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Activity Recognition on Subject Independent Using Machine Learning

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***Abstract*:** *Recent Activity Daily Living (ADL) not only tackles simple activities, but also caters to a wide range of complex activities. Although the same activity has been carried out under the same environmental conditions, the acceleration signal obtained from each subject considerably differs. This happens due to the pattern of action generated for each subject is diverse based on several aspects such as subject age, gender, emotion and personality. This project therefore compares the accuracy of various machine learning models for ADL classification. On top of that, this research work also scrutinizes the effectiveness of various feature selection methods to identify the most relevant attribute for ADL classification. As a result, Random Forest was able to achieve the highest accuracy of 83.3% on subject independent matter in ADL classification. Meanwhile, CFS Subset Evaluator is considered to be a good feature selector as it successfully selected the 8 most relevant features compared with Correlation and Information Gain Evaluator.*

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

1. Introduction

Recognition of the Activity Daily Living (ADL) has recently been garnered for providing a piece of valuable information to a human being. Small and portable, a wearable sensor such as an accelerometer has opened the space for researchers to explore the prior knowledge of pervasive computing. Today, most people own a personal smartphone regardless of their age [1]. Current technology enables users to detect daily activities based on the smartphone accelerometer readings while at the same time reducing the risk of injury. According to research reported by L i m [2] 279 out of 4842 elderly Malaysian over 60 years of age experienced home injuries [2]. This problem could lead to fatal injuries especially if the elderly is alone at home and no real-time action can be taken. In addition to the elderly risk of injuries, recognition of ADL can also be used for automated physical therapy where the doctor can observe the daily activities of the patient in order to identify their recovery status in intelligent manners. As a result, for example, high accuracy and efficiency of the ADL classification using a machine learning model are required. Doctors are difficult to track all the day-to-day activities of their patients to monitor their treatment progress, as the process is time-consuming. The same problem also happens in the old fork house, where the guardian has to take care of many elders at the same time. Elderly people with ADL disabilities may be hurt by themselves when they try to complete their daily work on their own. This is dangerous if an accident has occurred and nobody notices and is unable to provide any real-time assistance.

There are two types of ADL classification; subject-dependent and subject-independent. The former shall be carried out by evaluating the same group of subjects as the training group. The latter is done by separating the group of subjects for training and evaluation. Thus, the same subject has not been used to validate the learning model. In the previous research, most of the work on the ADL machine learning classification focuses only on the subject-dependent manner. In addition, most of the works reported involve a few numbers of subjects that are considered insufficient to describe the pattern of activity in effective ways. However, the accuracy of the recognition tends to decrease when a large number of a subject is involved. Theoretically speaking, when doing the same activities, different people will have a different posture and pattern. Also, when only a few subjects are involved in the training process using machine learning, it may be inaccurate to classify activities for other subjects [3]. On top of that, previously reported work also not performing feature selection to choose the most relevant attribute for improving the efficiency and accuracy of classification results [4]. The main contribution of this article is that the experimental work is able to prove an outstanding accuracy for subject independent matter which is there is very few works reported to tackle this issue. Even though some of the reported work capable to achieve high accuracy performance, the number of subjects used still low and ranges of 2-4 subjects compared to this work, which is 34 subjects in total. Furthermore, this work also evaluates several number of feature selections to measure the effectiveness of the selected features in handling subject independent matter. It is also proven that the use of too many features is not necessarily guarantee an outstanding performance. This article is an extension of our previous published work [12]. In our previous work, we are proposing a framework to address the recognition of subject-independent matter in ADL since there is no experiment has yet been carried out. Hence, this work is therefore an extension of our work by conducting an experimental analysis of the proposed framework in order to demonstrate our effectiveness of the proposed analysis.

The organization of this article is as follows: Section 2 describes the review of some related works that have been published regarding the topic discussed; Section 3 explains the data experiment and analysis of this work; Section 4 discusses the results of the analysis and discussion of the experiment that has been carried out; Section 5 describes the comparison studies of this work with some most related works and the last section explains the conclusion and open discussion for further research into this work.

2. Related works

Research on the classification of daily living activity using a machine learning model has been reported several times in the past. The comparative analysis performance of the previous work for both subject-dependent and subject-independent manners is shown in Table 1. The first column shows the name of the author, followed by the machine-learning model (method) used, including total activities involved. The last two columns show that neither the work reported involves subject independent manner on their analysis. The accuracy of each work has also been reported.

Table 1. A comparison of previous related work to ADL classification

Author	Method	Activities	Independence	Accuracy (%)
Cufoglu and Coskun [5]	IBL, KNN, K-star, J48, LWL, NB Tree	11	✗	70.86 (K-star with 9 datapoints)
Cheng et al. [3]	SVM, HMM, NN	5	✗	99.5 (SVM)
Cheng et al. [3]	SVM, HMM, NN	5	✓	61.9 (NN)
Walse, Dharaskar and Thakare [4]	Decision Stump, Hoeffding Tree, Random Tree, REP Tree, J48, Random Forest	6	✗	94.61 (REP Tree)
Fida et al. [6]	SVM, KNN, NB, MLP, DT	6	✗	96.3 (SVM)
Fida et al. [6]	SVM, KNN, NB, MLP, DT	6	✓	80~90 (SVM)
Cleland [7]	SVM, J48, NB, NN	4	✗	97.81 (SVM)
Awan et al. [8]	J48, NB, BN, KNN, MP, LR	11	✓	99.07 (KNN)
Nabian [9]	LR, KNN, RF, NB, DT, SVM, NN	12	✗	99.4 (KNN & RF)
Kwapisz, Weiss and Moore [10]	J48, LR, MP, Straw Man	6	✗	98.3 (MP)
Ravi et al. [11]	Decision Table, DT, KNN, SVM, NB	8	✗	>90 (plurality voting)
Ravi et al. [11]	Decision Table, DT, KNN, SVM, NB	8	✓	73.33 (Boosted SVM)

3. Data and experiment analysis

3.1. Activity daily living

The ADL is a term that describes the people’s daily self-care activities. There are many activities in the ADL category, ranging from simple activities such as sitting, running, jogging to more complex activities, such as bathing, grooming and dressing, going to the toilet and moving from one place to another. The basic ADL is not limited to the activities mentioned above; it also includes all the daily activities that a person can perform without the assistance from others. There are basically several types of daily activity; static, dynamic and complex. Static activity is described as an activity involving non-repetitive body movements such as sitting and standing. In the meantime, activity involving repetitive body movements such as jogging, running and walking is considered to be a dynamic group. On top of that, the complex activity consists of an activity that requires a sequence of actions such as shopping, preparing dinner and gardening. Previous work on the recognition of ADL using machine learning focuses mainly on static activities such as walking, standing, sitting, ascending stairs and descending stairs [4]. However, some researchers cover transition activities, such as from standing up to sitting down and followed by lying down on a couch [5, 3].

3.2. Dataset

The dataset provided by WIreless Sensor Data Mining (WISDM) Lab was utilized [10]. They have recorded a total of what was used to evaluate the performance of this work. A total of 1,098,207 samples were recorded to represent six different activities including walking, jogging, upstairs, downstairs, sitting and standing. The data is collected by means of a triaxial accelerometer located at the hip of the subject. The collected process is fully monitored and guided by its representative in the laboratory environment. In this experiment, the entire dataset is randomly separated to a ratio of 70% for training data and 30% for testing data. For the purpose of validation in a subject independent manner, a holdout validation strategy approach is used to evaluate the performance of the classification process. For a total of 36 subjects, therefore, subjects from 1 to 26 are assigned as a training subjects and subjects from 27 to 36 are assigned as a testing subsets.

3.3. Feature extraction

In order to extract additional information on the signal characteristic, a number of features need to be derived. The purpose of feature extraction is to increase the understanding of the signal by extracting some valuable additional information to describe the class characteristics. This study therefore uses a sliding window segmentation technique with a window size of five seconds and a 50% overlap between two adjacent window segments as shown in Fig. 1.

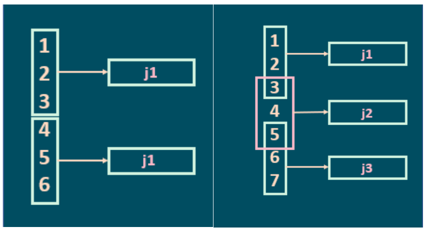

Fig. 1. Segmentation using sliding window approach

Therefore, the number of reduced instances can be defined as in the next equation:

$$j = \frac{m - \text{ovs}}{s - \text{ovs}}, \tag{1}$$

where j is the number of reduced, m is maximum number of instances, s is the window size, and ovs is the overlapping size.

Several features are extracted from each segment of the segmented window. The features extracted for this study are mean, standard deviation, kurtosis, skewness, variance, median, minimum value, maximum value, harmonic mean and the correlation between each axis. The number of instances is reduced from 1,098,207 to 21,503 after the extraction of the feature. The number of instances for each activity is shown in Table 2.

Table 2. Number of instances for each activity after feature extraction

Class	Number of instances	
	Training	Testing
Downstairs	1324	635
Jogging	4878	1733
Upstairs	1718	388
Walking	5995	343
Sitting	775	689
Standing	591	2434
Total	15,281	6222

3.3. Performance measurement

The confusion matrix is used to evaluate the performance of a machine learning model in classifying activity based on its accuracy as the main parameter. Fig. 2 shows the confusion matrix layout that describes the results of the classification. There are several parameters defined in the confusion matrix: a) TP indicates the number of true-positive classifications, b) TN indicates the number of true-negative classifications, c) FP indicates the number of false-positive classifications, and d) FN indicates the number of false-negative classifications. The performance of the classifier is defined by its accuracy in the classification of activities. The formula for accuracy is

$$\text{accuracy}=\frac{TN+TP}{TP+TN+FP+FN}. \tag{2}$$

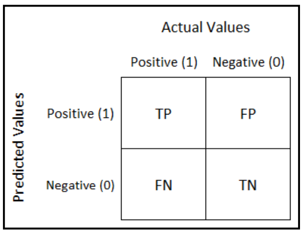

Fig. 2. A confusion matrix describing the classification outcome

4. Result and discussion

4.1. Classification

Classification for subject-dependent and subject-independent shall be performed for comparison using different machine learning models. As mentioned in the previous section, the entire number of subjects are divided into two different subsets (subjects 1 to 26 apply for training, while subjects 27 to 36 are reserved for testing). For validation purposes, 10-fold cross validation strategies are applied to ensure the effectiveness of this experiment by reducing the dependence on the particular data that is used from the entire datasets. The result is shown in Table 3.

Table 3. Comparison of various machine learning model's accuracy between subject dependent and subject independent classification

Machine Learning Model	Subject dependent	Subject independent	
	Testing (%)	Training (%)	Testing (%)
Random Forest	97.50	98.07	83.35
ANN	92.82	94.18	77.02
J48	93.04	93.61	75.96
REP Tree	91.15	92.31	74.64
KNN (IBK)	97.63	98.13	72.08
KStar	98.17	98.53	71.84
Naïve Bayes	66.83	70.28	63.89
SVM	78.02	78.61	55.45

Random forest shows the highest accuracy for both subject-dependent and subject-independent classifications. The confusion matrix for the best performance machine learning model is shown in Table 4 and Table 5.

Table 4. Confusion Matrix for Random Forest classifier on subject-dependent test

Activity	Downstairs	Jogging	Upstairs	Walking	Sitting	Standing
Downstairs	544	6	25	21	0	0
Jogging	1	1964	5	7	0	0
Upstairs	16	27	652	22	0	0
Walking	6	5	12	2505	0	0
Sitting	2	0	2	1	350	3
Standing	0	0	0	0	0	275

Table 5. Confusion Matrix for Random Forest classifier on subject-independent test

Activity	Downstairs	Jogging	Upstairs	Walking	Sitting	Standing
Downstairs	389	23	116	106	1	0
Jogging	13	1600	69	51	0	0
Upstairs	61	107	458	62	1	0
Walking	42	261	40	2091	0	0
Sitting	0	0	0	0	318	70
Standing	2	0	0	1	10	330

In the case of a subject-independent classification, 70 samples from sitting are misclassified as standing and 10 samples from standing are misclassified as sitting. This is because sitting and standing are a bit confused for the model to be classified because both activities are stationary and difficult to distinguish between the classifier models.

4.2. Feature selection

In any classification problems, dealing with higher dimension data leads to the prevalence of noisy, irrelevant and redundant data. This situation might cause overfitting of the model and also would increases the error rate of the learning algorithm [14]. The three feature selection methods, including the CFS Subset evaluator (CFS), Correlation based Attribute (CA) Evaluator and Information Gain (IG) Attribute Evaluator are evaluated in this study. The CFS Subset Evaluator uses the best first method and selected 8 of the 30 most relevant features. The eight features included the standard deviation of *X*-, *Y*- and *Z*-axis, the variance of *Y*-axis, the median of *Y*-axis, the minimum value of *Y*-axis, the minimum value of *Z*-axis, and maximum value of *Y*-axis. This feature selector uses many attributes related to the *Y*-axis because it has recorded an accelerometer reading of the vertical direction, which has the most significant changes when a subject performs the activity. The subject-independent classification result of the various machine learning models is shown in Table 6.

Table 6. The performance of various classifier using 8 attributes selected from CFS Subset Evaluator

Machine Learning Model	Time (sec)	Training (%)	Testing (%)
Random Forest	3.96	95.05	79.32
J48	0.35	90.92	77.39
REP Tree	0.15	89.86	75.41
ANN	14.19	84.59	76.21
Lazy IBK	0	94.88	75.06
K star	0	95.05	77.21
Naïve Bayes	0.03	77.89	73.06
SVM	28.18	92.70	76.44
Average Accuracy			76.28

It can clearly be seen that the total time required to evaluate the testing subset is low in average. Even though tree-based, instance-based and probability-based classifier are considered as highly efficient, the average accuracy is still low compared to an ensemble classifier, random forest. The CA cut-off value is 0.1, while the IG cut-off value is 0.4. The correlation of each attribute is tabulated in Table 7, while Table 8 shows the accuracy of different machine learning models using the 17 attributes obtained from CA feature evaluator. It has been proven that the 5 seconds building time is believed as good enough to prove the effectiveness of CA with random forest in recognizing different types of activities using 17 attributes. Although the rest of the classifier models except ANN are able to prove its efficiency, this matter might not be considered since the main indicator of this work is the accuracy performance.

Table 7. The correlation of each feature using Correlation Attribute Evaluator

Features	Correlation	Features	Correlation
Variance *Y*-axis	0.4229	Mean *Z*-axis	0.1508
Min *Y*-axis	0.3706	Mean *X*-axis	0.1106
Variance *X*-axis	0.3511	Skewness *X*-axis	0.0970
Std *Y*-axis	0.3420	Kurtosis *X*-axis	0.0942
Variance *Z*-axis	0.3323	Median *X*-axis	0.0901
Std *X*-axis	0.3084	Correlation $X – Z$	0.0813
Std *Z*-axis	0.3074	Skewness *Y*-axis	0.0757
Min *Z*-axis	0.2977	Skewness *Z*-axis	0.0732
Min *X*-axis	0.2803	Correlation $X – Y$	0.0689
Mean *Y*-axis	0.2585	Kurtosis *Z*-axis	0.0632
Median *Y*-axis	0.2440	Correlation $Y – Z$	0.0625
Max *Z*-axis	0.2123	Kurtosis *Y*-axis	0.0570
Max *Y*-axis	0.1783	Haar Mean *X*-axis	0.0101
Max *X*-axis	0.1674	Haar Mean *Y*-axis	0.0051
Median *Z*-axis	0.1556	Haar Mean *Z*-axis	0.0023

Table 8. The performance of various classifiers using 17 attributes selected from Correlation Attribute Evaluator with cut-off value of 0.1

Machine Learning Model	Time (s)	Training (%)	Testing (%)
Random Forest	5.16	97.38	80.99
J48	0.62	93.41	75.46
REP Tree	0.21	92.06	73.72
ANN	25.26	90.69	77.60
KNN (IBK)	0.01	97.49	72.97
KStar	0.0	98.18	72.89
Naïve Bayes	0.05	75.39	72.57
SVM	95.86	93.14	57.65
Average Accuracy			72.98

Similar to Correlation Attribute Evaluator, Information Gain Attribute Evaluator uses a ranking system to evaluate the most relevant features. The information gain is calculated for each attribute and the attribute with greater than a certain range of information gain is assumed to be the most relevant features. The detailed information gain for each attribute is shown in Table 9 and the performance of the different classifiers using 15 attributes selected from Information Gain Attribute Evaluator with cut-off value of 0.4 is tabulated in Table 10.

Table 9. Information gain of each feature using Information Gain Attribute Evaluator

Features	IG	Features	IG
Variance *Y*-axis	1.0289	Haar Mean *Z*-axis	0.3573
Std *Y*-axis	1.0289	Kurtosis *Y*-axis	0.3359
Min *Y*-axis	0.9229	Mean *Z*-axis	0.3330
Std *X*-axis	0.8358	Median *Z*-axis	0.3305
Var *X*-axis	0.8385	Mean *X*-axis	0.3174
Variance *Z*-axis	0.7071	Kurtosis *Z*-axis	0.2929
Std *Z*-axis	0.7071	Median *X*-axis	0.2697
Min *Z*-axis	0.6987	Kurtosis *X*-axis	0.2663
Max *Y*-axis	0.6282	Correlation $Y – Z$	0.2443
Mean *Y*-axis	0.5964	Haar Mean *Z*-axis	0.2443
Median *Y*-axis	0.5158	Skewness *Y*-axis	0.2396
Min *X*-axis	0.4648	Skewness *Z*-axis	0.2358
Haar Mean *Y*-axis	0.4539	Correlation $X – Y$	0.2309
Max *Z*-axis	0.4328	Correlation $X – Z$	0.1900
Max *X*-axis	0.4174	Skewness *X*-axis	0.1267

Table 10. The performance of various classifiers using 15 attributes selected from Information Gain Attribute Evaluator with cut-off value of 0.4

Machine Learning Model	Time (s)	Training (%)	Testing (%)
Random Forest	4.15	96.43	79.48
J48	0.78	91.95	73.27
REP Tree	0.11	90.83	73.75
ANN	25.84	89.61	76.05
KNN (IBK)	0.01	96.28	71.92
KStar	0.0	97.17	72.66
Naïve Bayes	0.07	76.57	74.30
SVM	108.9	86.60	58.39
Average Accuracy			72.48

For a more detailed comparison, each method of selection features method is visualized in Fig. 3.

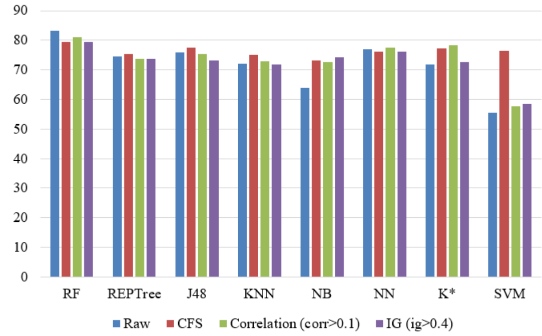

Fig. 3. Accuracy of various machine learning model with different Feature Selection Method

The highest accuracy is achieved by Random Forest without feature selection (30 attributes) with an accuracy of 83.3%. The most effective machine learning model, however, is achieved by Random forest with an accuracy of 80.99% using 17 attributes from correlation-based evaluator. For machine learning models such as REP Tree, KNN, NB, KStar and SVM, their accuracy with feature selection is higher than the accuracy without performing feature selection. This is because the irrelevant features have been removed during the selection process. Performance of feature selection evaluator is ranked from CFS Subset Evaluator, Correlation Attribute Evaluator and Information Gain Evaluator based on their overall performance. The features selected by CFS Subset Evaluator achieved higher accuracy compared to the other selectors. The most significant improvement in classification accuracy with feature selection can be seen in the SVM using CFS Subset Evaluator. Before performing a feature selection, the accuracy of SVM was 55.45%. However, after reducing the number of features from 30 to 8, the accuracy increased dramatically to 76.44%. This is because SVM is a linear classifier and the data stream from the 8 features obtained from CFS Subset Evaluator is believed to be distributed in linear order. The CFS Subset Evaluator is therefore considered to be capable of selecting the most relevant features to address the problem of classifying the subject-independent activity.

5. Comparison with previous work

Due to the variation in posture that exists in daily human activity, the subject-independent activity classification is considered to be more relevant for real-life application as it is not possible to involve each subject in the training process to train the machine learning model. Previous work such as the activity recognition by Kwapisz, Weiss and Moore [10] which focuses only on subject-dependent test is therefore considered less relevant for real-life application.

Some of the previous work such as the work of Cheng at al. [3] and Awan et al. [8], uses too few subjects for the subject-independent activity classification. As a result, the result is considered to be bias due to the limited pattern obtained from his work. L. Cheng uses four subjects in his previous work for the subject-independent classification to obtain an accuracy of 61.9%, whereas Awan uses only two subjects and achieved an accuracy of 99%. However, this model, which can precisely classify an activity for a person, does not necessarily mean that it can precisely classify the activity of others because everyone has a different posture towards performing activities.

This project also achieved an improvement in accuracy compared to the previous work carried out by Cheng et al. [3]. In his work, an artificial neural network achieved 61.9% of classification accuracy, while this work obtained 83.3% of accuracy with Random Forest.

6. Conclusion and future work

This paper presented the classification performance of the subject-independent activity using the data provided by WISDM. In general, Decision tree-based classifier is the most accurate in classifying subject-independent activity. This is proven by random forest with 83.3% of accuracy. At the same time, this paper also evaluates the most appropriate method of feature selection that can be used to select the most relevant attribute for ADL classification. As a result, the CFS subset evaluator has selected the most relevant features that have a high overall accuracy and a short time to build a model. The CFS subset evaluator is also effective in selecting the right features for SVM. It increased its classification accuracy from 55.4% to 76.4% by reducing the number of features from 30 to 8.

In terms of future work, dynamic activities involving transition such as walking to running, standing to sitting and standing to jumping may be included for classification. With the ability to classify transition activities, it is possible to recognize different orders of complex actions such as sports, laundry and so on [15, 16]. Fall detection can also be recognized when the classification model is effectively performed in the classification of the transition between activities. We are also planning to expand our analysis using MobiAct dataset in our experiment [13]. In the meantime, we are unable to conduct our experiment using different dataset since the MobiAct consists of a wide ranges of activities which involving falling activities with different angles, which are considered as beyond our scope of work for daily living activities.

Real-time classification could also be achieved in the future by implementing the innovation of Internet of Things (IoT). The accelerometer reading of the activity sensed from the smartphone will then be sent to the cloud so that the machine learning model can be classified in real-time. This will be helpful in collecting such large and practical data to be used for monitoring real-time activities.

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