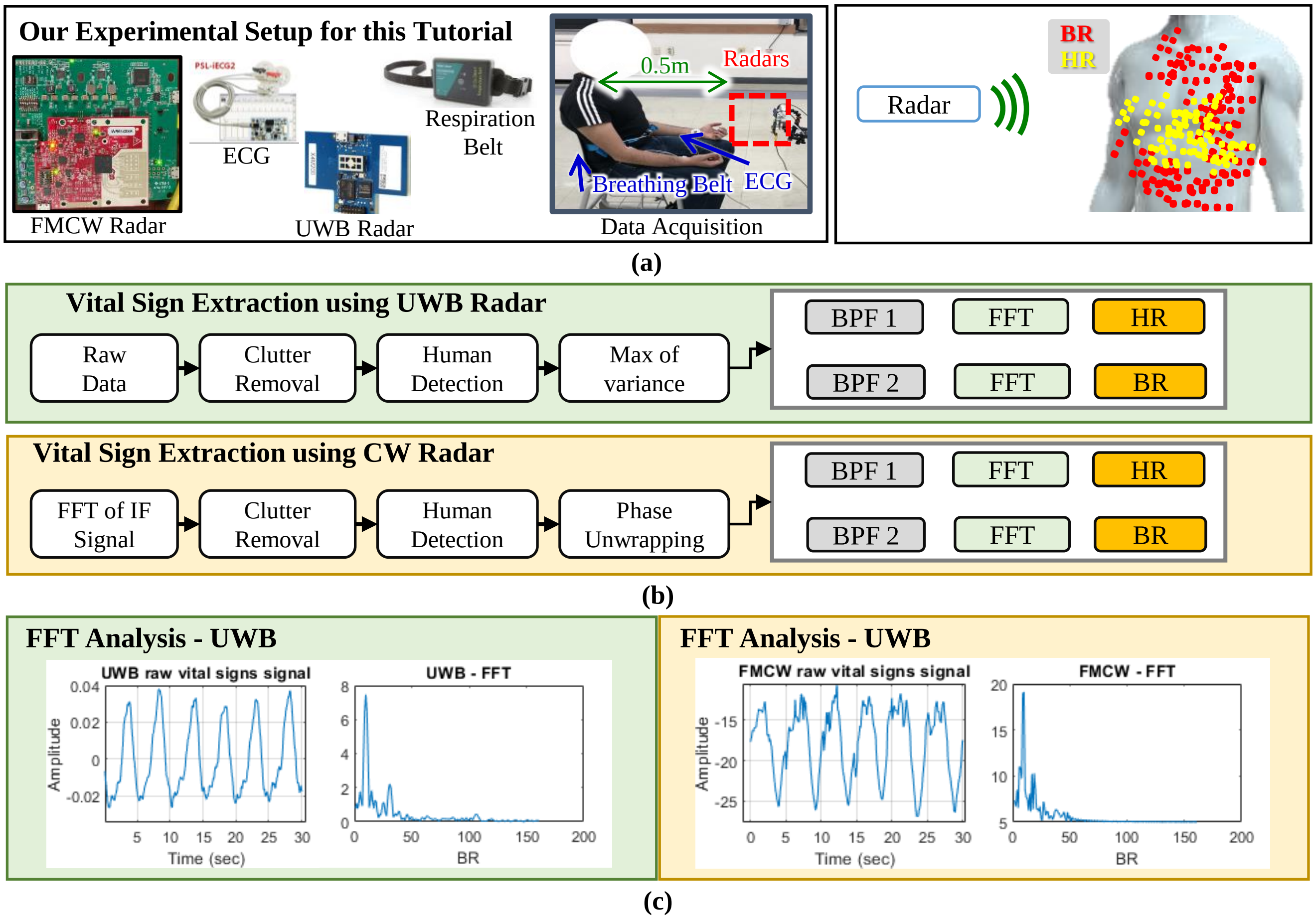


Fig. 7. Vital sign extraction through radar: (a) Experimental setup and materials, (b) signal processing work flow and (c) the extracted vital sign and its FFT analysis

Exemplary results based on signal processing chain shown in Fig. 7(b) are demonstrated in Fig. 7(c).The two peaks for UWB and CW (FMCW) radar provides the BR in both cases. The demonstrated process is repeated with a sliding window over the captured radar returns for a specific duration.

With a human subject at a distance of $d_o$ from radar as shown in Fig. 7, the mathematical model for radar-based VS can be presented as:

$$d = d_o + \Delta d(t) = m_b \sin(2\pi f_b) + m_h \sin(2\pi f_h), \quad (4)$$

where $d$ represents the overall change in distance due to chest vibrations, $m_b$ represent the breathing rate harmonic component, and $m_h$ represents the heart rate harmonic component. The corresponding breathing rate and heart rate frequencies are represented by $f_b$ and $f_h$ respectively. As stated earlier, two band-pass filters are used to independently extract the breathing rate and heart rate.

### C. Challenges Related to Vital Signs Extraction

Radar sensor-based framework shown in Fig. 7 facilitates a user-friendly measurement of VS in comparison to the competing (wearable) sensors. However, radar observations are sensitive to several ambient conditions for the case of VS measurements. The biggest challenges and research directions currently considered for VS monitoring are:

1) Random body movement during data acquisition
2) Breathing harmonics distorting the heart-rate harmonics
3) Human detection (accurate range point selection)
4) Low signal to noise ratio of the extracted vital sign signal
5) Fast signal acquisition (reducing the observation window for VS measurement)
6) Reconstruction of heart-beat waveform similar to ECG sensor.
7) Application development exploiting radar-extracted vital signs

As per our literature survey, it was observed that while VS measurements are often performed with the traditional Fourier Transform (FT) based signal processing approach shown in Fig. 7, ML is deployed on top of it to reduce the error encountered due to the aforementioned challenges.

### D. ML Empowered Vital Sign Measurement and Processing

This section summarizes the usage of ML based systems to overcome the aforementioned challenges.

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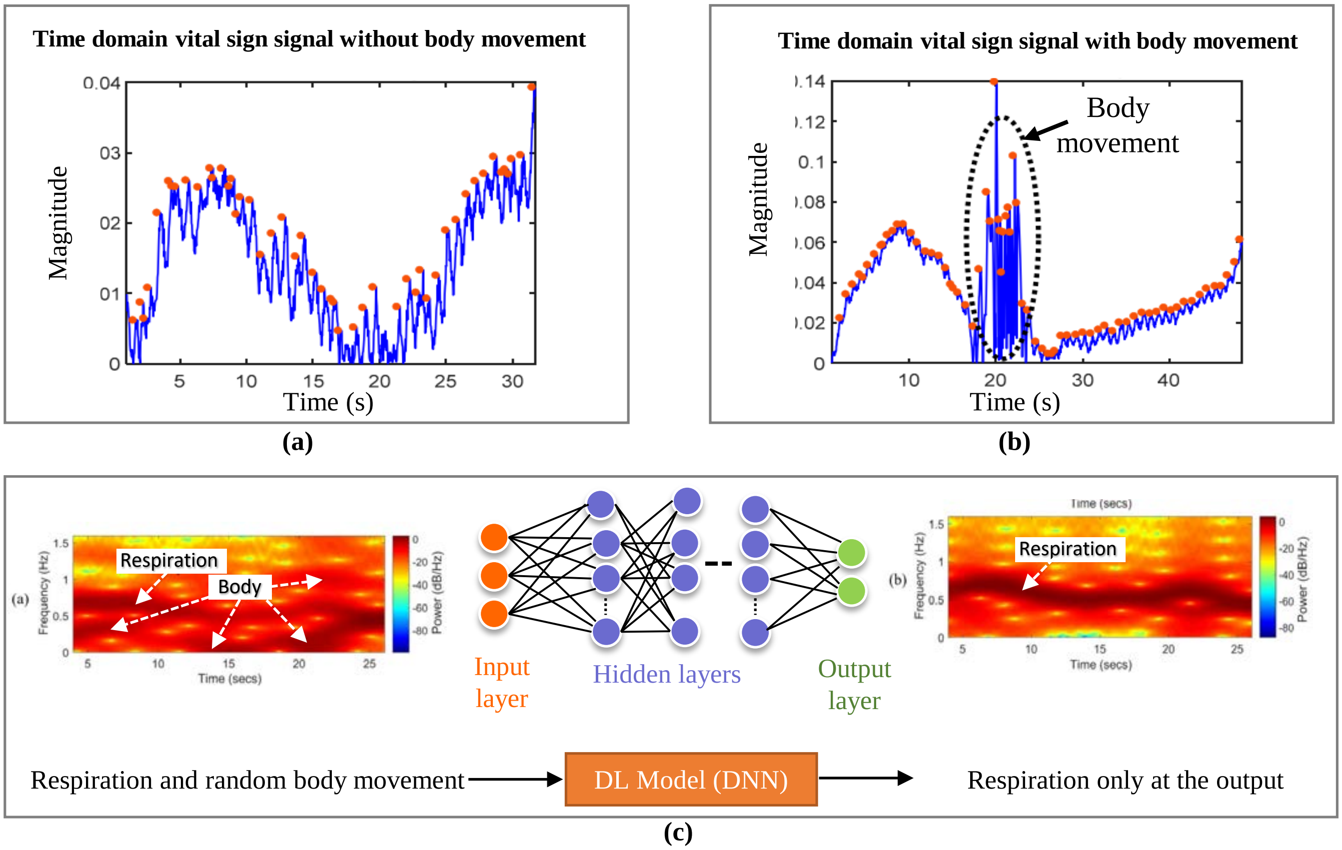


Fig. 8. Vital sign extraction (a) without body movement, and (b) under the influence of body movement adopted from [11]. (c) A DNN based regression approach extract respiration signal under the influence of body movement [44].

*1) Body Movement Cancellation:* Since radar measures the chest vibrations occurred due to heart and lungs movement, any other movement will create inaccuracies in VS measurement. In an ideal case, the human body should completely be at rest during VS measurement. However, one can expect several periodic and non-periodic body movements while acquiring data with radar. These movements such as neck vibration or hand movements are not linear in nature instead, they corrupt both the amplitude and phase of chest vibrations [51]. In fact, macro-movements such as limb movement alone will be a non-linear phenomenon. Simple source separation algorithms such as independent component analysis may not serve the purpose here.

Fig. 8 (a) and (b) respectively represents the radar extracted VS signals without and with the influence of body movement. As seen in Fig. 8 (a) and (b), the body movement signal appears as an abnormality in the extracted VS signal. Fig. 8(c) represents an exemplary DL study based on DNN to segregate body movement and respiration signal [44].

With the help of ML, several researchers have proposed methods to detect and mitigate body movements during data acquisition. For instance, Khan and co-workers [11] used a DL model to classify the stationary heart rate signal from the heart signal captured under the influence of random body movements. Pulsed radar was deployed in this study to capture data, and AlexNet was used to extract the features from both the classes which served as an input to the binary SVM classifier. The HR captured under body movement was discarded while keeping the resting HR which resulted in overall lower mean error.

In similar fashion, another research work [44] utilized Deep Neural Net to cancel the body movement (as expressed in Fig. 8). Chest vibrations were captured with CW radar and random body movements were added in the recorded signal. Later, a DNN model consisting of an input layer, two hidden layers and an output layer was trained to detect and quantify these body movements. Afterwards, based on the DNN prediction, the respiration signal was reconstructed successfully. A generalized DNN diagram can be seen in Fig. 5.

In reference [61], LSTM based model was proposed to solve the movement artifact issue where the body movement power and VS were analyzed to segregate the two quantities.

Performing regression on the radar extracted VS is another approach to resolve the issue of missing VS data due to body movement or any other reason. As expressed in Fig. 8 (b), the measurement error often appears as an outlier— Regression can be used to mitigate these errors. For instance, DeepVS, a 1D-CNN based regression model was trained to predict and minimize the effects of body movement in reference [54]. Authors used a two stream 1D CNN to extract features from both time and frequency domain. On a challenging data set, mean error of 7.4 beat per minute was achieved which in

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case of simple signal processing approach was 11.4 beats per minute.

Auto Encoders (AE) have also shown their effectiveness in removing random body movement. For instance, the work presented in reference [52] used a convolution based variational AE to reconstruct the VS from the mixture of signal containing body movement along with VS. In their work, simulated human movement data is mixed with a public VS dataset to create a mixed signal representing VS measured under the influence of body movement. Results suggest that AE does reduce the effect of unwanted movement in the radar-measured VS data. Another work presented by [178] extracts only the respiration rate from non-static humans using AE. BR while moving on treadmill, exercising on the same spot and turning over are extracted in their work and the AE generated respiration waveform was (more) close to the gold standard reference sensor in comparison to the respiration waveform extracted using only the signal processing methods (shown in Fig. 7). Similarly, [51] used a DL based AE to separate the components of body movement from the radar observed vital signs. The reminder of the body movement mitigation works are listed in Table VI along with other challenges.

*2) Breathing Harmonics Cancellation:* Harmonics of breathing signal residing between 1 to 2.5 Hertz (Hz), distorts the heart rate measurements since the amplitude of breathing harmonics is sometimes higher than that of heart rate peak. Table VI shows three studies related to breathing harmonics cancellation using ML approaches (along with other VS measurement challenges). Saluja and Lin [43] proposed a supervised ML algorithm based on gamma filter to remove the breathing harmonics from the signal.

In reference [180], convolutional sparse coding was used to mitigate the low Signal-to-noise ration (SNR) and the issue of breathing harmonics. Results showed above 95% accuracy in HR extraction.

*3) Human Range Point Detection:* Another, biggest concern is the fact that while measuring VS, human chest does not appear as a rigid reflective point [177], instead, it contains reflection from different portions of human abdomen as shown at the top of Fig. 7(a) where yellow and red scatter points represents the BR and HR respectively. Incorrect selection of range bin may result in measurement inaccuracies. To resolve this issue, Chang et al. [55] proposed a spatial correlation-based scheme to accurately detect the range bin. Several different range bins are selected, and a CNN based voting scheme is implemented to find the best. Each candidate range bins are considered as a class to be classified and CNN is used in supervised fashion. Results suggest that MAE is reduced from 3.95 to 2.70.

*4) Fast Signal Acquisition:* As discussed earlier, a window of few seconds is required to process the data and the size of window defines the time taken by the algorithm to predict VS. Analysis on different window sizes suggest that the increase in window size reduces the measurement error [182]. However, in practice, some scenarios require the algorithm to converge quickly. To meet this challenge, authors in [55] used DL to reduce the acquisition time with FMCW radar. In addition, DL based weighted scheme was introduced to find the best range-point of human chest during data acquisition. Reference [43] also reduced the acquisition time from 3 seconds to less than 1 second by utilizing supervised ML approach.

*5) Accuracy Improvement:* Few research works focused on improving the overall accuracy of vital sign measurement particularly by increasing the SNR of radar observations. As expressed in Fig. 7, radar-based VS are measured by taking the FFT of the extracted vital sign signal, however, Chang et al. [46] used an iterative frequency estimation scheme named as Newtonized Orthogonal Matching Pursuit (NOMP) instead of FFT approach. However, the proposed technique requires a high signal-to-noise ratio. As a result, authors proposed a DL aided NOMP scheme to increase the VS accuracy in comparison to the traditional scheme. The CNN model is utilized in this work to increase the SNR.

The issue of low signal to noise was also discussed in [46]. Similarly, Czerkawski [52] also used (variational) AE for de-noising the Doppler radar observations for VS measurement. The authors in [12] have proposed a multi radar data fusion network based on LSTM network to extract VS followed by a discriminator block to optimize the heart rate detection. OTS pulsed and FMCW radars were used together in this study. Research presented in [50] also utilized a neural network based regression model to increase the measurement accuracy.

*6) Reconstruction of Heart-Beat Waverform Similar to ECG Sensor:* The radar extracted heartbeat waveform (in its raw form) does not resemble greatly with the standard waveform extracted using ECG sensor. A chain of signal processing is required to process the radar-extracted heartbeat waveform. For heartbeat waveform reconstruction, work presented by Ha et al. [65] used FMCW radar and CNN based template matching to transform radar waveform into a seismocardiography. The radar extracted waveform is matched with a reference ECG waveform while training. The correlation between the reference HR waveform and the one extracted with CNN based template matching was 0.72 whereas for the same case, conventional FFT approach provided 0.66 only. Table VI summarizes all the related works.

*7) Heart Rate Variability Extraction:* Radar sensors also facilitate the Heart Rate Variability (HRV) extraction in non-contact fashion. The R-R interval which defines the peak-to-peak difference between consecutive heart beats in ECG waveform is an extensively used parameter in identifying cardiac diseases. AE has shown their usefulness in reconstructing the heart waveform, permitting radar to extract a waveform similar to that of ECG sensor. In practice, radar observed HR waveform (similar to ECG) is not robust in practical scenarios. Jang et al. [56] proposed an AE based approach to reconstruct more robust ECG signal out of CW Doppler radar measurements. The output of encoder-decoder pair was used to detect the R-R interval. For the similar task, Temporal convolutions network (TCN) based encoder was used by Chen and co-workers [57].

*8) Application oriented research works:* A few authors used the extracted breathing rate as an input to ML classifiers for user authentication purpose (Table VII). For instance, [45] used SVM classifier to classify six participants based on the breathing waveform. Another study used several shallow

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TABLE VI
ML AIDED VITAL SIGN MEASUREMENT STUDIES USING RADAR (SORTED YEAR-WISE).

| Study | Algorithm | Usage | ML class | Network | Main Focus | Radar | Implementation details and performance improvement |
|---|---|---|---|---|---|---|---|
| [179] (2018) | Gamma filter | Regression | Supervised | Shallow | Harmonics cancellation | CW | A supervised ML filter named as Gamma filter is used which is a calibration-free filter. |
| [43] (2019) | Gamma Filter | Regression | Supervised | Shallow | Breathing Harmonics and time reduction | CW | This work is a detailed and extended version of the work presented in [179]. Accuracy improvement of 1.2% and reduction in observation window by 3 seconds is reported. |
| [180] (2019) | Conv. coding | Regression | Unsupervised | Deep | Breathing Harmonics | Pulsed | Used the time domain sparsity to directly extract the HR and improved the accuracy by 15%. |
| [44] (2019) | DNN | Regression | supervised | Deep | Body Movement cancellation | CW | Body movement was added in respiration signal and DNN was trained |
| [49] | CNN+LSTM | Regression | Supervised | Deep | HR and BR Improvement | CW | Used CNN+LSTM based regression to reduce HR and BR measurement errors. Accuracy: DNN: 91%, CNN:94%, and CNN+LSTM:99%. |
| [53] | CNN | Regression | Supervised | Deep | HR Construction | FMCW | This model can extract ECG waveform by performing regression. R-R peak time error is of proposed was 17 millisecond(msec) whereas conventional approach provided 102.2 msec. |
| [65] (2020) | CNN | Classification | Supervised | Deep | HR Construction | FMCW | Template matching is performed to extract HR histogram. Conventional method yielded 0.66 correlation between radar and gold standard, proposed method yielded 0.72. |
| [46] (2020) | DNN | Regression | Supervised | Deep | Accuracy improvement | FMCW | Increased vital sign SNR by using DNN as denoising agent and reported above 25% accuracy improvement |
| [181] (2020) | CNN+LSTM | Regression | Unsupervised | Deep | ECG reconstruction | CW | Network learned the temporal and spatial features from radar and reference sensor to reconstruct HR waveform.Comparison was performed only with wearable sensors, not with the radar methods. |
| [50] | DNN | Regression | Supervised | Deep | Accuracy improvement | FMCW | Performed regression increase the measurement accuracy |
| [51] | AE | Regression & classification | Unsupervised | Deep | Body Movement and Range detection | Any radar | Encoder based sources separation method to segregate vital signs and body movements. The proposed method also provides a fast acquisition mechanism. Compared results with [65] and reported around 20% accuracy improvement. |
| [52] | AE | Classification | Supervised | Deep | Body movement | CW | AE based body movement separation method is provided |
| [55] | CNN | Classification | Supervised | Deep | Data Acquisition time | FMCW | For a short window length, the conventional vital sign method showed 6.3% error whereas proposed method showed 3.5%. |
| [56] | AE | Regression | Unsupervised | Deep | HR Construction | CW | Used AE to reconstruct radar extracted ECG waveform to find peak-to-peak differences (HRV). Proposed model shows over 30% improvement. |
| [57] | TCN | Regression | Unsupervised | Deep | HR Construction | FMCW | TCN to reconstruct ECG waveform. |
| [11] | AlexNet and SVM | Classifier | Supervised | Deep and Shallow | Body movement Removal | Pulsed | AlexNet to learn feature and SVM to classify body movements and stationary vital signs. |
| [54] | 1D CNN | Regression | Supervised | Deep | Body Movement | Pulsed | Performed regression at the output of radar measurements. the error for HR and BR is 7.4 and 4.9 beats per inute (bpm) whereas non-learning based competitor showed 11.8/7.3 bpm. |
| [67] | SVM | Classification | Supervised | Shallow | HR Construction | CW | SVM and SVD are used to find HR & BR waveforms. |

classifiers such as SVM and kNN for identity authentication during sleep [47]. Similarly, [48] assigned a unique breathing pattern to each involved human volunteer and used CNN based classifier to segregate each user. Rana et al. [58] used Doppler (CW) radar and SVM to detect VS in a home at different locations for surveillance purpose.

In the similar way, [60] proposed neural network based dengue fever detection using radar-recorded VS. In reference [59], the authors studied the feasibility of CNN to classify four different radar acquired vital signals. In similar line, an approach to segregate children based on age-group was presented using OTS FMCW radar by Yoo et al. [64].

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TABLE VII
ML AIDED APPLICATIONS BASED ON RADAR-EXTRACTED VITAL SIGNS

| Study | Algorithm | Usage | ML class | Network | Main Focus | Radar | Implementation details and performance improvement |
|---|---|---|---|---|---|---|---|
| [45] (2019) | SVM | Classifier | Supervised | Shallow | Application Oriented | CW | SVM Classifier to classify humans for identity identification |
| [47] (2020) | SVM and kNN | Classifier | Supervised | Shallow | Application Oriented | CW | Used SVM and several other classifier to classify different human subjects |
| [48] (2020) | CNN | Classifier | Supervised | Deep | Application Oriented | Pulsed | Used pre-defined unique breathing pattern for each subject and detected the pre-defined breathing pattern with CNN classifier |
| [183] (2022) | Stacked NN | Classification | Supervised | Deep | Application | FMCW | Four different types of reparations are being classified to monitor multi-human respiration abnormalities |
| [8] (2022) | DNN | Classifier | Supervised | Deep | Application oriented | FMCW | Used ECG sensor data to train DNN which was tested on radar data for arrhythmia detection. |

Since radar data is a scarce resource, to train a deep network for heartbeat signals classification is a challenging task. Authors in [63] proposed a Common Features Extraction Method (CFEM) which extracts the features from ECG waveform to train a model which works well with the radar recorded heart waveform features. Next section explains the activity recognition work based on ML.

### *E. Generative AI Concepts for Radar Based VS Measurement*

The concept of generative AI is yet to be explored for radar-based vital sign monitoring purposes. Nevertheless, a preliminary study based on GAN was presented by [66] where the authors tried to find the orientation of human body (while measuring vital signs) using signal from multiple radars.

### *F. A Brief Competitive Analysis*

In computer vision research domain, several open-source datasets exist for benchmarking purpose such as ImageNet [184] and COCO [185]. However, radar-based vital sign researches does not often use public dataset which consequently obstructs the comparative analysis among different algorithms. Based on the available data a brief comparison is stated here for VS measurement using radar. For body movement mitigation, two prominent ML models appeared to be 1D CNN and AE. 1D CNN showed an improvement of 4.4 and 2.3 beats per minute for HR and BR extraction respectively, which approximately constitutes 35% and 40% performance improvement [54]. In another study based on AE [51], 20% improvement can be observed however, the data capturing conditions were different in both the studies ( [51], [54]). In addition to that, regression based approaches [44], [51], [54] are able to mitigate the body movement unlike the classification based approaches which can only detect random body movement [11].

For breathing harmonics cancellation, supervised filtering appeared to be a prominent solution [43]. For HR reconstruction, it was found that AE showed the 30% improvement in-comparison to the conventional approach [56]. Template mathing based on CNN also achieved considerable improvement as presented in work by ha et al. [65] where the correlation betweeen radar and reference was increased to 0.72 which previously was 0.6.

## V. ML BASED HUMAN ACTIVITY RECOGNITION

This section discusses the second application of healthcare radars. According to projections, the elderly population aged 65 years and above is expected to exceed 1.5 billion by the year 2050, which is more than twice the current population. Aging brings several undesired impairments to perform activities of daily life. These activities are crucial to the ones well-being and studies suggests that inability to perform daily life activities have shown a five-fold rise in a yearly mortality rate [186].

Automatic human activity recognition has brought us many applications in the healthcare and smart living industries such as remote patient monitoring [187] and indoor surveillance [116]. More precisely, the focus can be shifted from cure to prevention, which will reduce the work load of already burdened healthcare infrastructure [2]. Due to the non-contact and non-invasive nature, radar-based activity recognition has become a hotly discussed research domain. As stated earlier, unlike the other competing non-contact technologies such as cameras, radar has no privacy concern.

To facilitate the activity recognition process, a set of activities are performed in the Radar Cross Section (RCS), and the acquired signal is processed either using ML approach (such as SVM [131]) or a simple signal processing approach such as distance manipulation [188]. However, as per our survey, radar-based activity classification studies with simple signal processing approach are very rare.

Radar-based methodology for activity recognition with ML is summarized in Fig. 9. First, the suitable radar sensor is selected to create a dataset. As per our survey, with few exceptions [111], supervised ML is used which additionally requires dataset-labelling [189]. Furthermore, as expressed in Fig. 9, pulsed, CW and FMCW radars offer different type of data representations. Suitable data representation scheme based on the nature of activity to be recognized and radar sensor being used, is selected to serve as input to the recognition algorithm. Radar data representation plays an important role in the overall performance of activity recognition framework. Few studies

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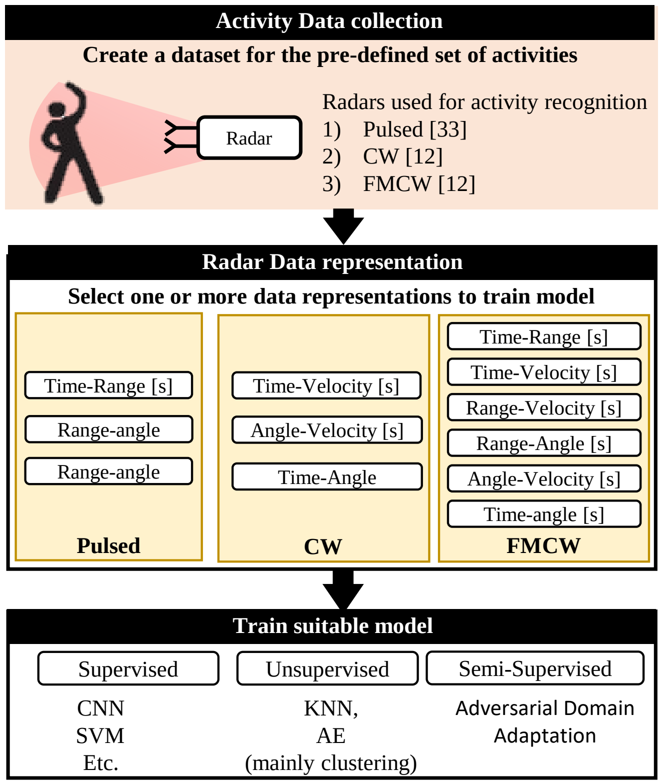


Fig. 9. Radar based activity recognition framework

have utilized radar data from different domains with the same ML algorithm for comparative analysis [83]. Afterwards, any or all of these types of data representations can be used to train a ML network. Several studies have used multi-domain data to recognize human activities [152] and gestures [4].

### A. Performance Evaluation Methods for Activity Recognition

Human activity recognition is often dealt as a multi-class classification problem. Consequently, formation of confusion matrix is a common way of evaluating the performances. Finding true positive, false positive, true negative, false negative, F-1 score, precision, recall, are also a common practice. The confusion matrix is capable of extracting this information as well (Refer to [190] for details). It must be noted that if the data is highly imbalanced, accuracy must not be considered as an evaluation criterion even for binary classification.

### B. Nature of Activities Being Classified

Web search with related keywords suggest that researchers are paying a huge attention on classifying activities of daily living such as drinking, going to bed, sleeping. For instance, Maitre et al. [80] classified fifteen such daily living activities. Exercise related activities such as walking, squatting, jumping crawling etc. are also being classified in several studies [105]. In addition to that, recognition of suspicious activities such as boxing, crawling, jogging (in army style), jumping with gun and throwing grenades etc. has also been considered in literature [151]. Another categorization of the activities is the activities performed at the same place and activities which involve leaving the original position [139].

In literature, few studies have considered task or situation-oriented studies such as store counter activities classification [144] and bed-room related activities [125]. In addition to that, preliminary results of toilet activity recognition using (FMCW) radar has also been observed in literature [156]. A few authors have attempted to classify the patient's activities such as trying to get out of bed, roll on bed, and walk in the room [83].

Next, we review different ML options available for activity recognition.

### C. CNN Based Classifiers

The pioneer study making use of DL for radar-based activity recognition was based on CNN, where a three-layered CNN was used to classify seven human activities using micro-Doppler images with a success rate of 90.9% (Kim and Toomajian [78], 2015). According to the claim made in the paper, this was the first study employing DL model for human activity recognition through radar [78]. Although the activity recognition accuracy was same as the shallow (SVM) classifier. the intention of this study was to show the usefulness of CNN for activity recognition work. Perhaps, the model was not tuned properly with different structural variations. Later, the same authors also used a similar three-layered CNN model for gestures recognition as well [191]. Afterwards, CNN based classifiers were extensively used for activity recognition using different types of radar data representation. Since CNN considers image at the input, research work in reference [68] used short-time Fourier transform (STFT) of the CW radar data to train a classifier consisting of five (hidden) convolutional layers.

Work presented by Axelsson and Gueorguiev [97] also used CNN and micro-Doppler images acquired by FMCW radar to classify three activities with 97.50% average accuracy. A three-layered CNN architecture to classify six activities recorded with OTS pulsed radar (which is also being used in reference [139]) was presented in [74]. Since algorithm was trained and tested for activities performed at three different incident angles which are 0, 15 and 30 degrees, an argument was made in their studies that range resolution is more robust than velocity resolution presented earlier by Kim et al [78].

Exercise activity classification has also attracted the attention of a few researchers. A work in this line was presented by Tiwari et al. [149] using FMCW radar and CNN. The exercises involved in the study were the usual gym exercises.

Normal practice of extracting features (using shallow or deep model) utilizes one or more radar-data-representation schemes as an input to the model (see Fig. 9). However, Ye and Li [94] proposed a unique idea of using CNN as an end-to-end framework. Raw radar returns of three activities were fed to a 1D CNN for features extraction. These extracted features further served as input to a 2D CNN network for training and classification. This research work demonstrated the feasibility of using a DL model on raw data without extracting any other information. The considered activities in this study are moving and boxing, only boxing, sitting, crawling, falling forward, falling aside, and walking with a stick.

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TABLE VIII
CNN BASED ACTIVITY RECOGNITION WORKS

| Study | Usage | ML class | Radar Data | Data | Details |
|---|---|---|---|---|---|
| [78] (2015) | Classifier | Supervised | Time-Freq. | CW | A three layered CNN architecture was used to classify seven activities |
| [68] (2016) | Classifier | Supervised | Time-Freq | CW | STFT images used as input to 5 Layered CNN architecture |
| [97] (2017) | Classifier | Supervised | Time-Freq | FMCW | Micro Doppler signatures were used to classify three activities using CNN |
| [74] (2017) | Classifier | Supervised | Time-Range | Pulsed | Data at different arrival angles was also tested and accuracy of 93.3% is reported |
| [72] (2018) | Classifier & generator | Supervised | Time-Doppler | CW | 371 fake samples were created using 1129 by utilizing GAN. CNN was used for classification |
| [108] (2019) | Classifier & generator | Semi supervised | Time-frequency | CW | Generate synthetic time-frequency plots for eight different human activities. |
| [157] (2019) | Classifier | Supervised | Time-Doppler | CW | Data being generated by GAN is used as input to DCNN classifier |
| [81] (2019) | Classifier | Supervised | Time-Doppler | FMCW | Classification of 6 activities with several different classifiers (GoogleNet, SVM based on alexnet) |
| [88] (2019) | Classifier | Supervised | Time-Doppler | Pulsed Doppler | An open set classification is proposed based on GAN. Classification is performed using CNN classifier. |
| [94] (2019) | Classifier | supervised | Raw-Data directly | CW | Used 1D CNN on raw-data directly (without extracting Doppler frequency) |
| [119] (2020) | Classifier | supervised | Range-Doppler | FMCW | Authors suggested that the use of multi dimensional data yields higher accuracy. |
| [70] (2020) | Classifier | Supervised | 4 different domains | FMCW | For 6 activities, Range-time & Doppler, amplitude & phase representations were used |
| [147] (2020) | Classifier | Supervised | 3D positioning | FMCW | Forked CNN: Range azimuth and elevation are used to draw human pose. Proposed mythology is aimed to replace voxel based approach |
| [148] (2020) | Classifier | Supervised | Range-Angle | FMCW | Range-azimuth and range-elevation maps are used as input to CNN to extract the pose of human |
| [71] (2020) | Classifier | Supervised | Time-Range | Pulsed | First moving direction is extracted using k-NN algorithm followed by CNN to classify 12 activities with 98% accuracy. |
| [152] (2020) | Classifier | Supervised | Range-Doppler-time | FMCW | 3D network known as pointNET is proposed based on range-doppler-time maps |
| [10] (2020) | Classifier | Supervised | Time-Doppler | CW | Used doppler images and CNN as binary classifier to detect Apathy (preliminary results). |
| [96] (2021) | Classifier | Supervised | Time-Freq. | CW | STFT of captured data was taken and two separated 1D CNN networks were used together to perform classification |
| [149] (2021) | Classifier | Supervised | Range-Doppler | FMCW | Classified seven exercise activities using rang-doppler features |
| [116] (2021) | Classifier | Supervised | Time-Frequency | CW | MS-CNN features and AE output was concatenated together to to classify 6 activities |
| [123] (2021) | Classifier | Supervised | Time-Doppler | FMCW | Six activities are classified using ResNet classifier on public dataset (accuracy = 96%) |
| [77] (2021) | Classifier & domain adoption | Supervised | Time-Doppler and Range | FMCW | Data with different FMCW radars having different settings is collected for domain adoption purpose since change in radar setting affects the classification outcomes |
| [95] (2021) | Classifier | Supervised | Time-Doppler | FMCW | Attention mechanism is added in 1D CNN to increase its accuracy. For 6 activities, proposed network showed 98% accuracy which is higher than the 1D baseline accuracy of 97%. |
| [79] (2021) | Classifier | Supervised | Time-Range | Pulsed | A through-the-wall public dataset of three different activities is proposed and CNN classifier example is also shown with 99% accuracy |
| [142] (2021) | Classifier | Supervised | Time-Doppler | FMCW | A tower CNN consisting of a parallel input layer is used to classify six activities. |
| [146] (2021) | Classifier | Supervised | Time-Doppler | FMCW | On an open dataset, six activities were classified using GooglNET. |
| [91] (2022) | Classifier | Supervised | Time-Doppler | CW | Used few shots and many shots learning to classify seven different activities. |
| [73] (2022) | Classifier | Supervised | 3D Positioning | FMCW | Posture was created from radar point cloud using voxels. |
| [83] (2022) | Classifier | Supervised | Range-Doppler | FMCW | Key finding: range-Doppler features are most robust than time-Doppler features. |
| [69] (2022) | Classifier & Generator | Supervised | Time-Doppler & Range | FMCW | An approach to create synthetic radar data is introduced and CNN is used for classification purpose. |
| [98] (2022) | Classifier | Supervised | 3D range-time-doppler | FMCW | A 3D map is used to train a 3D CNN which is generalizes better than 2D images based classifiers. Images were created using wavelet transforms instead of STFT. |
| [103] (2022) | Classifier | Supervised | Time-Doppler | FMCW | With an improved PCA features, a modified version of VGG net is used to classify six activities with accuracy of 96.3% which is 4.2% higher than the conventional PCA and VGGNET |
| [151] (2022) | Classifier | Supervised | Time-Doppler | CW | Six (suspicious) activities were classified using NN. Open dataset is also provided by the authors |
| [84] (2018) | Classifier | Supervised | Time-Doppler | CW | used DNN Synthetic data based on Synthetic data approach is used to train DNN model. Testing is being performed with real radar data. |

Several variants of CNN exist to the date and have shown their usefulness in different research domains. One such variant was used in reference [123] where the authors trained ResNet model to classify six activities and achieved 96%

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accuracy. In the similar way, GoogleNET has also shown its effectiveness to recognize six activities [146]. For the same dataset, ResNet with time-Doppler as input showed 85% accuracy [123] whereas GoogleNET with phase and amplitude of time-Doppler map as input showed 86% accuracy.

Recently, Yu et al. [73] proposed a four component framework consisting of 1) de-noising radar point cloud, 2) voxelization, 3) augmentation and 4) DCNN algorithm for classification. The authors compared the result on public data set proposed by singh et al. [105] and showed the dominance of voxel-based CNN approach over the simple CNN+RNN approach.

Kim and Seo [98] demonstrated that a FMCW radar-based range–time–Doppler maps can better train the CNN based classifiers in comparison to the similar classifier trained with range-Doppler maps only. A 3D map is used to train a 3D CNN which as stated by the authors, generalizes better than 2D images-based classifiers. In addition to that, images were created using wavelet transforms instead of STFT.

Another way of providing multi-domain radar to a CNN features extractor is presented by Helen et al. [142] where a tower CNN consisting of parallel input layer was used in their work.

The use of stepped frequency CW radar to capture time-range maps at different frequencies was reported by Jia et al. [116]. These multiple time-range images were used as input to a Multi-Stream CNN based classifier which yielded 96.42% accuracy. Table VIII summarizes the activity recognition works based on CNN.

Transfer learning deals with the studies where a model trained at one task is used as a beginning point for another task. As stated in earlier section, capturing radar data is a challenging task and open data sources are scarce, researchers realized the need of generating activity data synthetically. Seyfioglu and co-workers [84] used a similar MOCAP approach to generate synthetic radar data to train DNN model. Models train on MOCAP data were transferred to the real radar data. Another transfer learning approach was discussed in [81] and data was classified with GoogleNET classifier.

### D. SVM based classification

Table IX summarizes all the works related to activity recognition based on SVM, the second most widely discussed classification approach. The first use of ML for (CW) radar-based activity recognition was demonstrated in 2009 which used SVM trained on six time-frequency features to classify seven human activities [126]. Similarly, in reference [137], features-based on Principal Component Analysis (PCA) are used to classify activities based on FMCW radar. Another SVM based early implementation is presented in reference [138], where the authors have extracted similar features as discussed in [126] to train SVM. However, unlike the previous work [126], FMCW radar was used. Zenaldin and Narayanan [128] also used SVM to extract indoor and outdoor activities where STFT images of six activities were used to extracted features.

Authors in reference [102] used simulated human micro-Doppler data generated using infrared and video Motion Capture (MOCAP) approach. While the training was performed on synthetic data, the system was later tested with real data captured using a commercial radar to validate the findings.

The fist instance of ML usage for radar-based activity recognition was based on SVM and perhaps, Table IX suggest that the SVM is still in use. SVM based classifier can even consider the features extracted by DL models such as CNN and its variants [141].

### E. RNN and LSTM Based Classification

CNN processes the grid shaped data and extracts the spatial patterns and hierarchical representations, suitable for image data and lacks the ability to process the sequential data. RNN can handle sequential data and make decisions based on the present input and past decision. RNN has also been used for activity classification. Noori et al. [124] used pulsed UWB radar to classify five activities using RNN with an overall accuracy of 99.6%. The proposed network was also tested on a public UWB-gestures dataset [173], which yielded 98% accuracy. In addition, the authors also implemented discriminatory analysis and principal component analysis to reduce the features set. DL networks often require a huge amount of processing, and deployment of the DL model with radar is a challenging issue. In this context, Brabants et al. [125] proposed a method which first performs forward RNN at the device-premises and later, the processed information is again utilized at server with backward RNN for accurate prediction. Fourteen activities were considered in their work.

Traditional RNN was suffering from vanishing gradiant issue which gave rise to another sub-class of RNN known as LSTM, introduced in the earlier sections. LSTM has shown its effectiveness for the activity recognition task. Cheng et al [115] used LSTM based classifier on time-range maps extracted with stepped frequency CW radar and achieved 96.7% accuracy for five through the wall activities.

Since radar sensor specializes in sensing movement, most research works rely on the detection of dynamic movement being performed while pursuing the activity. Nevertheless, few studies have proposed posture recognition to recognize the activity [147], [148]. For instance, forked RNN based posture classification using range-angle (both azimuth and elevation) is presented in reference [147] (2020). It is needless to say that MIMO radar was used since angle of arrival requires multiple receiving antennas. Remainder of the studies related to RNN and CNN are summarized in Table X.

### F. CNN+RNN Based Classification

To introduce recursion in the CNN extracted features, a combination of CNN and RNN can be used as shown earlier in Fig. 5. LSTM is often considered as a special case of RNN. In reference [105], features extracted from two CNN layers were used as input to a bi-LSTM to introduce recurrence in CNN features which yielded 90.4% accuracy (2% higher than LSTM only based features). Five different exercise activities are being classified. Another similar approach is presented by Du et al. [92] where CNN features are used by a gated RNN to classify six activities.

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TABLE IX
SVM BASED ACTIVITY RECOGNITION STUDIES

| Study | Usage | ML class | Radar Data | Data | Details |
|---|---|---|---|---|---|
| [126] (2009) | Classifier | Supervised | Time-Frequency | CW | Classified seven activities using six micro Doppler features |
| [129] (2010) | Classifier | Supervised | Time-Range | Pulsed | Classified seven activities using six micro Doppler features |
| [132] (2010) | Classifier | Supervised | Time-Frequency | CW | A two class classifier was used to detect fall as an activity |
| [131] (2012) | Classification | Supervised | Time-Range | Pulsed | Used PCA based features to train SVM classifier to distinguish eight different activities |
| [130] (2012) | Classifier | Supervised | Time-Frequency | CW | Six features were extracted from Time-Doppler (frequency plot) |
| [133] (2014) | Classifier | Supervised | Time-Frequency | CW | A strategy was presented to classify activities even at non-line of sight condition |
| [137] (2014) | Classifier | Supervised | Time-Doppler | FMCW | SVM driven by PCA features was used for classification purpose |
| [136] (2014) | Classifier | Supervised | Time-range | Pulsed | SVM optimized by genetic algorithm was used in this study |
| [138] (2015) | Classifier | Supervised | Time-Doppler | FMCW | This study used same features extracted by [126]. However, radar is FMCW in this work instead of CW |
| [128] (2016) | Classifier | Supervised | Time-Doppler | CW | Used STFT images from six activities to extract features |
| [140] (2017) | Classifier | Supervised | Time-Velocity | FMCW | Classified two datasets consisting of seven and ten activities which yielded accuracy of 93 & 76 respectively |
| [139] (2018) | Classifier | Supervised | Time-range | Pulsed | Used weighted time-range frequency patterns to classify 12 activities using different shallow classifiers |
| [134] (2019) | Classifier | Supervised | Time-Frequency | CW | Performed through wall activity recognition |
| [118] (2014) | Classifier | Supervised | Time Range | Pulsed | Used energy, variance, skewness and kurtosis as features |
| [141] (2022) | Classification | Supervised | Range-Doppler | FMCW | Features were extracted from RDM using PCA and VGGNet to perform classification with SVM and KNN (separately) |

TABLE X
RNN AND LSTM BASED ACTIVITY RECOGNITION STUDIES

| Study | Usage | ML class | Radar Data | Data | Details |
|---|---|---|---|---|---|
| [106] (2019) | Classifier | Supervised | Time-Doppler | FMCW | Wearable and wireless sensor data is combined to provide a sensor fusion approach which yields 96% accuracy for six activities. |
| [115] (2020) | Classifier | Supervised | Time-Range | Stepped CW | Four activities in through wall condition are classified with accuracy of 96.7% |
| [124] (2021) | Classifier | Supervised | Time-range | Pulsed | Five activities were classified using a Neural Network. Data was collected in home environment |

The concept of Hybrid model based on CNN and RNN was also deployed by Ding et al. [87] (2021), where 1D CNN output was used as input to the RNN network. Authors used time-Range, angle and Doppler maps extracted by FMCW radar to classify six activities with an average accuracy of 93%. Maitre and co-workers [80] also used same hybrid CNN+LSTM approach with pulsed radar to classify fifteen daily-living activities.

Recently, Zhu et al. [107] used multiple CNN blocks and a single LSTM block to learn features. A radar sensor network consisting of five radars was used to collect data, and a single CNN network processed each radar data independently to extract features. Later, these features were combined to form a concatenated output for LSTM network. For nine activities, accuracy of 90.8% is reported.

Wang et al. [86] created images from both dynamic movement and static postures using 3D radar point-cloud map. The extracted point-cloud map comprising of (2D) range-angle was used to generate images using voxelization approach—a concept of clustering data-points into a geometric mesh.

The idea of using CNN+LSTM combination is also adopted in study presented by Gorji et al [85]. Combination of CNN and LSTM with a 3D data cube consisting of time-range-Doppler images as training input was used in their study. Two additional features, which are Doppler energy dissipation and temporal variation history, were also used as input feature to the multi-view network. Authors reported that the use of tracking feature will additionally increase 5% classification accuracy.

In the similar line, authors in reference [104] utilized pulsed (Doppler) radar-based time-Range information to train a hybrid CNN and LSTM based network to classify six activities.

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TABLE XI
CNN+RNN/LSTM BASED ACTIVITY RECOGNITION STUDIES

| Study | Usage | ML class | Radar Data | Data | Details |
|---|---|---|---|---|---|
| [105] (2019) | Classifier | Supervised | 3D range angle | FMCW | CNN + LSTM Generated a point cloud image to classify 5 exercise activities |
| [92] (2020) | Classifier | Supervised | Time-Doppler | Pulsed | CNN features are processed with gatted RNN to classify 6 activities with 88.19% accuracy. |
| [86] (2021) | Classifier | Supervised | 3D Range map | FMCW | Voxelization based image was created from point cloud as input to the model. CNN+RNN |
| [80] (2021) | Classifier | Supervised | Time-Range | Pulsed | 15 different activities are classified. CNN+LSTM An additional voting system is used to increase the robustness (overall accuracy=90%) |
| [87] (2021) | Classifier | Supervised | Time-Range, angle, Doppler | FMCW | Used 1D CNN followed by RNN to combine multi-domain data using feature concatenation. 93% accuracy for six different activities is reported |
| [125] (2022) | Classifier | Supervised | Time- Velocity | FMCW | Forward & Backward RNN are performed at device and server respectively to divide computation burden |
| [85] (2022) | Classifier | Supervised | Range, Doppler, Time | FMCW | Features and data was used to train the CNN+LSTM. It was reported that adding tracking features and Doppler energy increases generalization accuracy by 5% |
| [99] (2022) | Classifier | Supervised | Time-Range | Pulsed | Features extracted from CNN and LSTM are concatenated together to classify 15 different activities (accuracy = 96%) |
| [104] (2020) | Classifier | Supervised | Time-Range | Pulsed Doppler | Convolultional LSTM is used to classify six activities. Main focus is fall detection |
| [107] (2022) | Classifier | Supervised | Time-Range | Pulsed Doppler | Outputs of multiple CNN blocks from multiple radars are combined to make feature map for 9 activities (accuracy=90.8%) |

The solution was mainly optimized for fall detection purposes.

In the similar line, another work used pulsed radar for the hybrid CNN and LSTM based network for features extraction, which yielded 96% classification accuracy on fifteen different activities [99]. Refer to Table XI for the remaining studies.

### G. AE Based Classification

While most of the earlier attempts extracted features using CNN with different radar types and data modalities, few authors presented a contrary approach based on AE (Table XII). Since, AE tries to learn the non-linear data representation of input sample to reconstruct same sample at the output, the learned information contains a rich set of features related to the input sample—these features can be used as an input to classifier as well. Kanoci and Amin [120] presented similar approach of using a pair of stacked AE based on DNN to extract features. The authors demonstrated fall detection capability of FMCW radar and results suggest that the accuracy was higher than the traditional ML approaches. With fall-detection being the main focus of the study, four human activities were considered in their work. A sparse auto-encoders followed by logistic regression classifier was opted, which resulted in classification accuracy of 97%. OTS FMCW radar developed by Ancortek Inc. (SDR 2500) was used in this work.

### H. Miscellaneous Classification Approaches

Few studies have recently considered semi-supervised learning approach which requires a few amount of labelled training data. For instance, reference [76] proposed a semi-supervised learning method where a small portion of labeled and a huge portion of unlabeled data was used for training purposes.

Statistical features-based k-NN has also shown its effectiveness for recognizing activities using pulsed Doppler (Bumblebee) radar [112]. Another work utilized k-NN to classify seven activities with time-Doppler features [140].

Recently, graph CNN (or GNN) was employed to classify through the wall activities using stepped frequency CW radar data [153]. Another work presented by Zhen et al. [79] classified three activities in through the wall condition using CNN and provided a public dataset as supplementary material.

Aziz et al. [93] (2022) introduced Metric Learning approach for classification based on multi-domain target information in time-Doppler and time-Angle domains. For eight activities, 82% accuracy is achieved.

Lee and Kim [114] (2022) used GNN on the dataset provided by [105] to classify five activities. Another public dataset named MARS [192] was also used to evaluate the algorithm. In reference [109], authors reported that a fast computation approach for activity recognition is Hyper Domain Computing (HDC) which can provide accuracy similar to CNN.

Aziz et al. [93] (2022) introduced Metric Learning approach for classification based features extracted in time-Doppler and time-Angle domains. For eight activities, 82% accuracy is achieved.

### I. Generative AI and similar data sources

*1) Generative AIs:* As introduced earlier, generative AI such as GAN have shown a huge success in generating new data samples from a small dataset. Table XIII presents the studies utilizing GAN for radar-based activity recognition topic. GAN uses a generator and a discriminator block to generate new data samples from the input data distribution (see Fig. 5). One such example of the real and GAN generated radar data sample for human walking is shown in Fig. 10.

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TABLE XII
AE BASED ACTIVITY RECOGNITION STUDIES

| Study | Usage | ML class | Radar Data | Data | Details |
|---|---|---|---|---|---|
| [120] (2017) | Classifier | Supervised | Time-Frequency | FMCW | Four activities were classified. The main focus was detection of fall event |
| [70] (2020) | Classifier | Supervised | 4 different domains | FMCW | Considered AE, SVM, CNN to recognize 6 activities. Range-time & Doppler, amplitude & phase representations were used |
| [116] (2021) | Classifier | Supervised | Time-Frequency | CW | MS-CNN, AE MS-CNN features and AE output was concatenated together to to classify 6 activities |
| [76] (2022) | Classifier | Semi-supervised | Time-Doppler | CW | Both labelled & unlabeled data was used for training purpose enabling a semi-supervised learning. |
| [145] (2022) | Classifier | Supervised | Time-Doppler | FMCW | Used the dataset proposed in [105] to extract 3D point cloud with graph neural network (GNN) |

TABLE XIII
USE OF GENERATIVE AI FOR RADAR-BASED ACTIVITY RECOGNITION

| Study | Augmented Data | Radar | Details | |
|---|---|---|---|---|
| [72] (2018) | Supervised | Time-Doppler | CW | 371 fake samples were created using 1129 by utilizing GAN. CNN was used for classification |
| [108] (2019) | Semi supervised | Time-frequency | CW | Generate synthetic time-frequency plots for eight different human activities. |
| [157] (2019) | Supervised | Time-Doppler | CW | Data being generated by GAN is used as input to DCNN classifier |
| [88] (2019) | Supervised | Time-Doppler | Pulsed Doppler | An open set classification is proposed based on GAN. Classification is performed using CNN classifier. |
| [89] (2022) | Semi-supervised | Time-Doppler | CW | GAN based model capable of considering labelled and unlabelled data simultaneously was trained |
| [101] (2022) | Supervised | Time-Doppler | Pulsed Doppler | Using a two-stage domain adaptation, a generalized system is proposed where system designed on simulated dataset is tested on real data |
| [114] (2022) | Supervised | 3D Range | FMCW | Used the dataset proposed in [105] to extract 3D point cloud with graph neural network (GNN). Posture based approach is presenteds |
| [150] (2022) | Supervised | Time-Doppler | FMCW | Used GAN to generate augmented data samples |

In the real world, the human subject under the test may perform activities which may be out of the distribution of the data used for training. Most of the studies deal with the closed-set classification where the training and test set have the same activities. Open-set classification deals with the classification of classes which are not present in training set. The issue of open set for radar is discussed by Yang and co-workers [88]. GAN is used to create a negative activity class that is to say, the activity class other than the designated activity set.

Transfer learning based on GAN for activity recognition was performed by Shi and co-workers [72]. A total of 371 additional training samples were created from 1129 real radar spectrogram using GAN, and DCNN was used for classification purposes. In reference [108], researchers also used GAN to generate synthetic time-frequency plots for eight different human activities. Similarly, Ding et al. [89] used GAN to achieve semi-supervised activity recognition with micro-Doppler spectrum.

Recently, a study to generate simulated radar activity data using Kinect sensor followed by GAN to augment the data was presented in [150].

*2) Simulation Based Data Generation:* Few studies are utilizing synthetic data based on simulations for activity generation work. In this regard, MOCAP provides a simulation-based method to generate micro Doppler behavior synthetically. In this kind of approach, infrared sensors are placed on human body parts (or in the ambience), and distance-variation with time are recorded to generate human micro-Doppler spectrograms. A low-cost approximation of MOCAP can be achieved by using Microsoft Kinect sensor, which is markerless approach. Several works have confirmed the validity of Kinect sensor based MOCAP approach to generate activities data similar to radar [102]. Studies have used this (synthetic) MOCAP generated radar data to train shallow learning classifiers [102] as well as DL based classifiers [84].

In reference [100], an unsupervised adversarial domain adaptation (ADA) approach is proposed for radar micro-Doppler images to classify five activities. Authors considered two domains consisting of same activities and possessing similar feature space. A source domain is simulated dataset generated using MOCAP which is used for training. The trained model is tested on a real radar dataset (the target domain), and an accuracy of 81.6% is achieved. Similarly, domain adoption can be performed to train a network for different radar settings.

Recently, the issue of limited radar data is also discussed

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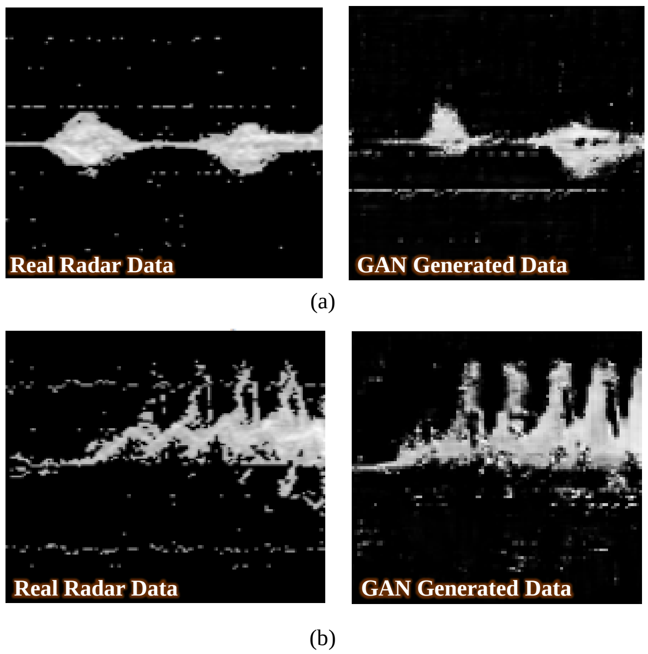


Fig. 10. Real and GAN (augmented) radar data for (a) bending down and (b) walking around (adopted from [108])

in [101] where a two-stage domain adaptation approach is provided for a generalized solution. Few samples are collected with OTS radar whereas few samples are generated using MCOAP dataset. Later the data is randomly paired together to be used as a pair input for GAN model. In reference [152], authors used range-Doppler information to create a point cloud map to classify eight activities using Mult-Layer Perceptron (MLP).

As stated earlier, few synthetic approaches to generate activity data exist. Hernangome and coworkers [69] generated a simulated radar returns for different activities using video camera. The joints information extracted using a computer vision approach was processed to get the simulated range-Doppler map. However, the simulated and the captured images had few differences. A DL based image transformation network was used to overcome these differences. Afterwards, CNN was used for classification purposes.

### J. A Brief Competitive Analysis

For activity recognition, it is hard to provide a direct answer to the question that which ML model has higher accuracy due to below factors:

- Lack of having a benchmark dataset causing variations in test environments: Unlike image processing, researchers exploring radar-based activity recognition often collect dataset first followed by training ML algorithm.
- Fairness in comparison: Few ML models converge on small datasets showing high accuracy on small amount of data. On the other hand, few models (deep-structured models in particular,) requires a huge amount of data however, the overall accuracy might be higher. Radar-based healthcare topics lack this kind of studies, making it hard to compare different models in terms of performance.
- A high set of intra-model variations such as number of (hidden) layers, learning rate, optimizer and activation functions.

Nevertheless, it was observed that a few research works utilized the same dataset in their investigations. Since, reference [94] used raw radar returns, Zhu et al. [96] used the STFT of captured data to train (lightweight) 1D CNN. Two separate 1D CNN networks are being used together to classify seven activities. This study used Mobile-Edge computing to provide a lightweight network. The activities were same in these two aforementioned studies ( [94] and [96]), and the accuracy of [96] was 1% higher in comparison to [94]. However, lightweight DL model was used in reference [94] to achieve low-latency algorithm. On the same dataset, another study by Liu et al. [91] used few shots learning based CNN to classify same seven activities. Few shots learning uses less training data in comparison to conventional learning algorithms. With five samples in each of the considered class, 91.6% accuracy is achieved.

On a same dataset, ResNet with time-Doppler as input showed 85% accuracy [123] whereas GoogleNET with phase and amplitude of Time-Doppler map as input showed 86% accuracy. Kim and Seo [98] demonstrated that a range–time–Doppler maps can better train the CNN based classifiers in comparison of range-Doppler map only. A 3D CNN model generalizes better than 2D images based classifiers.CNN with range-Doppler maps were more robust and efficient in comparison micro-Doppler spectrum. Later the same data was used with CNN+LSTM network.

## VI. Current Trends

### A. Vital Sign Measurement

Fig. 11 outlines the current research issues related to VS and their candidate solutions based on ML. For instance, body or any other unwanted movement can either be detected, or detected and discarded at the same time. The former solution reduces the amount of extracted VS data while reducing the overall MAE whereas the latter will reduce the overall MAE only. Similarly, for other limitations and challenges, corresponding solutions from literature are quoted in Fig. 11. Next, we present the survey of VS studies.

*1) Radar Hardware Usage:* As demonstrated in Fig. 11, we found that all the radar hardware are equally being utilized for ML based VS measurement (See Table XIV for references). However, since the VS measurement heavily relies on conventional methods whereas we have summarized the usage ML only, this finding cannot be generalized for the overall VS measurement topic. As explained earlier, several radar hardware choices exist and each hardware has its own strength and weakness, Table XIV provides a categorization from radar hardware perspective. Since this review considers the studies related to VS extraction using ML only, Table XIV can be used to study usage of ML for particular hardware. Note that the study presented by [51] can be used with any radar type.

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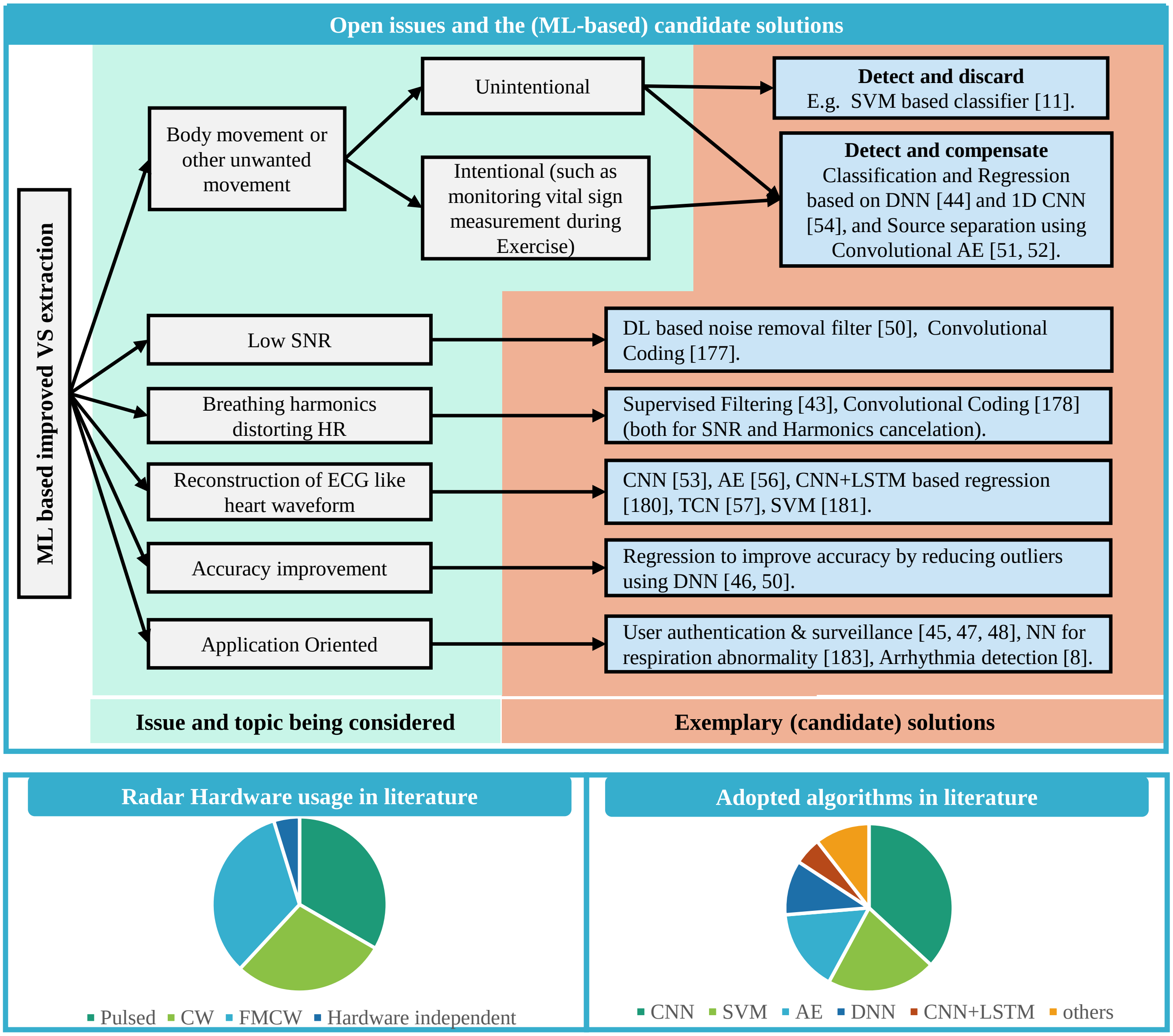


Fig. 11. Summary of research works being performed for ML based vital sign measurement through radar.

*2) Algorithmic Details:* Table XIV also presents the summary of the techniques being used in VS extraction. Readers can get an insight about how ML techniques are currently being deployed for VS measurement through Table XIV. Table XIV suggests that CNN is most widely being used so far followed by SVM. AE have also a huge potential since AE has shown its effectiveness as to de-noise images and several other types of data. In similar way, AE based models have a huge potential in de-noising the based radar measured VS.

Table VI suggests that ML offers several approaches to improve VS measurement and reduce the error between radar and reference gold standard devices. For instance, it can be observed that a supervised classifier can be deployed to classify the radar-recorded VS signal with and without body movement [11]. Currently, the measurement of VS under voluntarily and involuntarily body movements is getting huge attention. Similarly, regression analysis has also been proposed to increase accuracy of VS measurement.

## B. Activity Recognition

This section summarizes the activity recognition works being carried out using ML algorithms. The hardware and software related research trend for the activity recognition works are shown in Table XV.

*1) Radar Hardware Usage:* As per our survey, FMCW radar is the most widely used radar for recognizing human activities (Fig. 12). One of the core reasons is the fact that a MIMO FMCW radar can provide range, Doppler (velocity) and angle information simultaneously in contrast to pulsed and CW radars. In addition to that, FMCW radar usage is increasing in recent years in comparison to the other radars which were famous in 2010-2015. One of the reasons is the availability of several OTS FMCW radars which can be used directly for activity recognition.

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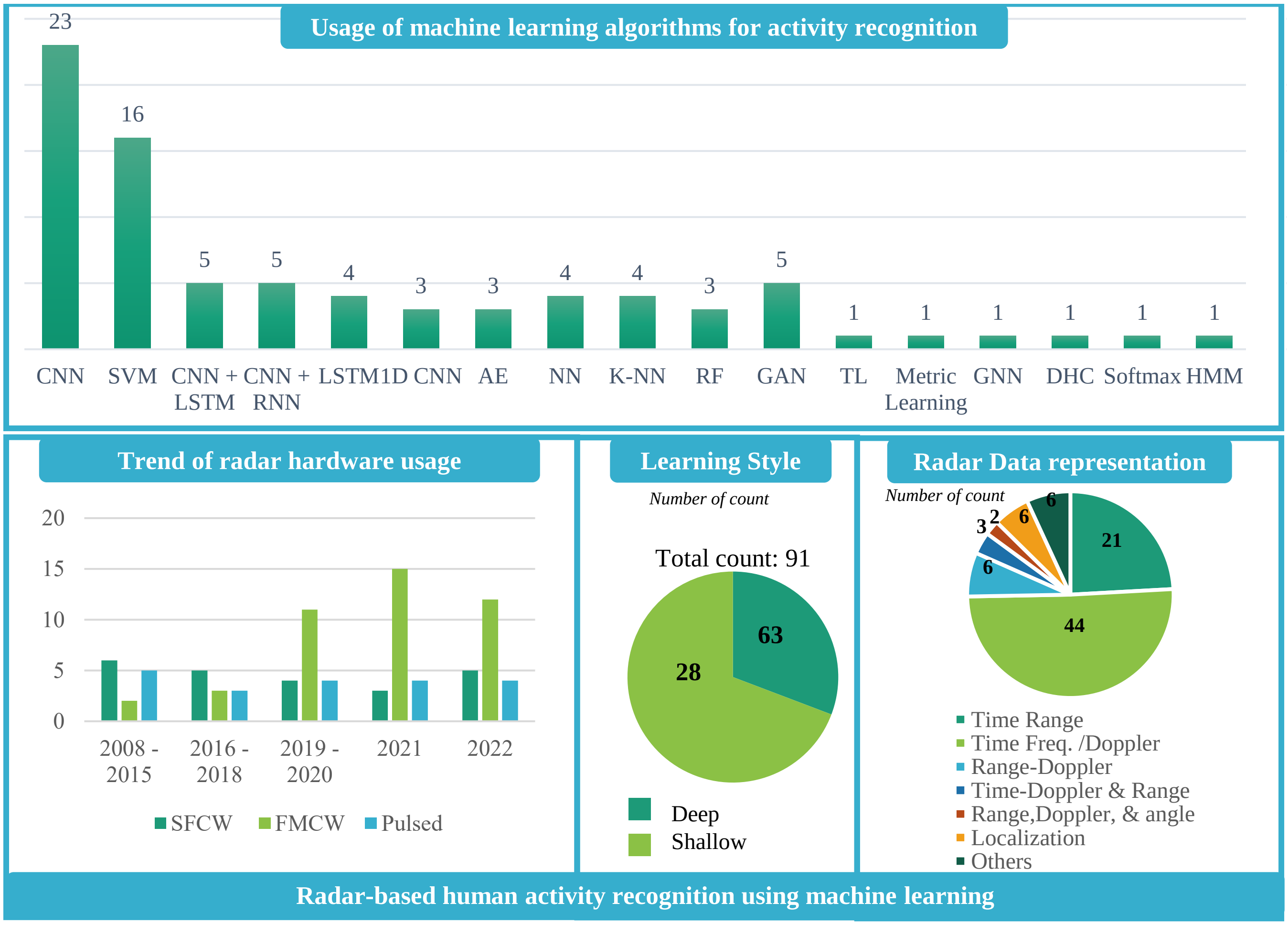


Fig. 12. Summary of current trends in radar based activity recognition.

*2) Learning Style:* Next analysis shown in Table XV summarizes the learning styles of algorithms being used for activity recognition through radar. ML algorithms have been in practice since 2009 whereas DL has emerged after 2015. Yet the overall count of using DL is higher than ML algorithms which suggests that the trend has shifted towards the use of DL for activity recognition with radar.

Shallow learning models are here to stay since a few recent studies are still deploying shallow models for activity recognition [134], [134], [141]. A recent work confirmed the effectiveness of SVM for through-wall activity recognition [134]. Another recent work presented in reference [113] (2020) used kNN to classify activities using IR-UWB radar.

The detailed study of related articles suggests that fewer features are used in shallow learning in comparison to DL approach. For instance, [126] used only six features from micro-Doppler pattern of different actuates. Such shallow networks also require less radar data samples in comparison to deep networks. Unlike the computer vision research area, there are few open-source datasets available for radars. Capturing data with radar sensor and creating labelled dataset is a challenging task. Few public radar-based datasets exist such as UWB-gestures [173] and [105]. A DL model would get over-trained with less amount of data. On the other hand, a shallow learned classifier may not be robust against different environmental conditions. DL model learns the hidden data hierarchy in more complex way in comparison to shallow models [176].

In general, shallow networks are considered to deal with small-scale data [193] driven with hand-crafted features and possesses lower generalization capability [194]. For radar-based activity recognition case, it was reported in one of the studies that the performance of SVM degrades significantly when the training and testing is done in separate environment whereas, the performance of CNN is more consistent and environment independent [70]. Nevertheless, shallow Learning models are still in use for radar-based activity recognition.

*3) Data Analysis and Processing Approaches:* Activity recognition with radar has mostly been considered as a classification problem and supervised ML algorithms are being used [27] which additionally requires data labeling. To the best of our knowledge, only two papers used unsupervised learning approach for activity classification using k-means [111] and HMM [110]. Additionally, semi-supervised learning for activity recognition is proposed in references [76], [89], [143]. The rest of the studies mainly relied on supervised learning approach for classification. Unsupervised learning have a huge potential in future applications and must be considered. In addition to that, few unsupervised features reduction and

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TABLE XIV
SUMMARY OF VS BASED STUDIES USING ML

| | | |
|---|---|---|
| VS Radar Hardware | Pulsed | [11], [42], [48], [54], [66], [178], [180] |
| | CW | [46], [50], [53], [57], [64], [65], [67] |
| | FCMW | [46], [50], [53], [55], [57], [64], [65] |
| | Any Hardware | [51] |
| VS Algorithms | CNN | [48], [53]–[55], [64], [65], [180] |
| | SVM | [11], [45], [47], [58], [67] |
| | DNN | [46], [50] |
| | Gamma Filter | [43] |
| | AE | [52], [56], [178] |
| | HMM | [42] |
| | TCN | [57] |
| | CNN+LSTM | [49] |
| | GAN | [66] |
| Learning Style | Unsupervised | [51], [56], [57], [180], [181] |
| | Supervised | [8], [11], [43]–[50], [52]–[55], [65], [179], [183] |

clustering approaches have been used in literature such as unsupervised PCA for features reduction [117] and DB-Scan clustering [73] to reduce noise.

*4) Algorithm Usage Trend:* As stated earlier, our analysis shows that initial studies were based on shallow classifiers [42], [129]–[133], [137], [138]. Afterwards, deep models such as CNN started to gain huge attention [68], [74], [78], [97] and CNN showed dominance over SVM in terms of classification accuracy. Few studies showed the dominance of CNN+RNN over other models on public datasets [105] however, the note on fine tuning the network and grid search is not discussed in details. CNN based deep architectures such as GoogleNet have also been considered in literature.

Recently, AE has shown its effectiveness for activity recognition works [70], [116], [120]. A work presented by [145] suggests that AE reduce the features space in comparison to the CNN architecture since AE has the ability to compress the data.

To show the overall trend of algorithms being used, data shown in Table XV is plotted in Fig. 12. It is evident that CNN algorithm is by far the widely used algorithm for activity classification. Note that the count for CNN based studies also contains the variants based on CNN such as ResNet and GoogleNet as well. SVM is the second most widely discussed classification algorithm. As stated earlier, multi-class SVM classifier is the first ML based approach to recognize activity through radar sensor [126]. To the date, few examples of SVM based activity recognition exist [141]. The use of reinforcement learning for radar-based healthcare applications has not been observed so far.

*5) Simulation and Public Data Sources:* Owing to the fact that capturing data using a radar might be difficult, simulation-based datasets can further elevate the generalization to avoid over fitting by providing a rich data distribution. Following methods are found in literature to create simulation-based dataset:

- MOCAP: Motion captured using RGB-D camera such as Microsoft-Kinect can be used to generate radar data [84], [102]. To our knowledge, this is the most widely used method for data synthesis.
- Kinematic Model: This approach is similar to MOCAP based approach where the joints movement is used to generate synthetic Doppler effect [72].
- Data expansion through GAN: GAN is a powerful tool to expand radar data, verified by many studies
- Direct conversion of videos into Radar data This method provides a DL based framework to generate Doppler data from video sequences [135] .

*6) Radar Data Representation Scheme:* Final survey shown in Table XV for activity recognition work is related to the the use of different radar-data as input to the ML classifiers. Several different types of data-representation schemes have been used. It can be seen that Time-Frequency or the Time-Doppler map which can be extracted with any CW radar, has been used in several researches. The Time-Range map which can be extracted from FMCW and Pulsed radar data has also been used extensively in literature. Several combinations of radar data such as 'Time-Doppler and Time-range', 'Time-range, Time-Doppler and Time-Angle' has also been discussed. The rest of the combination and detailed are summarized in Table XV. The overall trends are visualized in Fig. XV for convenience.

## VII. LESSONS LEARNED

The history of artificial intelligence dates to 1940s [167] whereas the first radar-based bio-medical signal was measured in 1960s [38]. Radar sensing is also getting integrated with the existing communication network [195]–[198]. Progress in both fields is complimenting each other to overcome traditional limitations. Reviewing the state-of-the art literature reveals that non-contact (radar) sensors are getting integrated into the healthcare industry at a rapid pace, and one may expect commercial-graded medical devices based on radar sensor very soon. Perhaps, a United States Food and Drug Authority (US-FDA) cleared radar sensor for HR monitoring is already in the market [199]. The overall summary of the survey being conducted in this work is presented in Fig. 13. The application being reviewed is shown in the middle whereas left and right sides represent the radar-sensor and ML network taxonomies. Here are a few learned lessons for the two topics in consideration.

### A. Vital Sign Measurement

- According to our survey, the use of ML for radar-based VS monitoring is still at the initial stage. VS measurements is mainly performed using conventional way with ML being a helping tool. Currently, research is being carried out to overcome the limitations and restrictions being imposed by the conventional VS measurement approach.
- As shown in Fig. 11, CNN is the most widely used network followed by SVM. Regarding hardware usage,

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TABLE XV
SUMMARY OF ACTIVITY RECOGNITION WORKS BASED ON MACHINE LEARNING.

| | | |
|---|---|---|
| Radar Hardware | Pulsed | [71], [74], [79], [80], [88], [90], [92], [99]–[101], [104], [107], [112], [113], [118], [122], [124], [129], [131], [136], [139], [144] |
| | CW | [10], [67], [68], [76], [78], [84], [89], [91], [94], [96], [102], [108], [110], [111], [126]–[128], [130], [132]–[134], [150], [151], [157] |
| | FCMW | [69], [70], [73], [75], [77], [81]–[83], [85]–[87], [93], [95], [97], [98], [103], [105], [106], [109], [114], [117], [119]–[121], [123], [125], [135], [137], [138], [140]–[143], [145]–[149], [152], [154]–[156], [158] |
| Learning style | Shallow (28 works) | [82], [90], [102], [110]–[113], [117], [118], [121], [122], [126]–[134], [136]–[141], [144], [156] |
| | Deep (63 works) | [10], [68]–[81], [83]–[89], [91]–[101], [103]–[109], [114]–[116], [119], [120], [123]–[125], [135], [142], [143], [145]–[152], [154], [155], [157] |
| Algorithms | CNN | **CNN:** [10], [68], [69], [71], [73], [74], [77]–[79], [81], [83], [84], [91], [97], [98], [103], [114], [116], [119], [123], [142], [146]–[149], [151], [152], [155] **1D- CNN:** [94]–[96] |
| | NN | **NN** [117], [118] **DNN** [120], [154] |
| | SVM | [126]–[134], [136]–[141], [144] |
| | LSTM | [106], [115], [124] |
| | GAN | [72], [88], [89], [101], [108], [114], [150], [157]. |
| | AE | [70], [76], [145] |
| | HMM | [110] |
| | RNN / LSTM | [106], [115], [124] |
| | k-Means & k-NN | **k-NN**: [90], [102], [112] **k-Means:** [111] |
| | CNN+LSTM/RNN | **CNN+LSTM:** [80], [85], [99], [104], [105]. **CNN+RNN**: [86], [87], [92], [107], [125] |
| | Random Forest | [113], [121], [122], [156] |
| | Misc | **Metric Learning:** [93] **Domain Adoption:** [100] **GNN & GCN:** [75], [153] **HDC:** [109] **HMM:** [110] **Transfer learning with CNN** [143] **Features based Softmax:** [82] |
| Radar Data Representation | Time-Range | [70], [71], [73], [74], [79], [80], [90], [99], [104], [107], [113], [115], [118], [122], [124], [129], [131], [136], [139], [155], [156] |
| | Time-Frequency / Time-Doppler | [10], [68], [72], [76], [78], [81], [84], [88], [89], [91], [92], [95]–[97], [100]–[103], [106], [108]–[112], [116], [123], [125]–[128], [130], [132]–[134], [137], [138], [140], [142], [143], [145], [146], [150], [151], [157] |
| | Range Doppler | [82], [83], [119], [120], [141], [149] |
| | Time-Doppler & Time-Range | [69], [77], [117] |
| | Time-Range, Doppler & Angle | [87], [121] |
| | 2D, 3D localization & point maps | [75], [86], [105], [114], [147] |
| | Others | **Time-Doppler& Angle:** [93]. **Raw-Data:** [94] **Range-Angle:** [148] **Range Time Doppler:** [98] **Range Time Doppler:** [98] **Time-Doppler & Time-Range & Range-Doppler:** [85]. |

Fig. 11 suggests that all types of radars are being used equally.

- For body movement cancellation, if the work focuses only on detecting and discarding body movement instances, CNN and SVM are good candidate solutions [11]. However, if the algorithm is trying to make measurements even under the influence of body movement, regression such as DNN based regression [44] can be performed. Similarly, an auto-encoder (based on DL) tries to learn the statistical properties for encoding purposes often used in compression. The learned properties (or features) are often used to learn normal breathing patterns. Hence can be used to detect and mitigate the body's movement accordingly.
- For the issue of breathing harmonics, several harmonics cancellation filtering approach exist such as comb filters or gamma filters [43]. However, these filters require high SNR and DL based filter such as DNN filter can be used accordingly.
- To extract heartbeat waveform showing R-R peaks, radar-extracted vital signs must be pre-processed since the radar extracted waveform often looks like a sinusoidal waveform [160]. Conventional CNN may not serve the purpose, instead template matching based on CNN [65] can be performed. In addition to that, unsupervised AE can be trained to transform radar extracted vital signs into ECG alike waveforms.
- To find accurate range-point, any ML algorithm providing

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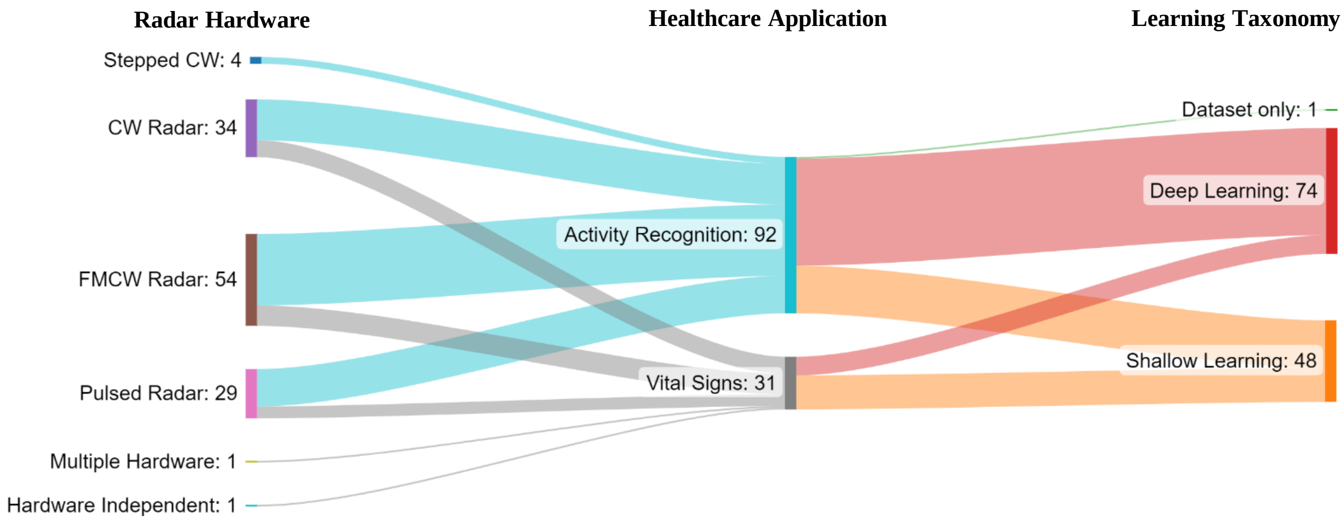


Fig. 13. High level summary of research works being reviewed in this article. Type of radar, application and learning style are summarized
.

a suitable voting scheme to select optimum range-bin can be used. Authors in reference [55] used CNN based voting scheme.

- A few applications oriented studies also exist such as usage of radar extracted vital signs for security and surveillance purposes [37], [45]. These algorithms require sophisticated classifiers such as CNN and SVM to detect and classify the individual person.
- Researchers have not yet utilized the potential of generative AI. To our knowledge, only one work has utilized generative AI for VS measurement [66].

### *B. Human Activity Recognition*

Literature survey suggests that activity recognition topic is dealt using ML only. Simple classifications based on signal manipulation are very rare. Consequently, the number of research works employing machine learning for this topic are considerably higher than VS measurement research works. Here are the few learned lessons based on the existing works:

1) Usage of DL based classifiers is significantly higher than ML based classifiers.
2) First ML algorithm used for activity recognition was based on SVM ( [126], 2008) and first DL classifiers was CNN ( [78], 2015)
3) CNN is the most widely used algorithm, followed by SVM and LSTM (Fig. 12).
4) Shallow model may show higher performances however, the deep models show consistent performances in different environments [70].
5) Considering multimodal data together such as range, time, and doppler simultanuously for features learning instead of range-Doppler only increases classification accuracy [98].
6) Fusion of radar and camera shows better precision in comparison to radar and camera alone [119].
7) Efficient algorithms can decrease need of having big dataset: Using FMCW radar, Zhao et al. [103] reported that the efficient algorithms can decrease the required data samples for training purpose. With an improved PCA, dimensional reduction is performed and a modified version of VGG net is used on the dataset provided by [81]. An overall accuracy of 96.3% is achieved which is 4.2% higher than the conventional PCA and VGGNET.
8) Shallow networks are still being used. For instance, we witnessed a two-stage classification approach based on random forest recently [121]. Another recent attempt utilizing random forest classifier to recognize fifteen activities of daily living [122]. In addition to that, shallow SVM and shallow NN are recently being used for activity classification in references [141]. Similarly, K-means clustering based unsupervised classification was also used recently in reference [111].
9) Currently, a pre-selected activity set is being considered, and the start and the finish instances of these activities are already determined. However, practical scenarios may require the detection of start and end time in autonomous fashion.
10) Comparative analysis on studies utilizing same dataset suggests that 1D-CNN with attention mechanism has higher accuracy in comparison to end-to-end-1D CNN, mobile-edge based lightweight CNN. However, few shots learning which requires very less labelled data samples, decreases the accuracy [91], [94]–[96].
11) The performance of shallow learning models (SVM in particular), degrades when training and test is performed in separate environment whereas DL model shows consistent performance [194].
12) Using FMCW radar, Zhao et al. [103] reported that efficient algorithms can decrease the required data samples for training purposes.
13) It has also been observed that efficient features extraction scheme and classifier can reduce the need of having big dataset [103]. Consequently, the small-scale dataset must be treated with efficient classification approaches.

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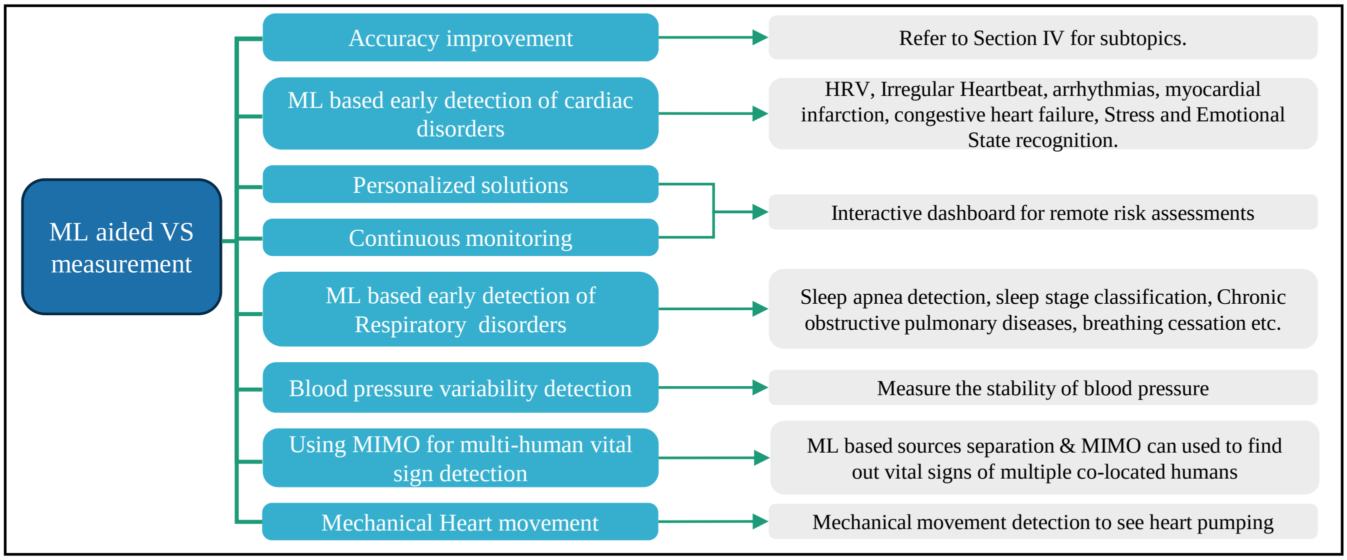


Fig. 14. Few Open Issues for VS Measurements.

14) Unlike vision-based activity recognition, public datasets are very scarce for radar-based activity recognition works.

### C. Integrated Well-Being Tracker Based on These two Applications.

As stated earlier, several research works are currently considering both the vital sign measurement and activity recognition in a holistic fashion [12]–[18]. Recently, concepts like activity-aware vital sign measurement [18] have been receiving increased attention. This is because a compact health monitoring system that can measure multiple physiological quantities simultaneously can offer integrated and personalized well-being tracking. For example, monitoring vital signs following a critical event, such as a fall, can help quantify the severity of the incident. Low vital signs observed in an elderly person after a fall can indicate an emergency situation.

## VIII. Future Directions

### A. Vital Sign Measurement

Survey suggests that the use of ML for radar-based VS is very recent and still in the preliminary stage, suggesting a considerable amount of room for new research. Each of the VS related challenges mentioned earlier can be considered as an open research topic. Fig. 14 shows a list of future directions for VS measurement. We conclude that a huge importance must be given to the early detection of cardiac and respiration anomalies in future. As shown in Fig. 14 both these vital signs can be used to build a wide range of detection and prevention systems.

Unlike activity recognition, VS measurements lacks the studies discussing generative ML concepts for training and testing. The only study using generative ML is based on where the data from multiple radar is fused together using GAN to find the orientation of human body while capturing vital signs [66]. We suggest the use of GAN to generate additional heart and respiration waveform signals based on radar sensors.

Section V suggests that most of the VS studies mainly focus on the extraction of breathing rate and heart rate. A similar mechanism can be applied to find out the heart mechanical movements as well. For instance, calculation of the point of maximal (heartbeat) impulse near chest can lead us to find out the size of heart. These topics are not yet been considered by the researchers.

### B. Activity Recognition

The future works related to activity recognition are summarized in Fig. 15. The discoveries may have shown huge success rate in research environment, the actual patients and clinicians are required to trust these findings which suggest that clinical and pre-clinical trials must be performed. Research works still lack the clinical and pre-clinical trials for radar-based activity recognition.

With few exceptions [154], activity from single human subjects are being classified all the time. The issue of multi-human activity recognition remains an open challenge.

Semi-supervised learning has great potential in this field as it can reduce the burden of labeling datasets. In addition to that, although the set of activities being classified is always pre-decided and fixed, unsupervised learning can also enable several novel applications. The addition of new activity by users can be accomplished using this approach.

ML system requires a massive data to create rules and adjust its parameters (automatically) for a generalized solution having negligible bias. This suggests the need to have a public dataset which additionally provides a competing platform for different algorithms as well. Regarding radar-data representation and type, comparative analysis is very rare. Research is required to compare the accuracy and robustness of different radar-data. Multi sensor data fusion can also be a future direction where radar sensors fused with other sensors such as camera or lidar

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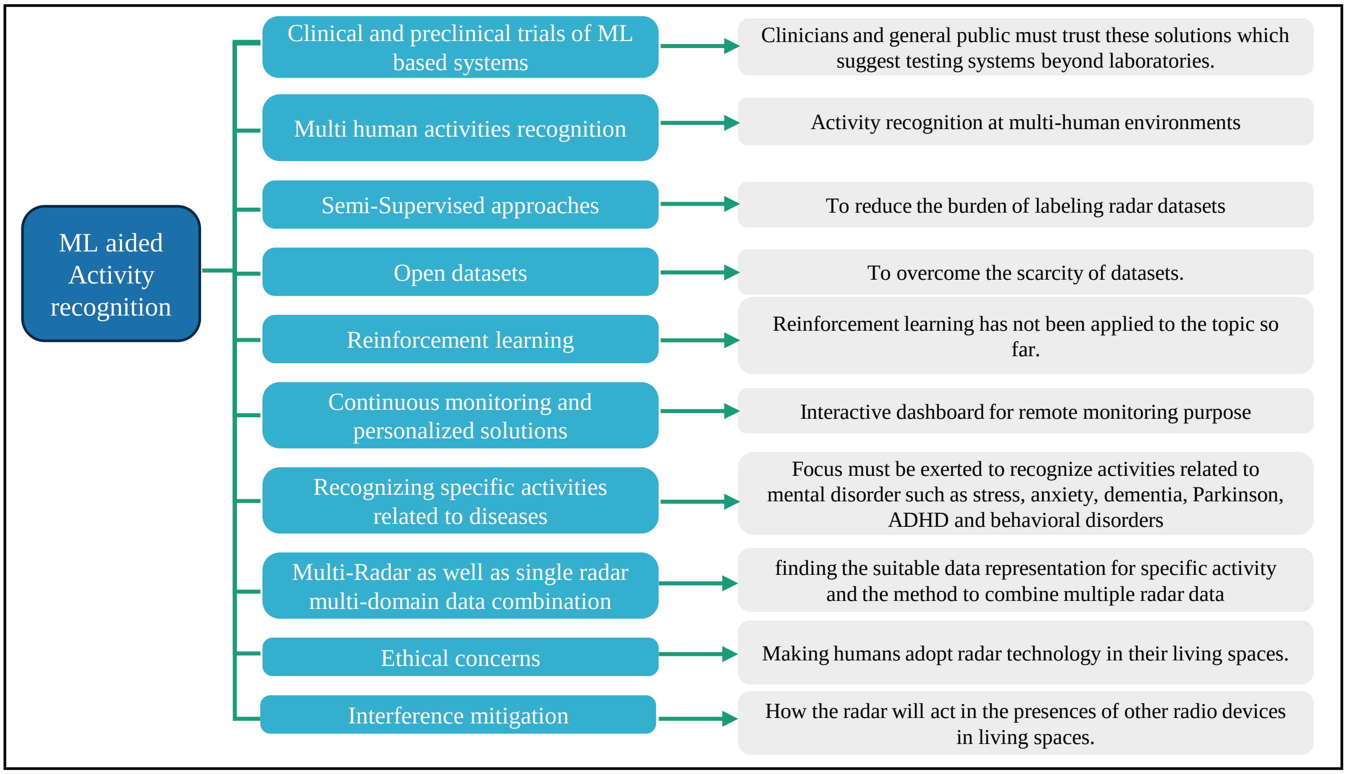


Fig. 15. Few Open issues and Future Directions for Human Activity Recognition.

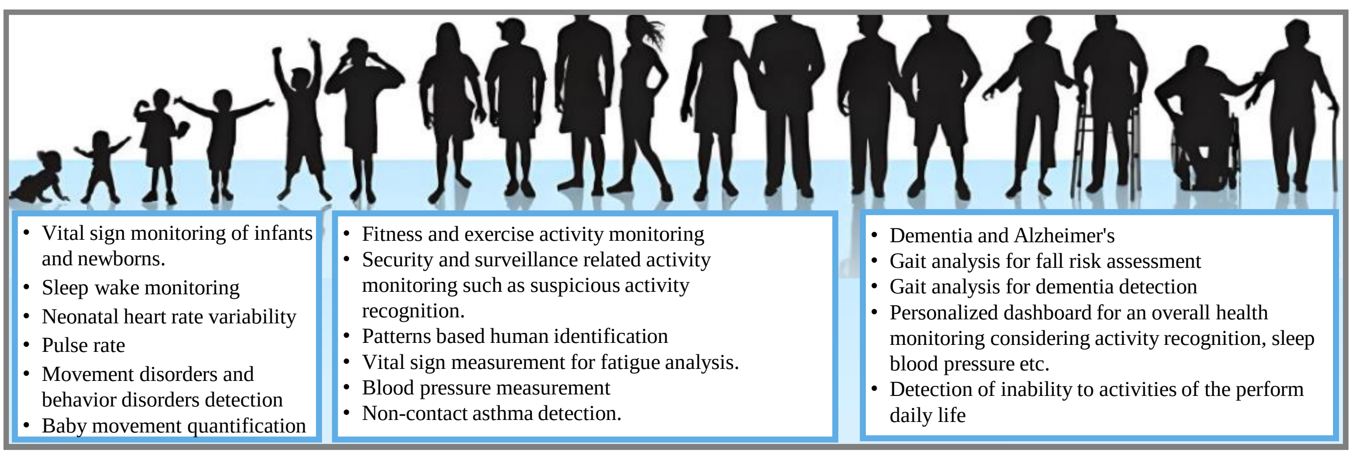


Fig. 16. Cradle to grave healthcare applications in nutshell: Overall Future potential of healthcare radars from a broad application perspective..

can complement the existing of each other. We already have witnessed a few works previously [106].

As defined earlier, the activities are often performed in discrete fashion. More work is required in future to recognize activity in a continuous set of motions being performed by the participants.

Another future challenge can be the situation based activity recognition aiming for elderly healthcare and well-being. For instance, radar-based medication reminder system can be proposed where the human subject must be reminded to take medicine while going to bed. However, the subject will not be reminded to take medicine while in living room. In the similar way, owing to the benefits of privacy preserving nature of radar, sensor can be deployed in the home environment to ensure that elderly patient is performing the medical doctor's recommended exercises (such as strokes rehabilitation exercises recommended by Phillips research [200]).

### C. Overall Healthcare Applications of Radar

Since healthcare radar applicability is not limited only to activity recognition and VS measurement, several other open issues are listed in Fig. 16. The health monitoring topics also vary based on age. For instance, neonates require vital sign monitoring and movement quantification which has already been attempted based on radar sensor by a few authors [201], [202]. The young and middle aged person may require fitness

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monitoring systems and fortuitously as stated earlier radar based fitness activity monitoring and vital sign systems already exist [50], [105]. The integration of these system is yet to be considered. In the similar way, elderly population often suffer form neurological disorders such as alzheimer, apathy, and dementia. Few others have discussed a vague applicability of radar to detect these issues [8]–[10]. However, an integrated radar-based solution using applications such as vital sign monitoring, sleep monitoring, activity recognition is yet to be proposed.

## IX. Conclusion

Fueled by the availability of OTS radars, an upsurge has recently been observed in non-military applications of radar, with healthcare industry being one of the beneficiaries. ML empowered healthcare-applications are breaking the traditional limitations, making radar-based healthcare more practical and robust. While the list of related applications is vast, in this article, a detailed overview of ML based VS measurement and activity recognition is presented.

We conclude that for the case VS measurement, the researchers are trying to use ML as an additional helping tool to increase the accuracy and robustness of the conventional algorithms. ML classifiers are often used to detect the abnormalities in the VS which are either discarded or recovered. To recover the distorted VS, regression using shallow and deep learning models has shown its usefulness. Auto-encoders based de-noising have also been used. ML has also enabled the measurement of VS while the human subject is non-stationary. In addition to that, the radar extracted VS can further be used to train ML systems to develop several novel applications such as non-contact user authentication by breathing and robust HRV extraction. However, the research works are still at the preliminary stages, suggesting a research gap in the corresponding field.

For activity recognition, we conclude that activity recognition is an application which is always being resolved using the ML approach. Most of the time, supervised leanring approach is considered, leaving a roam for semi-supervised and unsupervised learning approaches. The reinforcement learning based solutions are yet to be discussed. FMCW radar is the most widely used radar for activity recognition, particularly in recent years. A few public datasets also exist however, no such dataset exist which can be used to compare the performance of different radars. Unlike VS, activity recognition still lacks clinical and pre-clinical evaluation.

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## References

[1] Darcy Jones McMaughan, Oluyomi Oloruntoba, and Matthew Lee Smith. Socioeconomic status and access to healthcare: interrelated drivers for healthy aging. *Frontiers in public health*, 8:231, 2020.

[2] Albert Haque, Arnold Milstein, and Li Fei-Fei. Illuminating the dark spaces of healthcare with ambient intelligence. *Nature*, 585(7824):193–202, 2020.

[3] Shahzad Ahmed, Karam Dad Kallu, Sarfaraz Ahmed, and Sung Ho Cho. Hand gestures recognition using radar sensors for human-computer-interaction: A review. *Remote Sensing*, 13(3):527, 2021.

[4] Shahzad Ahmed, Wancheol Kim, Junbyung Park, and Sung Ho Cho. Radar based air-writing gesture recognition using a novel multi-stream cnn approach. *IEEE Internet of Things Journal*, 2022.

[5] Anuradha Singh, Saeed Ur Rehman, Sira Yongchareon, and Peter Han Joo Chong. Multi-resident non-contact vital sign monitoring using radar: A review. *IEEE Sensors Journal*, 21(4):4061–4084, 2020.

[6] Christoph Will, Kilin Shi, Sven Schellenberger, Tobias Steigleder, Fabian Michler, Robert Weigel, Christoph Ostgathe, and Alexander Koelpin. Local pulse wave detection using continuous wave radar systems. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, 1(2):81–89, 2017.

[7] Dilpreet Buxi, Jean-Michel Redouté, and Mehmet Rasit Yuce. Cuffless blood pressure estimation from the carotid pulse arrival time using continuous wave radar. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 5704–5707. IEEE, 2015.

[8] Srikrishna Iyer, Leo Zhao, Manoj Prabhakar Mohan, Joe Jimeno, Mohammed Yakoob Siyal, Arokiaswami Alphones, and Muhammad Faeyz Karim. mm-wave radar-based vital signs monitoring and arrhythmia detection using machine learning. *Sensors*, 22(9):3106, 2022.

[9] Imran M Saied, Tughrul Arslan, and Siddharthan Chandran. Classification of alzheimer's disease using rf signals and machine learning. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, 6(1):77–85, 2021.

[10] Xuebin Yue, Hengyi Li, Kenshi Saho, Kazuki Uemura, CV Aravinda, and Lin Meng. Machine learning based apathy classification on doppler radar image for the elderly person. *Procedia Computer Science*, 187:146–151, 2021.

[11] Faheem Khan, Stéphane Azou, Roua Youssef, Pascal Morel, and Emanuel Radoi. Ir-uwb radar-based robust heart rate detection using a deep learning technique intended for vehicular applications. *Electronics*, 11(16):2505, 2022.

[12] Xiuzhu Yang, Xinyue Zhang, Yi Ding, and Lin Zhang. Indoor activity and vital sign monitoring for moving people with multiple radar data fusion. *Remote Sensing*, 13(18):3791, 2021.

[13] Zhelong Wang, Cong Zhao, and Sen Qiu. A system of human vital signs monitoring and activity recognition based on body sensor network. *Sensor Review*, 34(1):42–50, 2014.

[14] Zhihua Wang, Zhaochu Yang, and Tao Dong. A review of wearable technologies for elderly care that can accurately track indoor position, recognize physical activities and monitor vital signs in real time. *Sensors*, 17(2):341, 2017.

[15] Francesco Fioranelli, Julien Le Kernec, and Syed Aziz Shah. Radar for health care: Recognizing human activities and monitoring vital signs. *IEEE Potentials*, 38(4):16–23, 2019.

[16] Dr Francesco Fioranelli, Dr Syed Aziz Shah, Haobo Li1, Aman Shrestha, Dr Shufan Yang, and Dr Julien Le Kernec. Radar sensing for healthcare: Associate editor francesco fioranelli on the applications of radar in monitoring vital signs and recognising human activity patterns. *Electronics Letters*, 55(19):1022–1024, 2019.

[17] Emanuele Cardillo and Alina Caddemi. A review on biomedical mimo radars for vital sign detection and human localization. *Electronics*, 9(9):1497, 2020.

[18] Todor Ivașcu and Viorel Negru. Activity-aware vital sign monitoring based on a multi-agent architecture. *Sensors*, 21(12):4181, 2021.

[19] James C Lin. Microwave sensing of physiological movement and volume change: A review. *Bioelectromagnetics*, 13(6):557–565, 1992.

[20] Enrico M Staderini. Uwb radars in medicine. *IEEE aerospace and electronic systems magazine*, 17(1):13–18, 2002.

[21] Changzhi Li and Jenshan Lin. Recent advances in doppler radar sensors for pervasive healthcare monitoring. In *2010 Asia-Pacific Microwave Conference*, pages 283–290. IEEE, 2010.

[22] Changzhi Li, Victor M Lubecke, Olga Boric-Lubecke, and Jenshan Lin. A review on recent advances in doppler radar sensors for noncontact healthcare monitoring. *IEEE Transactions on microwave theory and techniques*, 61(5):2046–2060, 2013.

[23] Changzhan Gu. Short-range noncontact sensors for healthcare and other emerging applications: A review. *Sensors*, 16(8):1169, 2016.

[24] José-María Muñoz-Ferreras, Zhengyu Peng, Roberto Gómez-García, and Changzhi Li. Review on advanced short-range multimode continuous-wave radar architectures for healthcare applications. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, 1(1):14–25, 2017.

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[25] Changzhi Li, Zhengyu Peng, Tien-Yu Huang, Tenglong Fan, Fu-Kang Wang, Tzyy-Sheng Horng, Jose-Maria Munoz-Ferreras, Roberto Gomez-Garcia, Lixin Ran, and Jenshan Lin. A review on recent progress of portable short-range noncontact microwave radar systems. *IEEE Transactions on Microwave Theory and Techniques*, 65(5):1692–1706, 2017.

[26] Julien Le Kernec, Francesco Fioranelli, Shufan Yang, Jordane Lorandel, and Olivier Romain. Radar for assisted living in the context of internet of things for health and beyond. In *2018 IFIP/IEEE International Conference on Very Large Scale Integration (VLSI-SoC)*, pages 163–167. IEEE, 2018.

[27] Xinyu Li, Yuan He, and Xiaojun Jing. A survey of deep learning-based human activity recognition in radar. *Remote Sensing*, 11(9):1068, 2019.

[28] Syed Aziz Shah and Francesco Fioranelli. Rf sensing technologies for assisted daily living in healthcare: A comprehensive review. *IEEE Aerospace and Electronic Systems Magazine*, 34(11):26–44, 2019.

[29] Zhengyu Peng and Changzhi Li. Portable microwave radar systems for short-range localization and life tracking: A review. *Sensors*, 19(5):1136, 2019.

[30] Carolina Gouveia, José Vieira, and Pedro Pinho. A review on methods for random motion detection and compensation in bio-radar systems. *Sensors*, 19(3):604, 2019.

[31] Zhaozong Meng, Mingxing Zhang, Changxin Guo, Qirui Fan, Hao Zhang, Nan Gao, and Zonghua Zhang. Recent progress in sensing and computing techniques for human activity recognition and motion analysis. *Electronics*, 9(9):1357, 2020.

[32] Brahim Walid, Jianhua Ma, Muxin Ma, Alex Qi, Yunlong Luo, and Yihong Qi. Recent advances in radar-based sleep monitoring—a review. In *2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, pages 759–766. IEEE, 2021.

[33] Alessandro Davoli, Giorgio Guerzoni, and Giorgio M Vitetta. Machine learning and deep learning techniques for colocated mimo radars: A tutorial overview. *IEEE Access*, 9:33704–33755, 2021.

[34] Fahad Jibrin Abdu, Yixiong Zhang, Maozhong Fu, Yuhan Li, and Zhenmiao Deng. Application of deep learning on millimeter-wave radar signals: A review. *Sensors*, 21(6):1951, 2021.

[35] Umer Saeed, Syed Yaseen Shah, Jawad Ahmad, Muhammad Ali Imran, Qammer H Abbasi, and Syed Aziz Shah. Machine learning empowered covid-19 patient monitoring using non-contact sensing: An extensive review. *Journal of pharmaceutical analysis*, 2022.

[36] Zehua Sun, Qiuhong Ke, Hossein Rahmani, Mohammed Bennamoun, Gang Wang, and Jun Liu. Human action recognition from various data modalities: A review. *IEEE transactions on pattern analysis and machine intelligence*, 2022.

[37] Md Islam, Sheikh Nooruddin, Fakhri Karray, Ghulam Muhammad, et al. Human activity recognition using tools of convolutional neural networks: A state of the art review, data sets, challenges and future prospects. *arXiv preprint arXiv:2202.03274*, 2022.

[38] Iu Ye Moskalenko. Application of centrimetre radio waves for non-contact recording of changes in volume of biological specimens. *Biophysics*, 5(2):259–264, 1960.

[39] Curtis C Johnson and Arthur W Guy. Nonionizing electromagnetic wave effects in biological materials and systems. *Proceedings of the IEEE*, 60(6):692–718, 1972.

[40] CHARLES Susskind. Possible use of microwaves in the management of lung disease. *Proceedings of the IEEE*, 61(5):673–674, 1973.

[41] James C Lin. Noninvasive microwave measurement of respiration. *Proceedings of the IEEE*, 63(10):1530–1530, 1975.

[42] Yogesh Nijsure, Wee Peng Tay, Erry Gunawan, Fuxi Wen, Zhang Yang, Yong Liang Guan, and Ai Ping Chua. An impulse radio ultrawideband system for contactless noninvasive respiratory monitoring. *IEEE Transactions on Biomedical Engineering*, 60(6):1509–1517, 2013.

[43] Justin Saluja, Joaquin Casanova, and Jenshan Lin. A supervised machine learning algorithm for heart-rate detection using doppler motion-sensing radar. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, 4(1):45–51, 2019.

[44] Changzhan Gu, Jian Wang, and Jaime Lien. Deep neural network based body movement cancellation for doppler radar vital sign detection. In *2019 IEEE MTT-S International Wireless Symposium (IWS)*, pages 1–3. IEEE, 2019.

[45] Shekh MM Islam, Ashikur Rahman, Narayana Prasad, Olga Boric-Lubecke, and Victor M Lubecke. Identity authentication system using a support vector machine (svm) on radar respiration measurements. In *2019 93rd ARFTG Microwave Measurement Conference (ARFTG)*, pages 1–5. IEEE, 2019.

[46] Hsin-Yuan Chang, Chia-Hung Lin, Yu-Chien Lin, Wei-Ho Chung, and Ta-Sung Lee. Dl-aided nomp: a deep learning-based vital sign estimating scheme using fmcw radar. In *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, pages 1–7. IEEE, 2020.

[47] Shekh MM Islam, Ashikur Rahman, Ehsan Yavari, Meheran Baboli, Olga Boric-Lubecke, and Victor M Lubecke. Identity authentication of osa patients using microwave doppler radar and machine learning classifiers. In *2020 IEEE Radio and Wireless Symposium (RWS)*, pages 251–254. IEEE, 2020.

[48] Seong Kyu Leem, Faheem Khan, and Sung Ho Cho. Remote authentication using an ultra-wideband radio frequency transceiver. In *2020 IEEE 17th Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–8. IEEE, 2020.

[49] Yu-Chiao Tsai, Shih-Hsuan Lai, Ching-Ju Ho, Fang-Ming Wu, Lindor Henrickson, Chia-Chien Wei, Irwin Chen, Vincent Wu, and Jyehong Chen. High accuracy respiration and heart rate detection based on artificial neural network regression. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 232–235. IEEE, 2020.

[50] King Leong Li, Shih-Hsuan Lai, Kyle Cheng, Lindor Henrickson, Irwin Chen, Vincent Wu, and Jyehong Chen. Exercise vital signs detection employing fmcw radar and artificial neural networks. In *CLEO: QELS_Fundamental Science*, pages JW1A–149. Optica Publishing Group, 2021.

[51] Zhe Chen, Tianyue Zheng, Chao Cai, and Jun Luo. Movi-fi: Motion-robust vital signs waveform recovery via deep interpreted rf sensing. In *Proceedings of the 27th Annual International Conference on Mobile Computing and Networking*, pages 392–405, 2021.

[52] Mikolaj Czerkawski, Christos Ilioudis, Carmine Clemente, Craig Michie, Ivan Andonovic, and Christos Tachtatzis. Interference motion removal for doppler radar vital sign detection using variational encoder-decoder neural network. In *2021 IEEE Radar Conference (RadarConf21)*, pages 1–6. IEEE, 2021.

[53] Daiki Toda, Ren Anzai, Koichi Ichige, Ryo Saito, and Daichi Ueki. Ecg signal reconstruction using fmcw radar and convolutional neural network. In *2021 20th International Symposium on Communications and Information Technologies (ISCIT)*, pages 176–181. IEEE, 2021.

[54] Zongxing Xie, Hanrui Wang, Song Han, Elinor Schoenfeld, and Fan Ye. Deepvs: a deep learning approach for rf-based vital signs sensing. In *Proceedings of the 13th ACM International Conference on Bioinformatics, Computational Biology and Health Informatics*, pages 1–5, 2022.

[55] Hsin-Yuan Chang, Chih-Hsuan Hsu, and Wei-Ho Chung. Fast acquisition and accurate vital sign estimation with deep learning-aided weighted scheme using fmcw radar. In *2022 IEEE 95th Vehicular Technology Conference:(VTC2022-Spring)*, pages 1–6. IEEE, 2022.

[56] Young In Jang, Jae Young Sim, Jong-Ryul Yang, and Nam Kyu Kwon. Improving heart rate variability information consistency in doppler cardiogram using signal reconstruction system with deep learning for contact-free heartbeat monitoring. *Biomedical Signal Processing and Control*, 76:103691, 2022.

[57] Jinbo Chen, Dongheng Zhang, Zhi Wu, Fang Zhou, Qibin Sun, and Yan Chen. Contactless electrocardiogram monitoring with millimeter wave radar. *IEEE Transactions on Mobile Computing*, 2022.

[58] Soumya Prakash Rana, Maitreyee Dey, Robert Brown, Hafeez Ur Siddiqui, and Sandra Dudley. Remote vital sign recognition through machine learning augmented uwb. 2018.

[59] Seong-Hoon Kim and Gi-Tae Han. 1d cnn based human respiration pattern recognition using ultra wideband radar. In *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pages 411–414. IEEE, 2019.

[60] Xiaofeng Yang, Koki Kumagai, Guanghao Sun, Koichiro Ishibashi, Nguyen Vu Trung, Nguyen Van Kinh, et al. Dengue fever screening using vital signs by contactless microwave radar and machine learning. In *2019 IEEE sensors applications symposium (SAS)*, pages 1–6. IEEE, 2019.

[61] Jian Gong, Xinyu Zhang, Kaixin Lin, Ju Ren, Yaoxue Zhang, and Wenxun Qiu. Rf vital sign sensing under free body movement. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(3):1–22, 2021.

[62] Shuqiong Wu, Takuya Sakamoto, Kentaro Oishi, Toru Sato, Kenichi Inoue, Takeshi Fukuda, Kenji Mizutani, and Hiroyuki Sakai. Person-specific heart rate estimation with ultra-wideband radar using convolutional neural networks. *IEEE Access*, 7:168484–168494, 2019.


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[63] Haoyu Zhang. Heartbeat monitoring with an mm-wave radar based on deep learning: A novel approach for training and classifying heterogeneous signals. *Remote Sensing Letters*, 11(11):993–1001, 2020.

[64] Sungwon Yoo, Shahzad Ahmed, Sun Kang, Duhyun Hwang, Jungjun Lee, Jungduck Son, and Sung Ho Cho. Radar recorded child vital sign public dataset and deep learning-based age group classification framework for vehicular application. *Sensors*, 21(7):2412, 2021.

[65] Unsoo Ha, Salah Assana, and Fadel Adib. Contactless seismocardiography via deep learning radars. In *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, pages 1–14, 2020.

[66] Xiuzhu Yang, Yibo Yu, Hongyu Qian, Xinyue Zhang, and Lin Zhang. Body orientation and vital sign measurement with ir-uwb radar network. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 485–488. IEEE, 2020.

[67] Hoang Thi Yen, Masaki Kurosawa, Tetsuo Kirimoto, Yukiya Hakozaki, Takemi Matsui, and Guanghao Sun. A medical radar system for non-contact vital sign monitoring and clinical performance evaluation in hospitalized older patients. *Biomedical Signal Processing and Control*, 75:103597, 2022.

[68] Tyler S Jordan. Using convolutional neural networks for human activity classification on micro-doppler radar spectrograms. In *Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Security, Defense, and Law Enforcement Applications XV*, volume 9825, pages 47–55. SPIE, 2016.

[69] Rodrigo Hernangómez, Tristan Visentin, Lorenzo Servadei, Hamid Khodabakhshandeh, and Sławomir Stańczak. Improving radar human activity classification using synthetic data with image transformation. *Sensors*, 22(4):1519, 2022.

[70] Mu Jia, Shaoxuan Li, Julien Le Kernec, Shufan Yang, Francesco Fioranelli, and Olivier Romain. Human activity classification with radar signal processing and machine learning. In *2020 International conference on UK-China emerging technologies (UCET)*, pages 1–5. IEEE, 2020.

[71] Rui Qi, Xiuping Li, Yi Zhang, and Yubing Li. Multi-classification algorithm for human motion recognition based on ir-uwb radar. *IEEE Sensors Journal*, 20(21):12848–12858, 2020.

[72] Xiaoran Shi, Yaxin Li, Feng Zhou, and Lei Liu. Human activity recognition based on deep learning method. In *2018 International Conference on Radar (RADAR)*, pages 1–5. IEEE, 2018.

[73] Chengxi Yu, Zhezhuang Xu, Kun Yan, Ying-Ren Chien, Shih-Hau Fang, and Hsiao-Chun Wu. Noninvasive human activity recognition using millimeter-wave radar. *IEEE Systems Journal*, 2022.

[74] Yuming Shao, Sai Guo, Lin Sun, and Weidong Chen. Human motion classification based on range information with deep convolutional neural network. In *2017 4th International Conference on Information Science and Control Engineering (ICISCE)*, pages 1519–1523. IEEE, 2017.

[75] Peixian Gong, Chunyu Wang, and Lihua Zhang. Mmpoint-gnn: graph neural network with dynamic edges for human activity recognition through a millimeter-wave radar. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2021.

[76] Christopher Campbell and Fauzia Ahmad. Semi-supervised attention-augmented convolutional autoencoder for radar-based human activity recognition. In *Radar Sensor Technology XXVI*, volume 12108, pages 113–118. SPIE, 2022.

[77] Hamid Khodabakhshandeh, Tristan Visentin, Rodrigo Hernangómez, and Miro Pütz. Domain adaptation across configurations of fmcw radar for deep learning based human activity classification. In *2021 21st International Radar Symposium (IRS)*, pages 1–10. IEEE, 2021.

[78] Youngwook Kim and Taesup Moon. Human detection and activity classification based on micro-doppler signatures using deep convolutional neural networks. *IEEE geoscience and remote sensing letters*, 13(1):8–12, 2015.

[79] Zhu Zhengliang, Yang Degui, Zhang Junchao, and Tong Feng. Dataset of human motion status using ir-uwb through-wall radar. *Journal of Systems Engineering and Electronics*, 32(5):1083–1096, 2021.

[80] Julien Maitre, Kévin Bouchard, Camille Bertuglia, and Sébastien Gaboury. Recognizing activities of daily living from uwb radars and deep learning. *Expert Systems with Applications*, 164:113994, 2021.

[81] Syed Aziz Shah and Francesco Fioranelli. Human activity recognition: Preliminary results for dataset portability using fmcw radar. In *2019 international radar conference (RADAR)*, pages 1–4. IEEE, 2019.

[82] Ronny Gerhard Guendel, Matteo Unterhorst, Ennio Gambi, Francesco Fioranelli, and Alexander Yarovoy. Continuous human activity recognition for arbitrary directions with distributed radars. In *2021 IEEE Radar Conference (RadarConf21)*, pages 1–6. IEEE, 2021.

[83] Geethika Bhavanasi, Lorin Werthen-Brabants, Tom Dhaene, and Ivo Couckuyt. Patient activity recognition using radar sensors and machine learning. *Neural Computing and Applications*, pages 1–16, 2022.

[84] Mehmet Saygin Seyfioglu, Baris Erol, Sevgi Zubeyde Gurbuz, and Moeness G Amin. Dnn transfer learning from diversified micro-doppler for motion classification. *IEEE Transactions on Aerospace and Electronic Systems*, 55(5):2164–2180, 2018.

[85] Ali Gorji, André Bourdoux, Sofie Pollin, Hichem Sahli, et al. Multi-view cnn-lstm architecture for radar-based human activity recognition. *IEEE Access*, 10:24509–24519, 2022.

[86] Yuheng Wang, Haipeng Liu, Kening Cui, Anfu Zhou, Wensheng Li, and Huadong Ma. m-activity: Accurate and real-time human activity recognition via millimeter wave radar. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 8298–8302. IEEE, 2021.

[87] Wen Ding, Xuemei Guo, and Guoli Wang. Radar-based human activity recognition using hybrid neural network model with multidomain fusion. *IEEE Transactions on Aerospace and Electronic Systems*, 57(5):2889–2898, 2021.

[88] Yang Yang, Chunping Hou, Yue Lang, Dai Guan, Danyang Huang, and Jinchen Xu. Open-set human activity recognition based on micro-doppler signatures. *Pattern Recognition*, 85:60–69, 2019.

[89] Yipeng Ding, Bo Jin, Jiawei Zhang, Runjin Liu, and Yongfu Zhang. Human motion recognition using doppler radar based on semi-supervised learning. *IEEE Geoscience and Remote Sensing Letters*, 19:1–5, 2022.

[90] Matti Hämäläinen, Lorenzo Mucchi, Stefano Caputo, Lorenzo Biotti, Lorenzo Ciani, Dania Marabissi, and Gabriele Patrizi. Ultra-wideband radar-based indoor activity monitoring for elderly care. *Sensors*, 21(9):3158, 2021.

[91] Ziyu Liu, Chaoyang Wu, and Wenbin Ye. Category-extensible human activity recognition based on doppler radar by few-shot learning. *IEEE Sensors Journal*, 2022.

[92] Hao Du, Tian Jin, Yuan He, Yongping Song, and Yongpeng Dai. Segmented convolutional gated recurrent neural networks for human activity recognition in ultra-wideband radar. *Neurocomputing*, 396:451–464, 2020.

[93] Fady Aziz, Omar Metwally, Pascal Weller, Urs Schneider, and Marco F Huber. A mimo radar-based metric learning approach for activity recognition. In *2022 IEEE Radar Conference (RadarConf22)*, pages 1–6. IEEE, 2022.

[94] Wenbin Ye, Haiquan Chen, and Bing Li. Using an end-to-end convolutional network on radar signal for human activity classification. *IEEE Sensors Journal*, 19(24):12244–12252, 2019.

[95] Guoji Lai, Xin Lou, and Wenbin Ye. Radar-based human activity recognition with 1-d dense attention network. *IEEE Geoscience and Remote Sensing Letters*, 19:1–5, 2021.

[96] Jianping Zhu, Xin Lou, and Wenbin Ye. Lightweight deep learning model in mobile-edge computing for radar-based human activity recognition. *IEEE Internet of Things Journal*, 8(15):12350–12359, 2021.

[97] Fredrik Axelsson and Pavel Gueorguiev. Human activity classification using simulated micro-dopplers and time-frequency analysis in conjunction with machine learning algorithm. Master's thesis, 2017.

[98] Won-Yeol Kim and Dong-Hoan Seo. Radar-based human activity recognition combining range–time–doppler maps and range-distributed-convolutional neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–11, 2022.

[99] Alexandre Beaulieu, Florentin Thullier, Kévin Bouchard, Julien Maître, and Sébastien Gaboury. Ultra-wideband data as input of a combined efficientnet and lstm architecture for human activity recognition. *Journal of Ambient Intelligence and Smart Environments*, (Preprint):1–16, 2022.

[100] Xinyu Li, Xiaojun Jing, and Yuan He. Unsupervised domain adaptation for human activity recognition in radar. In *2020 IEEE Radar Conference (RadarConf20)*, pages 1–5. IEEE, 2020.

[101] Yang Yang, Yutong Zhang, Haoran Ji, Beichen Li, and Chunying Song. Radar-based human activity recognition under the limited measurement data support using domain translation. *IEEE Signal Processing Letters*, 29:1993–1997, 2022.

[102] Cesur Karabacak, Sevgi Z Gurbuz, Ali C Gurbuz, Mehmet B Guldogan, Gustaf Hendeby, and Fredrik Gustafsson. Knowledge exploitation for human micro-doppler classification. *IEEE Geoscience and Remote Sensing Letters*, 12(10):2125–2129, 2015.

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[103] Yixin Zhao, Haiyang Zhou, Sichao Lu, Yanzhong Liu, Xiang An, and Qiang Liu. Human activity recognition based on non-contact radar data and improved pca method. *Applied Sciences*, 12(14):7124, 2022.

[104] Liang Ma, Meng Liu, Na Wang, Lu Wang, Yang Yang, and Hongjun Wang. Room-level fall detection based on ultra-wideband (uwb) monostatic radar and convolutional long short-term memory (lstm). *Sensors*, 20(4):1105, 2020.

[105] Akash Deep Singh, Sandeep Singh Sandha, Luis Garcia, and Mani Srivastava. Radhar: Human activity recognition from point clouds generated through a millimeter-wave radar. In *Proceedings of the 3rd ACM Workshop on Millimeter-wave Networks and Sensing Systems*, pages 51–56, 2019.

[106] Haobo Li, Aman Shrestha, Hadi Heidari, Julien Le Kernec, and Francesco Fioranelli. Bi-lstm network for multimodal continuous human activity recognition and fall detection. *IEEE Sensors Journal*, 20(3):1191–1201, 2019.

[107] Simin Zhu, Ronny Gerhard Guendel, Alexander Yarovoy, and Francesco Fioranelli. Continuous human activity recognition with distributed radar sensor networks and cnn–rnn architectures. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–15, 2022.

[108] Baris Erol, Sevgi Z Gurbuz, and Moeness G Amin. Gan-based synthetic radar micro-doppler augmentations for improved human activity recognition. In *2019 IEEE Radar Conference (RadarConf)*, pages 1–5. IEEE, 2019.

[109] Yirong Yao, Wenbo Liu, Gong Zhang, and Wen Hu. Radar-based human activity recognition using hyperdimensional computing. *IEEE Transactions on Microwave Theory and Techniques*, 70(3):1605–1619, 2021.

[110] Wenda Li, Yangdi Xu, Bo Tan, and Robert J Piechocki. Passive wireless sensing for unsupervised human activity recognition in healthcare. In *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 1528–1533. IEEE, 2017.

[111] Yordanka Karayaneva, Sara Sharifzadeh, Wenda Li, Yanguo Jing, and Bo Tan. Unsupervised doppler radar based activity recognition for e-healthcare. *IEEE Access*, 9:62984–63001, 2021.

[112] Bahri Çağlıyan and Sevgi Zübeyde Gürbüz. Micro-doppler-based human activity classification using the mote-scale bumblebee radar. *IEEE Geoscience and Remote Sensing Letters*, 12(10):2135–2139, 2015.

[113] Kevin Bouchard, Julien Maitre, Camille Bertuglia, and Sébastien Gaboury. Activity recognition in smart homes using uwb radars. *Procedia Computer Science*, 170:10–17, 2020.

[114] Gawon Lee and Jihie Kim. Improving human activity recognition for sparse radar point clouds: A graph neural network model with pre-trained 3d human-joint coordinates. *Applied Sciences*, 12(4):2168, 2022.

[115] Can Cheng, Fei Ling, Shisheng Guo, Guolong Cui, Qiang Jian, Chao Jia, and Qingxin Ran. A real-time human activity recognition method for through-the-wall radar. In *2020 IEEE Radar Conference (RadarConf20)*, pages 1–5. IEEE, 2020.

[116] Yong Jia, Yong Guo, Gang Wang, Ruiyuan Song, Guolong Cui, and Xiaoling Zhong. Multi-frequency and multi-domain human activity recognition based on sfcw radar using deep learning. *Neurocomputing*, 444:274–287, 2021.

[117] Baris Erol and Moeness G Amin. Radar data cube processing for human activity recognition using multisubspace learning. *IEEE Transactions on Aerospace and Electronic Systems*, 55(6):3617–3628, 2019.

[118] Mohammad Ahangar Kiasari, Seung You Na, and Jin Young Kim. Classification of human postures using ultra-wide band radar based on neural networks. In *2014 International Conference on IT Convergence and Security (ICITCS)*, pages 1–4. IEEE, 2014.

[119] Baptist Vandersmissen, Nicolas Knudde, Azarakhsh Jalalvand, Ivo Couckuyt, Tom Dhaene, and Wesley De Neve. Indoor human activity recognition using high-dimensional sensors and deep neural networks. *Neural Computing and Applications*, 32(16):12295–12309, 2020.

[120] Branka Jokanović and Moeness Amin. Fall detection using deep learning in range-doppler radars. *IEEE Transactions on Aerospace and Electronic Systems*, 54(1):180–189, 2017.

[121] Ali Gorji, André Bourdoux, Hichem Sahli, et al. On the generalization and reliability of single radar-based human activity recognition. *IEEE Access*, 9:85334–85349, 2021.

[122] Thomas Imbeault-Nepton, Julien Maitre, Kévin Bouchard, and Sébastien Gaboury. Filtering data bins of uwb radars for activity recognition with random forest. *Procedia Computer Science*, 201:48–55, 2022.

[123] Umer Saeed, Syed Yaseen Shah, Syed Aziz Shah, Jawad Ahmad, Abdullah Alhumaidi Alotaibi, Turke Althobaiti, Naeem Ramzan, Akram Alomainy, and Qammer H Abbasi. Discrete human activity recognition and fall detection by combining fmcw radar data of heterogeneous environments for independent assistive living. *Electronics*, 10(18):2237, 2021.

[124] Farzan M Noori, Md Zia Uddin, and Jim Torresen. Ultra-wideband radar-based activity recognition using deep learning. *IEEE Access*, 9:138132–138143, 2021.

[125] Lorin Werthen-Brabants, Geethika Bhavanasi, Ivo Couckuyt, Tom Dhaene, and Dirk Deschrijver. Split birnn for real-time activity recognition using radar and deep learning. *Scientific Reports*, 12(1):1–11, 2022.

[126] Youngwook Kim and Hao Ling. Human activity classification based on micro-doppler signatures using a support vector machine. *IEEE transactions on geoscience and remote sensing*, 47(5):1328–1337, 2009.

[127] Wenda Li, Bo Tan, Yangdi Xu, and Robert J Piechocki. Log-likelihood clustering-enabled passive rf sensing for residential activity recognition. *IEEE Sensors Journal*, 18(13):5413–5421, 2018.

[128] Matthew Zenaldin and Ram M Narayanan. Radar micro-doppler based human activity classification for indoor and outdoor environments. In *Radar Sensor Technology XX*, volume 9829, pages 364–373. SPIE, 2016.

[129] Jacob Bryan and Youngwook Kim. Classification of human activities on uwb radar using a support vector machine. In *2010 IEEE Antennas and Propagation Society International Symposium*, pages 1–4. IEEE, 2010.

[130] Jingli Li, Son Lam Phung, Fok Hing Chi Tivive, and Abdesselam Bouzerdoum. Automatic classification of human motions using doppler radar. In *The 2012 International Joint Conference on Neural Networks (IJCNN)*, pages 1–6. IEEE, 2012.

[131] JD Bryan, Joonsoo Kwon, Namyoon Lee, and Youngjae Kim. Application of ultra-wide band radar for classification of human activities. *IET Radar, Sonar & Navigation*, 6(3):172–179, 2012.

[132] Liang Liu, Mihail Popescu, Marilyn Rantz, and Marjorie Skubic. Fall detection using doppler radar and classifier fusion. In *Proceedings of 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics*, pages 180–183. IEEE, 2012.

[133] Dustin P Fairchild and Ram M Narayanan. Classification of human motions using empirical mode decomposition of human micro-doppler signatures. *IET Radar, Sonar & Navigation*, 8(5):425–434, 2014.

[134] Fugui Qi, Fulai Liang, Miao Liu, Hao Lv, Pengfei Wang, Huijun Xue, and Jianqi Wang. Position-information-indexed classifier for improved through-wall detection and classification of human activities using uwb bio-radar. *IEEE antennas and wireless propagation letters*, 18(3):437–441, 2019.

[135] Karan Ahuja, Yue Jiang, Mayank Goel, and Chris Harrison. Vid2doppler: synthesizing doppler radar data from videos for training privacy-preserving activity recognition. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–10, 2021.

[136] Jin Jiang, Ting Jiang, and Shijun Zhai. A novel recognition system for human activity based on wavelet packet and support vector machine optimized by improved adaptive genetic algorithm. *Physical Communication*, 13:211–220, 2014.

[137] Shahar Villeval, Igal Bilik, and Sevgi Zübeyde Gürbuz. Application of a 24 ghz fmcw automotive radar for urban target classification. In *2014 IEEE Radar Conference*, pages 1237–1240. IEEE, 2014.

[138] Svante Björklund, Henrik Petersson, and Gustaf Hendeby. Features for micro-doppler based activity classification. *IET radar, sonar & navigation*, 9(9):1181–1187, 2015.

[139] Chuanwei Ding, Li Zhang, Chen Gu, Lei Bai, Zhicheng Liao, Hong Hong, Yusheng Li, and Xiaohua Zhu. Non-contact human motion recognition based on uwb radar. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, 8(2):306–315, 2018.

[140] A Shrestha, J Le Kernec, F Fioranelli, E Cippitelli, E Gambi, and S Spinsante. Feature diversity for fall detection and human indoor activities classification using radar systems. 2017.

[141] Linda Senigagliesi, Gianluca Ciattaglia, Deivis Disha, and Ennio Gambi. Classification of human activities based on automotive radar spectral images using machine learning techniques: A case study. In *2022 IEEE Radar Conference (RadarConf22)*, pages 1–6. IEEE, 2022.

[142] A Helen Victoria and G Maragatham. Activity recognition of fmcw radar human signatures using tower convolutional neural networks. *Wireless Networks*, pages 1–17, 2021.


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This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2023.3334269




[143] Xinyu Li, Yuan He, Francesco Fioranelli, and Xiaojun Jing. Semisupervised human activity recognition with radar micro-doppler signatures. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–12, 2021.

[144] Daniel Avrahami, Mitesh Patel, Yusuke Yamaura, and Sven Kratz. Below the surface: Unobtrusive activity recognition for work surfaces using rf-radar sensing. In *23rd International Conference on Intelligent User Interfaces*, pages 439–451, 2018.

[145] Syed Aziz Shah, Ahsen Tahir, Julien Le Kernec, Ahmed Zoha, and Francesco Fioranelli. Data portability for activities of daily living and fall detection in different environments using radar micro-doppler. *Neural Computing and Applications*, 34(10):7933–7953, 2022.

[146] Xinyu Zhang, Qammer H Abbasi, Francesco Fioranelli, Olivier Romain, and Julien Le Kernec. Elderly care-human activity recognition using radar with an open dataset and hybrid maps. In *EAI International Conference on Body Area Networks*, pages 39–51. Springer, 2021.

[147] Arindam Sengupta, Feng Jin, Renyuan Zhang, and Siyang Cao. mm-pose: Real-time human skeletal posture estimation using mmwave radars and cnns. *IEEE Sensors Journal*, 20(17):10032–10044, 2020.

[148] Guangzheng Li, Ze Zhang, Hanmei Yang, Jin Pan, Dayin Chen, and Jin Zhang. Capturing human pose using mmwave radar. In *2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, pages 1–6. IEEE, 2020.

[149] Girish Tiwari and Shalabh Gupta. An mmwave radar based real-time contactless fitness tracker using deep cnns. *IEEE Sensors Journal*, 21(15):17262–17270, 2021.

[150] Mahdi Ostovan, Sadegh Samadi, and Alireza Kazemi. Generation of human micro-doppler signature based on layer-reduced deep convolutional generative adversarial network. *Computational Intelligence and Neuroscience*, 2022, 2022.

[151] Mainak Chakraborty, Harish C Kumawat, Sunita Vikrant Dhavale, et al. Application of dnn for radar micro-doppler signature-based human suspicious activity recognition. *Pattern Recognition Letters*, 162:1–6, 2022.

[152] Meng Li, Tao Chen, and Hao Du. Human behavior recognition using range-velocity-time points. *IEEE Access*, 8:37914–37925, 2020.

[153] Xiang Wang, Shisheng Guo, Jiahui Chen, Pengyun Chen, and Guolong Cui. Gcn-enhanced multi-domain fusion network for through-wall human activity recognition. *IEEE Geoscience and Remote Sensing Letters*, 2022.

[154] Khalid Z Rajab, Bang Wu, Peter Alizadeh, and Akram Alomainy. Multi-target tracking and activity classification with millimeter-wave radar. *Applied Physics Letters*, 119(3):034101, 2021.

[155] Shahzad Ahmed, Junbyung Park, and Sung Ho Cho. Fmcw radar sensor based human activity recognition using deep learning. In *2022 International Conference on Electronics, Information, and Communication (ICEIC)*, pages 1–5. IEEE, 2022.

[156] Wataru Takabatake, Kohei Yamamoto, Kentaroh Toyoda, Tomoaki Ohtsuki, Yohei Shibata, and Atsushi Nagate. Fmcw radar-based anomaly detection in toilet by supervised machine learning classifier. In *2019 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6. IEEE, 2019.

[157] Ibrahim Alnujaim, Daegun Oh, and Youngwook Kim. Generative adversarial networks for classification of micro-doppler signatures of human activity. *IEEE Geoscience and Remote Sensing Letters*, 17(3):396–400, 2019.

[158] A Ahmed and YD Zhang. Radar-based dataset development for human activity recognition. In *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, pages 1–4. IEEE, 2020.

[159] Fang Zhu, Kuangda Wang, and Ke Wu. Doppler radar techniques for vital signs detection featuring noise cancellation. In *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*, volume 1, pages 1–4. IEEE, 2019.

[160] Faheem Khan, Asim Ghaffar, Naeem Khan, and Sung Ho Cho. An overview of signal processing techniques for remote health monitoring using impulse radio uwb transceiver. *Sensors*, 20(9):2479, 2020.

[161] Anish Shastri, Neharika Valecha, Enver Bashirov, Harsh Tataria, Michael Lentmaier, Fredrik Tufvesson, Michele Rossi, and Paolo Casari. A review of millimeter wave device-based localization and device-free sensing technologies and applications. *IEEE Communications Surveys & Tutorials*, 2022.

[162] Steven M Hernandez and Eyuphan Bulut. Wifi sensing on the edge: Signal processing techniques and challenges for real-world systems. *IEEE Communications Surveys & Tutorials*, 2022.

[163] Francesco Fioranelli, Ronny G Guendel, Nicolas C Kruse, and Alexander Yarovoy. Radar sensing in healthcare: Challenges and achievements in human activity classification & vital signs monitoring. In *International Work-Conference on Bioinformatics and Biomedical Engineering*, pages 492–504. Springer, 2023.

[164] Radar Sensor Market growth rate market forecast. https://www.mordorintelligence.com/industry-reports/radar-sensors-market?gclid=CjwKCAjwtp2bBhAGEiwAOZZTuLY0Kc971E5CnNvBwpWqydgNm-wnhes_ji9IVkCM_HkEjcQoMHS90hoCgnUQAvD_BwE. Accessed: 2022-10-30.

[165] Emanuele Cardillo and Alina Caddemi. Feasibility study to preserve the health of an industry 4.0 worker: A radar system for monitoring the sitting-time. In *2019 II Workshop on Metrology for Industry 4.0 and IoT (MetroInd4. 0&IoT)*, pages 254–258. IEEE, 2019.

[166] Peter Karsmakers, Tom Croonenborghs, Marco Mercuri, Dominique Schreurs, and Paul Leroux. Automatic in-door fall detection based on microwave radar measurements. In *2012 9th European Radar Conference*, pages 202–205. IEEE, 2012.

[167] Amirhosein Toosi, Andrea G Bottino, Babak Saboury, Eliot Siegel, and Arman Rahmim. A brief history of ai: how to prevent another winter (a critical review). *PET clinics*, 16(4):449–469, 2021.

[168] Kunihiko Fukushima and Sei Miyake. Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. In *Competition and cooperation in neural nets*, pages 267–285. Springer, 1982.

[169] Geoffrey E Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006.

[170] Michael Stephan, Lorenzo Servadei, José Arjona-Medina, Avik Santra, Robert Wille, and Georg Fischer. Scene-adaptive radar tracking with deep reinforcement learning. *Machine Learning with Applications*, 8:100284, 2022.

[171] Pengfei Liu, Yimin Liu, Tianyao Huang, Yuxiang Lu, and Xiqin Wang. Decentralized automotive radar spectrum allocation to avoid mutual interference using reinforcement learning. *IEEE Transactions on Aerospace and Electronic Systems*, 57(1):190–205, 2020.

[172] Meng Wu, Xiaoxiao Dai, Yimin D Zhang, Bradley Davidson, Moeness G Amin, and Jun Zhang. Fall detection based on sequential modeling of radar signal time-frequency features. In *2013 IEEE International Conference on Healthcare Informatics*, pages 169–174. IEEE, 2013.

[173] Shahzad Ahmed, Dingyang Wang, Junyoung Park, and Sung Ho Cho. Uwb-gestures, a public dataset of dynamic hand gestures acquired using impulse radar sensors. *Scientific Data*, 8(1):1–9, 2021.

[174] Xinyu Huang, Kimiaki Shirahama, Muhammad Tausif Irshad, Muhammad Adeel Nisar, Artur Piet, and Marcin Grzegorzek. Sleep stage classification in children using self-attention and gaussian noise data augmentation. *Sensors*, 23(7):3446, 2023.

[175] Shahzad Ahmed and Sung Ho Cho. Hand gesture recognition using an ir-uwb radar with an inception module-based classifier. *Sensors*, 20(2):564, 2020.

[176] Nicholas D Lane, Petko Georgiev, and Lorena Qendro. Deepear: robust smartphone audio sensing in unconstrained acoustic environments using deep learning. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pages 283–294, 2015.

[177] Etienne Antide, Mykhailo Zarudniev, Olivier Michel, and Michael Pelissier. Comparative study of radar architectures for human vital signs measurement. In *2020 IEEE Radar Conference (RadarConf20)*, pages 1–6. IEEE, 2020.

[178] Tianyue Zheng, Zhe Chen, Shujie Zhang, Chao Cai, and Jun Luo. More-fi: Motion-robust and fine-grained respiration monitoring via deep-learning uwb radar. In *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems*, pages 111–124, 2021.

[179] Justin J Saluja, Jenshan Lin, and Joaquin Casanova. A supervised learning approach for real time vital sign radar harmonics cancellation. In *2018 IEEE International Microwave Biomedical Conference (IMBioC)*, pages 67–69. IEEE, 2018.

[180] Pengfei Wang, Fugui Qi, Miao Liu, Fulai Liang, Huijun Xue, Yang Zhang, Hao Lv, and Jianqi Wang. Noncontact heart rate measurement based on an improved convolutional sparse coding method using ir-uwb radar. *IEEE Access*, 7:158492–158502, 2019.

[181] Kohei Yamamoto, Ryosuke Hiromatsu, and Tomoaki Ohtsuki. Ecg signal reconstruction via doppler sensor by hybrid deep learning model with cnn and lstm. *Ieee access*, 8:130551–130560, 2020.

[182] Elliott Schires, Pantelis Georgiou, and Tor Sverre Lande. Vital sign monitoring through the back using an uwb impulse radar with body coupled antennas. *IEEE transactions on biomedical circuits and systems*, 12(2):292–302, 2018.


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[183] Ariana Tulus Purnomo, Kokoy Siti Komariah, Ding-Bing Lin, Willy Fitra Hendria, Bong-Kee Sin, and Nur Ahmadi. Non-contact supervision of covid-19 breathing behaviour with fmcw radar and stacked ensemble learning model in real-time. *IEEE Transactions on Biomedical Circuits and Systems*, 16(4):664–678, 2022.

[184] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25, 2012.

[185] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014.

[186] Margaret G Stineman, Dawei Xie, Qiang Pan, Jibby E Kurichi, Zi Zhang, Debra Saliba, John T Henry-Sánchez, and Joel Streim. All-cause 1-, 5-, and 10-year mortality in elderly people according to activities of daily living stage. *Journal of the American Geriatrics Society*, 60(3):485–492, 2012.

[187] Farzan Majeed Noori, Michael Riegler, Md Zia Uddin, and Jim Torresen. Human activity recognition from multiple sensors data using multi-fusion representations and cnns. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 16(2):1–19, 2020.

[188] Nan Ren, Xuanjun Quan, and Sung Ho Cho. Algorithm for gesture recognition using an ir-uwb radar sensor. *Journal of Computer and Communications*, 4(3), 2016.

[189] Saleem Asghar, Junhwan Choi, Daeung Yoon, and Joongmoo Byun. Spatial pseudo-labeling for semi-supervised facies classification. *Journal of Petroleum Science and Engineering*, 195:107834, 2020.

[190] Evaluation methods. https://towardsdatascience.com/performance-metrics-confusion-matrix-precision-recall-and-f1-score-a8fe Accessed: 2023-04-24.

[191] Youngwook Kim and Brian Toomajian. Hand gesture recognition using micro-doppler signatures with convolutional neural network. *IEEE Access*, 4:7125–7130, 2016.

[192] Sizhe An and Umit Y Ogras. Mars: mmwave-based assistive rehabilitation system for smart healthcare. *ACM Transactions on Embedded Computing Systems (TECS)*, 20(5s):1–22, 2021.

[193] Jie Xu, Yuan Yan Tang, Bin Zou, Zongben Xu, Luoqing Li, Yang Lu, and Baochang Zhang. The generalization ability of svm classification based on markov sampling. *IEEE transactions on cybernetics*, 45(6):1169–1179, 2014.

[194] Huijuan Wu, Jiping Chen, Xiangrong Liu, Yao Xiao, Mengjiao Wang, Yi Zheng, and Yunjiang Rao. One-dimensional cnn-based intelligent recognition of vibrations in pipeline monitoring with das. *Journal of Lightwave Technology*, 37(17):4359–4366, 2019.

[195] J Andrew Zhang, Md Lushanur Rahman, Kai Wu, Xiaojing Huang, Y Jay Guo, Shanzhi Chen, and Jinhong Yuan. Enabling joint communication and radar sensing in mobile networks—a survey. *IEEE Communications Surveys & Tutorials*, 24(1):306–345, 2021.

[196] An Liu, Zhe Huang, Min Li, Yubo Wan, Wenrui Li, Tony Xiao Han, Chenchen Liu, Rui Du, Danny Kai Pin Tan, Jianmin Lu, et al. A survey on fundamental limits of integrated sensing and communication. *IEEE Communications Surveys & Tutorials*, 24(2):994–1034, 2022.

[197] Nguyen Cong Luong, Xiao Lu, Dinh Thai Hoang, Dusit Niyato, and Dong In Kim. Radio resource management in joint radar and communication: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, 23(2):780–814, 2021.

[198] Jian Liu, Hongbo Liu, Yingying Chen, Yan Wang, and Chen Wang. Wireless sensing for human activity: A survey. *IEEE Communications Surveys & Tutorials*, 22(3):1629–1645, 2019.

[199] FDA clears radar-powered vital sign device fda clearance for xk. https://www.fiercebiotech.com/medtech/fda-clears-radar-powered-contactless-patient-monitor-from-xandar-kardian. Accessed: 2022-10-30.

[200] Privender Saini, Richard Willmann, Ruth Huurneman, Gerd Lanfermann, Juergen Te Vrugt, Stefan Winter, and Jaap Buurke. Philips stroke rehabilitation exerciser: A usability test. In *Proceedings of the IASTED International Conference on Telehealth/Assistive Technologies, ser. Telehealth/AT*, volume 8, pages 116–122, 2008.

[201] Johanna Gleichauf, Sven Herrmann, Lukas Hennemann, Hannes Krauss, Janina Nitschke, Philipp Renner, Christine Niebler, and Alexander Koelpin. Automated non-contact respiratory rate monitoring of neonates based on synchronous evaluation of a 3d time-of-flight camera and a microwave interferometric radar sensor. *Sensors*, 21(9):2959, 2021.

[202] Won Hyuk Lee, Seung Hyun Kim, Jae Yoon Na, Young-Hyo Lim, Seok Hyun Cho, Sung Ho Cho, and Hyun-Kyung Park. Non-contact sleep/wake monitoring using impulse-radio ultrawideband radar in neonates. *Frontiers in Pediatrics*, 9:782623, 2021.


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