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Wireless Sensing-based Daily Activity Tracking System Deployment in Low-Income Senior Housing Environments

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ABSTRACT

Maintaining independence in daily activities and mobility is critical for healthy aging. Older adults who are losing the ability to care for themselves or ambulate are at a high risk of adverse health outcomes and decreased quality of life. It is essential to monitor daily activities and mobility routinely and capture early decline before a clinical symptom arises. Existing solutions use self-reports, or technology-based solutions that depend on cameras or wearables to track daily activities; however, these solutions have different issues (e.g., bias, privacy, burden to carry/recharge them) and do not fit well for seniors. In this study, we discuss a non-invasive, and low-cost wireless sensing-based solution to track the daily activities of low-income older adults. The proposed sensing solution relies on a deep learning-based fine-grained analysis of ambient WiFi signals and it is non-invasive compared to video or wearable-based existing solutions. We deployed this system in real senior housing settings for a week and evaluated its performance. Our initial results show that we can detect a variety of daily activities of the participants with this low-cost system with an accuracy of up to 76.90%.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Hardware** → **Wireless integrated network sensors**; • **Computing methodologies** → *Machine learning*.

KEYWORDS

WiFi sensing, daily activity monitoring, senior housing.

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1 INTRODUCTION

Ability to perform daily activities independently is one of the critical needs for healthy aging. Loss of independence in older ages represents the transition from health to disability. Thus, older adults who lose the ability to ambulate or care for themselves are at a high risk of adverse health outcomes (e.g., falls) and decreased quality of life. Aging in place is difficult in particular for low-income older adults with multiple chronic conditions and disabilities, lack of transportation, and limited social capital. That is why it is essential to routinely monitor daily activities and mobility to capture early decline before a clinical symptom arises.

Traditional activity and mobility assessment tools are primarily self-report, subjective, and episodic. These assessments are prone to recall bias, especially among older adults with memory issues. Additionally, they do not capture variability over time, making it challenging to track a patient's decline in function. Recently, digital health technologies have been proposed to obtain objective, high-frequency, and remote monitoring. However, significant user challenges (e.g., loss of device, incorrect use) threaten the reliability of the data collected. Motion detection sensors in the context of in-home unobtrusive physical performance assessment show limited results as they could not detect different types of human behaviors (e.g., sitting, walking, eating, and leaving home). There is a need to develop and test new sensing technology that can characterize and quantify different types of daily activities in a real-world setting while also being discreet, affordable, and requiring minimal user engagement.

In this study, we propose to leverage ubiquity of WiFi technology and low-cost devices that can transmit WiFi signals to monitor the daily activities of senior adults in a home environment (see Fig.1 for sample setup). This allows for an activity recognition opportunity without any wearables on the body of the person that is monitored, and even allows monitoring beyond visual line of sight (i.e., in multiple rooms of the house) as WiFi signals penetrate through the walls. This is achieved through the fine-grained analysis of

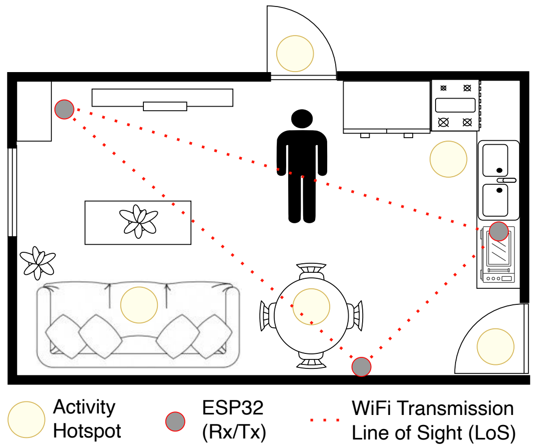


Figure 1: A typical deployment with potential activity hotspots in the living and kitchen area with sample WiFi RX/TX positions.

WiFi signals (i.e., Channel State Information (CSI) on subcarriers), which reflect from individuals' bodies while propagating in the environment and thus carry information regarding their location and movements. Existing studies on WiFi sensing usually consider a limited and controlled/lab environment (e.g., a room) and focus on recognition of random activities happening in a non-natural environment (i.e., subjects are asked to perform the activities rather than doing them in their daily routine). These studies also utilize specialized hardware (i.e., a laptop and an updated Network Interface Card [10]) to collect WiFi CSI data from the transmitter devices in the environment. Because these devices are costly and bulky, they are not amenable to scalable deployments. To address this, we recently developed an Internet of Things (IoT)-based standalone and lightweight solution to WiFi sensing which facilitates the large-scale deployments [11].

Utilizing our IoT based solution that uses low-cost ESP32 microcontrollers, we deployed our WiFi sensing based system in the houses of nine different older adults and evaluated its performance. In this study, we go through the steps we followed during deployment together with the challenges we faced. We also present our initial results from a subset of the data collected and discuss our further steps.

To the best of our knowledge, despite the variety of studies on WiFi sensing, there is no study that deploys a WiFi sensing-based system in a senior house setting for 5-7 days and collects data in a natural setting i.e., as the participants perform these activities in their daily routine, and provides its evaluation.

The rest of the paper is organized as follows. Section 2 provides a background on WiFi sensing technology and discusses related work in the field. Section 3 presents the details of our system setup, highlighting its features, and functionality. In Section 4, we go through the details of the deployment process together with the details of the participants involved. We then present the performance results of the WiFi sensing system in the deployed environments. Finally, we discuss our future directions in Section 5 and our concluding remarks in Section 6.

2 BACKGROUND

2.1 Channel State Information

WiFi sensing technology harnesses ambient WiFi signals to detect and perceive the physical properties of the surrounding environment [15, 21]. These radio frequency (RF) signals travel through the environment along multiple paths, moving from a transmitter (TX) to a receiver (RX). As these signals interact with various objects in the background, such as walls, furniture, and people, they undergo different types of variations.

CSI is a metric used in orthogonal frequency-division multiplexing (OFDM) systems. It is employed to characterize the amplitude and phase variations that wireless signals experience across different subcarrier frequencies during transmission between a transmitter and a receiver. The following equation models CSI:

$$y^{(i)} = H^{(i)}x^{(i)} + \eta^{(i)}, \tag{1}$$

where i is the subcarrier index, x is the transmitted signal, y is the received signal, η is a noise vector, and H is a complex vector containing the CSI denoting the transformation change required from the input x to the output y. The CSI value collected for each subcarrier is a complex number that consists of both a real component ($H_r^{(i)}$) and an imaginary component ($H_{im}^{(i)}$). Using these components, we can then compute amplitude $A^{(i)} = \sqrt{(H_{im}^{(i)})^2 + (H_r^{(i)})^2}$ and phase $\phi^{(i)} = atan2(H_{im}^{(i)}, H_r^{(i)})$.

2.2 Related Work

WiFi sensing based human activity recognition has gained significant attention in recent years due to its non-intrusive nature and the ubiquity of WiFi infrastructure [15, 21]. Our study contributes to this field by exploring the recognition of activities performed by elderly people during their daily routine in a week using low-cost WiFi chips, making it a unique study that deploys and evaluates a WiFi sensing system in practice.

There are a few studies [3, 6, 25, 26] exploring possibilities of deploying a series of wireless sensors like ZigBee, XBee, Arduino, temperature sensors, contact sensors, LPG sensors, GSM modules, wearable smartwatch, and so on forming a Wireless Sensor Network (WSN) to remotely monitor wellbeing of the elderly people. However, none of these studies utilizes ubiquitous ambient WiFi signals to track and monitor people.

A significant number of studies [9, 31–35] explore the usage of several WiFi capable devices to collect CSI data and then recognize several activities, even with centimeter-level accuracy in passive gesture tracking. However, only a handful of the studies [8, 12, 13, 29] explore the usage of low-cost devices like ESP32 for WiFi sensing.

Our study incorporates two other challenges, namely, activity recognition for long-term periods in a real-life ever-changing environment and deployment in different environments for different participants. Wireless signals like WiFi tend to change over time responding to either any kind of environmental change or due to some temporal effect on the WiFi chip as discussed in studies like [18]. The study [16] proposes an Environment Independent (EI) framework for WiFi CSI-based activity recognition by using CSI amplitude ratios between antennas, applying PCA for noise reduction, and employing weighted majority voting across subcarriers to mitigate environmental effects and improve cross-environment performance. The work in [20] reviews recent advances in deep unsupervised domain adaptation, focusing on techniques that transfer knowledge from a labeled source domain to an unlabeled target domain using various approaches, including discrepancy-based, adversarial-based, and reconstruction-based methods with their strengths and limitations for addressing domain shift problems, i.e., applying same setup in different environments. In this study, however, we have trained customized models for different deployments as their floor layouts were different.

Relating to our machine learning approach, we found a few studies exploring the application of ensemble learning with WiFi CSI data. In [4], multiple WiFi links are used to collect data and train different base models to benchmark the performance of several ensemble approaches. It leverages the advantage of having multiple WiFi links. Another study [19] also looks at the activity recognition problem by stacking ensemble approach with two separate models, i.e., ResNet and CNN with GRU, on the same datasets. These studies present performance improvement using ensemble over the base learner models, thus we take the advantage of ensemble learning in our study as well.

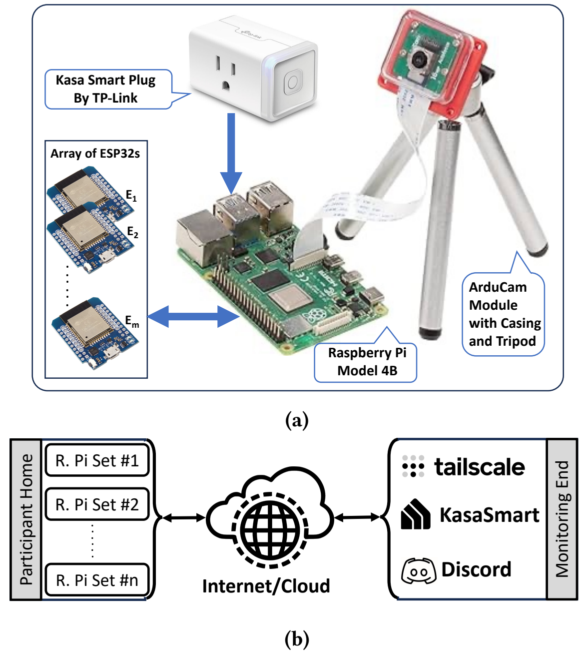


Figure 2: (a) Single set of devices with Raspberry Pi (R. Pi) 4B, multiple ESP32 WiFi receivers, Kasa SmartPlug, and camera module, (b) Overall end-to-end monitoring system.

3 OVERVIEW OF DEPLOYED WIFI SENSING SYSTEM

We have developed a complete IoT infrastructure to deploy in several nursing home apartments for old people. As shown in Fig. 2, our system involves both offline data collection components and online (over the Internet) remote monitoring components. The following subsections describe the functionalities of and challenges faced with these components.

3.1 Deployed System Components

Depending on the floor maps of the participants, we deployed several Raspberry Pi 4B devices to collect WiFi CSI data from ESP32 WiFi receiver (Rx) microcontrollers and record activities using camera modules to prepare the ground truths.

3.1.1 Raspberry Pi. We used CanaKit package with Raspberry Pi 4B boards having 2GB RAM. The principal function of this mini-computer is to collect CSI data from all the connected ESP32 Rx devices using our developed CSI-Pi [23] server app. This server app is also equipped with capabilities like recording and post-processing videos.

3.1.2 Camera Module. We recorded the video of the participant performing several daily activities through a connected ArduCam module using the PiCamera [17] library. The camera was often supported by a tripod, while a few deployments required it to be taped on some higher ground to have a better view of the apartment. As per IRB protocols, we recorded the activities from 8 AM to 8 PM giving the participant a fully private night time. Consequently, we consider only these 12 hours of CSI data in our system.

3.1.3 ESP32 Microcontrollers. We deployed multiple pairs of ESP32 WiFi receiver and transmitter. These were flashed with ESP32-CSI-Tool [11] firmware. We saved CSI data only from the receiver devices connected with Raspberry Pi. The transmitters were powered on at some far-reach corner of the apartment ensuring the line of sight (LoS) of some observable activities.

3.2 Remote Live Monitoring and Health Check

We developed a fully connected ecosystem of multiple online components, i.e., a continuous monitoring system to let us know the status of the data collection process and also to let us debug and even reset the system remotely.

3.2.1 Tailscale. Tailscale [28] is a partially open-source software-defined mesh virtual private network (VPN). Each of our Raspberry Pi devices was equipped with a Tailscale client app which made it accessible via SSH from our developer end in case of any discrepancy suspected in the data collection status. Tailscale ensures end-to-end encryption of any such remote connection using WireGuard [36] so that no man-in-middle attack can happen while we access any remote device.

3.2.2 Kasa Smart Plugs. Kasa Smart plug enables us to power on and off any connected IoT device remotely, even through the Internet. We powered almost all of our Raspberry Pi and ESP32 devices with these smart plugs. Each of these plugs was connected to the Internet and manageable through the Kasa smartphone app. Whenever we observed any device not working properly, we accessed it using Tailscale and tried to fix it first. If it did not work, we could restart the device by controlling its power through its connected smart plug.

3.2.3 Discord Webhook Messages. A summary of the collected CSI data and recorded videos were periodically sent to a webhook in the Discord messaging app to let all concerned personnel know the most recent status of the data collection process. We could analyze and proactively detect any failing ESP32, failing camera, power outage, etc. occurrences in the deployed home by looking into a few kilobytes of sent messages in the Discord app from time to time.

3.2.4 Verizon Orbic Speed 5G WiFi Hotspot. All of our Raspberry Pi and smart plug devices were connected to the Internet through one or more Verizon Orbic 5G WiFi hotspots. This was needed as there were no Internet available at the residences of participants.

3.3 Challenges and Issues Faced

We faced various practical issues in our live deployments which are not usual in a controlled lab environment. We gathered experiences through these issues as we solved those in consecutive deployments. However, some issues were found inevitable and costed us lose a significant amount of data.

3.3.1 Unexpected Person Attendance. WiFi sensing is susceptible to the presence of multiple people and we were to monitor the participant living alone in the apartment. However, we observed several occasions involving the presence of an outsider like a nurse, maintenance officials, visiting friends, our deployment team, and so on in the monitored environment. We needed to exclude those parts of the CSI data during data annotation looking into the recorded videos. Note that recent studies [2, 22] show that it can be possible to monitor multiple people's activities separately, however for the sake of our initial deployments we targeted single person based movements.

3.3.2 Device Heating. In one of our early deployments, we noticed our Raspberry Pi functioning extremely slow and barely was reachable. Investigation revealed that our used aluminum case of CanaKit was not good enough to release the device's heat and it was getting too hot to continue its operation at the usual speed. We then used only plastic casings with enough vents, thermal heat sinks, and a cooling fan installed inside for the consecutive deployments and never faced a similar issue.

3.3.3 Device Positioning. A few of the apartments were so challenging to cover with our camera and WiFi transmission LoS that we needed to tape our devices, i.e., camera and ESP32, onto the wall or high-standing types of furniture. While it might not be favorable to all the participants, it even left marks on the wall in a deployment. On several other occasions, either the taped camera or the camera with tripod or the Raspberry Pi was displaced due to activities around it. One positive takeaway of this type of issue is none of our ESP32 devices were displaced as those are comparatively lightweight and safely placed to maintain the same transmission line.

3.3.4 Pets. We tried to on-board participants with no pets, but one of them had two cats. We requested her not to let the cats out of the unmonitored private space, i.e., the bedroom. However, it is unlikely for the cats to do so. So we needed to look out while annotating that participant and clip our data during the presence of the cats inside our monitored space.

Table 1: The number of occurrences of the selected daily activities per participant.

Activity	Code	P03	P05	P09
Enter Apartment	enapt	16	16	5
Exit Apartment	exapt	27	24	5
Enter Private Area	enpri	48	38	28
Exit Private Area	expri	54	45	23
Kitchen Activity	kit	115	74	16
Fridge Open/Close	fri	65	41	27

3.3.5 Heaters and Fans in the Environment. Winds from fans can make random movements of lightweight materials in the environment. Besides, we observed a deteriorating data rate from a transmitter, leading it to not transmit anymore after a few days and discovered later that the participant was using a heater by its side. These issues caused us to lose a significant amount of data.

3.3.6 Maintenance Emergency. In one of our deployments, the participant had a water leak from her roof to the side wall. One of our smart plugs was soaked and fused in the leaked water, which made the attached Raspberry Pi power off. We noticed the device missing its periodic Discord messages while not reachable through Tailscale and found out about this issue after contacting the participant. We admit that this kind of maintenance emergency can cause havoc in this type of live deployment.

3.4 Post-processing

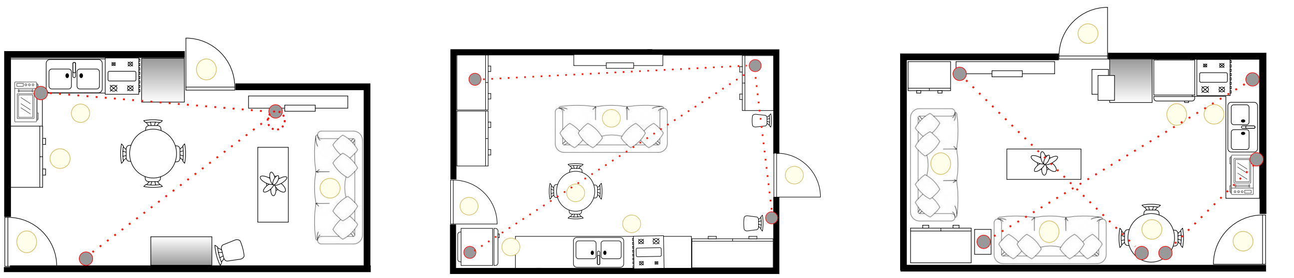
After collecting the data, a time-consuming step was to look into all the recorded videos and annotate the interesting activities to train our WiFi sensing ML model for activity classification. We recorded the videos with online synchronized timestamps embedded on top of each frame so that we could record the actual millisecond accurate timestamp of any activity. This manual post-processing step got particularly tougher with more camera angles recording movements simultaneously.

Additionally, the volume of the collected CSI data and recorded video files was over a hundred gigabytes per participant. With more participants deployed and more data accumulated, processing this volume of data became more challenging.

4 EXPERIMENTS

4.1 Participants Information and IRB

We deployed our system and collected data from nine participants after being approved by VCU Institutional Review Board (IRB). Among them, there are one African-American man, six African-American women, and two white women. Their ages range from 55 to 77, with an average of 67.3. We have annotated and run experiments with three participants' data in this study, namely P03, P05, and P09. Their floor maps are shown in Fig. 3 with sensor placements which are done mainly based on camera angle visibility



(a) (b) (c)

Figure 3: Deployed floor-maps of (a) participant 3 (P03), (b) participant 5 (P05), and (c) participant 9 (P09).

among the furniture positions, power outlets, and floor layout. Table 1 enlists the repetition counts per observable activity.

4.2 Data Collection

During the experiments, we collect CSI data using WiFi-enabled ESP32 microcontrollers and the ESP32-CSI Toolkit [11]. Unlike other data collection methods that require a host laptop with an updated Network Interface Card (NIC), these microcontrollers offer a compact, cost-effective, and independent solution. The portability and versatility of the ESP32s facilitate easy deployment. In order to run the proposed solution in resource limited edge devices efficiently, we integrate solutions like online sampling of collected CSI data [14]. In our system, each transmitter sends data frames at $100Hz$ to its respective receiver. Multiple pairs of these RX and TX devices are deployed based on the floor map of the apartment. The received CSI data at the RX ESP32 are exported to a file stored inside a Raspberry Pi 4B. Due to the multiple days-long deployment period, all video and CSI data stored grows beyond a hundred gigabytes in size and thereby makes it resource-consuming to transfer, annotate, and process for machine learning.

4.3 Preprocessing and ML Model Development

The CSI data undergoes preprocessing steps before being fed into the machine learning model for training. Initially, we denoise the collected CSI data by independently applying a moving average to each subcarrier using a window of size w. Next, we use Principal Component Analysis (PCA) to further denoise the collected data. We have not reduced the data dimension from 64 after applying PCA like many other studies. The preprocessing steps as well as the data flow throughout the developed CNN and Gradient Boosting Ensemble model, can be seen in the Fig. 4.

Once the preprocessing steps are finished, we use the data of each WiFi link to train separate CNN models independently. We train a CNN model $h_m(x)$ for mth WiFi link's CSI amplitude data, x. This training yields a residual $r_i^{(m)}$ for ith action, where

$$h_m(x) \approx r_i^{(m)} \tag{2}$$

This CNN takes the input x (CSI amplitudes) and is trained to minimize the difference between its output and the residuals. Note that we can think of each CSI window as a two-dimensional monochrome (gray-scale) image of dimension $\omega \times 64$, where ω is the number of CSI frames per window. Therefore, it can be processed by convolutional layers of a CNN model. We have used three such convolutional layers and two final dense layers to construct our CNN model. Each convolutional layer has a kernel of size (3, 3) and max pooling of dimension (1, 1). We have eight filters for the first layer, 16 for the next, and 32 for the third convolutional layer. A batch normalization or dropout layer follows each layer to prevent overfitting. We have used categorical cross-entropy as the loss function of the CNN model. This architecture is depicted in Fig. 4.

Ensemble learning [7] is a powerful paradigm enhancing the predictive performance of individual base or weak learner models by combining their strengths. It encompasses various techniques such as Bagging (or, Bootstrap Aggregating), Boosting, and Stacking. Each technique introduces different strategies to combine base learners. For example, Bagging reduces the variance of a model by training multiple instances of the same learning algorithm on different bootstrap samples and then averaging or voting their predictions. On the other hand, Boosting improves the overall performance of a model by sequentially training a series of base learners, with each learner focused on correcting the errors of the previous one. Our use case lures us to use a Boosting method. Among various Boosting methods, AdaBoost focuses on misclassified samples, Gradient Boosting builds models sequentially to minimize errors, and XGBoost optimizes Gradient Boosting with regularization and parallel processing. Moreover, Light GBM uses leaf-wise tree growth for faster training, while CatBoost handles categorical features efficiently and reduces prediction shifts. After trading between simplicity and applicability, we have chosen Gradient Boosting for this study.

Therefore, a Gradient-Boosting (GB) Ensemble model is initialized to create a stronger learner by combining the predictions of multiple CNN models as weak learners. If y_i is the true label for any ith action, then the initial GB ensemble prediction $\hat{F}_0(x)$ is calculated as -

$$\hat{F}_0(x) = \arg\min_{\theta} \sum_{i=1}^{n} L(y_i, \theta) \tag{3}$$

Here, L is the deviance or logistic loss function. For mth iteration, i.e., mth CNN model training, the negative gradients or residuals, $r_i^{(m)}$, of the loss function with respect to the current prediction

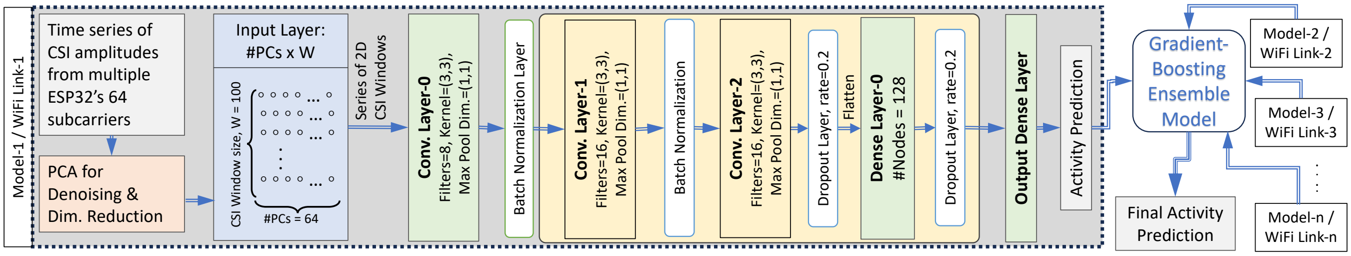


Figure 4: Data flow through the designed GB-Ensemble Model combining multiple CNN models for activity prediction.

$\hat{F}(x)$ for ith action is calculated using the equation:

$$r_i^{(m)} = -\left[\frac{\partial L(y_i, \hat{F}(x_i))}{\partial \hat{F}(x_i)}\right]_{\hat{F}(x_i)=\hat{F}_{m-1}(x_i)}. \tag{4}$$

We then update the model's prediction by adding the new CNN's prediction scaled by a learning rate α, as per this equation

$$\hat{F}_m(x) = \hat{F}_{m-1}(x) + \alpha h_m(x). \tag{5}$$

The final prediction using all the M WiFi links is given by

$$\hat{F}_M(x) = \hat{F}_0(x) + \alpha \sum_{m=1}^{M} h_m(x). \tag{6}$$

The implementation of this proposed evaluation system is completed using libraries as Tensorflow [1] version 2.16.2, Keras [5] version 3.4.1, and Sci-kit Learn [24] version 1.2.2. The models are then trained on the VCU Athena [30] server occupying 384GB RAM, one CPU of AMD EPYC 7763 64-Core processor, and one unit of NVIDIA A100 80GB GPU through Slurm [27] workload manager.

4.4 Experiment Results

After collecting CSI data for the specified actions in each environment, we developed corresponding deep learning models using the steps outlined in Section 4.3. Since there was no training data, we used 60% of the activity instances to train the models while the others were used for testing.

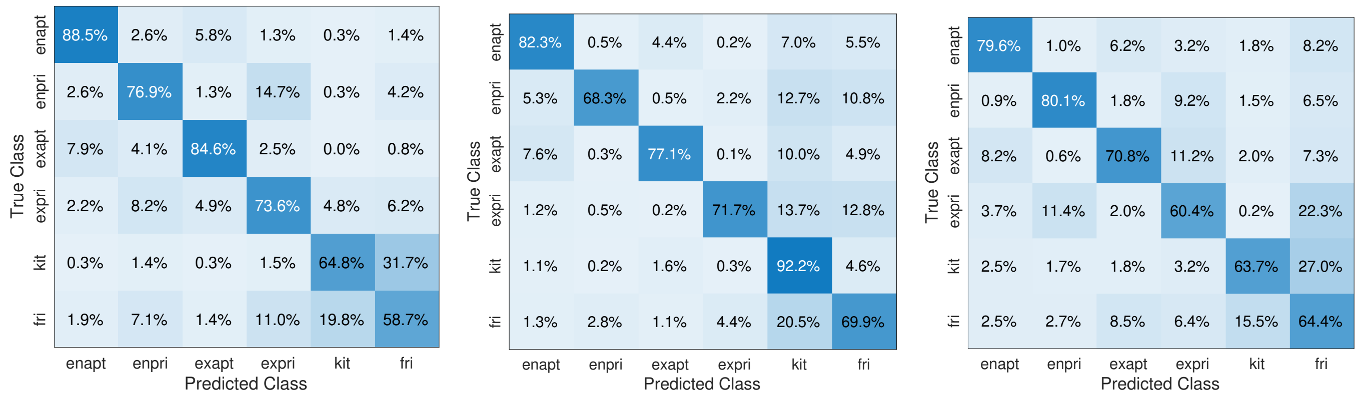
4.4.1 Results with Individual RX-TX pairs. Each optimized CNN model is trained with a single WiFi link, i.e., individual RX-TX pair data. As the activity locations are spread over the whole floor area and not all WiFi links cover the line-of-sight (LoS) for all the actions, different CNN models have different recognition capabilities for different activities. For example, if the apartment entrance is far from the kitchen area, then the WiFi link covering the kitchen area is observed to yield better accuracy in recognizing kitchen activities in comparison to the apartment entrance and exit actions. Therefore, when analyzed over the whole set of annotations, individual CNN models give poor accuracy independently. These activity recognition accuracies vary from 41.48% to 72.18% for different participants and WiFi links. This observation leads us to design the residual calculation per action during the training phase. This strategy yields better ensemble results as shown in Table 2 and discussed in the following subsection.

Table 2: Comparison of CNN and GB Ensemble Model Accuracies for Different Participants and RX-TX Pairs

Participant No.	RX-TX Pair	CNN Accuracy (%)	GB Ensemble Accuracy (%)
P03	1	71.53	74.53
	2	51.72	
	3	57.94	
P05	1	72.18	76.90
	2	41.48	
	3	66.52	
P09	1	54.68	69.82
	2	55.71	
	3	44.42	

4.4.2 Results with Multi-pair data. Once we train and optimize different CNN models with individual WiFi link's CSI amplitude data, we pass those prediction results through the Gradient Boosting (GB) model. This whole training process takes more time as there are several models in different phases to train, but, eventually, it yields better results. The Fig. 5 depicts the performance of our final GB Ensemble model having accuracies of 74.53%, 76.90%, and 69.82% respectively for the participants named P03, P05, and P09 with the considered six activities, e.g., enter apartment (enapt), exit apartment (exapt), enter private area (enpri), exit private area (expri), kitchen activities (kit), and open or close refrigerator (fri). Each of the accuracies is better than any of their respective base CNN learners' accuracies. Therefore, we can claim that our use of Gradient Boosting is a success in this case.

However, we admit that the activity recognition accuracy is still very low in comparison to existing WiFi sensing studies. This is due to the real-life deployment in a practical environment for a longer period. The room setup, furniture alignment, weather conditions, movement speed, etc. factors differ over the long duration of our deployment, which impacts the WiFi signals and so CSI data gets different for even the same activity done similarly over time. The surrounding wireless functions like emissions from microwave ovens, electromagnetic induction from television, refrigerators and other electrical equipment, moving objects due to fan or human movements, etc. interrupt our WiFi signals unexpectedly. Moreover, we observed that different repetitions of the same activity are performed differently by the occupant, which also makes it very difficult for any machine learning model to learn as a single activity.



(a) Participant 3 (accuracy 74.53%**)** **(b) Participant 5 (accuracy** 76.90%**)** **(c) Participant 9 (accuracy** 69.82%**)**

Figure 5: Confusion matrices of ensemble model for three participants

We plan to utilize various other signal processing techniques such as detrending and include CSI phase information to reduce these effects and increase the accuracy and reliability of the system.

Furthermore, our annotation is ongoing for more days of data for the referred three participants. We observe that participant P09's accuracy is the worst among the three, which is due to the lower number of action repetitions for the participant as numbered in Table 1. The better results for the other two participants with higher repetition counts increase our expectation of better accuracy as we annotate more data for the participants.

5 FUTURE WORKS

This is an ongoing study, and we have plans to perform experiments with more participants' data to strengthen our findings and improve the robustness of our system. By incorporating a larger and more diverse dataset, we aim to validate the generalizability of our approach and ensure that the system performs well across different demographic groups and usage scenarios. This expansion will help us identify potential limitations and areas for improvement, contributing to a more comprehensive understanding of our system's capabilities and limitations.

We aim to analyze the effect of temporal changes in the environment and the WiFi chip to understand their impact on sensing accuracy. Environmental factors such as furniture rearrangement, seasonal changes, and varying human activities can significantly influence WiFi signals. Similarly, the used ESP32 WiFi chip may have unique characteristics for long-term deployment that affect data consistency and accuracy. By systematically studying these variables, we can identify how they affect our system's performance and develop strategies to mitigate any adverse effects.

Additionally, we plan to apply an adversarial network, as done in [16], to neutralize any such effects, thereby making our system more resilient to environmental variations. Advanced machine-learning techniques, such as adversarial networks, offer promising solutions to enhance the robustness of our system against unpredictable changes. Further research will explore these techniques to refine activity recognition and reduce false positives. Through these efforts, we aim to enhance the practicality and reliability of WiFi sensing systems for real-life applications, particularly in senior housing settings, where accurate and unobtrusive monitoring is crucial for ensuring the safety and well-being of the residents.

6 CONCLUSION

In this research, we have presented the deployment and evaluation of our WiFi sensing system in senior housing settings to monitor daily activities in real life. We have discussed the details of our setup and the deployment process, the issues we faced, and the results obtained. Our findings demonstrate the potential of WiFi sensing systems in monitoring daily activities in a non-invasive way, which can also be leveraged to enhance the safety and well-being of seniors by detecting unusual activities or emergencies. The results indicate that our system can effectively capture and analyze daily activities, but there are areas for improvement to enhance accuracy and reliability and we will be working on them as part of our future efforts. As an ongoing study, this research project has immense potential to provide solutions to track the well-being of elderly people. Thanks to the low-cost setup we developed using microcontroller based devices, it also offers an affordable solution for low-income older adults, thus can be used widely.

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