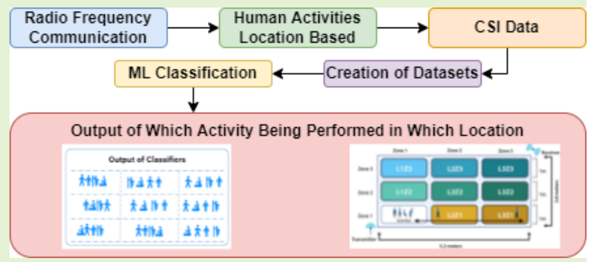
Non-Invasive Localisation Using Software-Defined Radios

Muhammad Zakir Khan, Ahmad Taha, William Taylor, Muhammad Ali Imran, and Qammer H. Abbasi

***Abstract*—Non-invasive indoor human activity detection using radio waves has attracted the interest of researchers, contributing to a range of new applications including smart healthcare. Localisation of activities can assist in developing advanced healthcare systems able to identify the location of patients. Radio frequencies have been shown in numerous studies as a non-invasive method to identify human activity. This is achieved by observing the signal propagation described in the Channel State Information (CSI). This paper presents experimental results using Universal Software-Defined Radio Peripheral (USRP) devices to identify and localise a single human subject performing activities by utilizing the CSI of radio frequencies. The experiments are carried out to retrieve CSI samples observing a single subject perform no-activity, sitting, standing, and leaning forward actions in various positions in a room. Additional CSI is captured for the subject walking in two directions across the observed area. Giving a total of 6 activities spanning the monitored area. CSI is also collected while the monitored area is empty for further comparison. Artificial intelligence is used to make classifications on collected CSI. The proposed approach uses a Super Learner (SL) algorithm that can identify the location of different activities with 96% accuracy, outperforming existing benchmark approaches.**



***Index Terms*—Human Activity Detection, Indoor Positioning, Occupancy Monitoring, Localisation.**

I. Introduction

Indoor localisation systems are designed to estimate the location of an entity within an indoor environment. Technologies such as WiFi, Ultra Wide-band Communication (UWB), Bluetooth, Radio Frequency Identification (RFID), Infrared (IR), inertial sensors, and cameras can be implemented to detect the location of an entity [1, 2, 3, 4]. In recent years, indoor localisation has become a popular topic due to its widely applied in a range of applications including battlefield surveillance, disaster prediction, intelligent traffic and indoor navigation [5, 6]. Accurate and reliable indoor localisation and tracking techniques have become both essential and desirable in healthcare monitoring technologies. The elderly population is growing as life expectancy increases as a result of advances in disease diagnosis and treatment. This results in hospitalisation capacity rapidly dwindling [7]. According to estimations from the United Nations (UN), the elderly population will increase by 2.1 billion by 2050 [8]. This emphasizes the need of using technology in elderly care.

Indoor localisation is challenged by noise, signal fluctuation, and the presence of obstacles like furniture etc. which is a factor to consider in the field of indoor localisation. Significant contributions to the field of indoor localisation have been achieved due to technological advances in wireless communication, computing, and detection techniques. Several techniques are used to detect human activities in an indoor environment such as wearable device-based, context-aware and contactless device-based systems. The ability to detect behaviours using a device worn by the user has proven the ability to recognize human activity without violating the user's privacy [9]. Context-aware is based on sensors such as floor sensors, pressure sensors, microphones, and cameras are utilised for monitoring. The disadvantage of these systems is that it is not possible to detect activities after the user exits the monitoring area. The most prevalent example of context-aware technology is video surveillance systems and the disadvantage is that it can adversely impact the privacy concerns of patients. As a result, some countries consider video surveillance to be illegal [10].

Localisation in outdoor environments has been successfully implemented using advanced satellite positioning systems, such as the Beidou and GPS which will provide users with more precise location services in the outdoors than indoors [11]. This is due to weak satellite signals, low penetration, and other issues. Radio Frequency (RF) is often used for indoor location media due to the extensive use of low-power sensors. Researchers have proposed popular technologies such as Ultra-wideband (UWB) [1], WiFi [2], Bluetooth [4], Audio [12], light [13], Zigbee [14], and Radio Frequency Identification (RFID) [15] to achieve indoor localisation. This paper makes use of RF-based Wi-Fi sensing due to the ability to make use of existing Wi-Fi infrastructures in place in many homes

All authors are with the James Watt School of Engineering, University of Glasgow, Glasgow, G12 8QQ (e-mail: m.khan.6@research.gla.ac.uk, ahmad.taha@glasgow.ac.uk, 2536400t@student.gla.ac.uk, Muhammad.Imran@glasgow.ac.uk and qammer.abbasi@glasgow.ac.uk).

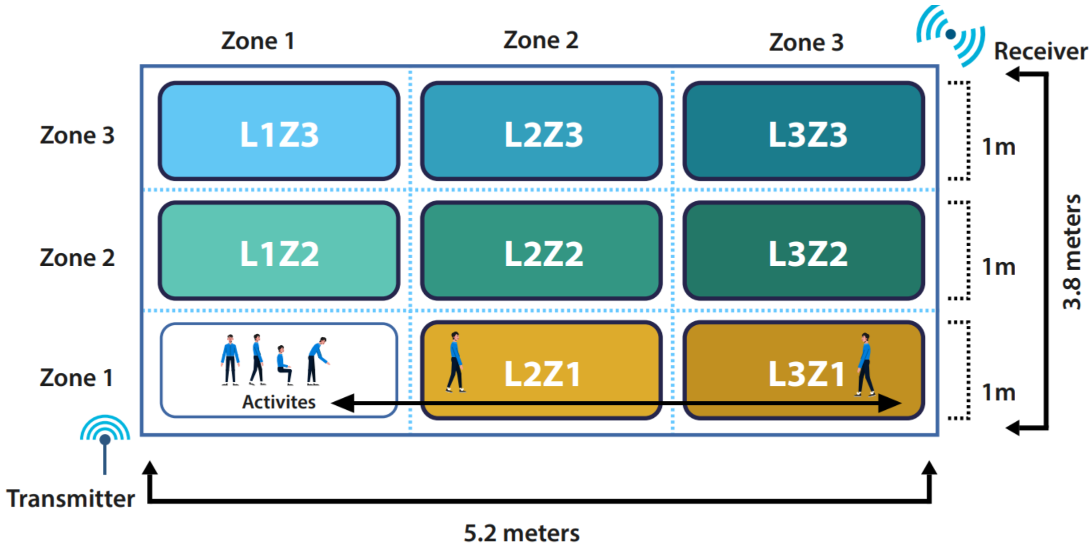


Fig. 1: Experiment Setup Diagram showing the position of the horizontal and vertical zones

removing the need to introduce additional sensing equipment. RF-sensing-based systems differ from one another in terms of hardware specifications, operational radio frequency, classification algorithms, number of activities to monitor, and number of subjects. RF signal activity recognition, available tracking systems can employ either the Received Signal Strength Indicator (RSSI) [16] or Channel State Information CSI [17]. According to research such as [18], CSI is fine-grained and measured per Orthogonal Frequency Division Multiplexing (OFDM) packet, but RSSI provides coarse information. CSI using Wi-Fi can be used to detect and localise human activity by observing the amplitude changes of radio signals when a human activity occurs [19]. This results in CSI being the better option for activity detection and localisation due to greater attention to detail. Several researchers have utilised the CSI of RF signals similar to Wi-Fi to detect small scale activities such as vitals [20], large scale body motions [21], and localisation and tracking [22]. The experiment detailed in this paper makes use of USRP devices using OFDM for 64 points of fast Fourier transformer (FFT) that produce 64 frequency carriers (subcarriers) [23]. The objective of this study is to use two USRP devices, one serving as a Tx and the other as the Rx to collect CSI data on a single human subject performing activities in different locations of a single room. The room is divided into three zones both horizontal and vertical directions (3x3 zones) shown in Figure 1. Each intersection point is referred to as a location. The six activities are carried out in all nine locations. The amplitude changes observed in the CSI differentiate between activities performed in each location. This allows for CSI to be used in the localisation of a subject as the radio signals are affected differently in human movements occurring in different locations.

Machine Learning (ML) is used to classify the different locations where six distinct human activities are performed. An Additional classification is used to represent an empty room. This research builds on previous work by proposing a single system that uses RF signals to identify activities in multiple locations as well as determining activity area occupancy and activity patterns [24]. The contributions in this paper can be summarised as using ML algorithms, namely Multi-layer Perceptron (MLP), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Bagging, Random Forest, Extra Trees (ET) and Super Learner (SL) classifier, to make predictions on CSI, received from USRP devices, to accurately identify and localise six different activities inside a room. The SL classifier combines the SVM, KNN, Bagging, Random Forest and Extra Trees classifiers to get the best results from each classifier in an essembled manner. Additional contributions made are to establish a link between detection accuracy and the position of the activity. This paper is structured as follows: Section II describes related work found in the literature. Section III describes the materials and methods and Section IV provides results and discussion. Section V concludes the paper.

II. Related Work

This section details work related to this experiment. Various literature details the use of RF signals to detect different movements. Iqbal et al. [25] employed a deep-learning-based system to classify different user movement states like forward, backward, and no movement. Wi-Fi sensor data was used to train their system. Using CSI data, Nipu et al. [26] and [27], attempted to identify different participants. During the experiment, different participants walked through two devices while data was being transmitted and saved the CSI information received while walking across radio frequencies. Afterwards, the data were subjected to ML techniques such as Random Forest and Decision Tree.

This work shows that the CSI patterns are differing in the movements of a human. The studies [28, 29, 30], used USRP N210 devices to detect activity with 91%, 92%, and 95% accuracy, respectively. The study [31] used two USRPs to propose a Deep Gated Recurrent Unit model for non-obtrusive human activity recognition using CSI and achieved results with an accuracy of 95% for all activities. The study

[21] used USRPs X300 and X310 included separating the sitting and standing activities and reported an accuracy of 96% using the Random Forest algorithm. The study [32] proposed a system that used the WiFi OFDM signal to detect and classify arm movements. They employed the Long Short-Term Memory (LSTM) deep learning algorithm to categorize data from CSI. The LSTM deep learning algorithm was able to achieve a high-accuracy result of 96%. Other literature details the use of RF signals to provide localisation of subjects. WiTrack2.0, developed by Adib et al. [33] is a multi-person localisation system that employs wireless signals reflected off people's bodies. An array of directional Tx and Rx antennas are used to emit the wireless signals. The distance between the user and the antennas is calculated using the time it takes for a signal to travel from the Tx to the Rx after signal reflection. The distance information is also utilized to identify the location of subjects. To provide accurate room-level localisation, other localisation and tracking experiments, such as [22], reported an accuracy score of 81% and a 5cm error in a 20*70 cm^2 region.

III. Materials and Methods

This section will cover materials and methods, as well as how data is collected utilizing an experimental setup to produce various test cases before applying ML. Subsections III-.1 and III-.2 describes the hardware and software components that were designed and used to collect CSI data depicting human activity from the sensing devices.

1) Hardware Specification: The hardware used for data collection is comprised of two USRP devices communicating with each other while activity occurs inside their coverage region. The National Instrument (NI) $X310/X300$ models of the USRPs are used and connected to two PCs each using 1G Ethernet cables, each with extended bandwidth daughterboard slots covering DC–6 GHz and up to 120 MHz of baseband bandwidth. The Two PCs had Intel(R) Core (TM) $i7 - 7700.360$ GHz CPUs, 16 GB RAM, and Ubuntu 16.04 virtual system to serve as the operating system. The USRP's had VERT2450 omnidirectional antennas attached for wireless communication.

2) Software Specification: The USRP devices had software configured to USRP device to transmit to the receiver USRP device. The GNU radio software package was used to configure the software used to power the USRP communication in the format of flow diagrams. GNU Radio is a free and open-source software package for signal processing used in research [34]. GNU Radio provides OFDM signal processing examples, which can be manipulated to work with the USRP devices and allow the extraction of CSI. GNU radio allows to set parameters for the USRP such as the centre frequency to $3.75GHz$, 64 OFDM subcarriers, and gain levels set at $70dB$ and $50dB$ for the Tx and Rx respectfully. The GNU Radio flow diagram is converted into a python script that can be used to start OFDM communication on the USRP devices. The python scripts output the CSI collected during transmission. The CSI is in the format of complex numbers. The amplitude of the signals can then be calculated by taking the absolute value of the complex number. The CSI amplitude information is then converted into CSV files. These CSV files can then be compiled into datasets that can be used to train and test ML algorithms. The data flow diagram of data collection for the six classes activities is shown in Figure 2.

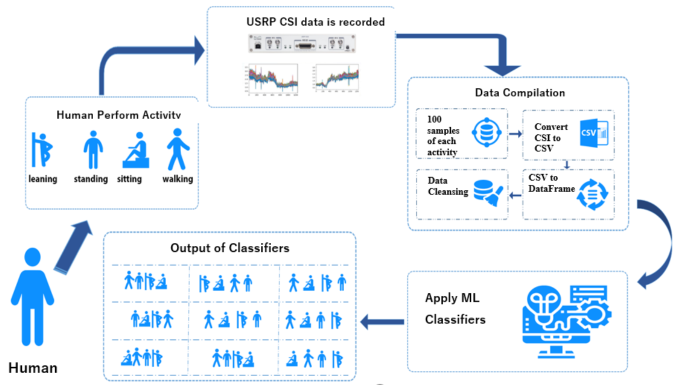


Fig. 2: Data Flow Diagram showing the process of how the human movement is recorded as CSI and compiled into a dataset for ML classification

A. Experimental Setup

The experiments presented in this paper is carried out in a $3.8 * 5.2\text{m}^2$ room in the James Watt South Building at the University of Glasgow, where an active and approved ethics application is in place. The experiment was conducted in an office setting where the room is divided into three zones both in the horizontal and vertical direction (see Figure 1). The three zones are separated by one meter where all the activities took place. The Tx and Rx USRP devices were placed in opposing corners of the room, facing each other at a 45° angle. The data is collected using the same single subject to perform the activities in each of the zones. This ensures that the only variables in the data collection are the activities and the location the activity is performed.

B. Data Collection

This section will go over the data collection process carried out using the hardware, software and experimental setup described in sections III-.1, III-.2 and III-A. The data collected in this section is used to create the datasets used for machine learning techniques. This experiment uses a total of 7 activities consisting of sitting, standing, leaning, no activity, walking from the Tx to the Rx device and walking from the Rx device to the Tx device and empty. Data for sitting, standing, leaning and no activity are collected from each of the zones areas illustrated in Figure 1. Walking from the Tx to the Rx will observe the subject travelling diagonally across the areas between the Tx device and the Rx device. Walking from the Rx to the Tx will observe the subject travelling diagonally across the areas between the Rx device and the Tx device. Finally, the Empty classification will consist of data being collected with no subject present in any of the areas of observation. Figure 3 shows examples of CSI amplitude patterns in all 6 activities and empty classifications. Each colour represents a subcarrier during an activity, with the amplitude of the subcarrier on the y-axis and the number of packets on the x-axis. Each data sample collected represents 3 seconds of OFDM communication. This results in a sample being approximately 1200 packets in size. 100 samples are collected for each activity. This gives a total of 4300 collected data samples. This is made up of 100 sitting, standing, leaning and no activity samples collected from each area shown in Figure 1 totalling 3600 (4 Activities x 100 samples x 9 areas). 600 samples were collected for walking in each direction (2 Activities x 300 samples) This is because walking includes 3 areas and when two directions are used, a total of 600 samples are chosen to represent 100 samples for each area walking in one direction and another 100 samples for each area walking in the other direction. 100 empty samples are also collected (1 Activity x 100 samples). During the collection of the empty samples, the subject clears the monitored area and exits the room entirely to ensure the empty samples are not corrupted. This gives a total of 43 classifications of 100 samples each. Each data sample is labelled with a name that corresponds to the zones and locations, such as L2Z1 mean data sample collected at location 2 and zone 1. Table I shows the 43 classes and the total number of data samples collected in each location.

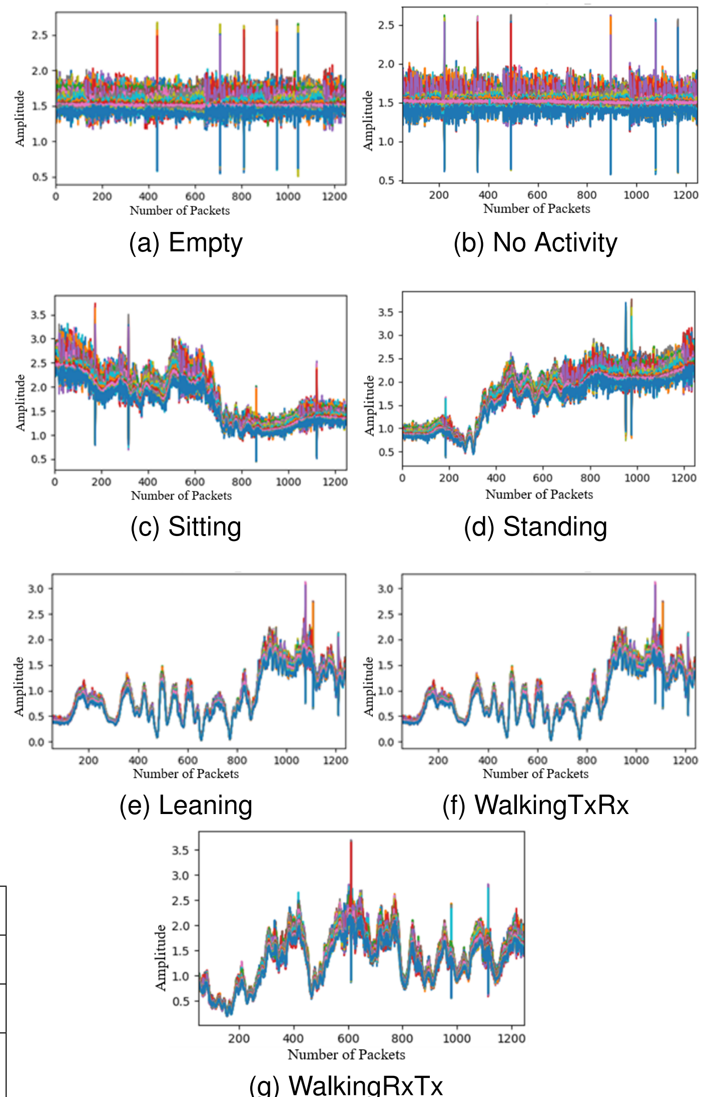
TABLE I: The data classes and their description

S. No	Class	Class Description	No. of Classes	Count
1	Empty Activity	No human subject in the activity area	1	100
2	No Activity	No activity performed by human	9	900
3	Sitting	The action of "Sitting" at the designated location within Zone	9	900
4	Standing	The action of "Standing" at the designated location within Zone	9	900
5	Leaning	Leaning forward with the upper body at the designated location within Zone	9	900
6	Walking Rx-Tx and Tx-Rx	Walking from the USRP X310 Rx side to USRP X300 Tx side and vice versa	3*2	600

1) System Hypothesis: The hypothesis is summarised as follows:

1) The position of the activity is determined with a 100% accuracy as we move vertically or horizontally in the room.
2) As we move vertically or horizontally, walking is more accurate than sitting or standing.
3) The horizontal and vertical distance between the Tx and Rx will affect the accuracy of activity detection.

The contribution of this paper is to determine if Artificial intelligence (AI) can identify which activities are occurring in what location by using RF signals.



(a) Empty (b) No Activity (c) Sitting (d) Standing (e) Leaning (f) WalkingTxRx (g) WalkingRxTx

Fig. 3: CSI examples for all 7 activities showing the amplitude values for all 64 subcarriers (Represented in each colour) in the OFDM communication

C. Test Cases

In this section, several test cases are presented, which are used to apply different ML approaches for activity localisation. In this study, A total of two test cases are presented based on the data collected as shown in Table II.

The test cases for the data collection is reported in Table II. The dataset description is given below.

- **L1L2Zone1**: The dataset contains data from locations 1 and 2 for Zone 1, with a total of 11 classes of activities from both locations.
- **L1L3Zone1**: The dataset contains data from locations 1 and 3 for Zone 1, with a total of 11 classes of activities from both locations.
- **L2L3Zone1**: The dataset contains data from locations 2 and 3 for Zone 1, with a total of 11 classes of activities from both locations.

TABLE II: Test cases of (Figure 1)

Test case	Dataset	Test case description
The relationship between the activity's location and the detection accuracy		
Test-1.1	**Zone 1** (L1L2Zone1, L1L3Zone1, L2L3Zone1)	To check the co-relation between zones and locations when we move horizontally or vertically from Tx towards Rx
Test-1.2	**Zone 2** (L1L2Zone2, L1L3Zone2, L2L3Zone2)	
Test-1.3	**Zone 3** (L1L2Zone3, L1L3Zone3, L2L3Zone3)	
Test-1.4	**Location wise combination** Location1-Z1Z2Z3, Location2-Z1Z2Z3, Location3-Z1Z2Z3)	
To check localisation overall accuracy		
Test-2.1	Combined location and Zones ($L_1L_2L_3 - Zone_{123}$)	To check the localisation accuracy of all the activities within Room

- **L1L2L3Zone1**: The dataset contains data from locations 1,2 and 3 for Zone 1, with a total of 15 classes of activities from three locations.
- **Location1-Z1Z2Z3** The dataset contains data from Zone 1, 2 and 3 for location 1, with a total of 19 classes of activities from three locations.
- **L1L2L3-Zone123** The dataset contains data from all areas with a total of 43 classes of activities from nine locations.

D. Data Pre-processing and Machine Learning

This section provides an overview of the data preprocessing and ML approaches that have been designed and implemented in this study.

1) Data Preprocessing: For data pre-processing and ML approach, we utilize *Scikit*, a commonly used data analysis toolkit in Python [35]. Additionally, *Pandas*, a python library, can also parse CSV files. It converts CSV files into python data frames that can subsequently be analyzed using *scikit-learn* [22]. Labels are added to data frames in the first column. Not a number (NaN) values are produced in the dataset generated by combining the data frames of each sample due to minimum mismatches in received packets during communication between the USRP devices. Using a *SciKit* built-in function called *SimpleImputer*, these NaN values are replaced with the mean of each row. It's worth noting that data cleansing like this does not affect the overall pattern of the data. After cleansing the data, it was input into ML algorithms.

2) Machine Learning: The proposed Indoor localisation of the human activity monitoring system is evaluated using seven different ML methods. In our experiment, the accuracy of successful localisation of various human activities is being used as an evaluation parameter. Each algorithm's accuracy is determined independently for each test case dataset. The accuracy is evaluated using two approaches to achieve a robust analysis: (i) k-fold cross-validation and (ii) train-test split. K-fold cross-validation, where k is the number of groups into which a given dataset should be divided, is a popular approach for testing the efficacy of an ML approach [21]. In this experiment k, is set to 10 resulting in the dataset being divided into 10 groups. Each group is used as testing data with the remaining 9 groups used as training data. The results of each group of classifications give the results of all samples featured in the dataset. The train-test split technique separates the dataset into training and testing data. The training data is used to train the ML model. The algorithm can then make predictions on the testing data based on what the algorithm has learned from the training data In this study, 80% of each of the datasets are used for training and the remaining 20% is used for testing. The parameters used to configure the algorithms are listed in Table III.

TABLE III: The Parameters of Machine Learning Algorithms

Algorithm	Parameters	N estimator
Support Vector Machine	Kernel = rbf and sigmoid	gamma='scale'
K-Nearest Neighbors	Euclidean distance and K = 3,7	n-repeat = 3
Bagging	max-features, default= 1.0	n-estimators=20
Random Forest	max-features: ['auto', 'sqrt']	n-estimators=20
Extra Trees	max-features = auto, sqrt	n-estimators=20
Super Learner	multi-threading	n-estimators=20

IV. Results and Discussion

This section will present and discuss the results of the test cases shown in Table II.

A. Test-1.1

The results of Test-1.1 are shown in the below Table IV. These results show the relationship between localising and identifying activities across the horizontal zones of:

- L1Zone1 and L2Zone1
- L1Zone1 and L3Zone1
- L2Zone1 and L3Zone1

TABLE IV: ML algorithms comparison using Cross-validation on test case 1.1 in (Table II)

Algorithm	L1L2Zone1 Accuracy	L1L3Zone1 Accuracy	L2L3Zone1 Accuracy
Multilayer Perceptron	66.87%	73.42%	72.70%
Support Vector Machine	74.28%	84.71%	79.40%
K- Neighbors Classifier	78.70%	84.95%	82.25%
Bagging Classifier	79.56%	86.38%	82.68%
Random Forest	80.95%	87.60%	84.44%
Extra Trees	86.00%	92.93%	89.08%
Super Learner	**87.27%**	**95.90%**	**91.12%**

The SL algorithm had the best accuracy on all three of the experiments in Test-1.1. L1Zone1 and L3Zone1 had the highest accuracy score with all of the algorithms in comparison to the results of L1Zone1 and L2Zone1 and L2Zone1 and L3Zone1. The SL algorithm was able to achieve an accuracy score of 95.90 % in the L1Zone1 and L3Zone1 experiment. These results show that the accuracy of the algorithms to differentiate between the different locations is increased when the locations have greater space between them. This is likely due to CSI fluctuations being greater as the distance from the transmitter increases. For locations closer to each other the difference between CSI fluctuations is decreased. However, there is still high accuracy achieved by the algorithms, particularly the SL algorithm.

B. Test-1.2

The results of Test-1.2 are shown in the below Table V. These results show the relationship between localising and identifying activities across the horizontal zones of:

- L1Zone2 and L2Zone2
- L1Zone2 and L3Zone2
- L2Zone2 and L3Zone2

TABLE V: ML algorithms comparison using Cross-validation on test case 1.2 in (Table II)

Algorithm	L1L2Zone2 Accuracy	L1L3Zone2 Accuracy	L2L3Zone2 Accuracy
Multilayer Perceptron	68.76%	87.59%	88.17%
Support Vector Machine	82.92%	82.22%	92.93%
K- Neighbors Classifier	85.98%	85.56%	90.84%
Bagging Classifier	85.58%	87.77%	90.47%
Random Forest	86.54%	87.81%	91.87%
Extra Trees	91.69 %	91.60%	95.07%
Super Learner	**95.54**	**94.23%**	**96.36**

The results of Test-1.2 showed the highest accuracy in the experiment L2Zone2 and L3Zone2. The SL algorithm again had the highest accuracy of all experiments with 96.36 % in the L2Zone2 and L3Zone2 experiment. These results show that as the subject is positioned further from the transmitter, the CSI fluctuations are more prominent in the adjacent locations.

C. Test-1.3

The results of Test-1.3 are shown in the below Table VI. These results show the relationship between localising and identifying activities across the horizontal zones of:

- L1Zone3 and L2Zone3
- L1Zone3 and L3Zone3
- L2Zone3 and L3Zone3

TABLE VI: ML algorithms Comparison using Cross-validation on test case 1.3 in (Table II)

Algorithm	L1L2Zone3 Accuracy	L1L3Zone3 Accuracy	L2L3Zone3 Accuracy
Multilayer Perceptron	56.65%	71.88%	77.91%
Support Vector Machine	74.61%	82.58%	85.62%
K- Neighbors Classifier	77.61%	84.16%	84.64%
Bagging Classifier	80.37%	84.68%	85.65%
Random Forest	81.33%	86.21%	88.35%
Extra Trees	82.27 %	87.22%	90.45%
Super Learner	**85.00%**	**92.27%**	**93.18%**

The results of Test-1.3 have shown similarly to the results of Test-1.2 that if the subject moves further from the transmitter then the CSI fluctuations are more prominent in the adjacent locations. This is shown in the L2Zone3 and L3Zone3 experiment, where again the best accuracy results are shown for all algorithms with the SL algorithm with the highest accuracy of 93.18 % compared to the other algorithms.

D. Test-1.4

The Cross-validation results of Test-1.4 are shown in the below Table VII. These results show the relationship between localising and identifying activities across the vertical zones of:

- Location1Z1, Location1Z2 and Location1Z3
- Location2Z1, Location2Z2 and Location2Z3
- Location3Z1, Location3Z2 and Location3Z3

TABLE VII: ML algorithms comparison using Cross-validation on test case 1.4 in (Table II)

Algorithm	Location1-Z1Z2Z3 Accuracy	Location2-Z1Z2Z3 Accuracy	Location3-Z1Z2Z3 Accuracy
Multilayer Perceptron	47.07%	64.46%	82.81%
Support Vector Machine	66.66%	75.45%	91.08 %
K- Neighbors Classifier	66.66%	69.00 %	91.08 %
Bagging Classifier	71.66 %	76.65%	89.46%
Random Forest	75.66 %	78.66%	91.14%
Extra Trees	77.00 %	83.36%	93.66%
Super Learner	**81.66 %**	**86.66%**	**96.66%**

The results of Test-1.4 have given further evidence of increased accuracy as the subject moves further from the transmitter as seen in results of Test-1.2 and Test-1.3. The Location3Z1, Location3Z2 and Location3Z3 experiment had the highest accuracy out of all the experiments for Test-1.4 and previous experiments of Test-1.2 and Test-1.3. The SL algorithm again had the highest accuracy out of all algorithms with 96.66 %. Therefore the dataset of Location3Z1, Location3Z2 and Location3Z3 is taken forward to be analysed using the train-test split technique. Table VIII show the results achieved using the train-test split technique.

TABLE VIII: ML algorithms comparison using train test on test case 1.4 in Table II

Algorithm	Location3-Z1Z2Z3 Accuracy	Precision	Recall	F1 score	Time (sec)
Multilayer Perceptron	66.00%	67.00%	67.00%	68.00 %	0.68
Support Vector Machine	91.66%	92.00%	91.00 %	91.00 %	0.77
K- Neighbors Classifier	89.66%	91.00 %	90.00 %	90.00 %	0.09
Bagging Classifier	88.87 %	89.00%	89.00%	88.00%	31.93
Random Forest	90.66 %	91.00 %	91.00 %	91.00 %	1.07
Extra Trees	94.33 %	95.00%	94.00 %	94.00 %	1.32
Super Learner	**95.33 %**	**95.00%**	**95.00 %**	**95.00 %**	1.50

For train-test split results, the SL algorithm again outperformed all other algorithms with an accuracy of 95.33%. ET has a 94.33% accuracy score, whereas SVM and Random Forest have a 91.66% and 90.66% respectively. As shown in Figure 4, bagged trees and KNN have the lowest accuracy, with scores of 88.87% and 89.66 %, respectively. The most unsatisfied result showed MLP with an accuracy of 66%.

Figure 5 shows the confusion matrix of the results achieved using the train-test split technique for the SL algorithm.

E. Test-2.1

The paper's main contributions are highlighted in Test-2.1 results. The first experiment includes all data from all locations and zones. Two other experiments are conducted using all

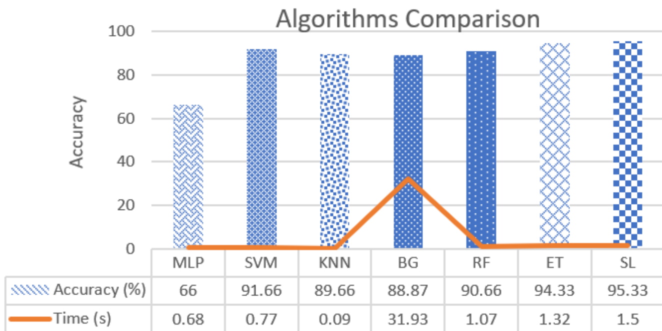


Fig. 4: Accuracy and time comparison of the tested machine learning algorithms on test case 1.4 in Table II.

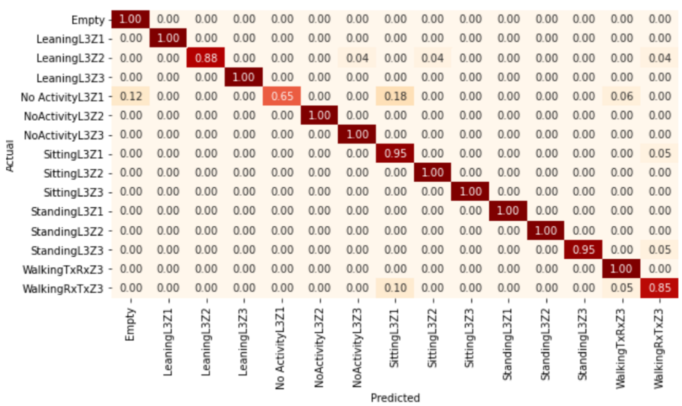


Fig. 5: The confusion matrix of SL algorithm on test case 1.4 Location3-Z1Z2Z3 (see Table II) showing how the algorithm classified each sample of data.

zones in location 1 and 3 and all zones in location 2 and location 3 for comparison. Table IX shows the accuracy for each algorithm.

TABLE IX: ML algorithms comparison using Cross-validation on test case 2.1 in (Table II)

Algorithm	Accuracy $L_1L_2L_3 - Zone_{123}$	Accuracy $L_1L3 - Zone_{123}$	Accuracy $L_2L_3 - Zone_{123}$
Multilayer Perceptron	57.44%	68.00%	71.00%
Support Vector Machine	62.33%	70.15%	76.97 %
K- Neighbors Classifier	63.66%	71.66%	72.57%
Bagging Classifier	68.66%	75.90%	76.66%
Random Forest	68.15%	77.12%	75.60%
Extra Trees	76.11%	82.27 %	81.97%
Super Learner	**79.00%**	**85.60%**	**85.60%**

The SL algorithm was able to identify activities and locations with 79 % accuracy and also had the highest accuracy of the other experiments. This is expected as it combines all the SVM, KNN, Bagged, Random Forest and Extra trees classifiers. This is consistent with the previous test cases. The SL algorithm was also the best performer for the other experiments conducted in Test-2.1.

V. Conclusion

This paper proposed a localisation system for an indoor activity that leverages RF sensing to identify seven different classifications taking place in different locations of the same room. The system was designed to identify the location of a performed activity, which activity took place and the occupancy of a room. The results also indicate detection of specific activities in an indoor environment The usage of RF sensing provides a non-contact method of human activity sensing and localising without the need for a wearable device. Comparisons of the machine learning classifiers found that the SL classifier performed the best due to the combination of several other algorithms used to create the super learner classifier. The study resulted in several fascinating results that will require further investigation through the acquisition of additional data. The localisation of different activities in location 3 and zone 3 is predicted to be higher than in other locations due to proximity to the receiver. When the activity is performed further away from the Tx, the system's activity detection accuracy increases in both horizontal and vertical direction, and what's more noteworthy is the precise increase of 3% horizontally and 14% vertically for every 1m away from the Tx. Future work will seek to test the scalability of the model by trying to perform the classifications in different environments. Additionally, future work will seek to provide the localisation of different subjects and provide the locations of the different subjects

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