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Millimeter-wave radar for intelligent sensing: A comprehensive review of techniques, applications, and challenges

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ABSTRACT

Millimeter-wave (mmWave) radar sensing has established itself as a robust technology across diverse applications, such as automotive, healthcare, security, and smart homes. Its exceptional capacity to function effectively in varying environmental conditions, detect concealed objects, sense physiological signals, and facilitate precise target detection positions it as a pivotal enabler for next-generation sensing solutions. The survey employs bibliometric analysis to critically evaluate the existing literature surrounding mmWave radar, highlighting key research trends, notable publications, and the challenges faced within the field. This work presents a comprehensive examination of mmWave radar-based sensing, detailing its fundamental operating principles, signal processing methodologies, advancements in hardware, and the latest developments in machine learning applications. It also addreses the key challenges in signal processing, including resolution enhancement, environmental adaptability, and data fusion with complementary sensors such as LiDAR and cameras. Furthermore, explored the potential of deep learning techniques to enhance target classification, activity recognition, gesture identification, and healthcare applications while addressing concerns related to accuracy and precision. This survey also sheds light on emerging trends by assessing the strengths, limitations, and prospects of mmWave radar technology. This review aims to provide insightful guidance for researchers and practitioners committed to advancing radar-based sensing and its real-world implementations.

Contents

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1. Introduction

Nowadays, sensing and interpretation of diverse physical, environmental, and biological phenomena are predominantly facilitated by an array of sensors such as cameras, LiDAR, ultrasound, radar, and many more. While these sensors possess the capability to extract pertinent features from their surroundings, but many struggle to capture the intricate details essential for effective perception and sensing. For instance, ultrasonic sensors are capable of providing one-dimensional data; they are often susceptible to inaccuracies that can affect the reliability of sensing [1,2]. Conversely, vision-based sensors, such as cameras, offer a higher resolution and richer detail in the information they capture. Nonetheless, these sensors often face significant challenges under adverse weather conditions, including rain, fog, and low-light scenarios. As a result, the effectiveness of vision-based solutions diminishes considerably during critical environmental conditions, underscoring the need for continued advancements in sensor technologies to enhance their robustness and reliability [3]. Moreover, certain critical features require extensive computational processing to be accurately identified, resulting in delays that can impact real-time applications. To mitigate some of these issues, particularly in low-light and nighttime scenarios, an effective approach involves integrating infrared (IR) camera sensors with traditional imaging systems [4]. This integration not only enhances the overall perceptual capabilities but also provides a more comprehensive understanding of the surrounding environment, thereby improving the reliability of sensor fusion in various applications. Nonetheless, cameras alone are insufficient for generating three-dimensional representations of environments. LiDAR technology has emerged as a compelling alternative for constructing 3D maps due to its ability to capture spatial information accurately [5]. However, several challenges remain to be addressed, including aspects related to cost, limited resolution, computational efficiency, and power consumption [4,5]. In contrast, millimeter-wave (mmWave) radar sensors excel in providing spatio-temporal characteristics of various environments or phenomena, demonstrating resilience to fluctuations in lighting and adverse weather conditions [6]. Consequently, radar sensors serve as a valuable addition to a sensor suite, effectively complementing the functionalities of other sensor types, such as cameras, LiDAR, and IR sensors. Furthermore, the benefits of radar sensors include low power consumption, compact design, and the potential for integration as System-on-Chip (SoC) devices.

1.1. Overview of mmWave radar and sensing

Millimeter wave radar sensing technology utilizes modulated signals to effectively detect and interpret environmental information. Operating within the frequency range of 30 to 300 gigahertz (GHz), these signals were initially harnessed to facilitate high-rate, ultra-reliable, and low-latency wireless communications. The unique attributes of mmWave technology – such as its extensive bandwidth, millimeter wavelength characteristics, and compact antenna arrays – have enabled the development of advanced sensing capabilities that extend beyond traditional wireless communication applications [7,8]. This evolution marks a significant advancement in the field, presenting new opportunities for integrating sensing functionalities into a variety of contexts.

A standard mmWave radar system comprises both a transmit antenna array and a receive antenna array. The transmit array continuously emits modulated mmWave signals into the surrounding environment. These signals propagate and interact with objects or targets, subsequently reflecting to the receiver antenna array. By analyzing the reflected signals, the radar system can extract comprehensive spatial and temporal information (range, velocity and angle of arrival) regarding the detected objects [9]. This capability facilitates contactless and passive sensing of the environment, thus broadening the horizons of real-time monitoring and advanced detection applications. The advantages of mmWave radar sensing are manifold when compared to traditional sensor technologies. Its non-intrusive nature allows for an unobtrusive user experience, significantly reducing deployment costs for various devices. Furthermore, mmWave radars demonstrate robust performance under challenging weather conditions [10] and in low-light environments, where conventional imaging technologies, such as cameras and LiDAR, may falter. This capability effectively relaxes the stringent operational requirements often associated with visual-based technologies.

In an era increasingly concerned with personal privacy, mmWave radar provides an advantageous alternative, as it mitigates the potential privacy invasions commonly associated with vision-based sensors [11]. It detects and tracks the person's movements without capturing their visual data, biometric data or facial data [12,13]. This ensures complete anonymity in the monitored area, and radars are less intrusive than cameras [14]. These attributes underscore the potential of mmWave radar as a transformative technology, offering promising applications extending far beyond traditional radar uses, encompassing autonomous vehicles, smart home systems, healthcare, and industrial automation.

Recent advancements in technology in different sectors have catalyzed significant research and development focused on the application of mmWave radar technology. Fan et al. [15] conducted a thorough mechanistic analysis of various sensor technologies, specifically reviewing 4D mmWave radar techniques and underscoring their significance in target detection and tracking within the context of autonomous driving. In a complementary study, Liang et al. [16] illustrated various machine learning (ML) and deep learning (DL) methodologies for vehicle detection, harnessing radar, LiDAR, and multi-sensor fusion approaches; their work also includes a comprehensive summary of available datasets pertinent to this domain. Brune et al. [17] explored DL-based odometry estimation for targets using a combination of mmWave automotive radar and spinning radar, alongside the integration of vision and radar data. They provided insights into the fundamental concepts of radar data processing and outlined relevant datasets. Yao et al. [18] advanced the conversation by presenting an object detection and semantic segmentation framework for autonomous vehicles, emphasizing the fusion of camera sensors with radar data through a detailed DL methodology. Frazao et al. [19] proposed a novel radar architecture tailored for healthcare applications, specifically focusing on cardiac monitoring, while also offering a bibliometric analysis covering the past five years of related literature. Wu et al. [20] delivered an extensive review on the utilization of mmWave radar for vital sign monitoring, discussing the applications of various deep-learning techniques in monitoring. Gharamohammadi et al. [21] conducted a comprehensive comparative analysis of in-vehicle gesture recognition, occupancy detection, and vital sign monitoring, providing valuable insights into these emerging fields. Tang et al. [22] delved into ML and DL strategies for gesture recognition, which included fundamental radar processing techniques as well as a review of existing datasets. Han et al. [23] presented a bibliometric analysis that classified applications of mmWave radar technology across diverse fields such as smart homes, healthcare, industry, and the automotive sector. Pandharipande et al. [24] focused on ML methodologies in radar sensing for autonomous vehicles, emphasizing both in-cabin and out-cabin applications. Pearce et al. [25] detailed the foundational aspects of radar architecture, alongside ML and DL algorithms aimed at multi-object detection, further enriching the body of knowledge in this rapidly evolving field. Soumya et al. [26] provided an in-depth examination of ML applications in mmWave radar-based sensing, emphasizing the processing of radar data and its implications for advancing the field. Srivastav et al. [27] articulated the implementation of DL techniques in autonomous vehicles, focusing on radar processing, detection-based tracking, and occupancy-based tracking, as well as identifying available datasets and emerging opportunities within radar technology. Zhou et al. [28] provided a detailed overview of existing datasets relevant to autonomous driving, coupled with an introduction to radar fundamentals and DL strategies. Their discourse also included an exposition on radar-based sensor fusion for enhanced detection capabilities. Venon et al. [29] compiled a comprehensive overview of literature discussing perception, localization, and recognition in the automotive sector, along with a concise account of globally available datasets. Their research illustrates the processing of radar data and highlights DL approaches applicable across numerous domains in autonomous vehicles, including motion estimation, semantic segmentation, simultaneous localization and mapping (SLAM), and place recognition, among others. Tang et al. [30] examined the integration of radar and vision-based sensors for enhanced detection and tracking capabilities in autonomous vehicles. Lastly, Abdu et al. [31] offered an exhaustive survey on the intersection of ML and DL in mmWave radar applications, framing an expansive overview of radar techniques alongside specialized DL methodologies designed for radar signal detection and classification, supplemented by a review of currently available datasets.

Table 1
Survey of published reviews.

Reviews	Year	Signal processing depth	ML/DL techniques covered	Datasets, devices and open tools	Application domains	Taxonomy	Target sectors	Unique contribution
[15]	2024	Advanced — covers FMCW, MIMO, 3D/4D imaging, Doppler/time dimension analysis	Primarily DL (CNNs, Transformer fusion), some ML for fusion tasks; focus on radar-camera fusion	Datasets: WAYMO, NuScenes; Devices: 4D mmWave radar sensors; Open Tools: not explicitly listed, but discusses fusion pipelines	3D object detection, target tracking, multi-modal fusion	Clear classification of techniques/processes	Automotive	Comprehensive survey on 4D mmWave radar perception, including advanced signal processing, DL fusion, and benchmark summary up to early-2024
[16]	2024	Intermediate — reviews radar/LiDAR preprocessing but emphasizes high-level detection pipelines	Summarizes multiple methods, mainly DL (CNN, YOLO, Faster RCNN, PointPillars, Transformer based fusion) and classic ML baselines	Lists major public datasets and sensors used in the field (KITTI, NuScenes, Waymo, BDD100K, etc.) and discusses open source detection frameworks	On road vehicle detection, object detection, multisensor fusion	Provides a clear multi level classification of sensors,algorithms, and evaluation metrics	Automotive	Collected vision/LiDAR/mmWave radar vehicle detection algorithms, align them with datasets/metrics, compare strengths/ weaknesses, and outline future trends up to May 2024
[17]	2024	Advanced — explanation of signal chain, representation formats (ADC, RAD, CFAR, point-cloud, BEV)	DL-centric: LSTM, GRU, GNN, Transformers, also multi-task learning and optimization strategies	Devices: Spinning/ Automotive FMCW radars; Datasets: Radar + LiDAR/Camera SLAM benchmarks; Open tools: no explicit mention	Odometry estimation, loop closure detection, ego-localization in autonomous driving	Organizes methods by data format, model architecture, fusion steps	Automotive	Systematically reviewed DL architectures for FMCW radar SLAM tasks—comparing RNN, GNN, transformer models and fusion methods
[18]	2024	Intermediate — overview of data types (ADC, tensor, point cloud) and fusion levels	Various DL models for detection and segmentation; fusion across data and feature levels	Datasets: NuScenes, RaDICaL, CARRADA, CRUW, FloW, SeeingThroughFog Devices: mmWave radar + camera; Tools: interactive website	3D object detection, semantic segmentation in automotive perception	Detailed classification by fusion “why, what, where, when, how”	Automotive	Focused review on radar-camera fusion covering both detection and segmentation, dataset survey (2019–2023), fusion taxonomy and challenges, along with an interactive retrieval website
[19]	2024	Advanced — covers FMCW, architectures and provide their performance impact	ML: spectrum analysis, periodicity analysis; DL: limited (review focused on signal processing)	Datasets: collated literature results; Devices: CW/FMCW/UWB systems; Open tools: none explicitly listed	Heart rate (HR), heart rate variability measurement	Clear classification by architecture, frequency, performance metrics	Smart Home, Health Care	Review analyzing how radar architecture and signal processing chain impact HRV accuracy, identifying design trade offs and best performing configurations
[20]	2023	Advanced — covers detailed signal models for micro-movement detection, signal chain	DL: RNNs/CNNs for vital- sign estimation; comparative analysis of DL vs. classical signal processing	Datasets: not explicitly named but refers to multiple vital-sign datasets; Devices: mmWave radar sensors; Tools: survey notes open research tools	Heartbeat, respiration, identity recognition, health monitoring	Structured signal-level taxonomy of MVSS models and algorithms	Health Care Smart Home	Comprehensive survey of mmWave vital-sign sensing: includes MVSS signal models, DL techniques for health monitoring, biometric authentication, and detailed future research directions.
[21]	2023	Advanced — includes FMCW principles, Doppler/micro Doppler, calibration and interference mitigation	ML: SVM, RF; DL: CNNs for gesture/vital signs; AI-based occupancy detection	Datasets: proprietary in-vehicle experiments, no public dataset; Devices: FMCW mmWave radars; Tools: discusses signal calibration and fusion pipelines	Occupancy detection, gesture recognition, vital sign, drowsiness/distracted driver, child left-behind detection	Classifies works into occupancy, gesture, occupant status groups	Automotive (cabin environment)	Comprehensive radar-based survey focusing solely on cabin monitoring applications—spanning occupancy, gesture, physiological state detection with taxonomy and system-level design review
[22]	2023	Advanced — covers FMCW basics, Doppler and micro-Doppler processing, feature extraction methods	Classical ML: feature-based classifiers; DL: CNNs, RNNs, hybrid models for feature extraction and classification	Datasets: surveyed across the literature from 2015–2023 (not a single dataset); Devices: FMCW radar hardware for gesture studies; Tools: overview of processing pipelines and feature extraction methods	Gesture recognition for HCI, VR, smart environments	Classifies works by gesture types, feature methods, classification results	Smart home, Health care, Automotive	Systematic review of FMCW mmWave radar dynamic gesture recognition, covering methodologies, feature fusion, generalization issues, and performance summaries from 2015–2023
[23]	2023	Intermediate — covers signal aspects; not signal-processing depth like FMCW pipelines	None/Minimal — analysis focused on scientometric trends, not algorithm review	Datasets: Multiple research articles metadata; Devices and Tools: not discussed	Autonomous driving, human activity, robotics, construction site monitoring, worker health	Offers bibliometric taxonomy via keyword clustering and scientometrics	Smart home, Health care, Industry	Survey of 4D mmWave sensing, with metadata -driven trend and cluster analysis for digital construction; identifies multiple articles since 2019 and highlights construction applications.
[24]	2023	Advanced — covers sensor modalities, multi-modal fusion pipelines, and safety-critical signal processing	ML: SVM, RF, HMM; DL: CNNs (2D/3D), ensembles, uncertainty-aware models; fusion architectures of multi-sensor	Datasets: NuScenes, RADIATE, CARRADA, KITTI; Devices: automotive radar, LiDAR, camera platforms; Tools: pipeline architectures, validation/safety frameworks	Object detection and tracking, SLAM, occupancy and driver monitoring, gesture control, environmental perception	Organizes methods by sensor modality, perception task, fusion strategy, safety validation	Automotive (external and in-cabin)	Holistic survey of sensing modalities and ML/DL architectures for both external and in-cabin automotive perception, with safety and performance validation–leverages public datasets and fusion models.

(*continued on next page*)

Table 1 (*continued*).

[25]	2023	Advanced — reviews FMCW chirp design, FFT based range/Doppler, micro Doppler feature extraction, MIMO antenna issues	Classical ML (kNN, SVM), DL (CNN/RNN) and sensor-fusion pipelines for track association and activity recognition	Compares studies built on TI IWR family and other COTS mmWave sensors; no large public dataset identified; summarizes typical open-source processing chains	Human target tracking, gait and activity recognition, tag-based asset tracking	Architecture based taxonomy: processing → clustering → data association → ID assignment	Smart home, Health care, Industry	Survey of mmWave multiobject tracking, defines a unified MOT architecture, analysis sensor fusion and micro Doppler methods, and maps open challenges/future directions up to early 2023
[26]	2023	Intermediate — covers basic IF processing, FFT, performance metrics;	ML: SVM, RF; DL: CNNs, RNNs for classification, detection, feature learning	Datasets: multiple domain-specific datasets; Devices: various mmWave radar hardware; Tools: performance metrics; no specific open-source suites	Gesture/human detection, collision avoidance, parking aids, automotive, medical, industrial, defense	Taxonomy by radar band, performance metric, application type and ML method	Smart Home, Health Care, Industry, Automotive, Defense, Space	Beginner-friendly survey: first to span mmWave radar working bands, performance metrics, varied applications (beyond typical AV/HCI), and ML techniques—ideal as cross-domain reference.
[27]	2023	Advanced — covers radar fundamentals, data representations (radar tensor, point cloud), clutter mitigation, uncertainty modeling	DL-centric: CNNs, RNNs; fusion techniques (early and late), occupancy flow estimation, uncertainty-aware models, multipath handling; limited ML focus	Datasets: curated list of recent radar datasets (4D radars); Devices: mentions radar sensors in benchmarks; Tools: overviews of representation tools, no specific code	3D object detection/ tracking, occupancy flow, early-fusion perception, multipath ghost suppression	Structures review around themes: data formats → fusion → perception → uncertainty → challenges	Automotive	DL-focused survey presenting data representations, fusion architectures, and challenge taxonomy—first to collate uncertainty, multipath, occupancy flow, and curated dataset listings for radar DL in Automotive
[28]	2022	Advanced — explains radar fundamentals, data representations (RD, RA, RAD tensors), doppler/ CFAR/DoA pipelines	DL: CNNs (2D/3D), GNNs, Bayesian/uncertainty-aware nets; limited ML focus	Datasets: lists 10+ public automotive radar datasets (e.g., NuScenes, TJ4DRadSet); Devices: 3D/4D sensors; Tools: calibration, augmentation, labelling, code repo	Depth completion, velocity estimation, object detection, tracking, sensor fusion	Structures content by signal → data → task → sensor fusion → challenges → future directions	Automotive	DL radar survey that constructs a full stack—from signal fundamentals and public datasets to fusion architectures and open challenges (e.g., multipath, uncertainty, weather), with code resources
[29]	2022	Advanced — reviews FMCW chirp design, range/doppler/angle estimation, MIMO, SLAM prep	Classical ML (e.g., clustering, k-NN), DL mentioned for recog-nition/localization pipelines	Datasets: not explicitly listed; Devices: 60–300 GHz FMCW radars; Tools: signal representations and algorithmic frameworks	Obstacle detection, SLAM, object recognition, vehicle localization	Presents taxonomy by signal processing block, task type, and algorithmic category	Automotive	FMCW-focused survey across perception, recognition, and localization; emphasizes signal-to-task pipelines, radar representations, and future challenges–spanning vehicles' navigation stacks
[30]	2021	Advanced — reviews radar preprocessing, calibration, sensor alignment, and fusion-ready signal processing	DL: Deep detectors and trackers (YOLO-based, R-CNN fusion); covers feature, decision, and data-level fusion pipelines	Datasets: NuScenes, KITTI, custom radar-camera datasets cited; Devices: automotive radar + RGB camera setups; Tools: pipeline diagrams and calibration workflows	Object detection, multi-object tracking	Categories: input type, fusion level, output type, challenges	Automotive	Systematic overview of radar—vision fusion for both detection and tracking—classifying fusion approaches (data/feature/ decision), analyzing DL-based fusion methods, and enumerating fusion challenges.
[31]	2021	Intermediate — covers radar basics, data representations (RAD tensors), signal projections	DL-focused: CNNs and fusion networks; traditional ML less emphasized	Datasets: surveyed emerging public radar datasets; Devices: automotive mmWave radars; Tools: deep fusion pipelines, signal representation methods	Object detection, classification, segmentation, multi-sensor fusion	Structured by signal representation → DL models → fusion types → tasks	Automotive	Survey focused exclusively on deep learning for radar signals; organizes content by signal representation and fusion architectures, and summarizes newly available radar datasets.
Ours	2025	Advanced explanation of the signal processing (range/doppler/angle FFT), TDM-MIMO, joint radar communication, data representation, CFAR, clustering & filters	Predominant ML algorithms, DL focuses on CNN, generative models, Transformer fusion, spatio-temporal networks for classification, detection, feature learning, activity & gesture recognition, pose estimation	Datasets: surveyed the curated list of the publicly available datasets; Devices : IWR/AWR mmWave radars, sensor-fusion techniques & challenges, Tools: performance metrics, processing chains, used algorithms	Object detection and classification, activity recognition, SLAM, in-cabin monitoring, vital-sign monitoring, concealed object detection, authentication, pose estimation	Detailed bibliometric analysis, classification of datasets, techniques, and algorithms, detailed application of ML/DL approaches, challenges	Automotive, Health care, Security, Smart home, other application usage in different sectors.	Survey presented a systematic application of ML & DL approaches in mmWave radar specially in predominant sector, challenges that the domain is currently facing and their possible approaches for resolving.

In contrast to existing literature, this paper aims to comprehensively examine mmWave sensing techniques across a diverse array of application domains, including automotive, healthcare, industrial sectors, and smart home environments. The analytical evaluation delves into the prevalent techniques and applications, addressing a gap in the literature that often focuses narrowly on specific areas [15–31].

This survey provides an in-depth exploration of the fundamental concepts of radar signal processing, alongside a discussion of pertinent data sources and globally accessible datasets that serve as the foundation for the development of effective sensing systems. This survey articulates a novel application taxonomy for mmWave radar technologies while offering a broad perspective on recent research endeavours in autonomous systems, healthcare, smart home technologies, and industrial applications. While prior studies have often concentrated on isolated applications, this work addresses a wider spectrum of scenarios.

Furthermore, this survey highlights several challenges and future directions within the field, presenting a bibliometric analysis of the mmWave radar sensing landscape, which has been touched upon in some previous studies. In comparison to a recent survey [15], this research encompasses a far more extensive range of application scenarios, extending beyond automotive perception to include healthcare, smart home innovations, and industrial uses, thereby contributing unique insights. The detailed application taxonomy for emerging uses establishes a framework for the classification of applications within mmWave sensing.

Table 1 provides a comprehensive survey of relevant published review articles, synthesizing their scope and contributions across several critical dimensions. This lists each review alongside its publication year, then delves into the technical depth of signal processing covered and the breadth of ML/DL techniques examined. The table further details the datasets, devices, and open tools utilized or discussed within these reviews, the specific application domains they address, and the primary target sectors they focus on. Additionally, it assesses whether each review establishes a structured taxonomy and identifies its core unique contribution to the field. This consolidated overview enables a systematic comparison of the literature, highlighting prevailing trends, methodological approaches, and significant gaps that inform the positioning of this current research.

1.2. Scope & organization

This survey provides an in-depth analysis of mmWave radar sensing techniques and their various applications. It commences by clarifying the essential elements and principles inherent to radar signal processing, establishing a robust basis for comprehending the topic. The introduction offers a succinct summary of prevalent mmWave radar techniques and the signal processing methodologies that underpin efficient sensing capabilities in radar technology. This review thoroughly examines data gathering initiatives from relevant devices and resources, emphasizing various datasets that are globally accessible. This survey subsequently examines the utilization of ML and DL methodologies in mmWave radar sensing across diverse domains. These encompass, but are not restricted to, detection, automotive advancements, healthcare developments, smart home technologies, and industrial uses. By placing mmWave radar in various contexts, this seeks to highlight its revolutionary potential and the influence of sophisticated analytical techniques on improving radar sensing efficacy. The primary contributions of this survey are summarized as follows:

- With the ongoing convergence of the physical and digital realms, mmWave radar sensing technology has emerged as a crucial instrument. This novel technology provides a non-invasive and economical means for sensing, resulting in a wide array of applications across several domains. This review aims to conduct a comprehensive analysis of mmWave radar sensing technologies, emphasizing their significance and application.
- This paper explores the essential principles of mmWave radar and the signal processing techniques vital to specialized radar systems. This analysis seeks to elucidate the fundamental mechanics that govern these technologies.
- Offered a comprehensive assessment of mmWave radar devices and datasets. This section outlines the equipment employed alongside the radar or only the radar for data acquisition. This also pertained to the globally accessible datasets and their utilizations. This introduction enables the effective execution of mmWave sensing.
- This survey analyses the emerging uses of mmWave radar sensing and developed a taxonomy for diverse applications. Furthermore, examined contemporary research endeavours tackling practical challenges and provided insights and answers for forthcoming developments.

This review initially elucidates mmWave radar and signal processing techniques in Section 2. Section 3 examines the trend analysis within the domain of mmWave radar and the suggested work to date. Section 4 provides a comprehensive overview of datasets and their classifications. Section 5 widely exploits the signal processing techniques used in the mmWave radar. Section 6 subsequently details the prevalent ML and DL approaches that are used in the mmWave radar for the sensing applications. Section 7 details the domain adoption of the radar data for ML and DL approaches, along with the challenges. Section 8 illustrates the application taxonomy of mmWave radar sensing inside ML and DL methodologies across several areas. Section 9 offers insights into the current technical challenges and their potential solution, and finally, the survey ends with a conclusion in Section 10.

2. mmWave radar

A radar system transmits a signal from the transmitter (TX) for sensing the environment, and then the receiver (RX) captures the reflected signal. The basic block diagram of the mmWave radar system is elaborated in Fig. 1. This reflected signal carries vital information regarding the characteristics of the targets, and processing this signal provides range, velocity, and angle, as well as other target characteristics to detect, locate, track, and identify objects. This section focuses on a particular type of radar system that employs the linear FMCW signal and introduces the range, velocity and angle estimation techniques enabled by the radar system.

2.1. Preliminaries

The utilization of Frequency Modulated Continuous Wave (FMCW) technology harnesses the capabilities of Channel Impulse Response (CIR) signals to effectively sense environmental conditions and gather data on various subjects [32]. The CIR characterizes the propagation channel by capturing how the transmitted signal is altered due to multipath, reflection, scattering, and absorption as it travels through the environment. One of the key advantages of FMCW is its ability to distinguish minute distances and detect objects with the weak received signals [33]. This characteristic significantly enhances both range and velocity resolution, making FMCW techniques highly advantageous in a wide array of applications. As a result, these attributes have led to a significant increase in the adoption of FMCW methodologies across diverse fields, thereby securing a prominent position in the contemporary market landscape.

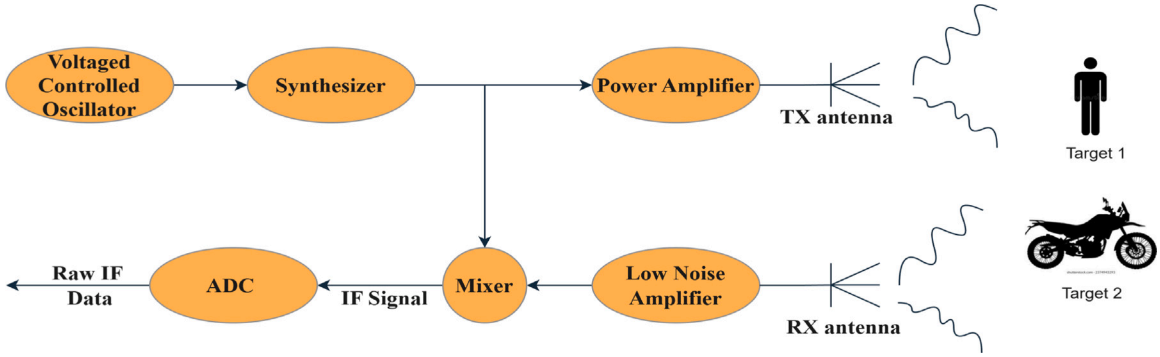

Fig. 1. Basic block diagram of radar.

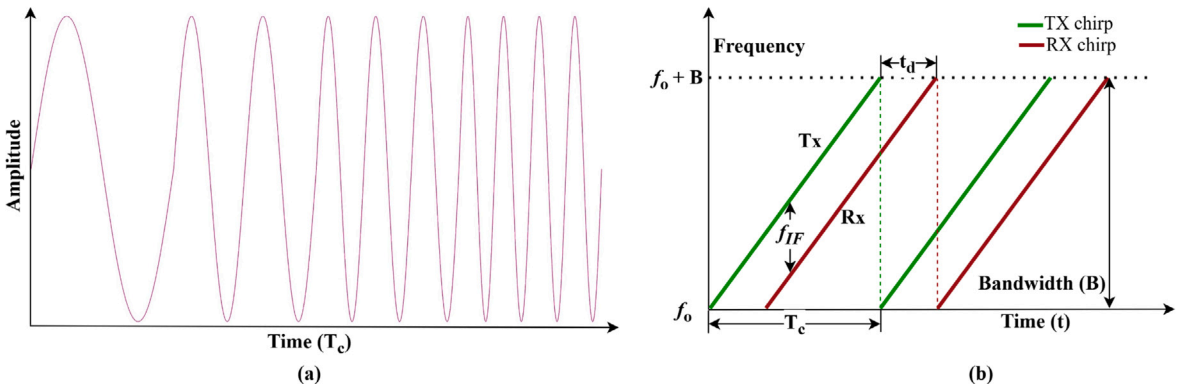

Fig. 2. TX and RX chirp.

The FMCW signal is characterized by the start frequency f_c, the bandwidth B, and time duration T_c as shown in Fig. 2. The transmitter transmits the FMCW signal over the duration T_c is known as a chirp. The frequency of the chirp signal increases linearly over time to a particular frequency. A sinusoidal representation of the transmitted FMCW signal can be represented as (1)

$$x_t(t) = \sin\left(2\pi\left(f_c t + \frac{Bt^2}{2T_c}\right)\right) \tag{1}$$

The received (RX) chirp is the delayed version of the TX chirp. The time retard (t_d) between the TX and RX chirp is given by (2)

$$t_d = \frac{2d}{c} \tag{2}$$

where d represents the distance between the radar and the obstacle and c represents the speed of light. The RX chirp in the time domain is provided by (3)

$$x_r(t) = \sin\left(2\pi\left(f_c(t - t_d) + \frac{B(t - t_d)^2}{2T_c}\right)\right) \tag{3}$$

The mixer produces the immediate frequency (IF) signal $x_{IF}(t)$ [34] using the transmitted and reflected back chirp signals. The produced IF signal is described by (4).

$$x_{IF}(t) = x_t(t) - x_r(t) \tag{4}$$

The instantaneous frequency of $x_t(t)$ and $x_r(t)$, is $f_t(t)$ and $f_r(t)$, are not same at the time of mixing. The frequency of the IF signal is not a function of time, and it remains constant. The frequency of the IF signal is known as beat frequency $f_{IF}(t)$. The expression of beat frequency is provided by (8).

$$f_{IF} = f_t(t) - f_r(t) = S * t_d \tag{5}$$

where S is the slope of the chirp and (t_d) is the time delay between the transmitted and received chirp.

The process of generating FMCW radar signal can be systematically outlined in several critical steps. Initially, the mmWave radar system produces a chirp signal, which is subsequently transmitted through the transmitting antenna. The transmitted chirp interacts with targets in the environment, resulting in a reflected signal that is captured by the receiving antenna. Following this reception, a mixer combines the transmitted and reflected signals, yielding an intermediate frequency (IF) signal. This IF signal, an essential component of the radar processing chain and can be interpreted as CIR estimation, is then subjected to digitalization to facilitate further analysis. Subsequently, the system processes the digitized data to derive essential target-related parameters, including range, velocity, and angular position. This intricate processing ultimately enables the accurate characterization of various targets, enhancing the radar system's operational effectiveness in diverse applications.

2.2. Range processing

The first and foremost information that is extracted from the raw IF signal, which is received after digitalization is the range estimation of the detected targets. The time domain representation of the IF signal is given by (4), and Fast Fourier Transform (FFT) [35] is performed to convert the time domain signal into a frequency spectrum. The IF signal $x_{IF}(t)$ is sampled N_s times with the sampling frequency F_s.

$$x_{IF}(t) \xrightarrow{\text{Sampled } N_s \text{ times}} x[n] \tag{6}$$

$0 \le n < N_s$; $N_s = Number\ of\ Samples$ The FFT of the finite-duration discrete-time signal $x[n]$ is represented in (7).

$$X[k] = FFT\{x[n]\} = \sum_{n=0}^{N_s-1} x[n]e^{-jn\omega}\Big|_{\omega=2\pi k/N_s} \tag{7}$$

$0 \le k < N_s$. According to the Fourier transform theory, the index of X[k] corresponds to the frequency $f_f = kF_s / N_s$. And the frequency range relation can be deduced with the help of from Eqs. (2) and (8). Therefore,

$$f_{IF} = S * t_d = 2Sd/c \tag{8}$$

$$d = f_{IF}\frac{c}{2S} \tag{9}$$

$$d_k = f_k\frac{c}{2S} = k\frac{cF_s}{2SN_s} = k\frac{c}{2ST_c} = k\frac{c}{2B} \tag{10}$$

where $T_c = N_s / F_s$ and B = Bandwidth of chirp. (10) gives the equivalent range bin with respect to the frequency of each sample after the FFT. Thus, d_s in (10) is referred to as the range axis while X[k] in (7) is referred to as the range-FFT. When plotting the range-FFT against the range axis, the magnitude spectrum $|X[k]|$ shows a peak at the range corresponding to the object that reflects the chirp signal back to the radar receiver [36]. Each peak in the frequency spectrum denotes an objects at a specific range, as shown in Fig. 3. Therefore, the range of multiple objects can be estimated by mmWave radar. According to the Eq. (10) the maximum range up to which the radar can estimate the range of the objects is given by

$$d_{max} = \frac{cF_s}{2S} \tag{11}$$

where, d_{max} is the maximum range.

when multiple objects are present, each object reflects a chirp signal, resulting in the production of a reflected chirp signal characterized by a delay that is directly proportional to the object's range from the radar source. This phenomenon leads to the instantaneous frequency (IF) signal comprising multiple distinct tones. Each tone exhibits a constant frequency, which corresponds uniquely to a different target in the radar's field of view.

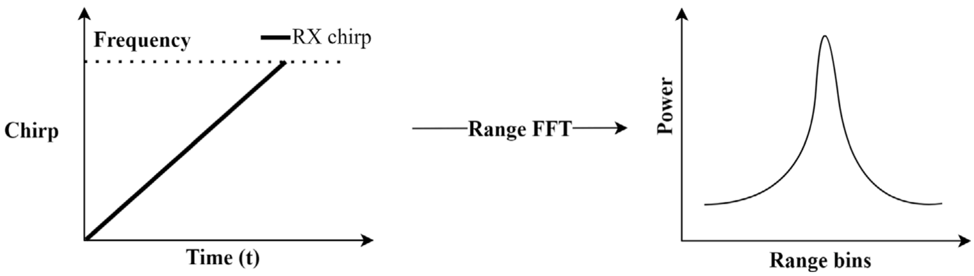

Fig. 3. Range estimation from one chirp.

FFT is utilized to analyze the IF signals containing these multiple tones, which allows for the separation of the various tones within the frequency spectrum. As a result, targets located at different ranges can be distinctly identified through the peaks observed in the resulting range spectrum [37]. This method not only enhances target detection capabilities but also improves the ability to differentiate between closely spaced objects, thus proving essential for advanced radar systems. As a result, the range resolution of the signal can be determined as

$$d_{res} = \frac{c}{2B} \tag{12}$$

Thus, it is possible to distinguish two objects that are separated by more than *c/(2B)* in range. For instance, a 4 GHz bandwidth system achieves a theoretical range resolution of approximately 3.75 cm. In practice, to enhance the quality of detection, practitioners often apply window functions such as the hamming, hanning, or blackman window to the time-domain signal prior to the FFT [38]. While the application of these windowing techniques is beneficial for minimizing sidelobe levels and spectral leakage, thus improving the detectability of objects, but it is important to note that they inadvertently compromise range resolution.

2.3. Velocity processing

Velocity estimation is the second processing step in the mmWave radar [39]. Velocity is an important information that describes the instant motion state of the sensed objects. To estimate the velocity of a moving object, a radar transmits two chirp signals separated by T_c in time and receives the signal after being reflected by the object. The movement of the object in time T_c leads to the change in the phase difference between the reflected chirp signals. The phase of a chirp signal can be given by [32]

$$\Delta\phi = \frac{4\pi\Delta d}{\lambda} \tag{13}$$

where λ is the wavelength of the chirp signal. The displacement of the object in the meantime can be denoted as $\Delta d = vT_c$, so the velocity of the object can be derived by

$$v = \frac{\lambda\Delta\phi}{4\pi T_c}; \quad \Delta\phi = \frac{4\pi v T_c}{\lambda} \tag{14}$$

where v is the velocity of the object, $\Delta\phi$ is the phase difference between the two reflected chirp signals. In practice, radar transmits a set of N_c chirps equally spaced by T_c in time, and it is known as a frame. The range-FFT of the mth chirp is given by

$$X_m[k] = FFT\{x_m[n]\} \tag{15}$$

for $0 \le m < N_c$ and $0 \le k < N_s$. The magnitude and phase of $X_m[k]$ is given by $|X_m[k]|$ and $\phi_m[k]$ respectively. For a moving object, the magnitude of the range-FFT over the chirps remains constant, but the phase changes linearly due to the equal spacing of the chirps in the frame. Thus,

$$|X_m[k]| = |X_0[k]|, \tag{16}$$

$$\phi_m[k] = \phi_0[k] + \frac{4\pi v T_c}{\lambda} m, \tag{17}$$

for $0 \le m < N_c$ and $0 \le k < N_s$. Furthermore, defining it more clearly

$$y_k[m] = X_m[k]e^{jm\omega_v} \tag{18}$$

where $\omega_v = \frac{4\pi v T_c}{\lambda}$

Thus, for a given k, $y_k[m]$ is a finite duration discrete time signal with the angular frequency ω_v. A second FFT is now applied to the $y_k[m]$ described in (18) to extract the object velocity at an instant [40]. It is often referred to as doppler-FFT.

$$Y_k[j] = FFT\{y_k[m]\} \tag{19}$$

for $0 \le j, m < N_c$ and $0 \le k < N_s$. For an unambiguous measurement of the velocity v, the angular frequency is limited to $-\pi \le \omega < \pi$, or equivalent to, $-N_c/2 \le j < N_c/2$. Hence, from the frequency velocity relation discussed above, the frequency of the $Y_k[l]$ can be converted to the velocity axis using the following formula

$$v_j = \frac{\lambda\omega_j}{4\pi T_c} = j\frac{\lambda}{2N_c T_c} \tag{20}$$

for $-N_c/2 \le j < N_c/2$. From the above calculation, the maximum detectable velocity of the object, which is limited to [41].

$$-\frac{\lambda}{4T_c} \le v < \frac{\lambda}{4T_c} \tag{21}$$

Consequently, the Doppler-FFT spectrum $Y_k[j]$ can be graphed for a specified k along the velocity axis. This spectrum is commonly shown through a two-dimensional heatmap known as a range-doppler graphic, as shown in Fig. 4. These visual representations offer essential insights into the range and velocity attributes of different objects within the seen environment [42]. This method improves the analysis of dynamic systems by facilitating a greater comprehension of the interactions between range and velocity characteristics. In the range-doppler figure, a positive velocity signifies the object is receding from the radar, while a negative velocity shows the item is approaching the radar.

When numerous objects reflect chirp signals back to the radar, the time-domain received intermediate frequency signal is a linear amalgamation of the individual intermediate frequency signals produced by each reflecting item [43]. Given that the range-FFT is linear, the range-doppler plot of objects constitutes a linear combination of the spectra of the individual reflecting entities. As a result, objects with varying ranges and/or velocities can be identified from the peaks in the range-doppler image. This plot is also capable of differentiating between objects having the same range but different velocities. As a result, the velocity resolution can be determined as

$$v_{res} = \frac{\lambda}{2N_c T_c} = \frac{\lambda}{2T_f} \tag{22}$$

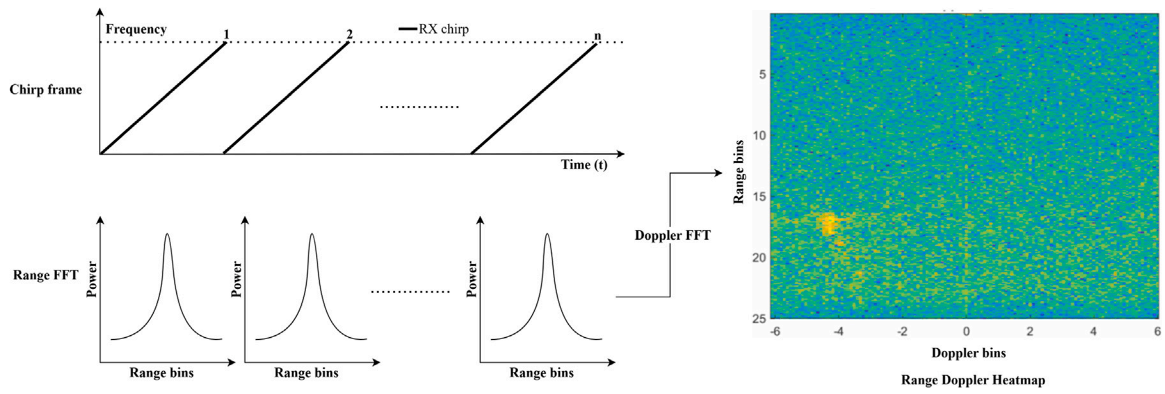

Fig. 4. Velocity estimation over a chirp frame.

where $T_f = N_c T_c$

Thus, it is possible to distinguish the objects at the same range but with a velocity difference that is greater than $\lambda/2T_f$ [44]. Furthermore, if the windowing is applied to minimize sidelobes before the Doppler-FFT, it will degrade the velocity resolution.

2.4. Angle processing

The angle processing constitutes the third phase in the mmWave radar processing sequence. The angle at which signals reach a radar is referred to as the Angle-Of-Arrival (AoA). The angle of the object relative to the radar can be determined based on the reflection of signals by the object. To estimate the angles of objects, the mmWave radar requires a minimum of two receiving antennas. Given that the distance between the two receiver antennas is negligible in comparison to the distance from the item to the radar, the reflected signals are considered parallel. The signal reflected by an item reaches the two receiving antennas via distinct pathways according to the object's relative angle to the radar. As seen in Fig. 5, θ represents the AoA of the received signal relative to the direction orthogonal to the receiver antenna array. As illustrated in Fig. 5, the relative delay encountered by signals received at two neighboring antennas is determined by the distance between the receiving antennas and can be determined by

$$\Delta d = d\, sin(\theta) \tag{23}$$

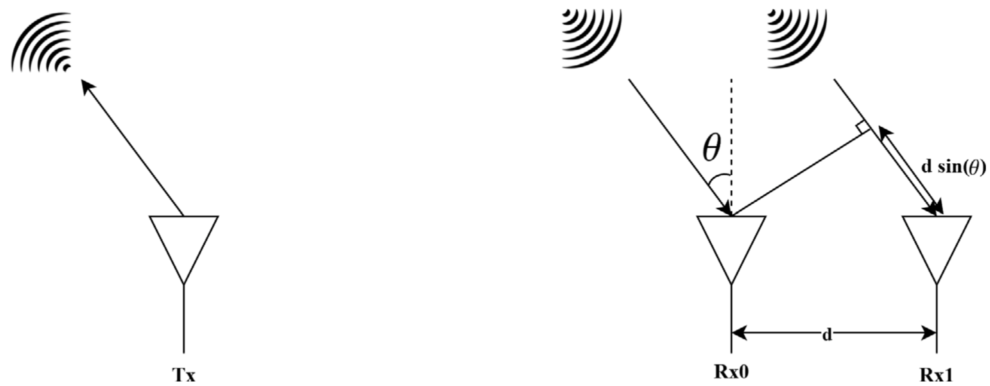

Fig. 5. Angle estimation with a uniform linear array of two receivers.

In the above equation, d is the spacing between the receiving antenna, and θ is the AoA of the received chirp signal. Due to this relative delay, there is a phase difference between the receiver antennas which is provided by

$$\Delta\phi = \frac{2\pi\Delta d}{\lambda} = \frac{2\pi d\, sin(\theta)}{\lambda} \tag{24}$$

In a uniform linear array at the radar reception, consider a configuration of N_r antennas arranged in a straight line with uniform spacing d, illustrated in Fig. 5. For each chirp signal transmitted by the radar, the receiver extracts one intermediate frequency (IF) signal from each of the N_r antennas. Denote the sampled IF signal from the ith receiver antenna as $x^{(i)}[n]$ for $0 \le i < N_r$ and $0 \le n < N_s$. Then the range-FFT of the samples signal from the ith receiver antenna can be represented by

$$X^{(i)}[k] = FFT\{x^{(i)}[n]\} \tag{25}$$

for $0 \le i < N_r$ and $0 \le k < N_s$. The magnitude and phase of the $X^{(i)}[k]$ is given by $|X^{(i)}[k]|$ and $\Delta\phi^{(i)}[k]$ respectively. The magnitude of $X^{(i)}[k]$ remains constant in all the receivers by the phase of $X^{(i)}[k]$ changes linearly due to the equal spacing of the receiver antennas in the uniform linear array. Thus,

$$|X^{(i)}[k]| = |X^{(0)}[k]|, \tag{26}$$

$$\phi^{(i)}[k] = \phi^{(i)}[k] + \frac{2\pi d\, sin(\theta)}{\lambda} i, \tag{27}$$

for $0 \le i < N_r$ and $0 \le k < N_s$. Furthermore, defining it more clearly

$$X^{(i)}[k] = X^{(0)}[k] e^{ji\omega_\theta} \tag{28}$$

where $\omega_\theta = \frac{2\pi d sin(\theta)}{\lambda}$ Consequently, discern the phase variation for the receivers during a singular chirp. Extending this to the number of chirps in a frame, which is determined from the Doppler-FFT for the ith receiver antenna.

$$z_{k,j}[i] = Y_k^{(i)}[j] e^{ji\omega_\theta} \tag{29}$$

for $0 \le k < N_s$, $0 \le j < N_c$, and $0 \le i < N_r$. Consequently, it is evident that for the specified values of k and j, $z_{k,j}[i]$ constitutes a finite duration discrete-time signal characterized by angular frequency ω_θ. In a manner analogous to the discourse on the range-FFT and Doppler-FFT, a third FFT will now be employed on the finite-duration discrete-time sequence $z_{k,j}[i]$ to ascertain the Angle of Arrival (AoA). The third FFT is designated as angle-FFT.

$$Z_{k,j}[\eta] = FFT\{z_{k,j}[i]\} \tag{30}$$

where $0 \le \eta < N_r$, $0 \le k < N_s$, and $0 \le j < N_c$. To get a definitive measurement of the angle θ, the angular frequency must be constrained to the interval $-\pi \le \omega < \pi$, or, equivalently, $-N/2 \le \eta < N/2$, with N being an even integer. Consequently, based on the aforementioned frequency-angle relationship, the frequency of the $z_{k,j}[i]$ can be transformed into the angular axis using the following formula.

$$\theta_n = sin^{-1}(\omega_n \frac{\lambda}{2\pi d}) \tag{31}$$

where θ_n is the angle of the nth object, and ω_n is the angular frequency derived by the FFT. The angular field of the linear antenna array can be determined as

$$-sin^{-1}(\frac{\lambda}{2d}) \le \theta < sin^{-1}(\frac{\lambda}{2d}) \tag{32}$$

Consequently, from the aforementioned formula, concluding that for a linear antenna array with a spacing of $d = \lambda/2$, the angular field is constrained to $-90^\circ \le \theta < 90^\circ$.

The angle-FFT spectrum $Z_{k,j}[\eta]$ may be graphed in relation to the ranges. This spectrum is depicted through a two-dimensional heatmap known as a range-angle plot. These visualizations offer essential insights into the range and angular features of diverse objects within the observed environment. This provides a precise comprehension of the range and angle of the identified items.

When numerous objects reflect the chirp signals back to the radar, the time-domain received intermediate frequency (IF) signal is a linear set of the individual IF signals produced by each reflecting object. As the DFT constitutes a linear combination, the angle-FFT also represents a linear set of the individual reflecting entities. As a result, objects with varying ranges and angles can be distinctly identified from the range-angle plot. This plot may also distinguish objects with identical ranges but varying angles. Consequently, the angular resolution can be ascertained as

$$\theta_{res} = \frac{\lambda}{N_r d\, cos(\theta)} \tag{33}$$

where θ is the foresight view angle, often set to zero ($\theta = 0$). For the linear array with a spacing of $d = \lambda/2$, the angular resolution is given by

$$\theta_{res} = \frac{2}{N_r} \tag{34}$$

Consequently, it is feasible to differentiate objects at the same range but with an angular disparity exceeding $2/N_r$. Moreover, the application of the windowing function results in a reduction of resolution. Thus, for a linear array of $N_r = 4$, the angular resolution is $\theta_{res} = 29^\circ$. A detailed description of the radar preliminary processing from the range to angle is illustrated in Fig. 6.

2.5. Time Division Multiplexing Multiple-Input Multiple-Output (TDM-MIMO)

As shown in (33), the angular resolution depends on the number of receivers of the radar. But increasing the number of receiver antennas makes the antenna array bulky, increases the complexity and costs of the radar. In contrast, the MIMO technology provides a cost-effective way to improve the angular resolution under limited hardware resources and antennas [6].

A mmWave radar with the TDM-MIMO technique equipped with multiple transmitters and multiple receiver antennas. This approach is designed to enhance the radar's performance by effectively expanding the number of virtual antennas through the strategic arrangement of transmit and receive antennas. Specifically, a radar configured with N_t transmit antennas and N_r receive antennas can simulate the operation of $N_t \times N_r$ receive antennas, facilitating accurate angle estimation even in radars with limited

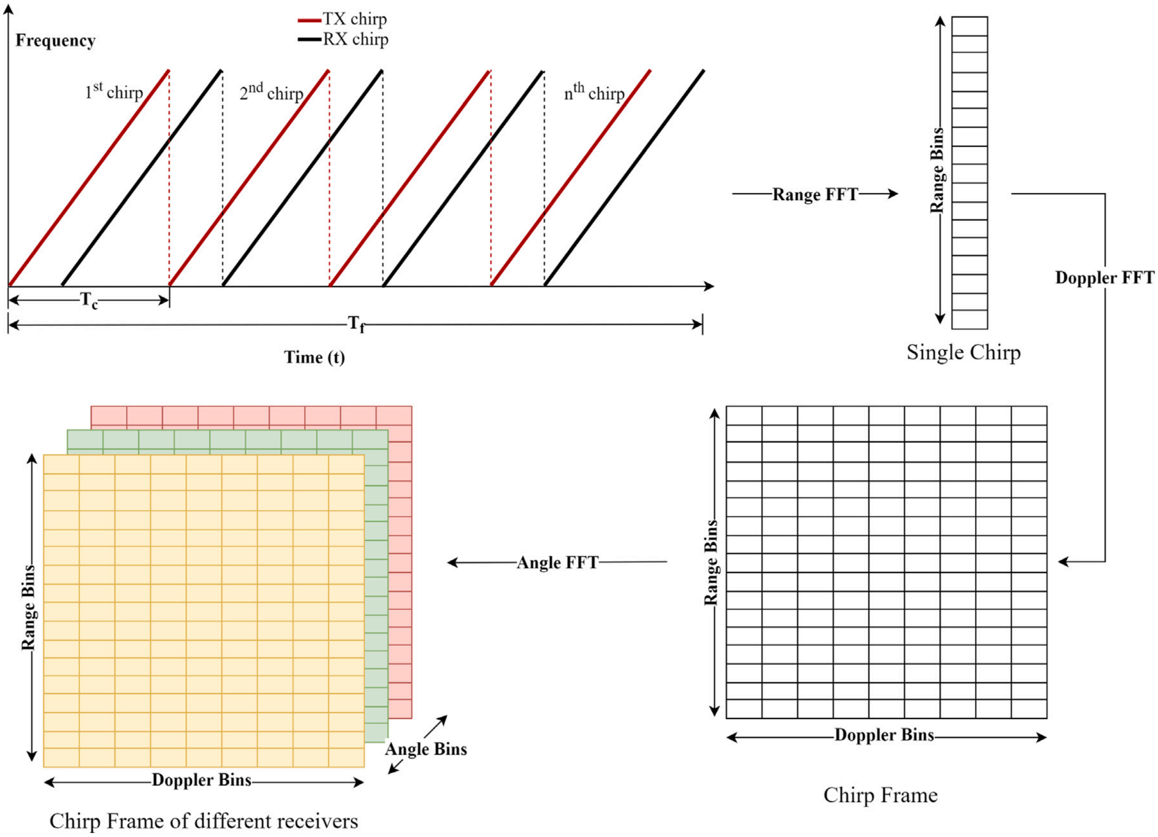

Fig. 6. Preliminary processing chain of mmWave radar.

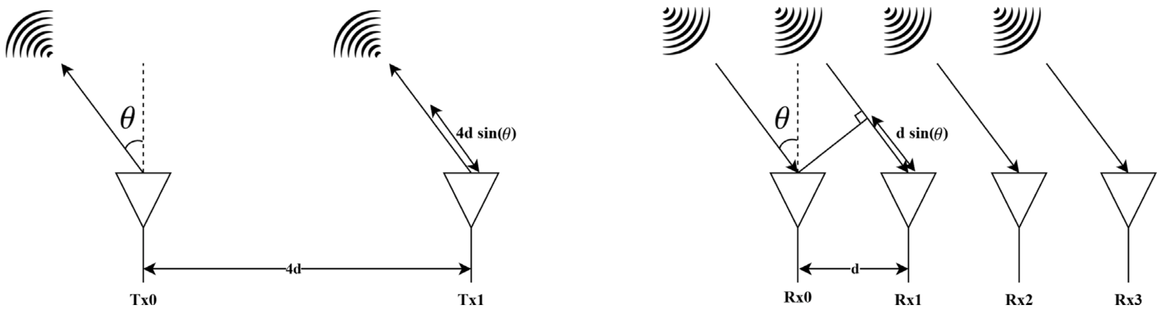

Fig. 7. TDM-MIMO diagram in linear array of antenna.

physical antennas. Fig. 7 illustrates this concept using an arrangement of 2 N_t and 4 N_r. The radar transmits signals from different antennas in succession according to the TDM strategy, allowing the system to discern between the signals based on their respective time slots. The distance between adjacent receive antennas as d, while the separation between transmit antennas is established at $4d$. As the signals from Tx0 reach the 4 receive antennas, a subsequent phase variation is observed due to the different path lengths. The signals from Tx1, which experience an additional path length of $4d\sin(\theta)$, introduce further subsequent phase variation for each receiving antenna. Fig. 7 illustrates the TDM-MIMO working with a linear array of antenna. This phenomenon effectively creates the effect of an additional 4 receive antennas, thereby enhancing the system's resolution. Thus, although only 4 physical receive antennas are present, the radar effectively operates as if it has 8, significantly improving angle estimation precision and demonstrating the advantages of TDM-MIMO techniques.

2.6. Joint Radar Communication (JRC)

The convergence of radar and communication systems has led to significant innovations in both domains. Joint Radar Communications (JRC) represents a sophisticated approach that leverages the synergy between sensing and communication, facilitating ubiquitous sensing services while enabling efficient communication protocols. The integration of JRC, emphasizing its ability to utilize a shared hardware platform for simultaneous operation of radar sensing and communication without detrimental interactions. This integration not only enhances operational capabilities but also optimizes resource utilization [45]. The effective reuse of communication systems for radar sensing necessitates Orthogonal Frequency Division Multiplexing (OFDM) [46]. As a modulation scheme, OFDM divides the available spectrum into multiple orthogonal narrowband subcarriers. This unique arrangement allows data transmission across distinct frequencies, thereby minimizing interference and maximizing throughput. The resilience of OFDM to adverse channel conditions distinguishes it as a robust solution for modern communication, especially in mmWave contexts. A study [47] illustrates the practical application of JRC using Raspberry Pi microcontrollers interconnected within a unified network. This investigation reveals the dynamic interplay between mmWave communication and radar functionalities, underscoring the potential of these integrated systems in real-world scenarios.

3. Trend analysis in research

The progress of a specific research topic is done via bibliometric analysis. The bibliometric analysis is an efficient research method to quantitatively analyze the insights of the research advancements, evolving innovations and emerging research fields. It serves as a complementary approach to the more labor-intensive traditional method of reading numerous published articles to evaluate trends and progress in research. The analysis is conducted by utilizing the Scopus and Web of Science databases, which are renowned for their comprehensive collection of cited data and critical metadata, including associated keywords, research classifications, publication details, and impact metrics. These databases serve as vital agents for illustrating interconnected research trends and can be effectively processed using analytical tools such as Bibliometrix [48]. The integration of these resources allows for a robust examination of scholarly literature, enabling researchers to uncover significant patterns and insights within their respective fields of inquiry.

The subsequent analysis of the data is collected from the Scopus database using the (TITLE-ABS-KEY (mmWave AND radar)) query in all the fields, outputting the relevant manuscript related to mmWave radar, producing an inventory of 1928 scholarly literature, which highlights the ongoing research in the field of the radar domain. The data is collected in the bibtex format and contains features including title, authors, keywords, publisher, year of publication and indexed keywords. These features were utilized for conducting the descriptive statistical analysis of bibliometric networks. The results are presented in the forthcoming sections.

3.1. Descriptive analysis

In the foundational stages of research on mmWave technology, scholars primarily concentrated on the generation, transmission, and reception of these high-frequency waves within various environments. Over the past decade, the application of mmWave has gained significant traction, particularly in the realm of radar technology, leading to a notable transformation within the radar industry.

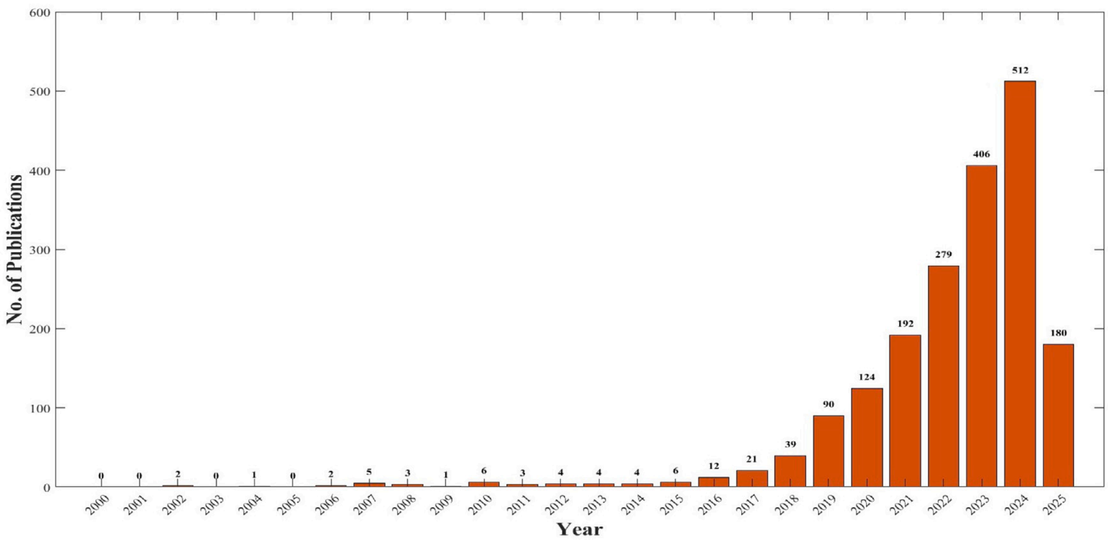

Fig. 8. Publications in 25 years.

Table 2
Distribution of publications in journals & conferences.

Sources	Articles
IEEE Sensors Journal	75
IEEE Access	54
IEEE Internet of Things Journal	47
Sensors	41
Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)	38
IEEE Transactions on Mobile Computing	37
IEEE Vehicular Technology Conference	32
Proceedings of SPIE - The International Society for Optical Engineering	28
Proceedings of the IEEE Radar Conference	27
Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)	25
Electronics (Switzerland)	20
IEEE Transactions On Vehicular Technology	20
IEEE Wireless Communications and Networking Conference, WCNC	18
IEEE Transactions on Instrumentation and Measurement	16
Proceedings of The Annual International Conference on Mobile Computing and Networking (MobiCom)	15
Proceedings of the International Conference on Mobile Systems, Applications, and Services (MobiSys)	15
Proceedings of the Conference on Embedded Networked Sensor Systems (SenSys)	12

Historically, the body of research dedicated to mmWave radar remained relatively stable and unaltered until the year 2014. This is vividly illustrated in the data presented in Fig. 8. However, subsequent to this pivotal year, the field has experienced a remarkable surge in academic and practical interest, characterized by both persistent and exponential growth. Indeed, among the total of 1928 publications identified in this domain, it is noteworthy that approximately 85% were produced after 2014.

This dramatic increase can be attributed to several factors, including advancements in technology, the growing demand for high-resolution imaging systems, and the proliferation of applications in areas such as automotive safety, telecommunications, and medical diagnostics. This redefined landscape presents opportunities for further exploration and innovation, inviting researchers to contribute to the expanding knowledge base around mmWave radar technologies.

In summary, the evolution of mmWave radar research not only reflects the transformative impact of technological advancements but also underscores the vital importance of ongoing inquiry in this dynamic field.

The second analysis presented in Table 2 offers significant insights into key scholarly journals that have extensively published research on mmWave radar technology. Notably, the IEEE Sensors Journal emerges as the leading publication in this field, with a substantial number of articles. It is closely followed by IEEE Access and the IEEE Internet of Things journal, both of which have contributed over 75 publications related to mmWave radar. This reflects the growing interest and the robust body of work being generated within the realm of mmWave radar systems.

3.2. Keywords and co-occurrence analysis

Keywords contain and represent the main ideas of the manuscript and are suitable for co-occurrence analysis. The co-occurrence analysis helps visualize the relationship between concepts and terms, revealing hidden patterns and connections. A co-occurrence network map of keywords was created using the Scopus database, processed by the bibliometrix software and is presented in Fig. 9.

Fig. 9 illustrates the ongoing research landscape in the realm of mmWave. The data is organized into distinct clusters, each representing various aspects of mmWave technology.

Cluster 1 (Purple) focuses on the fundamental applications of mmWave in radar systems. This cluster encompasses critical topics such as mmWave radar technology, FMCW radar, radar signal processing, and radar sensing techniques. These keywords are pivotal to understanding the foundational work in this area. The scope of the fundamental mmWave systems is related to their performance characteristics, which should be targeted more precisely.

Cluster 2 (Blue) explores the integration of advanced methodologies into mmWave radar systems. This section highlights the role of ML and DL techniques in enhancing radar functionality across various domains, including automotive, smart home, security and healthcare applications. The incorporation of these advanced algorithms represents a significant leap in radar technology, enabling improved performance and adaptability. There is a scope of development of advanced algorithms for clutter removal from the radar data, which ultimately improves the technique's performance and efficacy.

Cluster 3 (Red) addresses the application of mmWaves in communication systems, with a particular emphasis on 5G technologies. This cluster includes critical components such as antenna design and bandwidth management, which are essential for optimizing communication efficiency and reliability in next-generation networks. The 5G/6G communication is the newest exploration sector in the field of mmWaves.

Finally, Cluster 4 (Green) examines the integration of the sensing technologies with the communication systems. This highlights the joint radar communication approach with very little exploration. This makes this field a great scope for innovation and research. Utilization of sensing modalities for communication purposes improves system designs and has the advantages of sensing and communication in a single modality. There is great research scope in the domain of joint radar communication and integrated sensing, as the research articles is very less in this domain.

Overall, this structured representation of research areas underscores the multifaceted nature of mmWave technology and its significant implications across diverse fields.

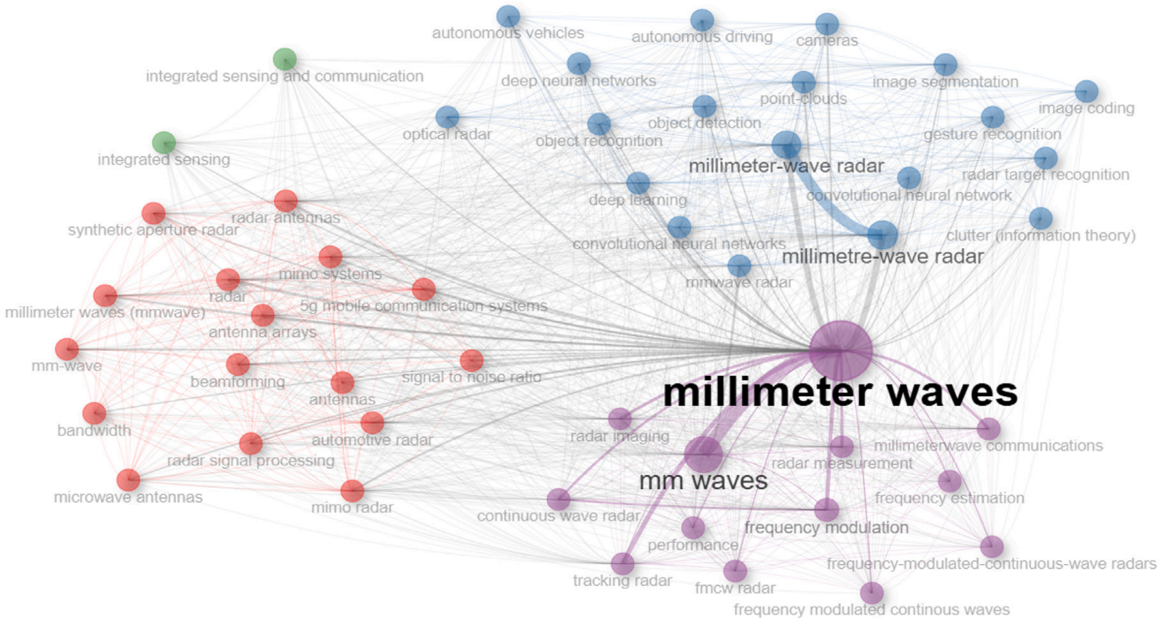

Fig. 9. Co-occurrence network map of keywords: mmWave AND radar.

4. Radar data

Upon conversion of the IF signal to a digital format, the data undergoes processing through multiple stages, each contributing uniquely to a range of applications. The information derived from these processing stages can be strategically employed to enhance various functionalities. The data obtainable at different stages are illustrated in Fig. 10. Furthermore, when combined with supplementary sensor data such as camera, LiDAR, and other sensors, the capabilities of mmWave sensing are significantly augmented. Globally accessible datasets play a crucial role in the advancement of new applications within this domain. These datasets not only facilitate the implementation of innovative methodologies but also provide a benchmark for fair evaluation and comparison of diverse techniques. This encourages broader participation within the field, driving progress and fostering collaborative efforts. This section delineates the types of radar data available, the sources from which data are obtained, and their categorization. This exploration provides a comprehensive understanding of the radar data landscape, elucidating its importance and application potential in modern sensing technologies.

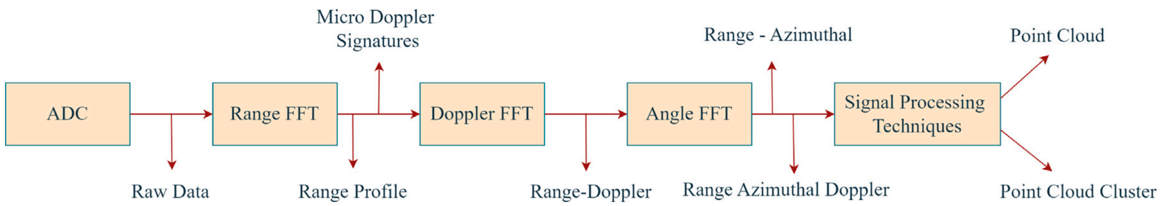

Fig. 10. Radar data processing at various phases.

4.1. Data source

The acquisition of radar data is an essential and meticulous process conducted through various experimental settings. Radar data can be acquired only through the radar device or in conjunction with additional sensors. Several commercially available firms provide mmWave radar, which is used by researchers for sensing purposes. Notable commercial corporations include Texas Instruments (TI) [49], Continental Engineering Services [50], Navtech Radar [51], and Infineon [52], among others. The mmWave radar sensors have been further divided into two categories, i.e., Automotive mmWave Radar (AWR) and Industrial mmWave Radar (IWR). Both of these sensors work in the 60 GHz/77 GHz band and are integrated with various other components to enable high-accuracy sensing in automotive, industrial, and smart home applications. The frequency band for the working of AWR and IWR sensors is the same, but it applies to different sensing ranges. The AWR sensors generally have a maximum range of 300 m, whereas the IWR sensors have a maximum range of 60–70 m. In addition, there are some differences in technical aspects, such as components, processing techniques, and many more.

4.1.1. Standalone

This section examined the datasets collected exclusively through the radar device, with no other sensors employed in the data acquisition process. Each data type holds intrinsic significance and possesses distinct applications.

Gambi et al. [53] gathered a dataset of people walking and made it publicly. The data consists of 19 users with different weights and heights who repeated the activities of slow walking, fast walking, swinging hands while walking and walking with hands in their pockets, with a total of 231 different acquisitions for a range of 10 m. The dataset is collected using a TI automotive radar sensor. RadHAR [54] presents a point cloud dataset named MMActivity collected using TI IWR1443BOOST mmWave radar. The dataset contains two users' data on 5 activities, including walking, jumping, jumping jacks, squats and boxing. Overall, 93 min of data are collected. M-Gesture [55] is a mmWave signal dataset of hand gestures. It consists of 144 users' data with 54,620 instances. The data is collected under not only direct sensing, but also sensing under paper, corrugated paper, metal board, etc. Mimogr [56] is a mmWave radar dataset that contains 7 types of gestures, including waving up, waving down, waving left, waving right, waving forward, waving backward, and double-tapping. The dataset consists of dataV, seven sets of gestures performed by 10 volunteers in an ideal indoor setting with a total of 6847 samples, and dataS, 2800 samples from a variety of complex environments and random users. mHomeGes [57] is an arm gesture dataset based on mmWave radar sensing. The dataset focuses on arm movement of humans, which was collected by TI IWR1443BOOST. It consists of 22,000 samples from 25 persons under 10 arm gestures. Pantomime [58] is another gesture dataset of mmWave signals. The mmWave signals are collected with IWR1443BOOST. The dataset contains 21 gesture types performed by 41 users in two indoor environments. mmGait [59] presents a human gait dataset collected by mmWave signals. The collection process involves 95 participants. In multi-user scenarios, up to 5 users walk simultaneously. The users can walk on fixed paths and freely. MiliPoint [60] provides a large-scale mmWave radar-based human activity dataset. It consists of 11 users' data in identification, key point estimation, and action classification. RADDet [61] proposes a mmWave radar dataset for object classification. The dataset consists of six different categories with more than 100K frames. Hemo et al. [62] is a dataset of human faces of 206 users. The dataset is available in raw data form. The data is collected using a Qualcomm 60 GHz mmWave radar. A total of 1400 frames were collected for each user. 3DRIED [63] is a 3D mmWave radar dataset for imaging. The dataset contains the raw echo data and the imaging results, in which 81 high-quality raw echo data are presented mainly for near-field safety inspection. The dataset is constructed by TI IWR1443BOOST radar sensors. SCORP [64] is focused on open space segmentation in parking scenarios. This radar-only dataset provides 408 samples across three radar data formats: RAD tensor, RA maps, and BEV (Bird's Eye View) representations. It enables research into close-range object detection under sparse radar point cloud conditions. Cts350-x [65] represents the oxford radar robot car dataset for scene understanding usign mmWave FMCW radar for autonomous vehicle applications targetting environmental conditions such as fog, rain, snow, or lens flaer. It covers a variety of weather, traffic and lighting conditions. The data was captured using scans from a radar, LiDARs, cameras, GPS and the groud truth. Radelft [66] represents the RaDelft dataset which is a large-scale, real-life multi-sensor dataset targetting various driving conditions. The radar data was provided in different processing levels, synchronized with lidar, camera and odometry along with the joint calibration of all the sensors. RadIOCD [67] is a privacy-preserving indoor object classification dataset containing 5776 radar recordings with 3D point clouds, doppler velocity, and intensity measurements. Collected via commercial mmWave radar, it supports ML for object recognition in smoke-filled environments (e.g., search/rescue operations) with 76,821 segmented samples across 10 volunteers and 5 object classes.

4.1.2. Sensor fusion

In this section, the data is collected by the radar device along with some other data-capturing sensors like LiDAR, camera, Inertial Measurement Unit (IMU), and many more.

HuPR [68] is a dataset of human pose estimation based on mmWave radars. The dataset contains 6 users' data under 3 different activities, including static actions, standing and waving hands, and walking with waving hands. Two TI industrial radars and one camera are used for data collection, where the two radars are placed vertically for capturing high angular resolution mmWave signals. The two radars and the camera are synchronously configured to capture data with a total of 235 sequences and 141,000 triplets. NuScenes [69] is a well-known public dataset related to mmWave radars. It is a multimodal dataset that combines several autonomous vehicle sensors, including 6 cameras, 5 mmWave radars and 1 LiDAR. The radars operate in 77 GHz to 81 GHz with FMCW techniques. The dataset comprises 1000 scenes, each 20 s long and fully annotated with 3D bounding boxes for 23 classes and 8 attributes. NuScenes has contributed to some works in automobile applications, especially multi-sensor fusion works. ColorRadar [70] is a multimodal dataset that incorporates mmWave radar data. ColoRadar comprises three distinct types of dense, high-resolution radar data generated from two mmWave radar sensors, in addition to data from 3D LiDAR and IMU sensors, with the mmWave radar data being acquired by the TI AWR1843. It also encompasses very precise ground truth for the sensor rig's attitude during nearly two hours of data collection in several 3D locations, including laboratories, hallways, creek pathways, and mines. The dataset intends to furnish radar sensor data for robotic perception applications. Astyx HiRes [71] is the inaugural 4D radar fusion dataset containing 500 synchronized frames of radar, LiDAR, and camera data with 3000 precise 3D annotations. Despite its limited size, it remains a benchmark for automotive object detection, demonstrating radar's superiority over LiDAR in certain detection tasks. CARRADA [72] dataset provides 23,000 synchronized radar-camera frames with range-angle-Doppler annotations, specifically designed for radar semantic segmentation. Features a semi-automatic annotation pipeline and baseline models for radar interpretation in complex driving scenarios. CRUW [73] contains systematic 3D annotations across

Table 3
Analysis on available radar dataset.

Data source	Dataset	Sensing modalities	Radar signal representation	Size	Type of objects	Year	Scope of work	Key features
Standalone	Gambi et al. [53]	Automotive radar	Raw data	Not specified	29 humans	2020	Human activity recognition	Focused on automotive radar applications
	RadHAR [54]	Automotive radar	Point cloud	~6000 samples	Human activities	2019	Activity recognition	Radar-based human activity recognition
	M-Gesture [55]	mmWave radar	Range-Doppler maps	~10,000 samples	Hand gestures	2019	Gesture recognition	First public mmWave gesture dataset
	Mimogr [56]	MIMO mmWave radar	Multi-feature maps	9647 samples	Hand gestures	2022	Gesture recognition	Seven gesture types, multi-feature representation
	mHomeGes [57]	mmWave radar	Range-Doppler	~15,000 frames	Home gestures	2020	Gesture recognition	In-home application scenarios
	Pantomime [58]	mmWave radar	Range-Doppler-Azimuth	22k gestures	Gesture actions	2021	Gesture recognition	Pantomime gesture set
	mmGait [59]	mmWave radar	Point cloud, Range-Doppler	Not specified	Human gait	2021	Gait recognition	Gait analysis and recognition
	MiliPoint [60]	mmWave radar	3D	>200K frames (Largest mmWave)	Human activities	2023	Human activity recognition	Largest mmWave dataset, 49 action classes, keypoint estimation
	RADDet [61]	Continental ARS408-21	Range-Azimuth-Doppler Maps	100K frames, multiple vehicles	Vehicles	2021	Object detection	mAP: 89.4%, Dual detection heads (RAD/Cartesian)
	Hemo et al. [62]	mmWave radar	3D point cloud	Not specified	Human face	2021	Face recognition	Qualcomm 60 GHz radar
	3DRIED [63]	mmWave radar	3D imaging	81 high-quality scans	Metal objects	2021	Safety inspection	High-resolution (2.8 mm × 2.8 mm × 3.75 cm), W-band 79 GHz radar
	SCORP [64]	Radar	SCA/RDA/DoA tensors	~3.9K frames	Vehicles, humans	2020	Open space segmentation	Medical imaging integration, shape correspondence
	Navtech CTS350-X [65]	Navtech spinning radar	360° rotation scanning	25K frames, 8.2K labeled	Vehicles, infrastructure	2022	Multi-Task learning	Detection mAP: 86.3%, Tracking MOTA: 79.2%
	RaDelft automotive [66]	Custom high-resolution radar	Lidar-like point cloud generation	>50,000 frames	Automotive objects	2023	Automotive perception	Chamfer distance reduction: 75%, DL improvement: 10%
	RadIOCD [67]	Automotive radar	ADC data, Range-Doppler	~7k samples	Indoor objects	2020	Indoor object classification	Raw radar signal processing

(continued on next page)

Table 3 (*continued*).

	HuPR [68]	mmWave radar	Range-Angle-Doppler	141k samples	Human poses	2020	Pose recognition	Multiple radar viewpoints
	NuScenes [69]	Continental ARS408-21	Range-Azimuth-Doppler Maps	1.4M frames, 1000 scenes	Vehicles	2019	Autonomous driving	mAP: 65.8%, NDS:71.2%, 360° coverage
	ColoRadar [70]	Dual FMCW Radars, LiDAR, IMU	Raw ADC, Heatmaps, Point clouds	2+ hours of data	General 3D Objects	2022	Odometry /Mapping	Support for signal processing research
	Astyx HiRes [71]	Radar, Visual cameras, 3D LiDAR	3D	500 frames, ~3K annotations	Car, Bus, Motorcycle, Person	2019	Object detection	High-resolution radar data
	CARRADA [72]	Valeo SCALA radar + cameras	Range-Angle-Doppler tensors	12,726 frames	Cars, Pedestrians, Cyclists	2020	Semantic segmentation	Segmentation IoU:73.2%, Synchronized camera-radar
Sensor Fusion	CRUW [73]	Bosch Gen5 77 GHz radar	Range-Azimuth spectrograms	400K frames	Vehicles, Pedestrians	2020	Robust object detection	ROD mAP:73.8%, 3D localization error:0.3 m
	Zenseact Open Dataset [74]	High-res camera, 3x LiDARs, GNSS/IMU	NA	100k frames	Vehicles in various conditions	2025	Object detection	High-precision sensor fusion, global driving scenarios
	K-Radar [75]	4D radar, LiDAR, Cameras, IMU	4D radar tensors	~93K bounding boxes	Vehicles	2022	Detection, Tracking	All-weather performance (rain/snow), elevation angle resolution
	WaterScenes [76]	4D radar, Camera, IMU	Point clouds	Multi-condition coverage	Marine objects	2023	Marine navigation	Pixel-level watercraft annotations
	RADIal [77]	Navtech CTS350-X radar	Raw ADC, RDI, Point clouds	25K frames (8.2K labeled)	Vehicles	2022	Multi-Task learning	Detection mAP:86.3%, 360° spinning radar
	View-of-Delft [78]	64-line LiDAR, Stereo cameras, 3+1D Radar	Range-Azimuth-Doppler Maps	8693 frames, 123K annotations	Cars, Cyclists, Pedestrians	2022	Urban traffic	Multi-sensor calibration, occlusion handling
	TJ4DRadSet [79]	4D radar, LiDAR, Camera, GNSS	Point clouds	7757 frames, 44 sequences	Vehicles	2022	Lighting challenges	Strong light/darkness conditions
	Dual Radar [80]	4D radar (Arbe Phoenix), LiDAR, Camera	Range-Azimuth-Elevation Maps	10K+ frames, 103K annotations	Car, Cyclist, Pedestrian	2023	Cross-Validation	Dual-radar setup for urban/rural environments

15.7 hours of driving data, combining radar RF images with camera RGB frames enabling pure Radar Object Detection (ROD) while using camera data for ground truth labeling in diverse scenarios. Zenseact Open Dataset (ZOD) [74] recently expanded with long-range radar data (8 MP camera, LiDAR, GNSS/IMU); this multimodal dataset offers 2+ years of European driving data across 14 countries. Its permissive license allows commercial use, with particular strengths in adverse weather perception and cross-sensor calibration. K-Radar dataset [75] contains 35K frames of 4D radar tensors synchronized with LiDAR point clouds (LPCs) and surround-view cameras. Unique for including challenging Korean winter conditions (snow/rain) with 93.3K annotated objects up to 120 m range. WaterScenes [76] is the first 4D radar-camera fusion dataset for aquatic environments, containing 54,120 synchronized sets across 200K+ objects. Captures diverse waterway conditions (rivers/lakes/canals) with multi-task annotations for object/waterline segmentation. RADIal [77] contains 2 hours of HD radar (25,000 frames) fused with LiDAR and 8MP cameras across highway/countryside/city environments. Features 9550 vehicle annotations with CAN bus/GPS traces for multimodal perception research. View-of-Delft dataset [78] features a fusion of radar, LiDAR, and stereo camera data, primarily focusing on urban traffic involving cars, cyclists, and pedestrians, complete with class annotations. In contrast, TJ4DRadset [79] offers a point cloud dataset that captures vehicle classifications but is challenged by lighting issues in its environmental context. The dual radar dataset [80] similarly combines radar, LiDAR, and camera technologies, providing insights into both urban and rural settings with thorough class annotations, presented as range-azimuthal-elevation images.

Table 3 serves as a critical reference by providing researchers with a structured analysis of publicly available mmWave radar datasets. It systematically compares key characteristics across datasets to support informed selection for diverse sensing and perception tasks. Each entry is identified by its data source and dataset name, along with its release year. The table details the sensing modalities used and the format of radar signal representation (including point clouds, raw ADC data, range-azimuth maps, and micro-doppler spectrograms), helping researchers match data formats to their processing pipelines. This also reports the size (e.g., frames, sequences, recording hours) and catalogues the type of objects detected (pedestrians, vehicles, gestures, etc.). Critically, it explicitly states the scope of work — identifying the primary research domains each dataset supports (like autonomous driving or healthcare monitoring). Finally, summarizes key features including environmental conditions, object/annotation counts, subject numbers, and collection scenarios. This consolidated comparison accelerates dataset selection, reduces experimental setup time, and provides clear benchmarks for future radar-based perception research.

Sensor fusion techniques for mmWave radar face several critical challenges that impact performance and deployment scalability. First, heterogeneous data alignment poses difficulties due to differing spatial–temporal resolutions between radar and complementary sensors (e.g., cameras/LiDAR), requiring sophisticated time synchronization and coordinate transformation methods. Second, dynamic environmental interference (e.g., multipath reflections, occlusion) degrades fusion reliability, necessitating robust noise suppression algorithms. Third, computational complexity escalates with real-time processing demands, especially for DL-based fusion architectures, creating bottlenecks for edge deployment. Additionally, calibration drift over time introduces errors in multi-sensor systems, while data-level fusion struggles with mmWave's sparse point clouds compared to dense pixel/voxel data from other modalities. Emerging challenges include explainability gaps in AI-driven fusion systems and privacy-utility trade-offs when fusing radar with optical sensors. Addressing these limitations requires advancements in adaptive fusion frameworks, lightweight neural architectures, and self-calibrating sensor networks.

5. Signal processing techniques

Once the signals are originally obtained with spatial information by mmWave radar techniques, the intermediate sensing data must undergo further processing to derive denoised and compressed representations for effective sensing. This section delineates essential strategies in mmWave signal processing, encompassing constant false alarm rate, clustering algorithms, and kalman filter.

5.1. Constant False Alarm Rate (CFAR)

The constant false alarm rate (CFAR) algorithm [81] stands as a cornerstone in the sphere of target detection, particularly within environments characterized by significant noise. This algorithm leverages the power of received signal samples to ascertain the presence of targets in the surrounding medium. A pivotal aspect of CFAR is the establishment of a threshold value; if the power of the reflected signal surpasses this threshold, the reflection is deemed a target. Conversely, if it falls short, it is classified as noise. Consequently, the determination of this threshold is of utmost importance for ensuring the accuracy of target detection.

In the CFAR methodology, the data cells are categorized into three distinct groups:

- Cell Under Test (CUT): The focal cell under examination for potential target presence.
- Guard Cells: Adjacent to the CUT, these cells contain energy contributions from the target and are crucial for the target.
- Reference Cells: These cells are utilized to characterize the background noise levels.

By strategically employing guard and reference cells, the CFAR algorithm calculates an appropriate threshold. This approach not only enhances target detection accuracy but also maintains a consistent false alarm rate. Ultimately, the CFAR algorithm plays a vital role in efficiently identifying targets amidst challenging noise conditions, making it an indispensable tool in radar and signal processing applications.

Various categories of CFAR exist for target detection, but Cell-Averaged CFAR (CA-CFAR) is the most prevalent approach [82]. Additional categories include Greatest Of CFAR (GO-CFAR), Smallest Of CFAR (SO-CFAR), Order Statistic CFAR (OS-CFAR), Order Statistic Smallest Of CFAR (OSSO-CFAR) and Order Statistic Greatest Of CFAR (OSGO-CFAR). Of the six categories, the OS-CFAR demonstrates superior performance in multi-target environments [83]. A comprehensive comparative analysis of the six categories of CFAR is detailed in [84], demonstrating that OS-CFAR is optimal for multi-target detection while incurring minimal computational costs, but the demonstration is solely based on the simulations, not in a realistic scenario.

5.2. Clustering algorithms

The radar-detected target reflections can be represented as points that incorporate the parameters of range, velocity, and angle. The reflection sites are typically abundant and concentrated, accompanied by the detection of noise. Therefore, a clustering method is anticipated to group target points and exclude solitary points to characterize the target.

Density Based Spatial Clustering of Applications with Noise (DBSCAN) is a powerful algorithm designed for clustering based on the density of data points. This method excels in identifying clusters of varying shapes and sizes, making it particularly advantageous in scenarios where traditional clustering techniques may struggle. By evaluating whether a point's local neighborhood – defined within a specified radius, (r) – contains a minimum number of points, DBSCAN distinguishes core points from noise [85]. This iterative process facilitates the expansion of clusters, allowing for dynamic and adaptable grouping of data. One of the notable strengths of DBSCAN lies in its robustness against noise, as it effectively discards isolated outliers that do not conform to the identified clusters. Additionally, the algorithm requires only a couple of parameters, which simplifies its application across various domains. These attributes make DBSCAN a highly suitable choice for complex tasks such as mmWave radar sensing, where accurate data interpretation is critical [86]. Its flexibility and efficacy in handling diverse data distributions enhance its utility in research and practical applications alike. Unlike other clustering algorithms, DBSCAN does not require prior specification of the number of clusters and is capable of identifying clusters of arbitrary shapes, making it particularly advantageous for scenarios with an unknown quantity of target point clouds and unusual geometries.

K-means clustering is a prevalent algorithm utilized in data analysis following the application of DBSCAN. This algorithm categorizes input data by partitioning samples (or observations) into k distinct groups or clusters. It is crucial to differentiate the clusters constructed by the k-means algorithm from those generated by radar extraction methods [87]. This analysis referred to the clusters produced by k-means as "groups". The k-means algorithm outputs both the individual samples of each measure and the centroids representative of each group formed. Like DBSCAN, k-means operates effectively with only a couple of parameters. However, a significant limitation is that the number of clusters, k, must be predetermined, necessitating careful parameter selection to avoid misclassifying noise as a target observation [88]. This requirement emphasizes the importance of thoughtful consideration in the algorithm's application to ensure meaningful clustering results. Thus, it allows the k-means for particular sensing applications.

5.3. Kalman Filter (KF)

Kalman Filters (KFs) [89] represent a robust methodology for addressing challenges in dynamic systems characterized by noise and uncertainty. These filters are instrumental in estimating the true state of such systems by leveraging a sequence of observations that vary over time, effectively filtering out unexpected disturbances and interference. The versatility of KFs has led to their widespread application across various domains, including navigation, localization, autopilot systems, and digital image processing.

In the context of mmWave radar sensing, KFs are particularly valuable for accurately estimating the trajectories of targets. The typical implementation of KFs unfolds through two primary stages: the estimate step and the update step. Initially, a state function is defined to represent the current condition of the target. During the estimate phase, KFs calculate the state of the target at a given timestep while concurrently determining the variance associated with this estimate. Following this, the update step involves acquiring the latest measurement of the state and calculating the corresponding variance. The synergy between estimated states and measurements within the KF framework adeptly addresses issues such as random noise and frame loss commonly encountered in mmWave radar systems. This mechanism not only enhances the identification of target centers but also facilitates the continuous tracking of their trajectories, crucial for applications requiring high precision.

Numerous studies have demonstrated the efficacy of extended KFs in specific applications related to mmWave radar sensing. Notably, they have been effectively deployed for indoor localization [90,91] and tracking [92]. The integration of KFs within these contexts showcases their potential to revolutionize accuracy and efficiency in target tracking technologies, paving the way for enhanced performance in real-world scenarios.

6. Machine learning techniques

The processed signals in the mmWave spectrum carry fundamental sensing information that is crucial for a variety of applications. To effectively harness mmWave radar for sensing tasks, ML techniques, particularly DL, have become integral to advancing these applications. By leveraging these sophisticated methodologies, a robust connection between the sensing tasks and the underlying signals can be established, facilitating the development of innovative sensing solutions.

This section provides a comprehensive overview of both established and cutting-edge ML techniques, encompassing traditional algorithms as well as the latest advancements in DL models. The working of the ML is illustrated in Fig. 11.

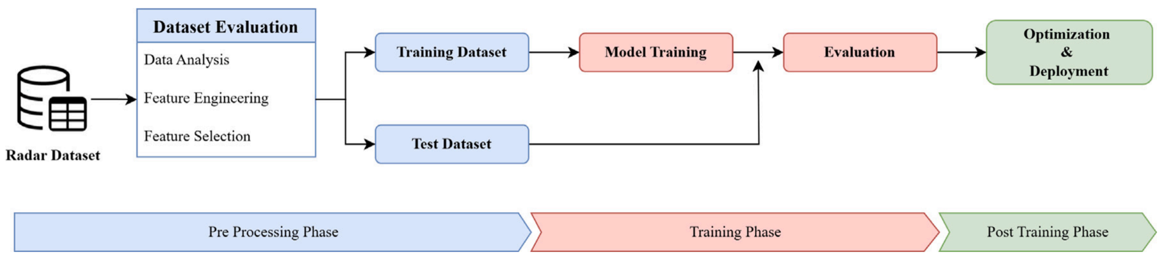

Fig. 11. Machine Learning workflow.

Conventional detection schemes rely on some manual features from mmWave radar data for doppler shift, range, and angle of arrival [93,94]. Classification is achieved through supervised ML methods, such as k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Gaussian Mixture Models (GMM), where objects are classified based on the extracted features.

6.1. Classical machine learning techniques

In the realm of sensing applications, classification and regression stand out as the predominant tasks that elucidate the intricate relationships within the data, providing valuable inferential insights for newly acquired radar information. A critical step in this process involves feature extraction, which aims to reduce data dimensionality while preserving essential information. This can be achieved through a variety of methodologies, including traditional signal processing techniques as well as modern ML approaches.

Recently, there has been a notable increase in the application of classical ML algorithms, marking a significant advancement in the design of mmWave radar sensing systems. Such developments promise to enhance the efficacy and accuracy of data interpretation in radar technologies.

- Support Vector Machines (SVM) [95] — It is popular supervised learning classifiers used in classification problems, especially in high-dimensional spaces where distinct decision boundaries are required. They operate by identifying the best hyperplane that distinguishes various classes with the largest margin. This makes them particularly effective in mmWave radar applications for object detection and recognition, human activity detection, and gesture recognition. As radar returns tend to incorporate a combination of linear and nonlinear relationships, SVMs can gain from kernel functions, which project the feature space into a high-dimensional space in which classes can be made separable. The kernel functions as well as the hyperparameters require careful selection so that maximum performance is attained.
- Decision trees [96] — It is an another supervised learning approach, work by iteratively splitting the data according to feature-based thresholds recursively, creating a tree-like architecture with every leaf node being a class label. Decision trees are easy to interpret and use and are suitable for classifying various motion signatures in applications involving mmWave radar. Decision trees suffer from overfitting, especially if they become too deep. To solve this problem, an ensemble method like random forests can be used. Random forests combine many decision trees, each trained on a different subset of the data, to produce more accurate predictions. This method minimizes overfitting and enhances generalization, which is especially useful when working with radar signals that can change due to environmental factors.
- The k-Nearest Neighbors (kNN) algorithm [97] — It is a simple supervised learning technique that predicts the class of a new point by looking at its closest neighbors in the feature space. It does not involve training a model explicitly but rather uses similarity measures like the euclidean distance to predict the data class. In mmWave radar sensing, kNN is used to predict various movement patterns or object categories using radar features extracted. But the algorithm gets computationally intensive as the size of the dataset increases, as it involves computing distances with all the training examples from the query point. For example, in kNN, similar data points are grouped into classes, thus making it amenable to gesture recognition and human activity monitoring.
- Gaussian Mixture Models (GMMs) [98] — These models serves the purpose of target clustering, particularly in monitoring traffic scenarios. GMMs represent data distribution as a mixture of a number of gaussians, where they can then cluster radar signals according to trained probability distributions. This method proves to be highly useful in applications where the quantity of target classes is unknown or where radar returns show overlapping signatures. GMMs, in contrast to deterministic classifiers, make an estimate of uncertainty, and this can be very helpful where confidence measures of detection are essential.
- Hidden Markov Models (HMMs) [99] — These are most suited for time-series data and sequential labeling. For mmWave radar, HMMs can be used to identify human actions, identify dynamic events, and monitor moving targets. HMMs take a position that the radar signals seen are produced by an underlying set of hidden states, which change over time according to a markov process. For instance, in gait analysis, every walking phase (e.g., heel strike or toe-off) can be represented as a hidden state, enabling HMMs to model sequential dependencies of movement. This is particularly fitting in applications where it is important to understand the temporal evolution of radar signals.

6.2. Deep learning techniques

Over the past decade, advancements in neural networks, particularly DL technologies, have significantly transformed various domains, including pattern recognition, gesture recognition, etc. By training neural network models on sufficiently large datasets, these systems acquire the intricate knowledge embedded within the data, enabling them to make informed predictions and decisions. In the realm of mmWave radar sensing, applications increasingly leverage diverse neural network architectures to extract critical features and generate accurate predictions.

- Convolutional Neural Networks (CNNs) [100] — These are well known for their capacity to extract spatial features from images and structured data. When used on mmWave radar, CNNs can analyze range-Doppler maps, spectrograms, and radar heatmaps to classify objects, detect motion, and identify complex patterns. The hierarchical structure of CNNs enables them to extract low-level and high-level features with ease, thus making them particularly useful for applications like vehicle detection in autonomous driving, hand gesture recognition, and human pose estimation. As radar data can be expressed in a 2D format, CNNs offer an effective method to detect unique patterns of motion in these representations.
- Autoencoders [101] — Neural networks applied in unsupervised learning, are good at feature learning and compressing data. Autoencoders encode input information into a lower-dimensional space and reconstruct it to its original state. In radar applications with mmWave, autoencoders are apt for radar signal denoising, extracting significant features, and identifying anomalies. For example, they can be learned on typical radar signatures and applied to detect strange patterns in the data, which might represent an unknown object or unanticipated motion.
- Recurrent Neural Networks (RNNs) [102] — These are DL architectures intended to handle sequential data. Because radar returns tend to reflect continuous motion, RNNs, especially long short-term memory (LSTM) and gated recurrent unit (GRU) networks, are ideal for observing long-term patterns in time-series radar data. They can be applied to inspect micro-Doppler signatures, follow moving objects, and estimate future states of an object based on previous states. RNNs are of particular importance in tasks like gesture recognition and human activity classification, where temporal relationships between radar signals need to be understood.

- Transformer networks [103] These are originally proposed for natural language processing tasks, have been adapted for various vision and perception problems due to their superior capability in capturing long-range dependencies and global context. In the domain of mmWave radar, transformer-based models offer promising avenues for modeling the spatio-temporal characteristics of radar data without the inductive biases associated with CNN or RNN. These networks can directly learn meaningful representations from radar raw signals or intermediate feature maps, enabling improved performance in tasks such as object detection, tracking, and activity recognition.
- Generative Adversarial Networks (GANs) [104] — It is an another DL method that has been applied to mmWave radar data analysis. GANs are two adversarial networks: a generator that creates new samples of data and a discriminator that tries to identify real and generated samples. In radar, GANs can be employed for data augmentation, allowing improved model training through the creation of realistic synthetic radar signals. They also have the ability to improve radar imaging, enhance resolution, and denoise signals by learning the underlying distribution of actual radar data. This capability to create high-fidelity data is useful for enhancing radar-based recognition and detection systems.
- Spatio-temporal networks [105] — These networks are particularly well-suited to this task. These networks are designed to jointly learn spatial features—such as object position, structure, or angular distribution—and temporal features—such as motion patterns or changes over time. Unlike conventional CNN or RNN models that process radar data independently per frame, spatio-temporal models leverage the temporal continuity and correlations across multiple frames to improve the performance of tasks such as object detection, trajectory prediction, gesture recognition, and tracking.
- PointNet [106] and PointNet++ [107] — These are DL architectures that are specifically trained to handle raw point cloud data, which makes them extremely relevant for 3D radar applications. As opposed to conventional approaches that transform point clouds into voxel grids or 2D projections, PointNet directly processes the unordered point sets while maintaining the geometric structure of the data. For mmWave radar sensing, where sparse point clouds are often utilized for object classification and recognition, PointNet-based methods have exhibited better performance in object detection and identification in autonomous driving, robotics, and security scenarios. PointNet++ advances this feature with the addition of hierarchical feature learning, enabling it to more accurately capture global and local structures of radar point clouds.

7. Radar data for ML/DL approaches

This section focuses on the mmWave radar data for the ML/DL applications and their challenges. Radar data possess unique characteristics such as sparsity, noise, etc. Therefore, to make this data domain suitable for ML and DL algorithms, this data requires preprocessing techniques such as denoising, etc.

- Sparsity and Noise — Unlike RGB images or dense LiDAR point clouds, mmWave radar data – particularly in micro-Doppler or range-angle representations – is inherently sparse and noisy due to low angular resolution and multi-path reflections. This sparsity leads to insufficient feature representation, particularly in cluttered or dynamic environments. Consequently, ML/DL models must be equipped with robust denoising techniques or learn from limited, high-dimensional data. Approaches such as sparse autoencoders, spatial–temporal filtering, and noise-robust CNNs have been explored to mitigate this issue.
- Domain shift and Adaptation — A significant challenge arises from the domain gap between different radar devices, environments, or synthetic and real datasets. Models trained on one domain often underperform when deployed in another due to variations in material reflectivity, interference patterns, and occlusions. Unsupervised domain adaptation methods, such as Maximum Mean Discrepancy (MMD), CycleGAN-based translation, and fine-tuning on few-shot samples, have shown promise in bridging this gap. Models trained on synthetic radar gesture data in real-world environments achieve considerable performance gains.
- Explainability in Deep Models — Deep models deployed in radar-based applications especially in safety-critical scenarios like autonomous driving or healthcare must provide interpretable decisions. The opacity of black-box DL models has spurred interest in explainability tools such as Grad-CAM, LIME, and SHAP. These methods help identify the radar spectrogram regions or temporal segments contributing most to a prediction. Saliency maps are used to interpret radar-based fall detection, enabling trust and traceability in clinical environments.
- Real-Time processing and Edge deployment — Real-time radar-based sensing often imposes strict latency and memory constraints, particularly in embedded systems such as autonomous vehicles or drones. Therefore, lightweight and efficient architectures – such as MobileNet, EfficientNet, and model pruning/quantization techniques – are increasingly adopted. The trade-off between model complexity and latency is an active research area, with some studies reporting sub-50 ms inference times using optimized CNNs and recurrent networks on edge devices.
- Sensor Fusion for Robust Perception — mmWave radar, while robust to poor visibility conditions, often suffers from limited spatial resolution and semantic ambiguity. To address this, sensor fusion approaches combining radar with vision, LiDAR, or ultrasound data have gained traction. These strategies leverage complementary features using early fusion (feature-level), late fusion (decision-level), or hybrid architectures. Fusion of radar data with other sensors increases the detection accuracy and efficacy of the model.

8. ML-driven in sensing applications

This section discusses the application taxonomy of ML and DL techniques, shedding light on the diverse range of novel applications that have emerged as a result of this synergy. Through this examination, a transformative impact of ML in the realm of mmWave sensing is illustrated and inspires future research in this promising field.

The first and foremost application of the mmWave radar is target detection. Target detection aims to identify the presence of targets or objects in the surrounding area. In certain literature, it is referred to as semantic segmentation. The application of range estimate techniques in mmWave radar facilitates target detection. Consequently, numerous studies utilize mmWave radars for target identification across various application contexts, including autonomous driving, security, and Unmanned Aerial Vehicles (UAVs). Target detection can be achieved solely by mmWave radars or by integrating mmWave radars with additional sensors, such as cameras.

In radar-only detection, mmWave radars produce range-Doppler images and point clouds, which are subsequently analyzed using DL models; conventional CNN-based real-time target detection techniques, such as YOLO (You Only Look Once) and Faster R-CNN, are frequently employed for target detection. The primary benefit of YOLO is in its rapidity and efficiency in processing radar data, whereas Faster R-CNN demonstrates superior recognition performance through the utilization of region proposal networks (RPNs). The limited angular resolution and noise in the radar point cloud present obstacles for radar-only detection, adversely impacting classification performance. Fig. 12 shows the explanation of target detection as well as classification using the mmWave radar.

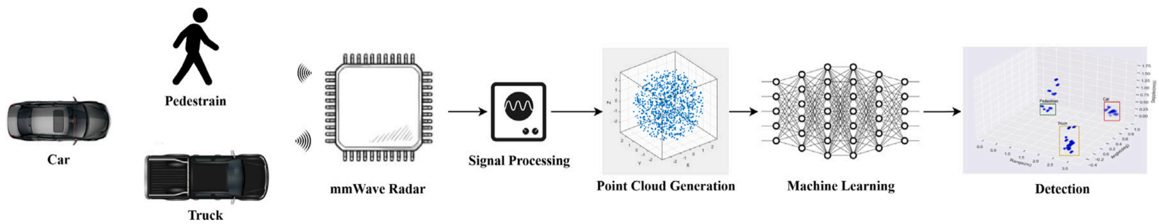

Fig. 12. Target detection using mmWave radar.

To address the limitations of the singular radar application, mmWave radar is frequently integrated with many alternative sensing modalities, including LiDAR and RGB cameras. DL methodologies for fusion exist, integrating radar properties with visual and depth data. Consequently, these factors enhance overall detection performance to the greatest extent possible [108,109]. Sensor fusion techniques improve target detection efficacy through structures including feature-level fusion, decision-level fusion, and intermediate fusion [93,94]. Consequently, leveraging the inherent complementary advantages of various sensors significantly enhances the performance of multi-sensor fusion, particularly in terms of detection robustness in intricate situations, such as pedestrian detection in low light or occluded vehicles in traffic scenarios.

[110] proposes ensembles of RNN utilizing one-vs-all correction classifiers, resulting in enhanced accuracy in the identification of novel classes. [109] employs two mmWave radar sensors for precise target detection and tracking. They specifically emphasize two phases of noise reduction to mitigate noise and differentiate cluster groups. The system can display the information about targets obtained by one radar on another radar. [111] concentrates on 4D mmWave radars, where elevation serves to furnish significant sensing data. They offer a three-dimensional target-detection framework utilizing multi-frame 4D mmWave radar point clouds. Relative velocity is employed as a compensatory measure to generate multi-frame mmWave point clouds for target detection.

The integration of mmWave radars with cameras enables the detection of targets in conditions of low visibility and illumination where cameras may be ineffective. A seminal study [69] introduces a dataset called NuScenes, developed using mmWave radars, cameras, and LiDAR. The dataset indicates that the subsequent works employ several methodologies to attain accurate target detection. [112] introduces Camera Radar Fusion Net (CRFNet) to autonomously determine the optimal level of fusion. RODNet [73] develops a deep radar target detection network that employs cross-supervision by integrating camera and radar data without extensive annotation, enabling the recognition of targets from radar spectrums. DL-based target detection network, MS-YOLO [113], is proposed to align radar and optical information at a uniform scale. milliEye [114] seeks to adjust to novel environments utilizing only minimal annotated pictures or radar data. It develops a learning-based fusion and an innovative decoupling architecture to effectively detect targets on edge platforms, achieving performance improvements compared to solely image-based target detectors while minimizing computational overhead on these platforms. [115] concentrates on decision-level fusion of mmWave radars and cameras for resilient multi-target categorization and tracking. [116] proposes a novel transformer-based radar object detection model and validates the results on the CRUW and CARADDA datasets. [117] introduced a radar transformer model for the classification of objects. [118] proposed a vision transformer-based enhanced object detection algorithm with an average precision of 61.90%. [119] proposed a two-camera-radar fusion architecture using a swin transformer on the NuScenes dataset. [120] proposes a novel technology for target classification using FMCW mmWave radar, where the statistical parameters from range FFT plots are used as input features for lightweight neural network model thus achieving an accuracy of 0.96. The methodology was validated by deploying on development boards also. [121] introduces a Reinforcement Learning (RL) based framework for target classification using FMCW mmWave radar by adopting statistical features obtained from the raw ADC data. The Double DQN achieves superior performance with an accuracy of 0.9889 over the test dataset. [122] proposed a hybrid CNN with a memetic algorithm for the

Table 4
mmWave radar applications in target detection.

Reference	Device	Data representation	Scenario	Algorithm used	Key features
[69]	mmWave radar, cameras, LiDAR	Multi-modal dataset	Urban autonomous driving environments	NuScenes framework	Radar mAP up to 70%
[73]	Camera & radar	Radar spectrums	Weak/strong lighting & bad weather conditions	RODNet	Achieves 87.5% mAP
[108]	TI IWR6843	Point Cloud	Adverse weather & lighting conditions	CNN-based approach	Achieves >95% detection accuracy
[109]	TI IWR1642BOOST & camera	Point Cloud	Indoor spaces with occlusions & crowded conditions	Improved DBSCAN	Clustering accuracy >92%
[110]	77 GHz radar	Point Cloud	Automotive/road environments	RNN ensemble method	Classifier ensemble reaches an averaged F1 score of 91.46%
[111]	4D mmWave radar	Point Cloud	Automotive environments	3D CNN	Detection accuracy 93.2%
[112]	Camera & radar	Feature-level fusion	Adverse weather conditions & low-light scenarios	CRFNet	The mAP raises by 12.96% as compared to RetinaNet
[113]	Radar & optical sensors	Uniform scale fusion	Intelligent vehicle environments	MS-YOLO	Detection accuracy 91.8%
[114]	mmWave radar & camera	Edge computing fusion	Low-light scenarios	Sensor fusion approach	Achieves accuracy of 89.7%
[115]	mmWave radar & camera	Decision-level fusion	Controlled parking lot environment	Multi-target classification	Resilient tracking with F1 score 92.1%
[116]	TI IWR6843	Feature-level fusion	Pedestrian liveness detection	Attention-based CRF fusion	mAP of 97.7%
[117]	mmWave radar & camera	Sensor fusion outputs	Intelligent transportation system (roadside ITS)	GM-PHD filter fusion	90.4% sensitivity on human detection
[118]	77 GHz RMT-based radar	RAD tensor	Adverse weather & low-light autonomous driving	TransRAD (Retentive Vision transformer)	2D mAP of 63.9% on RD & 47.5% on RA
[119]	COTS C-band radar	Waveform spectrums	Spy-radar detection & localization in indoor/outdoor	Swin transformer	96% detection rate; localization error within 0.3 m
[120]	TI AWR2944EVM	Range plots	Parking lot environment	Light NN	Achieved an accuracy of 96% in the classification of three classes.
[121]	TI AWR2944EVM	Range plots	Controlled parking lot environment	Reinforcement learning	Achieved an accuracy of 98.89% in the classification of three classes.
[122]	10.5 GHz HB100 radar	Micro-doppler	Indoor & controlled scenario	CNN & memetic algorithm	Achieved an accuracy of 99.06% for the flying object classification.

classification of flying objects. Table 4 compares how researchers have used mmWave radar to detect objects and people in real-world settings. For each study, the table lists the reference, the specific device used, and how the radar data was formatted (data representation — like point clouds or range-Doppler maps). The table then describes the testing scenario (e.g., tracking vehicles on highways or recognizing hand gestures in homes), the main algorithm used (such as ML models or signal processing techniques), and standout key features (like high accuracy in bad weather or efficient computation). This helps to quickly see which hardware and methods work best for different detection tasks, making it easier to choose approaches for their work.

8.1. Automotive applications

mmWave radar sensors have emerged as critical components in the automotive industry, playing a pivotal role in applications such as ranging, localization, and mapping. Their integration with complementary technologies like LiDAR and cameras is significantly advancing the development of autonomous driving systems. This multifaceted approach not only enhances the accuracy of environmental perception but also contributes to safer driving experiences. The automotive applications of mmWave radar are diverse and can be categorized into automobile, in-cabin monitoring and SLAM.

8.1.1. Automobile (outside vehicle monitoring)

In recent years, mmWave radar sensors have become essential in the automobile sector, delivering precise readings of distance, velocity, and the angle of dynamic objects. These sophisticated sensors are crucial for various functions that improve car safety and driver assistance systems. Principal uses encompass adaptive cruise control, autonomous emergency braking, blind spot recognition, lane change assistance, front and rear cross-traffic alerts, automated parking, and diverse applications pertaining to vehicle body and chassis dynamics.

Studies have shown the efficacy of mmWave radar in ascertaining the relative positions of vehicles. A thorough study in [123] demonstrates how these sensors can accurately evaluate vehicle interactions on the road. Additionally, [124] emphasizes vehicle detection in advanced driving assistance systems by employing radar data that includes range, azimuth, and doppler parameters. Additionally, [125] introduces a two-dimensional vehicle identification system tailored for autonomous driving, illustrating the ongoing progress in intelligent transportation technologies as shown in Fig. 13.

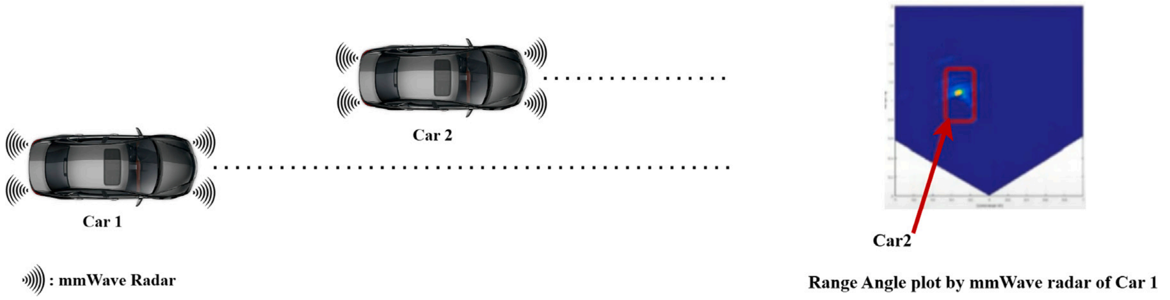

Fig. 13. mmWave radar in an automobile.

The comprehension of an autonomous vehicle's environmental perception capabilities is a vital study domain. [126] examines the role of mmWave radar in environmental detection, whereas [127] evaluates the feasibility of these sensors for vehicle identification in autonomous systems. In another notable contribution, [128] explores the amalgamation of mmWave radar and vision sensors to enhance obstacle detection in autonomous vehicles.

To get enhanced accuracy in next-generation Advanced Driver-Assistance Systems (ADAS), numerous studies have examined the integration of mmWave radars in automobiles. In a broader context, [129] proposes novel methodologies for terrestrial traffic surveillance and the management of both ground and aerial vehicles via angle estimation, demonstrating the diverse applications of mmWave radar technology beyond its traditional automotive applications.

These studies collectively highlight the pivotal role of mmWave radar in enhancing vehicle identification, environmental awareness, and user interaction, hence fostering a safer and more intuitive driving experience. Current research in this domain is facilitating future progress in intelligent mobility systems.

Ego-motion estimate is a crucial domain in robotic and autonomous navigation, concentrating on evaluating a device's movement based on data obtained from its sensors. This method, rooted in computer vision principles, primarily examines the motion of a device's camera by utilizing visual data. The importance of ego-motion estimation is highlighted by its crucial function in enabling navigation and interaction with the environment.

Recently, the utilization of mmWave radars for ego-motion estimation has increased, offering a persuasive alternative owing to their proficiency in efficiently capturing ambient data. This methodology is especially pertinent for applications in autonomous cars and robots, where dependable motion evaluation is essential. In contrast to conventional vision-based systems, mmWave radars exhibit resilience to fluctuating lighting and air conditions, facilitating efficient long-range environmental sensing. This capability positions mmWave technology as a viable tool for ego-motion estimation in automated environments. The use of radar-based systems in ego-motion estimation presents hurdles; the occurrence of ghost objects – erroneous reflections that might hide the actual positions of nearby objects – creates substantial difficulties. To mitigate this constraint, several ways have been suggested, including the application of landmark extraction techniques alongside the creation of specialized radar scan matching algorithms. These developments seek to improve the precision of ego-motion estimation, especially in situations marked by intricate rotations and significant translations.

In conclusion, although ego-motion estimation via mmWave radars holds significant potential for enhancing navigation technologies, continued study is imperative to address current challenges, such as ghost object interference, to improve the accuracy and dependability of these systems.

The subsequent study [130] further develops a gradient-based, one-parameter keypoint extraction technique. The approach renders ego-motion estimation exceptionally resilient against radar distortions, such as speckle noise and false positives, utilizing merely a single input parameter. [131] examines the impact of trajectory estimation inaccuracies caused by navigation, specifically regarding defocusing and incorrect target localization. A probabilistic methodology [132] can be utilized to tackle unstable and phantom measurements, as well as a significant prevalence of outliers in ego-motion estimation. [133] endeavours to address the

Table 5
mmWave radar applications in automobile.

Reference	Device	Data representation	Target environment	Algorithm used	Key features
[124]	mmWave radar	RAD tensor	Vehicles	CNN + LSTM	Model has 95.46% precision with 84.85% recall
[125]	Continental ARS 408-21 radar	Range-Azimuthal image	Cars	PointNet	Classification accuracy is 96.07% & segmentation accuracy is 82.64%
[126]	76 GHz mmWave radar	Radar cross-section grid	Cars, pedestrians, cyclists	2D CNN	Classify the static & the moving objects, has a precision of 76.89% & 82.74% recall
[127]	77 GHz mmWave radar	Range-Azimuthal image	Vehicles	DBSCAN & faster RCNN	The average detection accuracy is 96.95%
[128]	Radar, camera & LiDAR	Radar data fused with camera	Obstacles	ResNet-50 + faster RCNN	The average precision is 86.80%
[129]	TI AWR1843BOOST	Range-Angle spectral maps	Pedestrians	Polynomial regression	Achieved an RMSE of 2.523°
[130]	mmWave radar	Range-Angle spectral maps	Environmental objects	Gradient-based extraction technique	Radar odometry is better for autonomous system than visual odometry
[131]	TI AWR1243	Range-Angle heatmaps	Stationary ground control points	Autofocus algorithm	Estimates the velocity of the vehicle.
[132]	mmWave radar	Range Doppler heatmaps	Environmental features	Gaussian mixtures	Compared a ego-estimation on different datasets
[133]	mmWave radar	Point Cloud	Stationary objects	Radar odometery & point cloud clustering	Improved radar odometry with the velocity ambiguity.

invalidation of radar odometry algorithms resulting from radar velocity ambiguity. They investigate a method for joint velocity ambiguity resolution and ego-motion estimate in radar odometry. Table 5 shows how researchers use mmWave radar in different automobiles. For each study, the table lists the reference and the radar device tested. The table explains the data representation used (like point clouds or heatmaps), the target environment where it was tested (e.g., highways, parking lots, or snowy roads), and the main algorithm used (such as ML models or tracking filters). This helps to quickly compare methods and choose the right radar solutions for real-world driving situations.

8.1.2. In-cabin monitoring

mmWave radar sensing approaches are being significantly attracted to possible smart environments applications, especially in the automotive domain. One major example is that of in-cabin monitoring, where mmWave radars provide non-invasive, high-resolution sensing of passengers for health monitoring and assistant applications.

One of the twin challenges currently being faced in modern vehicles is passenger safety and driver assistance. In-cabin monitoring applications in vehicles have depended on cameras and infrared sensors to track specific behaviors of the driver and detect passengers [134,135]. However, these methods have several disadvantages, such as privacy issues and variable sensitivity with lighting conditions, as well as physical obstructions in the vehicle environment. Thus, with the advantageous properties offered by mmWave radar sensing, it paves the way for being an advanced alternative to in-cabin snooping in a quite invariant manner.

mmWave radar detects objects and movements in very high resolution across a spectrum of frequencies ranging from 30 GHz to 300 GHz [136]. While not relying on visible light, unlike optical sensor measurements, mmWave is quite effective in the most diverse environments and ranges, from darkness to fog and all the way into bright sunlight. This improves the reliability of in-cabin monitoring systems by ensuring continuous operation unaffected by the surrounding environment. One of the most important applications of mmWave radar in in-cabin monitoring is driver vital sign detection. [137] implemented a DCNN model for child presence detection in an automobile, which achieves 100% accuracy using the 74 different features. Using micro-Doppler, mmWave radars detect very slight physiological movements like respiration and heart rate without physical contact. With this capability, the system can monitor driver fatigue, stress, and medical emergencies such as cardiac arrest in real time [138]. In contrast to conventional wearable health monitors, mmWave radar requires no skin contact and is therefore extremely user-friendly.

Besides the driver, mmWave radar participates in passenger presence detection. Adults from children and pets can be distinguished, and airbags and seatbelt reminders can be appropriately deployed [139], illustrated in Fig. 14. [140] introduced an innovative approach utilizing a 2D CNN-LSTM network designed to effectively detect and classify occupants within a vehicle. This model achieves impressive performance metrics, with detection accuracy exceeding 95%, classification accuracy surpassing 74%, and an exceptional seat occupancy accuracy of over 89%. Additionally, [141] explored a Convolutional LSTM (ConvLSTM) framework that eliminates the need for handcrafted rules while demonstrating a high level of precision in identifying passengers and categorizing occupant types as empty, adults, or children. Noteworthy results from their study indicate an impressive precision of

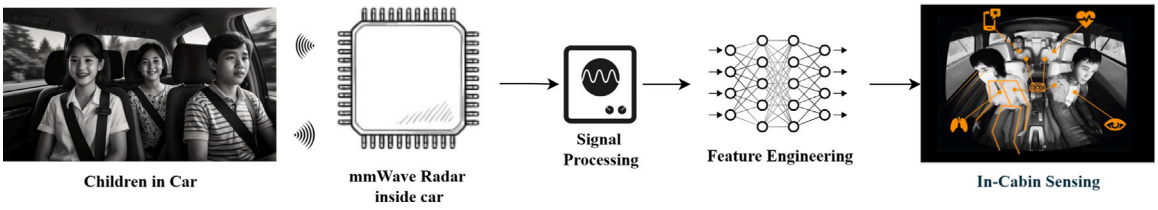

Fig. 14. In-Cabin monitoring using mmWave radar.

Table 6
mmWave radar applications in in-cabin monitoring.

Reference	Device	Data representation	Monitoring objective	Algorithm used	Key features
[134]	Camera, Infrared sensors	Raw 3D Point Cloud Matrix	Seat occupancy detection & classification	PointNet	Accuracy 99.04%, works on Transformer-PointNet
[135]	TI AWR6843	Point Cloud	Distinguishing adults, infants, & empty seats	Volume-based analysis	Accuracy of 96.7%, Velocity Resolution is 1.5 cm/s
[136]	24 GHz Doppler radar	Point cloud	Passenger presence for gesture control & HMI interaction	Signal processing	Micro-Doppler Effect
[137]	60 GHz radar	Range Angle heatmaps	Adults & Infant occupancy	XGBoost + DNN	100% occupancy detection of adults and infants in the automobile.
[138]	TI AWR1642	3D spatial data	Detecting subtle body movements to infer seat occupancy	Micro-Doppler analysis	96% accuracy, Seat-level CFAR
[139]	TI AWR1642	Point Cloud	Multi-occupant detection & classification	DL	Accuracy of 95.6%, uses multipass zoom CFAR
[140]	TI AWR6843 4-D imaging radar	Range-doppler heatmaps	Identifying adults, children, & infants for safety alerts	CNN-LSTM	Accuracy of 95%, 74% & 89% for detection, classification & seat occupancy
[141]	TI AWR6843	Range-doppler heatmaps	Classifying seats as empty, occupied by adult, or child	ConvLSTM	90% precision & 95% recall for unattended child in vehicle.

90% and a recall rate of 95% in the context of detecting unattended children in vehicles. These findings highlight significant strides in the application of DL for enhancing vehicle safety systems, particularly in protecting vulnerable occupants. Thus, child presence detection systems have been made mandatory in cars by agencies regarding safety, like European NCAP, to avoid horrendous incidents of leaving children unattended in vehicles. Because it detects minute patterns of breathing, mmWave radar presents the most suitable avenue for satisfying the regulatory conditions of avoiding such safety disasters. Table 6 shows how mmWave radar monitors people and activities inside vehicles. For each study, the table lists the reference and the radar device used. This explains the data representation (like point clouds or micro-Doppler signatures), the monitoring objective (e.g., checking driver alertness, detecting children in rear seats, or measuring passenger heart rates), and the algorithm used (ML models or signal processing methods). Finally, it highlights key features – such as working with reclined seats, ignoring dashboard clutter, or detecting subtle breathing movements. This helps to quickly compare solutions for real-world in-cabin safety and comfort systems.

8.1.3. Simultaneous Localization and Mapping (SLAM)

SLAM is a fundamental challenge in robotics and autonomous navigation. Traditional SLAM implementations have utilized multiple sensor modalities such as LiDAR, cameras, and IMU sensor. However, mmWave radar is emerging as a stand-alone sensor for SLAM due to its resilience in adverse environmental conditions, including fog, rain, and low-light scenarios [142].

SLAM enables an autonomous system to construct a map of an unknown environment while simultaneously determining its location within it. This process involves updating both the map and localization parameters in real time while mitigating errors arising from sensor noise, environmental variability, and computational limitations [143]. The accuracy of SLAM systems depends on the sensors used, their resolution, and the efficiency of data processing algorithms [144]. Conventional SLAM methods have predominantly relied on LiDAR and vision-based systems due to their high-resolution spatial and visual data. However, these sensors are constrained by challenges in extreme weather, low visibility, and occlusions, limiting their applicability in real-world conditions.

mmWave radar presents an alternative that functions independently of lighting conditions while also providing velocity and range data crucial for localization. Unlike optical sensors, mmWave radar is unaffected by visibility restrictions and can penetrate rain,

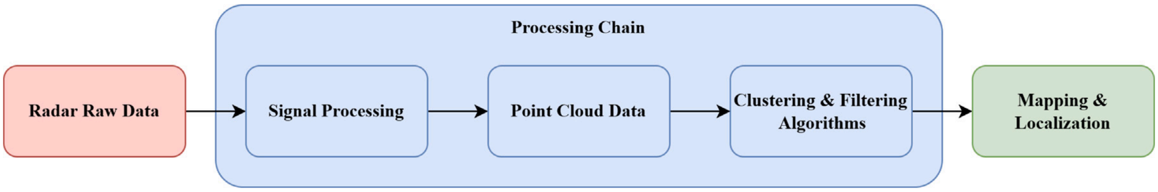

Fig. 15. SLAM workflow using the mmWave radar.

fog, and dust, making it advantageous in environments where traditional sensors falter [145,146]. Additionally, the Doppler velocity information from mmWave radar aids motion estimation. Despite these benefits, using mmWave radar alone in SLAM introduces challenges. Radar data typically produces sparse point clouds with lower resolution than LiDAR, making feature extraction and object detection more complex [93]. Moreover, radar signals are susceptible to multi-path reflections and clutter, increasing uncertainty in object localization. Addressing these challenges requires advanced signal processing, data association techniques, and ML approaches to improve robustness and accuracy. The working procedure of mmWave radar in the SLAM is illustrated in Fig. 15.

By adopting mmWave radar for SLAM, engineers and researchers can develop more adaptive and resilient autonomous systems capable of operating in dynamic and challenging environments [93]. This paper aims to highlight the key challenges and opportunities in radar-based SLAM and proposes novel data processing and learning methods to address existing limitations. In recent SLAM research, milliMap [10] has emerged as an innovative approach integrating LiDAR data and geometric priors with cross-modal supervision. This enables training a conditional GAN (cGAN) tailored for mapping sparse mmWave signal reflections. The goal is to create a dense grid map that enhances object detection and localization by analyzing mmWave signal responses.

By combining continuous radar scanning point clouds with IMU data, they address the challenge posed by limited data volume [144]. Firstly, preprocess the raw data to filter the outliers using the DBSCAN algorithm and then a refined correlative scan matching (CSM) technique is introduced, enabling the alignment of radar point clouds with local submaps within a global grid map, thus achieving a robust fusion of localization and mapping processes. [147] relies exclusively on mmWave radar, which converts sensor measurements into depth images using a sensor fusion network. This technique, however, demonstrates a considerable limitation, registering a high conversion error of 21.43%. [148] proposed a solution by fusing data from an Ouster 128 LiDAR with mmWave radar. This multi-modal system processes the environment as 3D point clouds and utilizes the well-established LiDAR odometry and mapping (LOAM) algorithm. This approach yields high accuracy, particularly in structured environments, and achieves a remarkably low localization error of only 0.88%, underscoring the efficacy of combining LiDAR with radar for precise mapping and localization tasks. [149] deployed a mmWave radar and generated the 2D spatial points to generate the grid map for the SLAM and they compare the results with the results obtained from the LiDAR in the same scenario. Additionally, another study [150] delves into the analysis of ego-motion in robotic systems, focusing on critical parameters such as rotation angle and velocity. Rotation is evaluated through the correlated distribution of identified points on a 2D plane over consecutive time intervals, while velocity is determined by analyzing the trend line of these identified points.

Expanding further, [151] employs two orthogonal mmWave radars to estimate three-dimensional motion in the localization map. By incorporating a radar instantaneous velocity factor into a pose-graph SLAM framework, they achieve robust 3D motion estimation alongside IMU data, demonstrating effectiveness across diverse environments with varying visibility and structural complexity. Additionally, [152] proposes a novel fusion framework combining mmWave imaging with advanced communication techniques. Their approach evaluates key localization metrics, including AoA and time of arrival (ToA), to enhance 3D imaging fidelity, achieving sub-centimeter precision in SLAM applications. [153] presented a deep RL approach with cGAN for the generative reconstruction of the environment for the navigation task. [154] explores the feasibility of utilizing mmWave radar as the primary sensor for SLAM. It examines signal processing techniques such as filtering and clustering methods to refine radar point clouds. Furthermore, ML-driven approaches, including deep neural networks and graph optimization algorithms, are analyzed to enhance localization accuracy. Additionally, mathematical models essential to radar-based SLAM, such as kalman filters, pose graph optimization, and radar odometry calculations, are discussed. The paper also reviews recent advancements in SLAM research and highlights future directions for improving radar-based mapping and localization. Table 7 compares mmWave radar applications for SLAM systems. Each entry lists the reference, the radar device used, and the data representation (such as point clouds, occupancy grids, or doppler heatmaps). The table then details the algorithm used (e.g., graph-based optimization, particle filters, or DL approaches), the target environment tested (like indoor warehouses, urban streets, or dense forests), and standout key features (such as robustness to weather, real-time processing, or low computational cost). This comparison helps identify reliable methods for building accurate maps while navigating complex or dynamic spaces.

In conclusion, advancements in mmWave radar technology and its integration with complementary sensors are driving the development of more resilient and precise navigation frameworks. These innovations are essential for the next generation of robotic systems operating in complex and dynamic environments.

8.2. Healthcare applications

Recent advancements in mmWave radar technology, coupled with sophisticated ML and DL approaches, have revolutionized non-contact healthcare monitoring capabilities. This section explores cutting-edge developments that demonstrate how ML enhances

Table 7
mmWave radar applications in SLAM.

Reference	Device	Data representation	Algorithm used	Target environment	Key features
[10]	mmWave radar & LiDAR	LiDAR-like point clouds	Conditional GAN (cGAN)	Complex indoor environments	Integrates LiDAR data and geometric priors with cross-modal supervision for enhanced mapping
[144]	mmWave radar & IMU	Point clouds with IMU data	DBSCAN, improved CSM	Indoor corridors & hallways	Filters outliers using DBSCAN; matches point cloud with local submap of global grid map
[147]	mmWave radar	Depth images	Sensor fusion network	General indoor environments	Converting radar measurements to depth images, error 21.43%
[148]	Ouster 128 LiDAR & mmWave radar	3D point clouds	LiDAR Odometry And Mapping (LOAM)	Structured environments	High accuracy in structured environments, localization error of 0.88%
[149]	TI IWR1443BOOST	2D spacial points	Optimization techniques	Indoor spaces with sparse features	TSDF-based maps; sensor-agnostic processing pipeline; robust scan matching for sparse, noisy radar data
[150]	mmWave radar	Temporal point distributions	Point distribution correlation	Dynamic indoor environments	Calculates rotation through point distribution correlation over estimates velocity using trend line analysis
[151]	Two mmWave radars with IMU	3D pose graphs with radar data	Pose-graph SLAM with radar velocity	Diverse indoor/outdoor environments	Across diverse environments with varying visibility and structural complexity
[152]	mmWave imaging system	AoA & ToA measurements	Fusion framework	High-precision indoor mapping	Evaluates AoA and ToA; achieves sub-centimeter precision
[153]	TI IWR6843 + LiDAR	Range Angle point data	Deep RL with cGAN	Indoor & outdoor environment	Uses Deep RL, achieving collision free navigation in smoke-filled mazes
[154]	mmWave radar + IMU	Occupancy grid maps	Bayesian prediction & DBSCAN	Outdoor environment (heavy smoke)	Achieves 81.89% precision in detecting road boundaries up to 30 m away

mmWave radar applications in healthcare, providing superior performance in vital sign monitoring, disease detection, and patient activity recognition while preserving privacy.

One of the most promising applications of mmWave radar in healthcare is in rehabilitation systems. The MARS (mmWave-based assistive rehabilitation system) is designed to support patients with motor disorders by tracking their joint movements in real-time and providing corrective feedback [93]. It is particularly beneficial for individuals recovering from stroke, spinal cord injuries, or neurodegenerative diseases such as Parkinson's. MARS utilizes mmWave radar to create high-resolution point clouds from which 19 human joints are reconstructed accurately. CNN process these point clouds for precise joint position estimation and analysis of movement patterns [155]. This DL technique facilitates automated identification of abnormal deviations from normal movement trajectories, allowing healthcare professionals to personalize rehabilitation programs for optimal recovery outcomes. Unlike conventional motion capture systems that use cameras or wearable sensors, MARS offers a contactless, privacy-friendly solution that is more convenient for home-based rehabilitation. It minimizes patient discomfort and improves compliance with rehabilitation exercises by eliminating the need to wear tracking devices during the recovery process. Additionally, the system provides consistent observation and feedback regardless of environmental conditions or lighting. Experimental evaluations have shown that MARS achieved an average error of 5.87 cm in joint position estimation, demonstrating its high accuracy. Furthermore, joint angle estimation for knee and elbow movements had mean absolute errors of 6° and 12°, respectively, indicating their potential for effective home-based rehabilitation monitoring.

Another critical application of mmWave radar in healthcare is vital sign monitoring, enabling contactless measurement of heartbeat and breathing rates shown in Fig. 16. This technology offers significant advantages over conventional monitoring systems that rely on wearable sensors or contact-based measurements like Electrocardiograms (ECG) and chest straps [156,157]. Using Doppler techniques, mmWave radar detects micro-motion of the chest wall during breathing and subtle vibrations caused by heartbeats [157,158]. This allows for continuous and non-invasive assessments, making it particularly suitable for hospital environments, home healthcare, and sleep applications. Unlike camera or light-based solutions, mmWave radar can measure through clothing and bedding, expanding its utility. Research has demonstrated the reliability of Doppler radar in measuring important physiological parameters, including heartbeat rate and breathing frequency, with high precision [156]. Signal processing algorithms such as the FFT and wavelet decomposition are used to isolate and analyze these signals, differentiating voluntary body movements from involuntary ones.

[159] explores the feasibility of monitoring heart rate using a hand-held device that employs mmWave radar technology. The primary aim of this innovative approach is to mitigate the interference caused by motion and changes in the orientation of the

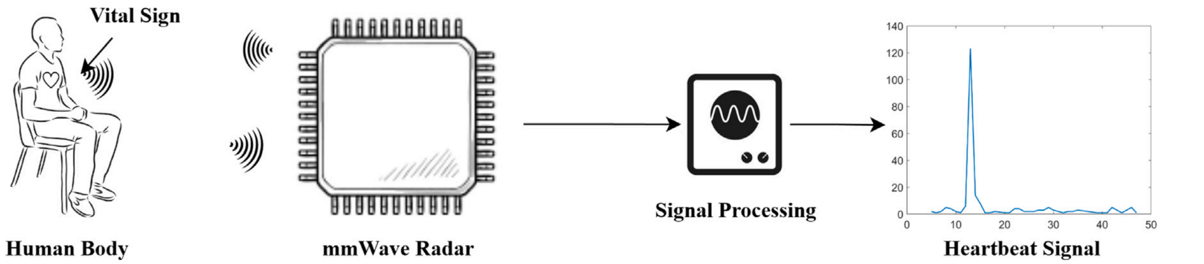

Fig. 16. Vital sign monitoring workflow using mmWave radar.

Table 8
mmWave radar applications in healthcare.

Reference	Device	Data representation	Target organ	Algorithm used	Key features
[155]	mmWave radar	Point cloud	Skeletal system (joints/bones)	CNN	Accurate reconstruct the human joints and skeleton.
[156]	1.6 GHz radar	Raw data	Heart and lungs	Range correlation method	Detects the heart and respiration at a distance of 50 cm.
[157]	24 GHz radar	Raw data	Heart	Phase modulation techniques	Measure the heart beat at different postures & compare the results with ECG.
[158]	60 GHz radar	Raw data	Lungs	Time-domain recovery algorithm	Recovery of respiration peak from the noisy raw data
[159]	mmWave radar	Raw data	Heart	Motion mitigation	Eliminate the device motion movements & monitors the heart rate in real time
[160]	mmWave radar	Range-doppler heatmaps	Heart and lungs	Random motion rejection	Success rate of 99.50% & 90% for respiration & heartbeat
[161]	mmWave radar	Range-doppler heatmaps	Respiratory system	Feature extraction	Non-contact sleep tracking Real-time apnea incident detection.

device, while still accurately capturing vital sign data. This advancement holds promise for enhancing the reliability of remote health monitoring systems, making it easier to track cardiovascular health in real time without compromising on accuracy due to user movements. [160] proposed a random motion rejection algorithm that can track and detect the vital signs of target users in the presence of movements. Future developments in mmWave-based radars are expected to integrate artificial intelligence models, either directly into the radar system or through other signal processing models. This integration will support advanced decision-making capabilities, such as early warnings for respiratory illnesses, cardiac malfunctions, or general health checks without patient intervention. mmWave radar has found significant application in sleep tracking, especially for sleep apnea detection. Unlike Polysomnography (PSG), which requires multiple sensors attached to the patient, mmWave radar allows for non-contact tracking of sleep patterns, offering a more convenient and comfortable option [161]. Studies have demonstrated the high sensitivity of continuous-wave and FMCW radars in detecting sleep apnea by recording chest wall movements and breathing interruptions [161]. These radars can detect apnea incidents in real-time without physical contact with the patient, penetrating bedding and clothing to provide unobtrusive monitoring. Table 8 compares mmWave radar applications in healthcare settings. Each entry lists the reference, the radar device used, and the data representation (such as micro-Doppler signatures or vital sign maps). The table specifies the target organ monitored (e.g., heart, lungs, or brain activity), the core algorithm used (like ML classifiers or signal decomposition methods), and practical key features (such as non-contact operation, real-time monitoring, or detecting subtle physiological movements). This helps medical researchers and engineers quickly identify suitable radar-based solutions for specific healthcare challenges.

8.3. Security applications

mmWave radar technology is progressively being integrated into security applications due to its exceptional attributes of accuracy, privacy protection, and robustness in various environmental conditions. The implementation of mmWave radar in security systems presents numerous advantages that render it a preferred option for contemporary surveillance and monitoring frameworks. These advantages arise from its high-frequency performance, precision capabilities, and effectiveness across diverse settings. In contrast to traditional cameras, mmWave radar does not capture visible or personalized identifiable information, which makes it particularly suitable for sensitive environments such as restrooms, locker rooms, and healthcare facilities. It is capable of detecting presence and motion while upholding privacy standards, thereby addressing ethical and regulatory considerations.

8.3.1. Concealed item detection

mmWave imaging technology has become increasingly prevalent for personnel security screening in various contexts, including airports, security checkpoints, and other public or military facilities. Utilizing a half-power criterion, mmWave radiation can effectively penetrate most types of clothing, rendering them virtually transparent in the imaging process. This capability enables mmWave is capable of generate imaging systems to generate detailed representations of individuals, including any concealed objects they may carry. The adoption of this technology enhances security measures by providing a non-intrusive means of detection, contributing to safer environments in critical areas [162]. [163] introduced a novel approach utilizing range-angle heatmaps. By effectively employing feature engineering techniques, the researchers extracted critical features of concealed objects, subsequently integrating these into an enhanced version of the ResNet model for improved classification accuracy and achieved an accuracy of approximately 80% for openly carried objects; however, the accuracy for concealed objects was lower, around 72%. This discrepancy was particularly evident across various placements, such as in pockets, bags, or held in different orientations. [164] who explored ZFNet-based object detection techniques tailored for mmWave images. They developed a concealed object detector specifically designed for security applications, utilizing convolutional and context embedding techniques. This approach aims to effectively capture intricate details and contextual information, resulting in an impressive average precision of roughly 85.61%. [165] implemented an innovative architecture, integrating Wavelet-Conv and Wavelet-Attention modules into the YOLOv8 framework, resulting in the Wavelet-YOLO system. They conducted extensive experiments on a large dataset, yielding impressive precision rates of 92.14% and recall rates of 88.27%. The workflow of the concealed item detection using the mmWave radar is explained in Fig. 17.

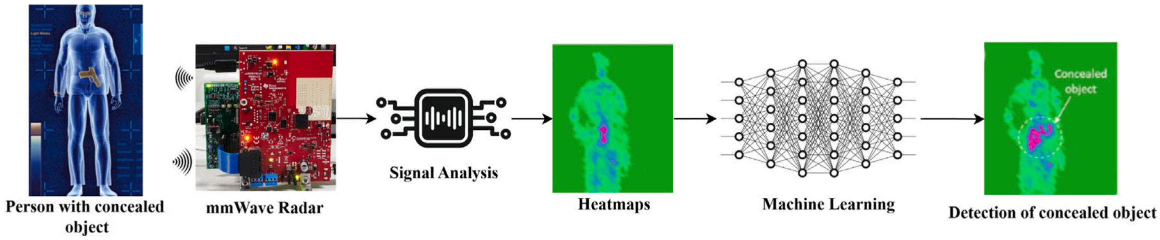

Fig. 17. Concealed item detection using mmWave radar.

Table 9
mmWave radar application in concealed item detection.

Reference	Device	Data representation	Algorithm used	Target item	Key features
[163]	mmWave radar & Camera	Range-Angle heatmaps	Improved ResNet	Carried objects (laptop, phone, knife)	80% & 72% accuracy for open carried & concealed objects.
[164]	mmWave radar & Camera	Range-Angle heatmaps & Images	ZFNet	General concealed objects	Average precision accuracy is around 85.61%
[165]	mmWave radar & Camera	Range-Angle heatmaps & Images	Wavelet-YOLO	Dangerous objects (weapons, threats)	Precision is 92.14% & recall is 88.27%
[166]	TI IWR1443BOOST	SAR images	SAR Image recognition	Metallic and non-metallic objects	Prediction accuracy is 98.18%

A notable contribution is the work by [166], who developed a sophisticated algorithm aimed at identifying concealed objects through the integration of multiple neural network architectures. This innovative approach has demonstrated remarkable efficacy, achieving a prediction accuracy of 98.18% on the SAR dataset. Such high performance underscores the potential of leveraging advanced neural network strategies in improving the detection of hidden objects, marking a significant step forward in the field of radar imaging. Table 9 compares mmWave radar systems for detecting hidden objects. Each entry lists the reference, the radar device used, and the data representation (range-angle heatmap, SAR images). The table documents the algorithm used (e.g., DL classifiers or anomaly detection methods), the target item searched for (like metallic or non-metallic), and practical key features (including penetration through fabrics, real-time operation, or low false-alarm rates). This helps security designers quickly evaluate suitable approaches for screening people or packages in high-risk environments.

8.3.2. User authentication

User authentication by mmWave radar has become a prominent application, utilizing both physiological and behavioral biometrics obtained through non-invasive sensing methods. In contrast to traditional biometric systems that depend on cameras or contact-based sensors, mmWave radar offers a privacy-preserving solution that operates efficiently under diverse environmental conditions.

Authentication based on gait analysis has demonstrated efficacy as a robust biometric for user identification via mmWave radar. Gait-based systems may accurately identify users by collecting their distinctive walking patterns while employing a discreet sensing method. Recent studies have investigated open-set gait recognition scenarios, wherein the system is required to detect both familiar and unfamiliar people. This signifies a substantial improvement over closed-set methodologies, since it more precisely mirrors real-world deployment scenarios. Point Cloud Adversarial Autoencoder (PCAA) architectures have been designed to analyze sparse mmWave radar point clouds for gait recognition, integrating supervised classification with unsupervised reconstruction to generate resilient latent representations of gait characteristics [167]. DL techniques for gait-based user recognition have shown considerable promise, particularly through the efficacy of convolutional neural networks and domain adaptation methods. These methodologies diminish the quantity of supervised data required for training, enabling models to generalize across diverse environments without the necessity for explicit retraining [167].

An alternative new method for mmWave radar-based authentication involves gesture recognition. By analyzing the unique execution of gestures, systems can discern both the gesture itself and the individual's identity. GesturePrint exemplifies this approach by leveraging standard mmWave radar sensors, integrating a robust signal preprocessing pipeline with a sophisticated network architecture known as GesIDNet. This architecture employs an attention-based multilevel feature fusion strategy, effectively extracting gesture features for recognition and individualized user motion patterns. Experimental results demonstrate a remarkable gesture recognition accuracy of 98.87% and user identification accuracy of 99.78% in controlled environments and achieved a gesture recognition accuracy of 98.22% and a user identification accuracy of 99.26% in offices with possible interference [168].

mmWave radar has exhibited exceptional proficiency in detecting vocal cord vibrations, facilitating an innovative method for voice-based authentication that is impervious to replay attacks. In contrast to traditional microphone-based systems, mmWave radar can identify the actual vibrations of vocal chords rather than merely the auditory signals, hence offering an enhanced level of protection against voice spoofing. The mmSafe system signifies a notable progression in this field, utilizing a 77 GHz FMCW radar to detect vocal cord vibrations during speech. This system analyses raw radar data using spurious wave cancellation, phase extraction, and filtering algorithms tailored for vocal cord vibration frequencies (90–200 Hz). The system attains a speaker verification accuracy of 93.4% and a miss detection rate of 5.8% for playback attacks by extracting weighted Mel-Frequency Cepstral Coefficients (MFCCs) from the vibration signal and utilizing a Weighted MFCCs and Hog-based SVM (WMHS) method [169]. This method presents significant benefits compared to conventional speech authentication systems, as it operates effectively in noisy settings and inherently safeguards against recorded voice replay assaults. The method is especially beneficial for safeguarding voice-activated smart devices, as it guarantees that orders originate from authorized users physically present at the site, rather than from recorded or synthetic speech.

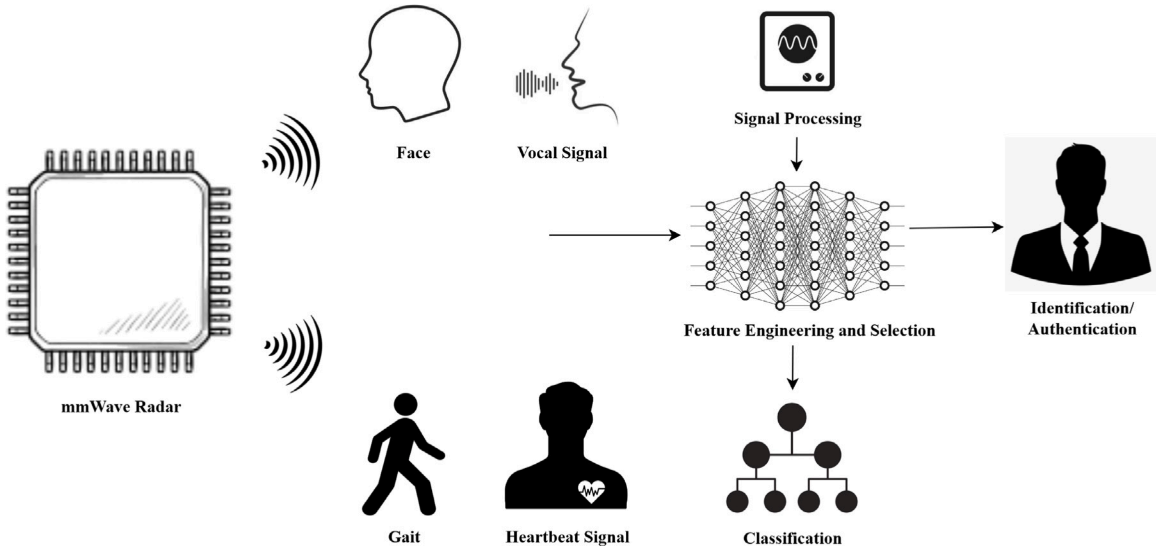

Fig. 18. User authentication workflow using mmWave radars.

The integration of various biometric characteristics obtained via mmWave radar has surfaced as a viable approach to improve authentication precision and resilience. Dual-biometric authentication systems that combine physiological factors, such as heart sounds, with behavioral characteristics, like walking, have enhanced performance relative to single-biometric methods. A recent study has introduced an innovative dual-biometric human identification system utilizing radar-based heart sounds and gait signals. The technology transforms acquired biometric signatures into visual representations, implements augmentation techniques, and utilizes deep transfer learning for classification. The heart sound biometrics can be utilized when individuals are immobile, whereas gait serves as the principal identifier during locomotion. Individual biometrics attained validation accuracies of 58.7% for heart sound and 96% for gait independently; however, their amalgamation via joint Probability Mass Function (PMF) yielded an exceptional 98% identification accuracy. This work has been effectively integrated into office access control platforms, attaining 76.25% accuracy in practical deployment contexts [170]. The complete workflow of the mmWave radar in the user authentication is provided in Fig. 18.

Table 10
mmWave radar applications in user authentication.

Reference	Device	Data representation	Algorithm used	Target organ	Key features
[167]	mmWave radar	Point Cloud	Point Cloud Adversarial Autoencoder (PCAA) + CNNs	Whole body (shape/posture)	The performance of the PCAA improves as the number of unknowns increases.
[168]	mmWave radar	Point Cloud	GesIDNet with multilevel feature fusion	Hand	98.87% gesture recognition accuracy, 99.78% user identification accuracy
[169]	77 GHz radar	Vibration signals with MFCCs	Weighted MFCCs & HOG-based SVM (WMHS)	Vocal cords/Larynx	93.4% speaker verification accuracy, 5.8% miss detection rate for playback attacks
[170]	TI AWR1642	Heart signal spectogram Range-Doppler heatmaps	GoogLeNet architecture & PMF fusion	Heart & legs(gait)	58.7% accuracy in heart sound biometric, 96.2% accuracy in Gait biometric, 98% combined identification accuracy.
[171]	mmWave radar	Micro-Doppler signatures	DCNN	Heart	Uses heart signals for identification Accuracy of 83% for 10 persons.
[172]	24 GHz radar	Raw data	DDLM	Heart	93.57% accuracy with an F1 score of 93.42% for 15 persons.
[173]	60 GHz radar	Micro-Doppler signatures	Convolutional autoencoder with random forest	Face	99.98& accuracy at 1 frame per second on 186 subjects
[174]	60 GHz radar	Micro-Doppler signatures	CNN with dimensionality reduction algorithms	Face	99.70& accuracy on 206 subjects

Another innovative approach to user identification involves analyzing vital signs. [171] introduced a deep CNN designed to recognize users based on heatmaps derived from heart signal data. The results of their experiments demonstrated an accuracy rate of approximately 83%, with the analysis conducted on a sample of 10 individuals. This method highlights the potential of physiological signals as reliable biometric indicators for user authentication. [172] utilizes a 24 GHz radar and proposed a Dipole Deep Learning Model (DDLM) for identification. The model leverages a 1D-CNN network for the feature extraction from the raw radar data, and then the features are trained through the dipole learning layer, which significantly bolsters the model's performance. The results from their experiments demonstrate commendable accuracy rates, achieving approximately 93.57% with an F1 score of 93.42% when identifying 15 individuals. When the model is scaled up to recognize 30 individuals, the accuracy improves remarkably to around 99.33%, accompanied by an F1 score of approximately 99.16%. Additionally, the authors have made their dataset publicly accessible, thus fostering further research and development in this area. [173] introduced an innovative approach utilizing a random forest in conjunction with a convolutional autoencoder, specifically applied to the dataset described in [62]. This research highlighted the model's performance across various frame rates, ultimately achieving a peak accuracy of 99.98% at a frame rate of 1 frame per second. However, the accuracy exhibited a gradual decline as the frame rate increased, underscoring the challenges associated with higher frame rates. In a complementary study, [174] explored a CNN-based methodology on the same dataset. This research emphasized the implementation of diverse subspace analysis techniques aimed at mitigating the effects of high-dimensional feature spaces inherent in radar data. The study reported an impressive accuracy of 99.70%, contributing further insight into the efficacy of CNNs in face recognition applications within this specific context. Table 10 compares mmWave radar systems for authenticating users based on unique body regions or responses from different organs. Each entry lists the reference, the radar device used, and the data representation capturing biometric signals (like micro-Doppler signatures from heartbeats or breathing patterns). The table details the algorithm used (e.g., neural networks or signal-matching techniques), the target organ measured, and practical key features. This helps security and biometrics researchers identify contactless methods for reliable identity verification.

8.4. Smart home application

mmWave radar technology is revolutionizing smart home applications through sophisticated sensing capabilities that improve user convenience, operational efficiency, and overall experience. In contrast to conventional sensors, such as cameras, passive infrared (PIR) sensors, or ultrasonic devices, mmWave radar offers distinct benefits, including enhanced privacy, exceptional sensitivity, and adaptability to various environmental conditions. These features render it especially well-suited for integration into smart home settings.

8.4.1. Activity recognition

Human Activity Recognition (HAR) is essential for the progression of many smart home applications, including human–computer interaction, elder care, and security surveillance. A promising approach in this domain is the utilization of contactless sensing

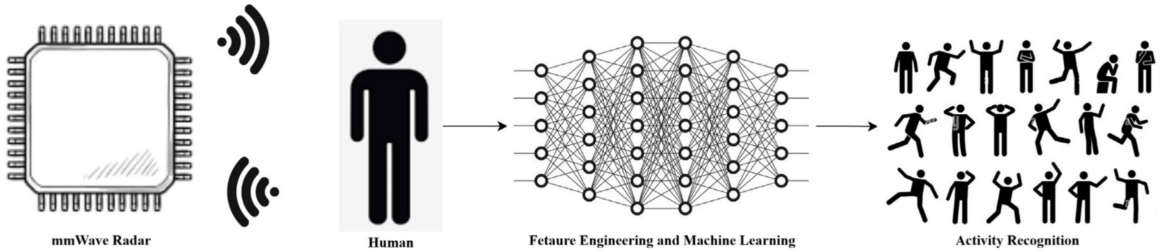

Fig. 19. Activity & gesture recognition workflow using mmWave radars.

techniques, particularly using mmWave radars. These radars can identify human activities by examining the reflections of signals emanating from the human body.

The integration of modern signal processing techniques with sophisticated ML algorithms improves the predictive capability of these sensing devices about various human actions with exceptional precision. This synergy enhances the effectiveness of human activity identification systems and broadens their applicability across diverse areas, delivering a more responsive and adaptive smart home environment. HAR is essential for facilitating various smart home applications, including human–computer interaction, elder care, and security monitoring. Utilizing a contactless sensing approach, mmWave radars may detect human actions by analyzing signal reflections from the human body. By amalgamating signal processing methodologies with ML techniques, sensing systems can anticipate various human actions. A short overview of the workflow of ML in activity recognition is provided in Fig. 19.

Researchers have found extensive applications of mmWave radar in HAR, particularly in the domains of healthcare, security surveillance, and smart-home automation. In human activity recognition, measured micro-Doppler signatures from the movement history of the human body can describe activities such as walking, sitting, running, standing, or falling [175,176]. For extracting spatial features from the range-Doppler images, a CNN-based feature extraction is employed, and LSTM networks, typically, are used for depicting the temporal dependencies in sequential radar data [93,177].

DL algorithms trained on HAR datasets work as real-time classifiers in human action recognition and are therefore invaluable for applications in the context of elderly care and patient monitoring. Applications may consist of fail detection and further alerting of caregivers in the smart home environment. CNN-LSTM model [54], CNN-GRU-based HARnet [178], Dual-view CNN [179], CNN-LSTM multi-model learning [180], deep CNN [181], etc., are designed to extract the spatial body features from a convolutional operation or temporal motion features from recurrent structure for activity recognition. M-Gesture [55] provides a pseudo-representative model specifically tailored for mmWave data. This model accurately represents the general trajectory and skeletal modifications of individuals to define gestures that are independent of the performer. A significant addition comes from mHomeGes [57], which introduces a user discovery mechanism centered on certain human gestures. This method guarantees that feature representations retain robustness across diverse locations, orientations, and subjects, thus enhancing the adaptability of gesture recognition systems. [58] uses sparse 3D point clouds to acquire high-resolution spatial and temporal data, and develops a DL model that integrates PointNet++ and LSTM for real-time gesture detection. [182] also contributes to hand gesture recognition by investigating ML methodologies, particularly employing CNN and LSTM architectures. Furthermore, research by [138] demonstrates the efficacy of mmWave radar in identifying passenger occupancy in vehicles, thereby enhancing safety and comfort. In addition, MMPoint-GNN [183] designs a GNN model with bidirectional LSTM to leverage temporal information for activity recognition. Advanced sensor fusion techniques also consolidate mmWave radars with wearable sensors or infrared cameras to improve their recognition precision. Recent research has also used attention-based transformer networks to improve HAR with the emphasis on considerably important motion features to increase robustness further in complex conditions. [184] presented a transformer decoding-based approach for the activity recognition of the person and achieved an accuracy of 95.20%. [185] employed a pointnet with attention, dual transformers and an adaptive weighted fusion transformer for activity recognition using the point cloud data. Furthermore, DIGesture [186] has advanced by developing a mmWave data augmentation system. This method utilizes the relationships between signal patterns and gesture changes to produce synthetic data that mitigates the issues associated with insufficient data collection. Consequently, it enables gesture identification that is robust against variations in environment, position, and speed, hence greatly expanding the practical applications of gesture recognition technology.

Newer DL techniques like CNNs use spatial features extraction, while RNNs and transformer-based architectures modulate temporal variations found in gestures [55,176]. mmASL [187] leverages expertise in American Sign Language (ASL) and introduces a multi-task deep learning model to acquire generalized feature representations, facilitating environment-independent gesture identification for ASL. [188] proposed a CNN-transformer-based network for gesture recognition and presented the results on the point-cloud data, range-doppler data, and data cube sequence. He achieved an accuracy of 99.75% and used 20 gestures from 20 participants. [189] uses range time maps as an input to the CNN-based transformer encoder network for the gesture recognition of the 9 persons performing 6 gestures and achieved an accuracy of 99.18%. [190] presented a dual-stream transformer-based network for alphabet gesture recognition with an accuracy of 99.17%. [191] conducted a data acquisition of 10 gestures from multiple persons using TI mmWave radar and proposed a multi-head self-attention model with a 1D-CNN network for gesture recognition, and also validated the proposed algorithm on the in-house developed mmWave radar with an accuracy of 97%.

Radar-based gesture recognition systems may classify hand movements such as swiping, pinching, rotating, or pointing by analyzing range-Doppler patterns and time-frequency features. Current methods for the representation and recognition of sequential

Table 11
mmWave Radar Applications in Human Activity & Gesture Recognition.

Reference	Device	Data representation	Algorithm used	Key features
[54]	TI IWR1443BOOST	Point Cloud	CNN-LSTM	Real-time classification for elderly care and patient monitoring
[55]	mmWave radar	Range-Doppler images	Deep CNN	99% accuracy in gesture recognition of 144 persons
[57]	TI IWR1443	Point Cloud	CNN	95.30% accuracy in the gesture recognition in various smart home scenarios
[58]	TI IWR1443BOOST	Point Cloud	PointNet++ and LSTM	95% accuracy in two indoor environments for 21 gestures of 41 persons
[178]	TI IWR6843	Point Cloud	CNN-GRU (HARnet)	Extraction of spatial body features and temporal motion features
[179]	TI IWR1843	Point Cloud	Dual-view CNN	Non-invasive monitoring for healthcare applications
[180]	mmWave radar	Point Cloud & range-doppler profile	CNN + LSTM	Integration of multiple models for improved performance
[181]	TI AWR1642BOOST	Range-Doppler Images	Deep CNN	95.74% accuracy in the activity detection of the multiple patients
[182]	TI IWR1443BOOST	Range-angle images	CNN + LSTM	92.74% accuracy with 12 subjects performing 12 different hand gestures
[183]	TI IWR6843	Point Cloud	GNN & Bi-LSTM	96.97% accuracy in activity recognition, 92.67% accuracy in gesture recognition
[184]	TI IWR1443BOOST	2D/3D features (Doppler, range, angle signatures)	Modified transformer-based learning	Continuous human motion recognition with high similarity, 95.2% accuracy with 3D features, 94.5% accuracy with 2D features
[185]	TI AWR1642BOOST	Sparse point clouds	Transformer	Human activity recognition using sparse radar point clouds
[186]	TI IWR6843	Range-Angle images	CNN & segmentation	Achieves an accuracy of 97.92% in different environmental scenarios
[187]	TI IWR1443BOOST	Spatial Spectrograms	Multi-task deep learning	87% average accuracy of sign recognition for 12K signs of 15 persons
[188]	60 GHz mmWave software	Range-Doppler images	TD-CNN-Transformer (DCS-CTN)	Subtle gesture recognition with interference robustness
[189]	TI IWR1843BOOST	2D Range-Doppler images	2D CNN-Transformer networks	Dynamic hand gesture recognition with 98% accuracy without interference &96% accuracy with interference
[190]	TI AWR1642BOOST	Sparse representation	Dual-stream transformers (SRDST)	Effective dynamic gesture recognition with sparse representation & dual-stream processing
[191]	TI IWR1642	Point cloud data	TRANS-CNN	Real-time gesture recognition combining transformer self-attention with 1D CNN for local feature extraction
[192]	TI AWR1642BOOST	Space velocity spectrograms	Improved CNN	93.47% accuracy on the cross-testing on new users.
[193]	TI AWR1642BOOST	Merged image of range, velocity and angle	VGG19 + Random forest classifier	100% gesture recognition accuracy on six dynamic hand gestures
[194]	TI IWR1443BOOST	Point Cloud	MPNN	98.1% accuracy on the pantomime dataset
[195]	TI IWR1443BOOST	Range-Doppler images	mSeeNet	96.7% accuracy for 5 different gestures with different subjects.
[196]	TI AWR1843	RA, RD, DA, & micro- doppler images	CNN-LSTM	97.79% accuracy for 6 gestures captured from 25 subjects in 6 different environments.

gestures are mostly based on probabilistic models like HMMs [180]. These models track the states of motion over time to classify gestures of different kinds into categories. Recent breakthroughs in gesture recognition technology have led to the development of numerous approaches aimed at improving the resilience and versatility of gesture detection in diverse contexts. Additional investigation into gesture characterization is seen in the study by [192], which formulates a unique parameterized representation of the temporal space-velocity spectrogram. This new method allows for the differentiation of hand gesture characteristics across several data modalities, improving the system's overall performance and precision. Furthermore, the GreBsmo technique, as outlined in [193], resolves the challenges of static backdrops and signal interference by facilitating the isolation of dynamic movements in an environment-agnostic manner. This facilitates a more lucid analysis and interpretation of gesture data, hence enhancing the advancement of efficient and scalable gesture recognition systems. These developments collectively demonstrate the dynamic nature of gesture recognition research and emphasize the necessity of creating systems that operate effectively across diverse contexts and settings.

Tesla-Rapture [194] creates a DL model that integrates temporal graph kNN with a self-attention message passing neural network (MPNN). The temporal graph kNN represents time-dimensional point clouds as temporal graphs, while the MPNN utilizes graph convolution to process motion point clouds. mTransSee [195] utilizes transfer learning methodologies for the adaption of training data, hence minimizing the training efforts required for gesture recognition in different situations. mmGesture [196] emphasizes semi-supervised learning for gesture recognition utilizing mmWave radar technology. It employs minimal labeled data in the source domain alongside substantial quantities of unlabeled data in the target domain, facilitating domain-independent gesture recognition. Table 11 consolidates mmWave radar research for human activity and gesture recognition, providing details about different works related to human activity recognition using mmWave radar. This systematically organizes studies by their reference, deployed device, and employed data representation (such as range-Doppler maps or micro-Doppler signatures). The table further details each work's algorithm used (e.g., CNNs, LSTMs, or transformers), target activity/gesture (including hand gestures, gait analysis, or fall detection). This synthesis enables direct performance benchmarking and reveals methodological trends across diverse recognition tasks.

8.4.2. Pose estimation

Human pose estimation is a key computer vision and sensing task that involves reasoning about the spatial body layout of the human body by detecting a constellation of anatomical keypoints—like head, shoulders, elbows, wrists, hips, knees, and ankles—on sensor measurements or images, and building a structured skeletal representation that mirrors the posture and motion of a person at an instant in time. [197] casts this as a two-dimensional or three-dimensional prediction problem, depending on the target application, and is an enabling factor for a wide range of downstream applications such as activity recognition, human–computer interaction, animation, surveillance, and healthcare monitoring. In recent work, pose estimation systems take advantage of sophisticated DL models, including CNN and transformer models, to both utilize the spatial properties and structured patterns of inter-body joint dependencies as mentioned in [198]. These models tend to be end-to-end trainable, enabling direct regression over joint coordinates or the production of keypoint confidence maps, and can utilize attention mechanisms to highlight the most informative features for each keypoint adaptively.

The transformer-based models, like TFPose and PETR, bring in a hierarchical method to pose estimation. The process generally starts off with a convolutional backbone to extract multi-scale features from the radar data, which are then encoded with positional information and fed to the transformer encoder [199] mentions how the transformer decoder works with a collection of learnable queries corresponding to body joints or a whole-body pose and iteratively updates the predicted coordinates by layers of feed-forward networks and attention. [200] mentions how hierarchical decoders, introduced in PETR, further update the pose by capturing inter-person and intra-person relations and use attention to resolve ambiguities and enhance localization accuracy in crowded or occluded environments. [201] explores the human pose capturing systems usign 77 GHz mmWave radar by using a coordination method to align two-radar devices and are labeled using camera through which they have realized two-radar system. They have used a trained neural network to transform radar producing heatmaps into the human skeleton. [202] have targetted a radar-to-pose system which converts the raw radar data into human poses through which the different human forms can be identified and activities monitored. By placing the radar in an elevated position and utilizing an ensemble predictor network, different human poses with accuracy in excess of 90% are being detected. [203] introduces a probability map guided multiformat feature fusionmodel, ProbRadarM3F which uses a traditional FFT method in parallel with a probability map based positional encoding method. By fusing the traditional heatmap features and the positional features, it achieves 14 keypoints of human body. [204] presents an RadarTensor-based human pose(RT-pose) dataset and a benchmark framework. The 4D radar tensor provides raw spatio-temporal information. Also, they have presented a single-stage architecture which extracts high-resolution representation of 4D radar tensors in 3D space to aid human keypoint estimation. [205] have proposed an approach to detect more than 15 distinct skeletal joints using mmWave reflected signals. The 3D XYZ radar point cloud data was first projected into Range-Azimuth and Range-Elevation planes followed by assignment of RGB channels. A forked CNN architecture was used to predict the real-world position of skeletal joints in 3-D space thereafter.

Loss functions in such models are constructed to be compatible with evaluation metrics like object keypoint similarity (OKS), and auxiliary losses (e.g., heatmap regression) are typically used during training to speed up convergence and improve performance. As mentioned in [206], the end-to-end differentiability of the transformer models obviates the necessity of non-differentiable post-processing operations such as non-maximum suppression or heuristic grouping, leading to more efficient and simpler pipelines. Table 12 compares mmWave radar methods for estimating human body positions and movements. Each entry lists the reference, radar device used, and data representation (such as 3D point clouds or skeletal joint maps). The table details the algorithm used, the target poses tracked, and practical key features (including average precision(AP)). This helps to identify robust approaches for applications in healthcare, sports science, and human–robot interaction where precise motion capture matters.

Table 12
mmWave radar application in pose estimation.

Reference	Device used	Data representation	Algorithm used	Keypoints from a human	Key features
[197]	TI IWR6843	2D front projection of 3D point cloud	Cross-view fusion transformer	14(HuPR Format)	AP: 58.1 (on mmWave radar dataset)
[198]	Dual antenna mmWave radar	2D RF heatmaps (horizontal/vertical)	Deep CNN	15 (OpenPose format)	AP: 58.1 (through-wall)
[200]	TI IWR1443BOOST	Keypoint heatmaps	Regional Multi-Person Pose Estimation (RMPE)	16 (MPII)	mAP: 76.7 (MPII multi-person validation set)
[201]	77 GHz mmWave radar	Radar heatmaps coordinated with visual inputs	CNN for heatmap-to-pose transformation	14 (Custom)	87.7% Accuracy obtained
[202]	TI AWR2243	Range-Doppler maps from elevated radar	CNN-based radar-to-pose system	13	>90% accuracy for various poses
[203]	TI IWR1843	Traditional FFT heatmaps	ProbRadarM3F	14 (HuPR format)	AP: 69.9% on HuPR dataset
[204]	Cascade imaging radar (4D tensor)	4D radar tensors with spatio-temporal information	HRRadarPose	16 (RT-Pose dataset format)	Mean Per Joint Position Error (MPJPE): 9.91 cm
[205]	mmWave radar (generic)	Range-Azimuth and Range-Elevation projections	Forked CNN architecture	25 (full skeleton)	3.2 cm depth error, 2.7 cm elevation error

Table 13
Role of ML & DL techniques in different application domains of mmWave radar-based sensing.

Application area	Traditional ML techniques	DL-based techniques	Input format/Features	Sensor setup	Evaluation metrics	Preferred approach	Why ML or DL	Remarks/Challenges
Human activity recognition	SVM, k-NN, RF, Decision trees	CNN, LSTM, 3D-CNN, CNN-LSTM, Transformer	R-D maps, micro-Doppler, R-A-D cube	Single radar (ceiling or wall-mounted)	Accuracy, F1-score, Confusion matrix	DL	Activities are dynamic & benefit from spatio -temporal pattern learning	Activities with subtle motion (e.g., standing vs. sitting) are hard to distinguish
Gesture recognition	HMM, k-NN, SVM	CNN, GRU, CNN-LSTM	R-D map sequences, Doppler phase shifts	Short-range front-facing radar	Accuracy, Precision, Recall	DL & ML	DL needed for subtle gestures; ML works if gestures are simple or few	Small gestures (e.g., finger movement) need high-res sensing, often affected by noise
Vital sign monitoring	Linear regression, PCA + SVM	1D-CNN, Bi-LSTM, Attention-RNN	Raw IQ data, phase variation	Short-range radar aimed at chest/torso	RMSE, MAE, Resp/HR detection rate	DL & ML	ML sufficient when signal is clean; DL handles noisy data better	Motion artifacts and multipath reflections degrade performance
Human presence detection	k-Means, GMM, SVM	DBN, CNN, Autoencoders	Range profiles, presence maps	Ceiling-mounted radar	Detection accuracy, False alarm rate	ML	ML is fast, low-resource, & interpretable for binary presence	Differentiating humans from static clutter can be tricky
Fall detection	Rule-based, Decision Trees, SVM	CNN, LSTM, CNN-RNN	R-D map sequences, sudden acceleration	Ceiling radar, corner-mounted radar	Sensitivity, Specificity, F1-score	DL	Falls are fast, need temporal & spatial learning	High precision needed in real- time scenarios; edge deployment is challenging
Driver monitoring	Logistic Regression, Thresholding, SVM	CNN, Transformer, Fusion Models	Breathing waveform, thermal or camera fusion	Cabin-mounted radar (dashboard or roof)	Heart/Resp rate error, accuracy	DL	DL can generalize across noisy, cluttered in-cabin data	Cabin clutter and driving motion pose signal stability issues
Object detection /Tracking	Kalman Filter, GMM, Particle Filter	3D-CNN, PointNet, VoxelNet	Point cloud, R-A-D cubes	Multi-radar system (e.g., front, side)	MOTA, MOTP, Precision, Recall	DL & ML	ML for classical filtering; DL for feature-rich object detection	Tracking multiple fast-moving targets needs real-time DL inference
Occupancy detection	k-NN, SVM, DBSCAN	U-Net, CNN, Autoencoders	Range FFT, Heatmaps	Overhead radar array	Accuracy, F1-score	DL & ML	DL generalizes better in cluttered environments	Multipath interference from furniture can mislead occupancy detection
People counting	DBSCAN, SVM	YOLO (R-D maps), CNN	Range-Doppler heatmaps, clutter map	Overhead or wall-mounted radar	Count error rate, MAE	DL	DL needed to distinguish overlapping reflections & infer count	Overlapping subjects & occlusions affect counting accuracy
Gesture authentication	SVM, k-NN	Siamese CNN, LSTM	Motion signature, Doppler profile	Near-field radar facing the user	EER, FAR, FRR	DL	Requires learning unique temporal motion patterns	Requires consistent gesture performance by users

Table 13 presents an in-depth overview of ML and DL applications in mmWave radar technologies. It distinguishes traditional ML methods from DL frameworks across diverse domains, detailing the types of input data used—such as raw data, range-Doppler heatmaps, spectrograms, and RAD cubes. Additionally, describes sensor configurations pertinent to each application and summarize the preferred methodologies for specific sensing tasks. By addressing challenges and implementation considerations, this study elucidates the pivotal role of ML and DL in enhancing mmWave radar applications, emphasizing their practical implications.

8.5. Other applications

mmWave radar technology has emerged as a groundbreaking sensing solution across a wide array of sectors, showcasing its high-resolution, non-contact detection capabilities. While its implementation in fields such as automotive, healthcare, smart home environments, security, and industrial applications is extensively documented, mmWave radar is also gaining traction in a range of innovative and emerging domains. The technology's remarkable ability to penetrate materials, including plastics and drywall, coupled with its reliability under challenging environmental conditions—such as fog, rain, and dust—positions it as a highly versatile tool. Furthermore, mmWave radar provides accurate spatial and temporal data, enhancing its effectiveness for various applications poised to redefine existing paradigms. This versatility opens new possibilities for research and development, encouraging exploration into previously uncharted areas where mmWave technology can offer substantial benefits. Table 14 maps current and emerging applications of mmWave radar sensing across industries. It organizes entries by domain (e.g., automotive, healthcare, smart infrastructure), specific application (like driver monitoring or vital sign tracking), and the radar's core function (detection, imaging, localization). For each use case, the table notes typical frequency bands (24 GHz, 60 GHz, 77/79 GHz), summarizes key benefits (high resolution, privacy compliance, weather resilience), and identifies potential challenges (hardware costs, signal interference, regulatory limits). This structured overview helps researchers and industry stakeholders evaluate adoption opportunities and innovation gaps in next-generation sensing systems.

9. Challenges and solutions

The progress of ML and DL in the radar sector has significantly heightened interest in the development of radar sensing applications. Nevertheless, certain challenges emerge in practical implementation, as identified during the survey. The subsequent subsections enumerate challenges and their corresponding recommendations for mitigation within the area. The future prospects in the field of mmWave radar is illustrated in Fig. 20.

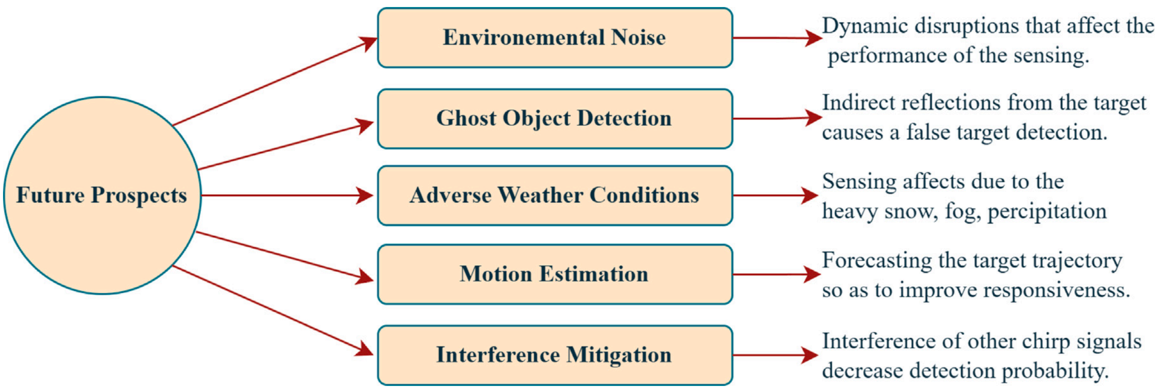

Fig. 20. Future prospects in mmWave radar.

9.1. Environmental noise

Environmental sounds present a complex array of background variations and dynamic disruptions that can significantly impact the efficacy of mmWave signal transmission. These auditory elements can lead to performance degradation in sensing applications, culminating in erroneous detections and unreliable results. Particularly when employing ML techniques, models optimized for specific environments may falter when confronted with varying signal patterns across different contexts. Thus, managing environmental noise has become a pivotal challenge in mmWave radar sensing applications.

This highlights the importance of addressing environmental noise as a pivotal topic for future research, especially as scholars increasingly integrate research methodologies with real-world applications. [178] focuses on utilizing physical properties to obtain target properties and neglect the noises. [210] proposed a different learning design for the models to mitigate the influence of noise on the actual target. There is potential for developing innovative strategies aimed at improving the resilience of signals in noisy environments. By adopting specific methodologies, it may be possible to effectively mitigate noise interference, thereby improving the robustness and accuracy of mmWave sensing technologies.

Table 14
Current and prospective applications of mmWave radar sensing.

Domain	Application	Function	Frequency bands	Key benefits	Potential challenges
Automotive [124,126, 129]	Adaptive Cruise Control (ACC)	Maintains safe distance and speed; assists with deceleration and stopping	76-81 GHz	Enhances driving comfort and safety	Susceptibility to environmental factors like heavy rain or fog
	Collision Warning	Detects obstacles/vehicles; alerts driver to prevent collisions	76-81 GHz	Provides timely alerts to avoid accidents	Potential false positives due to over-sensitivity
	Automatic Emergency Braking (AEB)	Enables automatic braking when obstacles or pedestrians are detected	76–81 GHz	Reduces crash impact or avoids them entirely	Limited detection of small or unexpected obstacles
	Blind Spot Monitoring	Detects vehicles in blind spots; warns driver	24 GHz, 76–81 GHz	Improves lane change safety	May produce false alerts due to sensor misreading
	Lane Keeping Assistance	Alerts or assists driver in maintaining lane position	76–81 GHz	Prevents unintentional lane drifting	Ineffective with faded or absent road markings
	Automatic Parking Assistance	Helps with autonomous parking by detecting spaces and objects	24 GHz, 76–81 GHz	Eases parking in tight spaces	Challenges in poor lighting or cluttered environments
UAV [207]	UAV Navigation	Detects position, speed, and direction to guide UAVs	60 GHz, 77 GHz	Enables precise routing	Signal loss due to obstruction or interference
	UAV Obstacle Avoidance	Detects and avoids obstacles during flight	60 GHz, 77 GHz	Safer autonomous operation	Reduced effectiveness in dense, complex terrain
	UAV Target Tracking	Tracks moving or stationary targets	60 GHz, 77 GHz	Useful for surveillance or mapping	High computational demands
	UAV Search and Rescue	Finds people or objects on the ground for rescue missions	60 GHz, 77 GHz	Crucial in disaster zones	Impacted by weather and terrain
	UAV Agriculture	Monitors crops and field conditions	60 GHz, 77 GHz	Enables precision farming	Requires integration with other sensors for best results
Aerospace [208]	Navigation and Monitoring	Detects aircraft and terrain; supports pilot decisions	94 GHz	Enhances airspace awareness	Performance may drop in storms
	Autopilot Systems	Supports autonomous takeoff and landing	94 GHz	Reduces human error	Integration with legacy systems may be complex
	Meteorological Monitoring	Collects atmospheric data for weather prediction	35 GHz, 94 GHz	Provides accurate weather models	Maintenance of sensitive instruments is critical
	Aircraft Braking Systems	Assists in controlled braking by sensing motion parameters	94 GHz	Prevents skidding and runway overshoot	Must operate with real-time accuracy
	Collision Avoidance Systems	Detects and prevents mid-air collisions	94 GHz	Critical safety system	Requires fine calibration to avoid false positives
Meteorology [209]	Precipitation Observation	Measures rainfall rate and type	35 GHz, 94 GHz	Improves weather forecasts & flood warnings	Accuracy can drop in heavy precipitation
	Atmospheric Layer Observation	Studies atmospheric density, temperature, & content	36 GHz, 94 GHz	Useful for climate science	Must be combined with other datasets for full picture
	Wind Speed and Direction Measurement	Tracks wind changes over time	37 GHz, 94 GHz	Enhances aviation safety & modeling	Sensitive to topography-induced turbulence
	Atmospheric Turbulence Observation	Detects turbulent zones and airflows	38 GHz, 94 GHz	Prevents accidents in aviation & improves forecasts	Complex data interpretation required
	Weather Radar	Maps precipitation, clouds, & storm systems	39 GHz, 94 GHz	Enables early warning systems	Infrastructure-heavy and costly

(continued on next page)

Table 14 (*continued*).

Healthcare [155,159]	Medical Imaging	Provides detailed scans for diagnosis (e.g., tumors, tissues)	60 GHz	Enables early, non-invasive diagnosis	Equipment cost and training needs
	Non-Invasive Monitoring	Tracks vitals such as respiration & heart rate remotely	60 GHz	Ideal for elderly or neonatal care	Interference from surroundings possible
	Object Detection	Tracks surgical instruments and internal markers	60 GHz	Improves surgical precision	Must work in real-time without latency
	Remote Surgery	Assists in image-guided operations remotely	60 GHz	Expands healthcare reach	Requires ultra-reliable networks
	Drug Delivery	Targets drug release using mmWave- controlled mechanisms	60 GHz	Minimizes side effects by targeted delivery	Needs precise synchronization with other systems
Entertainment & Sports [55]	Motion-Sensing Games	Detects body gestures for controller-free interaction	60 GHz	Enhances gameplay immersion	Needs accurate motion interpretation to avoid frustration
	Virtual Reality	Tracks head/body motion to simulate natural movement in virtual environments	60 GHz	Adds realism to virtual environments	High processing power needed to avoid lag
	Sports Performance Analysis	Analyses player movements, posture, & speed	77 GHz	Aids in training and performance optimization	Costly for consumer-level use
	Audience Engagement (Events)	Tracks audience movement for adaptive lighting/sound in venues	60 GHz	Creates dynamic, responsive experiences	Privacy and signal interference concerns
	Fitness Monitoring	Tracks posture and reps during workouts without wearables	24 GHz, 60 GHz	Encourages correct technique & reduces injury risk	Environmentally sensitive; limited detection range
Smart home & Smart city [116,168]	Security Monitoring	Detects movement near property; alerts homeowners or authorities	60 GHz	Enhances property protection	Must distinguish between people and animals
	Human Detection	Recognizes presence and posture for automation (lights, HVAC)	60 GHz	Boosts energy efficiency	False positives in crowded spaces
	Smart Lighting	Controls illumination based on motion patterns	60 GHz	Reduces energy usage	May not detect motion behind furniture or glass
	Smart Parking	Identifies available spots and parked vehicles	60 GHz	Streamlines parking management	Interference with other nearby radar systems
	Intelligent Transportation	Tracks and manages traffic flow, vehicle speed, and congestion	76–81 GHz	Supports efficient urban mobility planning	Infrastructure deployment can be expensive

9.2. Ghost object detection

Multi-path propagation represents a significant hurdle in wave physics, particularly within radar technology. This phenomenon arises when waves emitted from a transmitter traverse multiple pathways to reach a receiver, complicating the detection of targets due to simultaneous direct and indirect reflections. A critical challenge is the impact of these multi-path reflections on the Direction Of Arrival (DOA) estimation; when target and multi-path reflections converge within the same Range-Doppler cell, the efficacy of detection systems is notably diminished. However, should these reflections be classified into distinct cells, radar systems may produce phantom targets across varied directional paths, thereby complicating detection efforts.

The dynamics of ghost detection closely resemble those of genuine targets, rendering traditional detection approaches inadequate. Researchers systematically categorize the effects of multi-path propagation into three primary types. The first type involves reflections between the ego-vehicle and the targets, necessitating that clutter's distance and velocity considerably exceed measurement precision. The second type, underbody reflections, occurs beneath the vehicle, often revealing targets hidden from direct line-of-sight. Lastly, the third category involves ghost detections stemming from various reflective surfaces, further complicating the radar's operational landscape.

The long wavelength of automotive 77 GHz radar enables many flat structures – such as concrete walls, guardrails, and noise barriers – to act as reflective surfaces. Unlike clutter, ghost objects present a unique challenge in removal since they share similar kinematic characteristics with genuine targets, making them resistant to temporal tracking methods. Nonetheless, geometric approaches have been proposed for their identification, as outlined in [211].

Typically, ghost objects present themselves within a ring-shaped area at distances comparable to real targets. The structural characteristics of the surrounding scene, along with the relationships among various detections, serve as pivotal indicators for the recognition of ghost objects. In this regard, [212] advocates for the utilization of an occupancy grid map, which captures the underlying structure of the environment. Employing this grid can enhance the ability to predict the movement of ghost objects, emphasizing the importance of developing models that can effectively mirror the similarities between actual targets and their ghostly counterparts. This avenue of research holds promise in refining detection techniques, ultimately enhancing the reliability of radar systems in complex environments.

9.3. Adverse weather conditions

Adverse weather poses significant challenges to radar sensing applications, particularly in outdoor environments. Conditions characterized by heavy precipitation, snowfall, and fog can severely impact the performance of various sensors. For example, visual perception systems, including cameras, often struggle with issues such as blurriness, noise, and distortions in brightness, which can compromise their effectiveness in harsh conditions [213]. Similarly, LiDAR systems face reduced detection ranges and obstructed visibility when confronted with powdery snow, torrential rain, and dense fog [214].

In contrast, radar technology demonstrates significant resilience to adverse weather conditions, which primarily affect performance through attenuation and backscattering phenomena [215]. Attenuation reduces the power of received signals, while backscattering increases interference, complicating signal interpretation. For fully autonomous vehicles, effective operation in diverse environmental conditions is essential. However, a notable gap exists; current sensor fusion techniques inadequately account for weather influences. Networks trained under optimal conditions often exhibit diminished performance in adverse weather, underscoring a critical need for advancements in adaptive methodologies to enhance reliability in varying meteorological scenarios.

To address the challenges posed by varying weather conditions, several strategies can enhance network adaptability. One approach is the integration of a scene-switching module, enabling the system to employ distinct networks for specific weather scenarios. Although effective, this method may increase computational demands and memory consumption. An alternative involves embedding dynamic mechanisms in the network architecture, allowing real-time adjustments to environmental changes. Continued research in these domains is crucial for developing robust and adaptive systems for autonomous vehicles, ensuring their safe and reliable operation under adverse weather conditions.

9.4. Motion estimation

Radar technology plays a crucial yet often overlooked role in measuring Doppler velocity, offering significant advantages for detecting moving road users and enhancing motion forecasting — an essential component in autonomous driving research [216]. Accurate movement predictions of various road users enable path planning modules to respond more effectively to potential interactions.

For instance, [217] investigated trajectory prediction through a constant velocity model using binarised radar maps as input. Their results indicated that relying on the constant velocity assumption resulted in suboptimal performance in predicting vehicle trajectories [216]. In light of this, adopting a second-order nonlinear motion model that integrates measured Doppler velocity presents a promising alternative. This approach not only addresses the limitations of earlier models but also highlights the substantial potential of radar technology in advancing motion forecasting. Such advancements could significantly enhance the sophistication and responsiveness of autonomous driving systems, ultimately contributing to safer and more efficient roadways.

9.5. Interference mitigation

In the domain of FMCW radar systems, the challenge of mutual interference remains significant, particularly when multiple radars operate simultaneously within the same line of sight [218]. Interference can be classified based on the chirp configurations — specifically, their slope and duration in question. When both the interferer and the target radar share identical chirp configurations, the interference is termed coherent, often resulting in ghost detections. Alternatively, the use of differing chirp types leads to incoherent interference, which elevates the noise floor, thereby obscuring weaker targets and reducing the probability of detection [219].

In practice, the occurrence of partially coherent interference is far more prevalent, where variations in the chirp configurations between the interacting radars introduce additional complexities. Recent work by [220] has shown promise in mitigating these interference issues; however, these methods are frequently tailored to specific disturbances and can result in considerable computational demands.

Future research should focus on developing integrated frameworks that address interference mitigation concurrently with downstream tasks such as target detection, thereby fostering the creation of more resilient and efficient radar systems capable of thriving in challenging operational environments.

10. Conclusion

Millimeter-wave (mmWave) radar has emerged as a powerful sensing technology that is finding applications across many domains, including autonomous driving, healthcare, industrial monitoring, and smart homes. Its ability to provide accurate range, velocity, and angle information, while remaining robust under poor lighting and adverse weather conditions, makes it a valuable complement to existing sensors such as cameras and LiDAR. This review has presented a detailed overview of the fundamental operating principles, advanced signal processing methods, and the integration of machine learning and deep learning techniques that are pushing the boundaries of radar-based sensing. Through the discussion of datasets, devices, and multi-sensor fusion approaches, we highlighted how the research community is working toward building reliable and adaptable systems. The bibliometric analysis further showed the growing potential in mmWave radar research and the diversity of application areas it is beginning to target. From gesture recognition and in-cabin monitoring to SLAM and human activity recognition, the technology is steadily moving from experimental studies to real-world implementations. At the same time, several open challenges remain. Issues such as clutter removal, interference mitigation, computational complexity, and ensuring reliable performance in dynamic environments need sustained attention. Similarly, the adoption of deep learning models brings opportunities for improved accuracy but also raises questions about explainability, and scalability. Addressing these gaps will be crucial for enabling widespread deployment.

Looking ahead, the future of mmWave radar sensing is likely to be shaped by its integration with other sensing modalities and by the design of intelligent algorithms that can balance accuracy with efficiency. Advances in hardware miniaturization and joint radar–communication systems will further expand the possibilities of this technology. With continued research and cross-domain collaboration, mmWave radar has the potential to become a key enabler of intelligent, safe, and human-centered systems in the years to come.

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Declaration of competing interest

The authors declare that there are no conflicts of interest related to the publication of this research.

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Data availability

No new data were generated or analyzed in this study. All data discussed are based on previously published literature.

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