Single Triaxial Accelerometer-Gyroscope Classification for Human Activity Recognition

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***Abstract*—Evaluated activity as a detail of the human physical movement has become a leading subject for researchers. Activity recognition application is utilized in several areas, such as living, health, game, medical, rehabilitation, and other smart home system applications. For recognizing the activity, the accelerometer was popular sensors. As well as a gyroscope, in addition to dimension, low computation, and can be embedded in a smartphone. Used smartphone with an accelerometer as a popular solution for recognized daily activity. Signal was generated from the accelerometer as a time-series data is an actual approach like a human activity pattern. Traditional machine learning method in mid of the modern method worth it considering. Single position triaxial accelerometer-gyroscope Motion data have acquired in an of 30 volunteers. Basic actives (Laying, Standing, Sitting, Walking, Walking Upstairs, Walking Downstairs) were collected from volunteers. Decision Tree, Random Forest, Extra Trees Classifier, KNN, Logistic Regression, SVC, Ensemble Vote Classifier. The purposed method, logistic regression, achieves 98% accuracy. Furthermore, any feature selection and extraction method were not used.**

Keywords—Activity recognition, accelerometer-gyroscope sensor, health, human-computer interaction.

I. Introduction

Human activity recognition (HAR) is a field of study that increased with significant topic interest. Due to its wide application in human behavior, living assistance, home applied, security, medical, rehabilitation, and wider to smart cities, and transportation topics. From previous research on the medical, and rehabilitation topic has improved health status for diabetic patient, elderly monitoring, non-communicable disease (NCD), calories [1], [2] and fall detection [3], human behavior [4]. Daily activity recognition requires a robust technique that can be used under free daily motion, for example, recognition of fall detection, especially in elderly fall detection. Fall injuries caused an inability to live independently in a broader impact lead life-threatening [5].

Obesity, a part of NCD, is a preventable disease, from several factors, including education, behavior change, personality [6]. Poor diet, less movement, an increase of weight and body mass index (BMI) as an aspect that causes premature physical deterioration and cognitive decline [7]–[9]. Lifestyle changes and awareness of it are necessary, activity recognition as a technology for monitoring and improvement can suggest any information may be needed for it.

The rapid development of artificial intelligence also increases in activity recognition field. Several approaches were recognizing activities from one [10]–[14] or more sensor [9], [15], [16] placement at the human body. Another approach based on vision was used in previous research but with some limitations, such an environmental restriction [12]. The camera amount used as the sensor was created a dimension of image as data. In other, placement sensors as wearable devices have more reliable to measure an evaluation based on pattern activities.

Accelerometer, gyroscope (inertial sensor) were used in a few research. Single or combine that sensor make several opportunities for research. The main areas to find less complexity especially as an embedded system or applied as the mobile application. Accuracy of inertial sensors based on accurate signal processing recognizing pattern activities was becoming problems in the HAR field.

Previous research recognizing several activities from a different kind of sensor, except camera, and accelerometer, gyroscope sensor other author used electromyograph, audio infrared, and another sensor [5]. Accelerometer-based has several advantages, small, low computation, less expensive. With a small dimension as wearable devices or embedded in a smartphone, an accelerometer can use in the human body. The different position was tasted such as arm, waist, head, shoulder, pocket [17]. Several research methods from modern machine learning were recorded in this decade.

The proposed in this paper recognizes basic activity from public HAR datasets with traditional machine learning methods with more accuracy. Without feature reduction and selections, it can reduce the preprocessing process and computation. For this reason, we used a public dataset with a single position of accelerometer and gyroscope and have basic activity classified.

Section of this paper is organized as follows: Methods, provide information how this work was done, Data characteristic from HAR public datasets describe in Selection of data sets in Section 3, experimental result, model selection, testing models and at the last we will discuss and compare from previous research at end of this section. Conclusion is given in section 4

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II. METHODS

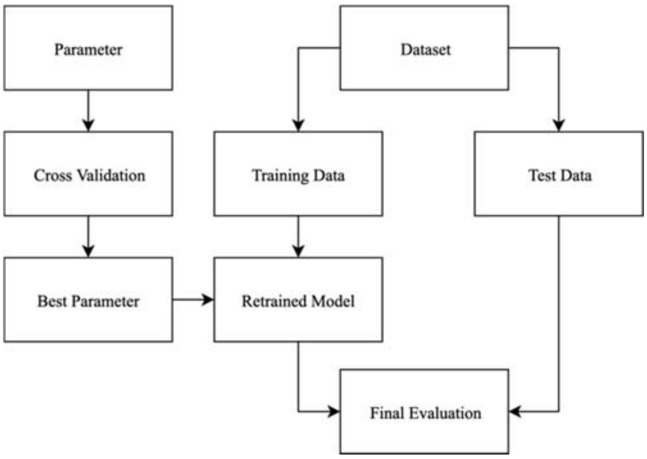

Fig. 1. Flow for model selection and evaluation

In this paper, we used two approaches to solve recognizing problems. Data from public dataset at first approach were used as data train for retrained model until has best parameters. The best parameter has an evaluation with the cross-validation score in Sklearn. The second approach evaluated the model in the previous step with the data test from the data set. For evaluation and comparison with another method, we used accuracy, precision, recall, and F1 score. For future research, the experimental result can be seen at [18].

III. EXPERIMENTAL RESULT AND ANALYSIS

A. Selection of Data Sets

Particular studies on this topic, the data are homogeneous such as age similarity in a certain range, the same range of education [19]. Research in this article chose public data from the UCI HAR dataset [20] which is a renewal of the previous dataset [14]. The selected data set has the characteristics of six basic activities, divided into three statistical activities (sitting, lying, and lying) as well as three dynamic activities, walking up the stairs, and walking up the stairs) as shown in Table 1. The sensor used in data retrieval uses an accelerometer and a gyroscope that is embedded in a smartphone (Samsung Galaxy SII). The accelerometer and gyroscope data have a frequency of 50Hz. The number of subjects used was 30 people with an age range between 19 to 48 years. Data is labeled manually by comparing video recordings. From a number of respondents, 70% is used for training data, and 30% is used for test data.

TABLE I. INSTANCE DISTRIBUTIONS AT EACH ACTIVITY

Activities	**Number of Instances**	
	Data Training	Data Test
Laying	1407	537
Standing	1374	532
Sitting	1286	496
Walking	1226	491
Walking Upstairs	1073	471
Walking Downstairs	986	420

B. Experimental Results

In this section, we will discuss the results attained using different machine learning approaches, including Decision Tree (DT), Random Forest (RF), Extra Trees Classifier (ET), KNN, Logistic Regression (LR), SVC, Ensemble Vote Classifier (ECLF). As stated, the empirical performed in this paper are two approaches. The first approach retrained suitable model selection of basic activity recognition. In order to generate a basic model, we used 70% of selected train datasets with performed supervised learning techniques. In the second approach, we used a selection model to evaluate 30% of the dataset. In this section, we will describe the experimental setup and result of each approach separately.

Model Selection

The experimental setup and the results obtained using supervised learning techniques. First, we will compare several differences in machine learning approaches. Activity recognition is performed using six basic class activity, “Walking", "Walking Upstairs", "Walking Downstairs", "Sitting", "Standing", "Laying" with a distribution of each data as shown in Table 1.

The LR consistently provides the best results with the normal distribution of each class in train datasets and closely followed by the Ensemble Vote Classifier, which classified each method described before. The accuracy Score for each is shown in Table 3.

Testing Model

Second approach can be performed from the experimental result used testing model. In the first step, we were obtained several supervised machine learning methods. It is important to consider that model selection at first approach was given the same result. It is noted that for each dataset from UCI HAR Datasets was classified into two separated data, train data and test data which each has have 563 features. We dropped one non-necessary feature (Subject) and separated one other feature as an activity label in train and test data. 30% of data that was separated as test data, and used to evaluation of selection model.

Table 2 as a selection model best result provided by LR, but slightly different from selection model ECLF give less accuracy than SVC may this was be affected by DT that have worst accuracy in this case:

TABLE II. CONFUSION MATRIX FOR THE MOST ACCURATE MODEL

True activity	Laying	Standing	Sitting	Walking	Walking Upstairs	Walking Downstairs
Laying	1	0	0	0	0	0
Standing	0	0.879	0.112	0	0	0.008
Sitting	0	0.024	0.971	0.003	0	0
Walking	0	0	0	0.996	0.004	0
Walking Upstairs	0	0	0	0.009	0.969	0.021
Walking Downstairs	0	0	0	0	0	1

TABLE III. *Confusion matrix for the most accurate model*

Method		Accuracy	Activities	Subject	Number of sensors	Number of Features
SVM [10]		93%	Stopping, Walking, Standing-up, Sitting-down	10 (20-55 Years)	Single triaxial accelerometer	100
SVM [11]		80%	Running (Competitive & recreational)	41 (30-35 Years)	Single triaxial accelerometer	
SVM [12] DT LR GP TH		98% 99% 97% 99% 99%	Laying, Standing, Sitting, Walking, Walking Upstairs, Walking Downstairs, stand-to-sit, sit-to-stand, stand-to-lie, lie-to-stand, sit-to-lie, and lie-to-sit	30 (19-48 years)	Single triaxial accelerometer & triaxial gyroscope	585
DCNN [13] FRDCNN		94.18% 95.27%	walking, jogging, jumping, and go upstairs and go downstairs, sitting, standing, lying to the left and right side, and lying supine and prone	20 (21-30 years)	accelerometer, gyroscope, and magnetometer	248
DT [21] NB KNN MLP SVM RF		70% 45% 81% 57% 57% 81%	Treadmill at 1 mph @ 0% grade, Treadmill at 2mph @ 0% grade, Treadmill at 3mph @ 0% grade, Treadmill at 3mph @ 5% grade, Treadmill at 4mph @ 0% grade, Treadmill at 5mph @ 0% grade, Treadmill at 6mph @ 0% grade, Treadmill at 6mph @ 5% grade, Seated & folding/stacking laundry, Standing/Fidgeting with hands while talking, 1 minute brushing teeth + 1 minute brushing hair, Driving a car, Hard surface walking w/sneakers, Hard surface walking w/sneakers hand in front pocket, Hard surface walking w/sneakers while carrying 8 lb. object, Hard surface walking w/sneakers holding cell phone, Hard surface walking w/sneakers holding filled coffee cup, Carpet w High heels or dress shoes, Grass barefoot, Uneven dirt w/sneakers, Uphill 5% grade w high heels or dress shoes, Downhill 5% grade w high heels or dress shoes, Walking upstairs (5 floors), Walking downstairs (5 floors)	77 (18-65 years)	Single triaxial accelerometer	176
SVM [14]		96%	Laying, Standing, Sitting, Walking, Walking Upstairs, Walking Downstairs, stand-to-sit, sit-to-stand, stand-to-lie, lie-to-stand, sit-to-lie, and lie-to-sit	30 (19-48 years)	Single triaxial accelerometer & triaxial gyroscope	561
A Predictive algorithm [22]		90	Sitting, standing, drive	1 (42 years)	Accelerometer	
ANN [23]		93%	Walking, Running, Sitting, walking Upstairs, Downstairs, and Standing	10 (age range not describe)	Single X, Y Accelerometer	4
Euclidean Distance [15]		95.8%	sitting (duration 60 s); 2. standing (duration 60 s); 3. lying supine (duration 60 s); 4. sitting and talking (duration 60 s); 5. sitting and operating PC keyboard (duration 60 s); 6. walking (duration 60 s); 7. stairs up (duration about 40 s); participants were asked to climb stairs (60 steps) at their usual speed in the laboratory building; 8. stairs down (duration about 40 s); and 9. cycling (duration about 40 s); participants rode a bicycle around the block.	24 (21-34 years)	Four Accelerometer	Not describe
DT [16]		84%	Walking, Walking carrying items, Sitting & relaxing, working on computer, standing still, Eating or drinking, Watching TV, Reading, Running, Bicycling, Stretching, Strength-training, Scrubbing, Vacuuming, folding laundry, lying down & relaxing, brushing teeth, Climbing stairs, Riding elevator, Riding escalator	20 (age range not describe)	Two biaxial accelerometers	512
Pattern recognition neural networks [9]		99.8%	standing, sitting, kneeling, crawling, walking, lying with the face down, lying with the face up and lying on one side.	4 (23-27)	Two Triaxial accelerometer	48
Purposed Method	DT RF XT KNN **LR** **SVC** ECLF	93.44% 96.73% 96.68% 96.21% **98.40%** **93.86%** 97.60%	Laying, Standing, Sitting, Walking, Walking Upstairs, Walking Downstairs	30 (19-48 years)	Single triaxial accelerometer & triaxial gyroscope	561

1. In many cases, sensors probably record thin difference accelerometer and gyroscope while "standing" and "sitting" human movement from this activity can capture perfect from one sensor, especially from this dataset previous researchers [20] shows that sensor on the waist during the experiment execution. However, adding a hearing sensor could solve this problem.
2. Also, in this paper focus on basic activity, a slight difference between two or more activities might happen particularly from static activities. Transition feature as an additional feature to more accurate classification for future research.

C. Discussions

In experimental multiple classification models such as decision tree, linear regression, and SVM were used to classified. At the note, in this paper we not use any feature selection and reduction, we used all featured given by public dataset was describe in the previous point. According to the experiments presented in this paper we comparing several previous kinds of research. From this method with two approach model, selection and evaluated model SVM has 93.86% accuracy. In previous research which used SVM as classified, Fuantes et. al. (93%) [10] with the best accuracy for stop and walking activities. They used 100 related features such as angle calculation, the acceleration module, increments, and averages. Another result has been recorded by Fan et. al [12] (98%) which used the same public HAR dataset, but as written by Anguita et.al. [14] that have 561 features, in [12] shown that used 585 features. However, both [12] or [14] have 98% accuracy they do more complex computing for feature selection and classification method and they used two classes, basic activity and transition activity that may more accurate result for recognizing static activity like standing and sitting. Yet has 93.86% accuracy we used just basic activity and less computation without feature selection it's something to be proud of.

Bao et.al. [16] that used decision tree with 84% accuracy used 512 features with more than 20 activity almost the same as Kim et.al [21] that have 70% accuracy but, Bao et.al. [16] used two biaxial accelerometers that are mean just have X and Y. In another result that more comparable with this experiment was have been by Fan et. al [12] with 98% but with more 20 features than we used that recorded 93.44% with just 561 features.

We just comparable again with Fan et. al [12] that used logistic regression, they recorded 97% accuracy slightly lower than the results we got 98.40%. However, Fan et. al [12] get proud results with 99% accuracy with the Gaussian process and threshold process. Although the results obtained not directly comparable with some previous studies. The purposed traditional machine learning is still relevant for use with basic activities amid the emergence of many modern machine learning techniques. Several modern methods that have been used by several researchers including DCNN and FRDCNN that has 94.18% and 95.27 accuracy [13] it is slightly lower than the results we got 98.40% with logistic regression or from another result from Euclidean distance with 95.8% [15] or Pattern recognition neural networks with 99.8% [9].

IV Conclusion

This paper provides a comparison of several traditional machine learning methods Decision Tree (DT), Random Forest (RF), Extra Trees Classifier (ET), KNN, Logistic Regression (LR), SVC, Ensemble Vote Classifier (ECLF). The method reported in experimental results, LR were classified as good with modern method machine learning, by using Basic activity is part of every daily movement. For example, living assistant, daily movement, medical application, rehabilitation, etc. For example, we can detect the early phase of falls from shifting of basic activities from standing to laying. Basic activities as walking, walking upstairs-downstairs as a fall motion that current topic research that causes a serious health problem.

Without feature extraction and selection provide the same accurate with previous research. Seven models were used then compared with two approach evaluation, the first approach for model selection and secondly approach for model testing for evaluation of model selection. The result has shown that LR has consistency accuracy results with a slight difference. However, from a static basic activity like standing and lying decreased accuracy. It is important to note that datasets for this research single position. The result purposed machine learning is still relevant for use with basic activities amid the emergence of many modern machine learning techniques. For the future possibilities, other machine learning can evaluate transitional activities as evaluated basic activity, in other we can evaluate with a characteristic of data feature as especially in public dataset was classified in arithmetic approach.

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