Human Activity Recognition Using Wi-Fi CSI

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Abstract. Wi-Fi signals were originally developed with a focus on communication. However, beyond communication applications, Wi-Fi signals have been recently studied as a possible powerful tool for human sensing applications. In this sense, we present in this paper an original approach for obtaining human activity recognition (HAR) through the use of commercial Wi-Fi devices. Using our proposal, it is possible to infer the position of a monitored person in an indoor environment (room). To achieve this, we clean and process the amplitude of the channel state information (CSI) data collected from the Wi-Fi channel. We selected and evaluated five different classification algorithms to infer the subjects position and compare their performance. The proposed method was evaluated on a dataset of Wi-Fi CSI data collected from 125 participants. The proposed system is trained with the data collected while a person performs a variety of activities in a room. For the scenario and dataset considered in this study, the results showed that the Random Forest algorithm had the best performance for all tests, reaching an accuracy of 93.03% on average.

Keywords: Channel state information · CSI · Wi-Fi · human activity recognition · HAR

1 Introduction

It is a consensus that the worldwide population is aging, making the demand for healthcare monitoring more urgent. Therefore, monitoring elder or physically

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impaired people during basic activities at home such as sleeping and sitting has gained a great interest mostly when discussing ambient intelligence technologies.

One of the most prominent topics regarding smart home technologies is human sensing. There is a huge amount of applications that can use human sensing to monitor people's conditions like fall detection, vital sign monitoring, identity detection, and human activity recognition (HAR) for example. HAR systems typically may use computer-vision-based technologies [1,9], wearable sensor-based technologies [19,21], or radio frequency (RF) [7,20].

Computer-vision-based systems have a limited operating area and require a direct line-of-sight (LoS) view of the environment, not to mention that users usually dislike them due to privacy concerns. Their performance is also subject to change under different lighting conditions. Wearable sensor-based HAR technologies are less user-friendly since they require users to carry or wear sensors, which may be uncomfortable or unpleasant for elderly and physically disabled people [12].

Recently, many studies have shown that Wi-Fi signals can sense human behaviors due to the interference of the human body on signal propagation [18]. The Channel State Information (CSI) of Wi-Fi communication [13], which represents how wireless signals propagate from the transmitter to the receiver at certain carrier frequencies along multiple paths, is a promising technology for human sensing and an alternative to video surveillance and sensor-based technologies. Wi-Fi CSI-based HAR systems take advantage of the widespread deployment of commercial Wi-Fi devices and ubiquity of Wi-Fi signals.

In this paper, we propose a Wi-Fi CSI-based system capable of identifying when an individual is performing each of 6 different activities: standing, sitting, lying, walking, running and sweeping in a room. We have used a CSI dataset collected from 125 participants from the eHealth CSI data set [5] available for the scientific community. The results obtained attest the effectiveness of the proposed method.

The main contributions of this work can be summarized as:

– Proposing a simplified CSI-based-HAR system.
– Performing an analysis over a huge amount of collected data compared to related work found in the literature.
– Comparison of five machine learning (ML) classification algorithms to evaluate the performance of the proposed system on human activity recognition.

The remainder of the paper is structured as follows. Section 2 gives an overview of Wi-Fi CSI systems. Section 3 gives a review of relevant related work. The data collection, processing steps, and proposed methodology are described in Sect. 4. In Sect. 5, we compare the obtained performance results of different ML algorithms. Finally, Sect. 6 brings the concluding remarks and future work directions.

2 CSI Overview

The basic properties of a Wi-Fi communication link between transmitter and receiver can be represented by the channel state information (CSI). It describes how a signal is modified while it propagates from the transmitter to the receiver. These modifications represent the combined effect of, for example, scattering due to multipath, fading, power decay with distance, etc.

The physical layer of Wi-Fi systems follows the IEEE 802.11g/n/ac specification [8], and uses the orthogonal frequency division multiplexing (OFDM) technique for both 2.4GHz and 5GHz frequency bands. OFDM is a modulation technique that divides the available bandwidth into several orthogonal subbands [23]. By doing this, the information can be independently transmitted over different OFDM symbols. The OFDM features make it a good solution for multipath channels and also for Multiple-Input Multiple-Output (MIMO) systems [10]. Besides, since the transmission over each subcarrier is orthogonal and independent, each subcarrier can be viewed as a sensor capable of collecting CSI data.

To measure CSI, the Wi-Fi transmitter sends Long Training Fields (LTFs), which contain predefined information in each subcarrier, in the frame preamble. The Wi-Fi receiver estimates the CSI using the received signal and the predefined LTFs. The amount of collected data depends on the channel bandwidth, which determines the number of subcarriers, and on the number of antennas used.

Considering a MIMO Wi-Fi system operating under IEEE 802.11n specification, and with P transmitting antennas and Q receiving antennas, the signal that contains the estimated CSI of each data stream can be mathematically expressed as:

$$h_{p,q} = |h|e^{j\theta}, \tag{1}$$

where $h_{p,q}$ represents the CSI between the p-th transmission antenna and the q-th receiving antenna.

We can also have a multipath channel, in this case, the representation of the received signal will become a vector. Let c be the number of paths, thus the state information of the channel established between a pair of antennas (p, q) can be mathematically represented by a vector with c elements. Thus we have

$$\boldsymbol{h}_{p,q} = [h_1, h_2, \ldots, h_c]^{\mathrm{T}}. \tag{2}$$

CSI data can be used to provide information about the environment and estimate changes and phenomena that occur over time, such as human presence detection, movements, and even vital signs.

3 Related Work

Wi-Fi CSI-based Human Activity Recognition (HAR) has gained high interest in recent years, as this technology takes advantage of the widespread deployment of commercial Wi-Fi devices and ubiquity of Wi-Fi signals to offer a cheap and convenient HAR system. As a consequence, we can find many studies in this area. In this section, we review the most recent works we found in the literature regarding Wi-Fi CSI-based HAR systems.

Wang et al. [22] developed a system called Wi-Fall mainly to detect falls using Wi-Fi CSI data. They analyzed different activities carried out at three different locations: a chamber, a laboratory, and a dormitory. The data was collected using three transmitting and three receiving antennas. As the first three eigenvalues of the single value decomposition (SVD) matrix describe most of the characteristics of the whole matrix, they were used for the classification. Two different classification algorithms were used, and a one-class support vector machine (SVM) was utilized to detect falls. Besides, to detect other activities in addition to falls, the random forest classifier was used.

Ding et al. [3] suggested using Deep Recurrent Neural Network (DRNN) to identify human positions. The idea was to extract features for Recurrent Neural Network (RNN) training and recognize the activity. Two features were extracted, namely channel power variation in the time domain and time-frequency analysis in the frequency domain. Then an LSTM (Long Short Term Memory) that is trained with extracted features is used to recognize an activity.

Another Wi-Fi CSI-based human activity recognition system, namely Wi-Motion, was proposed in [11], which can sensitively recognize 5 predefined different human activities. They jointly used the amplitude and phase information from the CSI sequence collected with Wi-Fi devices with three antennas. The SVM algorithm was also used to build two classifiers according to amplitude and phase information. When an unknown activity sample enters, consulting the prediction results of both classifiers, Wi-Motion performs a merge method based on the posterior probability to produce the final recognition.

Recently, Convolutional Neural Networks (CNNs) have also been applied together with bidirectional LSTM (Bi-LSTM) for the classification of human activities, including fall detection [17].

Furthermore, activity recognition using a Raspberry Pi and Nexmon firmware has also been used to extract the CSI data [4]. The only preprocessing step that was performed in that work was a low-pass filter. Additionally, a DeepConvLSTM classification model was implemented in Python using a deep learning API called Keras.

Another work focused on extracting the CSI information for different positions in the indoor LoS scenarios using Nexmon CSI tool on Raspberry Pi hardware with NIC Broadcom and Asus routers is published in [16]. Activities were classified by applying ML algorithms, SVM, and LSTM. Outliers were removed by using the Hampel filter, then a DWT (Discrete Wavelet Transform) was applied to denoise the signal and PCA to reduce the dimension of the information. Features were extracted from the preprocessed data to use in SVM and LSTM to classify the activities.

Bocus et al. [2] analyzed human position recognition using Ultra-Wideband (UWB) technology. Thy presented the techniques and addressed the feasibility of using UWB signals. They have extracted high-resolution Channel Impulse Responses (CIRs) from UWB modules and use them as features in ML algorithms for classifying different human activities. They also compared the activity classification performance using fine-grained Wi-Fi CSI in the same physical layout.

Yang et al. [24] explored three issues for recognizing human activity: (i) Based on the sensitivity of different antennas to actions, an active antenna selection approach was proposed to reduce the amount of data required for analysis; (ii) Two signal enhancement approaches were presented to strengthen the interval of active signals and weaken the impact of inactive signals; and finally, (iii) an activity segmentation algorithm was provided to detect the start and end times of an activity, which can get rid of inactive signals and retain the active signal interval.

Muaaz et al. [15] used a CNN to recognize human activities from environment-independent time-variant micro-Doppler fingerprints extracted from Wi-Fi CSI data. They also used both amplitude and phase information of the CSI data. First, they processed the CSI data to remove the noise and fixed objects present in the environment. The CSI data were then used to compute the spectogram corresponding to different human activities. The spectograms were stored as portable network graphics (PNG) images and used to train a deep CNN. The CNN used was capable of automatically extracting discriminative features from PNG images and classifying human activities.

A recent approach was proposed based on the Doppler effect [14]. First, an original phase cleaning was performed to extract micro-Doppler traces from the CSI data. The Doppler shift reveals the velocities of the scattering points during the transmission events and is not affected by static objects, allowing the gauging of the dynamic human position features. The micro-Doppler traces were used as input for a neural network architecture that was trained to recognize the activities of interest. It is important to note that this work focused on the recognition of dynamic activities. Identification of static activities, such as sitting and lying down, was outside of the scope of their work.

These works found in the literature demonstrate the sensitivity of SCI data to small body movements, allowing the identification of activities carried out by people using the collected SCI data. However, these work present proposals in controlled environments and with a limited number of people. As a difference, our work considers the recognition of human activity using a dataset with data collected from 125 people forming a very heterogeneous group, with different ages, sex, and different physical characteristics.

Based on the existing work, we proposed a simplified approach to identify the human position and/or movement based on CSI information. Furthermore, we have tested the proposed methodology on a huge amount of collected data available in the eHealth dataset [5], which corroborate its applicability. In [5] can be found more details about the data collection process and eHealth dataset construction.

4 Proposal and Experimental Methodology

Before the human activity recognition itself, it is necessary to treat the collected CSI signal to allow it to be used in Machine Learning (ML) algorithms. In this section, we describe step by step the proposed methodology. We divided our proposed system into three stages: Data collection, Signal processing, and Data treatment, as presented in Fig. 1.

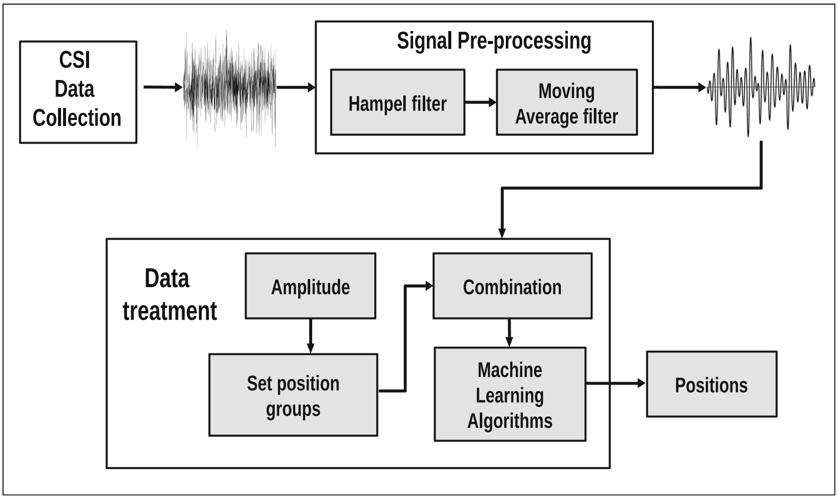

Fig. 1. Block diagram of the proposed methodology.

In the following, we describe each stage of the proposed methodology.

4.1 CSI Data Collection

For data acquisition, we have used the NEXMON firmware [6]. This firmware works on top of a Raspberry Pi 4B. NEXMON modifies the firmware of the Raspberry wireless board and allows the capture of CSI data in a wireless transmission between two devices on a Wi-Fi network. Data collection was carried out in an ordinary room with no electromagnetic isolation. We used a traditional Wi-Fi network in order to recreate an environment as close as possible to a real scenario. Figure 2 steep 1 shows the data collection scenario. The Wi-Fi network was configured in the 5 GHz frequency band, using a channel with a bandwidth of 80 MHz. For data acquisition, CSI makes use of OFDM technology, so with the configuration used, we obtain 234 subcarriers in each collection, after discarding the pilot and null subcarriers. The duration of each collection in each position was 60 seconds per participant's position, obtaining 500 samples with 234 subcarriers in each collection. More information on the functionality of NEXMON and other firmware is found in [18].

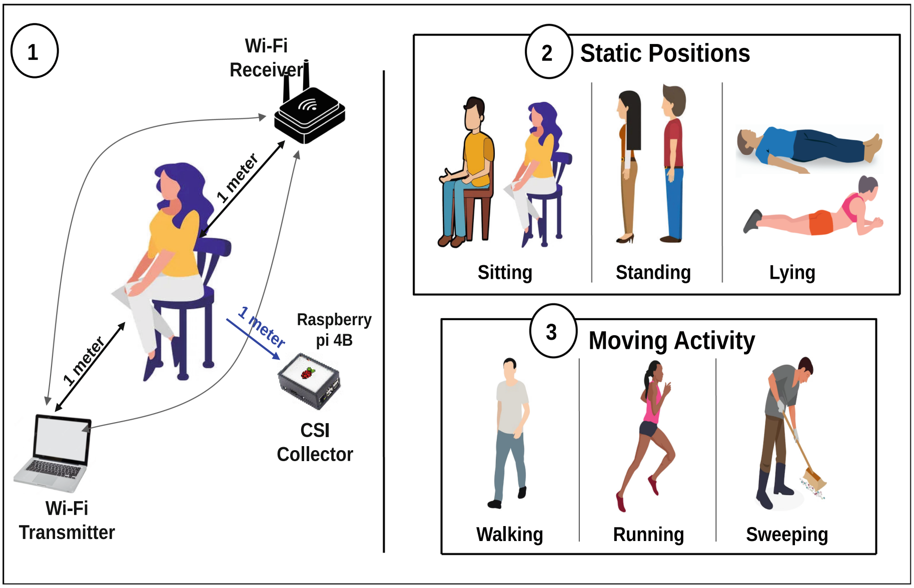

Fig. 2. (1) CSI data collection room, (2) statict positions and its different variations, (3) moving activity.

4.2 Signal Pre-processing

In the CSI data pre-processing stage, we use techniques to clean the signal from external factors. These factors perturb the signal making it harder to interpret. After collecting the data, it goes through a first filter called Hampel, which removes noise from the signal. The Hampel filter uses a sliding window of 30 and 3 standard deviations. The data then passes through another filter called Moving Average, eliminating outliers and smoothing the signal. The Moving Average filter uses a sliding window of size 10. With these two procedures, we ensure the cleaning of the signals collected by each subcarrier and that it is ready for data treatment.

4.3 Data Treatment

In the present study, we used the eHealth CSI dataset [5] created by our research group. The dataset contains the sitting, standing, and lying static positions and moving activities, such as walking and running, of 125 people, of different ages, gender, weight, and height.

In the Data treatment stage, we use as input the cleaned CSI data from the pre-processing stage. First, we use the amplitude of the signal from each subcarrier. Then we perform a data segmentation, dividing our data into four groups: sitting, standing, lying, and moving positions (walking and running).

In the eHealth CSI dataset, the collections describe 17 different positions of each participant. Among those, we have different activities performed in a seated position. Thus, to form a group of sitting positions, we take the positions where the participant is facing and facing away from the collecting device. For the lying position group, lying on their back and on their stomach positions are considered. We followed the same procedure to form the remaining groups. This way, we obtain a dataset with different variations for each type of position, which is closer to a real scenario. Therefore each participant has 6 activities as shown in Fig. 2 steep 2 and 3.

Once the CSI data is separated into groups of activities for each of the 125 participants involved in the experiments, we input the data to five different ML algorithms to infer the positions. We analyzed multi-class models and binary models for classification. The datasets corresponding to each type of activities are generated in such a way that it ensures the use of balanced datasets for classification. This was done to find the average results that are discussed in the following section.

5 Obtained Results

In our analysis, we considered the scenario of a person who requires supervision, such as an elder. In this scenario, our system could help by identifying whether the supervised person changed their position, as in a fall situation, for example.

We analyzed the classification for standing, sitting, and lying positions; walking, running, and sweeping activities. Also, the static vs. moving activities classification was analyzed. Each participant has a fully balanced dataset with a total of 1000 CSI samples for each position and 234 features representing the number of subcarriers.

The following ML algorithms were analyzed: Random Forest (RF), Support Vector Machine (SVM), Decision Tree J48 (DT-J48), MultiLayer Perceptron (MLP), and Gaussian Naïve Bayes (GNB), since they showed better performance for binary classification. For the proposed analysis, 70% of the data was used for training and 30% for testing. Metrics such as accuracy, precision, recall, and F1 measure were calculated to verify the performance of each ML model.

Initially, we performed a multi-class classification for 6 human activities: standing, sitting, lying, walking, running, and sweeping activities. As can be seen in Table 1, the Random Forest algorithm presented the best classification, reaching an accuracy of 86.65% and a precision between 85.68% and 88.35% for each class. Classification of running and sweeping classes had the best performance with a precision of 87.45% and 88.35% respectively. These results show that for activities in which people perform more body movements, the Random Forest Model achieves the best precision. This is consistent with the fact that body movement exerts greater influence over the wireless channel conditions and as a consequence, the CSI data is more affected.

Based on previous results and with the aim of improving classification results, a binary classification was performed, this time considering static positions and

Table 1. Metrics for multi-class classification (%).

Algorithm	Accuracy	Precision/ Sitting	Precision/ Standing	Precision/ Lying	Precision/ Walking	Precision/ Running	Precision/ Sweeping
RF	**86.65**	**85.68**	**86.29**	**86.67**	**86.63**	**87.45**	**88.35**
SVM	50.78	51,95	48.01	59.95	46.27	42.62	51.39
MLP	63.54	66.43	63.40	69.37	60.44	60.34	61.34
J48	41.44	45.72	42.38	49.42	37.36	38.05	38.46
GNB	30.87	34.80	30.60	39.91	26.48	26.77	27.83

moving activity. For this scenario, the moving activities group was formed by collections of each person walking and running and the static positions group contains a mixture of sitting and lying positions. Figure 3 shows the results achieved for this scenario. The best performance is achieved by Random Forest, reaching an accuracy of 91.72%. For this scenario, it is possible to identify whether a person is moving or in a static position with a precision of 93.19%.

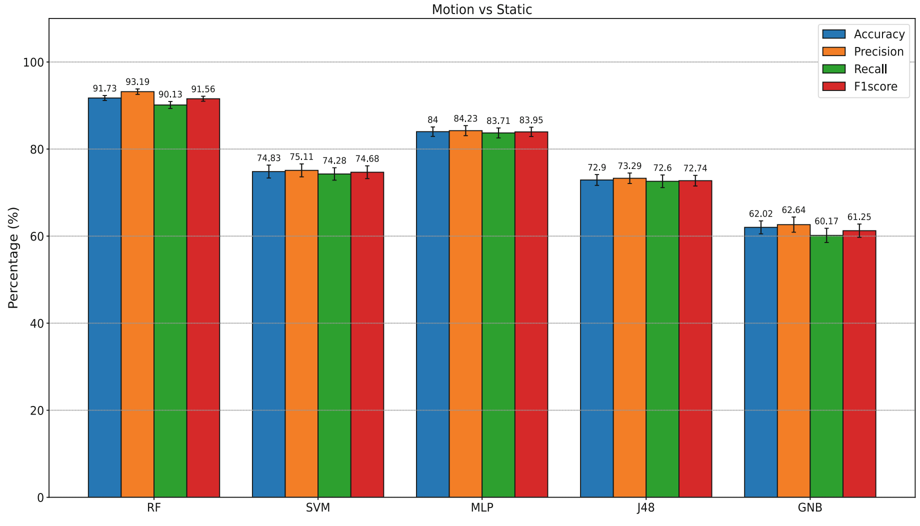

Fig. 3. Metric for `motion` vs `static` classification.

To assess the reliability of the obtained results, the classification was performed 30 times for each person, and in each round different training and test sets were randomly chosen. The same procedure was then performed for a group of 125 people. In this way, a model was generated for each person and the average of the 125 generated models was obtained with a 95% confidence interval computed through a bootstrap procedure. In Fig. 3 the average of the accuracy, precision, recall, and F1 metrics with their respective confidence intervals are presented. As shown in the figure, the results consolidate the Random Forest algorithm as the best classifier for this scenario, obtaining the highest average and the lowest confidence interval.

We also observed that when movement is detected, the RF model increases more than 5% in accuracy, and precision increases between 5% and 7.5% depending on the type of activity. In this sense, it is interesting to identify first when a person is moving and then identify what type of activity they are performing in case of movement, and in what position they are in the static case.

Further analyses were performed considering all possible combinations of static positions and movement activities, as well as the state of movement in combination with static positions. For each case, the performance of RF, SVM, MLP, DT-J48, and GNB algorithms was also analyzed based on accuracy, precision, recall, and F1 metrics.

In all cases, Random Forest presented the best performance. Figure 4 shows the values of the metrics for all classifications performed using the Random Forest algorithm, which was the best classifier. It can be seen that in all cases the metrics reach values greater than 90%.

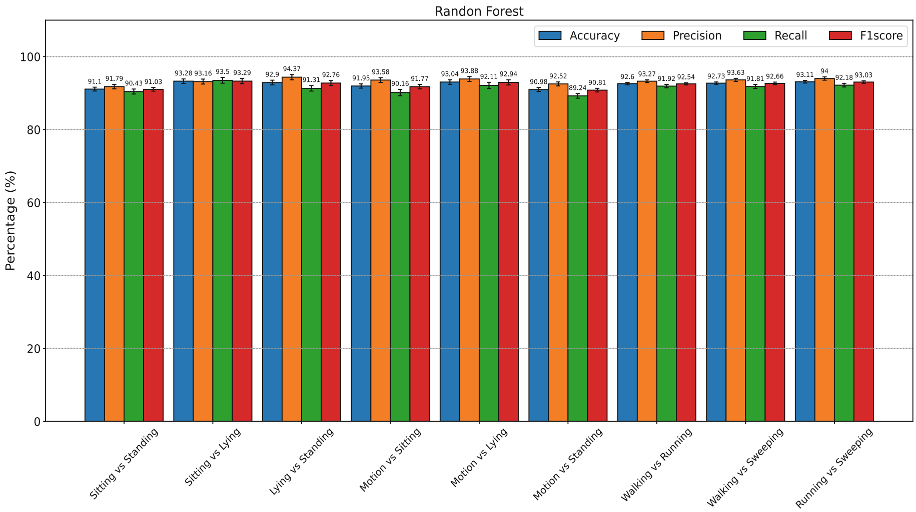

Fig. 4. Metric for all binary activity classification using Random Forest.

For static positions, analyzing sitting vs standing the classification has 91.09% accuracy and 91.79% precision. In turn, the sitting vs lying classification achieved the highest accuracy with 93.28% and 93.15% precision. For lying down vs standing the classification has 92.89% accuracy and 94.36% precision.

For moving activity, walking vs running classification achieved 92.60% accuracy and 93.27% precision. Walking vs Sweeping classification reached 92.73% accuracy and 93.62% precision. And for Running vs Sweeping the classification has 93.10% accuracy and 94% precision.

Comparing moving activity versus a specific static position also achieved values greater than 90% in the evaluation metrics. For example, for moving vs sitting, the classification has 91.95% accuracy and 93.50% precision. When classifying moving vs lying the accuracy was 93.03% and the precision was 93.87%. And for moving vs standing the classification accuracy was 90.98% and the precision was 92.51% precision.

The best results are achieved when comparing lying with any other activity. In particular, in the comparison between sitting and lying the accuracy was 93.28%, and between moving and lying it was 93.03%. This is due to the greater difference in body horizontal and vertical positions, which influences the propagation of radio waves in the environment and consequently reflects in the collected CSI data.

6 Conclusions

This work proposed a methodology based on CSI data analysis and machine learning models to recognize positions and activities of a single person in a room. This is a particularly relevant application in scenarios where a person in isolation must be monitored remotely. We evaluated our proposal using the eHealth CSI dataset with data from 125 people, of different ages, gender, weight, and height. The results consolidate the Random Forest algorithm as the best classifier for this application, obtaining the highest average and the lowest confidence interval with accuracy results between 92% and 94%.

These results for multi-class classification show that for activities in which people perform more body movements, Random Forest achieves the best precision with 87.45% for running and 88.35% for sweeping.

Also, results showed that the horizontal or vertical disposition of the body influences the propagation of radio waves in a different way and, as a result, this is reflected in the collected CSI data, allowing better classification results in the cases of sitting vs lying, standing vs lying and moving vs lying.

The proposal presented in this work achieves a increases of more than 5% in accuracy and precision increases between 5% and 7.5% depending on the type of activity, when compared with the multi-class classification. And for all scenarios analyzed, the performance metrics show values greater than 90%.

As future work, it is interesting to consider new features extracted from the CSI signal that can improve ML model performance for activity recognition. In addition, we intent to consider other more complex activities, as well as the transition between activities; Also, family environments where more than one person coexists are interesting questions to consider in future work.

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