

# Gesture recognition by learning local motion signatures using smartphones

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**Abstract-** In recent years, gesture or activity recognition is an important area of research for the modern health care system. An activity is recognized by learning from human body postures and signatures. Presently all smartphones are equipped with accelerometer and gyroscopes sensors, and the reading of these sensors can be utilized as an input to a classifier to predict the human activity. Although the human activity recognition gained a notable scientific interest in recent years, still accuracy, scalability and robustness need significant improvement to cater as a solution of most of the real world problems. This paper aims to fill the identified research gap and proposes Grid Search based Logistic Regression and Gradient Boosting Decision Tree multistage prediction model. UCI-HAR dataset has been used to perform Gesture recognition by learning local motion signatures. The proposed approach exhibits improved accuracy over preexisting techniques concerning to human activity recognition.

**Keywords-** Human activity recognition, Sensors, Smartphones, Grid search based logistic regression, Gradient boosting decision tree.

## I. INTRODUCTION

Human activity or motion signature is defined as any bodily movement produced by muscles that require energy expenditure. It encompasses all activities at any intensity performed during whole 24-hours. Since the last few decades, human activity recognition is a very crucial and challenging problem in the field of pattern recognition and data mining [1]. Meanwhile, the modern healthcare systems, monitoring the regular activities of daily living generate data regularly. These data make the body gesture recognition a prominent area of research [2]. Solid evidence proves that monitoring of physical activity on a daily basis can strongly manage and control the risk of many diseases such as obesity, cardiovascular diseases and diabetes. The recognition of the regular activities may assist the patients and elderly people to keep acquainted to their lifestyle. This phenomenon motivates the physician to monitor the patients properly. Continuous monitoring of the patient will reduce the stays in the hospital and improves the reliability of diagnosis. There is a new approach called remote health care [3], which is helpful for isolated elderly people for regular monitoring. In

today's era smartphones are very popular in daily life. Almost all the ages of the people are using it for different purpose such as online/offline learning, playing games, online shopping, banking applications etc. As the technology advances and the mobile phone upgrades approach for human activity recognition (HAR) constantly emerge.

Based on the complexity and duration, human activities are divided into three groups. The first kind of activities consists of short duration activities such as a transition from sitting to standing and standing to sitting. The second kind of activities consists of basic activities of daily living. The final group of activities is the combination of basic activities with multiple objects and individuals, such kind of activities can be partying or recognizing official meeting. In the proposed research, we focus on recognizing basic activities.

It is very difficult to recognize concurrent activities, (e.g. a person is watching the movie while talking to their friends) and interleaved activities (e.g. during cooking, if there is a phone call, a person pauses cooking for a while to receive a call, and after finishing the conversation resumes cooking). The interpretation of an activity may be different depending on the situation (e.g. an activity open refrigerator can belong to several activities such as cooking or cleaning). Hence, the generalization of activity recognition algorithm is a very challenging task. The accuracy of classification algorithms tends to drop when some activities are not included in the training phase. Activities are even more confusing when the location of wearable devices change or the orientation of the device once worn (the axes of the sensors change direction as well). This research considers all such scenarios and provides a robust solution using only smartphones.

The rest of the paper is organized as follows: In section II, pre-existing human activity recognition models have been discussed whereas section III describes the UCI-HAR dataset [5]. Section IV explains the proposed classification and ensemble algorithm for human activity recognition. Experiments and results have been discussed in section 5. The last section contains concluding remarks and future scope.

## II. LITERATURE REVIEW

Due to the wide range of human activities and the variations of how an activity is being performed, human activity recognition is a prominent scientific interest in recent years. Although, all pre-existing research works on gesture recognition focuses on accuracy, real-time ability, and robustness still none of the research work guarantees for accurate prediction of activity. This section of the paper gives an overview of some recent pre-existing research works for activity recognition using smartphones.

In the race of human activity recognition, Akram et al. [6] investigated the smartphone's accelerometer data to classify the activities and compared the performance of six popular classification algorithms, i.e. Multilayer Perceptron, Support Vector Machine, Random Forest, Logistic model tree, Simple Logistic and LogitBoost. In this research paper, Data is collected from two male and two female subjects and activity is classified into Running, Slow-walk, Fast-Walk, Aerobic Dancing, Stairs-up and Stairs-Down. Authors generated a dataset with smartphones keeping in a pocket and gripped in hand. This research also measures the accuracy of different combinations of classifiers with a similar orientation of smartphones. Experimental results show that along with multilayer perceptron, a combination of support vector machine and logicboost gives the highest accuracy i.e. 91.15 %.

It is evident from the literature that for activity recognition combination of multiple classifiers gives better performance over any single stand-alone classifier. To increase the accuracy of gesture estimation, Daghstani and Alshammari [7] proposed an ensemble model by combining AdaBoost with other classifiers (Decision Trees, Logistic Regression, Multilayer perceptron). In this research combination of AdaBoost with decision tree has given the highest accuracy of 94.03%. Afterwards, Walse et al. [8] studied the effect of adaptive boosting on performance and accuracy of the classifiers for human activity recognition. It was observed that Adaboost with Random Forest and Naive Bayes improves the overall accuracy. Particularly, with Naive Bayes accuracy was increased to 90.95 %.

Further, Yiyan et al. [9] implemented a hierarchical classification system to detect complex walking patterns based on the decision tree, random forest and hidden Markov model (HMM). The decision tree classifier achieves a coarse-grained distinction of the motion mode whereas, the random forest classifier further performs a fined-grained distinction of the motion mode. Finally, an HMM uses the advantage of the sequential motion recognition estimation by the random forest classifier. The experimental results demonstrate that the recognition success of complex walking pattern using the proposed method is more than 93.8% for eight complex motion modes.

In 2016, Chawla and Wagner [10] proposed a smartphone-based recognition system in which the application of a low pass filter is applied to separate the static and dynamic human gesture. They compare the accuracy of four classifiers (K-nearest neighbour, support vector

machine, Artificial neural network and decision trees). Among all the classifiers, the artificial neural network gave the highest accuracy of 96.77%. The subjects included generating the data are of different gender, height, age, weight, and conditions.

To achieve the similar goal Erhan et al. [11] implemented several classification algorithms with changes in the value of hyperparameters in the classification algorithm. The variation in the best parameters of the classification algorithm accounts for variation in accuracy for predicting the activity.

In the past, many authors have proposed several activity recognition models to get knowledge about persons' activities and behaviour [4]. The in-depth insight into the existing literature, it is evident that very limited literature is available for activity recognition with smartphones. This paper fills the identified research gap and aims to develop a model that is capable of recognizing multiple sets of real-time daily activities using smartphones by historical values of sensors (triaxial accelerometer and gyroscope), data. The accelerometer measures velocity and speed, and data retrieved from the accelerometer sensor is useful to detect sudden changes in the movement. Whereas, Gyroscope's reading is helpful to detect the alignment and position of smartphones. Data pre-processing is an important phase of the proposed activity recognition approach that involves several steps. Initially, data collected from accelerometer and gyroscope sensors are filtered to separate the AC and DC components. The AC component is related to the dynamic motion of the subject such as walking or running. DC component is mainly related to the influence of gravity. This filtered data is divided into small segments using a sliding window approach. Further, feature extraction followed by a classification process is applied to classify the human gesture into one of the activities of daily living.

## III. DATASET DESCRIPTION

This paper proposes a model that predicts human activities such as walking, walking upstairs, walking downstairs, sitting, standing or laying. To evaluate the performance of the proposed algorithm, experiments were carried out on UCI-HAR dataset [5]. Generally, sensors provide a continuous stream of data, therefore, it is required to transform the stream into a discrete form. Windowing is the most popular technique for feature extraction [12,13,14,15,16,17,18]. The windows are labelled according to the performed activity. It is also evident that the use of small window size is computationally good. In this research, the accelerometer and gyroscope signals are pre-processed by applying noise filters and then sampled in fixed-width windows (sliding windows) of 2.56 seconds each with 50% overlap. Both the time series and frequency domain data is converted to a numerical vector using signal processing. For experiments, 70% of the dataset is considered as training data whereas the remaining 30% data is treated as test data. The size of the dataset is 27MB. Table 1 and Table 2 depict the extracted features from the accelerometer and gyroscope sensors.

Table 1: Accelerometer Sensor Features

Analysis Domain	Features
Time Domain	tBodyAcc-XYZ, tGravityAcc-XYZ tBodyAccJerk-XYZ, tBodyAccMag tGravityAccMag, tBodyAccJerkMag
Frequency Domain	fBodyAcc-XYZ, fBodyAccJerk-XYZ, fBodyAccMag, fBodyAccJerkMag

Table 2: Gyroscope Sensor Features

Analysis Domain	Features
Time Domain	tBodyGyro-XYZ, tBodyGyroMag tBodyGyroJerkXYZ, tBodyGyroJerkMag
Frequency Domain	fBodyGyro-XYZ, fBodyGyroMag, fBodyAccJerkMag

#### IV. PROPOSED METHODOLOGY

This research paper focuses on recognizing the activities of daily living. The proposed method is a three-stage model where the first stage is the data pre-processing, and in the second stage, data is analyzed and visualized whereas in last stage classification techniques is applied. The novelty of the proposed model is the use of the grid search method to predict the best parameters of the classification algorithm. In the case of Logistic Regression, the value of  $\lambda$  is optimized and for Gradient Boosting Decision tree, the optimal depth of the tree is estimated using Grid Search.

##### A. Data-preprocessing

Data pre-processing is the initial step of the proposed model [19]. This phase helps to eliminate duplicates and class imbalance. It also assists to examine missing and unknown values in the data.

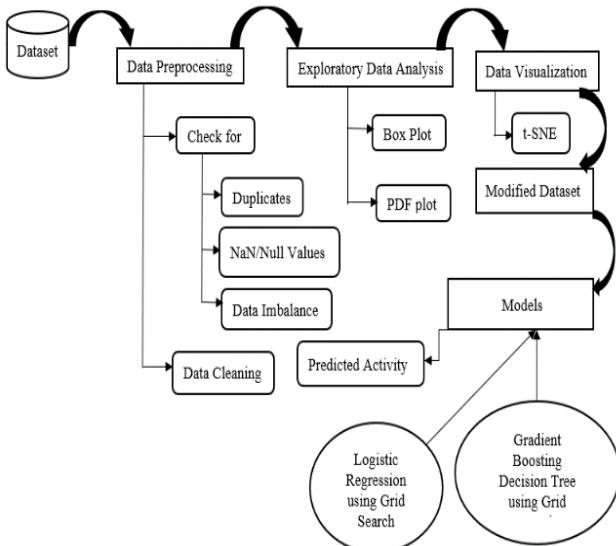


Fig 1: Block Diagram of Gesture Recognition Model

##### B. Exploratory Data Analysis

In static activities, features of motion information will not be very useful. Similarly, motion information will be significant for dynamic activities. Exploratory data analysis is performed to show univariate and multivariate analysis of features. The probability distribution function plot is used to show the difference between static and dynamic activities as shown in Fig 2. whereas Box plot [19] considers mean, median and percentiles for a specific activity and puts them

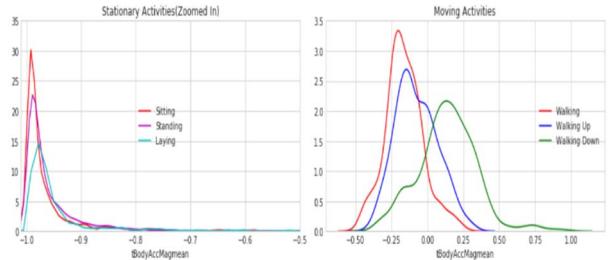


Fig 2: PDF plot on tBodyAccMagMean to differentiate between stationary and moving Activities

in graph form. Plotting the features using boxplot on one feature confirms that data is linearly separable as shown in Fig 3. T-SNE [20] is plotted to visualize the data in a lower dimension with multiple values of perplexity keeping number of iterations fixed. Perplexity is defined as the number of neighbours to be preserved during the transition from a higher dimension to lower dimension.

##### C. Classification Algorithms guided by Grid Search

In this section, Logistic Regression and Gradient Boosting Decision Trees guided by Grid search is discussed to classify the extracted features to the activities of daily living.

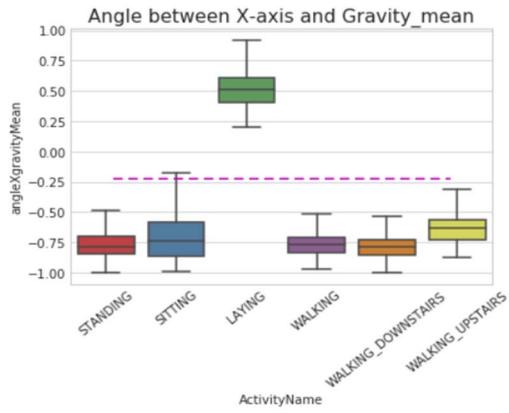


Fig 3: Box plots on angleXgravityMean to show data is linearly separable.

##### • Logistic Regression Using Grid Search

It is a model that is used to predict the probabilities of different possible outcomes of a categorically distributed dependent variable, given a set of independent variables. The core idea of implementing Logistic Regression is that classes are almost or perfectly linearly separable. It allows us to understand the impact of independent classes on dependent

classes while controlling for other independent classes. Multinomial logistic regression is employed to solve the following optimization problem:

$$w^* = \arg \min_w \sum_{i=1}^n \log(1 + \exp(-yw^T x)) + \lambda w^p \quad (1)$$

This expression is for logistic-loss and regularization where  $w$  is a unit vector orthogonal to the hyperplane. Regularization is achieved to maintain the trade-off between underfitting and overfitting. If the value of  $\lambda$  is low, the model suffers from overfitting and for a large value of  $\lambda$ , it suffers from underfitting. Minkowski Distance  $p$  is a metric in a normed vector space which can be considered as a generalization of both Manhattan and Euclidean distance. The dual Lagrange representation of the optimization equation (Eqn.1) is equivalent to:

#### Algorithm (Gradient\_Boosting):

Input: training set  $\{(x_i, y_i)\}_{i=1}^n$ , a differentiable loss function  $L(y, F(x))$ , number of iterations  $M$ .

1. Initialize model with a constant value:

$$F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma)$$

2. For  $m = 1$  to  $M$ :

2.1. Compute so-called pseudo-residuals:

For  $i = 1$  to  $n$

$$r_{im} = - \left[ \frac{\delta L(y_i, F(x_i))}{\delta F(x_i)} \right]_{F(x)=F_{m-1}(x)}$$

2.2. Fit a base learner (e.g. tree)  $h_{im}(x)$  to pseudo-residuals, i.e. train it using the training set  $\{(x_i, r_{im})\}_{i=1}^n$ .

2.3. Compute multiplier  $\gamma_m$  by solving the following one-dimensional optimization problem:

$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i))$$

2.4 Update the model:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$

3. Output  $F_M(x)$ .

$$\sum_{i=1}^n \log(1 + \exp(-yw^T x)) - \lambda(1 - w^T w) \quad (2)$$

In logistic regression, in place of directly final prediction, the scores for multi-class classification is used. Because there is a potential a problem that one sample might be classified to several classes or non-classes. Grid Search identifies the optimized value of  $\lambda$  values in a very wide window between  $[10^{-4}, 10^{-3}, 10^{-2}, \dots, 1, \dots, 10^3, 10^4]$  by measuring cross-validation error against multiple values of  $\lambda$ .

- Gradient Boosting Decision Trees using Grid Search

The Gradient Boosting [21] is a technique for regression and classification problems which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. In this research, to overcome from underfitting and overfitting an optimal depth of a decision tree is estimated using grid search. Decision trees with low variance and high bias are selected as base models in gradient boosting. The proposed model keeps variance constant and reduces bias. Each of the base models is trained to fit the residual error at the end of the previous stage. At the end of stage  $k$  residual error is:

$$F_k(x) = \sum_{i=0}^k \alpha_i * h_i(x) \quad (3)$$

Final residual error after stage  $k$  can be calculated as:

$$\text{error}_i = y_i - F_k(x) \quad (4)$$

In boosting the model at the stage,  $k+1$  is trained using  $\{x_i, \text{error}_i\}$ .  $k$  is a hyperparameter that represents the number of models to be trained. As the value of  $k$  increases, training error reduces and eventually bias also reduces. The algorithm [21] for gradient Boosting decision trees is as follows:

In the context of gradient boosting, a negative gradient can be thought of as a residual. It is often called as a pseudo-residual. Instead of residual, we replace error at any point with pseudo residual. The advantage of the pseudo-residual is that it allows us to have any loss function of our choice. This is the best way to incorporate any loss function of our choice that optimizes a cost function over function space by iteratively choosing a function that points in the negative gradient direction.

## V. EXPERIMENTS AND RESULTS

The objective of this research is to predict human activities such as walking, walking upstairs, walking downstairs, sitting, standing or laying using historical data. To evaluate the performance of the proposed algorithm, experiments were carried out on UCI-HAR dataset [6]. Confusion Matrix, Precision, Recall, F1-score, and support are used as performance evaluation parameters. The normalized confusion matrix and classification accuracy generated from logistic regression using grid search are depicted in Fig. 4 and Table 3 respectively. Whereas the experimental results of gradient boosting decision tree using grid search are depicted in Fig. 6 and Table 4. Grid search estimates the best parameters of logistic regression and gradient boosting decision tree (Fig. 5 and 7). Both the methods achieve an average accuracy of 96.27% and 86.43% respectively.

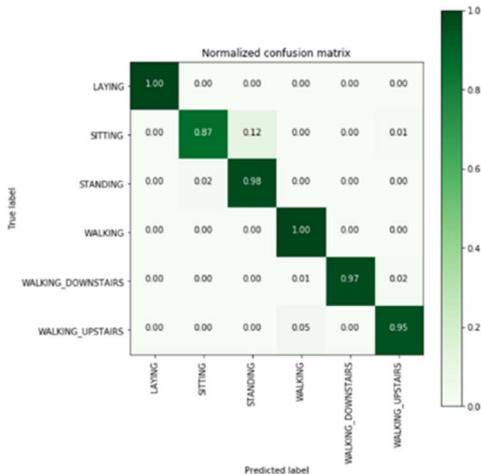


Fig 4: Normalized Confusion Matrix (Logistic Regression)

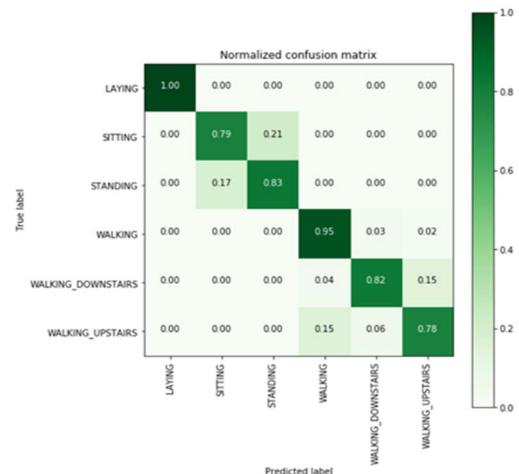


Fig 6: Normalized Confusion Matrix (Gradient Boosting Decision Tree.)

| Best Estimator |

```
LogisticRegression(C=30, class_weight=None, dual=False, fit_intercept=True,
intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
verbose=0, warm_start=False)
```

| Best parameters |

Parameters of best estimator :

```
{'C': 30, 'penalty': 'l2'}
```

| No of CrossValidation sets |

Total numbre of cross validation sets: 3

| Best Score |

Average Cross Validate scores of best estimator :

```
0.9461371055495104
```

Fig 5 : Attributes of Logistic Regression Using Grid Search

Table 3: Classification report (Logistic Regression)

ACTIVITY	PRECISION	RECALL	F1-SCORE	SUPPORT
Laying	1.00	1.00	1.00	537
Sitting	0.81	0.79	0.80	491
Standing	0.81	0.83	0.82	532
Walking	0.84	0.95	0.89	496
Walking_Downstairs	0.88	0.82	0.85	420
Walking_Upstairs	0.84	0.78	0.81	471
Average/Total	0.86	0.86	0.86	2947

| Best Estimator |

```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
learning_rate=0.1, loss='deviance', max_depth=5,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=140,
presort='auto', random_state=None, subsample=1.0, verbose=0,
warm_start=False)
```

| Best parameters |

Parameters of best estimator :

```
{'max_depth': 5, 'n_estimators': 140}
```

| No of CrossValidation sets |

Total numbre of cross validation sets: 3

| Best Score |

Average Cross Validate scores of best estimator :

```
0.904379760609358
```

Fig 7: Attributes of Gradient Boosting Decision Tree Using Grid Search

Table 4: Classification Report Gradient Boosting Decision Tree.

ACTIVITY	PRECISION	RECALL	F1-SCORE	SUPPORT
Laying	1.00	1.00	1.00	537
Sitting	0.81	0.79	0.80	491
Standing	0.81	0.83	0.82	532
Walking	0.84	0.95	0.89	496
Walking_Downstairs	0.88	0.82	0.85	420
Walking_Upstairs	0.84	0.78	0.81	471
Average/Total	0.86	0.86	0.86	2947

## VI. CONCLUSION AND FUTURE WORK

This research paper presents a novel smartphone-based approach for recognition of activities of daily living. Experimental results show that logistic regression with grid search achieves an average accuracy of 96.27% whereas Gradient Boosting Decision tree predicts the activities with an average accuracy of 86.43%. The experimental results justify the suitability of the proposed model (specially logistic regression with grid search) in gesture recognition and ensure better performance compared to other pre-existing models. These results clearly show that under the guidance of grid search, linear regression model outperforms over the gradient boosting decision tree. Data visualization shows that the dataset is linear hence it is concluded that in a linear environment linear regression ensures better performance. It is also evident that linear regression gives unbiased results in all the cases due to lesser variance in intra-class accuracy. As a future work, there is a scope to develop some other prediction model for non-linear data.

## REFERENCES

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### REFERENCES

  - [1] Kamath, R. S., & Kamat, R. K. Modeling Human Activity Recognition Using Kears and Tensorflow: Deep Learning Approach.
  - [2] Vrigkas, M., Nikou, C., & Kakadiaris, I. A. (2015). A review of human Activity recognition methods. *Frontiers in Robotics and AI*, 2, 28.
  - [3] Dehzangi, O., & Sahu, V. (2018, August). IMU-Based Robust Human Activity Recognition using Feature Analysis, Extraction, and Reduction. In *2018 24th International Conference on Pattern Recognition (ICPR)* (pp. 1402-1407). IEEE.
  - [4] bin Abdullah, M. F. A., Negara, A. F. P., Sayeed, M. S., Choi, D. J., & Muthu, K. S. (2012). Classification algorithms in human activity recognition using smartphones. *International Journal of Computer and Information Engineering*, 6, 77-84.
  - [5] Human Activity Recognition Using Smartphone Dataset, UCI Machine Learning Repository.
  - [6] Bayat, A., Pomplun, M., & Tran, D. A. (2014). A study on human activity recognition using accelerometer data from smartphones. *Procedia Computer Science*, 34, 450-457.
  - [7] Daghstani, T., & Alshammary, R. (2016). Improving accelerometer-based activity recognition by using ensemble of
  - [8] Morales, J., Akopian, D., & Agaian, S. (2014, February). Human activity recognition by smartphones regardless of device orientation. In *Mobile Devices and Multimedia: Enabling Technologies, Algorithms, and Applications 2014*(Vol. 9030, p. 90300I). International Society for Optics and Photonics.
  - [9] Rousseeuw, P. J., Ruts, I., & Tukey, J. W. (1999). The bagplot: a bivariate boxplot. *The American Statistician*, 53(4), 382-387.
  - [10] Maaten, L. V. D., & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of machine learning research*, 9(Nov), 2579-2605.
  - [11] Friedman, J. H. (2002). Stochastic gradient boosting. *Computational Statistics & Data Analysis*, 38(4), 367-378.
  - [12] Walsle, K. H., Dharaskar, R. V., & Thakare, V. M. (2017). A Study on the Effect of Adaptive Boosting on Performance of Classifiers for Human Activity Recognition. In *Proceedings of the International Conference on Data Engineering and Communication Technology* (pp. 419-429). Springer, Singapore.
  - [13] Yiyuan, L., Fang, Z., Wenhua, S., & Haiyong, L. (2016, November). An hidden Markov model based complex walking pattern recognition algorithm. In *Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS), 2016 Fourth International Conference on* (pp. 223-229). IEEE. “
  - [14] Chawla, J., & Wagner, M. (2016). Using Machine Learning Techniques for User Specific Activity Recognition. In *INC* (pp. 25-29).
  - [15] Bulbul, E., Cetin, A., & Dogru, I. A. (2018, October). Human Activity Recognition Using Smartphones. In *2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)* (pp. 1-6). IEEE.
  - [16] Parkka, J., Ermes, M., Korpiapaa, P., Mantyjarvi, J., Peltola, J., & Korhonen, I. (2006). Activity classification using realistic data from wearable sensors. *IEEE Transactions on information technology in biomedicine*, 10(1), 119-128.
  - [17] Chernbumroong, S., Atkins, A. S., & Yu, H. (2011, September). Activity classification using a single wrist-worn accelerometer. In *Software, Knowledge Information, Industrial Management and Applications (SKIMA), 2011 5th International Conference on* (pp. 1-6). IEEE.
  - [18] Kao, T. P., Lin, C. W., & Wang, J. S. (2009, July). Development of a portable activity detector for daily activity recognition. In *Industrial Electronics, 2009. ISIE 2009. IEEE International Symposium on* (pp. 115-120). IEEE.
  - [19] Siirtola, P., Laurinen, P., Haapalainen, E., Roning, J., & Kinnunen, H. (2009, March). Clustering-based activity classification with a wrist-worn accelerometer using basic features. In *Computational Intelligence and Data Mining, 2009. CIDM'09. IEEE Symposium on* (pp. 95-100). IEEE.
  - [20] Yang, J. Y., Chen, Y. P., Lee, G. Y., Liou, S. N., & Wang, J. S. (2007). Activity recognition using one triaxial accelerometer: A neuro-fuzzy classifier with feature reduction. In *Entertainment Computing—ICEC 2007* (pp. 395-400). Springer, Berlin, Heidelberg.
  - [21] Mannini, A., Intille, S. S., Rosenberger, M., Sabatini, A. M., & Haskell, W. (2013). Activity recognition using a single accelerometer placed at the wrist or ankle. *Medicine and science in sports and exercise*, 45(11), 2193.
  - [22] classifiers. *International journal of advanced computer science and applications*, 7(5), 128-133.