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Recognizing the Activity Daily Living (ADL) for Subject Independent

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Abstract*: Recently, Human Activity Recognition (HAR) has gained meaningful information for a human being. A wearable sensor like an accelerometer, small and simple to perform, has opened the room for scientists to explore an initial understanding of ubiquitous computing. The wearable sensor has begun to receive attention among researchers in some respects to conduct their studies in a wide area of recognition of human activity. Recent ADL discusses not only simple activities but also cater to the broad categories of complex activities. However, when involving enormous numbers of a subject, the accuracy of recognition tends to reduce. Although a different subject performed the same activity, the acceleration signal acquired considerably differs. This is due to the distinct pattern of action for each subject based on various factors such as subject age, gender, emotion and personality. Thus, by enhancing the accuracy of recognition of ADL, this article proposes the framework for addressing the subject independent matter. The signal acquired from an accelerometer sensor will undergo a segmentation process to extract important features. Some of the characteristics may be meaningless in some instances to determine the class. Therefore, proposing a variety of features to select the most relevant features that can lead to accuracy above 90%. Also, this article outlined a brief empirical evaluation of previous related work. Using several machine learning algorithms, this preliminary work will be examined and analyzed.

Index Terms*: Activity Daily Living (ADL), accelerometer, wearable sensor, machine learning.

I. INTRODUCTION

Today, most individuals owe a mobile smartphone regardless of their generation [1]. With today's technology, the daily operations of the user can be detected based on the accelerometer readings of the smartphone and the risk of injury can be reduced. According to the analysis study, 279 out of 4842 Malaysian elderly people over 60 years of the era were injured at home [2]. This issue could lead to deadly injuries, particularly if the elderly are at home alone and no action can be provided at real-time. In addition to the elderly risk of injury, recognition of daily living activity (ADL) may also be used for automated physical therapy where the physician can monitor their patient's daily operations to identify their rehabilitation status. As a result, ADL classification using machine learning model is required to be highly accurate and efficient. Doctors experience difficulties in getting track of all the daily activities of their patient to monitor their progress in treatment as the method takes a lot of time. The same issue also occurs in ancient fork house where at the same time the guardian has to look after many elderly people. Elderly people with ADL disabilities may harm themselves when they try to finish their daily job on their own. This is dangerous when an accident occurs and no one notices it and is unable to provide real-time assistance.

Most of the research on ADL classification using machine learning in the past studies is focused only on the subject-dependent matter and few numbers of topics are engaged in data collection. As we know, when we do some activities, different people will have a different posture and pattern. Thus, if the machine learning model trained with only a few subjects, classifying and differentiating activities for other people may be inaccurate [3]. Previous research also neglects to select the most relevant features to enhance the efficiency and accuracy of the results of the classification [4]. This is due to some of the features might irrelevant and less meaningful to describe the activity.

II. MATERIALS AND METHODS

A. Activity Daily Living

Daily living activity is a concept that defines people's day-to-day self-care activities. Many activities are categorized as ADL, such as bathing, grooming and dressing, going to the toilet and moving from one location to another. The fundamental ADL is not restricted to the above-mentioned activities; it included all the daily activities that an individual can do without assistance from others. Previous work of acknowledging ADL using machine learning that mostly focuses on static activities such as walking, standing, sitting, climbing stairs and downstairs [4]. Some study includes transitional activities such as standing up, sitting down and lying down [6][3].

B. Wireless Sensor Network

A wireless sensor network is a sequence of sensors that are mounted to retrieve binary occupancy information at a distinct place in the home.

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One common wireless network kit that is commercially accessible is RFM DM 1810, which is often used in studies to classify human activity [7]. The wireless network unable to function alone, it must be fitted with a variety of binary sensors such as reed switches to assess whether doors and cupboards are open or closed; pressure mats to measure sitting on a sofa or lying in bed; mercury contacts to detect object movement (e.g. drawers); passive infrared (PIR) to detect movement in a particular area; float sensors to measure the toilet has been flushed. This sort of sensor does not qualify for activities such as running, walking or sitting. Rather, it can acknowledge what activity a subject is currently doing (washing dishes, watching TV, etc.) based on its location [8].

C. Accelerometer

A tri-axial accelerometer is a sensory device found in most modern smartphones or wearable devices. It comprises of three detectors (x, y, and z-axis) which capable of measuring vibration (acceleration) in three perpendicular axes simultaneously. Y-axis reading is usually larger than the other two Earth-related axes. The reading for all three directions was recorded by the x, y and z-axes as shown in Figure 1 [5]. The number of accelerometers and their positioning play a significant part in achieving high accuracy performance in the ADL classification. The best location for single accelerometer placement is at the hip with an average accuracy of 97.8%, according to a document published by Cleland [9]. Six accelerometers are positioned in various locations of the human body (lower back, wrist, foot, neck, hip, and thigh) in his research. As a consequence, the use of various accelerometers will improve the classification accuracy statistically even if the distinctions are not substantial. By using two accelerometers placed at the upper and lower part of the body, the best classification result can be achieved.

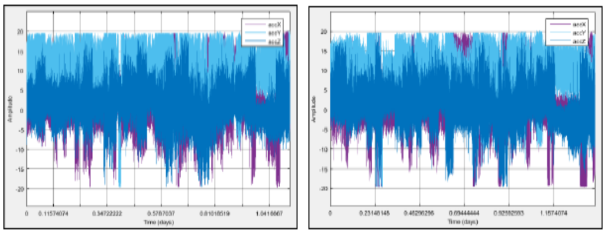

Figure 1. Raw signal from accelerometer sensor [29]

III. ADL CLASSIFICATION

Many machine learning models are available for ADL grading. Six machine learning models, including Instance Based Learner (IBL), K Nearest Neighbor (KNN), K-Star, J48, Locally Weighted Learning (LWL), and Naïve Bayesian Tree (NB Tree), are used in a study conducted by Cufoglu in 2016 to classify ADL [6]. The experiment was reiterated with 9 data points, 15 data points and 30 data points with respectively 11, 15 and 32 attributes. As a consequence, K-Star achieved the largest accuracy for nine data points with an accuracy of 70.86%. K-Star continues the best classifier with an accuracy of 70.53% when the data points have risen to fifteen. IBL took the first position with an accuracy of 69.7 % when 30 data points are used. Bruno et al. [14] provides the data used in the research at the UCI Machine Learning Repository [15]. However, Cufoglu used only data from three of the 16 volunteers (2 male and 1 female) in his research.

The effect of a machine learning model that is trained by using data with very few number of individuals can be observed by a study conducted by Cheng [3]. In his study, Cheng uses dataset collected from four individuals to conduct two types of classification experiment, 1-vs-own and 1-vs-all. The activities involved in this experiment are sitting, sitting down, standing, standing up and walking. The training data and testing data are acquired from the same person for 1-vs-own experiment, whereas 1-vs-all utilizes three individual datasets as training data to evaluate the remaining one individual's activity. The overall accuracy of 1-vs-own is above 90%. On the other hand, the accuracy of 1-vs-all is lower with 61.9% highest accuracy achieved by Neural Network (NN). The low accuracy is a result of overfitting phenomenon where the machine learning model fit too well on the training data [16].

A study conducted by Walse et al. uses human activity recognition (HAR) dataset provided by Wireless Sensor Data Mining (WISDM) Laboratory to classify six activities (walking, jogging, stairs, sitting, standing, and lying down) [4]. Walse et al. successfully achieved an accuracy of 97.83% with J48 using Adaboost.M1 meta-classifier. The other classifier (Random Forest, REP Tree, Random Tree, and Hoeffding Tree) also has a good performance on classifying the activities. However, Decision Stump has a significantly lower performance with an accuracy of 57.31%. This study uses 43 features extracted by Kwapisz et al. [5] from the three axes of accelerometer. The downside of this study is feature selection is not performed to increase the efficiency of the classification process. The use of abundant numbers of features in training data does not necessarily contribute to a better training effect with lower testing error because some of the attributes might be not relevant to the classification process. Instead, when too many features are used it will require more processing time for a computer program to perform the classification [3].

Fida conducted a study on varying different window sizes to classify static and dynamic activities from a single accelerometer [17]. The data was collected from 9 subjects to perform activities such as standing, walking, ascending and descending stairs, sitting and brief walking with an accelerometer attached to their waist. This study also involved dynamic activity where the data of transition between standing and sitting are recorded. The result of this study for 70-30% split subject dependent experiment shows that SVM outperformed KNN, NB, MLP and DT with accuracy over 90% for a window size of 1s and 1.5s. MLP's accuracy comes in second place with window size 1.5s over 90%. The study further experiments the accuracy for subject-independent classification. Turns out, the overall accuracy has a significant drop (average accuracy around 80%) and k-NN has the highest average accuracy.

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Cleland conducted an experiment to find out the best location for accelerometer placement for ADL classification [9]. The experiment has collected the data from eight male subjects by placing six accelerometers at various location of their body (chest, lower back, left foot, left hip, left thigh, and left wrist). Four machine learning model included Decision tree (J48), Naïve Bayes (NB), Neural Network (NN), Multilayer Perceptron and Support Vector Machine (SVM) were used to classify the activities. The best accuracy for single accelerometer was achieved with SVM (97.81%) with accelerometer placed at left hip. Similar to past study, Cleland also found that ascending and descending stairs are the most difficult to be classified compared to the other activities.

Subject independent activity classification study was rarely done in the past. However, Awan has conducted a study regarding subject independent human activity recognition with cloud support in 2015 [18]. The study collected training data limited from two people using smartphone accelerometer at a different position (hand palm, trouser pocket, waist-mounted, and armband) for 11 ADL. The classification process in this study is performed in a workstation module using Waikato Environment for Knowledge Analysis (WEKA) to reduce the processing burden for a smartphone. As a result, K-NN achieved the highest accuracy compared to NB, Bayesian Network, J48, Multilayer Perceptron and Logistic Regression. In terms of smartphone position, waist-mounted, and armband position has significantly higher accuracy probably because the smartphone was fixed and more steadied in those positions which can reduce the noise (unwanted data/ outliners) in the collected data.

Nabian conducted a comparative study on machine learning classification models for activity recognition [19]. The study used data provided by Baños [20] which consists of body motion recordings from 10 volunteers using sensors placed on the chest, right wrist, and left ankle. The dataset has 346,000 instances which are separated into 80% training data and 20% testing data. Ridge Logistic Regression, KNN, Random Forest, Decision Tree, NB, SVM, and NN are used as machine learning model to classify activities such as standing, sitting, lying down, walking, climbing stairs, jumping front and back, running, jogging, biking, knees bending, frontal elevation of arms, and waist bend forward. The performance of KNN and random forest is excellent with accuracy of more than 99% followed by Decision Tree and Artificial Neural Network (NN) with accuracy above 98%. On the other hand, SVM, NB and Ridge Logistic Regression performance were relatively poor with an accuracy of 68.9%, 84.2%, and 69.59% respectively. According to Nabian, the low accuracy of linear classifier (NB and Ridge Logistic Regression) is a result of the non-linearity data in different activities. The paper further study on the running time for each classifier. As a result, Random Forest and Decision Tree took a very short time to complete the classification process (19sec and 15.2sec respectively) whereas KNN and SVM took a very long time (149.2sec and 131.2sec).

Kwapisz and his team conducted their WISDM project using android phone's triaxial accelerometer to measure the acceleration in three spatial dimensions for activity recognition [5]. According to Kwapisz, an accelerometer is able to detect the orientation of the device by detecting the direction of Earth gravity, which plays an important role in classifying human activity. The study collects data through smartphone accelerometer with 20Hz (20 samples per second) from 29 subjects to collect 6 different activities (walking, jogging, ascending stairs, descending stairs, sitting, and standing). Four machine learning model including J48, Logistic Regression, Multilayer Perceptron, and Straw Man were used to classify the activities. As a result, Multilayer Perceptron recorded the highest overall accuracy in classifying the activities. The highest accuracy was also achieved by the same machine learning model on classifying jogging with an accuracy of 98.3%. Ascending and descending stairs are the two activities that is hardest to be classified. The highest accuracy achieved in classifying the two activities is 61.5% only by Multilayer Perceptron. On the other hand, Straw Man classifier performance is below average in the study. The highest accuracy is only 37.2% on classifying walking. The detailed accuracy of each classifier and their activities are listed in Table 1.

Table 1. Classification result by Kwapisz [5]

	% of Records Correctly Predicted			
	J48	**Logistic Regression**	**Multilayer Perceptron**	**Straw Man**
Walking	89.9	93.6	91.7	37.2
Jogging	96.5	98.0	98.3	29.2
Upstairs	59.3	27.5	61.5	12.2
Downstairs	55.5	12.3	44.3	10.0
Sitting	95.7	92.2	95.0	6.4
Standing	93.3	87.0	91.9	5.0
Overall	85.1	78.1	91.7	37.2

Ravi [21] conducted a study namely "Activity Recognition from Accelerometer Data" to classify eight human activities including standing, walking, running, ascending and descending the stair, sit-up, vacuuming, and brushing teeth. The study used one accelerometer located at pelvic and 5 machine learning model (Decision Table, Decision Tree, KNN, SVM and NB) to classify human activity. The paper is divided into four settings, the first setting collects data from a single subject over different days and performed mixing and cross-validation. Setting two is identical to setting one but the subject is increased to two people. Setting three used the same subject's data for training and testing but from a different day. Setting four is a subject independent approach where the first subject's data is used for training whereas the testing data comes from a different subject. As a result, setting one and setting two achieved very high accuracy for all classifier but setting three shows a lower accuracy. Setting four, however, its result is not satisfying as the highest accuracy was only 73.33 achieved by boosted SVM and the lowest accuracy is as low as 47.33%. The detailed comparison of each research in the past is tabulated in Table 2 where the first column is the name of the author, followed by their machine learning model (method) and a number of activities involved. The last two column shows if the study involves subject independent work and the highest accuracy achieved in the respective paper.

Table 2. Comparison of ADL classification

Author	Activities	Subject Independence	Accuracy (%)
Cufoglu [6]	11	No	70.86 (K-star with 9 datapoints)
L. Cheng [3]	5	No	99.5 (SVM)
L. Cheng [3]	5	Yes	61.9 (NN)
K.H. Walse [4]	6	No	94.61 (REP Tree)
B. Fida [17]	6	No	96.3 (SVM)
B. Fida [17]	6	Yes	80~90 (SVM)
Cleland [9]	4	No	97.81 (SVM)
Awan [18]	11	Yes	99.07 (KNN)
Nabian [19]	12	No	99.4 (KNN & RF)
J. R. Kwapisz [5]	6	No	98.3 (MP)
N. Ravi [21]	8	No	above 90%
N. Ravi [21]	8	Yes	73.33 (Boosted SVM)

IV. ADL FEATURES

Segmentation using sliding window is broadly used to segment the signal into a series of window segments. This process aims to divide the signal into several segments before any further calculation is performed [28]. The chosen of window sizes will affect the number of instances and must be sufficient to separate the transition between two activities. Fida [17] studied the use of sliding windows with distinct window size methods (0.5s, 1s, 1.5s, 2s, 3s and 2.5s) to discover the impact on a daily life activities classification. Features are used in the research such as mean, standard deviation, skewness and kurtosis. In both subject-dependent and subject-independent experiment, 1.5s window size demonstrates the highest overall accuracy. Cleland used a 512 sample window size with 256 overlapping samples to derive feature from 370,000 samples raw accelerometer data [9]. To acquire a total of 26 features, the research obtained 11 features from each window. The list of features obtained is shown in Table 3.

Table 3. Example of features

No.	Feature Description
1.	Mean value for each axis (x, y, and z)
2.	Average Mean over 3 axes
3.	Standard Deviation value for each axis (x, y, and z)
4.	Average Standard Deviation over 3 axes
5.	Skewness value for each axis (x, y, and z)
6.	Average Skewness over 3 axes
7.	Kurtosis value for each axis (x, y, and z)
8.	Average Kurtosis over 3 axes
9.	Energy value for each axis (x, y, and z)
10.	Average Energy over 3 axes
11.	Correlations: x_y, x_z, x_total, y_z, y_total, z_total

In a subject independent study conducted by Awan, six features were extracted from an accelerometer placed at four different parts of the body. The extracted attribute in this study included mean, standard deviation, a correlation between axis, variance, mode, and kurtosis. Mean and mode maintained a uniqueness of each axis even in the activities that had steady data patterns. Hence, they provide an adequate result compared to the other extracted feature. The mode, which has overall high accuracy in the classification process shows a surprising low accuracy (13%) using multilayer perceptron classifier. The study uses a sliding windows method with different window sizes in extracting new features. According to Awan, different activities require different span, therefore, the optimal window size cannot be determined. However, using a window size of 2-6s are recommended using smartphone accelerometer according to past research [5][18][22].

Baek conducted an experiment on user activity detection using accelerometer signal processing [23]. In his paper, he studied the relationship of five different attributes and their effectiveness on classifying human activity. Baek selected mean, standard deviation, skewness, kurtosis, and eccentricity as the signal features. According to Baek, mean and standard deviation can distinguish static (stand, sit and lying) and dynamic activities (walking, running, and using stairs) effectively. The x-axis of skewness, however, is able to differentiate walking and running from ascending and descending stairs. The y-axis, on the other hand can differentiate walking and ascending stair from running. Baek also mentioned that walking and running can be distinguish using stairs by the x-axis of kurtosis. Figure 2 illustrated how each statistical feature distinguishes their respective activity.

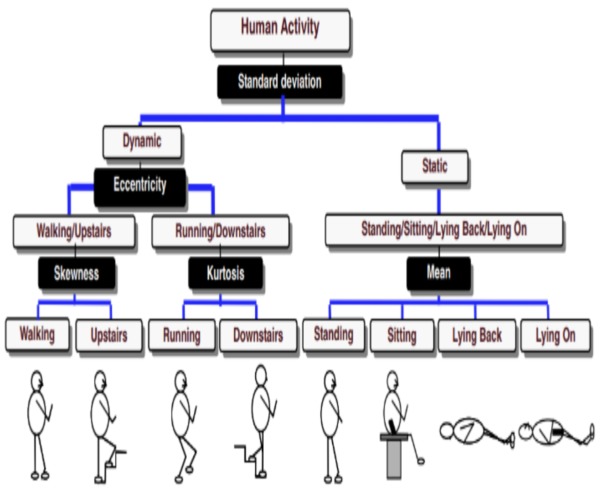

Figure 2. Features in ADL classification [23]

V. PROPOSING FRAMEWORK

We propose the work in recognition of ADL to address the subject independent, as emphasized in the beginning of this article. It might incapable to produce high accuracy when it involves a different pattern of a subject with a different action.

For instance, even if there are two different subjects working in the same activity, it does not have to produce the same pattern of acceleration. Moreover, it tends to make the learning algorithm more complex to learn the characteristics of the activity pattern. Therefore, we are proposing the framework to address this topic. The entire scope of our work is shown in Figure 3.

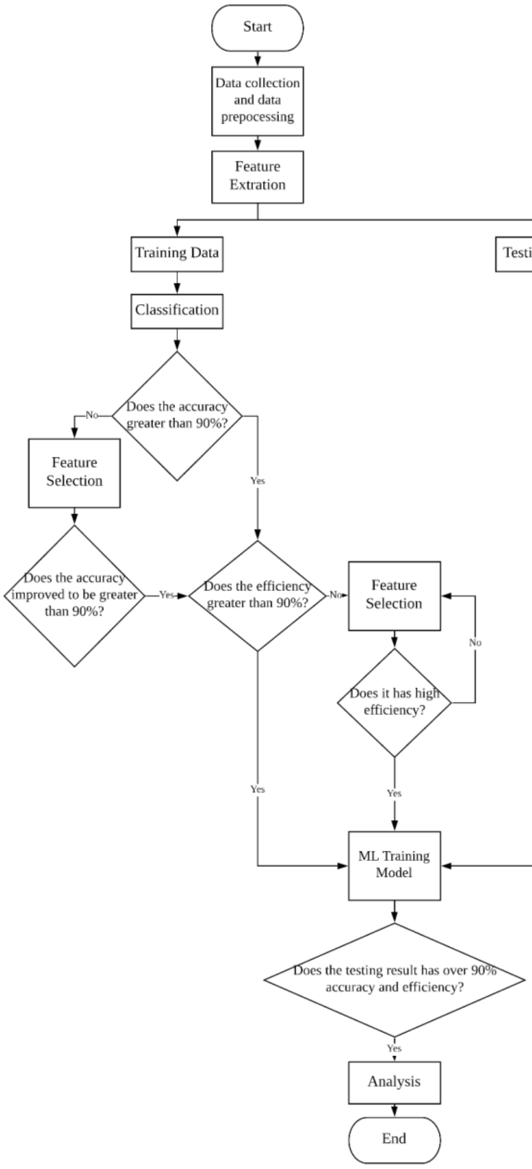

Figure 3. Overall proposed framework

Figure 3 shows the entire process flow of our proposed algorithm to address the issue of the independent subject's activities. At the outset, the acceleration signal will be filtered and unwanted data is removed before further processing begins. Next, several additional features by combining from mathematical and statistical features will be extracted and the extracted features subset will be separated into two subsets; training (70%) and testing (30%). The training subset is used to train the training model, while the learning model is assessed using the reserve testing subset when it achieves acceptable performance. The effectiveness of the classification is taken into account when the result has a more than 90% accuracy. However, some of the features might unnecessary to portray the activity. Hence, the selection of good features is taking into deliberation. We will then assess each feature's efficiency using various techniques of extraction until it achieves its desired accuracy. In order to improve its accuracy and effectiveness, the feature extraction method should also be repeated to obtain more meaningful features. Finally, the testing and training process is repeated and compared in detail for numerous machine learning models.

VI. CONCLUSION

The article describes the empirical analysis of the wearable sensor's recognition of daily activity. As mentioned in the early section, the use of wearable sensor such as an accelerometer is practical due to low cost and small in sizes. Hence, we obtained the activity recognition data from public dataset to undergo our research. On top of that, we propose the framework in which the different human activities are recognized without depending on their identity. As already said, many reported works are not regarded the matter of independent subjects. Although a number of the reports have addressed the subject independent matter, the accuracy achieved remains below 90%. This matter might be happening due to some of the features may irrelevant to describe the activity of a different subject. The selection of features is considered as critical to cater this issue. Hence, we are proposing to address subject independent matter to improve the recognition accuracy with a variety number of subject in our projection work. We also propose a feature selection method in order to evaluate the performance of each extracted features which leads to desired accuracy performance. In future work, we are planning to evaluate the performance of our proposed work by enhancing the recognition accuracy of subject independent matter using several machine learning and feature selection models using a wearable sensor.

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