Wireless Sensing for Human Activity Recognition Using USRP

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Abstract. Artificial Intelligence (AI) in tandem wireless technologies is providing state-of-the-art techniques human motion detection for various applications including intrusion detection, healthcare and so on. Radio Frequency (RF) signal when propagating through the wireless medium encounters reflection and this information is stored when signals reach the receiver side as Channel State information (CSI). This paper develops an intelligent wireless sensing prototype for healthcare that can provide quasi-real time classification of CSI carrying various human activities obtained using USRP wireless devices. The dataset is collected from the CSI of USRP devices when a volunteer sits down or stands up as a test case. A model is created from this dataset for making predictions on unknown data. Random forest was able to provide the best results with an accuracy result to 96.70% and used for the model. A wearable device dataset was used as a benchmark to provide a comparison in performance of the USRP dataset.

Keywords: Wireless sensing · Healthcare · RF sensing

1 Introduction

In recent years, healthcare monitoring technologies are becoming more common for improving the lives of vulnerable people [1,2]. Elderly people can be considered vulnerable people [3]. As the elderly population increases, the strain on nursing homes increase [4]. The United Nations (UN) estimates the global elderly population is likely to be around 2.1 billion in 2050 [5]. Healthcare monitoring can be used to provide real-time notifications to caregivers when care is required [6]. Monitoring can be achieved by observing the features of human movement obtained from technology [7]. The detection of elderly people falling is an example of how technology can be used to assist elderly people. Falling can cause serious injuries to people and in some cases cause death [8]. Fall detection

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systems used to alert care givers in real time so that care can be given when required. This relieves pressure from care givers and provides elderly people with more independence. The current methods of fall detection can be achieved using wearable devices such as mobile or smartwatches. The features of a human falling can then be passed to carers [9]. The main issue with wearable devices is when users do not wear the device for reasons of comfort or forgetfulness. Wearable devices are considered invasive as the wearable device is an instrument introduced onto the body. Non-invasive methods do not introduce instruments to the body. Recently, non-invasive and non-contact RF sensing based system is widely used to estimate human activity recognition. This is achieved by observing the Channel State information (CSI) that is represented in terms of amplitudes of the RF signals while humans move within the RF communication [10]. The wi-fi systems feature CSI to provide a description of how the RF signals propagate between transmitting and receiving nodes [11]. This research focus to exploit this CSI information. Therefore, the machine learning can be applied to detect patterns in the CSI and it can predict what human motion is taking place. This paper presents a machine learning model which can differentiate between a human standing up and sitting down using CSI with a real time application. Finally, the results are compared to a benchmark dataset which is collected using wearable devices.

The paper is organized as follows. Section 2 discusses related work on human activity recognition; Sect. 3 presents the proposed methodology; Sect. 4 provides the results and discussion and finally Sect. 5 concludes the paper.

2 Related Work

The following section lists some related works in the field of non-invasive RF sensing. Most of the current studies [12] used frequency-modulated continuous-wave (FMCW) radar systems. The human movements caused the radar signals to display a doppler shift. The doppler shifts is collected as samples of various human movements. The datasets are collected from multiple samples and machine learning is applied. The experimental results showed that the machine learning could distinguish differences in the doppler shifts for different human movements. The work of [13] used Wi-Fi signals to classify five different arm movements. The Wi-Fi router was used to communicate remotely to a laptop. In between the devices a human test subject made various arm movements. The CSI of the Wi-Fi signals was used as a data set for Long Short-Term Memory (LSTM) deep learning classification. Deep learning results achieved 96% accuracy. Other examples of work done on healthcare is present in [14]. Nipu et al. [15] exploited the CSI of RF signals for the identification of specific individuals. Experimentation used different volunteers to walk through the line of sight of two communication devices. The CSI was used as a dataset and machine learning was applied to try and extract the physical features of each volunteer. Random forest and decision tree algorithms were used and the results proved to have higher accuracy when the classification was only between two individuals. As the test subjects increased the accuracy decreased. Other work done using this dataset used four machine learning algorithms and ensemble learning of all four algorithms. The ensemble learning achieved an accuracy score of 93.83% [16].

3 Methodology

This section will discuss the experimental setup used in this research.

3.1 Data Collection

This research uses Universal Software Radio Peripheral (USRP) devices as the transmission and receiver of RF signals. The transmission device used is the USRP X300 model and the receiving device is the X310 USRP device. Each device is directly connected to its own a PC. On the PCs, the simulation software used is MatLab/Simulink. This simulation software enables the configuration of the devices to allow for the communication and capture of the CSI of the wireless exchange. Each USRP device is equipped with VERT2450 omni directional antennas. The devices were then setup in an office environment with 4 m between the communicating devices. The volunteers then performed the action of standing up and sitting down while USRP devices were communicating with each other. Each action was completed multiple times while the CSI for each instance was stored. multiple samples collected ensured that any error in performance could be filtered out in the data processing stage. The samples were collected while in a 7×8 m office which contained common furniture such as chairs and desks. The RF signals reflect on the volunteer as the sitting or standing motion occurs. The CSI data then stores the features of the movement in the form of signal propagation. There are many variations of how the signals will propagate, which is dependent on many factors just as posture, position of chair and different shapes and sizes of volunteers. However the general pattern of how the signals reflect from two different positions remains. Some ambient movement can cause the patterns to no longer be present in the CSI. These samples are not considered clear samples as the movement cannot be detected hence the reasoning behind taking a large range of samples for building a dataset. The complete dataset contains 60 samples. 30 samples for sitting and 30 samples for standing. Figures 1 and 2 show the 64 subcarrier CSI of the USRP transmissions. The time of transmission is shown along the X axis and the frequency change caused by the RF signals reflecting off the volunteer is shown in the Y axis. Figure 1 displays the CSI pattern of sitting down and Fig. 2 displays the CSI pattern of standing up. Figure 3 details the process used in this experimentation.

3.2 Machine Learning

Specifically, the dataset is used for various techniques of machine learning approaches. The machine learning algorithms are implemented using the Scikit

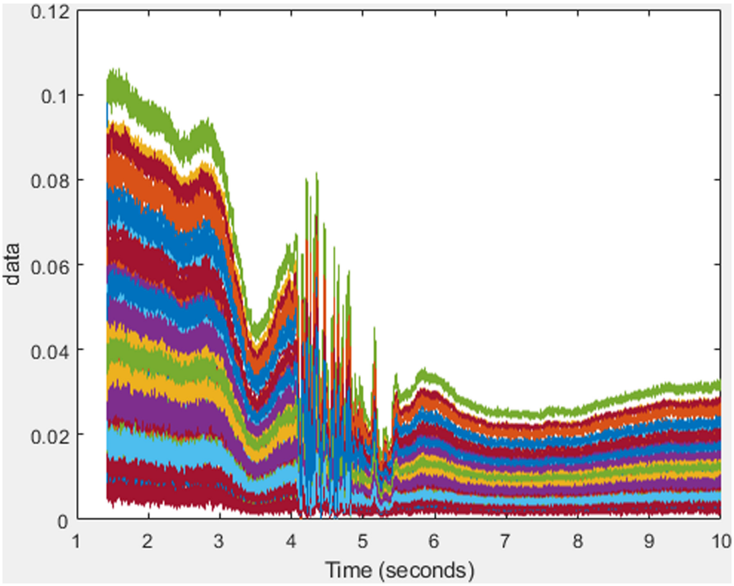

Fig. 1. Sitting down CSI

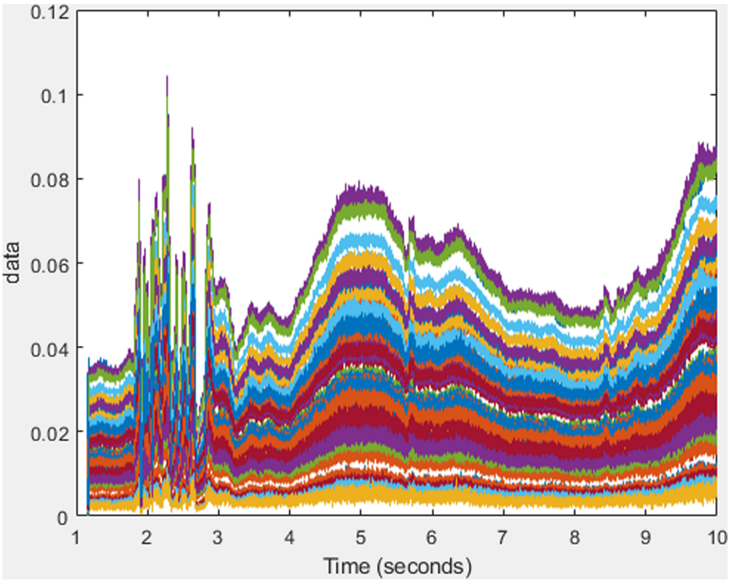

Fig. 2. Standing up CSI

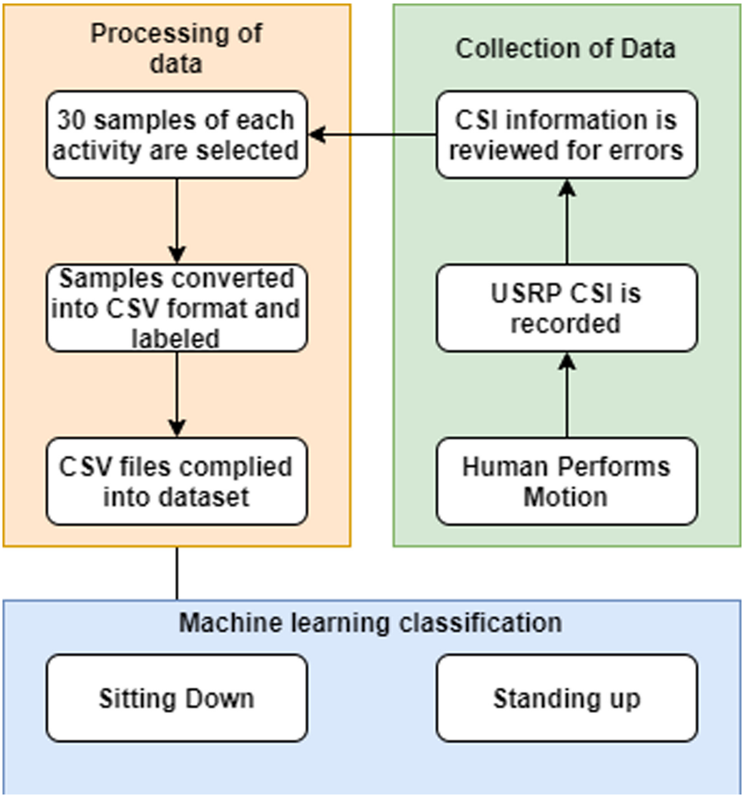

Fig. 3. Experiment flow chart

library of the Python programming language. Scikit is widely used in data science research and industry [17]. The CSI obtained from the samples is converted into CSV format so that Scikit can read the data for machine learning. The Pandas Python package is used to read and store the CSV data into a Python Variable. The data can then be labelled appropriately as sitting or standing. As the CSI data is always differentiating in each sample taken this can result in NAN values being present when python reads the CSV files. In order to overcome this challenge, the NAN values are replaced with 0 values. This does not affect the observed patterns when comparing different samples together. The CSV data is then divided between the actual CSI data of each sub carrier and the label for that sub carrier. The dataset is then divided between 70% training and 30% testing data. Ten machine learning algorithms used to test the performance of the dataset. Namely Random Forest, K nearest Neighbours (KNN), Support Vector Machine (SVM), Multi-layer Perceptron, Linear SVM, Gaussian Process, Decision Tree, Ada Boost, Gaussian and Naïve Bayes. The algorithms will be compared by considering the accuracy as evaluation metric. The comparative results will use the performance metrics of accuracy. Accuracy represents the

True positive (TP) classifications over the total classifications made. The other classifications made in machine learning are True Negative (TN), False Positive (FP) and False Negative (FN). The complete equation is shown in Eq. 1. It can be seen that the accuracy is the total number of correct classifications versus the total classifications made.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

4 Results and Discussion

4.1 Machine Learning Algorithms Comparison

The first experiment used a range of machine learning algorithms to test the performance of the newly collected USRP dataset. The results compare the accuracy of each algorithm. Figure 4 shows the accuracy of each of the algorithms and how they compare to each other and Table 1 presents the actual percentage of accuracy of each algorithm.

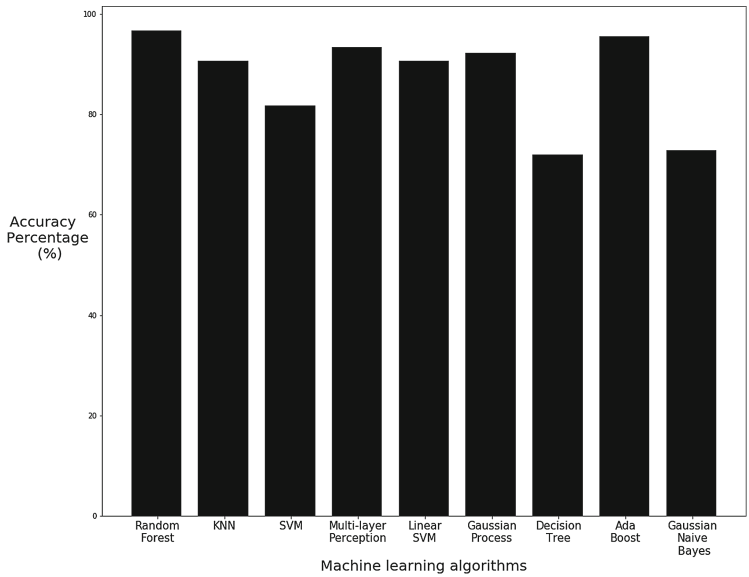

Fig. 4. Experiment flow chart

The machine learning experiments produced mostly high accuracy results with Random Forest, KNN, Multi layer Perception, Linear SVM, Gaussian Process and Ada Boost scoring over 90% accuracy. Random Forest had the best accuracy at 96.70% followed by Ada Boost with 95.48% accuracy. These results show that there are patterns in the CSI when volunteers stand up or sit down. These patterns can then be detected use machine learning techniques.

Table 1. Accuracy results of machine learning algorithms

Algorithm	Accuracy
Random Forest	96.70%
K nearest Neighbours	90.71%
Support Vector Machine	81.77%
Multi-layer Perception	93.40%
Linear SVM	90.71%
Gaussian Process	92.18%
Decision Tree	71.96%
Ada Boost	95.48%
Gaussian Naive Bayes	72.82%

4.2 Real Time Classification

The Random Forest algorithm achieved the highest accuracy of all tested algorithms. Therefore, Random Forest is used to create a model for making classifications on new unseen data. For creating a model, the data is no longer split between training and testing as the entire dataset is used for training. Python provides the Joblib library which can be used to save the Random Forest model for later use. The model is then used in an application which can provide real time classifications on new CSI received from the USRP devices. To create this application, the Flask web framework was used to create a web application. Flask was used as it is a python web framework and can execute the Python scripts to make predictions on new data using the previously saved model. The web interface presents users with a "Run Classification" button. This then allows a background script to use python to connect to MatLab and read the MatLab variables. When the USRP completes the transmission, the CSI is stored in a variable in MatLab. The Python script then connects to the MatLab session and the machine learning model can be used to make predictions on the CSI. While the script is running in the background, the web interface displays "Loading..." to the user. Once the prediction is generated the loading message is replaced with the prediction of what the model interprets the new CSI to be. Either standing or sitting down as shown in Fig. 5. However, the web application used to classify any amount of classifications. The number of classifications is dependent on the machine learning model used. The complete process of the web application is shown Fig. 6. For testing of this real time application, additional samples are taken. Six samples are taken for each sitting and standing. These samples are completely unseen to the training model. These samples are then used as the variable on MatLab and the real time application is used to make predictions on the samples. All 12 of these samples were correctly classified. This shows that the CSI for sitting and standing displays a specific pattern which can be detected by the created machine learning model.

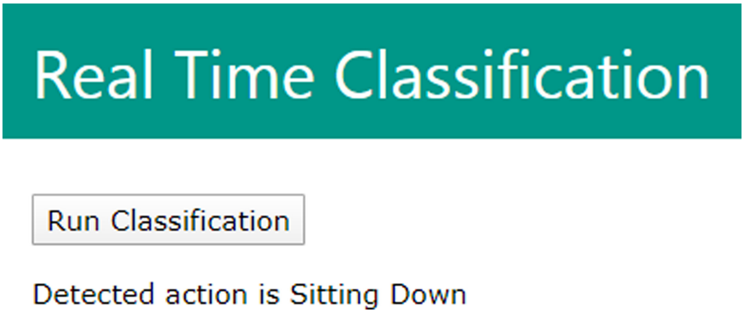

Fig. 5. Flask web interface displaying classification result

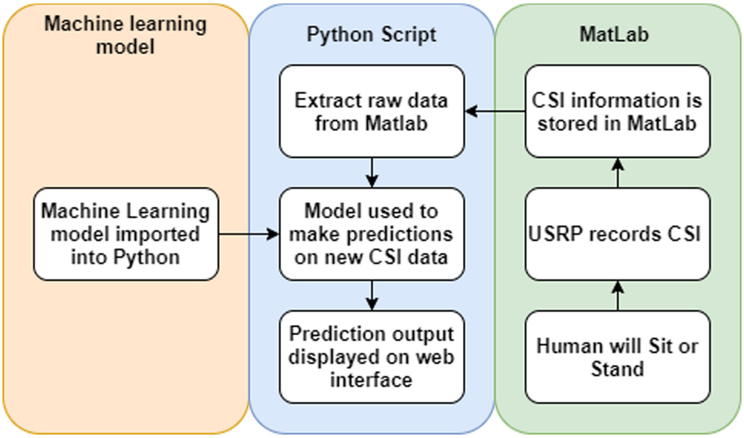

Fig. 6. Flask web interface process

4.3 Benchmark Dataset

The data collected from the USRP CSI has been shown to display patterns which can detected by most machine learning algorithms tested in this research. This shows that the Non-invasive CSI method is successful in motion detection. To provide a comparison between the performance of non-invasive techniques and invasive wearable devices, a publicly available dataset collected using wearable devices is used. D Anguita et al. [18] have publicly released a dataset detecting different human motions using accelerometers equipped on smartphones. The same machine learning techniques are applied to this dataset.

The results of the comparison show that the performance is similar with most of the algorithms between the two datasets. Random forest remained the highest performer between the two datasets with the results very similar around 96%. The accuracy for each algorithm between datasets is shown in Table 2 and the visual representation between the two datasets is shown in Fig. 7.

Table 2. Comparison of results

Algorithm	USRP accuracy	Benchmark accuracy
Random Forest	96.70%	96.49%
K nearest Neighbours	90.71%	92.48%
Support Vector Machine	81.77%	86.21%
Multi-layer Perception	93.40%	96.11%
Linear SVM	90.71%	91.85%
Gaussian Process	92.18%	54.01%
Decision Tree	71.96%	86.46%
Ada Boost	95.48%	92.23%
Gaussian Naive Bayes	72.82%	72.55%

The two best algorithms for the USRP dataset, Random Forest and Ada Boost both outperformed the wearable device dataset. This can be due to the USRP using multiple subcarriers. This allows for patterns in the wireless medium to be captured through the various subcarriers. Some of the lower performing algorithms of the USRP dataset showed improvement with the wearable device dataset. This is observed in decision tree algorithm. Gaussian Process showed a greater performance using the USRP dataset in comparison to the wearable device dataset. The rest of the algorithms observed similar results between the two datasets.

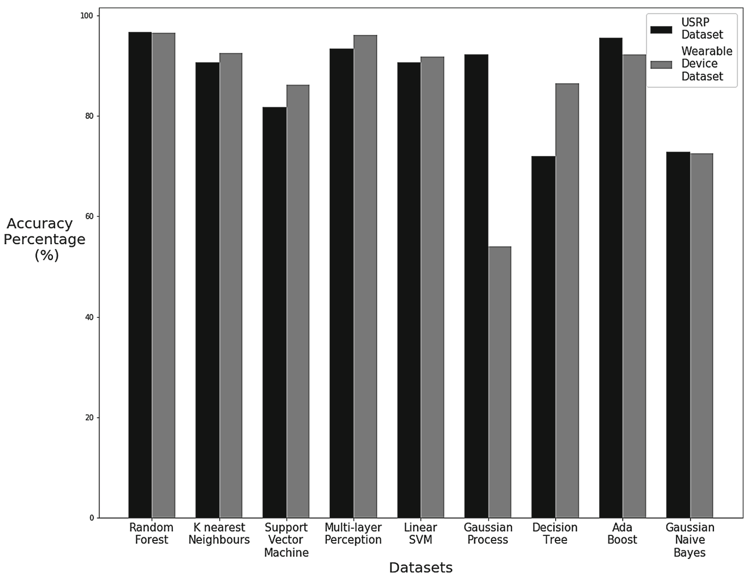

Fig. 7. Comparison of results

5 Conclusion

In this research paper, we have proposed a novel intelligent wireless sensing system using AI and USRP dataset and different algorithms that can detect the human motions of standing and sitting up. The dataset provides binary observations of CSI collected from USRPs as a volunteer stands and sits from a chair. The machine learning algorithms show good performance with the Random Forest algorithm producing the best performance with 96.70% accuracy. These results show that there is a distinctive pattern between the CSI of a volunteer sitting and standing. The web application designed was able to make predictions of new data based on a model build from training data. A comparison was also made between the newly created URSP dataset and a publicly available dataset, where data was collected using wearable devices. The same machine learning techniques were used, and results showed that performance was similar thus providing evidence that USRPs can detect motion at the same level as wearable devices.

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References

1. Dong, B., et al.: Monitoring of atopic dermatitis using leaky coaxial cable. Healthc. Technol. Lett. **4**(6), 244–248 (2017)
2. Abbasi, Q.H., et al.: Advances in body-centric wireless communication: Applications and state-of-the-art. Institution of Engineering and Technology (2016)
3. Yang, X., et al.: Diagnosis of the hypopnea syndrome in the early stage. Neural Comput. Appl. **32**(3), 855–866 (2019). https://doi.org/10.1007/s00521-019-04037-8
4. Mercuri, M., et al.: Healthcare system for non-invasive fall detection in indoor environment. In: De Gloria, A. (ed.) Applications in Electronics Pervading Industry, Environment and Society. LNEE, vol. 351, pp. 145–152. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-20227-3_19
5. Liu, Y., et al.: A novel cloud-based framework for the elderly healthcare services using digital twin. IEEE Access **7**, 49088–49101 (2019)
6. Yang, X., et al.: Monitoring of patients suffering from REM sleep behavior disorder. IEEE J. Electromagn. RF Microwav. Med. Biol. **2**(2), 138–143 (2018)
7. Zhang, T., et al.: WiGrus: a Wifi-based gesture recognition system using software-defined radio. IEEE Access **7**, 131102–131113 (2019)
8. Santos, G.L., et al.: Accelerometer-based human fall detection using convolutional neural networks. Sensors **19**(7), 1644 (2019)
9. Yao, X., Khan, A., Jin, Y.: Energy efficient communication among wearable devices using optimized motion detection. In: 2019 IEEE Symposium on Computers and Communications (ISCC), pp. 1–6. IEEE (2019)
10. Zhao, J., et al.: R-DEHM: CSI-based robust duration estimation of human motion with WiFi. Sensors **19**(6), 1421 (2019)

11. Lolla, S., Zhao, A.: WiFi motion detection: a study into efficacy and classification. In: 2019 IEEE Integrated STEM Education Conference (ISEC), pp. 375–378. IEEE (2019)
12. Ding, C.: Fall detection with multi-domain features by a portable FMCW radar. In: 2019 IEEE MTT-S International Wireless Symposium (IWS), pp. 1–3. IEEE (2019)
13. Zhang, P.: Complex motion detection based on channel state information and LSTM-RNN. In: 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), pp. 0756–0760. IEEE (2020)
14. Shah, S.A., Yang, X., Abbasi, Q.H.: Cognitive health care system and its application in pill-rolling assessment. Int. J. Numer. Model. Electron. Netw. Devices Fields **32**(6), e2632 (2019)
15. Nafiul Alam Nipu, Md., et al.: Human identification using WiFi signal. In: 2018 Joint 7th International Conference on Informatics, Electronics and Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR), pp. 300–304. IEEE (2018)
16. Taylor, W., et al.: An intelligent non-invasive real-time human activity recognition system for next-generation healthcare. Sensors **20**(9), 2653 (2020)
17. Hao, J., Ho, T.K.: Machine learning made easy: a review of Scikit-learn package in python programming language. J. Educ. Behav. Stat. **44**(3), 348–361 (2019)
18. Anguita, D., et al.: A public domain dataset for human activity recognition using smartphones. In: Esann (2013)