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Human Activity Recognition with Smartphones Using Machine Learning

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Abstract— **Human activity recognition is widely used now in many applications, such as smart homes, health care, and business as well as in a wide range of pattern recognition and human-computer interaction research. In this paper, we use the same sensors embedded in smartphones (Accelerometer and Gyroscope) to track and recognize human activities. We employ a machine-learning algorithm, which is the Support Vector Machine (SVM) to improve the performance of human activity recognition. The experimental results on the HAR Dataset from the UCI repository indicate that our approach is practical and achieves 96% accuracy.**

Keywords—Human activity recognition, smartphones, Support Vector Machine (SVM), classifying human activities, machine learning.

I. INTRODUCTION

Human Activity Recognition HAR, is a way to know what a person is doing based on a trace of his/her movement using sensors and then analyze their sensors inputs. In our research, we are going to use the accelerometer and the gyroscope. Some of human movements are often considered normal indoor activities such as standing, sitting, laying, and going up and down the stairs.

Steps app Fig 1 is a unique application where it calculates steps and distances travelled during walking, jogging or exercising, and the services provided by the app can be viewed easily and on attractive way. The app has an easy interface as well as automatic updating of steps while walking. In addition, it shows traveled distance, viewing day activities, and compares activities during past days. The application provides a summary of today's results, a number of steps, distance, time spent, and calories burned. The idea of the application is based on the data contained in the health application mainly. This app is unique where it tracks and measures physical activities include walking, running, cycling, and following your progress and encourage you to continue day by day continuously. It supports the iPhone’s health app and links with the Apple smartwatch as show in Fig 1 [1].

Fig 1. Steps App Pedometer [1]

Pacer Pedometer and Step Tracker is an application that tracks Human’s activities. It tracks steps whether the phone is in the hand, pocket, jacket, armband or in a purse. It records steps, flights, calories, distance and active time. Uses GPS to track outdoor walking, hiking, running and biking on a map [2], See Fig 2.

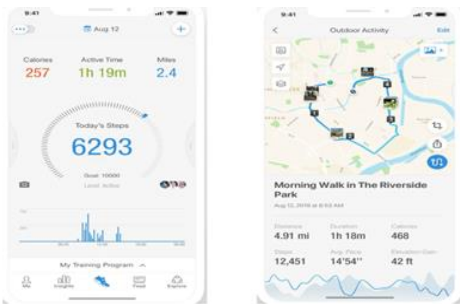

Fig 2. Pacer Pedometer & Step Tracker [2]

Health app is automatically counting your steps, walking and running distance from the Health app, you can know the distance you walked per day and statistics on calories without any extra devices as shown in Fig 3. The health app counts your steps using the accelerometer on your iPhone. The health app uses the accelerometer in your iPhone to track your steps and distance traveled, as long as you keep your iPhone with you. With this app, there is no need to wear a tracker to collect step or distance statistics [3].

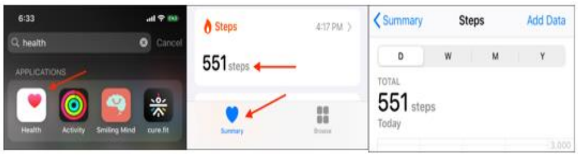

Fig 3. Health app count steps [3]

The Workout App has improved its ability to track your everyday activities and exercises. Running, swimming, cycling, gym sessions, and anything else that gets your heart beating is included. This app allows you to see how many calories you are burning and how well you are doing as shown in Fig 4. It can accurately track indoor and outdoor activities, such as rowing, indoor cycling, elliptical workouts, stair stepper, and high intensity interval training. There are also two wheelchair-specific activities.

When a user starts running, cycling, or walking, he/she can use the App to set a goal, such as a specified time, number of calories burned, kilometers covered, or even an open workout. The user can do the same for swim once he/she has input the length of the pool. He/she can keep track of your speed, distance, and overall time [4].

Fig 4. The Workout Application Interfaces [4]

II. Literature Review

To analyze human behavior, it is important to know the human activity attributed to the sensors, for the categories interested in practicing the walk. Authors[5] suggested that stacked Long Short-Term Memory (LSTM), which consists of two parts: single-layer neural network, a network of stacked (LSTM), starts to receive sensor data from the smartphone where two types of sensors are used accelerometer and the gyroscope. The data is passed for pre-processing through a single-layer neural network to be achieved normalize the input data by linear discriminant function and Rectified Linear activation Unit (ReLU) after the normalization of the input data is passed to a network of stacked LSTM, then the result of stacked LSTM is passed to SoftMax that can be used for multi-class classification to give the probability result of the six-way human behavior (walking, walking upstairs, walking downstairs, sitting, standing, lying) as showing in Fig 5. This approach was evaluated using the UCI dataset [26] and a device is the Samsung Galaxy S2 smartphone. It was concluded that the proposed method improved the average accuracy by 93%.

It is important to choose the features from time-series data in order to correctly identify human activities. The authors [6] proposed an approach based on recurrence plots to extract dynamic features from time-series human activity data. series sensor data from the smartphone is converted into recurrence plots diagnoses the dynamic system of time-series depending on Embedding theory, and for activity classification, it is entered as data into a deep convolutional neural network, the dataset that was used is a benchmark HAR dataset that is available from UCI for simulation which contains 30 subjects and each person performs six activities, and wearing a smartphone on the waist "Samsung Galaxy S2. Finally, the researchers find the dynamic feature with CNN is better than static feature with SVM classifier.

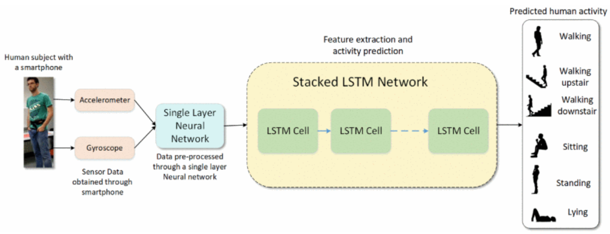

Fig 5. Stacked LSTM Network for Human Activity Recognition [5]

To identify human activity using time series, the authors [7] a bidirectional LSTM structure was proposed, which consists of bidirectional cells, which came to overcome the problem of not capturing some information correctly while using baseline LSTM, where bidirectional LSTM is not related only to the previous information only, but it is also related to the subsequent information, and as shown in Fig 6 [7]. The structure of the proposed model bidirectional LSTM, where the first layer represents the input layer, which represents signals from the smartphone sensors. The smartphone is wearing on the waist, those sensors are accelerometers and gyroscope, then the input data is converted through the sliding window to a "sequence" where this is considered the layer as a preprocessing of data through Rectified Linear units (ReLUs) to calculate feature map. The last layer represents the Full connected layer which is the coding layer where each of the LSTM layers has contains 28 cells. the proposed method was tested with the UCI dataset containing 30 volunteers with six activities.

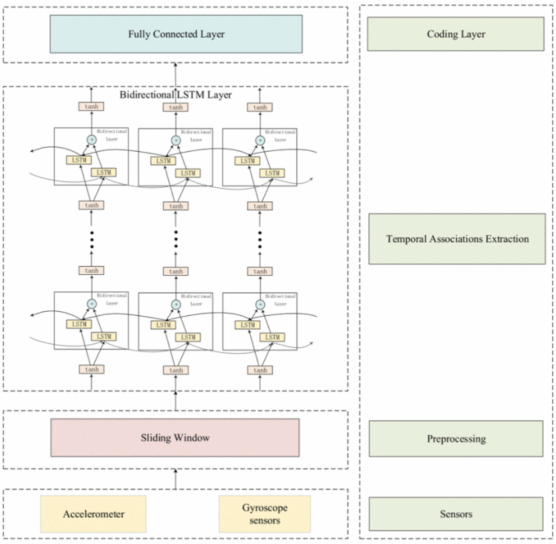

Fig 6. Human Activity Recognition using bidir-LSTM Networks [7]

In the paper [8], the authors proposed a model for classifying human activities has been proposed, which has two parts: The first part is to select activity-driven features based on neighborhood component analysis (NCA) and it is very important that the number of features is few. The NCA is working in selecting features using an optimized regularizer by increasing the accuracy of classification. The second part is based on the classification of human activities by inserting the features that were previously defined in a dense neural network model where DNN contains 4 layers. The input features are fed into a fully connected layer where they are used rectified linear unit (ReLU) as the activation function and has the dropout probability of 0:20. This combination of dense layers is repeated two times Fig 7 [8] shows a diagram of a dense neural network with numbers, units, and types of activation. The last layer of DNN with softmax activation is where you divide each feature into one of the following classes (W, WU, WD, ST, S, L). A dataset UCI HAR data set containing 7352 training and 2947 testing samples were used. The results showed that the proposed model achieved accuracy in addition to having a few advantages.

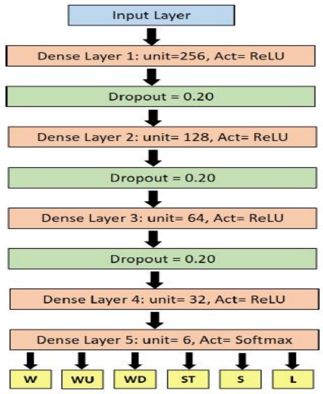

Fig 7. Human Activity Recognition with Dense Neural Network [8]

The authors [9] proposed a system designed to recognize five human activities through a smartphone system, using a built-in accelerometer the time-series signals are collected. 31 features were created in both the time and frequency domains. then, the performance was improved by reducing the feature dimensions. in this stage we have feature extraction and feature selection. 4 passive learning methods were used to train and test the human activity data, which are as follows: a Quadratic classifier, k-Nearest Neighbor algorithm, Support Vector Machine, and Artificial Neural Networks. In the experiment carried out by the researchers with the feature, the support vector machine was the best method, as it achieved 84%, and with the study and apply the Active Learning algorithm in order to reduce data computation, the results showed the effectiveness of the Support Vector Machine as the best classifier. the dataset that was used is collected by three-person using an HTC Evo Smartphone with a total sample is 1393 where use 75% of the data for training and the rest for testing.

Acceleration sensors collect the dataset gets several outcomes depending on smartphones' positions. The proposed system recognizes human activities and the smartphone's position. Histograms of Oriented Gradients HOG are used for extracting the features of the complex waveform of the acceleration dataset. Also, the Real AdaBoost algorithm is applied as a classifier depending on the acceleration sensor data and the location of the possession smartphone. The experiments show the effectiveness of the activity recognition system and the enhancement in recognition rate through the acceleration data analysis. The developed system learned seven categories of data: three locations of smartphones (inside a bag, inside a pocket, or handheld), and three human activities (training, walking, and running). There are 3000 samples gained for each category for learning purposes. The results of the recognition rate are 78% for walking-pocket, 95% for walking-hand, 74% for walking-bag, 84% for running-hand, and 71% for running-bag[10].

In analyzing the performance of several classification techniques to recognize the online activities of smartphones by the built-in accelerometers, Naïve Bayes and K-Nearest Neighbour classification (KNN) methods are performed. The Naïve Bayes classifier is used to assess activity recognition performance, and KNN with Minimum Distance algorithms is applied for enhancement. The clustered KNN removes the complexity of KNN by making clusters for each activity, which are called the training sets. The main objective is to define the activity classes from the training set depending on the features set with the magnitude of acceleration. Moreover, this study aims to reduce the comparisons with the training set created for an online classifier. Thus, test data is compared with the built-in training set chosen from the initial training set. The performance is assessed based on five test classes for activities; find, walk, run, sit and stand. The Naïve Bayes model obtained 47.61% for the classification accuracy, whereas clustered KNN obtained 92.13%, which is the best result achieved in this field [11].

Recognizing the complex activities on smart devices is developed by a platform to merge smartphones' sensors and smartwatches to identify human activities in actual time. A dataset of 16 subscribers is gathered, which contains daily activities and several physical exercises. In the data-gathering stage, time-series data from the sensors of the smart devices and the sliding window method are used for segmentation. Then, different approaches are improved for the accuracy and the complexity of the calculations to define the required classifier and features. That Naive Bayes model achieved 89.4%, which is the best result in the experiments' results, however Secure Virtual Machine (SVM) obtained 84.6%, which is the worst result. Then, SVM (Polynomial), Decision Tree, Linear Discriminant Analysis, Quadratic Discriminant Analysis, and KNN obtained more than 86%, whereas the total classification accuracy is 87% [12].

The authors [13] proposed a model to analysis the performance of two classification approaches in an online activity reorganization system of Android platforms based on the accelerometer data. The KNN model is applied, then Minimum Distance and Clustered KNN are used for the improvement. Clustered KNN removes the complications of KNN by dividing data into several clusters, i.e., creating training sets for each activity class for the online activity reorganization. The selected dataset is gathered from the original training set for each activity separately. These classifiers are assessed on four test classes for several activities: standing, sitting, walking, and running. The results present walking class as the worse performance compared to other activities. However, the total performance of all activities for clustered KNN is 92% accuracy.

Sensors as accelerometer and gyroscope are merged inside the smartphone to simplify the activity recognition. Using an optimization approach is essential to reduce the number of features in the dataset with less time consumption. This study proposed a dimensionality reduction approach called the fast feature dimensionality reduction method. The used data is UCI HAR which is available in the public domain. Results represent that the fast feature dimensionality reduction approach has decreased the number of features from 561 to 66. The reduction stage keeps the activity recognition accuracy at 98.72%. This study is used time consumption and a random forest classifier. Also, the reduction stage using FFDRT is lower than the other art approaches [14].

The authors [15] uses three algorithms to recognize human activity two of these algorithms are machine learning (random forest and Support Vector Machine) and one of them are deep learning (CNN), they collected the data using smartphone sensors like accelerometer and gyroscope. After using the algorithms, a comparative study is done shown that the deep learning algorithm (CNN) has a higher accuracy of identifying human activity.

Authors [16] takes physical attributes of human subjects such as height and weight into consideration when recognizing human activity that shows a higher accuracy compared to a traditional methods of human activity recognition using different classifiers.

In this paper [17] the authors use weighted support tensor machine algorithm (WSTM) to identify human activity and compare it with SVM algorithm, the WSTM algorithm avoid outliers by assign a weight to different data points based on their distance from the center, this helped to achieve more accuracy than SVM classifier.

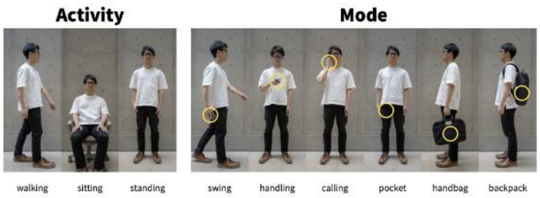

Fig 8. Person activities and modes [18]

The authors [18] proposed a system to identify person's activity using smartphone sensors which are accelerometer and gyroscope. This paper classifies three activities (sitting, standing, and walking) and six modes (swing, handling, calling, pocket, handbag and backpack) with 83.2% accuracy using LSTM network.

The authors [19] takes the power consumption of smartphones into consideration when it been used to detect human activity; this paper uses Decision Tree DT and SVM to learn the collected data on the smartphone.

Using smartphone inertial sensors such as accelerometers and gyroscope sensors, a novel approach for activity identification has been developed by [20]. Multiple robust features were recovered from the sensor signals, followed by dimension reduction using KPCA. Furthermore, for activity training and recognition, the robust features have been integrated with Deep Belief Network (DBN), a deep learning approach. When compared to a typical multiclass SVM strategy, the proposed method was found to be superior. The system was tested for twelve different physical activities, with an overall accuracy of 95.85 percent and a mean recognition rate of 89.61 percent.

The authors [21] provide a deep learning model that learns to classify human activities without any prior knowledge in this work. A Long Short-Term Memory (LSTM) Recurrent Neural Network was used to analyze three real-world smart home datasets for this aim. The findings reveal that the suggested approach improves existing approaches in terms of accuracy and performance.

The authors [22] use a hybrid deep learning model that combines simple recurrent units (SRUs) and gated recurrent units (GRUs) of neural networks to create an effective multi-sensors-based framework for human activity detection. They use deep SRUs to process multimodal incoming data sequences by taking use of their internal memory states. Furthermore, they use deep GRUs to store and learn how much of the previous information is delivered to the future state for vanishing gradient problems and solving fluctuations or instability in accuracy. The experimental findings on large datasets demonstrated good performance with 0.99 precision, recall, F1-score, and accuracies.

The authors [23] suggested to employing tri-axial accelerometer data to recognize human activities using an LSTM-based feature extraction approach. They build their model where the accelerometer on the phone measures the acceleration in the x direction. The y direction is Y, and the z direction is Z. as show in Fig 9. They integrate the acceleration of the three directions into a three-dimensional vector with a sliding window of length N in this work. As a result, the LSTM's input data is a time series of the NX3 matrix. Extraction of features from raw accelerometer data using a long short memory network with N time steps. The output of the LSTM joined to create a new Feature vector. Finally, a multi-classifier classifies the feature vector practically and achieves the best 92.1% accuracy.

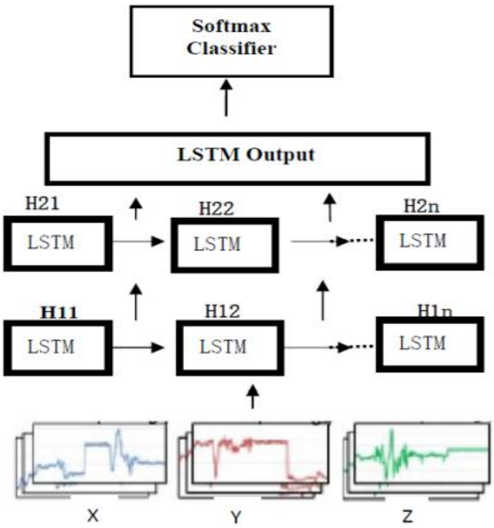

Fig 9. Structure of LSTM for Human Activity Recognition [23]

The authors [24] demonstrated a variety of elements to consider when it comes to data pre-processing. They have also made a list of sensing devices, sensors, and applications that can be used to gather data about activities. They have also done a thorough investigation of a few benchmark datasets. Finally, they gave a complete study as well as the current state of many issues of human activity recognition using wearable, environmental, and smartphone sensors, including the tradeoff between the number of sensors and performance, which should be handled with care. And the location of smartphones and wearable sensors may result in incorrect recognition of a specific activity, lowering recognition accuracy.

A questionnaire was distributed to solicit wearable technology users' opinions about the use of smart devices. The following are statistical data we collected:

- 89.4% of the participants have an apps that keep track to their steps or any other activity that they do, and 84.8% keep track of their steps, where as 37.9% keep track of their calories burning. Only 36.4% like to know how many meters they walked.
- 39.4% uses apps that keep tracks of human activity daily, only 19.7% uses them once a week and 18.2% uses them three to four times a week.
- 74.2% finds that these apps help them walk more, 40.9% finds it helps them to lose wait and 21.2% have a better sleep when they use these apps.
- 50% thinks that a human activity tracker apps have a positive effect in their lives.
- We asked the participants where they put their phone when they do every day activity:
- We found that 43.9% put their phone in their pocket, 37.9% put it in their hands and 15.2% put it in their purse.
- Most of the participants walk every day as a part of their routine.
- Most of the participants don't have any difficulties using human activity tracking applications.
- Some found it hard to use because of the language (most of these apps are in English) or because these apps only show the last three days activities.

III. Methodology

The methodology of this research as shown in Fig 10 consists of five steps for classification the human activity recognition using smart phones data and with the help of machine learning algorithms.

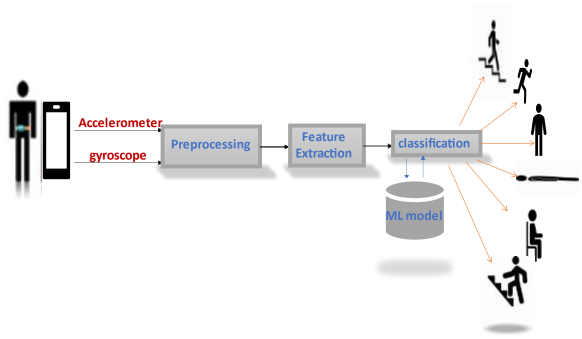

Fig 10. The Methodology for Human Activity Recognition Project

A. Collect Data

In this research, we used dataset of human activity recognition that has been labeled as "Walking", "Walking Upstairs", "Walking Downstairs", "Standing", "Sitting" and "Laying". We downloaded the HAR Dataset [25] from the UCI dataset repository. Inspecting the decompressed contents, we noticed that:

- In the "features.txt" file, a technical description of the engineered features can be found.
- There are "train" and "test" folders containing the split portions of the data for modeling (e.g. 70%/30%). Each folder contains the following:

- Train Folder:
  - The subdirectory is called "Inertial Signals." Which contains the preprocessed data.
  - In the "X_train.txt" file, the engineering features used for fitting a model are contained.
  - The file "y_train.txt" provides the labels for each observation's class (1-6).
  - Each line in the data files is mapped to their subject identifier in the "subject train.txt" file (1-30).

- Test Folder:
  - The subdirectory is called "Inertial Signals." Which contains the preprocessed data.
  - In the "X_test.txt" file, the engineering features used for fitting a model are contained.

- The file "y_test.txt" provides the labels for each observation's class (1-6).
- Each line in the data files is mapped to their subject identifier in the "subject train.txt" file (1-30).

- The subdirectory "Inertial Signals" include:
  - Gravitational acceleration data files for x, y and z axes: total_acc_x_train.txt, total_acc_y_train.txt, total_acc_z_train.txt.
  - Body acceleration data files for x, y and z axes: body_acc_x_train.txt, body_acc_y_train.txt, body_acc_z_train.txt.
  - Body gyroscope data files for x, y and z axes: body_gyro_x_train.txt, body_gyro_y_train.txt, body_gyro_z_train.txt.
  - In the "test" directory, the structure is mirrored.

B. Data Cleaning (Preprocessing Phase)

In this phase, we did three processes. First, we check for the duplicates then we checked for null values and we found that there is no duplicates or null values. Finally, we save the data frame of the collected data into csv file.

C. Exploring the data analysis

In this phase, we did many processes for exploring the data, which is a little bit complicated by visualizing many aspects of the dataset for better understanding.

D. Feature Extraction

In this phase we need to visualize the high dimensionality dataset and for this purpose we used the t-Distributed Stochastic Neighbor Embedding (t-SNE) tool, which is a great tool used for dimensionality reduction.

E. Training the data using ML

For training the dataset, we used the support vector machine algorithm, and For the hybrid parameters we assigned the kernel parameter as 'rbf', the C parameter as [2, 8, 16] and the gamma parameter as [0.0078125, 0,125, 2].

IV. RESULTS

For getting the accuracy, we used the confusion matrix, which tells us what type of errors and what type of confusion we have in the model, and the proportions of predicted classes with respect to the true classes is calculated see Fig 11.

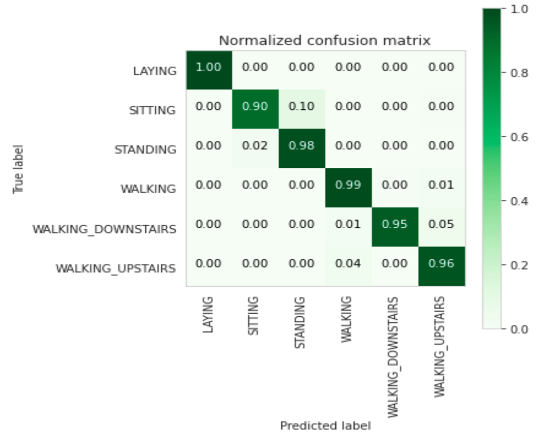

Fig 11. Confusion matrix of the model

Confusion matrix Fig 11 shows that the closer the color of the square on the main diagonal is to green, the higher the prediction accuracy of the category corresponding to the square. Our model detect laying activity effectively. We then apply the precision, recall, and f1-score for each label to measure the performance of the model. The result is shown in Table 1. In our model, we have 2947 testing samples and the number of samples for testing different activities is not evenly distributed but still well balanced see Table 1, precision and recall shows that our model has a good prediction of laying, walking, walking downstairs, standing, walking upstairs, and sitting respectively. Finally, the proposed model estimated about 96% total accuracy of our model by assigning the C parameter as (16) and the gamma parameter as (0.0078125). The result indicates that SVM is a very good model for human activity recognition.

Table 1. Classification Report of the model

Classification Report				
	Precision	Recall	F1-Score	support
Laying	1.00	1.00	1.00	537
Sitting	0.97	0.90	0.93	491
Standing	0.92	0.98	0.95	532
Walking	0.96	0.99	0.97	496
Walking downstairs	0.99	0.95	0.97	420
Walking upstairs	0.95	0.96	0.95	471

V. Conclusion

Pattern recognition experts are becoming increasingly interested in sensor-based user behavior and health status monitoring, with the prospect of improving people's wellness, health, and lifespan. Smart environments support applications that are frequently required when such goals are met .In this work we employ machine learning to predict the human activities using sensors (accelerometer and Gyroscope) embedded in smartphones. We achieved 96% accuracy by using the SVM model for classifying human activities in the HAR dataset. In addition, this work presents a questionnaire to solicit wearable technology users' opinions about the use of smart devices.

Acknowledgments

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References

[1] Steps App Homepage available at https://steps.app/ar

[2] Pacer Pedometer & Step Tracker app Homepage available at https://apps.apple.com/us/app/pacer-pedometer-step-tracker/id600446812 ,2021

[3] The Health App Homepage available at https://www.apple.com/ios/health/ ,2021

[4] The Workout app Homepage available at https://support.apple.com/en-us/HT204523 ,2021

[5] M. Ullah, H. Ullah, S. D. Khan, and F. A. Cheikh, "Stacked Lstm Network for Human Activity Recognition Using Smartphone Data," Proc. - Eur. Work. Vis. Inf. Process. EUVIP, vol. 2019-Octob, pp. 175–180, 2019, doi: 10.1109/EUVIP47703.2019.8946180.

[6] K. Nakano and B. Chakraborty, "Effect of dynamic feature for human activity recognition using smartphone sensors," Proc. - 2017 IEEE 8th Int. Conf. Aware. Sci. Technol. iCAST 2017, vol. 2018-Janua, no. iCAST, pp. 539–543, 2017, doi: 10.1109/ICAwST.2017.8256516.

[7] S. Yu and L. Qin, "Human activity recognition with smartphone inertial sensors using bidir-LSTM networks," Proc. - 2018 3rd Int. Conf. Mech. Control Comput. Eng. ICMCCE 2018, pp. 219–224, 2018, doi: 10.1109/ICMCCE.2018.00052.

[8] S. K. Bashar, A. Al Fahim, and K. H. Chon, "Smartphone Based Human Activity Recognition with Feature Selection and Dense Neural Network," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, vol. 2020-July, pp.58885891,2020,doi:10.1109/EMBC44109.2020.917623.

[9] C. Chen and Y. Lu, "Human Activity Recognition using Smartphone 2011 Fall CSCE666 Project Report Human Activity Recognition using Smartphone," no. January, 2014.

[10] Miyamoto, S., & Ogawa, H. (2014). Human activity recognition system including smartphone position. Procedia Technology, 18, 42-46.

[11] M. Kose, O. D. Incel, and C. Ersoy, "Online Human Activity Recognition on Smart Phones," Perform. Eval., no. January, pp. 0–4, 2012.

[12] Sefen, B., Baumbach, S., Dengel, A., & Abdennadher, S. (2016, February). Human activity recognition. In Proceedings of the 8th International Conference on Agents and Artificial Intelligence, SCITEPRESS-Science and Technology Publications, Lda (pp. 488-493).

[13] Paul, P., & George, T. (2015, March). An effective approach for human activity recognition on smartphone. In 2015 IEEE International Conference on Engineering and Technology (ICETECH) (pp. 1-3). IEEE.

[14] Hashim, B. M., & Amutha, R. (2021). Human activity recognition based on smartphone using fast feature dimensionality reduction technique. Journal of Ambient Intelligence and Humanized Computing, 12(2), 2365-2374

[15] M. Alema Khatun and M. Abu Yousuf, "Human Activity Recognition Using Smartphone Sensor Based on Selective Classifiers," 2020 2nd Int. Conf. Sustain. Technol. Ind. 4.0, STI 2020, vol. 0, pp. 19–20, 2020, doi: 10.1109/STI50764.2020.9350486.

[16] N. A. Choudhury, S. Moulik, and D. S. Roy, "Physique-Based Human Activity Recognition Using Ensemble Learning and Smartphone Sensors," IEEE Sens. J., vol. 21, no. 15, pp. 16852–16860, 2021, doi: 10.1109/JSEN.2021.3077563.

[17] Z. Ma, L. T. Yang, M. Lin, Q. Zhang, and C. Dai, "Weighted Support Tensor Machines for Human Activity Recognition with Smartphone Sensors," IEEE Trans. Ind. Informatics, vol. 3203, no. c, pp. 1–9, 2021, doi: 10.1109/TII.2021.3061559

[18] K. Motani, K. Wong, and S. Kamijo, "Classifying human activity and smartphone holding mode using accelerometer and gyroscope," 2019 IEEE 8th Glob. Conf. Consum. Electron. GCCE 2019, pp. 11–12, 2019, doi: 10.1109/GCCE46687.2019.9015384.

[19] W. Zheng, Y. Yoshihara, T. Noel, D. Tang, and N. Kubota, "Energy-Efficient Activity Recognition on Smartphone," Proc. - 2016 3rd Int. Conf. Comput. Meas. Control Sens. Network, C. 2016, pp. 1–4, 2017, doi: 10.1109/CMCSN.2016.32.

[20] Hassan, M. M., Uddin, M. Z., Mohamed, A., & Almogren, A. (2018). A robust human activity recognition system using smartphone sensors and deep learning. Future Generation Computer Systems, 81, 307-313.

[21] Singh, D., Merdivan, E., Psychoula, I., Kropf, J., Hanke, S., Geist, M., & Holzinger, A. (2017, August). Human activity recognition using recurrent neural networks. In International cross-domain conference for machine learning and knowledge extraction (pp. 267-274). Springer, Cham.

[22] Gumaei, A., Hassan, M. M., Alelaiwi, A., & Alsalman, H. (2019). A hybrid deep learning model for human activity recognition using multimodal body sensing data. IEEE Access, 7, 99152-99160.

[23] Chen, Y., Zhong, K., Zhang, J., Sun, Q., & Zhao, X. (2016, January). LSTM networks for mobile human activity recognition. In Proceedings of the 2016 International Conference on Artificial Intelligence: Technologies and Applications, Bangkok, Thailand (pp. 24-25).

[24] Antar, A. D., Ahmed, M., & Ahad, M. A. R. (2019, May). Challenges in sensor-based human activity recognition and a comparative analysis of benchmark datasets: a review. In 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR) (pp. 134-139). IEEE.

[25] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013.

[26] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 7657 LNCS, pp. 216–223, 2012, doi: 10.1007/978-3-642-35395-6_30.

التعرف على النشاط البشري باستخدام الهواتف الذكية من خلال تعلم الآلة

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المستخلص. يُستخدم التعرف على النشاط البشري على نطاق واسع الآن في العديد من التطبيقات، مثل المنازل الذكية، والرعاية الصحية، والأعمال التجارية، بالإضافة إلى مجموعة واسعة من أبحاث التعرف على الأنماط والتفاعل بين الإنسان والحاسوب. في هذه الورقة، نستخدم نفس المستشعرات المدمجة في الهواتف الذكية (مقياس التسارع والجيروسكوب) لتتبع الأنشطة البشرية والتعرف عليها. نعتمد خوارزمية تعلم الآلة، وهي آلة دعم المتجهات(SVM) ، لتحسين أداء التعرف على النشاط البشري. تشير النتائج التجريبية على مجموعة بيانات HAR من مستودع UCI إلى أن منهجنا عملي ويحقق دقة بنسبة 96%.

الكلمات المفتاحية. التعرف على النشاط البشري، الهواتف الذكية، آلة دعم المتجهات (SVM)، تصنيف الأنشطة البشرية، تعلم الآلة.