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Challenges and opportunities to location independent human activity recognition utilizing Wi-Fi sensing

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ABSTRACT

Wireless sensing has emerged as a dynamic field with diverse applications across smart cities, healthcare, the internet of things (IoT), and virtual reality gaming. This burgeoning area capitalizes on the capacity to detect locations, activities, gestures, and vital signs by assessing their impact on ambient wireless signals. This review critically examines the prevailing challenges within wireless sensing and predicts future research trajectories. Even with the potential for nuanced signal processing facilitated by Wi-Fi propagation, its efficacy is impeded by noise interference in confined areas during transmission and reception. Consequently, this work aims to augment signal processing performance accuracy by delving into the most promising techniques and underexplored methods utilizing channel state information (CSI). Furthermore, the work offers a view into the potential of human activity recognition predicated on CSI properties. The study focusses on exploring location-independent sensing technique based on CSI, discussing relevant considerations and contemporary approaches used in Wi-Fi sensing tasks. The optimal practices in analysis are based on model design, data collection, and result interpretation. The discussions analysis investigates in detail the representative applications and outlines the major considerations of developing human activity recognition human activity recognition (HAR) based on Wi-Fi by analyzing the current critical issues of CSI-based behavior recognition methods and pointing out possible future research directions.

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1. INTRODUCTION

In the era of pervasive connectivity, Wi-Fi sensing emerges as an indispensable technology, wielding transformative influence across multifaceted domains [1]. The ubiquity of Wi-Fi signals facilitates seamless data transmission and serves as an intricate tapestry for understanding and enhancing the world around us. Wi-Fi sensing impacts various sectors in today's era of modern urbanization, improving energy efficiency with intelligent systems and setting the stage for groundbreaking applications that redefine how humans interact with machines. Smart environment designs equipped with different sensors, including radio frequency (RF) sensing capabilities, play an important role in adapting to climate change effects and addressing future energy needs of energy-intensive systems like heating, ventilation, and air-conditioning

(HVAC) [2]. The contemporary landscape of wireless sensing reflects a dynamic convergence of technological advancements, reshaping the paradigms of wireless sensing across various domains [3]. At the forefront of these innovations is the continued evolution of Wi-Fi technology, transcending its conventional role as a communication protocol to emerge as a versatile tool for sensing and environmental monitoring. Modern Wi-Fi systems leverage complex algorithms to extract nuanced information from wireless signals, including the utilization of channel state information (CSI) to discern subtle variations in the wireless channel caused by environmental changes [4], [5]. This development facilitates accurate object tracking and localization within a given environment [6], [7], laying the groundwork for applications in indoor navigation [8], smart homes [9], and industrial automation [10]. This work provides a literature review on the advances in methods empowered Wi-Fi sensing focusing on human activity recognition and movement tracking and indoor localization, and the effects of environment of the sensing ability. Furthermore, the analysis highlights the challenges in the existing literature and discusses the possible future research directions in Wi-Fi-based human sensing assisted by deep learning (DL) techniques.

The synergy between Wi-Fi sensing and machine learning opens avenues for context-aware applications, where the system dynamically responds to changes in its surroundings based on learned patterns. The concept of Wi-Fi sensing assumes a pivotal role, representing the fundamental ability to identify human activities regardless of their spatial. However, within the narrative of wireless sensing and human activity recognition (HAR), an indispensable dimension emerges location independence [11]. However, within the narrative of wireless sensing and HAR, an indispensable dimension emerges: location independence [12]. Therefore, the pursuit of location independence marks a critical consideration at the crossroads of research, propelling investigations beyond the constraints imposed by specific environments [13], [14]. Despite the advancements in location-independent HAR methods using Wi-Fi, there are limitations to this method, such as the requirement of prior training at known locations, which may limit their applicability in real-world scenarios where data collection in specific areas is not feasible.

The challenges associated with CSI-based Wi-Fi sensing datasets, including generality, location dependence, and accurate detection of activities, necessitate innovative solutions for robust and adaptable Wi-Fi sensing systems in diverse real-world scenarios. Therefore, existing methods have limitations to recognize the same activity in different locations with variance hardware and structures. To address these challenges, this work offers an approach that analysis the critical reasons behind the location dependency while striking a balance between performance enhancement and reducing the need for an extensive training dataset through the concept of data adaptation. The primary contributions of this work are summarized as follows:

- To identify patterns and trends in literature of HAR using Wi-Fi to enable matching different environments and removing effects of surroundings from the signal.
- To identify new research gaps and recommend areas by enabling AI models, thus enhancing adaptability to different environments.
- To provide an experimental analysis of CSI HAR utilizing Wi-Fi based sensing with a combination of self-collected data and publicly available datasets.

This work reviews the most recent advancements in all these sub-areas of HAR and analyses the current research trends in device-free, and location independent Wi-Fi sensing. The paper atemps the deep and transfer learning techniques approaches to solve the location dependency of Wi-Fi based sensing and analyzing the suggested methods with pointing possible directions to achieve practical uses of Wi-Fi sensing. The remainder of the paper is organized as follows: section 2 analysis the advancement of Wi-Fi sensing technique followed by the framework of Wi-Fi sensing section to understand the concept of Wi-Fi sensing topology and theory of wireless sensing system. Section 4 elaborates experimental analysis of environmental effects of Wi-Fi sensing system. Finally, section 5 discusses the challenges encountered during the literature review, and the last section concludes the finding of this research.

2. ADVANCEMENT OF Wi-Fi SENSING

In recent years, the domain of wireless sensing technologies has witnessed significant enhancement, with a notable focus on the integration of Wi-Fi-based sensing techniques [15]. Wireless sensing has shown promise in gesture recognition [16], [17], enabling touchless control of devices, interactive gaming, and augmented reality experiences. As this technology continues to evolve, its integration into various domains holds the promise of revolutionizing the way we perceive and interact with environments. The intricacies of RF signals, including reflections and multipath effects, have been meticulously addressed through innovative algorithms, enabling precise extraction of relevant sensor data [18]. Figure 1 illustrates incorporation of machine learning techniques to enable Wi-Fi-based sensing in dynamic environments and optimizing their performance over time.

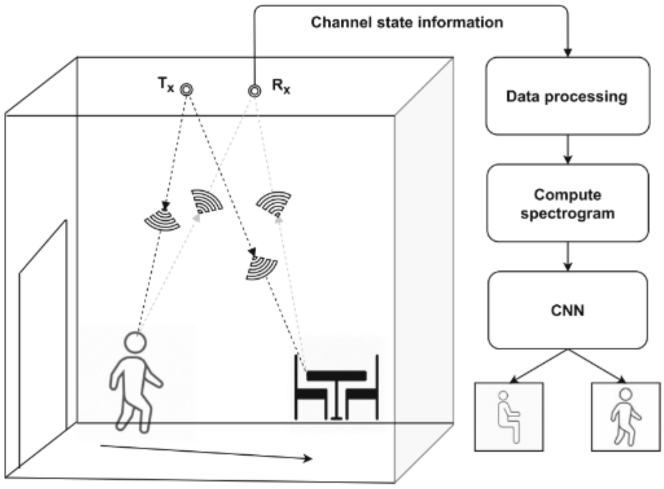


Figure 1. Illustration uses of wireless sensing [19]

The Wi-Fi sensing system comprises three essential modules: the RF sensing and data collection module, the data processing module, and the classification module. The sensing module for Wi-Fi incorporates a Wi-Fi transmitter (Tx) and receiver (Rx) that operate in either the 2.4 or 5 GHz band. The measurement and utilization of properties from the physical layer over wireless links, such as the received signal strength indicator (RSSI) and channel state information (CSI) [20], [21], facilitate the quantification of received Wi-Fi signals. These properties are accessible through modified software and commercial network interface cards (NICs), such as the Atheros 9580 NIC [22], Raspberry Pi [23] and Intel 5300 NIC [24]. While RSSI-based HAR has gained substantial attention due to its ease of acquisition and compatibility with commercial Wi-Fi devices, it needs to provide more coarse-grained information on channel characteristics, hampering its sensing capabilities. In contrast to RSSI-based HAR, CSI-based HAR demonstrates enhanced capabilities, providing reliable recognition for a broader spectrum of behaviors and performing effectively even in intricate environments [25], [26]. However, despite its appealing sensing capacity, CSI-based HAR encounters challenging issues requiring attention. Critical among these challenges is selecting and designing appropriate features, a factor directly influencing the sensing performance. Consequently, numerous efforts have been dedicated to developing diverse signal-processing techniques to address this concern, although feature extraction remains an open and active research problem in this domain.

The attainment of environmental effects holds significance within wireless sensing, constituting a pivotal aspect that enhances the applicability and effectiveness of sensing technologies [27]. The attribute is particularly crucial in scenarios where the deployment of sensors is dynamic or subject to frequent changes in the environment. In recent literature, researchers have proposed several methods to tackle the problem of location dependency in HAR. One approach uses the model to enhance the inter-class difference by extracting inter-class features of different activity samples and improving the generalization ability by pulling intra-class features of the same activity at various locations. The applications of deep learning enables more nuanced and context-aware analyses, contributing to enhanced precision in sensing ability [28], [29]. Furthermore, transfer learning has proven useful in Wi-Fi-based sensing as it allows models trained on specific tasks to be repurposed for related applications, thereby improving performance [30], [31]. This versatility enhances the efficiency of algorithmic frameworks, facilitating the adaptation of Wi-Fi-based sensing systems to diverse and dynamic environments. Collectively, these algorithmic improvements signify a transformative phase in Wi-Fi-based sensing, augmenting the capacity to extract meaningful insights from wireless signals and expanding the applicability of this technology across various domains. The scholarly works have covered a range of topics, including signal processing techniques, hardware requirements, and the effectiveness of CSI in diverse environments [32]. Table 1 lists a brief overview of papers and surveys in the field of Wi-Fi sensing, encapsulating the collective insights and findings from existing literature.

Zhang *et al.* [33] implemented the CSI-PCNH algorithm to achieve location independence by employing a parallel convolutional network model, which combines 3-D convolutional neural network (3DCNN) with channel attention mechanism (CAM) and 2-D convolutional neural network (2DCNN) with long short-term memory (LSTM) to extract activity samples' global and local spatial-temporal features. Experimental results have shown promising outcomes, with average recognition accuracies reaching 91.7% in indoor areas. Alternative attention-based activity recognition systems (AF-ACT) implemented to fuse semantic activity features and temporal features to better characterize activities at different locations [34]. The model uses convolutional neural network (CNN) and convolutional attention modules (CBAM) to extract semantic activity features. Furthermore, the system employs bidirectional gated recurrent units (BGRU) combined with self-attention mechanisms to eliminate temporal characteristics. These features are fused through an attention-based feature module, resulting in improved recognition accuracy. Experimental evaluations have demonstrated the potential of AF-ACT systems, reaching a maximum accuracy of 91.23% in recognizing various activities across different experimental conditions. Table 2 briefly outlines diverse approaches for resolving location dependency, employing various tools, techniques, and algorithms.

Table 1. Insights and advancements in existing literature Wi-Fi sensing reviews and surveys

Ref	Contributions	Methods used	Findings	Limitations
[35]	Mathematical model of CSI based sensing.	Domain-invariant feature extraction with virtual sample generation, Few-shot and Transfer learning	Environment effects encountering new domains using five algorithms.	Limited sensing performance and usability in new domains.
[36]	Analyzing Wi-Fi sensing principles and challenges.	Analyzing the available technology and utilization of ambient Wi-Fi signals for sensing applications	Robustness analyzes functionalities and applications in various industries.	Critical challenges such as environmental effects were not analyzed.
[4]	Review recent progress on Wi-Fi sensing & proposing Sense Fi benchmark.	Machine learning Few-shot learning, and natural language processing (NLP) algorithms.	Deep learning methods are effective for applications.	Data-efficient learning methods should be further explored for Wi-Fi sensing.
[37]	Proposed a dynamic Fresnel zone model for Wi-Fi sensing.	Dynamic Fresnel zone model for Wi-Fi sensing with prototype system.	The system measure receiver's relative motion with high-level accuracy	Location dependency and cross-domain localization was not analyzed.
[38]	Survey of Wi-Fi sensing systems over the past decade.	Categorizes systems into activity recognition, object sensing and localization.	Existing systems face challenges in accuracy and reliability.	Limitations such as location dependencies were not analyzed.
[39]	Exploring Wi-Fi sensing performance and challenges	Recent applications and performance of Wi-Fi sensing.	Wi-Fi sensing divided into dynamic and static categories.	limitations in terms of robustness and practicality.
[40]	Fresnel zone model and CSI-ratio model for device-free sensing.	Fresnel zone model CSI-ratio model	High potential of device-free sensing model using CSI-ratio model has.	Not adequately analyze the main challenges associated with Wi-Fi sensing
[41]	Roadmap of for Wi-Fi sensing integration & standards.	Analyzing Wi-Fi standards to enhance sensing capabilities.	Improve capabilities such as multiple user sensing.	Enhanced methods and challenges were not discussed.
[18]	Model-based human sensing methods and applications.	Describes the CSI framework, models, preprocessing, and applications.	Discussed model- sensing advantages, limitations, & future trends	Requires conducting investigations of boundaries of CSI model limitations.
[3]	Analyse of signal processing techniques and algorithms for improving applications	Signal processing techniques and algorithms for Wi-Fi sensing	Analyzing various applications and challenges including cross-layer integration.	Existing Wi-Fi sensing focuses on human activities, requires expanding to other domains.

Table 2. Location independent benchmarking summary of Wi-Fi based methods

Ref	Methods	Features	Freq GHz	Activities	Acc. %	Insights
[42]	Reinforceme nt learning	Multi-layers algorithm prediction	/	5	97%	Similar activities, RL requires huge training effort
[43]	Dynamic phase vector	dynamic phase vector	5.24	8	95%	Requires multiple receivers of APs, limited range and weak reflection
[44]	CNN, CNN-LSTM	Doppler frequency shift	5.32 Ghz	8	94%	Tested in single location, different positions & requires multiple APs.
[45]	CNN	Commodity real-time manner	5 Ghz	6	97%	Model requires training in some locations to adapt user’s motions.
[1]	CNN	Body velocity pattern	5 Ghz	6	87%	Different people have different body velocity, speed preforming actions.
[46]	LSTM	Activities generative	2,5 GHz	7	95%	Requires more analysis of activities to enable high accuracy.
[33]	2DCNN	Parallel convolutional networks	/	6	91%	Requires activity samples at more training locations

3. Wi-Fi SENSING FRAMEWORK

In the context of Wi-Fi sensing, CSI captures information about the channel's conditions, including signal strength, phase, and frequency response. Integrating CSI into wireless sensing applications introduces a dimension of granularity and precision [47]. Figure 2 depicts the diversity observed in the RSSI and CSI, demonstrating the superior reliability of CSI due to its capacity to account for fluctuations in temperature and humidity. Conversely, RSSI provides only a singular value, making it less robust under unfavorable environmental conditions. The CSI matrix conveys amplitude and phase information for orthogonal frequency division multiplexing (OFDM) subcarriers in the Wi-Fi protocol's physical layer [48]. Wi-Fi standards like 802.11 a/g/b/n/ac/ax are employed in virtual Wi-Fi routers, offering higher data rates through multiple input multiple output (MIMO) and orthogonal frequency division multiplexing (OFDM). These standards operate on 56, 114, and 232 subcarriers, facilitating various bandwidths (20 MHz, 40 MHz, and 80 MHz) at either 2.4 GHz or 5 GHz. The calculation for the optimal received power at the antenna is estimated by (1), considering various parameters, including the transmitted power, signal frequency, distance traveled, and antenna gains.

$$P_{rx} = P_{tx}G_{tx}G_{rx}\left(\frac{c}{4\pi Df}\right)^2 \tag{1}$$

The mathematical representation of CSI is denoted mathematically by (2) as y and x, where y signifies the received signal, x denotes the transmitted signal, and their relationship relies on the CSI matrix data formatted in the frequency domain via OFDM [49].

$$y = Hx + N \tag{1}$$

Equation (2) represents the CSI for OFDM subcarriers derived and incorporated into the complex matrix H [6]. It is important to note that the equation accounts for the presence of channel noise, represented by the variable n, which influences the accuracy of the CSI estimation for each subcarrier. Additionally, MIMO enables multiple channels to increase the transmission rate by inducing a matrix of connection links shown in (3).

$$H_i = \begin{bmatrix} h_i^{11} & h_i^{12} & \dots & h_i^{1N_T} \\ h_i^{21} & h_i^{22} & \dots & h_i^{2N_T} \\ \vdots & \vdots & \vdots & \vdots \\ h_i^{N_R1} & h_i^{N_R2} & \dots & h_i^{N_RN_T} \end{bmatrix} \tag{2}$$

In addition, the receiver extracts the captured signal changes by predicting the original and received data to determine the CSI. The Hi represents the CSI number of the i_{th} subcarriers between the receiver and transmitter antenna. The plotted signal in Figure 3 shows the CSI amplitude of the 64 subcarriers, which makes it very useful for figuring out activities based on Wi-Fi characteristics.

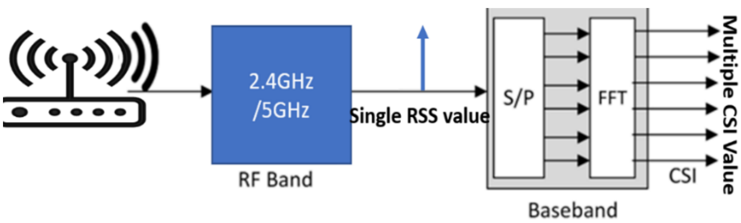


Figure 2. Frequency diversity in RSSI and CSI

The framework for Wi-Fi sensing is rooted in signal processing methodologies and comprises four distinct stages: data collection, signal extraction, signal preprocessing, and activity classifiers, as delineated in Figure 4. The organized approach commences with collecting relevant CSI data, followed by extracting pertinent signals. Subsequently, the signals undergo preprocessing procedures to enhance their quality and relevance for further analysis. The final stage involves the application of activity classifiers, a critical component facilitating the recognition of human activities.

3.1. CSI data collection tools

Hardware tools used for CSI data collection in wireless communication systems encompass various devices, including SDRs [50], WiGig devices [51], and Wi-Fi Network NICs. SDRs such as USRP offer the distinctive advantage of programmable RF signal processing capabilities, enabling versatile capture, and processing of CSI data. The continual enhancements of these tools represent a crucial advancement, affording unparalleled resources for experimentally validating algorithms using Wi-Fi devices. Table 3 records some predominant tools employed for capturing CSI and facilitating advanced analyses in research pursuits.

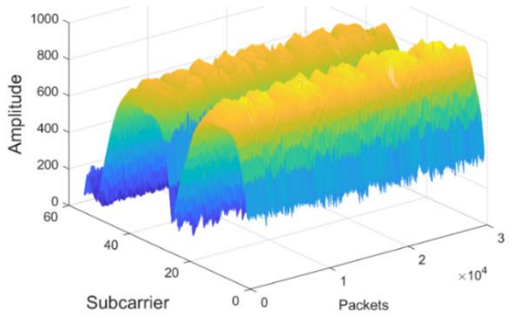


Figure 3. CSI amplitude for 2.4 Ghz/20 MHz bandwidth

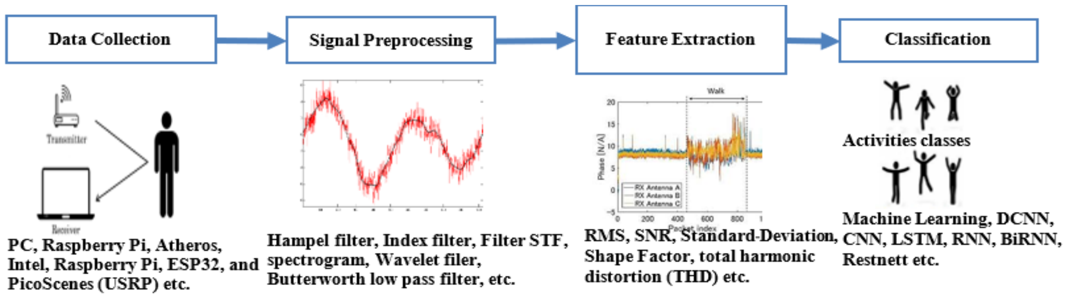


Figure 4. Framework of HAR using CSI

Table 3. List of available CSI hardware benchmarking

Ref.	Tool	Supported Chipsets	Protocol	Feature extraction	Performance
[1]	Linux 802.11n CSI Tool	IWL5300	802.11n	Dynamic time warping for waveform comparisons	Multi-antennas, with high performance.
[22]	Atheros CSI Tool	AR9580, AR9590	802.11n	Various supported PCI and NICs	Available, supported free Linux firmware
[21]	Raspberry pi	BCM4365, 66,39,58,455	802.11ac	Smart scheme for band-width optimization	Precise real-time with open-source Linux community

Furthermore, firmware updates enhance the functionality and performance of these tools by introducing bug fixes, incorporating new features, and improving compatibility with various CSI data collection software frameworks. Researchers have developed supported extraction firmware to extract data from CSI-Wi-Fi signals using tools like OpenWRT [52], Nexmon CSI Extractor, Linux 802.11n CSI Tool [53], Atheros CSI Tool [54], and OpenFWWF CSI Tool. These tools vary in bandwidth range, NSS×NRX, and used applications.

3.2. Signal processing

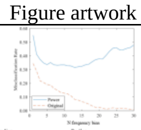
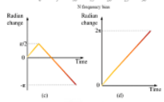
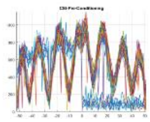
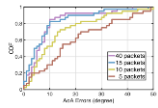
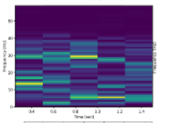
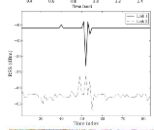
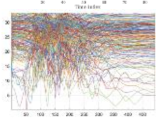
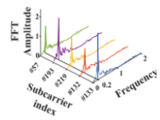
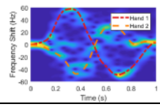
Wi-Fi sensing requires a robust filtering system utilizing and applying different filter methods to mitigate high-frequency noise and constant values arising from multiple-path effects [55]. Signal preprocessing is integral to reading and purifying data for subsequent analysis and modeling. Signal preprocessing encompasses the filtration of outliers, the elimination of noise, the adjustment of phase, and the mitigation of other unwanted factors. Researchers employ various techniques, including low-pass filters, Hampel filters, principal component analysis (PCA), independent component analysis (ICA), discrete wavelet transform (DWT), data interpolation, and phase sanitization, for denoising purposes. By effectively reducing the noise generated through multipath effects and hardware devices, this multifaceted approach ultimately enhances precision in behavior recognition.

3.3. Feature extraction

Researchers employ various methods to extract features that capture key signal aspects indicative of specific activities or behaviors. One commonly utilized approach involves time-domain features, encompassing statistical measures such as mean, standard deviation, and skewness. These metrics offer insights into the signal's central tendencies, variability, and asymmetry, allowing for the characterization of temporal patterns associated with human activities. Frequency-domain features, derived through techniques like the Fourier transform (FT), provide information about the signal's spectral composition. These features are crucial for discerning frequency-specific characteristics that may indicate activities. Additionally, time-frequency features, obtained through methods like short-time Fourier transform (STFT) or wavelet Transform, offer a more detailed understanding of how the signal's frequency content evolves, enabling the discrimination of transient changes in the environment.

Spatial features also play a role in feature extraction, particularly when multiple antennas are involved. Channel impulse response (CIR) characteristics, such as arrival time and amplitude, are extracted to capture spatial information about the signal. Furthermore, phase-related features, which involve analyzing the phase shifts of the signal, contribute valuable information about the spatial characteristics and multipath effects. By combining these time, frequency, and spatial features, researchers aim to construct a feature set that effectively encapsulates the diverse aspects of Wi-Fi CSI signals, enabling robust and accurate recognition of human activities. Table 4 provides an overview of the feature extraction methods employed in CSI-based Wi-Fi systems.

Table 4. Feature extraction methods in CSI-based Wi-Fi systems

Ref	Feature patterns	Pre-processing	Method	Classifier	Accuracy	Figure artwork
[56]	RSSI feature scaling of high variance.	Fingerprints acquisition	RSS	Neural network	66% to 80%	
[57]	Measuring the slope change of the tangent	CSI ratio changes	CSI ratio	CNN	93%	
[21]	Normalized standard of signal strength	DWT	LOS/NLOS	Support vector machines (SVM) recurrent neural network (RNN)	From 83% to 93%	
[58]	Ranging the CSI AoA estimate spectral entropy.	Phase calibration techniques	LPF, Dual Indirect Kalman, DWT	SVM	About 80%	
[59]	Motion image estimation	Sequential Monte Carlo Filtering	Variance	Segmentation algorithms	Error at least 47%	
[60]	The position of person and the fade level	non-Gaussian Kalman and DWT filtering	Skew Laplace Model	Clustering algorithm	Up to 86%	
[61]	Compute power spectral density	LPF	LoS and nLoS CSI	SVM	93%	
[62]	FFT-based	Moving Average Filter	CSI	/	92%	
[1]	Spatial feature extraction with time-frequency analysis	Quasi-static offsets Convo-filters	CSI ratio	CNN	92.7%	

3.4. Classification methods

HAR using CSI has seen notable advancements, encompassing a range of machine learning methods. Traditional approaches, including support vector machines (SVM) [63], random forests (RFs) [64], and k-nearest neighbor (KNN) [65], leverage pattern recognition to classify activities based on features derived from CSI signals. These algorithms have distinguished gestures, movements, and interactions within sensing environments. Integrating deep learning methodologies has elevated CSI-based HAR accuracy. CNNs and RNNs are pivotal in capturing intricate patterns and temporal dependencies within CSI data [38]. Their capacity to autonomously learn hierarchical features from raw CSI signals has proven effective in discerning complex human activities. Moreover, advanced transfer learning TL techniques have emerged, involving pre-trained models on extensive datasets for generic HAR [35]. These models are subsequently fine-tuned for specific CSI applications, enhancing adaptability across diverse sensing environments. Table 5 provides a list and description of existing deep-learning approaches utilized in Wi-Fi sensing.

Table 5. Existing deep-learning approaches for Wi-Fi sensing

Reference	Task	Classifier	Platform	Learning type	Limitations
[66]	HAR	LSTM	Intel 5300 NIC	Supervised learning	Vulnerable to vanishing gradient problem in capturing long-term dependencies sequences.
WiVi [67]	HAR	CNN	Atheros CSI Tool	Supervised learning	Struggle with classifying activities that have subtle variations or involve complex motion patterns.
DeepSeg [68]	HAR	CNN	Intel 5300 NIC	Supervised learning	Limited context understanding, may not capture finer-grained variations in activities
[69]	HAR	CNN-LSTM	Intel 5300 NIC	Supervised learning	Sensitive to sequence length variations, challenges in handling concurrent & overlap activities, reliance on labeled data quality.
[21]	HAR	LSTM	Nexmon Tool	Supervised learning	Prone to vanishing gradient, may struggle with capturing long-term dependencies.
[55]	HAR	CNN	Nexmon Tool	Supervised learning	Vulnerable to noise in wireless signal data, require substantial data for robust generalization.
[1]	Gesture Recognition	CNN-GRU	Intel 5300 NIC	Supervised learning	Simplified gating limit capturing complex dependencies, potential sensitivity to data quality.
WiONE [70]	HAR	CNN	Intel 5300 NIC	Few-shot learning	Limited availability of samples during few-shot adaptation, potential challenges in handling novel classes.
[42]	HAR	CNN, RNN, LSTM	Intel 5300 NIC	Supervised learning	Each sub-approach's limitations apply; RNNs and LSTMs might face vanishing gradient, CNNs might lack sequence modeling.
THAT [71]	HAR	Transformers	Intel 5300 NIC	Supervised learning	High computational demands, sensitive to hyperparameters, might struggle with capturing local temporal dependencies.
WiGr [16]	Gesture recognition	CNN-LSTM	Intel 5300 NIC	Supervised learning	Sensitive to sequence length variations, might not capture fine-grained variations in gestures.
[72]	HAR	CNN, GAN	Atheros CSI Tool	Semi-supervised learning	GAN stability issues, potential mode collapse, sensitivity to quality of pseudo-labeled data.
CAUTION [73]	Human Identification	CNN	Atheros CSI Tool	Few-shot learning	Limited labeled samples during adaptation, risk of overfitting to the few-shot set.
WiGRUNT [74]	Gesture recognition	CNN Attention	Intel 5300 NIC	Supervised learning	Attention mechanism's sensitivity to noise, potential reliance on specific attention patterns.
[75]	HAR	CNN	Atheros CSI Tool	Supervised learning	Potential challenges in handling diverse activities, reliance on labeled data for various activities.
AirFi [76]	Gesture Recognition	CNN-Multilayer perceptron (MLP)	Atheros CSI Tool	Transfer learning	Success of TL, influenced by source & target domains' similarities require retraining.

3.4. Environmental effects on Wi-Fi signals

The CSI estimates the amplitude and phases manipulated by the paths and experiences the number of amplitudes and phase shifts. Hence, the CSI entry corresponds to the channel frequency response, as (4) indicates [6].

$$h(f) = \sum_{l=1}^{N} \alpha_l exp^{-j2\pi f\tau_l} \quad (3)$$

Additionally, scattering occurs when the signal encounters obstacles, causing further signal distortion and multipath propagation. The attenuation is influenced by the wall material's properties and the transmitted signal's frequency [77]. Equation (5) is commonly used to model the received signal power and understand these factors' impact.

$$P_{rx} = \frac{P_{tx} * G_{tx} * G_{rx} * \lambda^2}{4\pi D^2 L} \quad (4)$$

In addition to the path loss exponent captures the effects of signal attenuation caused by factors such as wall characteristics and scattering. The path loss exponent captures the effects of signal attenuation caused by factors such as wall characteristics and scattering [1]. The received gain can be represented by (6):

$$G_{rx} = \frac{\text{Power density directed}}{\text{Power density } isotropic} = \frac{A_{\text{sphere}}}{A_{\text{ont}}} = \frac{4\pi R^2}{A_{\text{ant}}} \quad (5)$$

where

$$\mathrm{A_{ext}} \approx \theta_{\mathrm{Az}} \cdot \theta_{\mathrm{EL}} \approx \frac{\mathrm{R}\lambda}{\mathrm{b}} \cdot \frac{\mathrm{R}\lambda}{\mathrm{h}} \quad (6)$$

$$G_{rx} = \frac{4\pi}{2/2 \cdot \pi / h} \approx \frac{4\pi A}{\lambda^2} \Rightarrow A = \frac{G_r \lambda^2}{4\pi} \quad (7)$$

$$Thus, \mathrm{P_r} = \frac{\mathrm{G_t G_r} \lambda^2 \sigma \mathrm{F}}{(4\pi)^3 \mathrm{R}^4 \mathrm{L}} \quad (8)$$

Equations (6)-(9) demonstrates the area A effects in the signal covered by Wi-Fi transmitted power P_{tx} with transmitting gain G_{tx} in radiation cross section measured by σ, and propagation factor F. The range of propagation R with losses of strength L varies between transmitter and receiver in different locations. Moreover, the equation appears that F is the factor of environmental effect on that received signal illustrated in Figure 5.

Moreover, the performance of CSI-based human activity recognition systems heavily relies on the quality and consistency of the Wi-Fi signals, which can degrade in environments with complex layouts or dense infrastructures. For instance, in environments with multiple rooms, corridors, or floors, Wi-Fi signals may experience reflections, diffraction, and multipath effects differently at each location, leading to inconsistencies in the measured CSI. Consequently, the models trained on CSI data collected from one location may not generalize well to other locations within the same environment, limiting the robustness and reliability of the human activity recognition system.

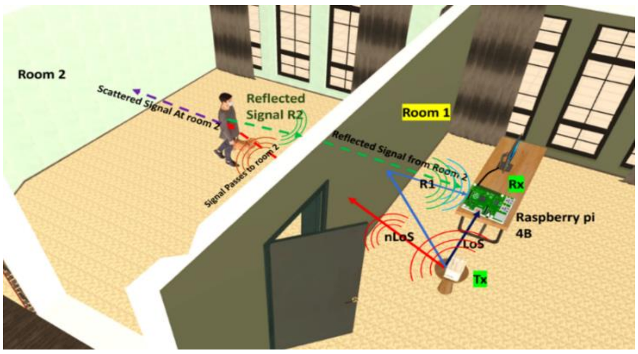


Figure 5. Wall effects on the propagation of CSI subcarriers in Wi-Fi signals

The unidirectional or spherical propagation of Wi-Fi signals also significantly affects CSI-based human activity recognition systems, contributing to location dependency issues. Figure. 6 illustrates the segmentation of the signal in a spherical manner, depicting how the signal strength varies across different segments at varying distances from the transmitter. In a real-world scenario, this spherical propagation pattern means that the signal strength attenuates as distance from the transmitter increases, leading to variations in CSI measurements even within a relatively small physical area. This uneven distribution of signal strength across different segments introduces challenges in accurately capturing the CSI measurements, particularly when deploying Wi-Fi devices in large or irregularly shaped environments. Consequently, the CSI data collected from different locations within the same environment may exhibit varying signal strengths and propagation patterns, further exacerbating the location dependency issues in CSI-based human activity recognition systems.

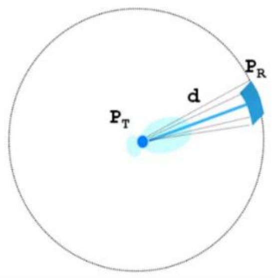


Figure 6. The propagation phenomenon of MIMO signals

4. EXPERIMENTAL ANALYSIS OF ENVIRONMENTAL EFFECTS OF Wi-Fi SENSING

4.1. Physical signal influence

The physical form of the signal is influenced by various factors, such as multipath fading, where the signal takes multiple paths to reach the receiver due to reflections, diffractions, and scattering. distortions alter the amplitude and phase characteristics of the received signal, subsequently affecting CSI. Signal polarization plays a role in CSI as well in varying signal attenuation, reflection, and scattering levels, impacting the quality and reliability of CSI measurements. The evaluation of Wi-Fi sensing methods for CSI analysis reveals the effectiveness of different techniques in extracting valuable information about the environment, objects, and human activities. CSI analysis involves the examination of variations in CSI caused by reflections, diffractions, and scattering, which allows for detecting the presence of objects or people. Researchers commonly employ machine learning algorithms and signal processing techniques to analyze CSI data. Doppler shift analysis, on the other hand, focuses on the changes in the frequency of the received signal due to the motion of objects or people, enabling the detection and tracking of movement and activities. We emphasize the pivotal aspect of location independence while conducting an empirical analysis of studies on Wi-Fi sensing in Table 6. The table notably covered a spectrum of methodologies, encompassing CSI-based sensing mechanisms and the exploration of Wi-Fi signals for human motion tracking. The selected works addressed inherent challenges such as robustness and the impact of location on the efficacy of Wi-Fi-based sensing systems.

Table 6. Location independence in Wi-Fi-based sensing, encompassing methods, accuracy, and challenges

Ref	Method	Classifier	No. of activates	No. of locations	Accuracy%	Limitation
[1]	Doppler frequency domains	Hybrid RNN-CNN	6	4	Cross-domain 82.6%	Systems require explicit adaptation efforts to new domains
[14]	CSI Amplitude	CNN-LSTM Meta learning	4	24	over 90%	Large-scale sensing is labor-intensive and time-consuming
[78]	CSI Amplitude	CNN with Bi-GRU & self-attention	8	12	Up to 91%	Different characteristics of same activity at different locations
[33]	CSI Amplitude	3DCNN	6	22	Up to 90%	Computational complexity, risk of overfitting
[79]	CSI Amplitude	CNN with GAN	3	3	Up to 76%	Labor-intensive training instability, and sensitive to hyperparameters
[42]	CSI Amplitude	2D-CNN with RL	5	/	82% to 92%	Handling partial observability & RL complexity
[46]	CSI Amplitude	Cascaded logical LSTM	8	5	Up to 95%	Requires intensive analyses of activities to achieve high accuracy.
[80]	Doppler shift of CSI	Convolutional based	5	3	/	Effected to the complexity of activities, orientation, and speed.

4.2. Frequencies effects

A comparative analysis between the 2.4 GHz and 5 GHz frequency bands reveals that lower frequencies exhibit superior coverage, penetration through solid obstacles, and wider-angle detection, making them more suitable for HAR. In addition, the wavelength λ of the Wi-Fi signal, measured in meters, and losses unrelated to the propagation process dynamically influence the transmission gain of Wi-Fi signals in LoS scenarios. To better understand the signal power attenuation, a plotted curve in Figure 7 illustrates the approximate loss of signal power for both 2.4 GHz, 5 GHz, and 5.7 GHz in the free space path in the LoS region.

The experiment conducted further investigations in buildings with varying wall compositions. Specifically, we focused on three building materials: 8-inch-thick concrete walls, 5-inch walls supported by steel frames with sheetrock, and tinted glass. Furthermore, the researchers conducted experiments in an open, unobstructed environment. Figure 8 presents the model's performance across different building materials. The detection rate represents the proportion of experiments in which the model accurately decoded the activities. It demonstrates the model's effectiveness in detecting human presence and accurately identifying activities across a range of indoor building materials, including tinted glass, solid wood doors, 5-inch walls, and, to a notable extent, 8-inch concrete walls. As expected, the thickness and density of the obstructing materials directly influence the sensing capability to capture reflections from behind them, with thicker and denser materials presenting greater challenges.

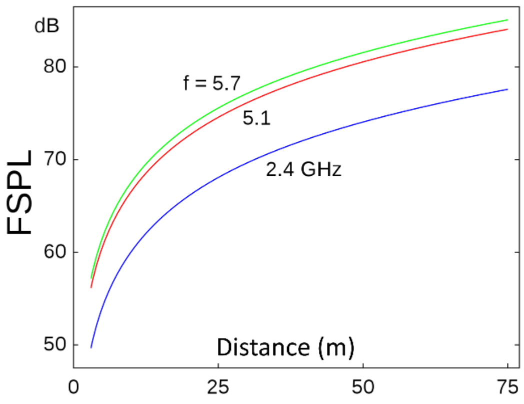


Figure 7. Impact of frequency on free-space path loss (FSPL) in Wi-Fi sensing

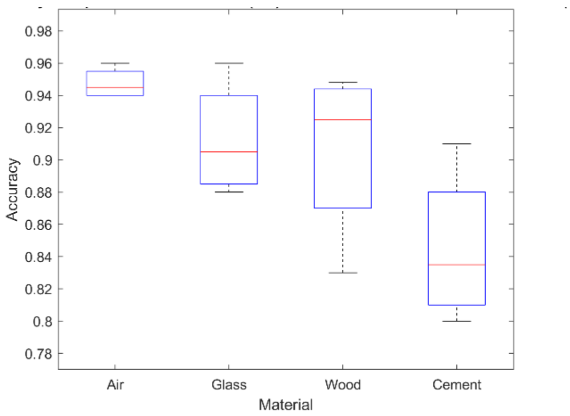


Figure 8. Different material detection accuracy at position 1 with 2.4 GHz frequency

The dataset for the experimental evaluation was obtained using the Nexmon CSI extraction tool on a Raspberry Pi 4B in high-throughput mode with an 80 MHz bandwidth. CSI samples provided complex-valued channel data from 242 subcarriers (80 MHz) and 56 subchannels (20 MHz) for each antenna pair. The study details the data acquisition process and hardware configuration, using the Broadcom BCM43455c0 NIC with the Raspberry Pi 4B as the receiver and a TP-Link AC1350 router as the transmitter. Both devices, running Linux version 5.10.92 and Nexmon, support IEEE 802.11n/ac standards and multi-user MIMO, offering 20 MHz, 40 MHz, and 80 MHz bandwidths within a dual-band frequency spectrum. Figure 9 illustrates the experimental setup for data collection, detailing the arrangement and connectivity of the Raspberry Pi 4B receiver and TP-Link AC1350 router transmitter in the test environment.

Figure 9. Data collection process

As humans engage in various activities within the monitored space, the Wi-Fi signals experience alterations due to the presence and movement of the human body. The receiver nodes then extract the CSI data from the received signals, which serves as the foundation for subsequent data processing and feature extraction. The two-node Wi-Fi sensing system offers a non-intrusive and scalable approach to human activity recognition, leveraging the ubiquity of Wi-Fi infrastructure in modern environments.

4.4. Impact of dataset rate

It is important to note that there is a potential linear relationship between the size of the training dataset and computational efficiency. As the training set grows, the computational demand on the algorithm increases, potentially affecting its efficiency. Balancing these aspects becomes crucial in optimizing algorithmic performance. The number of samples in the dataset is also a core factor in capturing a clear detailed representation of each activity, contributing to improving accuracy, as shown in Figure 10. However, the computational cost of processing many samples will impact the algorithm's efficiency.

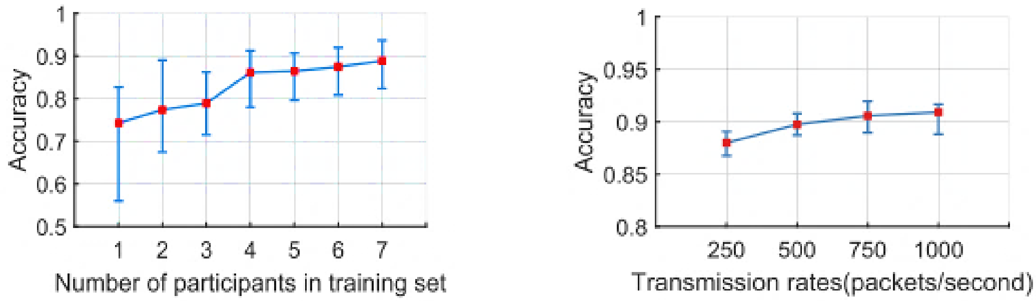


Figure 10. Illustration depicting the impact of the number of training datasets and transmission data rate on accuracy [1]

Additionally, the number of transmitters (Tx) and receivers (Rx) in the communication system directly influences the quality and quantity of CSI data available for activity recognition. Increased Tx and Rx enhance the granularity of CSI measurements, potentially leading to more accurate recognition of subtle human movements. Furthermore, the effects of different individuals and the number of locations on algorithmic performance are notable considerations. Variations in how different individuals perform activities and the diverse environments across multiple locations introduce challenges in achieving precise classification. Robust algorithms should demonstrate adaptability to other individuals and locations, ensuring generalization beyond specific scenarios. Striking a balance between adaptability and specificity is crucial in addressing the challenges of diverse human behaviors and environmental contexts.

HAR advancement and Computational efficiency

To rigorously assess the evaluation and robustness of proposed models, we applied publicly available datasets [21], [55], [80], and self-collected datasets. The considered methods encompass LSTM, CNN+RL, CNN with generative adversarial network (CNN+GAN), CNN with (CNN+Bi-GRU+Attention), and meta-learning with CNN-LSTM. The comparison revolves around the trade-off between computational efficiency and accuracy between these algorithms. The LSTM method leverages memory retention capabilities, while CNN+RL exploits reinforcement learning for dynamic adaptation. CNN+GAN introduces a generative adversarial approach, and CNN+Bi-GRU+Attention incorporates bidirectional processing and self-attention for context awareness. Meta-learning with CNN-LSTM combines the strengths of both CNN and LSTM. Achieving a harmonious balance between computational efficiency and accuracy is paramount, as it ensures the practical applicability of these methods in real-world scenarios, particularly in the challenging domain of CSI-based. Figure 11 illustrates the computational efficiency and accuracy across diverse locations for the proposed algorithms in CSI-based HAR.

The RL paradigm requires more epochs to learn new features due to its reliance on trial-and-error interactions with the environment. In contrast to seq2seq algorithms like LSTM and CNN, which focus on capturing temporal dependencies and spatial patterns, RL emphasizes learning optimal decision-making strategies through repeated interactions, making it particularly suited for dynamic environments with evolving features. The pursuit of interpretability aligns with the broader ethos of responsible and ethical artificial intelligence deployment, ensuring that the inner workings of these algorithms remain accessible and understandable to various stakeholders. Figure 12 shows that LSTM and algorithms exhibit lower interpretability scores due to their inherent complexity and intricate architectures. The sequential nature of LSTM, designed for capturing long-term dependencies, makes it challenging to discern the specific features and patterns driving predictions. In contrast, algorithms with superficial structures or those explicitly incorporating interpretable components, such as attention mechanisms, offer precise insights into the decision-making process, contributing to higher interpretability scores.

The evaluation encompasses different locations, acknowledging the impact of environmental variability on algorithmic performance linked to several critical parameters, each of which influences their accuracy and efficiency. Primarily, the number of activities undertaken within a dataset poses a notable impact. A higher diversity of activities requires algorithms to possess robust discriminatory capabilities, ensuring accurate recognition across a spectrum of human movements. Algorithms capable of adapting to a broad range of activities exhibit enhanced accuracy in recognizing different actions, thereby underscoring the importance of datasets. The efficacy of the considered algorithms in CSI HAR is reflected in their robustness to environmental changes, showcasing their adaptability and reliability across diverse scenarios and varying conditions, as shown in Figure 13.

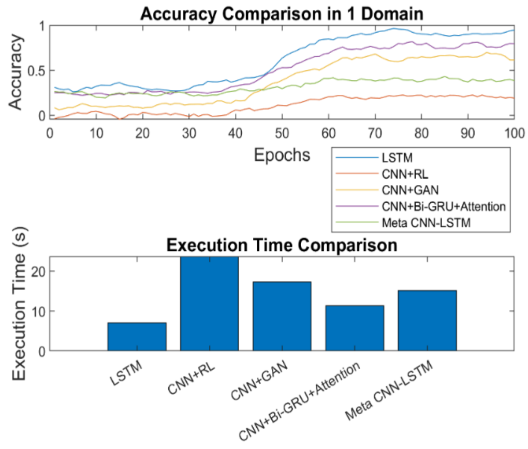


Figure 11. Comparative analysis of computational efficiency and accuracy for listed algorithms in single location domain

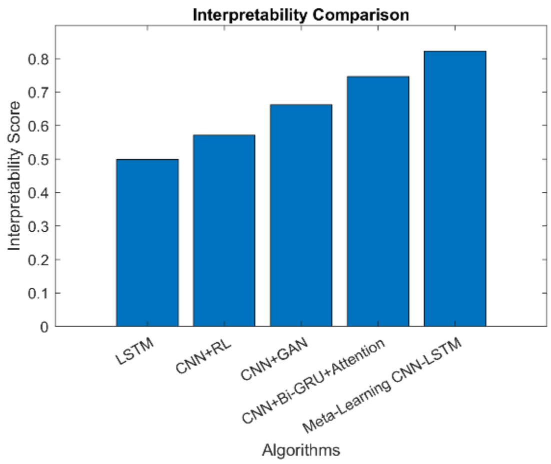


Figure 12. Comparative interpretability scores of algorithms in CSI-based HAR using Wi-Fi

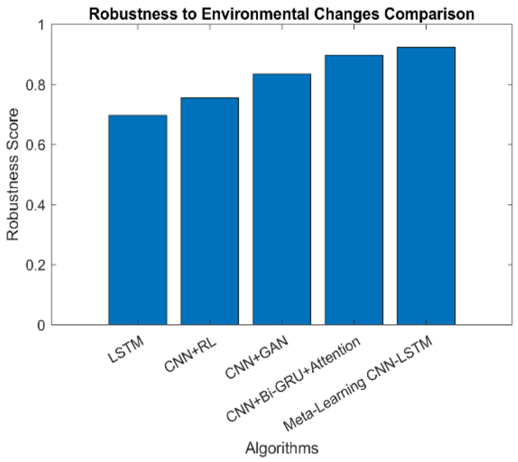


Figure 13. Comparable robustness scores of modules in CSI-based HAR resilience to environmental variations

4.5. Deep learning benchmarks in Wi-Fi sensing

The choice of model architecture plays a crucial role in determining the models' performance in this study. The models investigated encompass various approaches, including SVM, NB, GRU, LSTM, bidirectional long short-term memory neural network (BiLSTM), attention mechanism, MLP, CNN, vision transformers (ViT), CCT, and SWIN transformers. Each model brings its unique characteristics and capabilities to the table, and their performances on the given task are assessed based on their respective architectures and implementations. The models investigated in this study include MLP, CNN, ResNet with different depths, RNN, GRU, LSTM, Bi-LSTM, CNN, and ViT and CCT. The number of layers characterizes each model's architecture, and the experimental procedures provide specific design details. The study utilizes four datasets, which [21], [55], [80], and self-collected datasets. To facilitate comparison, the study visualizes the results in Figure 14, leading to several key observations. MLP, CNN-5, GRU, LSTM, and ViT demonstrate good performance across all benchmark datasets, suggesting their suitability as feature extractors for Wi-Fi CSI data.

MLP, GRU, and CNN consistently exhibit stable and superior performance compared to other models, while also having fewer parameters and lower computational complexity. Furthermore, the study reveals that transformer architecture, specifically ViT, does not operate satisfactorily when the training dataset size is inadequate, or the task is difficult. Additionally, the study highlights that no single model consistently performs well across all datasets.

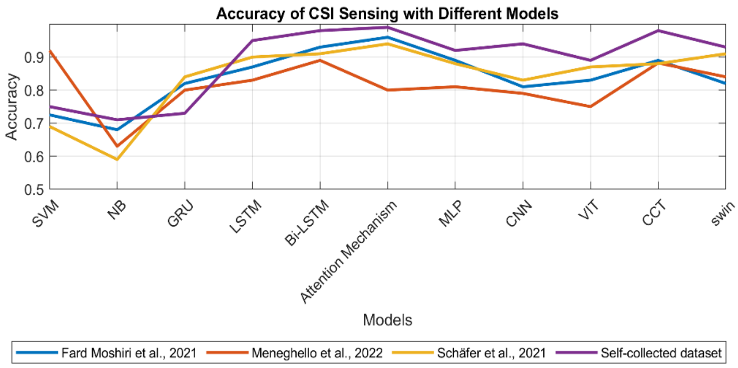


Figure 14. Comparative performance analysis across four distinct dataset scenarios

4.6. Wi-Fi based free environment localization

Understanding and analyzing complex human activities in analytics can be complicated for several reasons. First, human can do same activity activities with variation in motion patterns, timings, and postures. This complexity makes it challenging to detect and classify activities using traditional methods accurately. Furthermore, amplitude and phase characteristics are often considered exclusive factors to enhance the accuracy of indoor localization in complicated indoor environments. Table 7 summarizes localization methods based on the RSSI and CSI. The table categorizes indoor localization into three types: i) amplitude-based, ii) phase-based, and iii) a combination of both amplitude and phase of CSI. In indoor localization.

Table 7. Recent studies on localization and fingerprinting using Wi-Fi technology

Ref.	Method	Classifier	Tool	Freq GHz	Localization Method	Real time	Accuracy error	Performance and Limitations
[81]	CSI-Amplitude	AdaBoost	Intel NIC	5	Multi-user Localization	×	~0.8m-1.1m	Limitations in highly dynamic environments
[31]	CSI Phase	Meta learning	Intel NIC	x	Device-free localization	×	~1.3m	Requires extensive offline training
[82]	CSI-Phase Calibration	SSIM-based Augmentation	x	x	Device-free localization	×	~2.4m	Not suitable for dynamic environments or with obstacles
[83]	CSI amplitude and phase	AdaptDNN	Intel 5300 NIC	5	Device-free localization	×	~0.61m	Location-dependent limitations and requires training
[84]	CSI amplitude and phase	Multilayer extreme learning machine (ML-ELM)	Intel 5300 NIC	5Ghz	Device-free localization	✓	~1.1	Requires large training data and may vary by location
[23]	CSI Amplitude	Untrained	Raspberry pi 4B	5	Device-free localization	✓	~0.9m	Provides dynamic environmental localization using CSI amplitude with untrained model.

5. BARRIERS OF LOCATION-BASED SENSING WITH Wi-Fi

The significance of location independence lies in its capacity to elevate the flexibility and scope of wireless sensing technologies, foster their broader integration into various domains, and optimize their potential impact. Besides, achieving location dependency in Wi-Fi-based systems, whether through pattern-based or model-based approaches, entails several challenges. In the pattern-based paradigm, the variability in signal patterns influenced by environmental factors poses a challenge [83]. In the model-based approach, generalization across diverse backgrounds presents a substantial hurdle, demanding a balance between overfitting and underfitting [46]. Furthermore, acquiring and labeling extensive datasets that represent various locations is resource-intensive, and ensuring the real-time adaptation of models to dynamic changes in Wi-Fi signal patterns remains a challenge.

Addressing these challenges requires development of a systems that adapt to diverse environments without the need for extensive retraining or sample collection. Techniques such as CNNs and RNNs, two popular deep learning architectures, face challenges adapting to the location independence challenge in the Wi-Fi sense. CNNs are known for their ability to extract spatial features effectively [19], [72]. However, in the context of Wi-Fi signals, the spatial characteristics can vary across different locations. Variations in signal strength, multipath effects, and obstacles introduce spatial variability that can affect the performance of CNNs in recognizing activities across different environments. On the other hand, RNNs model sequential data and capture temporal dependencies [21], [55]. While RNNs can capture the temporal dynamics of Wi-Fi signals, they need help with longer sequences and suffer from the vanishing or exploding gradient problem. Additionally, CNNs and RNNs require labeled training data to learn discriminative features and generalize well. Collecting labeled data from various locations can be challenging and time-consuming.

Moreover, to address these challenges, current studies are exploring alternative architectures and techniques. For example, researchers employ attention mechanisms to focus on informative regions or time steps in the data, enhancing the models' ability to capture relevant features across different locations [85]. Researchers are also investigating transfer learning and domain adaptation techniques to leverage pre-trained models from one location and adapt them to new environments [4], [35]. However, one limitation is that the source and target domains should share some similarities for effective transfer. If the variations between locations are too, the transferred knowledge is applicable, and the model's performance improves. Additionally, meta-learning and few-shot learning are promising approaches for location-independent Wi-Fi sensing. They aim to develop models that quickly adapt to new environments with minimal training data [14], [31]. However, meta-learning requires a diverse set of meta-training settings that adequately represent the target environments [14]. In addition to the limitation of few-shot learning is the reliance on accurate and semantic representations [86]. Furthermore, zero-shot learning needs help to recognize activities not encountered during training or exhibiting variations across different areas. Researchers are exploring new techniques, such as RL and graph neural networks, reinforcement learning, or hybrid architectures, to address the limitations of existing methods [42]. However, these techniques still have their limits and challenges and require additional computational resources, extensive fine-tuning, or specialized data preprocessing methods.

6. CONCLUSION

In conclusion, this paper offers a comprehensive and in-depth analysis of contemporary HAR methods combined with localization techniques utilizing CSI. It presents a meticulous survey of relevant research, shedding light on the fundamental principles behind CSI-based behavior recognition. The study introduces models that effectively leverage CSI for HAR, addressing the issue of location dependency by incorporating insights from deep learning approaches. These models prioritize features that have versatile applications across different locations. Furthermore, the article discusses considerations regarding factors that impact HAR and provides clear categorizations of models, making the content accessible to a wide range of readers. The study explores various techniques, including the incorporation of additional testing locations, which illuminates the potential for enhancing the precision and capabilities of Wi-Fi sensing systems. In a departure from previous efforts, this review identifies areas that require further evaluation, specifically outlining methods, approaches, and algorithms that warrant scrutiny to guide future researchers entering this domain. Moreover, the work examines specific applications, facilitating in-depth discussions on recognition techniques and performance assessment. Future advancements in location-independent Wi-Fi sensing will benefit from incorporating transfer learning techniques. Transfer learning offers a promising avenue, especially for pre-training on large datasets or related tasks. Researchers can explore methods such as domain adaptation to transfer knowledge gained from one Wi-Fi environment to another, fostering improved generalization across diverse locations.

Furthermore, exploring unsupervised learning techniques, including self-supervised learning will contribute to overcoming limitations associated with labeled data scarcity. By designing innovative self-supervised tasks based on the inherent structure of Wi-Fi data, models will learn meaningful representations without explicit supervision. Additionally, exploring the adaptation of reinforcement learning frameworks for Wi-Fi sensing tasks opens a compelling opportunity. This allows agents to acquire optimal strategies for location-independent sensing by interacting with their environment. The future directions underscore the evolving landscape of Wi-Fi sensing research, emphasizing a multi-faceted approach toward achieving location independence and anticipating emerging technological trends.

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