Analysis On Human Activity Recognition Using Machine Learning Algorithm And Personal Activity Correlation

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ABSTRACT

Personal Activity Recognition (PAR) has been animportant and interesting problem is solved and also many upgradations are to be added. It is mainly be used for Biometric, Fitness and M healthcare as an assistive technology when ensemble with other technologies likes Machine Learning, Wireless sensor, Internet of Things (IoT) with the help of sensors, smart phones or pictures, PAR can be achieved. We present various up-to-the-minute methods in this study and explain each of them through literature surveys. For each of the methods in which the data is obtained through various means, such as sensors, photographs, accelerometers, gyroscopes, proximity, etc., various datasets are used and the implementation of these machines in different places and the movement of human beings. The results obtained by each and every process and the dataset form are then compared. Machine learning techniques such as decision trees (DT), K-nearest neighbours (KNN), support vector machines (SVM), hidden models are tested for PAR, and deep neural network techniques such as artificial neural networks (ANN), convolution neural networks (CNN) and recurrent neural networks are also examined later.Here, we presented a unified model for finding 95 percent accuracy in the identification of personal behaviour with improvement in the current working application. And we can predict the fitness rate of a specific region among cities, regions and even in a state using this application

Keywords

Activity recognition; Mobile sensors; Wireless Sensor Network; Pattern recognition; Android; GPS; Human Activity Recognition

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Introduction

Sensors:

In personal activity detection, sensors are the primary source of raw data collection[3]. We define sensors in three ways: visual sensors, sensors dependent on the environment, and wearable sensors. Video sensors are essentially cameras mounted in fixed locations, such as the entrance/exit of public places (to track the arrival and behavior of people) or living rooms to control the everyday life of the user.In many applications such as surveillance, anti-terrorist, and anti-crime protection, as well as life logging and assistance, visual tracking for activity recognition is used.

To detect the interaction of the consumer with the environment, environmental-based sensors are used. They are sensors that are radio-based, such as Wi-Fi, Bluetooth and infrared sensors. Such sensors are commonly used indoors, such as office buildings or houses.They passively track the user's presence at a certain position or the user's contact with objects fitted with sensors as well[6]. Their drawbacks are that (1) they can be applied only to some fixed sites, and (2) the cost of full deployment of such sensors is always very high.Wearable sensors are small-sized handheld sensors designed to be worn on the human body during everyday activities.They can document the physiological status of the user, such as position changes, changing directions, speed, etc. These sensors include accelerometers[5,6], microphones, GPS, barometers, etc. Most mobile sensors are equipped with smartphones.

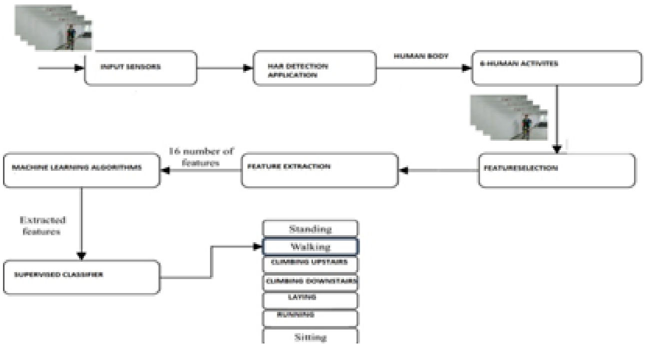

Fig 1: Activity Recognition Process

Fig 1 Explanations for data collection: Sensors are the basis for data collection for behaviour recognition. Sensors include Video Sensors, Environmental Sensors, Wearable Sensors and Activity Recognition Mechanism.

After collecting data from various sensors, the next step is to pre-process and stream the data before making any further calculations. One of the aims of pre-processing data is to reduce the noise from the consumer and the sensors themselves and to enhance correctness.

Training and testing on the same group of multiple data has the second highest accuracy. The accuracy decreases when the test data is collected from same subject but on different days and different movements and from different sensors the data is tested the lowest accuracy is in the setting where the training data is collected from one subject on one day and testing is conducted on another subject on a different day.

Different classifiers and rule-based strategies are used for different activity recognition [1, 3] and the transition states. Activity recognition is a core building block behind many interesting applications. The classified applications of

mobile activity recognition according to their targeted beneficial subjects are: Applications for the end users such as fitness tracking, health monitoring, fall detection, behaviour-based context-awareness, home and work automation, and self-managing system;
After all these practices and activity recognition [1], the application will be able to find the actual activity.

Existing Mobile Based Applications

Personal activity detection has seen a tremendous growth in the last two decades playing a major role in the field of pervasive computing. This emerging popularity can beattributed to its myriad of real life applications primarily dealing with person-centric problems like healthcare,eldercare,HumanActivity Recognition(HAR) is classifying activity of a person using responsive sensors that are affected from person movement. Both users and capabilities(sensors) of smartphones increase and users usually carry their smartphone with them. These facts make PAR more important and popular. Many research attempts with Personal Activity Recognition System. Here are some of the predictive apps related to Personal activity and Nutrition and a comparison on different applications.
AAPTIV ---Thisparticular app was introduced by Ethan Agarwaland this app is featured by 15 fitness trainers who create new fitness course every other week. Besides, the ascepp allows users to groove to the music while working out
SWORKIT ---The ability to help people progress in their fitness levels, the effectiveness of the workouts, and other science-y guidelines set by the ACSM (American College of Sports Medicine). This is well suited for everyone ranging from beginners to athletes.
RUNKEEPER--- Track Workouts - Go for a run, walk, jog, bike, or any activity really. With GPS, we will be able to get a clear view of our training in real time. It will keep track of the person.
MYFITNESSPAL ----This particular app was introduced by Albert Lee Mike Lee ---MyFitnessPal has an impressive built-in food library, making it a favorite among experts. "MyFitnessPal is my go-to," says Nashville-based nutritionist McKel Hill, RD, founder of Nutrition Stripped, adding that the calorie counts within the app are usually very accurate.
FITBIT----One of the popular app.It was introduced by James Park Eric and Friedman. This is one of the world’s leading apps for health and fitness. Use the Fitbit app to join community, track basic stats and stay motivated. Fitbit tracker or smartwatch is used to see how our activity, workouts, sleep, nutrition and stress all fit together.
BMI CALCULATOR ----Body Mass Indicator calculator was introduced by Lambert Adolphe Jacques Quetelet---BMI Calculator is free app that allows us to monitor BMI and percentage of fat in your body. This app calculates the ideal weight we should gain. To calculate it app uses the D. R. Miller formula. Body fat percentage is estimated from BMI by formula derived by Deurenberg and co-workers

Related Work

ADLAuth: Passive Authentication Based on Activity of Daily Living Using Heterogeneous Sensing in Smart Cities:For smart cities, the Internet of Things is a rapidly expanding paradigm that offers a way toCommunication, recognition and sensing capabilities between devices which are physically distributed. User dependency on smart systems and utilities, with the evolution of the Internet of Things (IoTs), There has been a rise in smart appliances, smartphones, security, and healthcare applications. This includes secure mechanisms of authentication to protect the privacy of users while communicating. With devices that are smart. "This paper was proposed a heterogeneous "ADLAuth" system for passive and passiveImplicit user authentication using either the built-in sensor of a smartphone or wearable sensorsBy evaluating the users' physical activity habits. Multi-class learning algorithms for machines areApplied to identity authentication by consumers. Analyses are conducted on three independent datasets ofFor a diverse range of operations, heterogeneous sensors. A variety of studies have been carried out.Carried out to test the effectiveness of the framework proposed. The findings suggest the betterCompared to current work for user authentication, the implementation of the proposed scheme

Human Activity Recognition Using Smartphones:Recognition of human activity (HAR) is known asA person's behavior using sensitive sensors that are affectedfrom human motion. User and sensor feature in bothSmartphones are increasing and consumers are typically bringing theirwith them on your mobile. These facts are what make HAR moreRelevant and famous. This dissertation focuses on the acknowledgment ofHuman behavior through the use of mobile sensors using various sensorsClassification approaches to machine learning. Retried datathe accelerometer and gyroscope sensors for smart phones arein order to identify human behavior, classified. Outcomes of thein terms of performance and efficacy, the methods used are compared.

Detailed Human Activity Recognition using Wearable Sensor and Smartphones:The use of recognition of human behavior is growing day by day. Smart home by day, eldercare, remote health monitoringIntent and supervision. In order to best fulfil these needs,Recognition of events in depth, viz. Sitting on the floor or on a chair,Slow or rapid walking, load-running, etc. Very few works are aimed atto differentiate between intense activities (such as walkingWeight) from its counterpart (walk), which is critical for performance.Health monitoring for older adults and rehab patientsan operation. In this job, a solution to this has been suggestedwith the support of wearable and smartphone-embedded, aimwith sensors.The contribution of this work, therefore, is to presentA system for detailing both static and static recognition as well aswell as their extreme counterparts, dynamic practicesby Designing a classifier ensemble. The design of the ensemble isThis refers to the weighted majority vote for test classification,Examples. The weights of the base classifiers are estimated by Feeding a training dataset of their production performance in aNetwork neural network. They have found that their work crosses over 94 percentAccuracy.

Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning:The ubiquity of smartphones and their wide range of on-board sensors have created a variety of excitingNew opportunities where smartphones are used to perceive and evaluate powerful computing platformsomnipresent info. One significant mobile sensing technology is smartphone-based activity recognition.Inertial sensors, which are a fundamental building block for a variety of conditions, such as pedestrian indoorMobile health care, mapping, and smart cities.

Daily Human Activities Recognition Using Heterogeneous Sensors from Smartphones:

Online knowledge of human activities can lead to solving some of the problems that exist in the smart city environment, such as health care, urban mobility or safety. Wearable sensors, especially smartphone-embedded sensors, turn out to be excellent data streams for human activity recognition (HAR) tasks. Sadly, most of the current approaches are tested on small and fixed-size datasets, and lack of knowledge exchange as well as re-training functions for classifiers. When facing issues of volume and variety of data, these problems will lead to the challenge of unadaptable learning.Functions of g. When facing issues of volume and variety of data, these problems will lead to the challenge of unadaptable learning. This paper proposes a new approach with adaptive, interactive, and general-personal-model training elements, and data sharing on the cloud, to resolve these issues. The key benefit of the proposed approach is that it is very easy to detect a new user's human activities at the beginning (i.e. deploying a device to a new user) with a reasonable detection accuracy using the general model. The personal model would then help to improve the precision of the identification of events by communicating with users directly.The approach suggested is to share data (e.g. sensory data, templates, processes, and user profiles) amongst users/apps who have entered the system. Such data can help to improve the accuracy of models in a timely manner through frequent re-training. In addition, the method can be used as a sensor for human activity that transmits human activities detected to relevant components of the smart city scheme. The suggested solution is tested and compared to de-facto and state-of-the-art HAR datasets using smartphones.

A Personal Activity Recognition System Based on Smart Devices

Mobile devices are becoming more and more important in people's lives with the ongoing evolution of technology. Similarly, new needs emerge related to the knowledge supplied by their users, illustrating the need to build systems that take advantage of their everyday use. The first validation test and for the second validation test, 80.7 percent.They presents the use of knowledge given in various acquisition schemes by two smart devices, analyzing traditional supervised classifiers in order to recognize personal behavior by defining seven classes. Classifiers were trained by eight users with a generated database and were tested in offline mode with two other generated databases.By using the F1-score predictor, the prediction experiments were eligible and compared with the cellphone's native prediction. For the first validation test and 80.7 percent for the second validation test, the obtained results showed a cumulative F1-score of 100 percent.

Review And Analysis On Human Activity Recognition

SL. NO	AUTHOR NAME	TITLE	PROBLEM STATEMENT	HUMAN ACTIVITIES	METHOD/ALGORITHM	CONCLUSION	LIMITATIONS	FUTURESCOPE
1	1.Maryam Naseer Malik 2.Muhammad Awais Azam 3.Muhammad Ehatisham-ul-Haq 4. Waleed Ejaz	ADLAuth: Passive Authentication Based on Activity of Daily Living Using Heterogeneous Sensing in Smart Cities	A Heterogeneous Framework was used for implicit and continuous User Authentication # Data Sets used are 1.HAR 2.PAMAP2 3.MobiAct	HAR: 6-Activites PAMAP2 :8 MobiAct :9	Activity of Daily Living (ADL)-based Authentication SVM Decision Tree Random Forest	Best results were obtained on the MobiAct data set with Random Forest machine Learning Algorithm is 97.13%	User Recognition can be improved by incorporating more no of activities such as complex and transitional activities to make a generic framework	A Comprehensive smart phone dataset which includes multiple body positions for smart phone placement A Position -aware user identification can be used to improve the user recognition.
2	1.Erhan Bulbul 2.Aydin Cetin 3.Ibrahim AlperDogru	Human Activity Recognition Using Smartphones	HAR is classifying activity of a person using responsive sensors from human movement. Data retrieved from accelerometer, gyroscope are compared in terms of efficiency and precision	Data Set consists of 6 activites WALKING CLIMBING UP STAIRS CLIMBING DOWN STAIRS SITTING STANDING LAYING	Supervised Machine Learning Model:5 -fold cross Validation Decision Tree Support Vector Machine KNN Ensemble Classification Methods-Boosting,Bsgging,Stacking	Binary DT :53,1 DT(20) :91,1 DT(100):91,1 SVM :99,4 KNN K=1:97,1 KNN K=3:97,5 Boost :97,4 Bagging :98,1 Stacking:98,6 SVM is the most precise approach	In this study contain data generated from soley accelerometer and gyroscope signals	This work can be improved by increasing the number of activities and situations to classify and add other sensors like magnetometer, Light sensor, proximity sensor, pedometer , heart pulse meter
3	A. Nandy, J. Saha, C.Chowdhury K. P. D. Singh,	Detailed Human Activity Recognition using Wearable Sensor and Smartphones	Distinguish between static activities (Sitting,Sitting with weight,Standing,Standin with weight) and dynamic activities(Walking,Walking with weight,Climbing stairs,Climbing stairs withweight	dynamic activities(Walking,Walking with weight,Climbing stairs,Climbing stairs with weight)	Ensemble Classifier is used to distinguish between static activities and dynamic activites.	Experiments conducted on 4 users having with different heights and body weights 94% accuracy	In this Study Experiments are conducted only with 4 users if number increased performance may vary.	Perfect Dynamic activities recognition is a challenging issue
4	Ran Zhu Zhuoling Xiao Ying Li Mingkun Yang Yawen Tan Liang Zhou Shuisheng Lin Hongkai Wen	Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning	Human activity recognition framework based on convolutional neural networks (CNNs) with two convolutional layers using the smartphone-based accelerometer, gyroscope, and magnetometer.	7 –Activities Going Upstairs Going Downstairs Standing Running Walking Bicycling Swinging	CNN-based human activity recognition model using the nine-axis motion signals of accelerometer , gyroscope and magnetometer in common smart phones	CNN SVM DT Random Forest HMM XGBoost CNN which extracts the local dependence and scale invariant characteristics of the sensor time series and reached an accuracy up to 96.11%.	Ensemble model based on CNN which extracts the local dependence and scale invariant characteristics of the sensor time series and reached an accuracy up to 96.11%	Conducting Experiments with large dataset to recognize more human activities under more placements of smart phone
5	Minh-SonDao Tuan-[AnhNguyen]-Gia[b]Van-CuongMai	Daily Human Activities Recognition Using Heterogeneous Sensors from Smartphones	The proposed method is evaluated and compared to de-facto datasets as well as state-of-the-art of HAR using smartphones. The paper introduces a new method to recognize daily human activities using SAX-based features, and adaptive learning (i.e. general and personal models)	6-Activities Walking Jogging Upstairs Downstairs Sitting Standing	J48(A/B) 9 Logistic Regression(A/B) 9 Multi-layer Perceptron(A/B) 9 General Model(C)/Personal Model(C) SAX –based features and adaptive learning	The system built upon this method can immunize the influence of smartphone's platforms, quickly adapt to a new environment (e.g. smartphones, users), and improve the accuracy when using heterogeneous sensors.	Only with 10 vulunteers these experiments are conducted	Increse in number of Valunteers the experimental results are going to be changed.

Issues in current system:

In the existing papers and their limitations are that They can only be applied to certain fixed locations The cost for the full deployment of such sensors is often very high. In all these papers the algorithms used were nonlinear and ensemble machine learning algorithms, specifically:

Nonlinear Algorithms:

k-Nearest Neighbours
Classification and Regression Tree
Support Vector Machine
Naive Bayes
Ensemble Algorithms:
Bagged Decision Trees
Random Forest
Extra Trees
Gradient Boosting Machine

The results form different Machine Learning classifiers
>knn: 90.329
>cart: 86.020
>svm: 94.028
>bayes: 77.027
>bag: 89.820
>rf: 92.772
>et: 94.028
>gbm: 93.756

Personal Activity Correlation:

Personal Activity Recognition (HAR-Train set and HAR Test set Segmentation of sequential sensor data streams and classification of each segment are common steps in personal activity correlation dealing with the detection of events of interest in Activity data. In this work, we introduce two correlation analysis-based methods for classifying time series data in har data set. Our first method is a lightweight supervised approach utilizing to jointly segment data and classify each segment into a class corresponding to an event of interest. The theoretical model of the solution to the resulting optimization problem is presented in detail. Classification of human activity from inertial measurement unit (IMU) sensor data is used as a case study to demonstrate the applicability and effectiveness of the proposed methods

Input Sensors:

video sensors
environmental-based sensors
wearable sensors.

Type of Activities

The six activities performed were as follows:
Walking Walking Upstairs Walking Downstairs Sitting Standing Laying

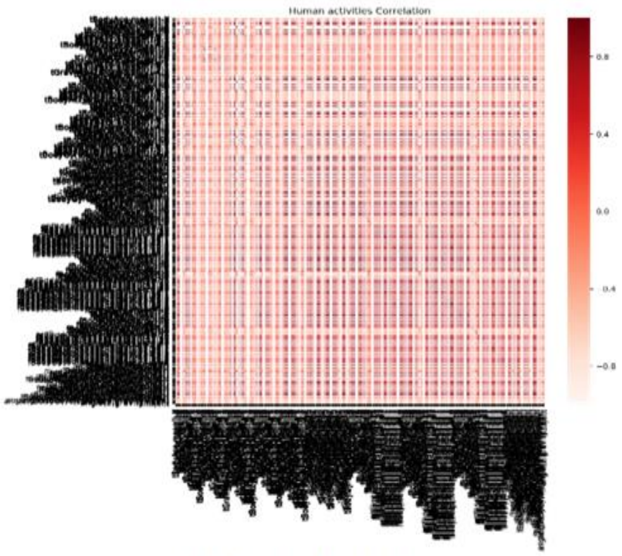

Fig 2. Personal Activity Correlation

Expected Output and Challenges:

Activities recognized by the sensor's data can be classified in different ways. For example, they can be classified in terms of the complexity of activities. A simple locomotion could be walking, jogging, walking downstairs, taking elevator, etc. The complex activities are usually related to a combination of a longer period of activities (e.g., taking bus and driving). The activities may only correspond to the movements of certain parts of the body (e.g., typing and waving hand). There are several healthcare related activities, such as falling, exercise, rehabilitations, etc. Location-based activities include dining, shopping, watching movies, etc. Vision-based activities include leaving or entering a place. The latest versions of Android and Raspberry pie both provide an API to detect a user's current activity in one of the four activities: Walking, Stationary, Running, and Automotive [2].

Challenges& Objectives:

More Algorithms. Only eight machine learning algorithms were evaluated on the problem; try some linear methods and perhaps some more nonlinear and ensemble methods.
Algorithm Tuning. No tuning of the machine learning algorithms was performed; mostly default configurations were used. Pick a method such as SVM, Extra Trees, or Gradient Boosting and grid search a suite of different hyperparameter configurations to see if you can further lift performance on the problem.
Data Scaling. The data is already scaled to [-1,1], perhaps per subject. Explore whether additional scaling, such as standardization, can result in better performance, perhaps on methods sensitive to such scaling such as kNN.
Future Scope: Here we proposed a unified model for finding an accuracy of 95% above in human activity recognition with an advancement in the current working application.
And using this application we can predict the fitness rate of a particular region among cities, regions and even in a state.

Conclusion &Futures cope:

This Research work designates and analyzed smart phone-based activity of a person and fitness monitoring applications. Recognition of Personal behavior is a crucial building block behind such applications. This takes the reading of the raw sensors as inputs, and predicts the movement behavior of a consumer. Precise evaluation of their behaviors and enables them to track the effect of any changes in behaviors, including monitoring of application usage? By using some machine learning algorithms, we propose a prediction method for a personal activity by using advance machine learning algorithms we can recognize the activity of a person and also we are proposing a new development for prediction of fitness rateof population in a particular region for a particular category people like children,adults,middle age,oldage etc. and also based on gender we can predict the fitness rate in a particular region

References

[1] S. B. Rekha and M. V. Rao, "Methodical activity recognition and monitoring of a person through smart phone and wireless sensors," 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), Chennai, 2017, pp. 1456-1459, doi: 10.1109/ICPCSI.2017.8391953

[2] Bhagya Rekha Sangisetti, Suresh Pabboju,“Review on Personal Activity Analysis Using Machine Learning Algorithms” in TEST Engineering and Management “ “May – June 2020 ISSN: 0193-4120 Page No. 12041 – 12050

[3] Naseer, & Azam, Muhammad Awais&Ehatisham-ul-Haq, Muhammad & Ejaz, Waleed & Khalid, Asra. (2019). ADLAuth: Passive Authentication Based on Activity of Daily Living Using Heterogeneous Sensing in Smart Cities. Sensors. 19. 2466. 10.3390/s19112466.

[4] E. Bulbul, A. Cetin and I. A. Dogru, "Human Activity Recognition Using Smartphones," 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, 2018, pp. 1-6, doi: 10.1109/ISMSIT.2018.8567275.

[5] A.Nandy, J. Saha, C. Chowdhury and K. P. D. Singh, "Detailed Human Activity Recognition using Wearable Sensor and Smartphones," 2019 International Conference on Opto-Electronics and Applied Optics (Optronix), Kolkata, India, 2019, pp. 1-6, doi: 10.1109/OPTRONIX.2019.8862427.

[6] R. Zhu et al., "Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning," in IEEE Access, vol. 7, pp. 75490-75499, 2019, doi: 10.1109/ACCESS.2019.2922104.

[7] Minh-Son Dao, Tuan-Anh Nguyen-Gia, Van-CuongMai,Daily Human Activities Recognition Using Heterogeneous Sensors from Smartphones,Procedia Computer Science,Volume 111,2017,Pages 323-328,ISSN 1877-0509

[8] [8]A. Subasi, M. Radhwan, R. Kurdi and K. Khateeb, "IoT based mobile healthcare system for human activity recognition," 2018 15th Learning and Technology Conference (L&T), Jeddah, 2018, pp. 29-34, doi: 10.1109/LT.2018.8368507

[9] A. Bhavan and S. Aggarwal, "Stacked Generalization with Wrapper-Based Feature Selection for Human Activity Recognition," 2018 IEEE Symposium Series on Computational Intelligence (SSCI), Bangalore, India, 2018, pp. 1064-1068, doi: 10.1109/SSCI.2018.8628830.

[10] Ran Zhu, Zhuoling Xiao, Ying Li, Mingkun Yang, Yawen Tan, Liang Zhou, Shuisheng Lin, Hongkai Wen, "Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning", Access IEEE, vol. 7, pp. 75490-75499, 2019.

[11] K. Lee, S. Chae and H. Park, "Optimal Time-Window Derivation for Human-Activity Recognition Based on Convolutional Neural Networks of Repeated Rehabilitation Motions," 2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR), Toronto, ON, Canada, 2019, pp. 583-586, doi: 10.1109/ICORR.2019.8779475.

[12] C. Liu, J. Ying, F. Han and M. Ruan, "Abnormal Human Activity Recognition

using Bayes Classifier and Convolutional Neural Network," 2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP), Shenzhen, 2018, pp. 33-37, doi: 10.1109/SIPROCESS.2018.8600483.

[13] M. C. Sorkun, A. E. Danişman and Ö. D. İncel, "Human activity recognition with mobile phone sensors: Impact of sensors and window size," 2018 26th Signal Processing and Communications Applications Conference (SIU), Izmir, 2018, pp. 1-4, doi: 10.1109/SIU.2018.8404569.

[14] A. Nandy, J. Saha, C. Chowdhury and K. P. D. Singh, "Detailed Human Activity Recognition using Wearable Sensor and Smartphones," 2019 International Conference on Opto-Electronics and Applied Optics (Optronix), Kolkata, India, 2019, pp. 1-6, doi: 10.1109/OPTRONIX.2019.8862427.

[15] M. Mario, "Human Activity Recognition Based on Single Sensor Square HV Acceleration Images and Convolutional Neural Networks," in IEEE Sensors Journal, vol. 19, no. 4, pp. 1487-1498, 15 Feb.15, 2019, doi: 10.1109/JSEN.2018.2882943.

[16] Malhotra, Akshay&Schizas, Ioannis&Metsis, Vangelis. (2018). Correlation Analysis-Based Classification of Human Activity Time Series. IEEE Sensors Journal. PP. 1-1. 10.1109/JSEN.2018.2864207.

[17] Bhagya Rekha Sangisetti, Suresh Pabboju, and SrinikhilRacha. 2019. Smart call forwarding and conditional signal monitoring in duos mobile. In Proceedings of the Third International Conference on Advanced Informatics for Computing Research (ICAICR '19). Association for Computing Machinery, New York, NY, USA, Article 1, 1–11. DOI:https://doi.org/10.1145/3339311.3339312

[18] Murcia H., Triana J. (2019) A Personal Activity Recognition System Based on Smart Devices. In: Figueroa-García J., Duarte-González M., Jaramillo-Isaza S., Orjuela-Cañon A., Díaz-Gutierrez Y. (eds) Applied Computer Sciences in Engineering. WEA 2019. Communications in Computer and Information Science, vol 1052. Springer, Cham. https://doi.org/10.1007/978-3-030-31019-6_41

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