Position-independent Human activity recognition using smartphone sensors

Zhe Yan

yanzhe@stanford.edu

1. Introduction:

The purpose of Human Activity Recognition (HAR) is to distinguish human daily physical behaviors through the analysis of relevant data obtained from various methods (e.g., video-based and sensor-based approach). Compared with other systems, smartphone-based sensor system has significant advantages in terms of computing power, portability, ubiquity and cost [1][2]. This system has been widely used in many fields, such as health care, smart home, game entertainment, Robot R&D, surveillance, sport and fitness [3][4][5][6]. However, previous work mainly focuses on several specific on-body positions, such as hand, trouser pocket, jacket pocket, hand, armband [7][8][9][10][11]. In fact, people also carry their smartphones in other locations. Moreover, the position of smartphone influences the performance of human activity recognition [12][13][14]. For example, data collected from waist produces different signal patterns from hand. Therefore, it is meaningful to develop a HAR system with considering of various locations where the phone is placed. In general, there are 4 fundamental steps in sensor-based HAR: data pre-processing, segmentation, feature extraction and classification. In this paper, the data is collected from 10 positions including hand, front trouser pocket, back trouser pocket, jacket pocket, upper arm, forearm, backpack front pocket, satchel handbag pocket, tote bag pocket, cross bag pocket, and fanny bag pocket. The main purpose of this paper is to present an effective system which is capable of identifying 6 types of human daily activities including walking, jogging, going upstairs, going downstairs, biking and standing, by using accessible signals collected from 9 subjects' smartphones platform. To eliminate the effect of smartphone's orientation, reduce calculation cost and speed up activity identification, the experiment investigates whether it is possible to successfully recognize human activity through the acceleration data in only one direction (gravity direction in earth coordinate system) instead of 3-axis acceleration and 3-axis gyroscope data from smartphone's local coordinate system. After feature extraction and selection in time domain and frequency domain, 7 classification techniques including Naïve Bayes, K-Nearest Neighbors, Linear Regression, Decision Tree, Support Vector Machine, Random Forest, and Deep Neural Network, are applied to conduct activity recognition tasks.

The contributions of this paper are as follow:

- A new dataset with some new positions of smartphone is presented.
- A model related to acceleration data in only one direction (calculated from 3-axis acceleration and 3-axis gyroscope data) achieves 93% accuracy of HAR with time and frequency domain features under 7 classification methods.
- Data from hand and thigh produces relatively low accuracy using our method.

2. Related Work:

The position of smartphone sensors is a factor which greatly influence the quality of data collection and the accuracy of classification algorithms. Table 1 shows a list of papers separated by the position of smartphones.

Position	Papers
Any position	[20][22][26][27][28]][29][34][35][37][42][43]
Waist	[2][11][15][23][30][31][36][40][41][44][45][46]
Trouser pocket	[2][8][9][10][16][17][18][19][21][23][25][32][33][38][39][40][44][45][46]
Coat pocket	[2][16][18][19][21][24]
Hand	[2][17][18][19][25][32][40][46]
Arm	[2][11][33][36][40]
Chest	[11][19][25][33][36][45][46]
Head	[11][36]
Backpack	[18][33]
Shin	[11][36]
Thigh	[11][36]

Table 1. List of papers separated by the position of smartphones

It is meaningful to develop a HAR system without considering the position of the smartphone [47]. To tackle down this problem, one solution is to extract activity-sensitive and position-invariant features which are greatly altered by various human activities but free from different positions under the identical behavior [48][49]. But few satisfactory handcrafted features extracted from domain experts limits this approach. Also, those shallow features cannot be generalized for diverse scenarios. Another method is to firstly determine the specific position of smartphone before the classification of human activity for this position [50][51][52]. The limitation of this way is the uncertainty of position in real application and the requirement of high computing power and long computing time since the model is required to identify the position first and then the activity for each instance. Neither of these two solutions achieves very ideal performance on human activity recognition.

The classification algorithms for generating models to recognize human activities are divided into two groups: conventional machine learning algorithm and deep learning algorithm. The former is relatively shallower and requires feature extraction which is limited by domain knowledge [53]. However, the simpler structure of conventional machine learning (e.g., Support Vector Machine, K-Nearest Neighbors) is more suitable for fast calculation and small database calculation [18][25][54]. The most common deep learning algorithms on HAR, such as Convolutional Neural Network, Recurrent neural network, Long Short-Term Memory and Stacked Autoencoder, provide benefits to generate high-level features that effectively represent the attributes of data [55][56][57][58][59][60]. However, there is a trade-off between HAR model performance and data processing time [61].

3. Database:

The collection of data is carried out in a group of 9 volunteers. The dataset consists of smartphones (iPhone 8/X/11) located at 10 different positions: hand, front trouser pocket, back trouser pocket, jacket pocket, upper arm, forearm, backpack front pocket, satchel handbag pocket, tote bag pocket, cross bag pocket, and fanny bag pocket. Each person performs 6 human daily activities: walking, jogging, going upstairs, going downstairs, standing and biking. Accelerometer and gyroscope data are recorded at a constant rate of 16 Hz. An important feature of dataset is that gravity and device motion acceleration signals can be directly obtained from iPhone Operation System (iOS) Core Motion System without the separation of gravitational and body motion components from sensor acceleration signal [62]. Previous studies tested different window size and features [63][64][65]. Overlapping windows have been proved to be more suitable because they expand dataset and handle transitions more accurately. The accuracy of human activity recognition from window lengths of one to two seconds are larger than those from other windows [61]. Based on those results, the collection of sensor signals is divided into segments with the identical 2-second window length and 50% overlapping. The dataset is randomly partitioned into 70% as training set and 30% as test set.

4. Coordinate Transformation:

3-axis accelerometer and gyroscope data, which are related to smartphone's local coordinate system, are recorded from iOS Core Motion System during the process of data collection. *User Acceleration* $\overrightarrow{A_u}$ attempts to define the 3-axis acceleration vector that the user imparts to the device rather than gravity force. *Gravity* $\overrightarrow{A_g}$ represents 3-axis gravity acceleration vector in the smartphone's local coordinate. A_{gx}, A_{gy}, A_{gz} are the three components of resultant gravity acceleration whose magnitude is supposed to be 1.000g.

In order to recognize human activities with uncertainty in different orientation, coordinate transformation from smartphone's reference frame to earth's coordinate system are required. This conversion can be interpreted in terms of Eulerian angle differences of two frames [66]. Although it is meaningless to determine whether the smartphone is back-to-front during human activity recognition process, the absolute value of horizontal component of acceleration can be derived. The vertical acceleration (A_v) and horizontal acceleration (A_h) can be formulated as

$$A_v = \frac{\overrightarrow{A_g} \cdot \overrightarrow{A_u}}{\left\|\overrightarrow{A_g}\right\|_2}$$

$$|A_h| = \left\|\overrightarrow{A_u}\right\|_2 \times \sqrt{1 - \left(\frac{\overrightarrow{A_g} \cdot \overrightarrow{A_u}}{\left\|\overrightarrow{A_g}\right\|_2 \times \left\|\overrightarrow{A_u}\right\|_2}\right)^2}$$

where $\left\|\overrightarrow{A_g}\right\|_2$, $\left\|\overrightarrow{A_u}\right\|_2$ represents Euclidean norm of A_g and A_u.

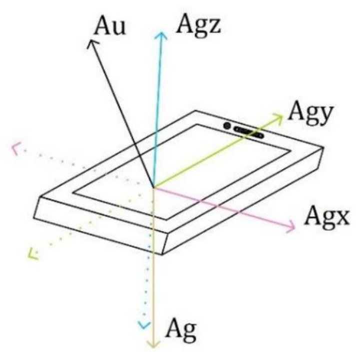

Figure 1. Smartphone's local coordinate system and transformation

5. Feature Extraction and Selection:

The basic idea of feature extraction is the computation of feature vector from signal windows. To avoid the influence of smartphone orientation, the most common features based on A_v have been extracted in time domain and frequency domain. Frequency-based features are transformed from time-based features through Fast Fourier Transform. In fact, due to different aims and settings, it is difficult to compare different but overlapping feature sets from preceding studies [67]. However, some features, such as frequency-based features and autoregression coefficients in time domain, have been proved to be a good factor in activity recognition improvement [68]. Those special features are capable of mitigating the variation in motion data of identical activity in different positions. There are 29 features have been used to recognize human activities in this research:

Domain	Feature
Time domain	Mean, Max, Min, Median, Mad, Std, Interquartile Range, Entropy, Zero Crossing Rate, Signal Magnitude Area, Root Mean Square, Energy, Skewness, Kurtosis, 1^{st} – 4^{th} Autoregression Coefficient
Frequency domain	1^{st} – 8^{th} Fast Fourier Transforms Coefficients, Skewness, Kurtosis, Entropy

Table 2. Summary of extracted features

Feature extraction can sometimes generate irrelevant features which causes the negative impact on the performance of classification algorithms. To improve the performance of models and reduce the computational cost, feature selection is a vital process to select those features which contributes most to the result. In this research, High Correlation Filter method is used to remove features that are highly correlated with others and provide redundant information through the calculation of the correlation between independent numerical variables.

6. Classification:

In this study, 7 classifiers are used for the classification of human activity. Naïve Bayes (NB) simplifies learning based on Bayes' theorem with strong independence assumptions between the features. K-Nearest Neighbors (KNN) is a non-parametric classification method, which classifies data by finding the training data with a minimal Euclidean distance to the samples in the test set. Linear Regression (LR) is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables. Decision Tree (DT) classifies data by constructing a flowchart-like structure which consists of internal nodes (test on an attribute), branches (outcome of the test) and leaves (class label after computing all attributes). Support Vector Machine (SVM) separates data by finding hyperplanes that effectively differentiate the classes. The map of data from input space into a higher dimensional feature space improve the classification performance. Random Forest (RnF) is an ensemble learning method for classification which operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. Deep neural network (DNN) is a network of neurons organized in a sequence of multiple layers, where neurons receive as input the neuron activations from the previous layer, perform a simple computation and output a result. Hyperparameters are the variables which determines the network model and the network result. Generally, there are many different approaches to find the best hyper-parameter values in deep neural network. In this paper, a randomized search over parameters is implemented, where each setting is sampled from a distribution over possible parameter value. This has two main benefits over an exhaustive search: ①A budget can be chosen independent of the number of parameters and possible values. ②Adding parameters that do not influence the performance does not decrease efficiency. Three gradient descent optimization algorithms including traditional stochastic gradient descent (SGD), RMSprop, and Adam, are used to tune network weights iteratively. SGD is adapted as it revealed higher performance. The best performance of model is achieved when dropout rate was 0.2. The optimal number of fully-connected layers is determined to be 6 layers after spanning a range of 0 to 10 layers. For the number of neurons in each layer, 300 neurons are selected after testing values from 150 to 500 neurons. Rectified Linear Unit (ReLU) activation function, which computes efficiently and performs better than other methods (e.g., linear function, tanh function and sigmoid function), is used in deep neural network.

7. Result and analysis:

The activity recognition performance of 7 classifiers is shown in Table 2. The best result from DNN algorithm shows an overall accuracy of 93% for the test data consists of 14644 samples. A comparison of the results demonstrates that different classification methods significantly affect accuracy. DNN outperforms the other classifiers. In contrast, SVM and RnF achieves reasonable results. Among six activities, bike, jog and stand exhibit better performance with the recognition accuracy higher than 95%. The classification performance also shows that go upstairs and downstairs have relatively low identification accuracy which is close to 80%. In particular, there is a noticeable misclassification overlap between these two activities and walk. From signal windows, the characteristics of walking, going upstairs and going downstairs are distinguishable for just one subject but similar between different users. Those suggests that the vertical component of device motion acceleration in global coordinate system do not sufficiently represent all human activities and advanced experiment is required to improve classification performance. However, if we only consider two basic activities: dynamic activities (e.g., walk, bike) and static activities (e.g., stand), the model can easily recognize. More detailed results are presented in appendix.

F-Score	NB	KNN	LR	DT	SVM	RnF	DNN
Bike	0.93	0.94	0.95	0.96	0.97	0.97	**0.98**
Go downstairs	0.55	0.70	0.64	0.65	0.77	0.76	**0.81**
Jog	0.86	0.93	0.92	0.90	0.95	0.95	**0.96**
Stand	0.98	0.97	0.99	0.99	0.99	0.99	**0.99**
Go upstairs	0.50	0.65	0.62	0.61	0.75	0.74	**0.78**
Walk	0.74	0.86	0.80	0.82	0.90	0.89	**0.92**
Weighted avg.	0.79	0.87	0.86	0.85	0.92	0.91	**0.93**

Table 3. F-score of the proposed models for human activity recognition

To further analyze HAR accuracy in each location, the number of mislabeled cases is calculated and shows in Table 4. In this paper, the worse recognition performance (error rate > 8%) exists in four positions including hand, satchel handbag, front trouser pocket and back trouser pocket. Human activities are complex procedures. Data collected from smartphone sensors reflect the movement pattern of the part where the phone is placed. One part of motion data (e.g., data from hand or thigh) at a time makes HAR a difficult task. It is difficult to extract information related to body movement using data from hand or thigh. The result shows the impact of the difference in flexibility of hands, thighs and body during the specific activity.

Mislabeled cases	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Overall cases	Error Percent
hand	0	24	6	5	27	5	610	**11%**
front trouser pocket	2	31	0	0	23	12	791	**9%**
back trouser pocket	0	21	1	1	43	18	860	**10%**
jacket pocket	7	19	0	3	20	3	872	6%
upper arm	0	11	0	2	26	6	878	5%
forearm	0	17	0	0	17	5	801	5%
backpack	0	35	10	1	47	9	1855	5%
satchel handbag	5	89	30	3	120	49	3082	**10%**
tote bag	7	45	0	1	47	4	1626	6%
fanny bag	10	31	0	2	47	22	1543	7%
cross bag	9	27	4	1	50	31	1726	7%

Table 4. Mislabel cases on each position

8. Conclusion and future work:

This paper introduces a new dataset including several new possible positions for HAR of 9 subjects through smartphone sensors and acknowledge some results using 7 classification methods. The result shows that the best performance of classification algorithm is achieved with Deep Neural Network technique. In this paper, the overall human activity recognition accuracy is 93%. However, the vertical acceleration on gravity direction (A_v), which can eliminate the impact of smartphone's orientation, is not very ideal to recognize highly similar activities (e.g., go upstairs and go downstairs) based on the existing work in this paper. Subsequently, mislabeled cases show that hand, satchel handbag, front trouser pocket and back trouser pocket are the worst positions for human activity recognition due to high flexibility of hand and thigh during human activity process. To continue this research, there are several straightforward improvements: (1) applying more complex deep learning models, such as CNN, RNN and LSTM, to improve the HAR performance using acceleration signals in only one direction. (2) generating more sophisticated but meaningful features (e.g., features in wavelet domain). (3) using some advanced feature selection techniques (e.g., Recursive Feature Elimination) or dimensionality reduction methods (e.g., PCA, t-SNE, ICA). (4) making full use of more data (i.e., 3-axis acceleration and 3-axis gyroscope data collected in this paper). (5) collecting data from more subjects and more potential positions of smartphone. (6) investigating and eliminating the impact of smartphone's orientation on human activity recognition using another method.

9. Appendix:

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2597	15	0	0	21	163	0.93
Go downstairs	5	850	148	0	272	374	0.52
Jog	3	155	1520	0	82	121	0.81
Stand	47	2	0	3152	0	0	0.98
Go upstairs	38	134	47	0	769	839	0.42
Walk	98	232	23	0	187	2750	0.84
Precision	0.93	0.61	0.87	1.00	0.58	0.65	

Table 1. Confusion matrix of classification results on test data using Naïve Bayes

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2602	8	3	124	15	44	0.93
Go downstairs	13	1088	117	0	214	217	0.66
Jog	7	41	1787	0	14	32	0.95
Stand	11	0	0	3190	0	0	0.99
Go upstairs	70	196	33	0	1039	489	0.57
Walk	31	97	11	1	116	3034	0.92
Precision	0.95	0.76	0.92	0.96	0.74	0.80	

Table 2. Confusion matrix of classification results on test data using K-Nearest Neighbors

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2696	3	0	14	24	59	0.96
Go downstairs	7	978	124	0	256	284	0.59
Jog	16	65	1724	0	11	65	0.92
Stand	10	0	0	3191	0	0	0.99
Go upstairs	47	114	25	0	1102	539	0.60
Walk	68	151	16	0	223	2832	0.86
Precision	0.95	0.75	0.91	0.99	0.68	0.75	

Table 3. Confusion matrix of classification results on test data using Linear Regression

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2656	5	4	3	37	91	0.95
Go downstairs	4	1033	111	0	245	256	0.63
Jog	9	93	1655	0	23	101	0.88
Stand	13	0	0	3188	0	0	0.99
Go upstairs	33	178	26	0	969	621	0.53
Walk	34	136	14	0	179	2927	0.89
Precision	0.97	0.71	0.91	0.99	0.67	0.73	

Table 4. Confusion matrix of classification results on test data using Decision Tree

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2741	6	2	3	20	24	0.98
Go downstairs	12	1239	70	0	199	129	0.75
Jog	3	53	1797	0	15	13	0.96
Stand	6	0	0	3195	0	0	0.99
Go upstairs	47	116	25	0	1352	287	0.74
Walk	27	62	8	0	112	3081	0.94
Precision	0.97	0.84	0.94	0.99	0.80	0.87	

Table 5. Confusion matrix of classification results on test data using Support Vector Machine

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2733	5	0	1	23	34	0.98
Go downstairs	4	1183	98	0	217	147	0.72
Jog	4	21	1824	0	7	25	0.97
Stand	12	0	0	3189	0	0	0.99
Go upstairs	41	106	26	0	1287	367	0.70
Walk	18	59	3	0	112	3098	0.94
Precision	0.97	0.86	0.93	0.99	0.78	0.84	

Table 6. Confusion matrix of classification results on test data using Random Forest

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2756	3	1	0	22	14	0.99
Go downstairs	5	1299	67	0	168	110	0.79
Jog	1	30	1830	0	9	11	0.97
Stand	18	0	0	3183	0	0	0.99
Go upstairs	37	159	21	0	1360	250	0.74
Walk	14	48	4	0	98	3126	0.95
Precision	0.97	0.84	0.95	0.99	0.82	0.89	

Table 7. Confusion matrix of classification results on test data using Deep Neural Network

10. Reference:

[1] Lane, N., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., & Campbell, A. (2010). A survey of mobile phone sensing. *IEEE Communications Magazine, 48*(9), 140–150.

[2] Chen, Y., & Shen, C. (2017). Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition. *IEEE Access, 5*, 3095–3110.

[3] Bakar, U. A. B. U. A., Ghayvat, H., Hasanm, S. F., & Mukhopadhyay, S. C. (2015). Activity and Anomaly Detection in Smart Home: A Survey. *Smart Sensors, Measurement and Instrumentation*, 191–220.

[4] Roy, N., Misra, A., & Cook, D. (2015). Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments. *Journal of Ambient Intelligence and Humanized Computing, 7*(1), 1–19.

[5] Higgins, J. P. (2016). Smartphone Applications for Patients' Health and Fitness. *The American*

Journal of Medicine, 129(1), 11–19.
[6] Shah, M. S., & Borole, P. B. (2016). Surveillance and rescue robot using Android smartphone and the Internet. *2016 International Conference on Communication and Signal Processing (ICCSP)*.
[7] Reyes-Ortiz, J. L., Oneto, L., Samà, A., Parra, X., & Anguita, D. (2016). Transition-Aware Human Activity Recognition Using Smartphones. *Neurocomputing, 171,* 754–767.
[8] Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2011). Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter, 12*(2), 74–82.
[9] Malekzadeh, M., Clegg, R. G., Cavallaro, A., & Haddadi, H. (2018). Protecting Sensory Data against Sensitive Inferences. *Proceedings of the 1st Workshop on Privacy by Design in Distributed Systems.*
[10] Micucci, D., Mobilio, M., & Napoletano, P. (2017). UniMiB SHAR: A Dataset for Human Activity Recognition Using Acceleration Data from Smartphones. *Applied Sciences, 7*(10), 1101.
[11] Sztyler, T., & Stuckenschmidt, H. (2016). On-body localization of wearable devices: An investigation of position-aware activity recognition. *2016 IEEE International Conference on Pervasive Computing and Communications (PerCom).*
[12] Atallah, L., Lo, B., King, R., & Yang, G. Z. (2011). Sensor Positioning for Activity Recognition Using Wearable Accelerometers. *IEEE Transactions on Biomedical Circuits and Systems, 5*(4), 320–329.
[13] Purpura, S., Schwanda, V., Williams, K., Stubler, W., & Sengers, P. (2011). Fit4life: the design of a persuasive technology promoting healthy behavior and ideal weight. *Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems - CHI '11.*
[14] Sousa Lima, W., Souto, E., El-Khatib, K., Jalali, R., & Gama, J. (2019). Human Activity Recognition Using Inertial Sensors in a Smartphone: An Overview. *Sensors, 19*(14), 3213.
[15] Anguita, D., Ghio, A., Oneto, L., Parra, X., & Reyes-Ortiz, J.L. (2013). A Public Domain Dataset for Human Activity Recognition using Smartphones. *Computational Intelligence and Machine Learning, ESANN 2013.*
[16] Miao, F., He, Y., Liu, J., Li, Y., & Ayoola, I. (2015). Identifying typical physical activity on smartphone with varying positions and orientations. *BioMedical Engineering OnLine, 14*(1).
[17] Gu, F., Kealy, A., Khoshelham, K., & Shang, J. (2015). User-Independent Motion State Recognition Using Smartphone Sensors. *Sensors, 15*(12), 30636–30652.
[18] Anjum, A., & Ilyas, M. U. (2013). Activity recognition using smartphone sensors. *2013 IEEE 10th Consumer Communications and Networking Conference (CCNC).*
[19] Shi, D., Wang, R., Wu, Y., Mo, X., & Wei, J. (2017). A novel orientation- and location-independent activity recognition method. *Personal and Ubiquitous Computing, 21*(3), 427–441.
[20] Zhang, S., McCullagh, P., Nugent, C., & Zheng, H. (2010). Activity Monitoring Using a Smart Phone's Accelerometer with Hierarchical Classification. *2010 Sixth International Conference on Intelligent Environments.*
[21] Sun, L., Zhang, D., Li, B., Guo, B., & Li, S. (2010). Activity Recognition on an Accelerometer Embedded Mobile Phone with Varying Positions and Orientations. *Ubiquitous Intelligence and Computing,* 548–562.
[22] Yang, J. (2009). Toward physical activity diary. *Proceedings of the 1st International Workshop on Interactive Multimedia for Consumer Electronics - IMCE '09.*
[23] Miluzzo, E., Lane, N. D., Fodor, K., Peterson, R., Lu, H., Musolesi, M., Eisenman, S. B., Zheng, X., & Campbell, A. T. (2008). Sensing meets mobile social networks. *Proceedings of the 6th ACM*

Conference on Embedded Network Sensor Systems - SenSys '08.
[24] Khan, A. M., Lee, Y. K., Lee, S. Y., & Kim, T. S. (2010). Human Activity Recognition via an Accelerometer-Enabled-Smartphone Using Kernel Discriminant Analysis. *2010 5th International Conference on Future Information Technology.*
[25] Khan, A. M., Tufail, A., Khattak, A. M., & Laine, T. H. (2014). Activity Recognition on Smartphones via Sensor-Fusion and KDA-Based SVMs. *International Journal of Distributed Sensor Networks, 10*(5), 503291.
[26] Berchtold, M., Budde, M., Gordon, D., Schmidtke, H. R., & Beigl, M. (2010). ActiServ: Activity Recognition Service for mobile phones. *International Symposium on Wearable Computers (ISWC) 2010.*
[27] Anderson, I., Maitland, J., Sherwood, S., Barkhuus, L., Chalmers, M., Hall, M., Brown, B., & Muller, H. (2007). Shakra: Tracking and Sharing Daily Activity Levels with Unaugmented Mobile Phones. *Mobile Networks and Applications, 12*(2–3), 185–199.
[28] Iso, T., & Yamazaki, K. (2006). Gait analyzer based on a cell phone with a single three-axis accelerometer. *Proceedings of the 8th Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '06.*
[29] Sohn, T., Varshavsky, A., LaMarca, A., Chen, M. Y., Choudhury, T., Smith, I., Consolvo, S., Hightower, J., Griswold, W. G., & de Lara, E. (2006). *Mobility Detection Using Everyday GSM Traces. Lecture Notes in Computer Science, 212–224.*
[30] Lane, N., Mohammod, M., Lin, M., Yang, X., Lu, H., Ali, S., Doryab, A., Berke, E., Choudhury, T., & Campbell, A. (2011). BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing. *Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare.*
[31] Fontecha, J., Navarro, F. J., Hervás, R., & Bravo, J. (2012). Elderly frailty detection by using accelerometer-enabled smartphones and clinical information records. *Personal and Ubiquitous Computing, 17*(6), 1073–1083.
[32] Shoaib, M., Bosch, S., Incel, O., Scholten, H., & Havinga, P. (2016). Complex Human Activity Recognition Using Smartphone and Wrist-Worn Motion Sensors. *Sensors, 16*(4), 426.
[33] Reddy, S., Mun, M., Burke, J., Estrin, D., Hansen, M., & Srivastava, M. (2010). Using mobile phones to determine transportation modes. *ACM Transactions on Sensor Networks, 6*(2), 1–27.
[34] Mladenov, M., & Mock, M. (2009). A step counter service for Java-enabled devices using a built-in accelerometer. *Proceedings of the 1st International Workshop on Context-Aware Middleware and Services Affiliated with the 4th International Conference on Communication System Software and Middleware (COMSWARE 2009) - CAMS '09.*
[35] Khan, A., Siddiqi, M., & Lee, S. W. (2013). Exploratory Data Analysis of Acceleration Signals to Select Light-Weight and Accurate Features for Real-Time Activity Recognition on Smartphones. *Sensors, 13*(10), 13099–13122.
[36] Vahdatpour, A., Amini, N., & Sarrafzadeh, M. (2011). On-body device localization for health and medical monitoring applications. *2011 IEEE International Conference on Pervasive Computing and Communications (PerCom).*
[37] Lu, H., Pan, W., Lane, N. D., Choudhury, T., & Campbell, A. T. (2009). SoundSense: Scalable sound sensing for people-centric applications on mobile phones. *Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services - Mobisys '09.*
[38] Bieber, G., Koldrack, P., Sablowski, C., Peter, C., & Urban, B. (2010). Mobile physical activity

recognition of stand-up and sit-down transitions for user behavior analysis. *Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments - PETRA '10.*

[39] Das, B., Seelye, A. M., Thomas, B. L., Cook, D. J., Holder, L. B., & Schmitter-Edgecombe, M. (2012). Using smart phones for context-aware prompting in smart environments. *2012 IEEE Consumer Communications and Networking Conference (CCNC).*

[40] Shoaib, M., Bosch, S., Incel, O., Scholten, H., & Havinga, P. (2014). Fusion of Smartphone Motion Sensors for Physical Activity Recognition. *Sensors, 14*(6), 10146–10176.

[41] Sousa, W., Souto, E., Rodrigres, J., Sadarc, P., Jalali, R., & El-Khatib, K. (2017). A Comparative Analysis of the Impact of Features on Human Activity Recognition with Smartphone Sensors. *Proceedings of the 23rd Brazillian Symposium on Multimedia and the Web.*

[42] Siirtola, P., & Roning, J. (2013). Ready-to-use activity recognition for smartphones. *2013 IEEE Symposium on Computational Intelligence and Data Mining (CIDM).*

[43] Martín, H., Bernardos, A. M., Iglesias, J., & Casar, J. R. (2012). Activity logging using lightweight classification techniques in mobile devices. *Personal and Ubiquitous Computing, 17*(4), 675–695.

[44] Thiemjarus, S., Henpraserttae, A., & Marukatat, S. (2013). A study on instance-based learning with reduced training prototypes for device-context-independent activity recognition on a mobile phone. *2013 IEEE International Conference on Body Sensor Networks.*

[45] Hynes, M., Wang, H., McCarrick, E., & Kilmartin, L. (2010). Accurate monitoring of human physical activity levels for medical diagnosis and monitoring using off-the-shelf cellular handsets. *Personal and Ubiquitous Computing, 15*(7), 667–678.

[46] Schindhelm, C. K. (2012). Activity recognition and step detection with smartphones: Towards terminal based indoor positioning system. *2012 IEEE 23rd International Symposium on Personal, Indoor and Mobile Radio Communications - (PIMRC).*

[47] Shoaib, M., Bosch, S., Incel, O., Scholten, H., & Havinga, P. (2015). A Survey of Online Activity Recognition Using Mobile Phones. *Sensors, 15*(1), 2059–2085.

[48] Yang, R., & Wang, B. (2016). PACP: A Position-Independent Activity Recognition Method Using Smartphone Sensors. *Information, 7*(4), 72.

[49] Henpraserttae, A., Thiemjarus, S., & Marukatat, S. (2011). Accurate Activity Recognition Using a Mobile Phone Regardless of Device Orientation and Location. *2011 International Conference on Body Sensor Networks.*

[50] Sztyler, T., Stuckenschmidt, H., & Petrich, W. (2017). Position-aware activity recognition with wearable devices. *Pervasive and Mobile Computing, 38,* 281–295.

[51] Coskun, D., Incel, O. D., & Ozgovde, A. (2015). Phone position/placement detection using accelerometer: Impact on activity recognition. *2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP).*

[52] Esfahani, P., & Malazi, H. T. (2017). PAMS: A new position-aware multi-sensor dataset for human activity recognition using smartphones. *2017 19th International Symposium on Computer Architecture and Digital Systems (CADS).*

[53] Bengio, Y. (2013). Deep Learning of Representations: Looking Forward. *Statistical Language and Speech Processing,* 1–37.

[54] Yang, J. (2009). Toward physical activity diary: motion recognition using simple acceleration features with mobile phones. *Proceedings of the 1st International Workshop on Interactive*

Multimedia for Consumer Electronics - IMCE '09.
[55] Yao, S., Hu, S., Zhao, Y., Zhang, A., & Abdelzaher, T. (2017). DeepSense: A Unified Deep Learning Framework for Time-Series Mobile Sensing Data Processing. *Proceedings of the 26th International Conference on World Wide Web.*
[56] Chen, Z., Le Zhang, Cao, Z., & Guo, J. (2018). Distilling the Knowledge From Handcrafted Features for Human Activity Recognition. *IEEE Transactions on Industrial Informatics, 14*(10), 4334–4342.
[57] Guan, Y., & Plötz, T. (2017). Ensembles of Deep LSTM Learners for Activity Recognition using Wearables. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1*(2), 1–28.
[58] Ha, S., & Choi, S. (2016). Convolutional neural networks for human activity recognition using multiple accelerometer and gyroscope sensors. *2016 International Joint Conference on Neural Networks (IJCNN).*
[59] Ronao, C. A., & Cho, S. B. (2015). Deep Convolutional Neural Networks for Human Activity Recognition with Smartphone Sensors. *Neural Information Processing*, 46–53.
[60] Ordóñez, F., & Roggen, D. (2016). Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. Sensors, 16(1), 115.
[61] Das Antar, A., Ahmed, M., & Ahad, M. A. R. (2019). Challenges in Sensor-based Human Activity Recognition and a Comparative Analysis of Benchmark Datasets: A Review. *2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (IcIVPR).*
[62] Apple Inc. (n.d.). *Apple Developer Documentation.* Apple. Retrieved May 31, 2021, from https://developer.apple.com/documentation/coremotion
[63] Lara, O. D., & Labrador, M. A. (2013). A Survey on Human Activity Recognition using Wearable Sensors. *IEEE Communications Surveys & Tutorials, 15*(3), 1192–1209.
[64] Liang, Y., Zhou, X., Yu, Z., & Guo, B. (2013). Energy-Efficient Motion Related Activity Recognition on Mobile Devices for Pervasive Healthcare. *Mobile Networks and Applications, 19*(3), 303–317.
[65] Huynh, T., & Schiele, B. (2005). Analyzing features for activity recognition. *Proceedings of the 2005 Joint Conference on Smart Objects and Ambient Intelligence Innovative Context-Aware Services: Usages and Technologies - SOc-EUSAI '05.*
[66] Ozer, E., & Feng, M. Q. (2017). Direction-sensitive smart monitoring of structures using heterogeneous smartphone sensor data and coordinate system transformation. *Smart Materials and Structures, 26*(4), 045026.
[67] Sztyler, T., Stuckenschmidt, H., & Petrich, W. (2017). Position-aware activity recognition with wearable devices. *Pervasive and Mobile Computing, 38,* 281–295.
[68] Preece, S. J., Goulermas, J. Y., Kenney, L. P. J., & Howard, D. (2009). A Comparison of Feature Extraction Methods for the Classification of Dynamic Activities from Accelerometer Data. *IEEE Transactions on Biomedical Engineering, 56*(3), 871–879.