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Abstract

This paper delves into the transformative potential of Machine Learning (ML) in Radio Frequency (RF) sensing applications. We focus on pivotal domains such as device localization, occupancy detection, activity monitoring, and biometric sensing, showcasing how ML is redefining the boundaries of what is possible. By harnessing the power of ML, we showcase how to unlock unprecedented performance enhancements in these critical areas. We provide a comprehensive review of cutting-edge ML-driven RF sensing methodologies and offer an overview of publicly available datasets that are propelling this field forward. Moreover, we present key challenges that remain - from the quality and labeling of RF sensor data to robustness, privacy, and explainability of ML models. Through this exploration, we lay the path for future scientific and engineering innovations in the ever-evolving landscape of RF sensing.

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Machine Learning-Powered Radio Frequency Sensing: A Review

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***Abstract*—This paper delves into the transformative potential of Machine Learning (ML) in Radio Frequency (RF) sensing applications. We focus on pivotal domains such as device localization, occupancy detection, activity monitoring, and biometric sensing, showcasing how ML is redefining the boundaries of what is possible. By harnessing the power of ML, we showcase how to unlock unprecedented performance enhancements in these critical areas. We provide a comprehensive review of cutting-edge ML-driven RF sensing methodologies and offer an overview of publicly available datasets that are propelling this field forward. Moreover, we present key challenges that remain - from the quality and labeling of RF sensor data to robustness, privacy, and explainability of ML models. Through this exploration, we lay the path for future scientific and engineering innovations in the ever-evolving landscape of RF sensing.**

***Index Terms*—Machine Learning, RF Sensing, Wi-Fi, Bluetooth, Ultra-Wideband (UWB), Radar, Localization, Activity monitoring, Biometric Sensing.**

I. Introduction

RF sensing uses radio propagation characteristics to detect, measure, and analyze various environmental and system states. An advantage of RF sensing in comparison to infrared and vision based sensing is that they work through obstacles in non-line-of-sight environments, providing a versatile and non-intrusive approach to detection and monitoring. These characteristics make RF sensing attractive in a wide range of applications in healthcare, industrial automation, and smart buildings.

In the healthcare domain, RF sensors can be used for sleep monitoring, vital sign monitoring, respiration and heart rate measurement, without physical contact, [1]–[10]. RF sensors can be used in elderly care environments for activity monitoring [11]–[15] and even severity of fall detection [16], supporting their well-being without loss in privacy. RF imaging techniques may be used in medical diagnostics for in-body imaging, tumor detection, monitoring tissue properties, and localization of in-body RF sources [17], [18]. In security and surveillance applications, RF fingerprinting can be used to uniquely identify devices based on their RF emissions to limit unauthorized access and provide network security. In industrial applications, RFID sensors support efficient tracking of assets in warehouses and factories [19], [20]. RF sensors are also used in real-time monitoring of parameters such as temperature, pressure, and liquid levels to monitor industrial processes, detect and diagnose anomalies and failures [21]–[23]. Finally, RF-based positioning and navigation systems enable robotics and automation in connected buildings, manufacturing and logistics [24]–[29].

One approach to categorizing RF sensing technologies is based on operational frequencies. RFID (Radio Frequency Identification) employs sub-GHz bands to automatically identify and track tags. RFID applications are common in asset tracking, logistics, supply chain management, and inventory control. Bluetooth and Wireless Fidelity (Wi-Fi) sensing use the license-free 2.4 GHz band and find applications in consumer devices for indoor positioning and presence detection applications. Another active sensing technology is based on UWB operating in the 3.1 GHz to 10.6 GHz range. UWB sensing is suitable for short-range, high-precision applications like ranging, gesture recognition, and activity detection. Finally, radar sensing technologies span different frequency bands covering sub-GHz for air surveillance and defense, 4-8 GHz C-band for weather radar and sea monitoring, 60 GHz for industrial applications, home monitoring, and in-cabin sensing, 76-81/94/120 GHz for automotive road sensing, and THz bands for body scanning applications.

These RF sensing technologies have traditionally been driven by signal processing techniques, often based on well-developed analytical signal models. In some application scenarios, theoretical models may have limitations. Over the past years, rich amounts of RF sensor data have become available, along with advances in ML. This combination of data and ML in RF sensing opens new data-driven, as well as hybrid data- and model-based, approaches to deliver improved sensing performance. New sensing information can also be derived by processing patterns across diverse RF data streams. Furthermore, large amounts of such RF data is being labeled and contextualized. This allows use of supervised learning approaches for training models on labeled data in RF sensing applications like positioning, anomaly detection, and activity classification. In such cases, deep neural networks have also been used to improve performance by identifying complex patterns underlying in large datasets. In use cases where labeled data is limited or non-existent, unsupervised learning approaches are being employed.

The remainder of the paper is organized as follows. Different ML paradigms for RF sensing are presented in Section II. Diverse ML approaches in RF sensing to realize different func-

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tions like localization, occupancy and biometric sensing at the device and human level are reviewed in detail in Section III. Finally, in Section IV, challenges and new directions in ML-driven RF sensing are outlined, with conclusions drawn in Section V.

II. Machine Learning Paradigms for RF Sensing

Traditional signal processing methods used for RF sensing rely on underlying signal models, as well as an understanding of the RF propagation, transceiver system, RF footprint, and other dynamic changes in the application environment. These methods are effective when operating conditions align with those specified during design and underlying model assumptions are valid. In such cases, employing machine/deep learning techniques for well-defined problems with satisfactory performance is often an overkill. In practice, however, operating conditions deviate from design assumptions. Moreover, RF sensing problems are often mathematically intractable or cannot be simplified into numerical input-output explanations. In such cases, ML models can prove to be effective, given that they can be trained to be more generalizable than a priori specifications. ML solutions are also more adaptable to dynamic conditions, requiring rapid updates or extensions, which can be challenging for traditional solutions. Moreover, when the input dimension is large or design choices are numerous, deep learning becomes a superior choice for implicit feature extraction and improved performance with smaller footprint.

As machine learning-based solutions move from theoretical concepts to real-world applications, optimized integration in a sensor data processing chain becomes essential for maximum performance benefits, without incurring high complexity. The application of deep learning to sensors requires careful consideration of input feature representation and network architectures. The most straightforward method involves feeding pre-processed RF data, such as time-frequency representations such as Doppler Trace, involving standard FFT operations across Wi-Fi packets, as input to the ML model to perform a sensing task as depicted in Fig. 1(a). This approach leverages established signal processing techniques for feature extraction, enabling the ML model to benefit from domain-specific knowledge [30] [31]. Often, diverse input representations and transformations are applied to the input data to extract meaningful information that are fed to a ML model for a specific task, such feature representations across various RF sensors are outlined in Table I. In addition to these representations, unsupervised learning can be employed to pre-learn domain-specific input representations, mapping them to latent vectors. These latent vectors can then be utilized as initial transformations for downstream supervised learning tasks, leveraging larger unlabeled training datasets to improve performance. A notable example is wav2vec [32], which vectorizes bio-signals for downstream tasks using deep networks. Such techniques are helpful particularly in low Signal-to-Noise Ratio (SNR) environments.

Another paradigm of ML use in a RF system pipeline is by transforming traditional processing blocks into ML models. RF systems can be represented as a sequence of processing steps, where each block performs specific operations on the signal, progressively extracting relevant information. ML models can be incorporated into this processing chain by potentially replacing existing Digital Signal Processing (DSP) blocks entirely, aiming to achieve similar functionality with potentially improved performance or generalization capabilities under unexpected operating conditions. For instance, in radar signal processing, a complex neural network can replace traditional blocks to output range-angle images, as shown in Fig. 1(b) [40]. When replacing traditional blocks, the objective is to maintain functionality under normal conditions while achieving superior performance under unexpected environments, thereby significantly enhancing system robustness. Another notable example of this paradigm is KalmanNet [54], a novel approach to state estimation in dynamical systems, particularly those with non-linearities and uncertain model knowledge. KalmanNet offers a robust solution for RF-based tracking in real-world scenarios, where accurate system models are unavailable and non-linearities exist.

Another paradigm is cross-integration of ML models into RF processing pipeline. ML models can also be employed to create new processing blocks within the chain, addressing novel tasks or limitations of traditional methods. For e.g. in Fig. 1(c) ML models output are fused with traditional signal processing block [55], namely Kalman filter, to jointly improve the performance of signal processing tasks (detection in this case) and machine learning tasks (classification in this case). Cross-modal learning, where tasks from different modalities are jointly optimized to improve separate individual tasks simultaneously are also an example of this paradigm.

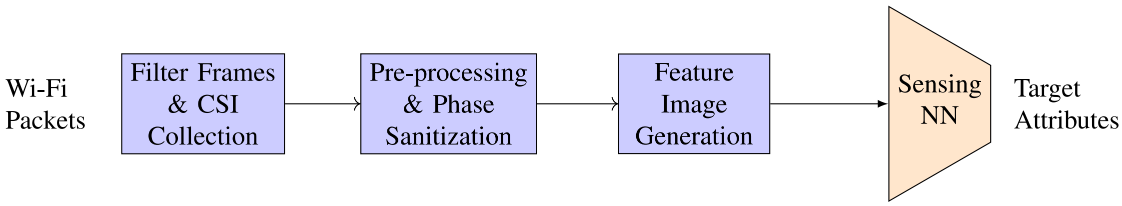
Furthermore, recent advancements have led to the development of parametric neural networks [56], such as non-uniform Discrete Fourier Transform (DFT) NN and sinc-Net [57], which embed signal processing principles within neural network architectures. These hybrid models preserve the interpretability of model-based designs while leveraging data-driven approaches to accelerate performance, bridging the gap between traditional processing and deep learning methodologies.

III. Machine Learning Techniques in RF Sensing Applications

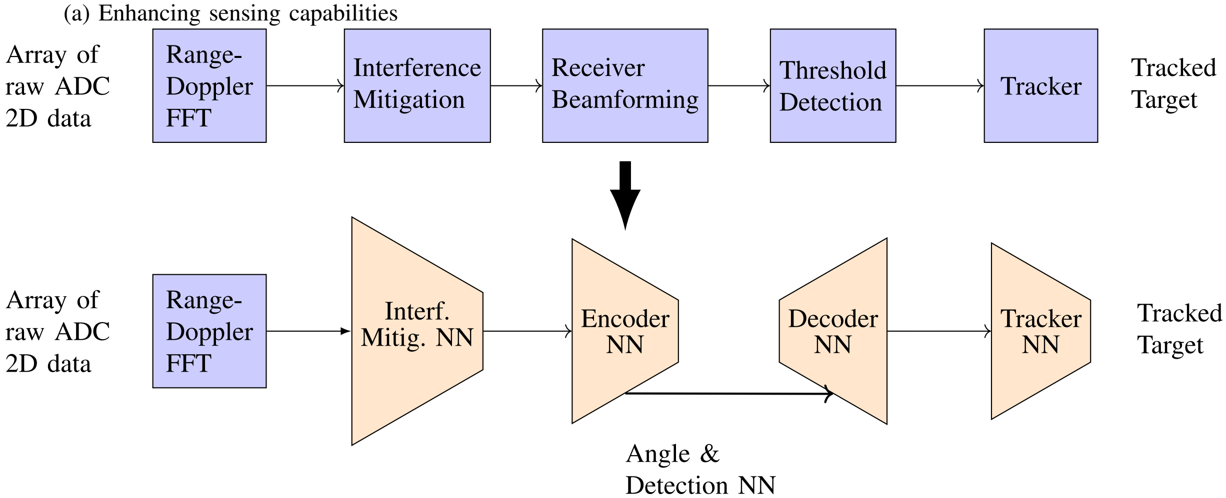
A. Localization and Navigation

The integration of machine learning into localization mechanisms, such as RF (Wi-Fi/UWB/Bluetooth Low Energy (BLE)) fingerprinting for indoor localization, has revolutionized the field by leveraging the capabilities of neural networks to improve accuracy and efficiency. As illustrated in Fig. 2, RF fingerprinting, a technique reliant on matching RF signal patterns or features (fingerprints) from surrounding access points or anchors to a database of known locations, has been significantly enhanced by deep learning advancements.

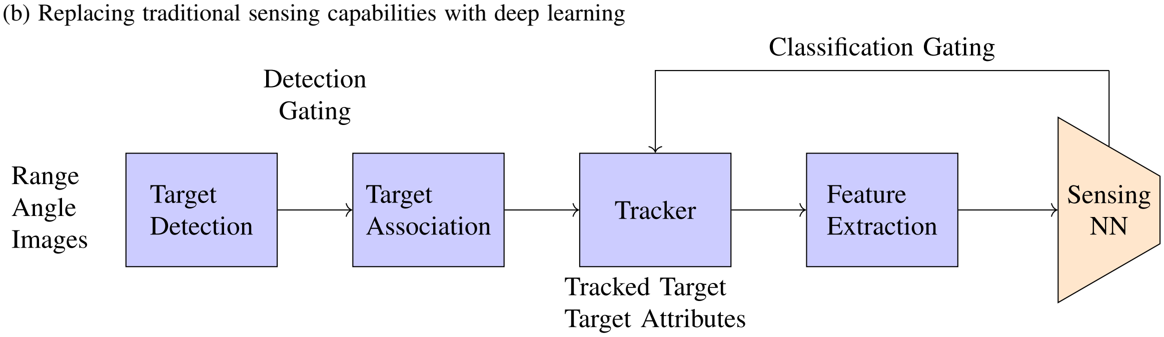
Wi-Fi fingerprinting approaches received early attention due to the easy access to Received Signal Strength Indicator (RSSI) from commercial Wi-Fi devices [58], [59]. Considered as a *coarse-grained* channel measurement, RSSI represents a simple superposition of signal power over multipath propagation



(a) Enhancing sensing capabilities



(b) Replacing traditional sensing capabilities with deep learning



(c) Integrating deep learning with traditional sensing pipeline

Fig. 1: Various paradigm of adopting ML in RF Sensing Pipeline

but may fluctuate over time. It can be used directly as fingerprinting data in systems such as Radar [60], Compass [61], and Horus [62]. Classical machine learning methods such as the k-Nearest Neighbors (kNN) and Support Vector Machine (SVM) and deep learning methods such as multi-layer neural networks have been applied to RSSI fingerprinting [63]–[67].

The *fine-grained* channel measurements such as Channel State Information (CSI) provide a better capability to resolve multipath components in the time or frequency domain. Although CSI is not accessible by 802.11 standards protocols, modified firmware on commercial Wi-Fi devices have enabled access to the CSI over a bandwidth of up to 160 MHz [68], [69], [70], [71]. This has sparked a large swath of learning-based Wi-Fi sensing applications [72]–[76]. For instance, ConFi [77] used convolutional neural networks (CNNs) to train CSI measurements from three antennas, to classify the location and estimate location coordinates. [78] fingerprinted full CSI over multiple time instants, calibrated their phases, and fitted one autoencoder for one location. DeepFi exploits 90 CSI amplitudes from all the subcarriers at three antennas for feature extraction using an autoencoder architecture [79]. Channel Impulse Response (CIR) can be also acquired without channel estimation by using the concept of time-reversal radio transmission which creates a resonating effect of focusing the energy of the transmitted signal only onto intended location, e.g., multipath reflections [80]–[84]. As a result, the TR-based CIR can be fingerprinted along with traditional correlation-based or more advanced deep learning approaches for localization and navigation.

At higher mmWave bands such as 60 GHz, *mid-grained* mmWave beam training measurements, required by 802.11ad and 802.11ay standards protocols, may be accessible with modified firmware in [85]–[90]. Earlier efforts formulated a direct localization using the beam SNR measurement as a constrained optimization [85], [91], [92] and considered model-based signal processing to map the beam SNR to the location and orientation [86], [87]. More advanced deep learning approach was applied in Line of Sight (LOS) [88] and

TABLE I: Input Feature Representations for RF-based Sensing Tasks

Technology	Feature Category	Features	References
Wi-Fi	CSI	Doppler Trace, Delay-Doppler Images	[33] [34] [35]
	RSSI	Mean, Variation	[36] [37]
	FTM	Arrival Times, Intervals	[38]
Radar	Time-Domain	Raw-ADC data, Range waterfall	[39] [40]
	Frequency-Domain	Spectral Power Density, range-Doppler images, range-azimuth images, 3D tensors	[41] [42]
	Micro-Doppler	Doppler spectrogram, Doppler Spread	[43] [44] [45]
BLE	RSSI	Mean, Variation	[46]
	Packets, AoA	Arrival Times, Intervals, Establishment time	[47] [48]
	Phase Changes	Spectral gain images, Peak Frequencies	[49] [50]
UWB	Time-Domain	Amplitude, Phase	[51]
	Frequency-Domain	Spectral Power Density, Spectral images	[52]
	FTM	Time-of-Arrival, Time-Difference-of-Arrival, Angle-of-Arrival, Angle-of-Departure	[53]

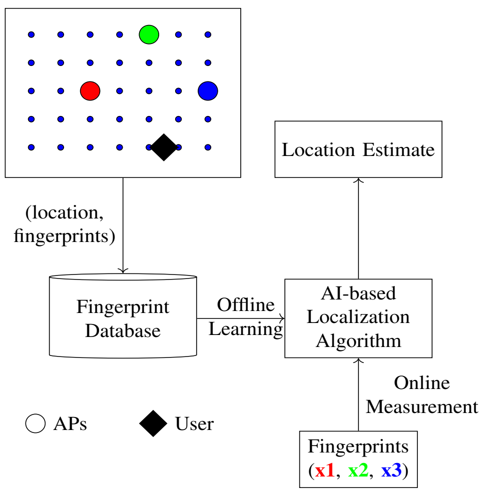


Fig. 2: A schematic illustration of RF-fingerprinting for localization and navigation system. Different signals use various channel measurements and preprocessed intermediate results to construct the fingerprinting database. For instance, RSSI, CSI, FTM for Wi-Fi, TOF and CIR for UWB, and AoA for BLE.

Non-Line of Sight (NLOS) scenarios [93]. A pretrained fusion network between the CSI at sub-7 GHz and the beam training measurements at 60 GHz was proposed for localization [89].

Wi-Fi Time of Flight (ToF) measurements can also be used for fingerprinting. Fine Time Measurement (FTM) defined in IEEE 802.11-2016 (REVmc) and 802.11az protocols is the result of a handshaking protocol between an initiating station, e.g. a smartphone, and a responding station, e.g., an Access Point (AP), and yields direct time-of-flight measurements such as Round Trip Time (RTT) between the two stations [38]. Commercial Wi-Fi devices including smartphones such as Galaxy S20, G8X ThinQ, and Pixel 4/5/6, and Nest and Aruba APs support the FTM feature. Under LOS scenarios, it can lead to a sub-meter localization accuracy by a simple trilateration in the presence of multiple APs [94]. However, its use in NLOS environments is still challenging [95], [96] and identifying RTT from LOS/NLOS paths was considered in [97] to improve the FTM-based localization accuracy. To better account for Wi-Fi propagation including blockage, reflection, attenuation, RTT-based fingerprinting using machine learning and deep learning approaches was considered in [98] for three indoor scenarios and shows improved localization accuracy over the trilateration-based method.

UWB technology offers superior capabilities for separating direct path components from multipath components compared to Wi-Fi, leveraging its larger bandwidth (e.g., 500 MHz vs. 160 MHz for 802.11az Wi-Fi). The IEEE 802.15.4z standard has established a UWB physical layer for indoor localization and tracking applications, utilizing anchors or sensors in fixed positions to achieve accurate localization and tracking [99]. In multipath and reflective scenarios, one challenge for the UWB-based localization is the NLOS identification and mitigation. [100] considered the use of non-parametric machine learning techniques, e.g., SVM, to perform NLOS identification and mitigation using hand-crafted features such as signal energy, maximum amplitude, mean excess delay from UWB CIR. Gaussian process (GP) was considered to determine the a *posteriori* distribution of the CIR-based ranging error and such errors were accounted for the final localization result [101]. Advanced deep learning approaches such as the MLP [102], [103], Convolutional Neural Network (CNN) [51], [104], [105], Capsule networks [106], and 3D CNN [107] have been applied to extracting features directly from UWB RSSI, ToA, and CIR to assist NLOS identification. Figure 3 illustrates a configuration of three UWB receivers (marked by their coordinates (x_i, y_i)) and one UWB transmitter (user), where the 3D location of the transmitter is inferred from the features extracted by 3D CNN over the multi-anchor UWB waveforms. Local embedded neural networks are employed to enable on-device UWB localization with small memory and computation footprints. An example is given in [108], where a mean UWB ranging error below 1 cm is achieved using a threshold-based multipath mitigation algorithm (STM) enhanced by STMnet which features 330-KB memory and $232K$-FLOP computation footprints.

BLE localization is another affordable, power-efficient, easy-to-deploy localization option that is compatible with ubiquitous BLE-enabled devices. Similar to Wi-Fi, traditional approaches rely on BLE RSSI using either signal processing techniques or machine learning approaches to map it to distance or ToF estimates [109]–[112]. [112] exploits the 3D CNN for better feature extraction from the BLE RSSI [113]. More recently, the Bluetooth SIG specifies Phase-Based Ranging (PBR) [46] as a feature in the new release Bluetooth 5.4 and opens a door for Angle of Arrival (AoA)-based localization using low-cost switch antenna arrays [114],

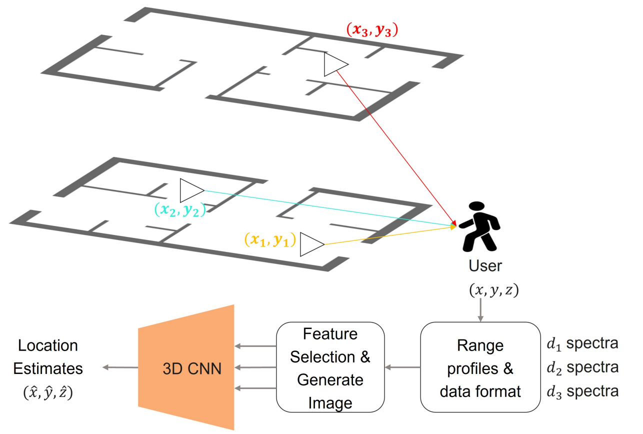


Fig. 3: Schematic illustration of AI-assisted Bluetooth or UWB locationing system via trilateration principles.

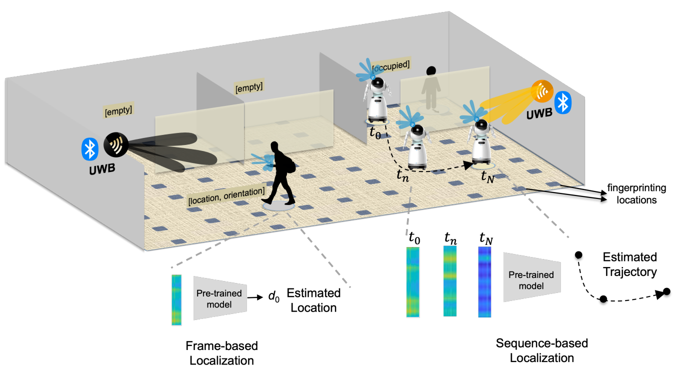


Fig. 4: Frame-based localization versus sequence-based localization using RF (Wi-Fi/UWB/BLE) channel measurements.

[115]. CNN has been utilized to improve the AoA estimation with limited RF chains [116]. Combination of both BLE RSSI and AoA was also considered in [48], [117]. In [118], neural network is proposed to identify unusual patterns in the frequency tones of BLE PBR ranging system corrupted by noise and interference from other devices and aids in predicting the corrupted frequency tones using neural network.

Other fingerprinting signatures may include preprocessed intermediate results from the above channel measurements such as AoA and Angle of Departure (AoD) powered by the Multiple-Input Multiple-Output (MIMO) operation with multiple antennas, and ToF. For instance, SpotFi [119] groups all subcarrier CSIs over multiple antennas to obtain AoA-ToF propagation path clusters via a 2D smoothing MUSIC. DLoc [120] converts CSIs at multiple antennas into ToF-AoA heatmaps (similar to SpotFi) in a unified x-y coordinate shared by multiple APs and learns the heatmap features for direct localization. Moreover, 802.11 protocols, e.g., 802.11az, can provide detailed information about the AP's location via the Location Configuration Information (LCI) and Basic Service Set Identifier (BSSID) [31], [121], [122] and further enhance location accuracy.

Most of the above approaches are *frame-based*, as shown in Figure 4. That is, the task such as localization or sensing is inferred from current RF (Wi-Fi/UWB/BLE) frame, without integration of past measurements or previous trajectory history. *Sequence-based* approaches take consecutive Wi-Fi frames as the input, and state estimation (e.g, Kalman filter-like approaches [123], [124]) and recurrent neural networks (e.g., Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) [125]) can be applied for trajectory estimation with the RSSI and CSI [126]–[129] at sub-7 GHz. LSTM networks have also been utilized to extract temporal-dependent features from the UWB time-of-arrival (TOA) measurements [130], [131], raw UWB CIR [105], [132], BLE RSSI [133], and BLE AoA [115] for user localization. More recently, the sequence-based formulation has been applied to mmWave Wi-Fi beam training and multi-band Wi-Fi measurements with a neural ordinary differential equation (ODE) model to overcome the sampling irregularity and low data rate [134]–[136]. A multi-model recurrent localization approach involving UWB, Inertial Measurement Unit (IMU), and Wi-Fi RSSI was proposed in [137] by accounting for sensor modality uncertainty.

The generalizability of deep learning models is another significant advancement in RF fingerprinting. By training models on large datasets encompassing diverse indoor environments, they can learn to recognize patterns and relationships that are universally applicable, reducing the need for extensive fingerprint database creation for every new location. This enables deep learning-based Wi-Fi fingerprinting systems to adapt to new environments with minimal additional training data, making them more practical for real-world applications. Extracted environment-independent Doppler profile [138] from the CSI phase information can represent human activity, and such phase information can be also used for indoor localization. In [139], domain adaptation schemes have been considered to Wi-Fi localization with the test dataset is collected from different dates and the room environment varies from the training data collection.

B. Occupancy sensing, activity monitoring, and people counting

Reliable occupancy detection, people counting and occupancy flow information are crucial in smart home and building applications. This information can be used in lighting, Heating, Ventilation and Air Conditioning (HVAC) controls, building energy management, and space management systems [25], [140]–[145].

A typical Wi-Fi sensing pipeline for presence, activity, gesture, or people counting typically involves a series of processing stages. First, CSI is filtered from a specific Medium Access Control address. Next, CSI from either beacons or data frames or both are extracted, depending on the application. This is followed by phase sanitization, feature images generation and neural network for specific task classification. SVM on Wi-Fi fingerprint CSI features was proposed in [146] for occupancy detection and localization. Such a method relies on signal variations and is susceptible to environmental humidity and temperature changes. A resource-efficient deep learning approach using Wi-Fi CSI for occupancy detection with considerations to explainability and robustness to humidity and temperature changes was presented in [143]. An ensemble learning approach with random forest, gradient boosting and extreme gradient boosting Machine learning methods based on engineered features and deep learning with Wi-Fi CSI were presented for crowd counting and localization in [147]. A reinforcement learning using an enhanced deep Q-network based on Bluetooth features and feedback from Internet of Things (IoT) devices and environment sensors was considered in [148].

An advantage of RF sensing is that the signal propagates across obstructions. Through-the-wall occupancy detection was considered in [149], [150], [151]. In [151], engineered features like variances of signal and respiration rates were used in different ML models. Occupancy sensing for multi-room scenarios using a time-selective conditional dual feature extract recurrent network with Wi-Fi CSI was presented in [152].

Radar-based people counting using signal pattern analysis and feature design was considered in [153]. To overcome challenges associated with feature handcrafting, deep learning approaches were proposed [154], [155]. The proposed model in [155] included a a clutter suppression pre-processing step followed by a 1-D CNN-Recurrent Neural Network (RNN) fusion model, to better leverage the spatio-temporal characteristics of radar data. However if the environment changes, such deep learning models need to be re-trained with new data. As a solution, in [156], environmental dependency was mitigated through radar-centric signal augmentations and unsupervised domain adaptation, thus enabling fully unsupervised people counting in variable clutter environments. For people counting in large surveillance areas, a RNN was used in [157] to regress the crowd count through sequential Wi-Fi spatial-temporal matrices.

In [158], [159], people counting using short-range 60-GHz radar was proposed using distance metric learning and cross-modal learning, which work on range micro-Doppler images and range macro-Doppler images to distinguish between quasi-static and moving humans in the field of view. In [160], a label-aware ranked (LAR) loss was proposed for people counting in automotive in-cabin environments using one transmit and three receive antenna single 60-GHz Frequency-Modulated Continuous Wave (FMCW) radars. Contrary to classical classification, LAR loss exploits distance information among labels shaping the embedding space to achieve ordered/ranked classification, enhancing the robustness and stability of people counting estimates. In the context of vehicle in-cabin driver monitoring, radar technology offers unique advantages. RF vital sign sensing for detecting fatigue or health issues was considered in [161], [162], with [42] presenting a review on in-vehicle monitoring using radars. For infotainment gesture sensing and control, [163] demonstrated the possibility of using ML and radars for infotainment control from any seat within a 5-passenger car. NN-based classifier was considered in [164] to detect 12 predefined gestures made by the person sitting on the passenger seat of a vehicle, with the designed NN requiring less than 20KB of memory. These studies demonstrate the potential of ML-driven radar technology in creating intuitive and non-contact control systems within vehicles.

Recent studies have proposed various deep learning approaches for sensing and processing radar signals. For instance, [165] presents a deep auto-encoder for fall-motion detection from Doppler spectrograms. In [16], ML and radar digital twins were used to detect falls and classify their severity. In [166], an LSTM network is trained on raw Analog-to-Digital Converter (ADC) data, while [167] uses a DCNN to classify images transformed from I/Q trajectories. A DCNN with a Fourier layer is proposed in [168], where the kernels are initialized with Fourier coefficients and adapted during training. Inspired by audio signal processing, [39] a neural network that uses bank of 1D bandpass sinc filters with learned cutoff frequencies, specialized for different artifacts of activities' Doppler are extracted leading to faster convergence and physically interpretable architectures. Recent studies [169]-[170] have leveraged deep autoencoder architectures to surpass traditional detection and clustering methods in radar signal processing. In [171], authors have proposed a parametrically constrained autoencoder, incorporating parametric non-uniform DFT in the initial layers.

Both activity recognition and gesture recognition are promising human-machine interaction modes, and can deliver achieving high accuracy using deep learning in closed and controlled setups [172]–[174]. However, commercial adoption is hindered by challenges in developing product-ready systems, particularly addressing robustness against non-gesture motions, changes in data distribution due to device or environments, leading to false alarms [175]. To handle non-gesture motions, explicit background classes have been traditionally proposed [176], however they may not capture all artifacts during training. Therefore, Out-of-Distribution (OOD) detection has emerged as a fundamental and crucial paradigm, enabling the identification of unknown or unseen patterns or changes to data distribution. One mechanism of achieving OOD detection are to estimate model uncertainty providing a measure of confidence in its predictions. Epistemic uncertainty refers to the uncertainty in the model's predictions due to limitations in the training data or model complexity, while aleatoric uncertainty represents the inherent noise and variability in the RF signals and sensor readings. By quantifying both epistemic and aleatoric uncertainty, the model can provide a more robust and reliable prediction of occupancy states, accounting for both the uncertainty in the model's knowledge and the noisy nature of the sensor data [177].

Furthermore, environmental changes, device variations, and user diversity can significantly affect RF signal characteristics, leading to decreased recognition accuracy. Domain adaptation is crucial in RF-based activity recognition and gesture recognition to address the mismatch between training and deployment environments [178]. Environmental changes, device variations, and user diversity can significantly affect RF signal characteristics, leading to decreased recognition accuracy. Domain adaptation enables robust recognition performance and maintains accuracy in changing conditions through continuous updating and refinement of the model using real-time data, enhancing its generalization capabilities and reliability in diverse environments [40], [179].

C. Biometric Sensing

During the cardiovascular and respiratory activity, the chest wall moves as a result of the diaphragm and intercostal muscle movement among others. This small and periodic displacement can be detected by radar, allowing accurate estimation of the breathing and heart rate under certain conditions. Figure 5 illustrates the basic operational principle of a radar-based vital sign monitoring system where the received signal is a scaled and time-shifted version of the transmitted signal and the phase variation over time, which contains valuable information regarding the body surface movement, is recovered by radar processing. In fact, the body surface displacement, $d(t)$, can be recovered from time-varying phase as $d(t) = \frac{\theta(t)\lambda}{4\pi}$ where λ is the radar operating wavelength.

CW radars have been extensively employed to extract the phase information for vital sign monitoring [180]–[182]. Recently, the application of millimeter-wave FMCW radars to short-range vital sign monitoring has been widely investigated [3], [42], [183], [184], owing to their improved resolution and sensitivity.Based on the nature of the radar waveform, components of the front-end and Digital Signal Processing (DSP) are adapted in Figure 5 yielding the classical Model based processing output.

Despite recent advances, accurate vital sign monitoring is still challenging in practical scenarios, especially in relation to heart rate estimation. The recovered displacement signal is comprises not only of the breathing and heartbeat fundamental frequencies but also interference from their associated harmonics and additional reflections from other parts of the body as well as the environment [185]. In [186], an IEEE 802.15.4z compliant Impulse Radio Ultra-Wideband (Impulse Radio (IR)-UWB) radar system is demonstrated for in-cabin monitoring for automotive applications. The presented system demonstrates three in-cabin use cases running in real-time: occupancy detection, breathing rate estimation, and gesture detection. The IR-UWB radar system detects occupancy and estimates the breathing rates of persons sitting in a car's driver and/or front passenger seat. Furthermore, the radar system detects if the passenger is performing a pre-defined gesture. The experimental results demonstrate the effectiveness of the system in a real-time platform, confirming its potential for enhancing automotive safety and comfort. In the presented demo, we achieve a false alarm probability of lower than 10^{-3}, a breathing rate accuracy of less than 1 beat per minute (bpm), and gesture detection accuracy of more than 90%.

In addition, due to varied nature of the subjects being monitored, their conditions, the diverse amplitudes of the chest wall motion and range of possible breathing rates, random body movements and environment changes, pose significant SP challenges in relation to highly curated scenarios. In fact, the SP framework needs to be adjusted to each scenario, and setting up correct algorithms and parameters for each application therefore remains a complicated task. These indicate the necessity for ML based sensing using radar measurements and Figure 5 presents the model-based, data-driven and hybid approaches.

Learning based approaches have revolutionized the field of contactless heart activity detection. Recent advancements in this area have seen significant contributions from the application of deep learning methods, which have substantially improved the precision and reliability of heart rate estimation. For instance, work [187] focused on deriving seismocardiogram from radar signals using deep learning methods. A novel transformer block after the CNN block was proposed in [4] to encode the temporal and spatial features, and the compressed features were then decoded by the temporal convolutional network to generate the fine-grained Electrocardiogram (ECG) output. Their approach involved reconstructing ECG waveforms from radar signals, achieving results that are remarkably similar to traditional electrocardiograms. CNNs were employed to learn the special patterns of the heartbeats in [188]. The capability of radar systems to accurately detect heart rate and analyze Heart Rate Variability (HRV), which is a critical measure of autonomic nervous system activity and cardiovascular health was demonstrated in [189]. The use of radar for comprehensive heart activity detection, achieving high accuracy in both heart rate measurement and HRV analysis was explored in [190], [191]. Recently, custom design of encoder-decoder model that can perform arrhythmia feature encoding, sampling and fusion over raw IQ sensing data directly, so as to discriminate normal heartbeat and arrhythmia was presented in [192]. These studies collectively illustrate the growing potential of radar-based systems in medical diagnostics and health monitoring. By integrating advanced deep learning algorithms with sophisticated radar technology, researchers are pushing the boundaries of what's possible in contactless cardiac monitoring, offering promising new tools for improving patient care and expanding the capabilities of telemedicine.

Radar technology has recently emerged as a promising modality for on-body biometric monitoring, offering non-invasive and continuous measurement capabilities. The application of machine learning techniques to radar data has further enhanced the accuracy and robustness of these systems, particularly in wearable configurations for cardiovascular monitoring, glucose monitoring, and blood pressure assessment. Wearable radar sensors placed on the chest have shown significant potential for cardiovascular monitoring. In [193], a chest-wearable ML-enabled 60-GHz radar system was developed for continuous extraction of cardiorespiratory displacement waveforms. This system achieved over 96 percent accuracy in respiratory rate estimation and over 95 percent accuracy in HRV measurements. For wrist-worn applications, radar technology offers unique advantages in capturing subtle physiological changes as demonstrated in [194] The application of radar technology to glucose monitoring represents an exciting frontier in non-invasive diagnostics. In [195], [196], a low-cost portable ML-enabled microwave sensor was propose for non-invasive monitoring of blood glucose levels. The concept fueled numerous subsequent studies [197]–[199], demonstrating the feasibility of ML-powered radar-based systems in detecting subtle changes in blood composition associated with changes in glucose levels. Most recently, [200] introduced a machine learning metasurface-enhanced millimeter-wave radar system for advanced near-field bio-sensing, demonstrating a notable

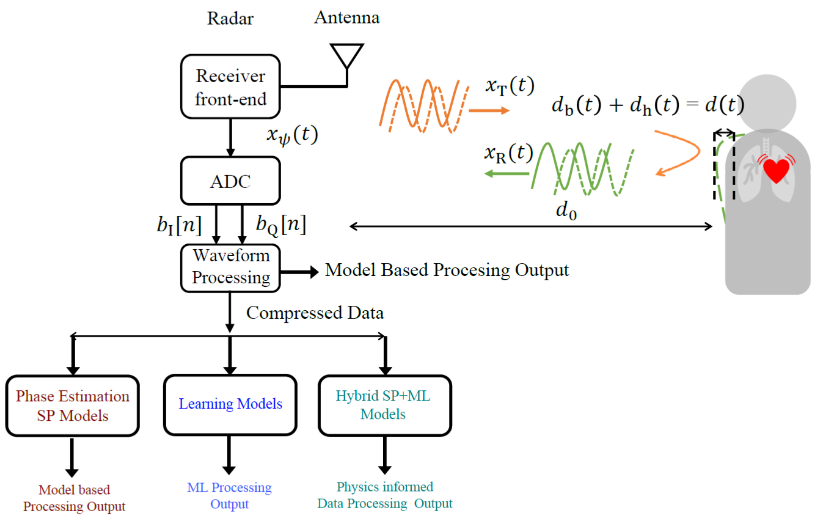


Fig. 5: Contactless radar-based vital sign monitoring: operating principle with classical model based and ML based processing blocks. Displacement signal, $d(t)$ ideally corresponds to the chest wall motion due to the breathing, heart-beat and other physical mechanisms during illumination

increase in signal to noise ratio. Blood pressure monitoring using radar technology is an area of active research, with potential applications in continuous, cuffless monitoring of hypertension and cardiovascular health. The principles of detecting subtle body movements and vascular changes could potentially be applied to estimate blood pressure through pulse wave velocity or other related metrics [201]–[204]. The integration of machine learning techniques with radar-based biometric monitoring has significantly enhanced the capability of these systems. Deep learning approaches, such as those employed in [187] for contactless seismocardiography, could potentially be adapted for on-body radar sensors to improve signal processing and feature extraction. Similarly, the encoder-decoder model proposed in [192] for arrhythmia detection could be modified for use with wearable radar data to provide more accurate cardiovascular health assessments.

Table II presents the key takeaways from the sensing applications and future opportunities presented in this section.

IV. Challenges and Opportunities in ML-based RF Sensing

The increasing use of ML-based methods has opened new frontiers. This section presents a canvas of the research challenges brought out by these new avenues and early works emphasizing the opportunities in addressing these challenges.

A. RF sensing data : Availability, Quality, and Augmentation

A challenge in ML-based RF sensing is the lack of high-quality, diverse, and representative data. An overview of public RF datasets with key sensor characteristics is presented in Table III. RF sensing data can be affected by various factors, such as noise, interference, multipath effects, and environmental conditions, which can degrade the quality of the data and impact the performance of the ML models.

Moreover, the availability of labeled data for supervised learning is often limited, especially for rare or critical events like heart attacks or severe falls. For example, in the prediction of heart attack, there is a scarcity of RF sensing data collected during or before an actual heart attack event. This lack of data makes it challenging to train ML models that can accurately predict the onset of a heart attack and alert a remote healthcare service provider. Similarly, in fall detection applications, there is a limited amount of data that captures the severity of falls, and the subsequent health impact. To address these challenges, more attention is needed towards well-annotated data collection and augmentation approaches. Reliable methods are required for (automated) labeling data under diverse application environments. The impact of factors like data collection duration, sensor specifications including number of RF transmitters/receivers and environmental impact on training of ML models for sensing needs to be studied well [227]. Additionally, to increase the diversity and volume of available data with reliable labels, augmentation techniques like synthetic data generation are gaining interest [228], [229], [43]. The various components in the data synthetic generation process continue to evolve with the aim of capturing the nuances of real-world measurements offering interesting research and development avenues.

B. RF Sensing System Digital Twins

These are virtual replicas of the RF physical system and the environment. Digital twins can be used to optimize the placement and configuration of RF sensors, evaluate the performance of different ML algorithms, and test the robustness and reliability of the RF sensing systems in different conditions [230], [231]. Furthermore, digital twins can enable personalized and adaptive ML models that can learn from the individual's unique characteristics and behaviors, leading to more accurate and reliable RF sensing applications. Digital

TABLE II: Key takeaways in ML-based RF sensing

Application	State-of-the-Art Achievements	Challenges and Future Directions
Localization and Navigation	• Multi-modal fusion of WiFi, UWB, and BLE • Sequence-based approaches for trajectory estimation • Domain adaptation techniques for environment generalization	• Development of edge-optimized lightweight models • Self-supervised learning to reduce training data requirements • Improved robustness to multi-path effects and interference
Occupancy Sensing	• Through-wall detection capabilities • People counting and tracking in dynamic environments • Activity classification with human-artifact handling • Gesture recognition in complex environments	• Advanced domain adaptation for diverse environments • Unsupervised anomaly detection • Real-time processing optimization • Integration of RF sensors with building management systems
Biometric Sensing	• Non-contact vital sign monitoring • Heart rate variability analysis • Breathing pattern detection • Motion artifact compensation	• Multi-modal sensor fusion for improved accuracy • Personalized sensing models • Advanced artifact removal techniques • Multi-subject separation in crowded scenarios

TABLE III: An overview of public RF datasets

Dataset	Application	RF sensor	Data	Reference
WILD-v2	Indoor Localization	Wi-Fi	RSSI, location IDs, AP locations	[205]
WiSig	RF fingerprinting	Wi-Fi	raw IQ samples, processed samples	[206]
-	Activity Recognition	Wi-Fi	Traces	[207]
-	Detecting Social Interactions	BLE	RSSI	[208]
-	Fingerprinting	Wi-Fi (and Magnetic/IMU)	raw data	[209]
-	Activity Recognition	Radar	range-Doppler data	[210]
-	Activity Recognition	Wi-Fi	CSI	[211]
-	Passive Localization and HAR	UWB	CIR	[212]
UTIL	Localization	UWB	TDOA	[213]
H-WILD	Localization	Wi-Fi, UWB	RSSI, CSI, AoA	[214]
-	Activity Recognition	Radar Network	ADC data	[44]
mRI	Pose estimation	Radar (and RGB/Inertial)	Point cloud	[215]
HIBER	2D/3D Pose Estimation	Radar (and RGB)	Multi-view radar heatmaps	[12]
MCD-Gesture	Gesture Recognition	Radar	Raw ADC Data	[216]
HuPR	2D Pose	Radar (and RGB)	Multi-view radar heatmaps	[217]
MMVR	2D Pose/BBox/Seg Estimation	Radar (and RGB-D)	Multi-view radar heatmaps	[218]
MM-Fi	Pose/Position Estimation, Activity Recognition	Radar, Wi-Fi, (and LiDAR, RGB-D)	Point cloud, CSI, images	[219]
RadarEyes	Object Detection, Imaging	Radar, (and LiDAR, RGB)	Point cloud	[220]
-	Vital Sign Monitoring	Radar	Raw ADC Data	[221], [222], [223]
-	Vehicle Occupancy	Bluetooth	RSSI	[224]
K-Radar	Object Detection	Radar	Range, Doppler, Angle Maps	[225]
Eat-Radar	Gesture Recognition	Radar	Range-Doppler	[226]

twins can be used to create continuous interactions of humans and environments, allowing for new healthcare prediction capabilities [232]. It also becomes possible to simulate rare or critical scenarios, like severe falls [16], and generate synthetic data that can be used for training and testing ML models.

Interestingly, the applications of digital twins to RF sensing extend beyond healthcare and can be applied to many other emerging fields, from predicting the performance of autonomous systems under extreme conditions [233], [234], to the reliable detection and classification of unmanned aerial vehicles [235]–[237].

Some challenges in the development of RF sensing system digital twins include the accurate and realistic modeling of the physical systems, the integration of data from various sensors and devices, and the validation and verification of the digital twin models. These challenges will require interdisciplinary collaboration, advanced modeling and simulation techniques, and RF testing and evaluation methods.

C. Robust ML in Interference Dominated Environment

RF sensing in interference-dominated environments necessitates transparent ML designs regarding uncertainty. OOD detection is crucial for reliable ML systems, particularly in such environments [238], [239]. Another aspect to robust ML model is to ensure models have both discrimination (inter-class separability) and separability (intra-class compactness). Approaches such as metric/representation learning [240], [241] are proposed for such objectives. The goal of these methods is to learn an embedding space where similar data points are clustered together, while dissimilar data points are separated, effectively capturing the essence of the data. However, training these frameworks can be time-consuming and may require online data mining. To address this, modifications to the softmax classifier, such as D-softmax, center loss, arc-Face, and SoftTriple loss, have been proposed to alleviate data mining requirements. Additionally, label smoothing and focal loss techniques can be applied to the cross-entropy loss to improve the robustness of ML for RF Sensing models to an under-performing class, noise and prevent overfitting. Another aspect of training ML models for RF Sensing is their ability to handle measurement noise, which can be achieved using noise regularization [242].

Quantifying uncertainty in ML predictions is another important aspect of developing robust artificial intelligence (AI) systems. Techniques such as post-training calibration, Bayesian neural networks, and deep ensembles have been explored to better estimate the uncertainty in model outputs [243]. From a probabilistic perspective, the generalization of ML for RF sensing depends on the support (range of the dataset) and inductive biases (model class performance) of a model. Bayesian deep learning [244] can capture uncertainty in ML for RF Sensing by treating neural network weights as random variables, allowing for the quantification of both aleatoric and epistemic uncertainty. This enables the quantification of uncertainty, allowing for more informed decision-making about when to trust model predictions and handle out-of-distribution data, thereby enabling ML models to fail gracefully in corner cases [245].

D. Edge Constraints

The deployment of RF-based deep learning models is often hindered by their high model complexity, which can result in significant computational resources and energy consumption [246]. This is particularly problematic for edge computing applications, where resources are limited. To address this issue, researchers have proposed various model compression and optimization techniques, such as pruning, quantization, and knowledge distillation [247], [248]. These techniques have been shown to reduce the complexity of RF-based deep learning models while maintaining their accuracy. By leveraging these techniques, RF-based deep learning models can be efficiently deployed on resource-constrained devices with real-time processing.

The dependency of sensors on batteries and their energy consumption limit their lifetime and require frequent maintenance, posing challenges for long-term deployment and sustainability. In [249], deep reinforcement learning was used to design sensing policies by learning energy availability and event patterns. RF energy harvesting offers an alternative power source, thereby extending sensor lifespan and supporting a sustainable sensing solution by reducing the need for battery replacements [250]–[253] . In particular machine learning algorithms can optimize energy harvesting and consumption by, or optimize duty cycling patterns [254], [255]. This leads to smarter, more efficient RF sensor systems capable of supporting a wide range of applications from precision agriculture to smart cities.

E. Privacy-preservation in RF Sensing

When compared to vision based systems, RF sensing paired with ML present multiple inherently privacy-preserving opportunities in a multitude of applications [14], [15], [256], [257]. Moreover, there is a potentially tight coupling between user identity authentication and behavior recognition using RF sensing, given that signal propagation characteristics caused by the human body are exploited [258]. In [259], it was shown that radars powered by ML can identify various individuals using their palmprint. In [248], correlated knowledge distillation was used for human pose estimation in a privacy-preserving way. In [260], a Siamese network-based deep neural network was proposed to increase the similarity among the signals of different behaviors, while maintaining the ability to distinguish among distinct user identities. A smart reflector design with conditional Generative Adversarial Network (GAN) was used in [261] for privacy protection by injecting fake trajectories against eavesdroppers who use FMCW radars for TTW user monitoring. Given the unique TTW RF propagation characteristics, more work is needed to develop sensing approaches that enable preservation of user privacy preferences.

F. New ML Approaches for RF Sensing

In some RF sensing applications, data or training may be distributed across various devices and environment. Federated Learning (FL) is a decentralized approach that enables multiple devices or nodes to collaboratively train a shared ML model on their collective data without sharing the data itself [262]. In [246], FL was used for Wi-Fi sensing by training in parallel at the edge instead of at a central server. In [263], privacy-maintaining person identification models based on FL with radar data were considered. A number of challenges still need to be addressed in RF sensing, since RF data from different devices and environments can be heterogeneous, leading to issues in model convergence and performance [264]. Frequent model updates can result in significant communication overhead, necessitating efficient communication strategies. Moreover, FL models can be vulnerable to attacks and data poisoning, compromising the integrity of the shared model. Robust security measures, like differential privacy, secure multi-party computation, and homomorphic encryption, are being explored to protect FL models and data [265].

At the circuit and device level, ML has been applied for dealing with RF hardware impairments, and also in the form of new neuromorphic architectures. In [266], nonlinear sensing based on RF intermodulation response was considered for vital signs monitoring and user localization. A low-power neuromorphic radar sensing was proposed in [267] that jointly optimizes the analog hardware and the neuromorphic compute. A 4-b-weight Spiking Neural Network (SNN) for extreme-edge radar gesture recognition application was considered in [268] with limited power and die area. An interpretable federated learning approach that employs spiking time-dependent plasticity to train the SNN on the resource-constrained edge for radar gesture recognition was presented in [269]. A further exploration of the suitability of neuromorphic architectures for diverse RF sensing applications would help in understanding the versatility of these architectures in different scenarios. Attention is also required towards hardware-constrained ML algorithmic techniques, such as quantization and pruning, for SNNs to reduce memory and computation requirements that fit embedded sensor applications. The design of neuromorphic processors for SNN acceleration to support diverse RF sensing application requirements is yet another area for future exploration.

Given the black-box nature of many deep learning models, the field of Explainable AI has emerged to provide explanations to ML models and indicate how input data affects the model output. Model explainability tools, such as Saliency Maps [270], GradCam [271], and GradCam++ [272], have been increasingly employed in RF-based sensing applications utilizing deep learning. These techniques enable the visualization and interpretation of model decisions, providing insights

TABLE IV: Emerging applications and approaches in ML for RF sensing

Emerging Applications	Precision Farming, Soil Permittivity Measurement, Terahertz Sensing, Food Quality Inspection, Healthcare Applications, Materials Science, Driver Monitoring
Emerging Methodologies	Federated Learning, Explainable AI, Edge AI, Transparent and Reliable Models, Privacy-Preserving ML, Analog Hardware Optimization, Neuromorphic Computing, Digital Twins
Emerging Techniques	Uncertainty Quantification, Out-of-Distribution Detection, Representation Learning, Noise Regularization, Bayesian Neural Networks, Deep Ensembles, Post-training Calibration

into the complex relationships between RF signals and the physical environment. In RF sensing, explainability tools have been applied to various tasks, such as gesture recognition [273], material classification [274] among others. By leveraging these tools, researchers can develop more transparent and reliable deep learning models for RF sensing applications.

G. ML for Emerging RF Sensing Applications

The integration of RF sensing technologies is transforming agriculture by enhancing precision, efficiency, and sustainability. RF sensing technologies in agriculture provide precise soil data, integrate sensing with communication, and support autonomous operation [275], [276]. Frequency domain and time domain sensing techniques are both employed in RF sensing to achieve high precision and sensitivity in soil permittivity measurements and agriculture applications. Frequency domain sensing involves analyzing the response of the soil to RF signals at different frequencies. On the other hand, time domain sensing involves sending a time-varying RF signal through the soil and analyzing the signal's time-based response [277], [278]. The use of machine learning techniques for soil data analysis is expected to create new opportunities in agriculture, hydrology, and sustainability studies, such as those presented in [279], [280].

Terahertz sensing is an emerging technology for imaging, spectroscopy and localization with wide applications in in food quality inspection, biomedical, and materials science [281]–[283]. Feature-engineered ML methods with THz sensing were used for fruit inspection at a cellular level [284]. The detection and classification of cancer biomarkers using ML methods on time and frequency domain with THz sensing features was considered in [285]. Advanced ML methods integrated into THz systems will open new advances in high-resolution cancer imaging and is a topic of future research.

Another application benefiting from ML-driven RF sensing is in-cabin vital sign monitoring, occupant counting, gesture recognition, and driver monitoring [286], [287]. Accurate detection and counting of occupants within a vehicle are essential for optimizing in-cabin climate control, entertainment systems, and ensuring overall passenger safety. By leveraging RF sensing technologies such as radar, deep learning models like CNN, LSTM and transformers have been proposed to accurately monitor heart rate, respiration rate, and other physiological parameters [288]–[290]. The use of in-vehicle sensing in safety critical applications brings about the need to enhance robustness of these solutions in future in the presence of environmental noise and motion artefacts. Development of privacy-preserving personalized ML models for sensing driver vital signs is another future direction. Besides vehicle in-cabin-sensing, machine learning in automotive radars have been used for driving environment perception to support higher levels of autonomy. This is an active area of research with a number of recent overview articles [287], [291]–[293].

Table IV summarizes some emerging ML-driven RF sensing along with new RF sensing applications. The growth of low-cost RF sensors and opportunistic Wi-Fi use has expanded applications to commercial and diverse human-centric/instrument-centric use cases. To address these nuances and sensor specifications, various emerging ML methods are being explored, as listed in Table IV. We also note that in some of the emerging applications like THz sensing, food quality inspection and driver monitoring listed in Table IV, other modalities like thermal and optical imaging are been actively studied in literature. However, such alternate visible/infrared optical sensing approaches to be beyond the scope of this RF-focused sensing review.

V. Conclusions

We presented an overview of ML techniques in RF sensing that is driving improved performance with greater robustness in device localization, occupancy sensing, activity monitoring and biometric sensing. There is a growing eco-system of applications around these sensing functions benefiting from this enhanced performance. To realize this potential of ML in RF sensing, greater inter-disciplinary collaboration is required across different disciplines: RF sensors, devices and circuits, signal processing, machine learning, and system applications. Collaboration between ML algorithm developers, low-power sensor and processor design engineers will ensure that ML RF sensing solutions can run on resource-constrained edge devices in real time. Another aspect is robustness and explainability of ML-driven RF sensing models in safety-sensitive applications that requires tight interaction of domain experts, sensor engineers, data scientists, and AI regulators. Further, standardization is critical for advancing sensor-based research and applications, particularly in areas where deep learning has shown significant promise. By establishing a common standard for sensor data collection and metadata management, we can ensure interoperability, facilitate data sharing and collaboration, and enable the creation of large-scale datasets that fuel deep learning and generative AI research and applications.

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