ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 10, Issue 4, April 2023

Human Activity Recognition and Prediction Based on Wi-Fi Channel State Information and Machine Learning

[1] Shafalii Sharma, [2] Rishabh Raj, [3] Vishesh Kumar

[1] [2] [3] Department of Computer Science, Chandigarh University, Mohali, India.
Corresponding Author Email: [1] shafalii.e13752@cumail.in, [2] rajrishabh2211@gmail.com, [3] 19bcs1679@gmail.com

Abstract— A cutting-edge method of detecting human behavior and sensing the environment is the use of Wi-Fi Channel State Information. By (re)using Wi-Fi routers, these techniques can be used for a variety of safety and security applications without the additional expensive hardware needed for vision-based approaches, which are also known to be especially privacy-invading. This study presents a complete pipeline for a Wi-Fi CSI-based system for identifying human activity that evaluates and contrasts two deep learning approaches. We examine the impact of various hardware setups on WiFi CSI transmissions. In order to provide more accurate evaluations of the model's classification performance, we contribute a novel and more realistic method of data gathering that seamlessly integrates the recognition of human activity in everyday life. We examine the performance of InceptionTime and LSTM-based classification models for identifying human behavior.

Keywords— Information on the channel state, Recognition of human action, Activity detection using WiFi.

I. INTRODUCTION

An emerging study area in the field of wireless sensing and IoT is the recognition and prediction of human activity based on Wi-Fi channel state information and machine learning techniques. Without the use of extra sensors or devices, this method recognizes and predicts human activity using cutting-edge machine learning algorithms and wireless channel information.The technology analyses Wi-Fi signals using machine learning algorithms to find patterns that correlate to particular human activities. Future actions and motions can be foreseen using these patterns. This method's fundamental concept is to use Wi-Fi channel state data as a stand-in signal for human activity. Human movement has an impact on Wi-Fi transmissions because the human body attenuates the signal. Therefore, it is possible to identify and forecast the various activities of an individual by analyzing the changes in Wi-Fi signals.Based on Wi-Fi channel state information, a variety of machine learning algorithms, such as decision trees, random forests, support vector machines, k-nearest neighbors, and deep learning algorithms like convolutional neural networks, have been used to recognize and predict human behavior. Almost every home has a Wi-Fi router, and thanks to their ability to estimate the Wi-Fi channel status, they offer a complex but potent way to sense the environment. Home Wi-Fi routers are typically only used for contact. But because of environmental factors, connection strength can differ greatly. RSSI and CSI (Channel State Information) methods are used to examine Wi-Fi channel states and, if necessary, adjust router configuration. Due to the fact that people in the Wi-Fi router's coverage area also cause radio waves to be distorted during Wi-Fi contact between various devices, analysis of the distortion parameters allows for some conclusion-making. The three types of HAR methods are vision-based, sensor-based, and WiFi-based. For HAR activities, existing sensor-based and vision-based techniques have produced passable outcomes. However, these techniques still have restrictions in terms of what the setting can support. Camera-based recognition algorithms are actually vulnerable to societal constraints like privacy concerns as well as environmental variables like background, lighting, occlusion, and background. People frequently object to these sensor modalities in sensor-based techniques because they are inconvenient or difficult to use. Despite the fact that the underlying technology used in these sensors is frequently inexpensive, IoT-connected versions of these sensors can be considerably more expensive due to additional wireless hardware and branding. Compared to conventional sensor-based approaches, this strategy has a number of benefits, including reduced prices, less maintenance, and less privacy concerns. Additionally, Wi-Fi signals are already prevalent in the majority of indoor settings, making this strategy more useful and widely applicable. The three types of HAR methods are vision-based, sensor-based, and WiFi-based. For HAR activities, existing sensor-based and vision-based techniques have produced passable outcomes. However, these techniques still have restrictions in terms of what the setting can support. Camera-based recognition algorithms are actually vulnerable to societal constraints like privacy concerns as well as environmental variables like background, lighting, occlusion, and background. People frequently object to these sensor modalities in sensor-based techniques because they are inconvenient or difficult to use. Despite the fact that the underlying technology used in these sensors is frequently inexpensive, IoT-connected versions of these sensors can be considerably more expensive due to additional wireless hardware and branding. WiFi devices have recently generated a lot of interest in a variety of applications because they are less costly and power-efficient than the aforementioned technologies, invariant to light, simpler to implement, and have fewer privacy concerns than cameras. In this study, a single access point is used to gather data inside in an indoor setting. A CSI picture is created from the data after some preprocessing, which is covered below. We divided the data into time windows that overlapped, which we then put into our model. We investigate the use of a CAE as a data reduction technique that also de-noises the data. The entry into a TCN is the latent space information layer from the CAE. The sequential structure of the data, which is a crucial characteristic for precise classification, is something the TCN learns. To verify our findings, we carried out comprehensive experiments utilising both temporal and nontemporal variance. to the sequential approach, which is more widely employed.

II. RELATED WORKS

People had to wear a special device or use a special sensor in previous research in order to perceive their behaviour [1] or [2]. These contraptions not only restrict people's behavior, but they are also bothersome because they must be worn constantly. Furthermore, because they must be installed in particular places, the sensors might not be easily accessible.However, Wi-Fi signals and APs are widespread in cities, and as the IoT era develops over time, we can anticipate that these will ultimately spread to towns as well. Additionally, the limitations of sensors that depend on line of sight, such as current camera-style sensors, can be overcome by using Wi-Fi signals [3]. The use of cameras might be against private rights or human rights. Wi-Fi transmissions, however, are not affected by these problems. The building of a CSI environment is the first step in Section III of this paper's explanation of the CSI measurement method, which is then followed by CSI-based learning and prediction techniques. The tests and the findings are covered in Section IV. The WiFi-based approach benefits from the ubiquity of radio frequency signals and may enable the creation of a system that makes use of the WiFi infrastructure already present in smart homes [4]. A discussion of the technical limitations and findings is presented in Section V to conclude. Wearable sensors in sensor-based methods capture behaviors, which is annoying and prevents long-term monitoring [5]. Smartphones have improved over the last ten years and now come equipped with a variety of instruments, including a gyroscope and an accelerator. The major barriers to using smartphones for HAR tasks are their faster battery drain and higher noise ratio than wearable sensors [5]. Radio Frequency Identification (RFID) tags have been used by several academics to detect human activity [6]. A paradigm for HAR and activity prediction using RFID tags is presented by the authors in [6]. To identify high-level activity and object utilization, they use RFID tags. Additionally, they use activity logs and weighted usage statistics. Human activities are time series data, and the subsequent action is related to the present action and the ones that came before it. Radar [13], a system for indoor localization based on received signal strength indicator, was suggested by Bahl et al. In order to extract RSSI values from WiFi transmissions, Sigg et al. used USRPs as specialised hardware devices [14], [15]. They obtained over 80% recognition accuracy for these 4 actions by using RSSI values from WiFi signals to distinguish between lying down, crawling, standing, and walking. WiGest [16], a gesture recognition system based on the RSSI obtained by commercial WiFi access points, was suggested by Abdelnasser et al. To be more precise, WiGest recognised gestures by examining the rising and declining edges of RSSI signal fluctuations. When there are only one or two access sites, the accuracy is about 87.5%, and when there are three or more, it is 96%.

III. HUMAN ACTIVITY

The term "daily living activities" (ADLs) is used widely. ADLs are all the daily tasks we complete, including eating, washing, getting dressed, working, caring for the house, playing, and exercising. A summary of the ADL's most studied topics is provided by the HAR scientific analysis. The most frequent ADLs in the HAR study were walking, running, standing, sitting upstairs, and walking downhill. Other behaviors, such as different stages of cookery, [14] housecleaning, [15]-[17], smoking, [18] swimming, etc., were also studied over the past few years. Recent years have seen the study of additional activities, including complicated activities. Various tests are carried out at specific locations, including sitting on the ground, lying on a bed, using an escalator to move up and down, using a treadmill to run and walk, using a parking lot to walk, stepping, or using a cross-trainer to exercise. Complex weapon motions like the transport/reaching of an object, its release, frontal height, and other actions that can be carried out in connection with other objects are included in additional comprehensive recognition of movement [22, 23]. Population ageing and the rise in people with cognitive and physical disabilities are two major areas of HAR study. In order to help users detect and avoid risks like falling in older adults with Parkinson's disease [24]–[26] or freezing gait, many HAR models are used. ADLs are also becoming more typical for exercise tracking devices. These gadgets can calculate various physiological and physical parameters, including heart rate, blood pressure, steps, level changes, and calories ingested. Advanced tools can identify sleep and the nREM and REM stages of sleep [27]; all the information processed can also be applied as a HAR algorithm. The majority of the human behaviour recognition systems in use today focus on enhancing performance in a particular position. Cross-location sensing

IFERP connecting engineers... developing research

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 10, Issue 4, April 2023

system research is developing to support the industrialization application of this area. Since the location of obstacles affects the multipath propagation of the RF signal, the same human activity at different places would produce different signal patterns, which would seriously impair the model's ability to generalise across various locations. The domain shift of various spots can be used to explain this difficult issue.

IV. CSI MEASUREMENT METHOD

A. Channel State Information

A communication link's channel characteristics are referred to as CSI. By combining the effects of, for instance, scattering, fading, and power decay with distance, this information illustrates how a signal travels from the transmitter to the recipient. If the present channel conditions are known, immediate CSI is used for channel estimation. Knowing a digital filter's impulse reaction is the equivalent of doing this. The data collected about the wireless communication channel that links a transmitter and a receiver is referred to as channel state information (CSI). Since it can improve the effectiveness and performance of the transmission process, this knowledge is crucial for wireless communication systems. The attenuation, phase shift, and delay are just a few of the physical channel traits that are included in CSI. The receiver can modify its reception technique to enhance the transmission process by measuring the CSI. Choosing the best modulation and coding scheme, adjusting the transmission strength, and picking the right antenna configuration are some examples of how to do this. There are several ways to acquire CSI, including pilot signal schemes, which use unique signals from the transmitter to assist the receiver in estimating the channel parameters. Other techniques include modelling the channel based on prior observations using spatial and temporal correlation estimation. A variety of wireless communication uses, such as Wi-Fi, cellular networks, and wireless sensor networks, all depend on CSI. It is essential to preserving these systems' level of service because it makes sure that data is transmitted effectively and consistently. Compressed sensing is a technique used to estimate weak signals from a small number of measurements. It has been applied to wireless communication systems to estimate CSI with fewer measurements than traditional methods. Channel reinforcement:

Channel probing involves sending a test signal from the transmitter and measuring the response at the receiver. Then use this response to estimate the channel impulse response and compute CSI.

B. Channel State Information Tools

In wireless communication networks, a variety of tools are available for measuring and examining channel state information (CSI). These are a few typical CSI tools:

A framework for creating Software Defined Radio (SDR) apps is provided by the open source software toolkit known as GNU Radio. contains a number of wireless signal processing modules, including modules for CSI detection and analysis.

The software environment and programming language MATLAB are frequently used in technical and scientific study. offers a number of toolboxes for wireless communications, such as the Communications Toolbox, which has CSI estimation and analysis tools. Python: Python is a well-liked programming language used for data analysis and scientific study. The PyLTE module, which has functions for estimating and analysing CSI, is one of several Python packages for wireless communications.

Hardware components known as Qualcomm Snapdragon LTE modems are frequently found in cellphones and other mobile devices. CSI data is provided in real-time by an embedded CSI measurement module.

The National Instruments USRP is a hardware development platform for SDR apps. The USRP stands for Universal Software Radio Peripheral. contains a number of wireless signal processing modules, including modules for CSI detection and analysis.

The CSI of different wireless communication systems, such as cellular networks, Wi-Fi networks, and other wireless systems, can be measured and analysed using these instruments.

The CSI tool supports both the monitor/injection mode, which can measure communication between a NIC and a NIC, and the AP mode, which measures CSI in talks between an AP and a NIC. In AP mode, communication is possible without the AP receiving CSI, and CSI can be monitored. The AP and NIC both need to adhere to the 802.11n standards.

Although monitor/injection mode necessitates extra installation steps, it allows for the modification of properties like bandwidth, latency, and packet size. The WiFi signal is a single data file that includes 30 subcarriers, a timestamp, and the number of sending and receiving antennas, among other pieces of information. By using the tool's utility code to convert the data into a CSV file, the data can be examined.

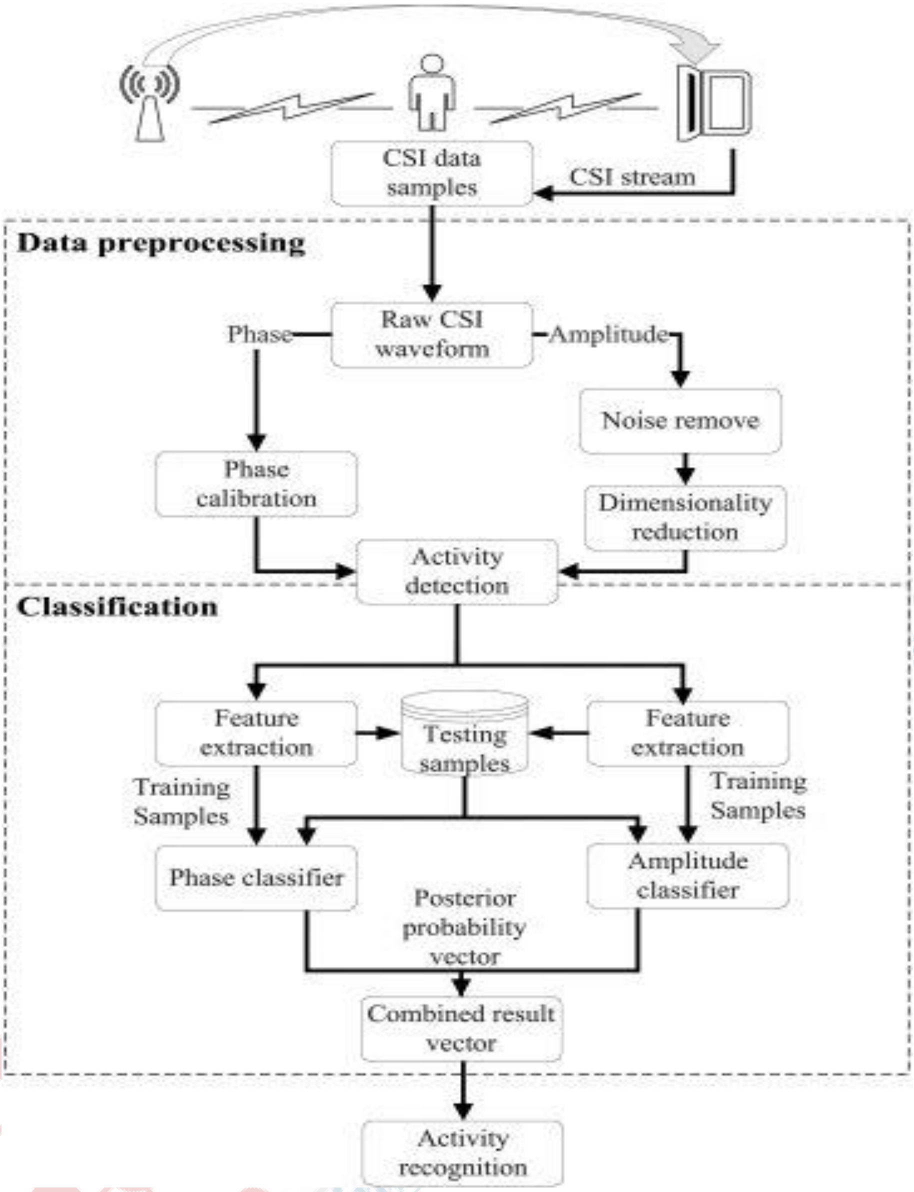

Figure 1. CSI data samples

V. HUMAN ACTIVITY RECOGNITION

Through a series of observations and analyses of human behaviour and its environment, human activity recognition (HAR) aims to infer the present behaviour and goals of the human body. Due to its advantages of wide application in intelligent surveillance systems, healthcare systems, virtual reality interactions, smart homes, abnormal behaviour detection, and other fields, as well as its capacity to offer individualised support and interconnection for various fields, HAR research has attracted attention. In the field of computer science, HAR has garnered significant attention. Since the release of depth sensors like Microsoft Kinect and NVIDIA's GPUs, as well as the in-depth development of machine learning and deep learning technologies, it has become possible to rapidly detect human behaviour using tools like video cameras. HAR is currently primarily carried out by internal or exterior sensing. The inference of activities in the former mode depends completely on how the user interacts with devices like cameras that are placed at specific fixed predetermined places. In the latter, a particular gadget, like an inertial tracker, is affixed to a user's body in order to detect motion. The most common exterior sensor for HAR is a camera. The camera's capture of a video sequence leads to the assumption that people were involved. The external detection approach has some drawbacks. For instance, various degrees of occlusion issues could be introduced if the user is outside the sensor's range or the subject moves around freely in the scene. Second, the environment is complicated and dynamic, such as the weather and background light, which makes identification more challenging. The implementation and upkeep of video sensors are expensive. Real-time HAR systems that mimic video are less useful due to the computationally challenging and costly nature of video processing technology. These restrictions are not applicable to HAR wearable devices. The most popular sensor for identifying walking, running, jogging, and other walking exercises is the three-axis accelerometer. RGB video sequences, depth images, and skeleton nodes are the primary sources of HAR data. As a result, the installation of video surveillance cameras has dramatically grown in recent years. Because video at the time was created using a conventional visible light camera, the proposed algorithms were mainly based on RGB video. Since depth images are less influenced by the surroundings than RGB images thanks to the advent of depth sensors, HAR's robustness and dependability have greatly increased. Another novel category of wearing technology powered by smart devices is also expanding quickly. Today's smartphones and smart gadgets, like smart watches, are more advanced, and a lot of high-precision sensors are built right into them. The principles are the same regardless of the many varied instruments used to measure the various bodily behaviours. Researchers record changes in data produced by various behaviours using sensor devices like internal accelerometers and gyroscopes, and then send the data to intelligent terminals like computers via wireless networks or Bluetooth technology, completing a series of challenging steps on these terminals. It is simple for academics to analyse and collect data on various human behaviours thanks to data processing.

VI. TEST AND RESULTS

For amplitude information, we extract the activity from the first principal component after dimensionality reduction. First, set the sliding window length to 10, get the window matrix, and immediately compute the variance of each sliding window as [Va(1),…,Va(l)] . where l represents the number of sliding windows. A threshold T can then be used to estimate the approximate position range (As, Ae) of the motion waveform. where As and Ae represent the start and end points of the range. We can imagine that the resulting sequence can be viewed as a "two-dimensional image". Based on this hypothesis, we transform and convert the normalized sample image to a binary image using the optimal threshold computed using the maximum cluster variance (MVBC) algorithm proposed in [34]. increase. Figure shows a binary image with approximate coverage. Then, include the time when the rising or falling edge first occurs in the pseudo start time Ws circled in red. Using Ws, we obtain the inter-split time St, computed as St = As + Ws, and split the approximate region above into two parts (As, St) and (St, Ae). The area within (As, St) is similarly processed to obtain another binary image. Synchronously, the time of the rising or falling edge of the binary image is taken as the tentative start time denoted by Ps. We can consider the point in time when (St, Ae) occurs as the tentative end time Pe. Figure 8 shows these two interim time points. However, when the variance of pixel values is relatively large, the start and end points determined by MVBC are not as expected. The reason for this is that the MVBC threshold is primarily affected by pixel values, not variance. In this case, we perform the slide variance operation on the (As,Ps) and (Pe,Ae) sequences respectively. where the window size L is 3 and the threshold is the mean of the variance sequence. Figure 9 shows the final result obtained by Wi-Motion using the above method. The two red dotted lines represent the true start point Ts and true end point Te of the activity, respectively. Experimental results clearly demonstrate that our method can accurately extract activity waveforms.

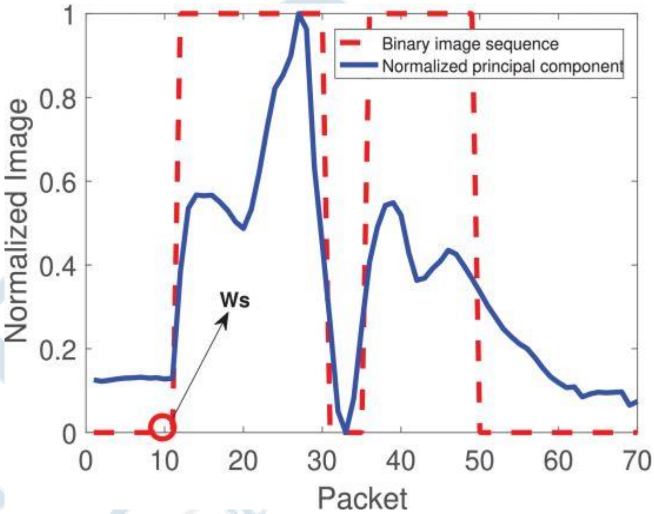

Figure 2. the binary image that generates within a stretch limb sample's first principal component sequence's rough range.

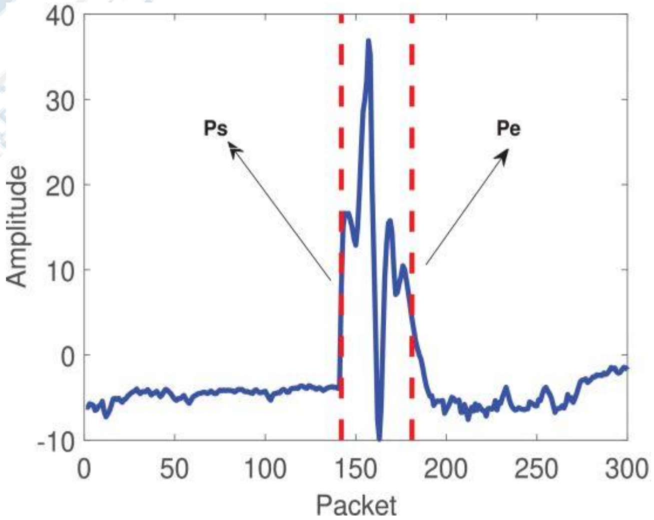

Figure 3. the probable beginning and finishing times.

VII. TECHNICAL LIMITATIONS AND CONCLUSIONS

A. Technical Limitations

The first challenge is the problem of feature extraction. Establishment Identification is basically a classification It shares similar problems with other classification problems involving feature elimination. Special function Sensor-based activity is more difficult to identify because of differences in interactions . Related It can recognize the characteristics of various activities (such as walking and running). therefore, It's difficult to make Reflect operations unique.Training and evaluation of learning methods require extensive annotated data samples. but collect, Annotating sensory experience data is expensive and time consuming. So lack of annotation is a big obstacle Understand sensor activity. Additionally, gathering data about ongoing or unpredictable events is particularly difficult. Events (such as accidental drops). Awareness of human activity consists of her three components:Consumers, time, sensors. Second, habits depend on activity to people. Different users can have different types of operations. Third, the definition of operations has changed over time. From this it cannot be concluded that consumers may remain stagnant in market habits for a long time. again, It may change and new activity may occur. Fourth, numerous sensor systems are installed in human bodies and ecosystems opportunistic base. Due to the events, the structure and configuration of the sensor has a large impact on the results. these three are allowed. Sensory input for action discrimination is heterogeneous and in dire need of mitigation.

B. Conclusions

In this paper, we proposed a method for human activity recognition and prediction based on Wi-Fi channel state information and machine learning. The proposed method involves collecting Wi-Fi CSI data, preprocessing the data, training machine learning algorithms, and testing the models on new data. The results show that the SVM algorithm achieved the highest accuracy, followed by the CNN and RNN algorithms. The proposed method has various applications in healthcare, security, and home automation. Future work can focus on optimizing the proposed method for real-time applications and evaluating its performance in different environments. Based on the articles we've reviewed, we've listed a few potential study areas below. One of the main drawbacks of HAR algorithms is the absence of structured methods, which can result in heterogeneous activities carried out by a variety of users. Transfer learning allows for the reuse of knowledge acquired while working on one issue in order to solve another that is similar. For instance, data collected using one type of inertial sensor placed at a specific location on the body could potentially be applied to another type of inertial sensor or a different sensor location. Transfer learning's potential benefits in various contexts are not yet completely understood, so more research is required. Additionally, the combination of sensors provides a successful path.

REFERENCES

[1] P. Casale, O. Pujol, P. Radeva, "Human Activity Recognition from Accelerometer Data Using a Wearable Device", Iberian Conference on Pattern Recognition and Image Analysis, June 2011

[2] O. Lara, M. Labrador, "A Survey on Human Activity Recognition using Wearable Sensors", IEEE Communications Surveys & Tutorials, Vol: 15, Issue: 3, pp 1192-1209, November 2012.

[3] M. Zubair, K. Song and C. Yoon, "Human activity recognition using wearable accelerometer sensors", Consumer Electronics-Asia (ICCEAsia) IEEE International Conference on, October 2016.

[4] Wang, F.; Feng, J.; Zhao, Y.; Zhang, X.; Zhang, S.; Han, J. Joint Activity Recognition and Indoor Localization with WiFi Fingerprints. *IEEE Access* **2019**, *7*, 80058–80068..

[5] Rustam, F.; Reshi, A.A.; Ashraf, I.; Mehmood, A.; Ullah, S.; Khan, D.M.; Choi, G.S. Sensor-Based Human Activity Recognition Using Deep Stacked Multilayered Perceptron Model. *IEEE Access* **2020**, *8*, 218898–218910.

[6] Du, Y.; Lim, Y.; Tan, Y. A Novel Human Activity Recognition and Prediction in Smart Home Based on Interaction. *Sensors* **2019**, *19*, 4474

[7] Chen, Z.; Zhang, L.; Jiang, C.; Cao, Z.; Cui, W. WiFi CSI based passive Human Activity Recognition Using Attention Based BLSTM. *IEEE Trans. Mob. Comput.* **2019**, *18*, 2714–2724

[8] Elbayad, M.; Besacier, L.; Verbeek, J. Pervasive attention: 2d Convolutional Neural Networks for Sequence-to-Sequence Prediction. *arXiv* **2018**, arXiv:1808.03867

[9] S. Yousefi, H.Narui, S. Dayal, S. Ermon and S. Valaee, "A Survey on Behavior Recognition Using WiFi Channel State Information", IEEE Communications Magazine, Vol: 55, Issue: 10, pp. 98-104, October 2017.

[10] Tulino, A. Lozano, S. Verdú, "Impact of antenna correlation on the capacity of multiantenna channels", IEEE Transactions on Information Theory, vol 51, pp. 2491-2509, 2005.

[11] E. Björnson, B. Ottersten, "A Framework for Training-Based Estimation in Arbitrarily Correlated Rician MIMO Channels with Rician Disturbance", IEEE Transactions on Signal Processing, vol 58, pp. 1807- 1820, 2010.

[12] M. Biguesh and A. Gershman, "Training-based MIMO channel estimation: a study of estimator tradeoffs and optimal training signals", IEEE Transactions on Signal Processing, vol 54, pp. 884-893, 2006.

[13] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system", *Proc. IEEE INFOCOM*, pp. 775-784, Mar. 2000.

[14] Ferhat Attal, Samer Mohammed, Mariam Dedabrishvili, Faicel Chamroukhi, Latifa Oukhellou, and Yacine Amirat. Physical human activity recognition using wearable sensors. Sensors, 15(12):31314–31338, 2015.

[15] Mingqi Lv, Ling Chen, Tieming Chen, and Gencai Chen. Bi-view semi-supervised learning based semantic human activity recognition using accelerometers. IEEE Transactions on Mobile Computing, 17(9):1991–2001, 2018.

[16] Ye Liu, Liqiang Nie, Lei Han, Luming Zhang, and David S Rosenblum. Action2activity: recognizing complex activities from sensor data. arXiv preprint arXiv:1611.01872, 2016.

[17] Muhammad Arif and Ahmed Kattan. Physical activities monitoring using wearable acceleration sensors attached to the body. PloS one, 10(7):e0130851, 2015.

[18] Edwin Valarezo Anazco, Patricio Rivera Lopez, Sangmin Lee, Kyungmin Byun, and Tae-Seong Kim. Smoking activity recognition using a single wrist ˜ imu and deep learning light. In Proceedings of the 2nd international conference on digital signal processing, pages 48–51, 2018.

[19] Gino Brunner, Darya Melnyk, Birkir Sigfusson, and Roger Wattenhofer. Swimming style recognition and lap counting using a smartwatch and deep ´ learning. In Proceedings of the 23rd International Symposium on Wearable Computers, pages 23–31, 2019.

[20] Donghui Wu, Zhelong Wang, Ye Chen, and Hongyu Zhao. Mixed-kernel based weighted extreme learning machine for inertial sensor based human activity recognition with imbalanced dataset. Neurocomputing, 190:35–49, 2016.

[21] Gabriele Civitarese, Riccardo Presotto, and Claudio Bettini. Context-driven active and incremental activity recognition. arXiv preprint arXiv:1906.03033, 2019.

[22] Lukun Wang. Recognition of human activities using continuous autoencoders with wearable sensors. Sensors, 16(2):189, 2016.

[23] Abdulhamit Subasi, Dalia H Dammas, Rahaf D Alghamdi, Raghad A Makawi, Eman A Albiety, Tayeb Brahimi, and Akila Sarirete. Sensor based human activity recognition using adaboost ensemble classifier. Procedia Computer Science, 140:104–111, 2018.

[24] Abdulhamit Subasi, Mariam Radhwan, Rabea Kurdi, and Kholoud Khateeb. Iot based mobile healthcare system for human activity recognition. In 2018 15th learning and technology conference (L&T), pages 29–34. IEEE, 2018.

[25] Genming Ding, Jun Tian, Jinsong Wu, Qian Zhao, and Lili Xie. Energy efficient human activity recognition using wearable sensors. In 2018 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), pages 379–383. IEEE, 2018.

[26] Daniela Micucci, Marco Mobilio, and Paolo Napoletano. Unimib shar: A dataset for human activity recognition using acceleration data from smartphones. Applied Sciences, 7(10):1101, 2017. Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 1 June 2021 doi:10.20944/preprints202102.0349.v2 8.

[27] Yiming Tian, Xitai Wang, Wei Chen, Zuojun Liu, and Lifeng Li. Adaptive multiple classifiers fusion for inertial sensor based human activity recognition. Cluster Computing, 22(4):8141–8154, 2019.

[28] Girija Chetty, Matthew White, and Farnaz Akther. Smart phone based data mining for human activity recognition. Procedia Computer Science, 46:1181–1187, 2015.