# *A Mobile Based Activity Recognition Model*

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## Abstract

In the last decade, activity recognition (AR) of humans via smart phones became important and attractive subject for scholars and developers in many areas from health care to real-time security systems. In this research, we worked on AR that based on data collected from Android-based smart phone's accelerometers held at waist region while performing different activities (i.e. walking, jogging, climbing stairs, downing stairs, sitting, and standing). To achieve this goal, six classification algorithms were performed: Naïve Bayes (NB), Multi Layer Perceptron (MLP), Bayes Network (BN), Sequential Minimal Optimization (SMO), Kstar, and Decision Tree (DT). Experimental results of the six models were illustrated and analyzed. Comparison results declare that MLP algorithm outperforms other algorithms.

**Keywords*: Activity Recognition, Mobile Sensor Data, Data Mining, Accelerometer Data***

### 1. Introduction

The task of identifying actions, activity recognition (AR), through sensor devices in recent years has received considerable attention in many research, yet still faces many challenges because human activities are not all simple and might not be accurately recognized through the sensors. In specific, there are human activities that are difficult and complex which make the task of AR more difficult. However, the advances in technology and the development of technologies in many fields have been the spread of different types of sensors. Instantly, there is a type of sensors that are wearable by the user while they are performing daily life activities. These devices can be held on any part of the body such as the chest, hand or waist. The data are then collected from the sensors, to be preprocessed, analyzed and extracting its usable features to identify various activities (i.e. activity recognition). The recognition of human activities has a practical effect in our real life, which is one of the most typical applications in health care, monitoring the movement of elder people and providing pro-active assistance to them. Additionally, applications that AR can be useful in might include security, guarding, and military applications [1].

However, there is a challenge in solving the complex problems that arise when identifying sequential, simultaneous and interrelated activities [2].

## 1.1 Objectives

This research aims to:

- Evaluate and analyze some well known machine learning methods on accelerometer data in order to recognize human activities.
- compare the results of various models that have been evaluated.
- Suggest a robust and effective Activity Recognition model.

This research will be devided into sections. In the second section, there will be some explanations about the main terms definition, background of the research, related work (i.e. previous studies on the function of identifying the activities through the sensors), and exploration of the collected data. In the third section, we will discuss the classification algorithms we have used as we will explain these algorithms. These algorithms are **Naïve Bayes, J48 , MLP , SMO** and **KSTAR** and we will explain and discuss the results obtained from these algorithms in section 4. In section 5, the conclusion will be presented, in addition to ideas for future work.

## 2. Background

### 2.1 Data mining

The process of working on big sets of data for the purpose of extracting meaningful information is known as Data Mining. However, this field also encompasses some other related fields such as: cleansing of data, integration, and visualization [3]

### 2.2 Machine Learning

Machine learning is a field of computer science that aims to generalize useful and meaningful facts out of data samples. Machine learning is common and frequently used and utilized in the fields that require knowledge extraction, such as biometrics, activity recognition, machine vision, and behavior and traits recognition [4]

### 2.3 Activity Recognition

There has been a lot precedent work on AR [5,6,7,8], and there has been some works used personal models [9,10], that was exclusively built by utilizing labeled training data set collected from the meant subject. On the other hand, most of works concentrated on using universal models [11,12,13,14], that was built by utilizing labeled data set collected from not meant subjects. However, a newer work [13] has tried the universal model to individuals, but a few work has submitted a comparison between the universal and the personal models based on a fairly good size of population. In addition, there is no work that has accurately statistically discussed these types' relative performance. However, analysis of these models' relative performance has provided, which show that personal-based AR models outperform and are more effective than universal models.

**2.4 Related Work**

There are many previous research related to activity recognition. One of which was complementary to the work of the other. These studies were the basic to write this research. However, the most related works are discussed below:-

A wavelet-based activity recognition approach employing a set of accelerometers was suggested by Mannini et al [15]. In this study, the components of gravity and dynamic action were separated. The result showed that the proposed model performance is 98.4%

Foerster and Fahrenberg [16], collected fourteen different activity data from 31 individuals via five accelerometers, to build a hierarchical recognition model for the purpose of identifying body activities and positions. From the results obtained, we might say that the proposed model performance is acceptable and recognized activities successfully.

Casale et al [17], collected accelerometer data by wearable device on subjects performing different activities. This approach performance is 94%.

Bao and Intille [5], used five wearable bi-axial accelerometers to be worn on the subject's dominant wrist and ankle, right hip, and non dominant arm and thigh, in order to observe and collect 20 different activities from 20 individuals. Four different classifiers were employed: decision tables, Naïve Bayes, C4.5, and Instance Based (IB). Results show that the accelerometer put on the thigh part was the best position to be used for activity recognition.

Nishkam and Nikhil [18], got the users worn a single 3D accelerometer near their pelvic to detect eight different activities (i.e. standing, running, walking, climbing stairs, downing stairs, sitting up, vacuuming, and teeth brushing). The dataset was collected under four settings: (i) collecting data from a single user during different days, (ii) collecting data from different users during different days, (iii) which is similar to (i) but here the data collected over a day is used for training and the data collected over another day is used for testing, and (iv) collecting data from a single user during a day is used as training and the data collected from other users during other days is used for testing. The result showed that voting classifier is the highest performance when experimented with settings 1 to 3. In addition, the performance of setting 4 is 73.33%.

Kwapisz et al in [19] and [20], used twenty nine individuals carrying Android-based mobiles on their pockets while performing six different activities (i.e. walking, standing, climbing stairs, downing stairs, jogging and sitting). Next, this data was used on three classifiers: MLP, LR, and J48 in order to recognize activities. Results showed that the accuracy of recognizing climbing/ downing stairs activities is low if compared to other activities which performed much better with 90% of accuracy.

However, smartphones based AR applications has many advantages (i.e. device portability, and user comfortability with wearable sensors). In Contrast, some AR systems used special purpose sensors. In specific, although of the increasing accuracy in AR using numerious sensors, it is not easy to be applicabale for majority of the users due to the restrictions of time and difficulty of wearing sensors everyday. The main drawback of mobile-phone based AR is the sharabiltiy of data with other applications [21].

Veenendaal et. al [22] examined the use of dynamic probabilistic networks (DPN) for human action recognition. The actions of lifting objects and walking in the room, sitting in the room and neutral standing pose were used for testing the recognition. The research used the dynamic interrelation between various different regions of interest (ROI) on the human body (e.g. face, body, arms, and legs) and the time series based events related to the these ROIs. This dynamic links are then used to recognize the human behavioral aspects of the scene. Firstly, a model is developed to identify the human activities in an indoor scene and this model is dependent on the key features and interlinks between the various dynamic events using DPNs. The sub ROI are classified with DPN to associate the combined interlink with a specific human activity. The recognition accuracy between indoor (controlled lighting conditions) is compared with the outdoor lighting conditions. The accuracy in outdoor scenes was lower than the controlled environment. They used video included 6 participants walking into a room and lifting objects. The video of participants resulted in 24 action scenes. The result showed that for the noisy sequences the recognition accuracy dropped from 78% to 74% for picking up action and dropped from 79% to 71% for keeping object down on the floor. The DBN performed better for the lifting object activity under controlled lighting, standing, and sitting. In case of the activities representing walking, HMM had a better accuracy over the proposed method.

In this scenario the recognition accuracy for neutral was better (63% and 71%) as compared to the candidate activity of picking up objects (59% and 65%) for both lighting conditions (dim and controlled).

Veenendaal et al [23], used dynamic, and temporal data to compare with decision rules and templates for activity recognition. The human shape is extracted using a geometric model across multiple frames. The extracted shape is transformed into a binary state using eigen space mapping and parametric canonical space transformation. The image data frames are down sampled using activity templates to a single candidate frame. This candidate frame was compared with the decision rule driven model to associate with an activity class label. The decision rule driven and activity templates method produced a 64% recognition accuracy, indicating that the method is feasible for recognizing human activity. In this scenario, the recognition accuracy of neutral was better (63% and 71%) as compared to the candidate activity of picking up objects (59% and 65%) for both lighting conditions (dim and controlled).

Veenendaal et al [24], Anne and Elliot et. Al [25], described HMM algorithm to build human activity recognition model. Thirty one individuals worn sensors were asked to track some aggressive activities (i.e. running in anger, holding a gun, and charging toward somebody. Next, the data collected is used to train the HMM model and result showed that the accuracy of activity recognition is improved by 3% under controlled lighting situation. On the other hand, the accuracy of activity recognition is decreased by 2% under natural and outdoor lighting situations.

### 2.5 DATA SIZE AND DIVERSITY

A lot of studies did use small data sets, oftenly with less than 5 subjects [26,27,28,29,30,31,32] or 10 subjects [33,34,35,36,37]. However, COSAR and OPPORTUNTY used the most widely AR data set, they have data from only 4 and 12 subjects, respectively [38,39]. Larger sets (e.g. HASC 2010 and 2011), simplified sets of activities, yet with poor amount of data. Therefore, in this research the dataset used is that presented in [40].

#### 2.5.1 EXPERIMENTAL SETUP

Algorithms in the open source Weka suite for machine learning tools [41] were used to validate a set and build of classifiers, jointly with specialized scripts to automate the process and prepare data.

#### 2.5.2 Data Set

The dataset used in this research is available in [40], which was used in (http://www.cis.fordhom.edu/widm/includes/files/sensorkdd-2010.php). The data was collected from 59 individuals holding Android smartphones in pockets during fulfilling six of everyday actions (i.e. jogging, sitting, walking, standing, climbing up and downing stairs. The dataset collected consists 5418 instances, each with 12 features (i.e. values of energy, correlation, mean, and standard deviation of each axis).

## 3. CLASSIFICATION ALGORITHMS

In this research, our suggested AR models are evaluated using the labeled examples of dataset using the following machine learning classification algorithms: MLP, DT, SMO, BN, and Kstar. A brief explanation of each algorithm is presented below:

### 3.1 Multilayer Perceptron (MLP)

This algorithm has the ability to learn, extract, and detect complex patterns from primitive labeled data that humans cannot observe. MLP is an expert in analysis of information given to it, and then the expert to give the introduction of new expectations and answer questions. It also has several other advantages, including adaptive learning. It can learn how to perform tasks based on the data provided to the experiment. It is also a preferred application for gestures, and it gives the decision function directly.

The MLP does not make assumptions about the probability density functions [42]. In one study, the data were categorized using the MLP algorithm. This analysis suggested two false functions for the experiment. In the first case, the error function **ESMF** (A simple monotonic error function) is an error function that applies to a second-class problem. The results showed good performance but this does not serve us. A good function of the multilayered problem. In the second function was used error function **EEXP** (Exponential error function) is a function that can simulate the behaviors of the classical error functions where it was reached the best results that can be obtained from the error function and modify them. Although the results were good with the **MLP** algorithm, other training algorithms or other types of artificial networks can be used to classify and analyze data[43].

### 3.2 Naive Bayes

This algorithm calculates a range of possibilities by synthesizing values in a given data set. This algorithm is a quick algorithm in classification as well as it deals with discrete data and the truth[44]. This algorithm uses the naive bayes base or bayes idiot as this rule assumes that the data is independent. One of the advantages of this algorithm is that we can apply it to a huge set of data It is also easy to interpret the results so algorithm users who do not have experience in classification technology can understand why the classification is so. This algorithm may not be the best algorithm but it is highly reliable to do a good classification [45,46]

### 3.3 Sequential Minimal Optimization (SMO)

This algorithm is only a simple algorithm that can solve any problem to the high speed and fast without the need to store an extra matrix and it never uses the steps of the QP (quadratic programming). This algorithm relies on the theory of Osuna in its work. Each step is the best solution to the smallest problem possible You choose two of the complications of Langer, which must be represented on the linear equality and then extract the optimal values and then work against these optimal values of complications and because of this advantage enjoyed by the HH, which is the choice of two complications of Langer make them get rid of the cup and can solve Numbered subprojects are an optimal solution as they are less prone to numerical precision problems[47].

### 3.4 KSTAR

Describe three learners that rely on increased development. IB1 Implement the nearest neighbor algorithm function .IB3 found in order to improve tolerance among the chaotic data where negligence cases be classified as bad and took well-classification cases.IB4&IB5 It deals with innovative features and was not related to the subject[48].

### 3.5 Decision tree

Use a known method of divide and rule to build appropriate for train a group of cases tree [49]. Some systems are classified evolution of trees decision functions for the classification of these trees constructed with the beginning of the root of the tree down to the leaves [50] Defects trees decision it lacks understanding [51]. For example, if the S case belongs to the same class or if the tree is a small group are the most common in the S-set. If on the contrary it is selected tests on the basis of the one trait with at least two or more of the results in this way is the root of the tree with one branch each test results are divided S into subsets S 1 and Group and S-2 according to the results of each case and is repeated these actions so is access to each subgroup[52]. J48 It is the algorithm of the decision tree C 4.5 learner. This algorithm uses the greedy technique to induce trees decision on the rating is also used to reduce the proportion of errors[53]. The C-4.5 uses two methods to detect how things process.

Criteria for the ordering process potential tests: the acquisition of information, which reduces the total entropy of the S1and depending on the information provided by the test results are divided profit information could be numeric or symbolic attributes. As can be complex big tree fragmented into small and simple trees where it gives similar results to the results of a complex tree and this helps to produce Decision tree understandable[52]. The flaws algorithm is the complexity of the execution time of the algorithm to match the depth of the tree as he can not be larger than the number of features. The C 4.5 is slow when using large groups of noisy data Aerospace and complexity of a very big and we need that we do the stock valuable frequently much in matrixes[54].

## 4. Results and Discussion

A number of machine learning algorithms were applied, compared in aspects of performance, precision, recall, and mean absolute error (MAE). Firstly, the MLP algorithm is tested and the confusion matrix is presented in Table 1 below:

| a | b | c | D | e | f | classified as |
|---|---|---|---|---|---|---|
| 2027 | 2 | 25 | 26 | 0 | 1 | a = Walking |
| 6 | 1609 | 6 | 3 | 1 | 0 | b = Jogging |
| 14 | 1 | 520 | 93 | 3 | 1 | c = Upstairs |
| 21 | 2 | 161 | 340 | 1 | 3 | d=Downstairs |
| 3 | 0 | 2 | 0 | 292 | 9 | e = Sitting |
| 3 | 0 | 5 | 2 | 4 | 232 | f = Standing |

Table 1: Confusion matrix of MLP

From the confusion matrix in Table 1, it can be noticed that 5020 out of 5418 instances was classified correctly.

Secondly, SMO algorithm is applied and the confusion matrix is presented in Table 2 below:

| A | b | c | d | e | f | classified as |
|---|---|---|---|---|---|---|
| 2041 | 2 | 34 | 3 | 0 | 1 | a = Walking |
| 0 | 1616 | 6 | 3 | 0 | 0 | b = Jogging |
| 206 | 4 | 307 | 113 | 2 | 0 | c = Upstairs |
| 167 | 4 | 223 | 132 | 1 | 1 | d=Downstairs |
| 0 | 0 | 0 | 2 | 295 | 9 | e = Sitting |
| 0 | 0 | 12 | 3 | 0 | 231 | f = Standing |

Table 2: confusion matrix of SMO

From the result of SMO confusion matrix in Table 2, it can be concluded that 4622 instances was classified correctly.

Thidly, the BN algorithm is tested and the confusion matrix is presented in Table 3 below:

| A | b | c | d | e | f | classified as |
|---|---|---|---|---|---|---|
| 1851 | 60 | 94 | 52 | 15 | 9 | a = Walking |
| 29 | 1551 | 19 | 6 | 7 | 13 | b = Jogging |
| 203 | 38 | 250 | 98 | 13 | 30 | c = Upstairs |
| 225 | 7 | 90 | 170 | 15 | 21 | d=Downstairs |
| 0 | 0 | 0 | 0 | 286 | 20 | e = Sitting |
| 0 | 0 | 6 | 7 | 27 | 211 | f = Standing |

Table 3: Confusion matrix of NB

From the result of NB confusion matrix listed in Table 3, it can be noticed that 4319 instances was classified correctly.

Fourthly, the Kstar algorithm is examined and the confusion matrix is presented in Table 4 below:

| A | b | c | d | e | f | classified as |
|---|---|---|---|---|---|---|
| 1902 | 3 | 89 | 87 | 0 | 0 | a = Walking |
| 28 | 1551 | 27 | 19 | 0 | 0 | b = Jogging |
| 101 | 12 | 344 | 175 | 0 | 0 | c = Upstairs |
| 112 | 4 | 129 | 283 | 0 | 0 | d=Downstairs |
| 8 | 1 | 17 | 5 | 256 | 19 | e = Sitting |
| 19 | 1 | 20 | 23 | 1 | 182 | f = Standing |

Table 4: Confusion matrix of Kstar

From the result of Kstar confusion matrix listed in Table 4, it can be noticed that 4518 instances was classified correctly.

Fifthly, the DT algorithm is experimented and the confusion matrix is presented in Table 5 below:

| A | b | c | d | e | f | classified as |
|---|---|---|---|---|---|---|
| 646 | 7 | 15 | 16 | 1 | 3 | a = Walking |
| 8 | 560 | 5 | 4 | 0 | 0 | b = Jogging |
| 21 | 11 | 140 | 28 | 0 | 2 | c = Upstairs |
| 15 | 4 | 36 | 136 | 1 | 0 | d= Downstairs |
| 0 | 0 | 0 | 1 | 97 | 2 | e = Sitting |
| 0 | 0 | 3 | 1 | 0 | 79 | f = Standing |

Table 5: Confusion matrix of DT

From the result of DT confusion matrix listed in Table 5, it can be noticed that 4847 instances was classified correctly.

However, Table 6 illustrates the accuracy and overall precision, recall and the mean absolute error rate for each algorithm.

| | MAE | Precision | Recall | % Accuracy |
|---|---|---|---|---|
| MLP | 0.0278 | 0.928 | 0.927 | 92.65 |
| SMO | 0.2267 | 0.834 | 0.853 | 85.31 |
| Bayes Net | 0.0703 | 0.779 | 0.797 | 79.71 |
| Kstar | 0.0561 | 0.841 | 0.834 | 83.40 |
| Decision Tree | 0.038 | 0.892 | 0.895 | 89.46 |

Table 6: Accuracy parameters

From Table 6 it is observed that the best algorithm is MLP with 92.65% performance. The DT algorithm is in the second place with 89.46% performance, and SMO and Kstar comes in the third and fourth place with performance of 85.31% and 83.40%, respectively. And the lowest performance is for BN with 79.71%. On the other hand, the value of mean absolute error for SMO is the highest with 0.23 in comparison with the other four classifiers. Additionally, the value of MAE for MLP is the lowest with 0.027, and near to this is the MAE value of DT with 0.038. Furthermore, MAE of Kstar and BN are 0.056 and 0.07, respectively.

## 5. Conclusion

Human activity recognition (AR) is an important field of research, and useful in many applications. However, there are many applications that can benefit from domain of AR such as health and security fields. In this research study, a smart phone accelerometer data of 5418 instances is used on five machine learning classification methods (i.e. MLP, DT, SMO, BN, and Kstar) in order to perform AR task. First of all, it is observed that activities can be recognized with a high accuracy rate using a single tri-axial accelerometer. Specifically, results show that the best classification algorithm is MLP, which has the best accuracy in recognizing human activities with 92.65%. On the other hand, BN performance is the worst among other used methods with 79.71%.

For future work suggestions might be to develop more efficient methods and tools. Also, building AR models that can work online effectively.

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decision rules and templates for activity recognition.

The human shape is extracted using geometric model across multiple frames. The extracted shape is transformed to binary state using eigen space mapping and parametric canonical space transformation. The image data frames are down sampled using activity templates to a single candidate frame. This candidate frame was compared with the decision rule driven model to associate with an activity class label. The decision rule driven and activity templates method produced 64% recognition ac eometric model across multiple frames.

The extracted shape is transformed to binary state
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The image data frames are down sampled using activity templates to a single candidate frame. This candidate frame was compared with the decision rule driven model to associate with an activity class label. The decision rule driven and activity tdecision rules and templates for activity recognition. The human shape is extracted using geometric model across multiple frames. The extracted shape is transformed to binary state using eigen space mapping and parametric canonical space transformation.

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**الملخص :**

لقد اصبح التعرف على نشاط البشر عبر الهواتف الذكية من اهم المواضيع التي جذبت الباحثين في السنوات الاخيرة حيث يعتبر من المواضيع المهمة في تطوير مجالات الرعاية الصحية وانظمة الامن .يعتمد (AR)على البيانات التي تم جمعها من اجهزة الاستشعار التي تم وضعها في مناطق مختلفة من الجسم اثناء القيام بالانشطة اليومية المختلفة (المشي,الركض,تسلق السلالم,نزول السلالم,الجلوس,الوقوف) كما تعتبر البيانات التي تم الحصول عليها من اجهزة الاستشعار في منطقة الخصر من ادق البيانات . تم تنفيذ خوارزميات التصنيف( Naïve Bayes , Multi Layer Perceptron , Bayes Network , Sequential Minimal Optimization , Kstar, and Decision Tree)على هذه البيانات ومن ثم تحليل النتائج التجريبية للخوارزميات ومن خلال مقارنة نتائج الخوارزميات توصلنا الى ان خوارزمية MLP هي افضل خوارزميات التصنيف المستخدمة.