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WiFi-based human activity recognition through wall using deep learning

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ABSTRACT

Wireless sensing is a promising method that integrates wireless mechanisms with strong sensing capabilities. The current focus of using WiFi Channel State Information (CSI) for human activity recognition (HAR) is the line-of-sight (LoS) path, which is mainly affected by human activities and is very sensitive to environmental changes. However, the signal on non-line-of-sight (nLoS) paths, particularly those passing through walls, is unpredictable due to the weak reflected signals destroyed by the wall. This work proposes a method to achieve high-accuracy wireless sensing based on CSI behavior recognition with low-cost resources by showing through-wall and wider-angle predictions using WiFi signals. The technique utilizes MIMO to exploit multipath propagation and increase the capability of signal transmission and receiving antennas. The signals captured by the multi-antenna are delivered into parallel channels with different spatial signatures. An RPi 4 B is attached to an ALFA AWUS 1900 adapter utilizing Nexmon firmware monitors and extracts CSI data with flexible C-based firmware for Broadcom/Cypress WiFi chips. Preprocessing techniques based on CSI are applied to improve the feature extraction from the amplitude data in an indoor environment. Furthermore, a deep learning algorithm based on RNN with an LSTM algorithm is used to classify the activity instances indoors, achieving up to 97.5% accuracy in classifying seven activities. The experiment shows CSI can achieve accurate wireless sensing in nLoS scenarios with extended antennas and a deep learning approach.

1. Introduction

Human Activity Recognition (HAR) has gained considerable attention in recent years due to its potential applications in various domains, such as surveillance, healthcare, and smart environments. The concept of occupying the ability to perceive objects beyond solid barriers has captivated the human imagination for decades. Recent advancements in signal processing with artificial intelligence (AI) have facilitated the prediction of human activities by leveraging the available WiFi signals for HAR(K. Wang et al., 2019). Traditional HAR techniques heavily rely on direct line-of-sight observations or wearable sensors, which may be intrusive or limited in their capabilities. However, advancements in wireless communication technologies, specifically the Channel State Information (CSI) obtained from WiFi signals, have opened up new possibilities for non-intrusive HAR approaches. WiFi signals propagate through obstacles such as walls, furniture, and doors without requiring a line of sight LoS, enabling detection over more significant regions (Wu et al., 2019). Moreover, recent progress in Multiple-Input Multiple-Output MIMO communications and the utilization of WiFi signals presents a promising avenue for realizing this aspiration (see Table 1).

The underlying concept of seeing through obstacles shares similarities with radar and sonar imaging techniques and garners significant attention within this domain (Z. Li et al., 2023). By encountering a non-metallic wall, a portion of the RF signal penetrates the wall, interacts with objects and human subjects within a closed room, and returns with a distinctive imprint of the room's contents, simplified in Fig. 1. Classifying the activity concealed behind the wall becomes possible by capturing and analyzing these reflected signals (Chen et al., 2022). However, human sensing through a wall using WiFi encounters challenges, including technical limitations such as signal attenuation (Sun, 2019), multipath interference (Soltanaghaei et al., 2018), signal noise, environmental factors including wall composition (Depatla and Mostofi, 2018), dynamic environments (H. Li et al., 2020a,b), and privacy concerns and ethical considerations. Addressing these challenges is crucial for the advancement of the field. Robust algorithms, models, and frameworks are needed to mitigate signal degradation (Xie et al., 2023),

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and adapt to dynamic environments. Overcoming these challenges will unlock the full potential of human sensing through walls using WiFi for various applications.

By leveraging the unique characteristics of WiFi signals and their interaction with the environment, detecting and classifying human activities without the need for visual line-of-sight becomes possible. While numerous CSI and machine learning-based algorithms have been proposed to accurately identify and quantify individuals within each coverage area of WiFi sensing, the practical limitations of network interface cards (NIC) persist due to inherent physical transmission effects. Nonetheless, a significant challenge remains due to WiFi signals' limited range and penetration capabilities, particularly in scenarios where physical barriers impede signal propagation, resulting in signal degradation and restricting connectivity. This work develops see-through-wall technology with low bandwidth, power consumption, compact size, and accessibility. Additionally, the primary objective of this work is to examine the feasibility of harnessing WiFi signals and advancements in MIMO technology to develop a device capable of capturing the movements of individuals concealed behind walls and within enclosed spaces.

Factors such as the surface material and the surrounding atmosphere's properties directly impact the CSI data obtained from signal reflections. In particular, signals tend to pass through common materials like plastic surfaces. At the same time, the reflective properties of an object are influenced by its fabric, which is classified as diffuse or specular reflections (Huang et al., 2014). Furthermore, the hardware and software components involved in the reception and transmission processes of the multipath channel introduce internal disturbances and noise that alter the patterns of CSI data (J. Yang et al., 2021). Another technical challenge is the segmentation of activities within continuously streamed signals, as there is typically no natural transition between the CSI amplitude or phase signatures of different activities. That leads to erroneous segmentation, incorrect categorization, and overlooking variations in the distance between human activity and the speed of action (Chowdhury, 2018). To address these challenges, we leverage the available components to generate waveforms, thereby minimizing the need for excessive processing and ensuring appropriate physical sensitivity during the sensing process. Challenges often include frequency hopping and noise in the context of HAR using WiFi signals (Schäfer et al., 2021). Apart from the inherent noise in the atmosphere, additional noise is induced by hardware and firmware, leading to data waste.

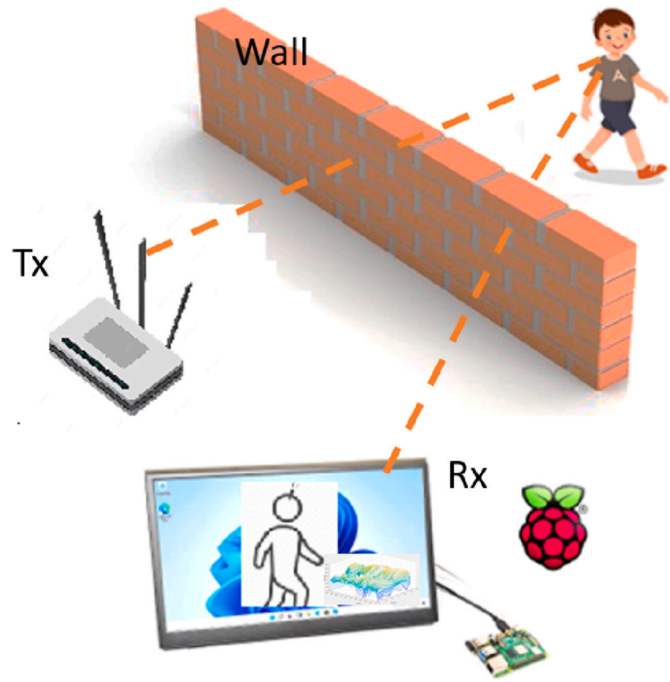
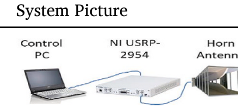
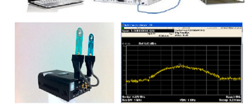
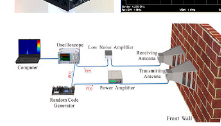
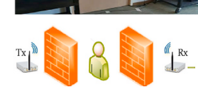
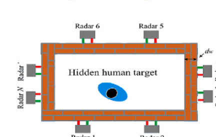


Fig. 1. Through wall human activity recognition using WiFi.

In order to guarantee high precision and dependability in data extraction, this work proposes a system that utilizes Nexmon firmware implemented on the Raspberry Pi (RPi). This setup ensures that all subcarriers are regulated and fully exploited, enhancing the system's performance and adaptability to network and router configurations (Chowdhury, 2018; Schäfer et al., 2021). Unlike existing solutions that rely on ultra-wideband approaches to mitigate the flash effect, our model adopts a more focused approach. It operates within a narrower 20/80 MHz-wide Wi-Fi channel, which allows for improved efficiency and practicality. Additionally, the system eliminates the need for a large

Table 1
Hardware and sensing techniques used in human motion sensing through walls.

Ref.	Hardware	Methods	Limitations	Classifier	System Picture
Sun (2019)	R&S signal Generator, USRP 2954	Forward scattering, radar system	Complex system, Limited to detecting motion, does not provide detailed information about human pose	Not specified	
Liang (2016)	Inc PulsON 220 UWB radar	UWB radar sensing	Limited to detecting motion, does not classify types of activities/position	Not specified	
Xu et al. (2022)	Random Code Generator, Oscilloscope	Random code radar sensing, feature fusion	Complex system	SVM	
Zhao et al. (2018)	USRP	Radio signal-based pose estimation	Limited to estimating human pose, may not accurately capture fine-grained movements	MUSIC	
Uysal and Filik (2022)	USRP	RF sensing framework	Limited to LoS, Limited activities classifications	SVM/Decision Tree Algorithms.	
Chen et al. (2022)	Multi-Radars	RF sensing framework	Complex system and limited functionality	Transfer Learning	

antenna array, commonly employed in previous systems, and instead utilizes a four-antenna MIMO radio configuration. This strategic design choice contributes to the device's reduced size and enhanced portability.

The experimental setup, illustrating the geometrical configuration of the system, is visually depicted in the provided diagram. The system utilizes the Nexmon firmware for data extraction to ensure high precision and reliability implemented on the RPi. This firmware enables precise regulation and utilization of all subcarriers (Chowdhury, 2018; Schäfer et al., 2021). Additionally, the platform allows for broadcast power, received power, and operating frequency swing customization, allowing the system to be easily adapted to different network setups and routers. The proposed model significantly contributes to HAR by offering a cost-effective solution that provides wider angle coverage for activity recognition through walls. Our primary focus is to investigate and analyze the impact of frequency on the performance of activity recognition through walls. The proposed approach involves utilizing CSI data from multiple Wi-Fi access points (APs) strategically placed around the environment of interest. Analyzing the changes in the CSI caused by human movements makes it possible to extract meaningful features that can be used for activity recognition. The wider-angle system, involving multiple APs, provides a broader coverage area, allowing for improved detection and localization accuracy.

One key advantage of utilizing CSI for HAR is its ability to penetrate through walls and obstacles, enabling monitoring of human activities in adjacent rooms or behind physical barriers. The main contributions of this work are summarized as follows.

1. To design a novel, cost-effective system capable of collecting data through walls by harnessing the wider-angle ability. This system aims to enable non-intrusive monitoring and recognition of human activities in limited direct line-of-sight observation scenarios.
2. To occupy the low-layering structure of the LSTM algorithm, enhancing the robustness and generalizability of activity recognition systems.
3. To evaluate the WiFi sensing through wall robustness via extensive experiments and comparative analyses to assess its accuracy. The evaluation process involves thorough testing under various scenarios and conditions to ensure reliable and consistent results.

These contributions boost non-intrusive HAR techniques, providing a cost-effective solution for recognizing human activities through walls. The performance exploration of RNN-LSTM and other machine learning algorithms adds to the existing body of knowledge, aiding in selecting appropriate algorithms for accurate activity classification. The extensive evaluation ensures the reliability and robustness of the proposed approach, reinforcing its applicability in real-world scenarios. Ultimately, this research strives to enhance the understanding and implementation of HAR through walls using CSI with a wider-angle system, with potential applications in security, healthcare, and smart home automation.

This article provides an in-depth exploration of the principles and mechanisms underlying WiFi signal attenuation caused by walls and obstacles, with the primary objective of achieving high accuracy in through-wall HAR using WiFi. The first section introduces the fundamental principle of HAR using WiFi and highlights its potential to address the challenges associated with WiFi penetration. The second section examines related works and research directions in the field of HAR, providing valuable insights into the existing studies in this area. Section three offers a detailed explanation of the methods employed and the model's structure. Furthermore, it presents a comprehensive discussion and evaluation of the results, encompassing the potential advantages, limitations, and ongoing research in HAR. Finally, the article summarizes the essential findings and discusses the implications of HAR technology in real-world scenarios, emphasizing its role in enhancing through-wall wireless sensing.

2. Related works

The development of HAR technology has the potential to revolutionize wireless sensing by extending the range and penetration capabilities of RF signals. It introduces the possibility of seamless sensing access in environments where obstacles have traditionally hindered reliable connections. This technology holds significant relevance and implications across various domains, including smart homes (Dang et al., 2022), industrial automation, healthcare, and public infrastructure. Wall monitoring using RF involves various techniques, including Ultra-Wideband (UWB) (K. Wang et al., 2019), Frequency-Modulated Continuous Wave (FMCW), and Doppler shift (Cao et al., 2021; Zhang et al., 2021), 5G (Ashleibta et al., 2021), and WiFi (Cheng et al., 2020). UWB technology employs short-duration pulses with a wide frequency range to achieve high-resolution ranging and precise localization, allowing for accurate detection and tracking of individuals through walls. Nonetheless, the adoption of UWB is still constrained by its cost-intensive nature and the necessity for specialized hardware.

FMCW radar systems enable precise localization and tracking by continuous variation of the frequency transmitted signals and measuring the frequency variation between transmitted and received signals. However, this method is limited to monitoring dynamic activities and has a restricted detection range, primarily due to its reliance on high-frequency operations. The advent of WiFi technology brings many advantages, including higher bandwidth, reduced latency, and enhanced connectivity. These advancements promise to enable real-time tracking of human presence and movement, surpassing the limitations posed by physical barriers such as walls. With improved penetration capabilities, WiFi technology allows HAR to extend WiFi coverage beyond conventional boundaries. This potential breakthrough has far-reaching implications, ranging from heightened productivity and efficient monitoring to a high overall quality of life for individuals and organizations.

The classification of methods for through-wall HAR includes hardware and sensing techniques, machine learning and recognition techniques, localization and tracking, and counting and enumeration methods. These methods have potential applications in medical contexts. The following subsections aim to provide a comprehensive overview and understanding of the scope of each technique.

2.1. Hardware and sensing techniques

Various hardware and sensing techniques have been explored in human motion sensing through walls. As studied by (Sun, 2019), the forward scattering methods provided valuable information about human presence and movement, offering good range resolution and compatibility with different wall materials. However, accurately distinguishing between multiple human targets and differentiating human motions from other environmental factors proves challenging. On the other hand (Liang, 2016), utilized Ultra-Wideband (UWB) radar sensors, benefiting from high-resolution range and Doppler measurements. UWB radar enables precise localization and motion detection. However, it faces difficulties differentiating human targets from clutter and various activities and is susceptible to signal reflections and multipath effects caused by wall structures. Integrating these approaches enhances human motion sensing through walls, but further enhancement is required to address the limitations and challenges associated with target discrimination, activity differentiation, and interference mitigation (see Table 2).

Recently, several studies have proposed hardware tools and techniques for sensing human activities through walls. A motion recognition approach was introduced using random code radar sensors and multi-domain feature fusion, aiming for robust motion recognition despite challenges in accurately differentiating between similar activities. In their study (Zhao et al., 2018), explored radio-based sensing for estimating human poses behind walls, offering non-invasive full-body pose estimation with limitations in capturing fine-grained details and distinguishing between similar poses. Moreover, the RF sensing framework for human detection through walls proposed by (Uysal and Filik, 2022) aims to enhance performance but faces challenges in complex environmental conditions and limited validation. Further research is needed to overcome these limitations and validate the effectiveness of these hardware tools in practical scenarios. Table 3 provides a comprehensive summary of the hardware tools utilized for (HAR) through walls, highlighting the employed methods, tools, techniques, and their respective limitations.

2.2. Machine learning and recognition techniques

Machine learning and recognition techniques are essential in HAR through walls. Recently, work by (Chen et al., 2022) employed transfer learning and ensemble learning to enhance motion recognition, while (Xie et al., 2023) proposed a CNN-based approach for joint positioning and pose recognition using through-wall imaging radar. Additionally (Z. Li et al., 2023), address resource constraints through adaptive thresholding, and (Kılıç et al., 2019) focus on posture recognition using CNNs and through-wall radar (Wu et al., 2019). utilized commodity WiFi devices for activity recognition. However, challenges include labeled data dependency, accurate measurements, resource efficiency, differentiating similar postures, and WiFi signal variation. Table 4 provides a comprehensive summary of the machine learning techniques utilized for HAR through walls, highlighting the employed methods, tools, techniques, and their respective limitations.

2.3. Localization and tracking

Various techniques have been explored in through-wall human localization to capture the moving paths, vital signs, and layout reconstruction. Through-wall sensing techniques to capture the trajectory of human movement and vital signs employed by (K. Wang et al., 2019) contribute to understanding human behavior and health monitoring (H. Li et al., 2020a,b). proposed a scale-adaptive tracking algorithm for robust human target tracking through walls, addressing the challenge of accurate target detection and adapting to changing conditions (Song et al., 2018). utilized UWB MIMO through-wall imaging radar for building layout reconstruction, contributing to understanding through-wall imaging and its applications in building security and emergency response. These studies collectively advance the field of through-wall HAR, highlighting the strengths and weaknesses of the techniques employed. Future research focuses on integrating these techniques and addressing the identified limitations to improve the accuracy and applicability of through-wall activity recognition systems.

2.4. Counting and enumeration and medical applications

Counting people through the wall has been studied by (Jia et al., 2021) using Residual Neural Networks (ResNet) to calculate moving targets behind walls accurately. Deep learning techniques and ResNet's feature extraction capabilities improve counting performance. However, the study's limitation is its focus solely on moving targets. Human target detection approach using Fully Convolutional Networks (FCN) proposed by (H. Li et al., 2020a,b) for through-the-wall radar imaging, enabling pixel-wise classification and robust detection of human targets. Nonetheless, their reliance on radar signal quality and the need for sufficient training data may affect performance reliability. These works contribute to the progress of through-wall HAR, but further research is needed to address the identified limitations and improve overall performance.

Table 3
Through-wall human localization methods.

Ref.	Hardware	Methods	Limitations
(K. Wang et al., 2019)	Simulation	Multivariate empirical mode decomposition	Very limited to theory, and not applicable method.
(H. Li et al., 2020a, b)	Through-wall imaging radar system, Multi Antennas; FMCW	Mean-Shift Tracking	Only Moving Objects can be detected
Song et al. (2018)	UWB MIMO through-wall imaging radar system	Doppler BP	complexity of building structures and the presence of clutter in the radar measurements

Furthermore, the impact of noise and environmental effects poses limitations on through-wall-HAR. We propose a simplified system design with a wider angle and higher gain to tackle these issues, enhancing monitoring capabilities and overcoming complexity limitations. The proposed system is based on a layered, cost-effective MIMO signal processing design that ensures the extraction of clean activity signals while filtering out noise and environmental interference. The proposed approach improves the overall signal quality and enables more accurate activity recognition by focusing solely on the desired information. We enhanced the system classification efficiency by adopting LSTM networks to boost monitoring capabilities, tackle the complexity of machine learning algorithms, and mitigate the influence of noise and environmental factors.

3. Preliminaries

3.1. CSI-propagation

WiFi routers transmit radio waves to enable seamless connectivity across locations and surroundings, ensuring reliable and widespread access in most buildings. The presence of a human within the radio wave's trajectory alters its properties, consequently influencing the multipath propagation and its behavior due to human mobility within the range of a WiFi network (W. Wang et al., 2017). The CSI utility is employed to assess quantitative data acquired by the terminal, encompassing parameters such as transmission rate, the count of received and transmitted antennas, and the CSI Fig. 2 demonstrates the diversity of the Received Signal Strength Indicator (RSSI) and CSI, highlighting the superior reliability of CSI due to its ability to account for variations in temperature and humidity. In contrast, RSSI provides only a single value, rendering it less robust in adverse environmental conditions

Table 2
Through wall HAR using Machine Learning and Recognition Techniques.

Rf.	Hardware	Methods	Limitations	No. Activities	Performance
(Z. Li et al., 2023)	Radar sensors	Adaptive thresholding	Resource-constrained platforms may limit accuracy and performance	6	93%
Xie et al. (2023)	3D through-wall imaging radar	CNN, joint positioning and pose recognition	Complex and many antennas required, UWB MIMO system with 4 transmitting and 15 receiving antennas	Localization	Not specified
Wu et al. (2019)	Commodity WiFi devices	Or-PCA)	Limited to range and signal strength of WiFi devices	7 activities	94%
Cao et al. (2021)	FMCW radar	Transfer Learning	Limited to dynamic activities and requires high domains of dataset for training.	6 Activities	93.6%

Table 4
Performance Comparison of through wall HAR using machine learning methods.

Rf.	Methods	Features Used	Computational Complexity	No. Of Activities	Acc.
(Z. Li et al., 2023)	Adaptive thresholding	features are extracted from 4 data domains (mask, masked spectrogram, masked phase, and masked unwrapped phase)	Simple image processing technique used for segmentation. The computational complexity of Adaptive Thresholding is relatively high due to the requirements of feature extracting and fusing and selection process	6	93%
Wu et al. (2019)	Or-PCA	PCA reduces high-dimensional CSI data by projecting it onto a lower-dimensional subspace, leading to information loss.	Matrix factorization technique used for robust principal component analysis. It involves iterative optimization techniques, making it relatively more computationally demanding.	7 activities	94%
Cao et al. (2021)	Transfer Learning	micro-Doppler	High computational requirement	6 Activities	93.6%
This work	LSTM	LSTM based CSI Feature Generation	Simplified layers, and low computation required.	7 Activities	97.5%

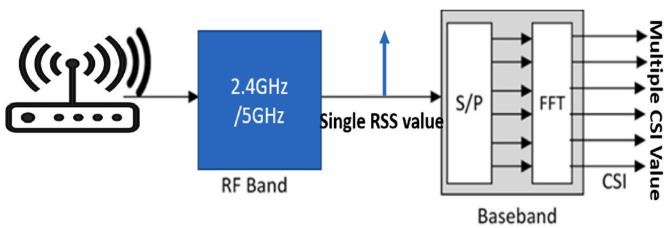


Fig. 2. Frequency diversity in RSSI and CSI.

(Sharma et al., 2021).

CSI typically encompasses each path's transmission power and arrival time when derived from Orthogonal Frequency Division Multiplexing (OFDM). OFDM is a wireless modulation technology employed in WiFi and LTE-modulated signals, enabling the simultaneous transmission of multiple frequency signals. Therefore, the LoS and multipath waves may be distinguished based on their arrival times. The signal propagation path in Fig. 3 recognizes the dependency of the LoS path on RSSI. On the other hand, CSI is crossing multipath and considering a range of subcarriers to be recognized accordingly.

Eq. (1) estimates the calculation of the optimal power received at the antenna, considering parameters such as the transmitted power, signal frequency, distance of travel, and antenna gains (Z. Yang et al., 2013).

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

P_{rx} represents the power arriving at the receiver (watts), and Ptx is transmitted power in watts. Moreover, G_{tx} is the transmitted gain, G_{rx} received gain and c is the speed of light. In addition to noise, phase, and amplitude are affected by the distance between Rx and Tx and the reflection (Sharma et al., 2021). The mathematical representation of changes occurs to the CSI signals from the transmitter (denoted as x) to the receiver (denoted as y), and the channel is represented mathematically by Eq (2).

$$y = Hx + n \tag{2}$$

Eq. (2) represents the CSI for OFDM subcarriers derived and incorporated into the complex matrix H (J. Wang and Park, 2021). 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* as *shown in* Eq (3).

$$H_i = \begin{bmatrix} h_i^{11} & h_i^{12} & \dots & h_i^{1N_T} \\ h_i^{21} & h_i^{22} & \dots & h_i^{2N_T} \\ \vdots & \vdots & \vdots & \vdots \\ h_i^{N_R 1} & h_i^{N_R 2} & \dots & h_i^{N_R N_T} \end{bmatrix} \tag{3}$$

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

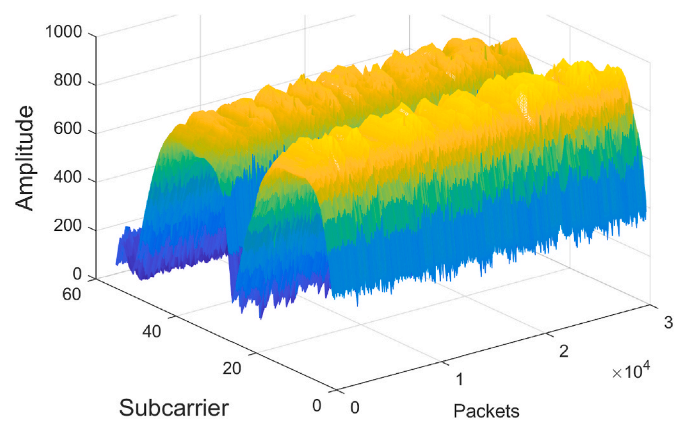


Fig. 4. CSI amplitude for 2.4Ghz/20 MHz bandwidth.

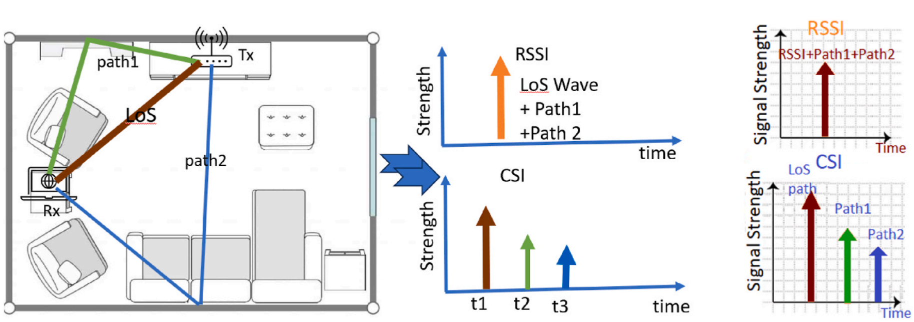


Fig. 3. Signal propagation path and RSSI/CSI.

transmitter antenna (Sharma et al., 2021). The plotted signal in Fig. 4 shows the CSI amplitude of the 64 sub-carriers, which makes it very useful for figuring out activities based on WiFi characteristics.

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 Eq (4) indicates (J. Wang and Park, 2021).

$$h(f) = \sum_{l=1}^{N} \alpha_l \, exp^{-j2\pi f \tau_l} \tag{4}$$

The reflected signal experiences fluctuations and distortions as it passes through the wall. These fluctuations are attributed to the varying properties of the wall, such as thickness, density, and composition. Additionally, scattering occurs when the signal encounters obstacles or irregularities in the wall, causing further signal distortion and multipath propagation, as shown in Fig. 5. Power losses also contribute to the degradation of the reflected signal, as shown in Fig. 5. As the signal passes through the wall, it experiences attenuation, which reduces signal strength. This attenuation is influenced by the wall material's properties and the transmitted signal's frequency. Eq. (5) is commonly used to model the received signal power and understand these factors' impact.

$$P_r = \frac{Pt * G_t * Gr * \lambda^2}{4\pi d^2 L} \tag{5}$$

This equation illustrates the received signal power is influenced by the transmitted power Pt, antenna gains G_t, wavelength λ, distance d, and path loss exponent L. 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. Another challenge is collecting reflected signals through walls and processing high-quality CSI data due to commercial WiFi devices' limited bandwidth and sensitivity (Adib and Katabi, 2013). The received gain can be represented by:

$$G_r = \frac{\text{Power density directed}}{\text{Power density isotropic}} = \frac{A_{sphere}}{A_{ont}} = \frac{4\pi R^2}{A_{ant}} \tag{6}$$

$$\text{where } A_{ext} \approx \theta_{Az}\cdot\theta_{EL} \approx \frac{R\lambda}{b}\cdot\frac{R\lambda}{h} \tag{7}$$

$$G_r = \frac{4\pi}{2/2\cdot\pi/h} \approx \frac{4\pi A}{\lambda^2} \Rightarrow A = \frac{G_r\lambda^2}{4\pi} \tag{8}$$

$$\text{Thus } P_r = \frac{G_t G_r \lambda^2 \sigma F}{(4\pi)^3 R^4 L} \tag{9}$$

Eq. (9) demonstrates the area A effects in the signal covered by WiFi transmitted power P_t with transmitting gain G_t 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 Fig. 5.

4. Methodology

4.1. System architecture overview

The proposed system architecture is incorporated with Raspberry Pi 4 B connected to an Alfa router attached to four extended antennas demonstrated in Fig. 6. Incorporating RPI 4 B as the designated receiver to streamline the system architecture presents numerous advantages. Raspberry Pi, renowned for its versatility and cost-effectiveness, is a widely adopted single-board computer utilized in diverse domains, encompassing IoT and wireless communication systems. Its compact form factor, low power consumption, and extensive support from the community render it an optimal choice for the present system. Within this architecture, the RPI assumes a pivotal role by executing the Nexmon firmware, facilitating the monitoring of transmitted signals from the router. Nexmon, a firmware patch specifically developed for Broadcom WiFi chips like those integrated with RPI devices, bestows augmented functionalities, enabling access and manipulation of low-level WiFi parameters, including manipulating CSI data.

By incorporating an Alfa router with extension antennas into the system, the Raspberry Pi's sensing capabilities are significantly enhanced. The extension antennas are designed to provide higher gain, which increases the received signal strength and improves the system's ability to detect signals. The gain enhancement is particularly beneficial when detecting signals that need to propagate through obstacles like walls. Furthermore, the extension antennas allow for a wider angle of sensing. Traditional built-in antennas on devices like the RPi have limited coverage, primarily focused on the front-facing direction. The system workflow encompasses data collection, preprocessing, feature extraction, and model classification stages shown in Fig. 7. The initial step involves data collection containing valuable details of the wireless channel's characteristics acquired during this process. The acquired CSI amplitude data undergoes a preprocessing stage to refine its quality and ensure its suitability for subsequent analysis. Various preprocessing

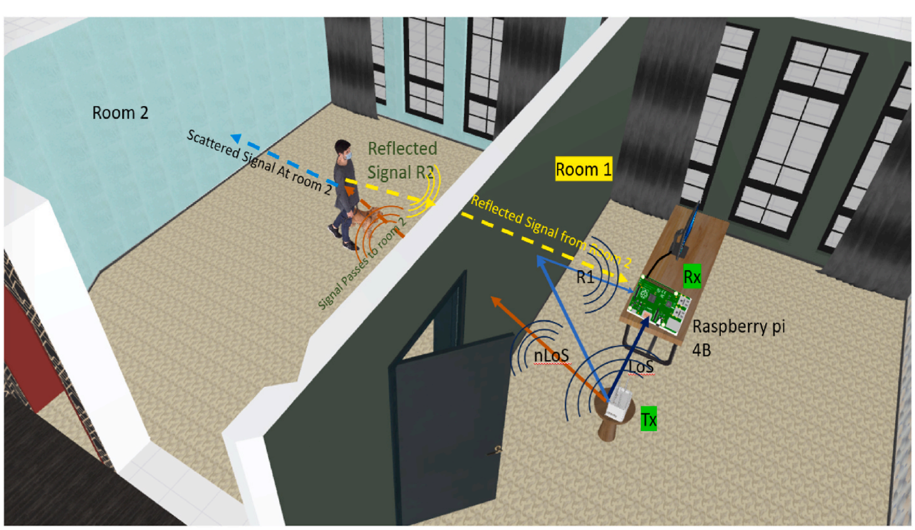


Fig. 5. An Environment effects of different paths modulated in the WIFI signals of CSI subcarriers amplitude in different activities.

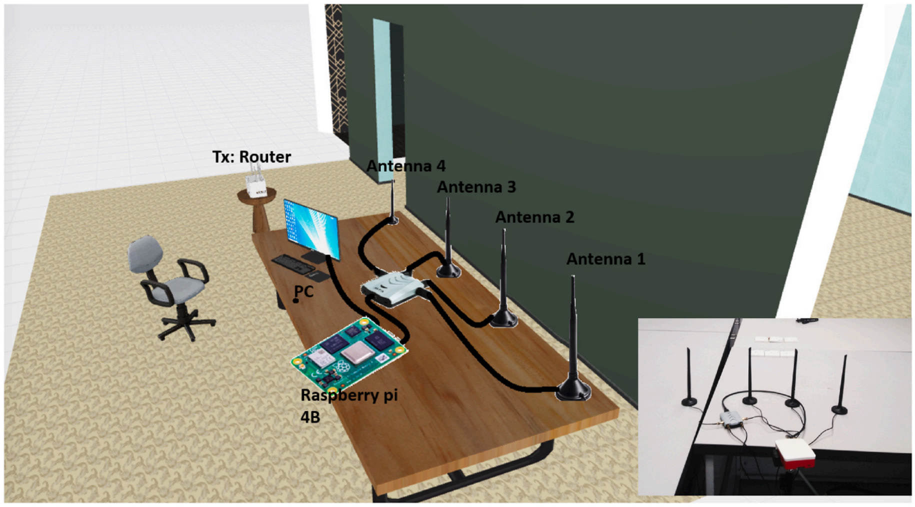


Fig. 6. Hardware system architecture using Raspberry Pi 4 B and Alfa AWUS1900

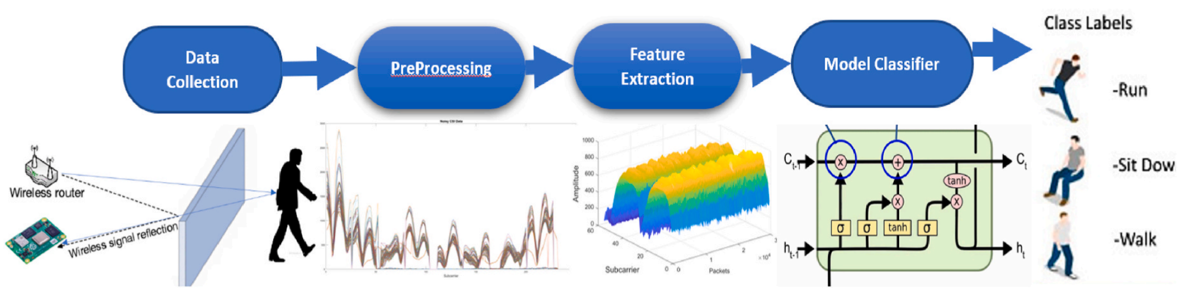


Fig. 7. System flowchart architecture.

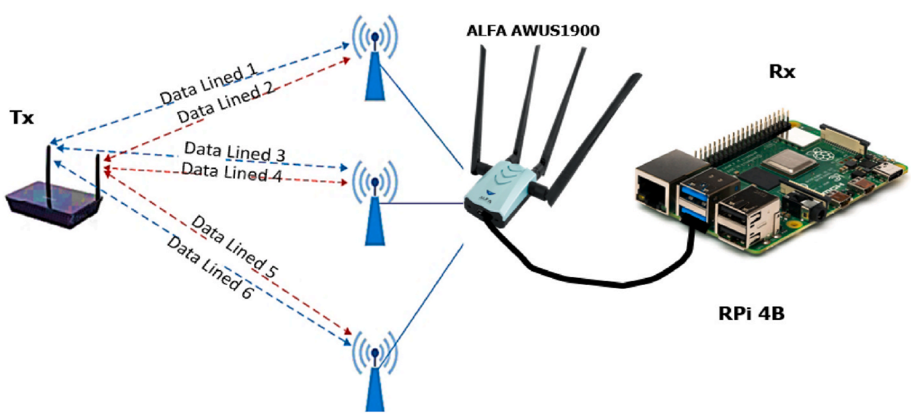


Fig. 8. Integration of Raspberry Pi with Alfa AWSUS1900 router.

techniques are applied to the data, including cleaning, normalization, and noise reduction methodologies. By eliminating inconsistencies and unwanted artifacts, the preprocessing phase ensures the integrity and reliability of the data for further processing (see Fig. 8).

Subsequently, feature extraction techniques extract informative features from the preprocessed CSI amplitude data. These extracted features serve as representative indicators of different activities. Statistical measures such as mean, variance, and other relevant parameters are commonly utilized to capture meaningful data characteristics. The selected features aim to encapsulate essential information and discriminative patterns that can differentiate various human activities. Finally, for classification purposes, an LSTM model is employed. LSTM is a recurrent neural network architecture known for its ability to effectively model sequential data, making it well-suited for time series analysis tasks such as HAR. The LSTM classifier utilizes the extracted features as input and is trained on labeled data to learn the complex relationships between the features and the related human activities. Once trained, the LSTM model classifies and recognizes human activities accurately using the CSI amplitude data.

4.1.1. *Data collection*

Virtually, the Raspberry Pi, serving as the central unit, facilitates the data collection procedure. By leveraging the Nexmon firmware with kernel version 5.10.92, the RPi injects specially crafted packets into the wireless network. These injected packets carry unique identifiers that allow monitoring and collecting CSI data. The Alfa 1900 router, integrated with the Raspberry Pi, significantly enhances the coverage region of data collection. The system is equipped with high-gain antennas and extended-range capabilities. The Alfa 1900 router extends the gain of the wireless signals, enabling the RPi to capture CSI data in wider angles and phases. This expanded coverage region is particularly advantageous when dealing with scenarios where the desired signals may originate from locations beyond the immediate vicinity of the receiver.

TCPDUMP is executed on the Raspberry Pi, which listens to the network traffic and captures packets containing CSI data. These packets are then written to TCP files, preserving the integrity and chronological order of the captured data. By storing the data in TCP file format, it becomes more manageable for subsequent processing and analysis. The TCP files can be transferred and accessed on other systems or platforms for more extensive analysis and feature extraction. The installation and setup process for operating the ALFA AC1900 adapter in RPi involves several steps, including installing supporting packages such as DKMS and NetworkManager. These packages provide essential functionalities and compatibility required for seamless integration. The outlined steps below elucidate the installation and setup process.

ALFA AC1900 WiFi Adapter Setup with Raspberry Pi using Nexmon	
1	Start NetworkManager service/Execute command: sudo service NetworkManager start
2	Restart NetworkManager service/Execute command: sudo service NetworkManager restart
3	Restart NetworkManager service using systemctl/Execute command: sudo systemctl restart NetworkManager
4	Check wireless devices/Execute command: sudo iw dev
5	Disable wlan0 interface/Execute command: sudo ip link set wlan0 down
6	Set wlan0 interface to monitor mode/Execute command: sudo iw wlan0 set monitor control
7	Set wlan0 interface type to managed/Execute command: sudo iw wlan0 set type managed
8	Enable mon0 interface/Execute command: sudo ip link set mon0 up
9	Check current wireless regulatory domain/Execute command: iw reg get
10	Set wireless regulatory domain to US/Execute command: sudo iw reg set US
11	Install linux-compiler-gcc-10-x86 package/Execute command: sudo dpkg -i linux-compiler-gcc-10-x86_(supportive_Raspi_kernal).deb
12	Install linux-kbuild-5.10.92 package/Execute command: sudo dpkg -i linux-kbuild-5.10_5.10.92-4kali1_amd64.deb
13	Install required build dependencies/Execute command: sudo apt install build-essential dkms git libelf-dev
14	Create src directory/Execute command: mkdir src
15	Clone 8814au repository from GitHub/Execute command: git clone https://github.com/morrownr/8814au.git

4.1.2. Pre-processing

The preprocessing stage for CSI data involves a comprehensive set of techniques to enhance the data quality and reduce noise following the process shown in Fig. 9. The first step in the preprocessing stage is the removal of null and pilot subcarriers from the CSI amplitude data. These subcarriers, utilized for channel estimation and synchronization, need to carry important information for subsequent analysis and are thus discarded. Hamming filters are applied to the CSI amplitude data. Hamming filters, belonging to the family of windowing filters, effectively smooth the data by attenuating abrupt variations and suppressing high-frequency noise. This filtering process enhances the overall signal quality and reduces unwanted artifacts (see Fig. 10).

The Hampel filter is a robust outlier detection and smoothing technique used in signal processing. It involves calculating the median absolute deviation (MAD) to identify and replace outliers with the median value.

Subsequently, wavelet decomposition techniques are employed to denoise the CSI amplitude data. Wavelet decomposition offers the advantage of capturing time and frequency information in a signal. The data is decomposed into different scales, resulting in approximation and detail components at each level. The detail components contain high-frequency information, including noise, while the approximation components capture low-frequency information. The noise components are attenuated by selective thresholding and discarding the detail coefficients at each level while the essential signal characteristics are preserved as shown in Fig. 11. The preprocessing stage ensures the quality enhancement and noise reduction of the CSI amplitude data, making it more suitable for subsequent analysis and feature extraction tasks (see Fig. 12).

4.1.3. Feature extraction

The feature extraction stage involves leveraging the model's ability to capture temporal dependencies and patterns in LSTM-based HAR from CSI amplitude data. LSTM, as a recurrent neural network architecture, is well-suited for analyzing sequential data like CSI amplitude. LSTM-based feature extraction excels in capturing temporal aspects of the CSI amplitude data without sacrificing valuable information. Unlike PCA, which leads to a loss of temporal patterns by reducing dimensionality, LSTM inherently considers the sequential nature of the data. The model automatically learns to extract features that encapsulate discriminative aspects of the CSI amplitude, enabling accurate representations for subsequent classification or regression tasks.

4.1.4. Model classifier

One of the critical advantages of LSTM in WiFi-based HAR is its ability to capture long-term dependencies. Human activities often exhibit intricate temporal patterns, and capturing these extended dependencies is crucial for accurate recognition. The unique architecture of LSTM, with memory cells and gates, empowers it to retain and utilize information over long periods. This characteristic enables LSTM to capture and model HAR's complex and extended dependencies using WiFi data. Moreover, LSTM models excel at handling variable length sequences, which is particularly relevant in WiFi-based HAR, where different activities may have varying durations. LSTM models dynamically adjust their internal state and memory, allowing them to adapt to sequences of different lengths. This flexibility enables LSTM to handle variable-length sequences without needing fixed-size inputs or additional preprocessing steps, making it well-suited for the diverse durations of human activities.

The proposed architecture encompasses a sequential model that leverages LSTM layers for classification, as depicted in Fig. 13. The model's input layer receives data input, which comprises a sequence length of 56/242 dimensions representing denoised CSI subcarriers. This sequential data is then forwarded to an LSTM classifier, a specialized recurrent neural network layer adept at handling sequential information. The LSTM layer is equipped with memory cells, enabling it to retain and process information over time, thereby effectively capturing and modeling long-term dependencies within the data. This capability proves crucial in tasks where temporal relationships play a significant role. To mitigate the risk of overfitting and enhance generalization, a dropout layer is incorporated after the LSTM layer.

The dropout layer is a regularization technique by randomly deactivating a subset of input units during training. By introducing this

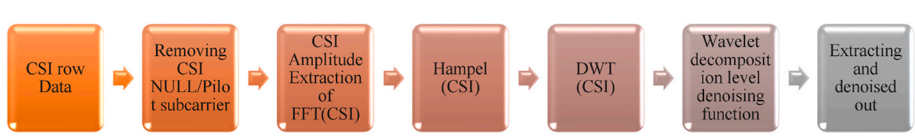


Fig. 9. Stages of data preprocessing and signal filtering.

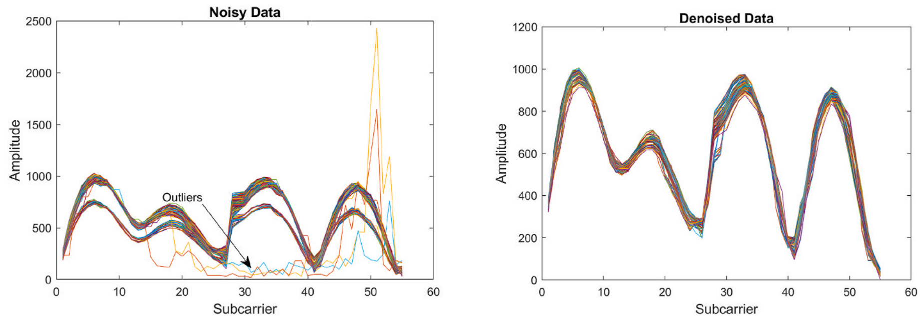


Fig. 10. CSI amplitude signal filtering using outliers' removal.

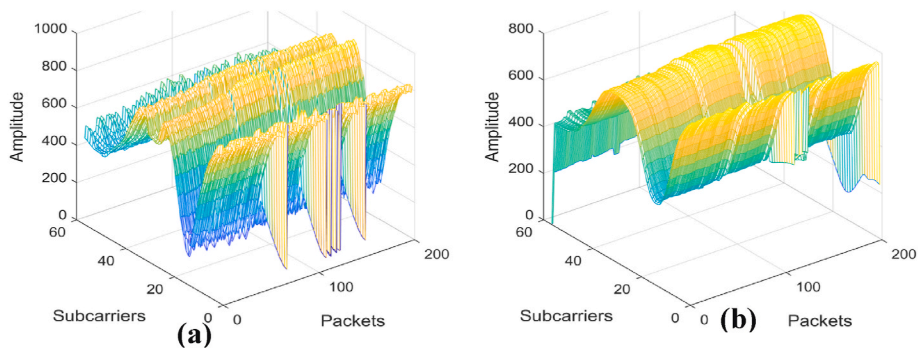


Fig. 11. CSI Signal denoising using wavelet decomposition (a) CSI Amplitude for empty activity, (b) Denoised CSI data.

randomness, the layer promotes the independence of neuron learning and reduces the propensity for overfitting. Consequently, the model becomes more robust and less prone to memorizing noise or irrelevant patterns, thus improving its ability to generalize and perform well on unseen data. The subsequent layer, labeled as "Fully Connected LSTM Layer 2," involves applying fully connected operations to the output from the previous LSTM layer. This fully connected layer establishes connections between all neurons, facilitating detection of intricate relationships and complex patterns within the data. Next, the model includes an output layer with two fully connected neurons, serving as a classifier. An LSTM layer labeled "LSTM 3″ is present, presumably to further capture temporal dependencies and information. The layers are followed by a dropout layer labeled "Dropout 3″ for regularization. Lastly, a fully connected layer is employed before a Softmax layer, which outputs probability distributions over the seven possible classes. The architecture culminates with the output layer, which utilizes a classifier to assign the input data to one of the seven defined output classes.

Algorithm 1 describes the processes for HAR using CSI to classify human activities based on the LSTM classifier. Initially, CSI data is collected using WiFi devices with multiple antennas, capturing variations in the wireless channel caused by human activities. The collected CSI data undergoes preprocessing to enhance quality and remove noise, followed by feature extraction to capture relevant patterns. A machine learning model, such as LSTM, is then trained using labeled data to learn the relationship between CSI features and activities.

Algorithm 1. Through Wall HAR via CSI wider angle radar and LSTM

Input: Raw data as CSI Amplitude H
Output: Activity Classification
while (true)
  [Data Preprocessing], CSI $_{\text{precond}}$ ← CSIraw - CSIp - CSInull - CSIun
  [Outliers Removal],
  Compare the current sample (i) with $n_\sigma \times \sigma_i$
  if $CSI_{\text{mag}}(i) - CSI_{\text{med}}(i) > n_\sigma \times \sigma_i$ then
    $\text{CSI}_{\text{mag}}(i) = CSI_{\text{med}}(i)$
  end if
  $CSI_{\text{ham}} \leftarrow CSI_{\text{mag}}(i)$
  [Denoising]
  $CSI_{DWT} \leftarrow$ DWT on $\left(CSI_{\text{ham}}\right)$ with wavelet decomposition (level = 5)& (wavelet scheme = sym6)
  $CSI_{\text{ham + denoised}} = CSI_{DWT}$
  [Feature Extraction]
  CSI_{out}[200x56] ← FeatureExtraction on χ with (CSI[200x56])
  $CSI_{\text{Features}} \leftarrow CSI_{\text{out[200x 56]}}$
  [Classification]
  LSTM Training Classifier
  Apply the trained model to classify activities based on the extracted features from the CSI amplitude data.
  Obtain the predicted activity labels
end

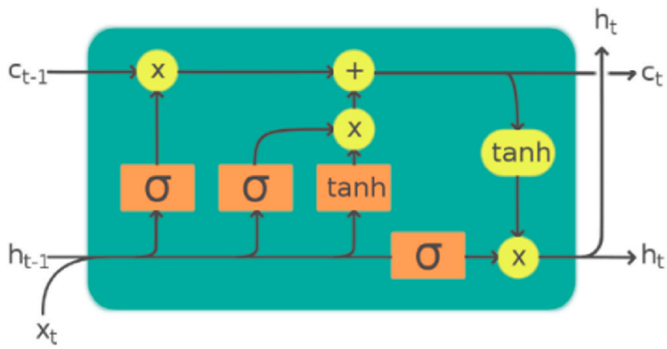


Fig. 12. LSTM architecture.

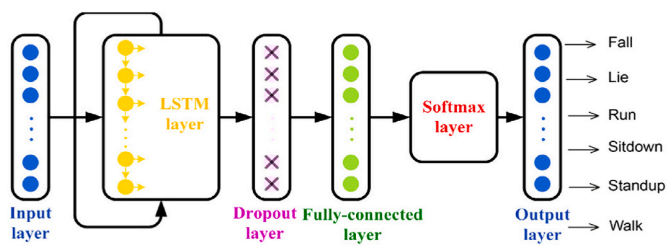


Fig. 13. Schematic of LSTM architecture layers used in this work.

5. Implementation and evaluation

5.1. Experiment setup and environment layout

The model's performance in through-wall sensing is assessed by evaluating its ability to detect seven activities. These activities are evaluated at five distinct positions behind a wall, as Fig. 14(a) indicates. A Raspberry Pi 4 B is set up in monitoring mode to capture data during the experiments. This involves using an AC1350 TP-LINK router as a transmitter (Tx), illustrated in Fig. 14(b). The experiments took place in the utility room of the FKEKK faculty at Universiti Teknikal Melaka Malaysia (UTEM). The Utility room serves as the primary experimental area and has a rectangular layout measuring 15 m in width and 12 m in length. The lab room, housing the transmitter and receiver units, also has a rectangular shape with dimensions of 15 m in width and 16 m in length.

The experimental setup encompasses an environmental layout meticulously structured to simulate real-world scenarios. The configuration of this layout is visually depicted in Fig. 14, offering a graphical representation of the spatial arrangement during the experiments. Fig. 14(b) illustrates explicitly the experimental arrangement, highlighting three distinct positions (1, 4, and 5) that provide extended angular coverage behind the wall. With strategic placement behind the wall, the transmitter (Tx) and receiver (Rx) are situated in the laboratory room to facilitate investigations. Within this experimental framework, the transmitter and receiver are situated in the Lab room, each contributing to their respective functions. Seven distinct activities are conducted within the utility room to evaluate the system's performance under diverse conditions comprehensively. The activities are executed across five discrete positions to provide comprehensive evaluation thoroughly analyzes the system's efficacy and functionality across various configurations and spatial arrangements.

5.2. LoS and nLoS path evaluation

The evaluation of LoS and NLoS paths in CSI HAR involves assessing the impact of these signal paths on the quality and characteristics of the received CSI data. This evaluation aids in understanding the challenges posed by NLoS scenarios and the potential benefits of LoS scenarios in accurately recognizing and classifying human activities. Evaluating LoS and NLoS paths involves experiments where the Tx and Rx are placed in scenarios shown in Fig. 15 with obstacles, such as walls or furniture, obstructing the direct signal path. The setup introduces signal reflections and diffractions, resulting in changes to the CSI data characteristics. Fig. 15 displays the experimental setup for the LoS analysis of the experiment involves placing the transmitter (Tx) in two rooms distant

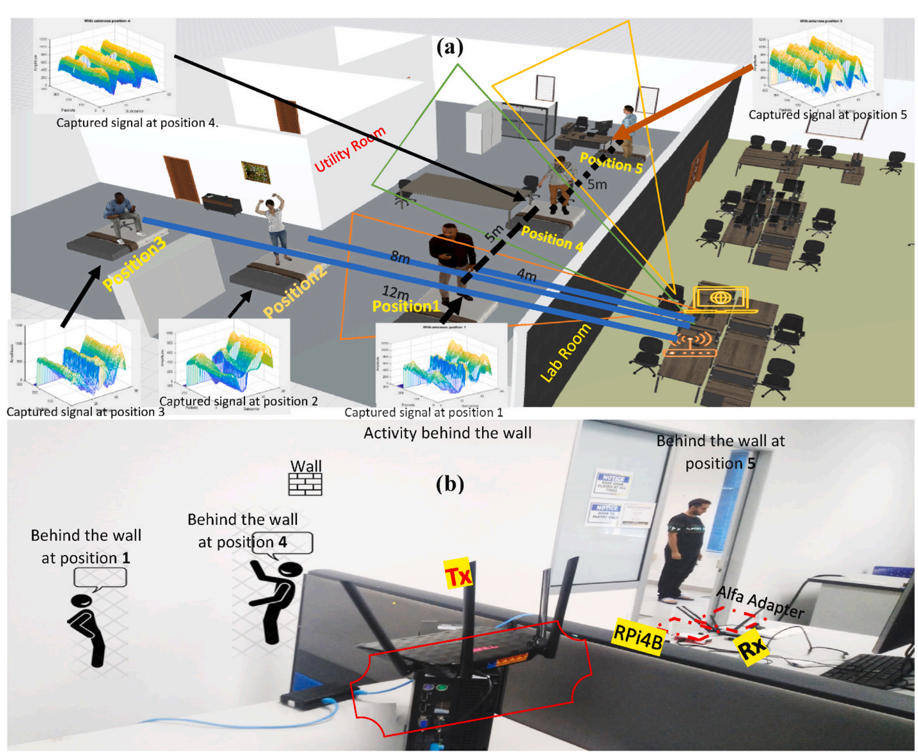


Fig. 14. (a) Experimental layout depicting the positions (1, 2, 3, 4, and 5) for through-wall HAR, (b) experimental location for capturing activities through a wall.

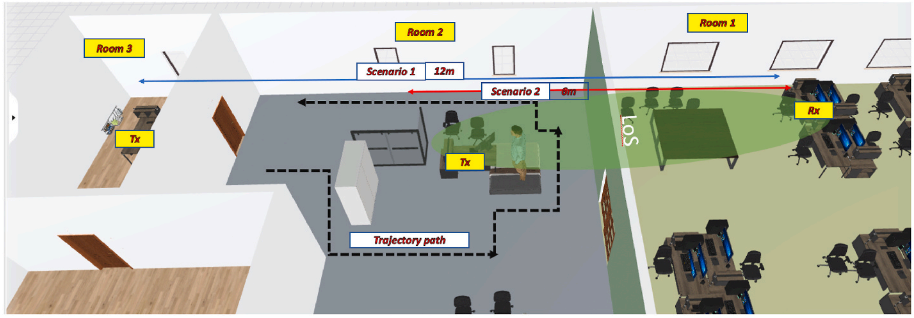


Fig. 15. LoS and nLoS Analysis with two walls blocking signal.

from the receiver (Rx), thereby assessing the received signal. Specifically, scenario one is examined at the 12-m distance and two walls obstructing the signal path.

Evaluating NLoS paths provides insights into the challenges posed by signal degradation, multipath effects, and reduced signal strength, which affect the accuracy and reliability of HAR algorithms. This knowledge helps to develop robust and reliable systems for HAR in real-world environments with varying signal obstruction and multipath effects. The analysis of the received signal in scenario 1 reveals distinct fluctuations attributed to the activities occurring in both the LoS and nLoS paths, as indicated in Fig. 15. Notably, the presence of two walls blocking the signal results in weaker signal fluctuations.

The received CSI data demonstrate reduced variations due to the impact of activities in both the LoS and nLoS paths. Furthermore, the proximity between the transmitting and receiving devices plays a critical role in the power of the CSI signal and, consequently, the accuracy of the measurements. The devices are positioned closer to each other, and the strength of the CSI signal increases, leading to higher accuracy in the analysis, as shown in Fig. 16.

5.3. Evaluating the influence of distance, frequency

The ability to sense through a wall via WiFi is acquainted, but many implementations appear to face positioning retractions. The comparison of 2.4 and 5 GHz shows that lower frequency performs better for HAR through the wall regarding coverage, penetration through solids, and wider-angle detection. Furthermore, the transmission gain at the LoS of WiFi signals is dynamically dependent on an isotropic radiator wavelength λ in meters and losses not associated with the propagation. The plotted curve in Fig. 17 approximates the lost signal power behind the wall for both 2.4 and 5 GHz in the LoS region.

Moreover, an assessment was conducted to compare the effectiveness of capturing signals using RPi with and without attached antennas in conjunction with the Alfa router. This evaluation explored the advantages of utilizing proposed wider angles facilitated by the attached antennas. Fig. 18 depicts activities at position 3, representing the farthest point from the sensing Access Points (APs).

The signals captured through wider angles exhibited improved patterns and higher accuracy in activity classification, as demonstrated in Fig. 18(a). In contrast, Fig. 18(b) illustrates the signals captured using RPi without attached antennas, showcasing comparatively lower accuracy and less distinct patterns. By employing wider angles by implementing attached antennas, the system yielded superior results in pattern recognition and activity classification, mainly when activities were conducted at a greater distance from the sensing APs. The findings illustrated in Fig. 18 provide evidence of the advantages of wider angles and their positive impact on signal capturing and subsequent accuracy in activity classification. The illustrated diagram provides experimental evidence of the enhanced performance achieved by employing a wider-angle configuration for the 2.4 GHz frequency, in contrast to signal capture without antennas. Furthermore, the wider-angle configuration extends its coverage to encompass a broader range of angles. By examining activity classification at position 5, the system equipped with RPi and Alfa-attached antennas demonstrates superior performance. This augmented system, featuring antennas, exhibits heightened sensing capabilities for three activities, as depicted in Fig. 19.

The results unequivocally demonstrate that the wider-angle configuration and Alfa-attached antennas significantly improve system performance. As discerned from the activity classification outcomes, this configuration enables more significant signal gain, expanded distance coverage, and more precise detection of activities.

5.4. The effect of materials on HAR through wall

In addition to the previously described layout of the experimental location at the lab, experimentation was extended to buildings featuring walls composed of diverse materials. Three building materials were specifically investigated: 8-inch-thick concrete walls, 5-inch walls supported by steel frames with sheetrock, and tinted glass. Furthermore, experiments were conducted in an open, free-space environment with no physical barriers. Fig. 20 illustrates the performance of the model across different building materials. Specifically, the detection rate indicates the fraction of experiments in which the model accurately decoded the gesture. The figures vividly demonstrate the model's proficiency in

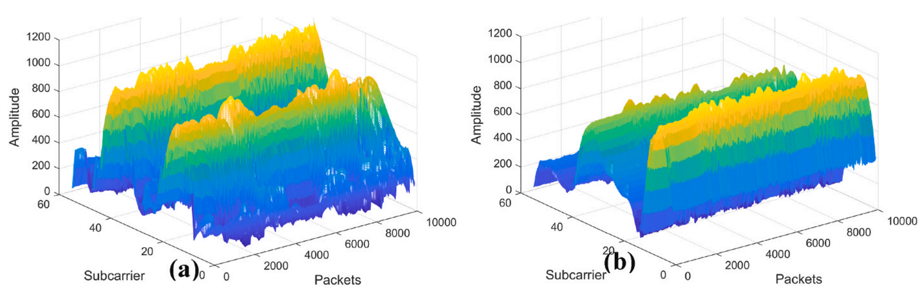


Fig. 16. (a) The captured CSI amplitude during a walking activity along the illustrated path in scenario 2, covering 6 m distance when Tx and Rx are separated by one wall, (b) the signal representation demonstrates the CSI when there is a separation of 12 m between the transmitter (Tx) and receiver (Rx) in scenario 1 with separation of two walls.

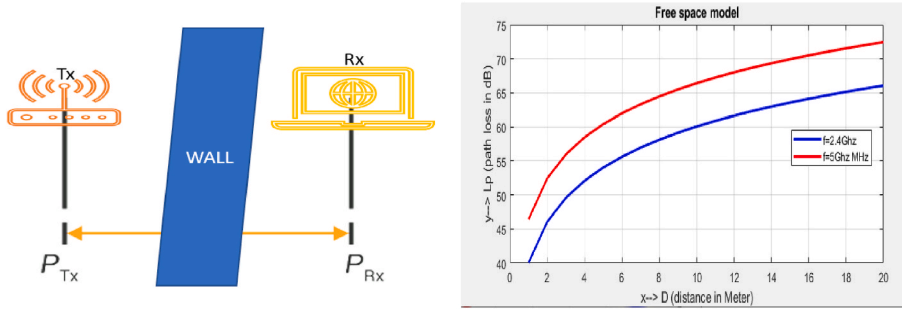


Fig. 17. Through signal power transmission at (a) the LoS, (b) LoS transmitted power losses for 2.4 and 5 GHz.

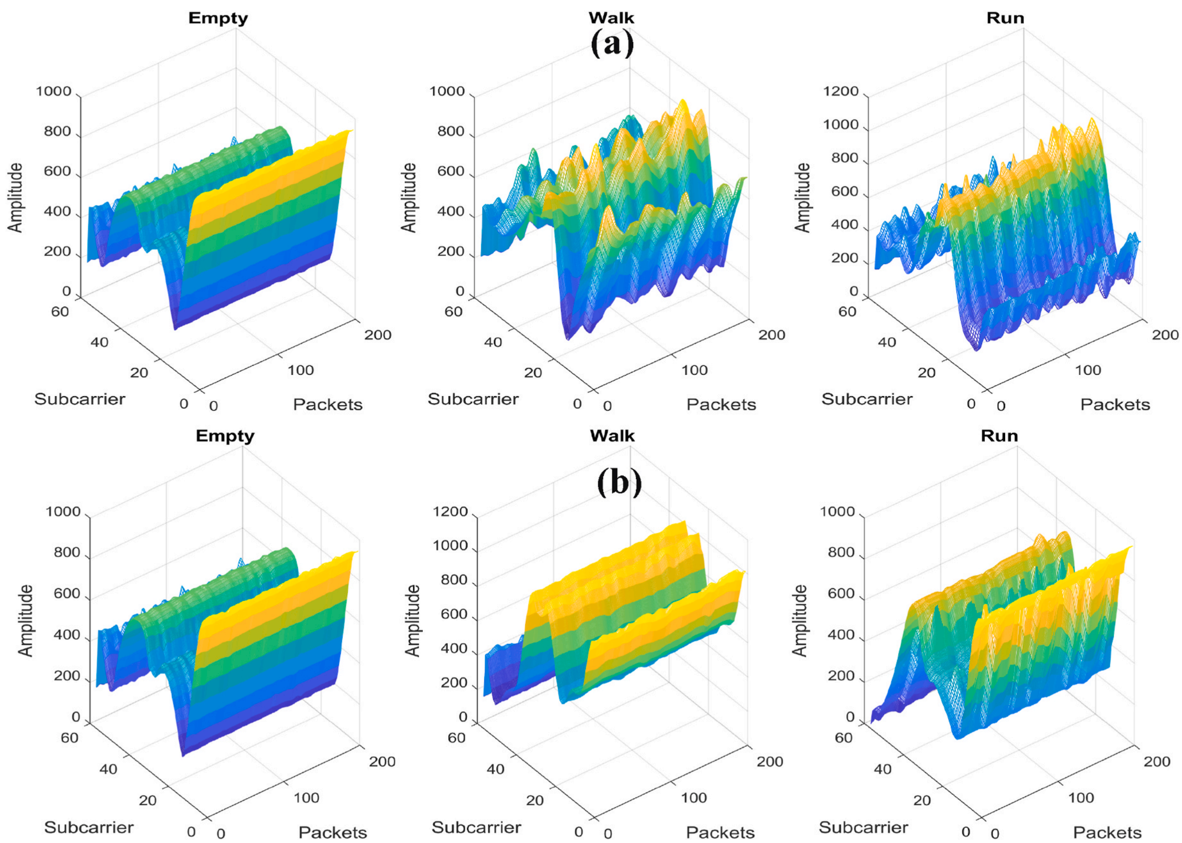


Fig. 18. CSI amplitude captured for activities at Position 3, located approximately 12 m away behind a wall. In (a), the CSI is obtained using the proposed Wider-Angle system, while in (b), the signal captured solely using the Raspberry Pi (RPi).

detecting human presence and accurately identifying their activities across various indoor building materials, including tinted glass, solid wood doors, 5-inch, and, to a significant extent, 8-inch concrete walls. As anticipated, the thickness and density of the obstructing materials directly impact the sensing ability to capture reflections from behind them, with thicker and denser materials posing more significant challenges.

5.5. Robustness of multi-antenna system

Using attached antennas in various positions at different angular degrees behind the wall enhances both gain and sensitivity in angular detection. This improvement enables the system to achieve a wider range of signals and angles, as shown in Fig. 21. The figures depict the dynamic changes caused by activities behind the wall. Fig. 21(a, c) illustrates the average subcarrier captured for through-wall activities using RPi and extended antennas at the 2.4/5 GHz frequency. The signal exhibits superior feature patterns with stable angular degrees at positions 4 and 5. Conversely, Fig. 21(b, d) displays the signals captured using the RPi antenna alone for the same activities at identical locations and angles.

While some activity patterns are discernible, more noise is evident. Comparatively, the signal pattern captured by the 2.4 GHz frequency with attached antennas demonstrates a more favorable dynamic response than that captured by the 2.4 GHz frequency without antennas, as depicted in Fig. 21. This signifies the enhanced performance achieved through extended antennas, including improved feature patterns and reduced noise levels in the signal. The performance analysis indicates that using a system with antennas results in higher activity classification accuracy than without antennas for both 2.4 GHz and 5 GHz frequencies. The accuracy comparison shows that the system with antennas consistently achieves higher accuracy for all activities than without antennas. The results imply that the presence of antennas improves the precision of activity classification, resulting in more accurate predictions, as shown

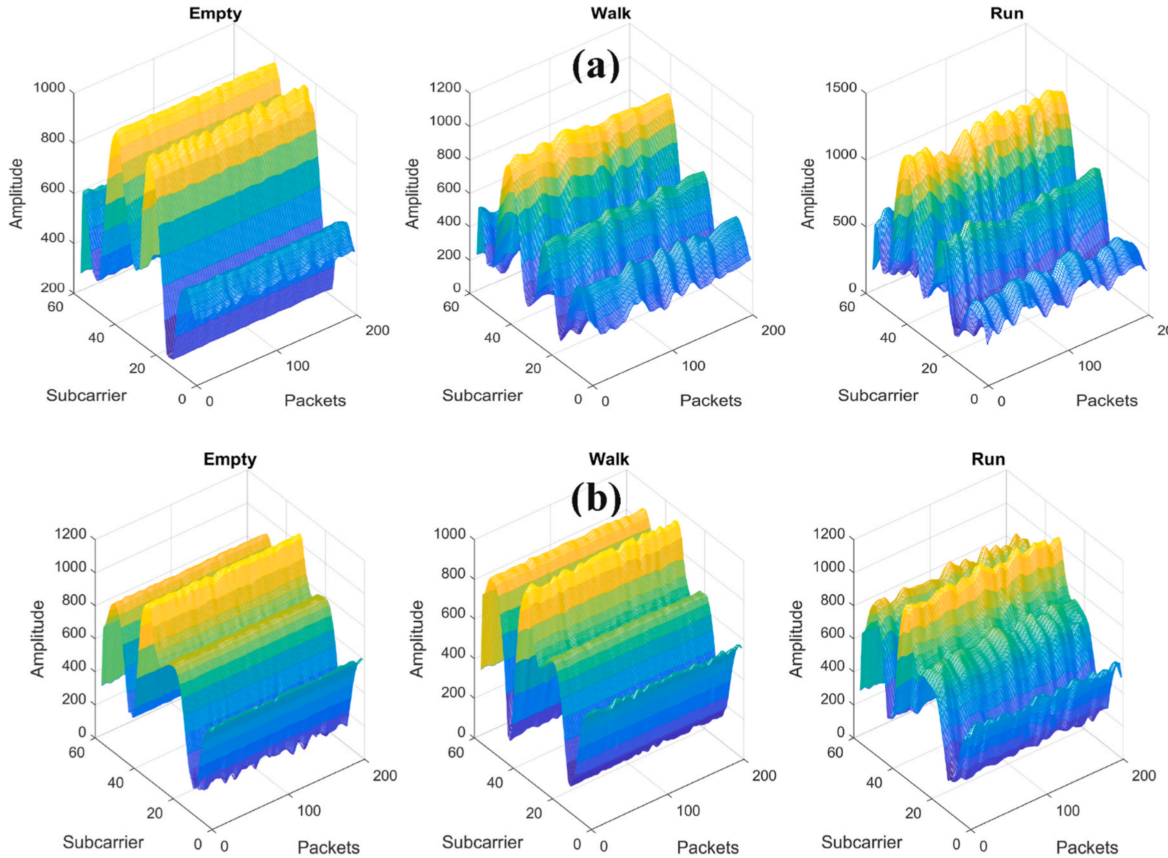


Fig. 19. Performance evaluation of the Wider-angle system: (a) CSI data obtained using the Alfa router in conjunction with RPi, and (b) CSI data acquired solely with the RPi.

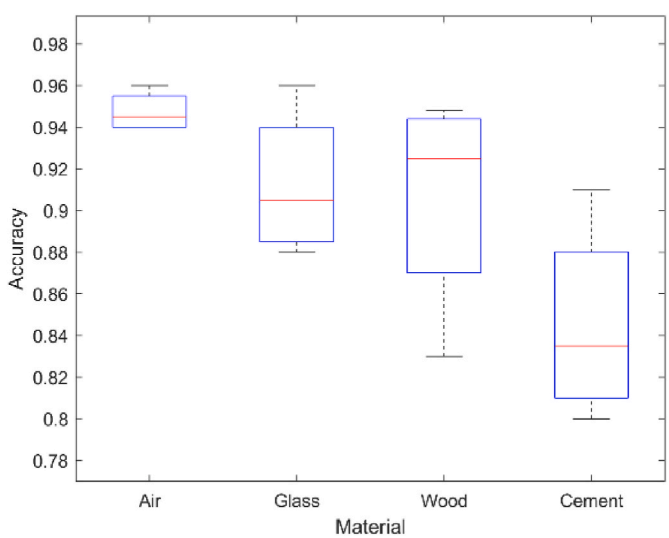


Fig. 20. Different Material Detection Accuracy at position 1 with 2.4 GHz Frequency.

in Fig. 22(a and b).

The precision analysis of the system is conducted through a series of experiments depicted in Fig. 22. The system's performance is evaluated using 2.4 and 5 GHz frequencies for activity classification through obstructing walls which shows the preference for using 2.4 over the wall compared to 5 GHz. Subsequently, activity recognition accuracy is assessed, considering the 2.4 GHz and 5 GHz frequencies at designated positions (1–3) shown in Fig. 22 (c). Furthermore, the classification accuracy of activity recognition through walls shows the better performance of data captured by the Alfa router, where the inter-antenna spacing between antennae is varied to gauge its impact, as shown in Fig. 22(d). This analysis comprehensively explains the system's precision under diverse scenarios and configurations.

5.6. *Performance comparison*

Table 4 presents a comprehensive comparative analysis that aims to evaluate the performance of the proposed work in relation to existing studies. This analysis encompasses several key aspects, such as the methodologies employed, features utilized, computational complexity, and other relevant factors. Considering these various elements, a holistic evaluation is conducted, enabling a deeper understanding of the proposed approach's performance compared to its counterparts. This comparative assessment provides valuable insights into the strengths and limitations of the proposed work and contributes to advancing knowledge in the field.

A comparative analysis of the performance and computational efficiency of diverse models, including SVM, DT, RestNet, KNN, and LSTM, unveils discernible attributes and distinctions among them in the context of sequential HAR presented in Fig. 23. SVM and DT models are commonly used for classification tasks. However, when applied to sequential activities with CSI, they exhibit limitations in capturing temporal dependencies. RestNet models capture some temporal aspects but still face challenges in fully leveraging the sequential nature of CSI data. On the other hand, KNN models consider local similarity but struggle with CSI's high-dimensional and sequential nature. In contrast, LSTM models demonstrate superior performance in sequential HAR with CSI. LSTM effectively learns and remembers long-term dependencies in the CSI data, leading to higher accuracy in activity recognition.

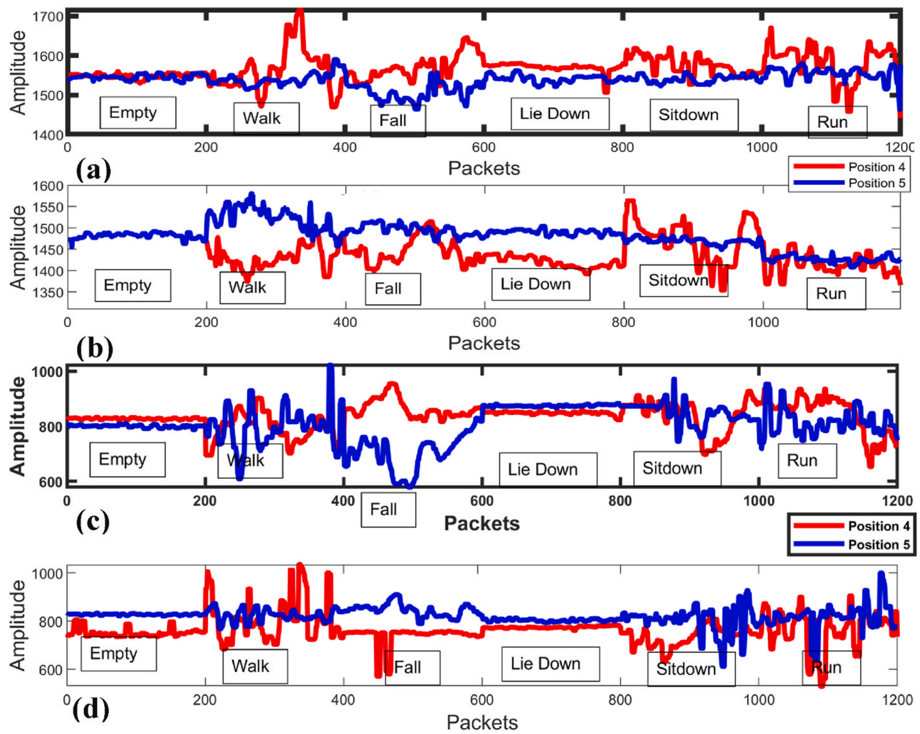


Fig. 21. Comparative performance evaluation of 2.4 and 5 GHz with and without antennas for wider-angle through-wall detection. (a, b) Signal in positions 4,5 with/without antennas using 5 GHz frequency, (c, d) shows signals in positions 4,5 without antennas using 2.4 GHz frequency.

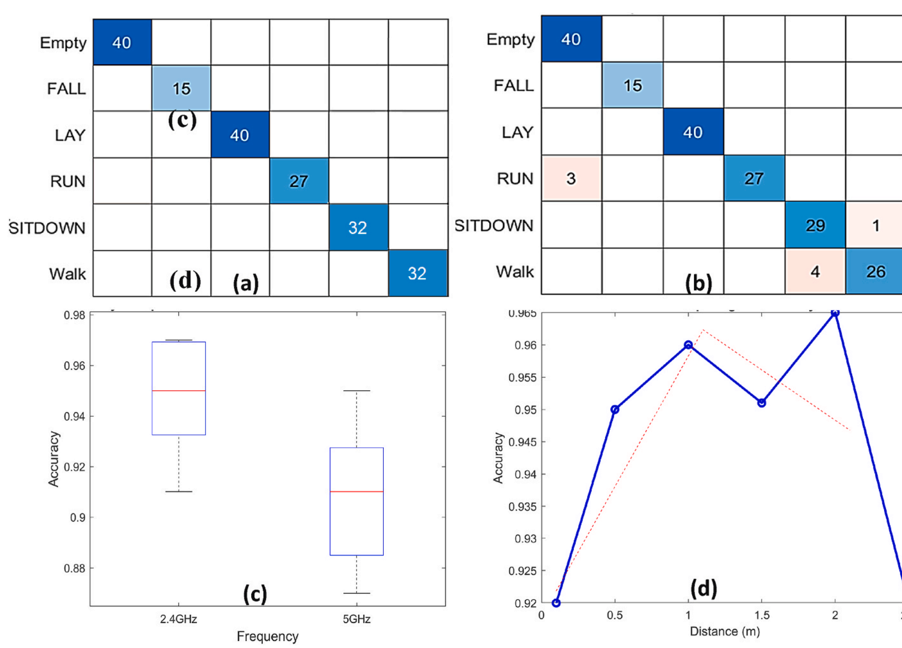


Fig. 22. Accuracy analysis of the system conducted under experimental conditions (a) LSTM at position 1 with antennas using 2.4 GHz and (b) utilization of 5 GHz frequency, (c) analyzing the accuracy of using 2.4 GHz and 5 GHz frequencies at designated positions (1–3), and (d) shows the accuracy evaluation through walls employing an Alfa router with varying inter-antenna spacing.

Using CSI for HAR through walls has significant implications for real-world applications such as medical monitoring, smart cities, and industrial automation. CSI-based HAR enables non-intrusive patient monitoring and post-operative recovery assessment in the medical field. Smart cities enhance security measures by detecting and classifying human activities within buildings. Additionally, in various domains, CSI HAR through walls facilitates eldercare assistance, intelligent home automation, and improved industrial workflow optimization. Continued research and development in this field will further unlock the potential of CSI HAR for a wide range of practical applications.

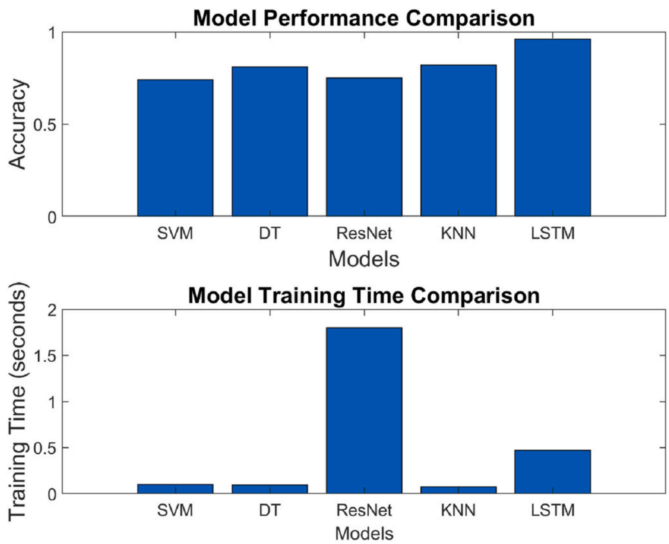


Fig. 23. Comparative analysis of model performance and computational efficiency in sequential HHAR using CSI data.

5.7. Limitations

Although the proposed system exhibits competence in accurately classifying a range of pre-trained activities, its efficacy is intrinsically tied to the specific location in which it is deployed. This dependency on environmental factors implies that fluctuations in environmental conditions directly influence the quality and reliability of the received WiFi signal. Consequently, CSI HAR systems continue to grapple with the adverse impact of environmental effects, leading to uncertainties in activity classification outcomes. Moreover, the current system is primarily designed for single-person activity classification, thereby necessitating advancements to enable robust identification and discrimi nation of multi-person activities. Furthermore, the heterogeneous characteristics of various walls necessitate customized configurations to account for signal reflections and the inherent diversity of wall materials. Additionally, the complexity inherent in human activities poses another considerable challenge, demanding substantial efforts and a vast training dataset to develop models that accurately capture the intricacies of such activities.

6. Conclusion

In conclusion, this work presents a narrative-based approach to human activity identification systems utilizing signal processing techniques for enhanced prediction of human activities through walls using WiFi sensing. The proposed method enables human sensing in LoS and nLoS regions by employing extended antennas inspired by MIMO and deep learning concepts. The experiment focuses on the impact of frequency selection between 2.4 and 5 GHz on through-wall prediction accuracy in static indoor environments. The method derives discriminative characteristics for various activities by emphasizing a wider sensing angle and the ability to predict activities behind walls. The results demonstrate that the WiFi wider angle sensing system achieves high accuracy at training sites, even with limited samples for testing in different locations. Technically, the model utilizes LSTM feature representation and a human activity identification system based on metric learning. Overall, this work provides a practical and cost-effective approach for enhancing feature extraction using available WiFi signals, enabling wider angular sensing through firmware enhancements based on Nexmon and RPi platforms integrated with commercially available WiFi routers.

Future endeavors in through-wall HAR research should explore advanced signal processing techniques capable of mitigating signal attenuation and interference effects. Integrating WiFi sensing with complementary sensing modalities, such as vision-based or inertial sensors, holds promise for augmenting the robustness and accuracy of activity recognition. Furthermore, developing specialized deep learning algorithms tailored for through-wall HAR contributes to extracting meaningful activity features, ultimately enhancing the classification performance.

CRediT authorship contribution statement

Fahd Saad Abuhoureyah: designed the hardware and structural components of the system. **Yan Chiew Wong:** contributed idea/concept, the necessary hardware and materials for the study and supervised the work. **Ahmad Sadhiqin Bin Mohd Isira:** supported and guided the research, providing leadership throughout the project, We acknowledge that the research article has been reviewed and approved by all authors, who have agreed to take responsibility for its content, The authors have also declared that the article represents their original work and does not infringe upon copyright or intellectual property rights.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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