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A Contactless Smart WiFi-Based Application Presence or Fall Detection System: Analyzing Channel State Information (CSI) Signals

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Abstract

Falls are considered to be the most common accident among people of determination and the elderly. Recently, many solutions have been proposed, whether wearable or noncontact, for people presence or falling detection (FD). These solutions can use wearable sensors to effectively monitor the health condition of elderly people at home and ensure their performance. However, all of these solutions require users to always wear specialized devices and sensors in their bodies, which limits the deployment of large-scale systems. Additionally, camera-based systems can raise privacy concerns. Recently, the non-contact Wi-Fi approach is becoming more and more popular because of its ubiquitous and non-invasiveness. In this paper, we propose a smart contactless system that uses Artificial Intelligence (AI) to analyze the Channel State Information (CSI) signals extracted from Wi-Fi signals. Our proposed application can help the people of determination and senior citizens (e.g., remote monitoring of the elderly) to be engaged all the time through closed monitoring based on ability to analyse the CSI signals extracted from Wi-Fi signals. The use of this promising technique can detect the presence, and falls of users without requiring them to wear any specialized devices or sensors. We believe that this application can help elderly and disabled people to remain engaged and monitored at all times, providing their communities with the means to better care for and serve them.

Keywords: Channel State Information; Elderly; Fall detection; People of determination; Wi-Fi signals

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1. Introduction

Falls are a leading cause of hospitalizations, particularly among elderly people and senior citizens living alone. Refusing domestic help and neglecting the use of advanced technologies like smart watches with fall alert system or wearable devices only exacerbates the issue [27, 28]. Timely notifications to paramedics or relatives can reduce the level of fatality, making fall prevention critical. Installing cameras in every nook and corner can be an expensive and risky approach, especially in today's world where cybersecurity and privacy are not always guaranteed.

With the rise in life expectancy, there has been a growing demand for remote surveillance technology to provide medical care for people of determination and the elderly. Among the primary health threats faced by those living alone are falls. However, traditional methods of detecting falls, such as optical, sensor network, or wearable-based systems, have inherent limitations and are challenging to implement in real-world settings [29].

Given the significant and growing proportion of the older population, fall detection programs or systems can effectively lower or avoid death, disease, and suffering for older individuals and their families, as well as the significant social expenses associated with hospital and nursing care admissions. Wearable and non-contact solutions for fall detection have been developed, with Wi-Fi technology gaining popularity due to its pervasiveness and lack of invasiveness [30].

In this paper, we propose a smart mobile application that can assist people with determination, elderly, and senior citizens in remaining engaged at all moments through closed monitoring based on the ability to analyse the CSI signals generated from Wi-Fi signals to sense the presence, movement, and vital signs of users using AI. Our application intends to use the most readily available technology, Wi-Fi, in confined and indoor environments without the use of additional wearable devices to recognize people's movement and vital signs. This approach can address many shortcomings in prior systems, as the Internet of Things (IoT) devices consume little energy, contribute to the development of sustainable communication networks, offer fewer privacy concerns than other devices such as smart cameras, and accomplish a high level of accuracy.

This research paper makes several significant contributions, including (1) Implementation of readily available technology: This paper utilizes the most available technology CSI signals generate from Wi-Fi commercial devices in closed and indoor environments without requiring additional wearable devices to detect the movement and vital signs of individuals, (2) Improved care technology for vulnerable populations: The proposed application provides a high-performance and user-friendly technology to enhance the care of people of determination and senior citizens, who are at an increased risk of falling, and (3) Development of a smart application: This paper aims to develop a smart mobile application that easily monitor and predict the fall of loved ones. This technology has the potential to significantly reduce the incidence of falls and improve the safety and wellbeing of vulnerable populations.

The structure of this paper is as follows: Section 2 offers an extensive review of the background and the relevant literature in the field. The methodology used in the study is discussed in details in Section 3. The experimental design and setup are presented in Sections 4. Section 5 contains an analysis and discussion of the results. Finally, in Section 6, a conclusion is drawn based on the results of the study.

Background and Literature Review

The majority of elderly accidents are caused by falling. According to the World Health Organization (WHO) [1], the incidence of falls in people over the age of 65 is 28-35%, and it rises to 32-42% in people over the age of 70. The more frequently the elderly fall, the higher the expense of medical treatment in each country. Furthermore, falls among the elderly are the major cause of mortality and serious damage if they are not rescued quickly. Therefore, the advancement of technology around the globe has made us motivated to improve healthcare and remote monitoring technology for the elderly. This reality has prompted the design of several systems such as those based on vision [2], sensor networks [3], or wearable devices have some inherent limitations [4], which makes it difficult to be popularized in engineering applications.

WiFi Signals Application:

On the spread of the COVID-19 pandemic in Torino, the government decided to search for solutions to stop the spread of the virus, and capacity restrictions in public places were established to limit the number of individuals who gathered. Therefore, Wi-Fi signals were used by Kalkidan Gebru et al. [5] in tracking people's flows to identify the number of public transportation users necessary on a daily basis. The experimental results showed that the proposed ways of people counting can reach a high level of accuracy while being relatively inexpensive [5]. Wi-Fi signals have also been employed in the MiFi system devised by Pengming Hu et al. to detect mildew infestation in wheat [6]. In their investigation, they discovered that as a Wi-Fi signal propagates through the grain, such physiological change causes significant and detectable changes in the received signal, as represented in the matching CSI data. They offer a device-free wheat Mildew detection system based on Wi-Fi CSI amplitude data [6]. Furthermore, the utilization of radio frequencies in wireless communications, such as Wi-Fi signals, has been examined in the development of systems for detecting human motions. Mu-Cyun et al. [7] proposed exploiting ambient wireless signals to identify gestures using a passive Doppler radar. For demonstration reasons, a prototype radar was created, and field-tested in a typical indoor Wi-Fi scenario. Two antennas are used to provide enough isolation of radar echo and reference signals to the quadrature receiver. The proposed radar can employ wireless signals of any form or combination. It is straightforward to implement as part of the RF (Radio Frequency) circuitry in a mobile device without consuming too much power [7]. Furthermore, Chokemongkol Nadee and Kosin Chamnongthai presented an ultrasonic array sensor for monitoring human fall detection by classifying fall gestures and positions in their research. Their proposed system utilizes the changing distances acquired by each ultrasonic sensor, this system can classify fall gestures and positions.

Wi-Covid, as presented by Li et al.[8] is a non-invasive and contactless framework for detecting COVID-19 symptoms and monitoring patients. It leverages Wi-Fi signals from the patient's home to facilitate the reporting of their Respiratory Rate (RR) without the need for physical contact or surgical intervention. The framework utilizes a Raspberry Pi board connected to a cloud server to assess the patient's shortness of breath. A visualization tool enables medical professionals to track the patient's respiration data over time while the patient is in self-quarantine or isolation. The authors were able to estimate the patient's RR by exploiting the benefits of Channel State Information (CSI), which can be obtained from common household devices such as routers. The CSI data was processed using a pre-processing method to reduce noise, eliminate outliers, and achieve highly accurate results. Moreover, Zhou et al. [9] proposed DeepFocus, a primary model for estimating characteristic human action data. DeepFocus is a Wi-Fi-based system designed to quantify and monitor human movement and activities, applicable to various applications. The model combines convolutional and time-recurrent layers to collectively learn features from the collected data. Additionally, it incorporates modules for temporal and channel-spatial attention, enabling the capture of significant activities without requiring additional supervision or manual intervention. The experiments in this paper utilize the WISDM dataset, the UCI HAR Dataset, and a self-collected Wi-Fi signal strength dataset. These datasets were obtained from diverse environments, including indoor office spaces and outdoor public areas. To collect CSI data for DeepFocus, two ThinkPad laptops equipped with Intel 5300 NICs were set up in monitoring mode and placed on channel 165 at 5.825 GHz. In addition, a work by Guo, et al. [10] examined how Wi-Fi applications may be impacted by movements or motions in the surrounding environment. This paper delved into various Wi-Fi signal-based applications, such as indoor localization and human activity recognition, to explore the effectiveness and importance of Wi-Fi signals. It provided valuable insights that can benefit further research in wireless technology. The CSI, RSSI (Received Signal Strength Indicator), and other examples of wireless technology are utilized in many applications and were vital in the collection of precise data that was valued. They also account for the influence of various types of motions on the data quality. This paper shows a promising result that demonstrate how these wireless technologies can achieve valuable outcomes, make them useful in a variety of applications. Furthermore, Zhu, et al. [11] proved how Wi-Fi signal, particularly CSI, may be an efficient way to monitor for and identify human movement in an indoor environment. It explored an idea for using CSI on radar pulse signals to improve application accuracy. Furthermore, using a distributed pilot system based on the wireless local area network (WLAN) protocol can improve joint sensing abilities and exceed traditional methods like GPS (Graphical Positioning System) tracking systems. According to the study's findings, CSI may be applied as a new type of radar pulse signal for detecting and sensing in enclosed spaces. In addition, Cheng, et al. [12] proposed a framework that can distinguish fall in indoor environment with a commercial equipment. It utilized the CSI stage distinction development lattice as its component for recognizing falls and utilizes sliding window and naming strategies to block signals connected with falling action and relocating Gaussian Blend Model-Stowed away Markov Model (GMM-Well) from 3D skeleton-based human movement acknowledgment for ID purposes. The paper leads an examination in various indoor environment with six volunteers that each has an alternate attribute.

Ding and Wang [13] presented an innovative fall detection system for elderly individuals living alone. The system utilizes Wi-Fi technologies to detect falls without the need for sensors or wearable devices. It collects motion-induced noises from the Wi-Fi signal, which are then transmitted to a data analysis platform for further processing. The collected data undergoes discrete wavelet transform (DWT) to remove random noise, followed by classification using a recurrent neural network model to identify fall patterns automatically. The processed data is accessible through a Web Application Programming Interface (API) for client applications and can be displayed on a dedicated consumer mobile app. The system's performance is evaluated through comprehensive real-world experiments, demonstrating accurate fall detection and quick alerting of caregivers or family members, surpassing other state-of-the-art algorithms and systems. Moreover, an algorithm using Wi-Fi signal was proposed to allocate people within cameras framework by

Cao et al. [14]. It can estimate the number of persons in the camera's field of view (FOV) by leveraging Wi-Fi signals, which includes triangulation based on received signal strength indicator (RSSI) and counting the media access control (MAC) addresses of mobile devices. Simultaneously, statistical data collected via WiFi technology is compared to the number of moving objects identified by the camera. The detection results and background complexity are determined based on this comparison, allowing relevant settings to be modified accordingly via a feedback mechanism. Additionally, The work of Liu et al. [15] is cantered on Wi-Fi-based intrusion detection for intrusion safety applications. They emphasized the limitations of previous Wi-Fi-based systems for dataset gathering and feature extraction. To overcome these constraints, the authors suggested an Encryption Policy Intrusion Detection (EPID) approach. The EPID approach makes use of CSI, as well as additional techniques such as signal denoising, phase calibration, data augmentation with Generative Adversarial Networks (GAN), and feature extraction with sparse autoencoders (SAE). Furthermore, Zhou et al. [16] developed a device-free solution for detecting some objects concealed by walking people, such as metals and liquids, using CSI Wi-Fi signals. As a result, as pedestrians passed via the transmission connection, CSI data was captured and analysed for suspicious stuff detection.

Damodaran and Schafer [17] proposed Activity Recognition (HAR) employing CSI to track human movements and activities such as standing, walking, and running. The research focuses on two HAR methods, one of which uses a support vector machine (SVM) for classification and the other a long short-term memory (LSTM) recurrent neural network. The system employs a variety of approaches for feature extraction, including Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) for both algorithms and wavelets for denoising raw data before feeding it into the LSTM algorithm. The experiment was conducted in an indoor setting to detect the actions mentioned above. Using Wi-Fi CSI, an accurate characterization of activities and human presence may be accomplished by comparing the accuracy and performance of both algorithms since the presented methods outperform prior work in terms of accuracy. In addition, Li and Fang [18] used CSI to identify human presence in the absence of wearable gadgets. Their research is divided into three parts: processing, feature extraction, and decision-making utilizing a basic decision tree. The applied bandpass filter in the pre-processing procedure isolates breathing frequency signals and accentuates the finding that presence data may display values beyond a certain range while absence data does not. Their work concludes that the presented notion may be used in a variety of applications such as senior care, home security monitoring, and emergency response, as well as recommending more work to improve accuracy. Moreover, Pan et al. [19] presented a methodology that uses Received Signal Strength (RSS) derived from numerous Wi-Fi nodes to achieve high simple gesture identification. In addition, to handle differing hand gesture rates, they used a state machine and a linear scaling algorithm. They also presented a recognition architecture based on 1D-CNN and two data gathering methodologies, gesture extending and gesture shifting. This framework will enable Wi-Fi signals to traverse a large range, providing a universal solution for dynamic hand motion detection with promising outcomes.

A study focused in ensemble learning for seated people counting using Wi-Fi signals by Bernaola et al. [20]. The study explores the use of ensample learning, a branch of supervised machine learning that combines the outputs of individual predictors for detecting seated people. It also evaluates the transferability of knowledge learned by ensemble models across different frequencies. Although the ensample achieves a satisfactory level of predictive accuracy, their knowledge cannot be transferred among different frequencies. This paper highlights the lack of studies on ensemble learning for seated people detection. Moreover, Shi et al. [21] used Wi-Fi signals to develop an environment-independent in-baggage object detection system. Its goal is to improve public safety and the industrial process. Using CSI, researchers created a system that catches the material and forms features of things within the baggage. To analyse Wi-Fi signals, the Polarization feature, and the CSI complex difference feature are extracted, which will improve the accuracy of object recognition. To combine these characteristics, a convolutional neural network (CNN)-based model is built. A real-world challenge is handled by employing polarized directional antennas and an adversarial learning-based material-based domain adaptability technique. Furthermore, Oshiga et al. [22] demonstrated a crowd counts estimating method based on CSI. For person identification and crowd estimates, the method employs statistical mechanics and machine learning techniques. The authors include background noise removal using the Chebyshev filter and singular value decomposition, dimensionality reduction using Principal Component Analysis (PCA), and feature extraction using spectral descriptors as pre-processing procedures. Following that, the extracted feature is utilized to evaluate several classification algorithms to properly estimate crowd count. The framework trials yield encouraging results, with accuracy improving with increasing crowd size. Additionally, Tang et al. [7] introduce a distinctive passive Doppler radar system that detects and recognizes human gestures at a short distance using ambient wireless signals. This radar requires no correlated source and is not affected by radio interference. This system's prototype was created and tested after it successfully detected typical gestures. An injection-locked quadrature receiver, a directional coupler, and two antennas are part of the system design. The wireless signals that are received are retransmitted as radar source signals, and the radar echo and reference signals are connected to the receiver. To acquire the in-phase and quadrature components, the received signals are processed with injection-locked oscillators and quadrature mixers. Finally, arctangent demodulation is used to recover the gesture information. Various gestures, including back-and-forth and forth movements, push and pull motions, and circular gestures, are effectively detected by the radar. Besides, Zhang et al. [23] developed a creative Wi-Fi-ID system that recognizes people based on their distinct walking ways. The system analyses the CSI and extracts different characteristics from the disturbances caused by human mobility in the Wi-Fi spectrum. The system used extraction techniques to distinguish incense signals in certain frequency bands and picked the desired characteristic for reliable identification. The system has the potential to be used in a variety of applications, including smart homes, assisted living, and security, to provide a convenient and secure means of identification in a variety of real-world circumstances. The system may provide an achievable choice for authentication, with implications for improving privacy, simplicity, and security in a variety of settings. Also, the use of ambient Wi-Fi signals for human motion detection and categorization is investigated by Siebert et al. [24]. The researchers discovered that various people's movements produce distinct patterns in the RSS waveform. Two techniques are presented in this study that use statistical characteristics collected from raw RSS data and their domain frequency components. Empirical Mode Decomposition (EMD) is used to decompose the RSS signal into Intrinsic Mode Functions (IMFs). Furthermore, Ming et al. [25] presented a HumanFi system to identify humans based on the uniqueness of the Wi-Fi signal fluctuations reflected by a walking person. The technology combines fine-grained gait patterns collected by a commercial Wi-Fi device with an LSTM network. A buffer and filtering method is used in the signal to address short-term anomalous fluctuations. Following that, the LSTM network was utilized to extract temporal characteristics of the gait feature for recognizing various individuals. The study includes the problem analysis, system framework, data pre-processing approaches, feature fusion, and gait detection algorithm. Moreover, Ge et al. [26] suggested a respiration detection method for individuals with little activity utilizing commercial Wi-Fi devices. CSI has been used to extract information pertaining to people, such as reparation and heartbeat. The system is designed to eliminate time-varying phase noise generated by sampling frequency offset (SFO) and carrier frequency offset (CFO). The authors describe calibration procedures to generate a reliable reference connection and eliminate multipath noise. The estimate is carried out for one and two human subjects' peak detection (PD) and auto-correlation function (ACF) techniques. The system yields good results, highlighting the suggested technology's potential in other applications such as tin mobility detection. Table 1 lists down the different types of technologies used in the literature. It represents the hardware and software details.

Table 1. Different technologies used in the literature

References	Software	Hardware
[7]	-	Doppler radar, IEEES02.11 b/g/n access point
[8]	Nexmon firmware to extract CSI, InfluxDB, Grafana visualizer	WiFi router and a Raspberry Pi.
[9]	CNN-BiLSTM, MATLAB, Windows 10, support vector machine (SVM) algorithm	2 ThinkPad laptops, Intel 5300 NIC, three antennas, Intel i7-5700HQ 2.70 GHz CPU.
[10]	Probability Models, Fingerprint-based, Crowdsourcing-based	Antenna Arrays, Mobile devices, sensors (Accelerator, Gyroscope), APs (Access Points), IoT Devices
[12]	Custom Modified open-source driver, Ubuntu 14.04 LTS, Matlab2017a	A desktop with 3 antennas, A desktop with 1 antenna, Intel 5300 NIC
[13]	Mobile app, Custom Modified NIC driver,	2 Routers, Mobile device, Laptop
[16]	Linux 802.11n CSI Tool	2 Laptops, Intel 5300
[17]	Ubuntu version 14.04 LTS, modified wireless driver, modified NIC firmware, Linux 802.11n CSI Tool	2 Lenovo laptops, Intel 5300
[18]	Ubuntu 10.04 LTS	Intel 5300 NIC, LINK TL-WR841N, laptop
[19]	-	2 IoT WiFi device CC3200, 2 USRP devices
[22]	Linux 802.11n CSI Tool	Router, laptop, Intel 5300 NIC
[23]	Ubuntu 10.10, modified Intel NIC driver, MATLAB	HP 8530p laptop, Intel 5300 NIC equipped in the laptop, Netgear R7000
[24]	-	NI USRP-2954R
[25]	Linux 802.11n CSI Tool	Intel 5300 NIC, laptop

Methodology

The whole solution depends on the meta data of the WiFi signal which is so called the Channel State Information (CSI) produced by the transmitter. Figure 1 presents a proposed framework architecture of the proposed solution. The main idea of our proposed solution is to extract detection data from the environment surrounding people of determination and senior citizens (elderly people) using WiFi receivers and perform presence and fall recognition on data analysis platforms. On the other hand, the results of the detection are sent to the mobile application.

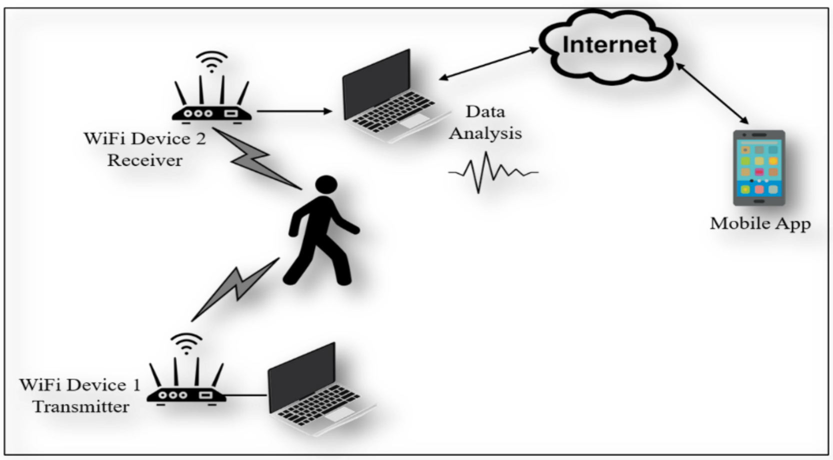

Figure 1. A framework architecture of the proposed project

The solution architecture shows that the produced CSI data by the transmitter (usually the WiFi routers) is affected and changed by the human body movement. The focus in the proposed solution is to monitor and analyze the CSI data streams in a simple design with no technical complexity. The accessibility is fully depending on the internet with no addition setup. Moreover, the recognition is low-cost and easy to deploy without additional dedicated equipment. The mobile application helps in visualizing and illustrating the analyzed data in an interactive way. This solution is considered user-friendly, offering efficient monitoring capabilities, remote access, easy configuration with user profile management, and comprehensive storage of historical fall records with enhanced management features.

The following is a proposed methodology for using WiFi signals to detect and record human activities based on the conducted literature review:

1. Data collection: Collect WiFi signal data using WiFi receivers, such as laptops or smartphones, in various settings where human activities are taking place. It is important to ensure that the data collection is done in a controlled and consistent manner, in order to minimize any interference or noise that may affect the accuracy of the results.
2. Data preprocessing: Preprocess the collected data by filtering out any high-frequency noise and calibrating the phase of the signals. This step is important in order to extract relevant features from the data that can be used to identify human activities.

3. Human identification: Use the detected human activities and additional features, such as gait patterns, to identify individuals from the WiFi signals. This can be done using techniques such as feature fusion and variance analysis.
4. Deployment: Deploy the human activity detection and identification system in a real-world setting, such as a public space or a building, and monitor the performance of the system in terms of accuracy and efficiency. Alongside building a mobile app for receiving positive fall detection urgent notifications.

It's worth noting that fall detection using CSI is a challenging task and it requires a lot of data to be collected and labeled, and this data needs to be processed and analyzed properly to detect falls. It's also important to consider the type of fall detection you are trying to achieve, because falls can happen in different ways, and the system should be able to detect all types of falls, not only specific types.

Data Collection

The whole solution depends on the meta data of the WiFi signal which is so called the Channel State Information (CSI) produced by the transmitter. Figure 2 presents the steps of collecting the data.

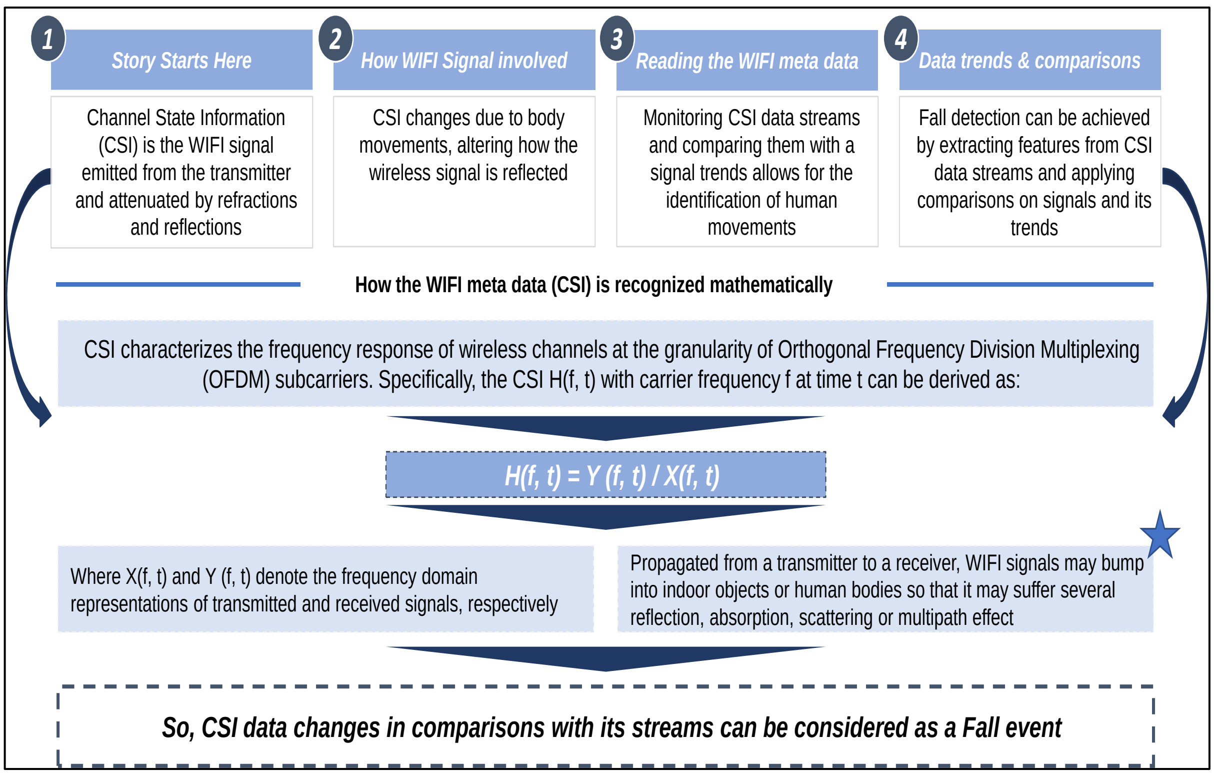

Figure 2. Process of the CSI data collection

The Proposed Application

The proposed mobile application is designed with a sophisticated event-based approach, which promises an easy way to interact and find actions quickly. By employing event-driven programming, the app can efficiently manage and respond to various user actions and system events, delivering a seamless and intuitive user experience. We developed the app using Java for the Android operating system in an Android development environment known as Android studio where we also connected it to Firebase for authentication and other user functionalities.
When the app first launches, it will show a login or registration selection screen which shows an aesthetic look with stunning visuals and a user-friendly interface as shown in Figure 3.

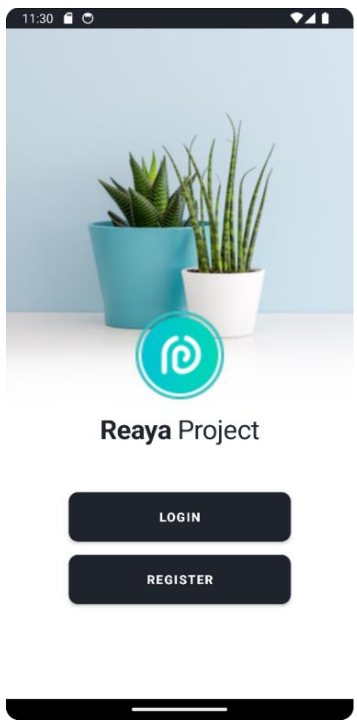

Figure 3. Login Screen

One of the core functionalities of the app is its family members profiling and how we can add elders to our account with an easy to find floating action button to the bottom right as in Figure 4, the addition is not meant for elders only while it can also be used for other family members like kids and Person of Determination (PoD) members.

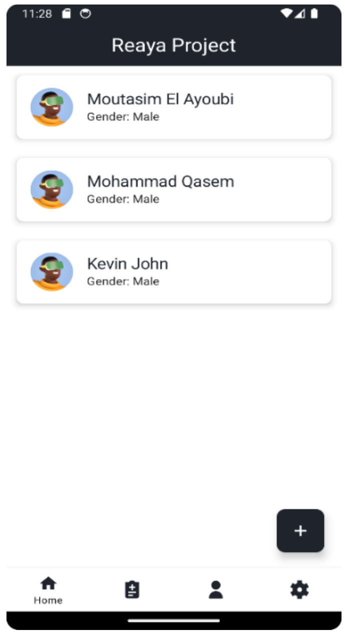

Figure 4. User profile screen

Moreover, this system enables tracking of historical information about the elderly individual. Users can select a specific date to access a comprehensive history of events, presented in a line graph format, as shown in Figure 5. Additionally, we have included a detailed list of logged activities, providing information about the type of detection and other relevant factors such as the room, date, and time of occurrence. These enhancements aim to improve predictions concerning the severity of the fall incidents.

Figure 5. Browsing through the historical statistics of fall detection for elderly individuals.

Another remarkable aspect of the app is the ability to add multiple emergency contacts by accessing the "Contacts" fragment from the bottom navigation bar as shown in Figure 6, we also added a floating action button which will forward the user for another screen to add new contacts to be alerted in case of emergency, the implementation is currently through push notifications but can also be through calls which can be a better alternative or additional option to choose from.

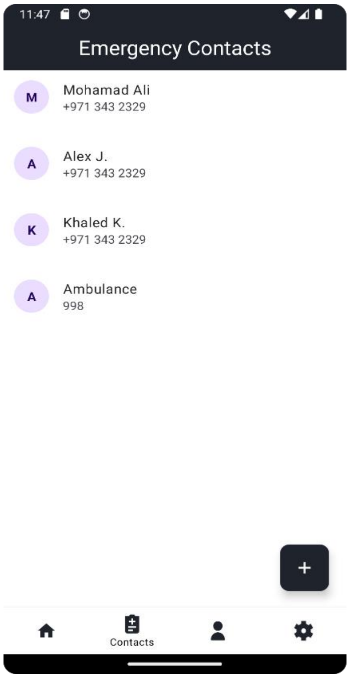

Figure 6 Emergency contacts' screen

Experiments

For our experiments, we used a number of two TP-Link TL-WDR4300 routers were used, one as transmitter and the other as receiver with a custom Atheros network interface card (NIC) which works in Access Point (AP) and Client modes for transmitter and receiver respectively, alongside the Custom Atheros CSI Tool firmware which is responsible for information extraction from the physical layer. The OpenWRT, a Linux distro for embedded devices, was used to create AP which allowed us to configure the channel bandwidth, operating frequency, mode, etc. In the next stage the client router (receiver) should connect to the AP using the OpenWRT interface just as normal WiFi connection. Figure 7 summarizes the main software and tools used to experiment the proposed solution as per the designed architecture and it involved mainly the Routers, Laptops and mobile devices.

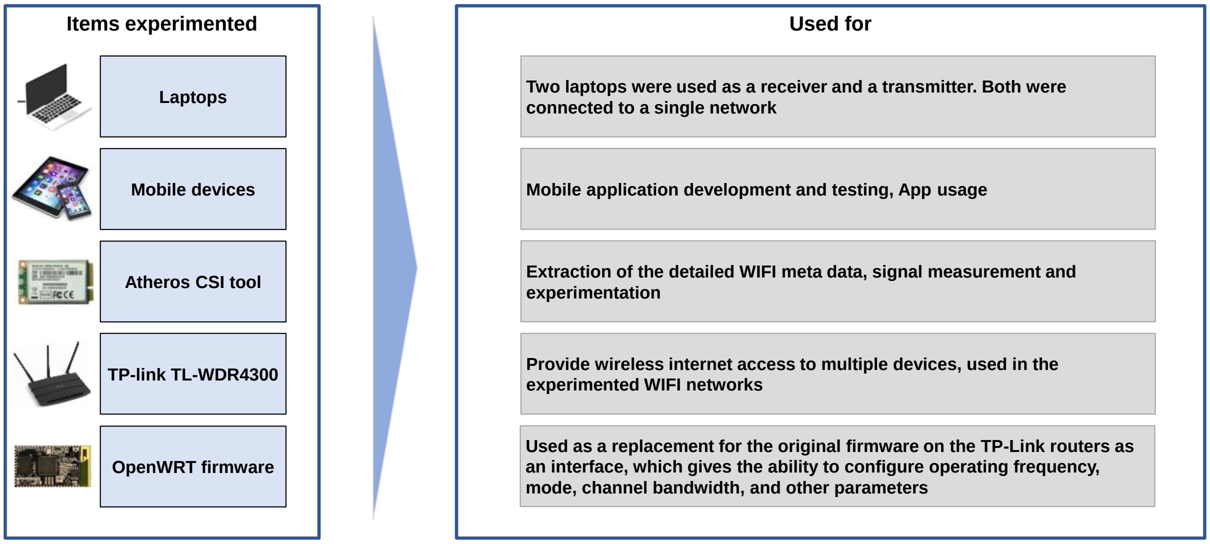

Figure 7. Summary of the software and tools utilised for the proposed solution

Note that we used the Atheros platform unlike other publications that mostly used the Intel 5300 NIC and the Linux 802.11n CSI tool, we decided to go with the more modern solution and not an outdated alternative which was made upon a proprietary platform.

Experimental Design

To set up the experiment environment we applied the following:

1- Setting up the experimental environment: Two TP-Link TL-WDR4300 routers would be used, one as the transmitter and the other as the receiver. The transmitter would be configured as an Access Point (AP) using the OpenWRT Linux distro for embedded devices. The receiver would be configured as a Client using the same OpenWRT Linux distro.
2- Installing the custom Atheros NIC: A custom Atheros network interface card (NIC) would be installed on both the transmitter and the receiver. This NIC would work in both AP and Client modes and would be responsible for information extraction from the physical layer.
3- Configuring the wireless network: The wireless network would be configured using the OpenWRT interface on both the transmitter and the receiver. The channel bandwidth, operating frequency, and mode would be set as required.
4- Connecting the client to the AP: The client router (receiver) would connect to the AP using the OpenWRT interface just as a normal WiFi connection.
5- Collecting CSI data: The custom Atheros CSI Tool firmware would be used to collect CSI data from the physical layer. This data would be used to detect falls.
6- Analyzing the CSI data: The collected CSI data would be analyzed to detect falls.
7- Improving the system if necessary: Based on the results of the evaluation, the system could be improved if necessary. This could involve modifying the wireless network configuration, using different machine learning algorithms, or collecting additional data.

The process for in the above environment starts by making the transmitter sending data to the receiver which will then compute the CSI and send it to the user laptop, the user data will store and visualize the data received. Figures 8 (a) and (b) reflects the environment setup for the experiments.

(a) (b)

Figure 8. Complete setup of the Experiment environment based on the solution architecture and design

Dataset Description

During the project experimentation, we have conducted our own data collection utilizing the available WIFI signals at five different rooms in five different houses (locations). Table 2 summarises the data collected and the signal parameters used in order to collect and read the CSI data.

Table 2. Dataset Description

Activities	Presence and walk, fall, no activity
Labels	Activity and person bounding box (Fall, normal movement)
# of people involved	5
# of scene used	5
WiFi router	TP-Link TL-WDR4300
Bandwidth	40 MHz
Channel	60
Frequency	5 GHz
Antennas	3Rx x 3Tx
№ of subcarriers	114

Results and Discussion

The relationship corresponding to the fall occurrence and the change in CSI signal amplitude is shown during sharp fluctuations in CSI amplitude as presented in Figure 9.

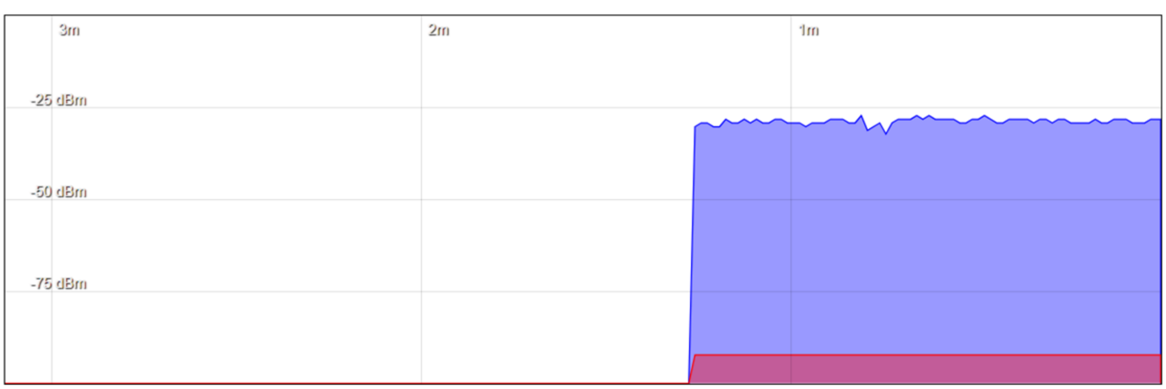

Figure 9. Relationship between the fall occurrence and the change in the CSI signal amplitude

Figure 9, shows the signal and noise of CSI data, with the blue line representing the noise and the red line representing the signal. This data can be used to detect human activity recognition by looking at the changes in the signal over time. For example, if the signal suddenly increases, it could be a sign that the person is walking or running. If the signal decreases, it could be a sign that the person is sitting or lying down. The noise in the data can make it difficult to detect human activity recognition, but there are a number of techniques that can be used to remove the noise. One technique is to use a bandpass filter to remove frequencies that are not associated with human activity. Another technique is to use a statistical filter to remove outliers in the data. Once the noise has been removed, the signal can be analyzed to determine what type of human activity is taking place.

The signal strength of CSI data is affected by the distance between the person and the Wi-Fi access point. This means that the accuracy of human activity recognition can be improved by using multiple Wi-Fi access points. The frequency of the CSI data is also important. Higher frequencies are more sensitive to human movement, but they are also more susceptible to noise.

As shown in Figure 10, the red line in the graph indicates that a fall happened. The blue line indicates that a full attention log was recorded. The fall detection log shows that the amplitude of the signal suddenly increased, which is a sign that the person fell. The full attention log shows that the signal remained high for a period of time, which is a sign that the person was lying on the ground.

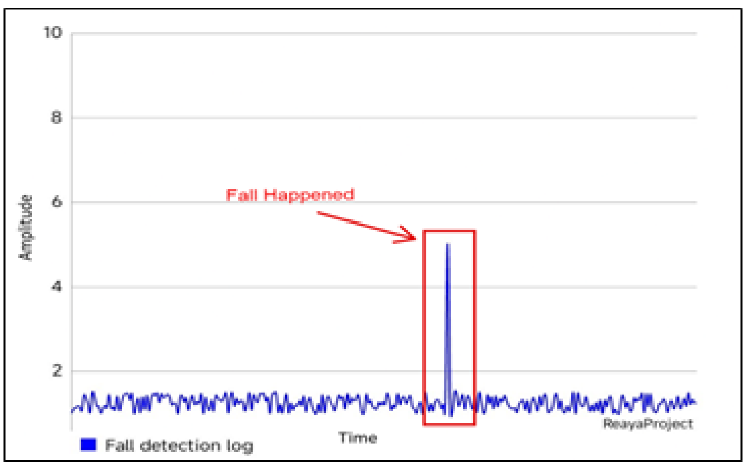

Figure 10. Indicating when a fall happens when analysing the CSI data

This data suggests that CSI data can be used to detect falls. The sudden increase in the amplitude of the signal can be used to detect the impact of the fall, and the sustained high signal can be used to detect that the person is lying on the ground. This data could be used to develop a fall detection system that could alert caregivers or emergency services in the event of a fall.

Furthermore, figure 11shows that the signal strength of the network that the person was connected to suddenly decreased at the time of the fall, and then remained low for a period of time. This is consistent with the impact of a fall, which can disrupt the signal as it passes through the body. The sudden decrease in the signal strength could be used to detect the impact of the fall, and the sustained low signal could be used to detect that the person is lying on the ground. This data could be used to develop a fall detection system that could alert caregivers or emergency services in the event of a fall. Overall, the figure shows that CSI data can be used to detect falls. The sudden decrease in the signal strength could be used to detect the impact of the fall, and the sustained low signal could be used to detect that the person is lying on the ground. This data could be used to develop a fall detection system that could alert caregivers or emergency services in the event of a fall.

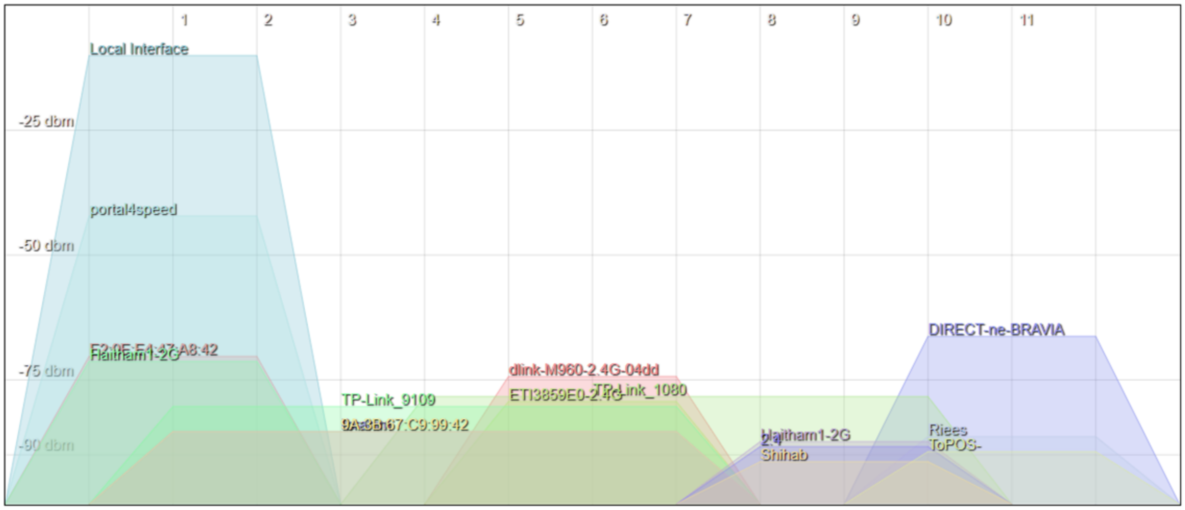

Figure 11. signal strength of the network that the person was connected to

2. Conclusion and Future Work

Conclusion

In this paper, we have presented an approach for falls and presence detection, particularly aimed at serving people of determination and the elderly. Our proposed smart contactless system leverages the analysis of Channel State Information (CSI) signals extracted from Wi-Fi signals using Artificial Intelligence (AI) techniques. By eliminating the need for specialized wearable devices or invasive camera systems, our application offers a non-intrusive solution that facilitates continuous monitoring and engagement for vulnerable populations. The results of our experimental evaluation demonstrate the feasibility and effectiveness of our approach in detecting the presence and falls of users. The use of Wi-Fi signals and AI-enabled analysis provides a reliable method for capturing movement patterns. This technology has the potential to significantly reduce the incidence of falls among the elderly and people of determination, thereby enhancing their safety and well-being.

Recommendations

Looking ahead, several paths and development can be explored to further enhance the capabilities and impact of our proposed system:

- Real-world Deployment and Long-term Monitoring,
- More personalization and user-friendly design,
- Expanding the capabilities of the system to monitor additional health parameters and detect early signs of medical emergencies, such as abnormal heart rates or sudden changes in activity levels,
- Integration with official healthcare systems.

Future Work

In conclusion, our smart contactless system represents a promising advancement in fall detection and presence monitoring for people of determination and senior citizens. By applying the power of Wi-Fi signals and AI analysis, we have presented a viable solution that addresses the limitations of traditional methods and promotes continuous care. Through ongoing research and development, we aspire to contribute to the betterment of the lives of vulnerable populations, fostering independence, safety, and engagement in their daily activities.

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The authors have not disclosed any competing interests or personal relationship that might affect the work in the paper.

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