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Evaluation of Smartphone and Smartwatch Accelerometer Data in Activity Classification

Nguyen Canh Minh
Faculty of Electrical-Electronic Engineering
University of Transport and Communications
Ha Noi, Viet Nam
ncminh@utc.edu.vn

To Hieu Dao[1,2*]
[1]University of Information and Communication
[2]Viet Nam Academy of Science & Technology
Thai Nguyen, Viet Nam
dthieu@ictu.edu.vn

Duc Nghia Tran
Institute of Information Technology
Vietnam Academy of Science and Technology
Ha Noi, Viet Nam
nghiatd@ioit.ac.vn

Nguyen Quang Huy
Institute of Information Technology,
Vietnam Academy of Science and Technology
Ha Noi, Viet Nam
nqhuy@ioit.ac.vn

Nguyen Thi Thu
Faculty of Electronic Engineering
Hanoi University of Industry
Ha Noi, Viet Nam
thunt@haiu.edu.vn

Duc Tan Tran
Faculty of Electrical and Electronic Engineering
Phenikaa University
Ha Noi, Viet Nam
tan.tranduc@phenikaa-uni.edu.vn

Abstract—— **In recent years, the need to monitor health using sensors integrated on popular smart devices is receiving attention. The development of the human activity classification (HAR) system allowed the monitoring and assessing human health status. Most research in this area has been done on smartphones with the limitation of a fixed position on the body to collect raw data and combine it with other machine learning algorithms to improve activity classification performance. However, the phone's location on the body in many studies was not the same, leading to different data collection. Smartwatches solved this problem because they were worn on the human hand and had stability and sensitivity to the body's activities. This research would evaluate the accuracy using data from accelerometers on smartphones and smartwatches, combining with some machine learning algorithms to classify four activities: sitting, standing, walking, and jogging. The classification performance was evaluated through accuracy, sensitivity, and specificity. The overall results showed that the data from the smartwatches accelerometer had higher accuracy than data from smartwatches.**

Keywords— Accelerometer; evaluation; smartphone; smartwatch; machine learning; activity classification.

I. INTRODUCTION

In modern life, smart devices such as smartphones and smartwatches are more and more popular. These devices were integrated with various sensors, long life, and powerful processing capabilities, but they are compact. On these devices, data collected from high-precision sensors is easy to harness for research and building healthcare applications [1], [2]. Thanks to these applications, healthcare professionals will intervene when patients need help most [3]. There were two directions of data collection: i) On the smartphones [4]–[7]; ii) On the smartwatches [3], [8]–[10].

With smartphones, data such as acceleration depends on the orientation of the X, Y, Z axes. This data will be different when the orientation and position of the phone on the body are different. In contrast, smartwatches are usually fixed on the human wrist, so the collected data is uniform. In addition, the human hand works even when the person is non-moving, and the accelerometer data collected on the smartwatch is susceptible to the activities that the hand follows typically, such as typing, jogging, walking, etc. While with smartphones, the data collected from these actions has changed little. Vaizman et al. [8] combined data collected on smartphones and smartwatches with different body positions. In various contexts (Figure 1), they surveyed six activities: lying, sleeping, walking, running, bicycling, etc. However, the results obtained were significantly different when applied in other contexts.

Fig. 1. Device position on the body

Shoaib et al. [11] used three algorithms, including decision tree, k-nearest neighbor (kNN), and support vector machine (SVM) based on data collected from smartphones and smartwatches in the activity classification model. Previously, Parkka et al. [12] collected data on six common activities of ironing, vacuuming, walking, running, and cycling on an exercise bicycle using accelerometers and gyroscopes. The collection device was mounted on locations sensitive to the intensity of human movements such as the waist, wrist, and ankle.

In this paper, we would evaluate the accuracy using three-axis accelerometer data collected from smartphones and smartwatches. Activity classifier models were built with five features and machine learning algorithms to assess the accuracy of these collected datasets (Figure 2). This research used wireless sensor data mining (WSDM) dataset collected from 51 people with five activities, including standing, sitting, walking, jogging, and stairs [13]. Human activities data was segmented by time (sliding window [14]) with different sizes (5 seconds - 10 seconds) to increase the amount of information needed. If the time window size were too short, there would not be enough information about the activity. In contrast, if it were too long, the rate of more than one activity would increase, leading to high latency and misclassification. Accuracy when using a dataset on smartphones and on smartwatches was evaluated via a confusion matrix [15].

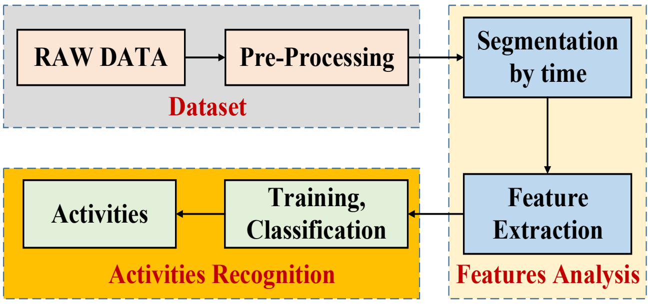

Fig. 2. Overview of the activity classification system

II. METHODS

A. Accelerometer

1) Accelerometer working principle

An accelerometer was a module with built-in sensors that measured the body's mechanical vibrations or changes in velocity during movement by converting those mechanical impacts into electrical signals. The sensor would map those vibrations into a voltage signal containing the velocity of change and direction based on the vibration senses. The accelerometer sensed the impacts on smart mobile devices such as phones or watches and converted them into an electrical signal that the smart device could read and process. Therefore, the unit of acceleration is g or m/s^2, which the following equation could calculate:

$$A_D = -\frac{1}{mass}\sum F_S \tag{1}$$

F_S : Force acting on the sensor itself. The relationship between clan and gravity (gravity) was shown by formula (2):

$$A_D = -g - \frac{1}{mass}\sum F_S \tag{2}$$

Due to the action of gravity, the total acceleration of an actual object always has a minimum value of 1 g whether the object is at rest or in motion (g = 9.800665 m/s^2). Therefore, when calculating the actual acceleration of an object, it is necessary to remove the influence component caused by the earth's gravity. The accelerometers have sensed movement in the X, Y, and Z-axis. The three-axis acceleration values will change when the device rotates or changes direction, such as tilting left or right, flipping upside down. The acceleration unit on smart mobile devices is usually m/s^2.

2) Raw accelerometer sensor data

On smart devices such as phones and watches, the accelerometer value could be read by specialized software. Depending on hardware configuration and programming language, accelerometer accuracy might vary due to sensor quality and programming language. These values were returned as multidimensional arrays (Table I). Source code for reading sensor information on mobile was publicly shared on android development [16].

TABLE I. ACCELEROMETER ON THE ANDROID PLATFORM

Accelerometer	Sensor event data	Description
TYPE_ACCELEROMETER	SensorEvent.values[0] SensorEvent.values[1] SensorEvent.values[2]	Acceleration force along the X, Y, and Z-axis (including gravity)
TYPE_ACCELEROMETER_UNCALIBRATED	SensorEvent.values[0] SensorEvent.values[1] SensorEvent.values[2]	Measured acceleration along the X, Y, Z axis without any bias compensation.
	SensorEvent.values[3] SensorEvent.values[4] SensorEvent.values[5]	Measured acceleration along the X-axis with estimated bias compensation

The following code [16] showed ours how to get a real acceleration sensor value:

```
val sensorManager = getSystemService(Context.SENSOR_SERVICE) as
SensorManager
val sensor: Sensor? =sensorManager.getDefaultSensor
(Sensor.TYPE_LINEAR_ACCELERATION)
```

Thus, raw accelerometer data on a smartphone could be recorded at the desired frequency. A little bit different from a phone, a smartwatch needed to connect to a smartphone via Bluetooth or wifi. The acceleration data on the smartwatches would be saved on the phone.

B. Dataset

Gary M. Weiss [11] collected acceleration data on both smartphones and smartwatches at 20Hz, 50 milliseconds each sample as Table II.

TABLE II. DEVICES INFORMATION

Device	Name	Operating system
Smartphones	Google Nexus 5/5X Samsung Galaxy S5	Android 6.0 (Marshmellow)
Smartwatches	LG G Watch	Android Wear 1.5
Sampling frequency	20Hz	20Hz

The raw time-series sensor data was recorded by both the phone and watch at a rate of 20Hz. Activities data was collected from 51 people and 18 different activities. Each action was performed for about 3 minutes and was labeled accordingly (A, B - S). Thus, the total recording time taken was almost 54 minutes, and there were nearly 64800 lines of data. Our research would present results on five activities of this dataset (Table III).

TABLE III. ACTIVITIES REPRESENTED IN THE DATASET [11]

Activity	Label	Phone	Watch
Walking	**A**	279,817	210,495
Jogging	**B**	268,409	205,787
Stairs	**C**	255,645	207,312
Sitting	**D**	264,592	213,018
Standing	**E**	269,604	216,529

The raw data format to be recorded was: Subject-id (1600-1651), label (A-S), timestamp, X-axis value (m/s^2), Y-axis value (m/s^2), Z-axis value (m/s^2). Example:

1600,A,252207666810782,-0.36476135,8.793503,1.0550842;

1600,A,252207717164786,-0.8797302,9.768784,1.0169983;

1600,A,252207767518790,2.0014954,11.10907,2.619156;

This paper would use accelerometer data for five actions: walking (A), jogging (B), stairs (C), sitting (D) and standing (E).

C. Feature extraction

The dataset used includes phone accelerometer data (F_acc phone) and watch accelerometer data (F_acc_watch). In this research, five features (mean, median, standard deviation, root mean square, and range) would be extracted of 3-axis acceleration X, Y, and Z on each data. These features would be the input to classification models using machine learning algorithms. Thus, there were 15 input feature vectors with accelerometer data from a phone or watch. The above data features were extracted according to the following formulas (3)-(7):

Mean $$\mu(X_j) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (3)$$

SD $$\sigma(X_i) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[x_i - \mu(X_j)\right]^2} \quad (4)$$

RMS $$RMS(X_j) = \sqrt{\frac{1}{N}\sum_{i=1}^{k} x_i^2} \quad (5)$$

Median $$Med(X_i) = \frac{x_{(\#N/2)} + x_{(\#N/2+1)}}{2} \quad (6)$$

Range $$Range(X_i) = \left[\min_{i=1}^{N}(x_i), \max_{i=1}^{N}(x_i)\right] \quad (7)$$

To improve feature quality, the data of the five actions would be segmented by time (sliding windows) with a fixed size of 6 seconds (s). Therefore, the number of features increased many times (Table IV).

TABLE IV. DATA SEGMENTATION OF 5 ACTIVITIES

	Number of windows with size 6s					
Raw	**Sitting**	**Standing**	**Walking**	**Jogging**	**Stairs**	**Total**
Phone	2025	2247	2331	2237	2130	11150
Watch	1775	1805	1754	1715	1727	8776

D. Machine learning algorithms

Machine learning algorithms used to train the data: The segmented data was trained and tested at a ratio of 75/25. On every 6s window, a feature set was extracted on all three axes X, Y, and Z. Then, these features were trained with machine learning algorithms, including decision tree, gradient boosted decision tree (GDBT), support vector machine (SVM), random forest (RF), and k-nearest neighbors (KNN). This research would, in turn, compare the effectiveness of data feature on phones and watches through two classification models and machine learning algorithms: Model 1 with sitting, standing, walking, and jogging; Model 2 Same as model 1 but more than one activity (stairs).

E. Evaluation

The performance of a classification model was evaluated on the test results of the dataset and the confusion matrix [17] containing the actual output and the predicted output to estimate the classifier performance: accuracy (acc), sensitivity (sen), and specificity (spe).

$$acc = \frac{TP + TN}{TP + FP + TN + FN} \quad (7)$$

$$sen = \frac{TP}{TP + FN} \quad (8)$$

$$spe = \frac{TN}{TN + FP} \quad (9)$$

Consider the case with the activity of standing: True positive (TP) was the number of correctly classified standing activities compared to actual observations. False negative (FN) was the number of standing activities classified as other activities. False positive (FP) was the number of other activities classified as standing activities. True negative (TN) was the number of other activities that are correctly classified compared to actual observations.

III. RESULTS AND DISCUSSION

A. Four activities classification model

Four activities classification models obtained for each algorithm were presented in Figure 3. Overall, the percentage of accelerometer data on smartwatches trained by the GBDT algorithm was the highest at 89.55%. In contrast, the figure for the KNN algorithm on the phone made up the lowest rate at 81.31%. The result of data on the phone was a little higher on the watch with algorithms of DT (85.27%) and RF (87.66%). GBDT and RF algorithms had a negligible difference on both datasets.

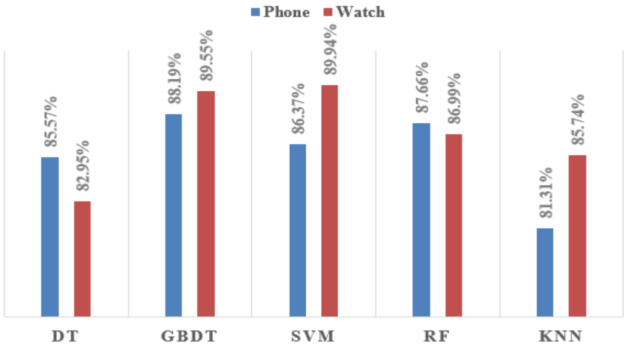

Fig. 3. Results for four activities classification model

The prediction of accuracy when classifying the four activities was presented in Table V.

TABLE V. THE ACCURACY IN CLASSIFYING FOUR ACTIVITIES

Accuracy smartphone				
Algorithm	Sitting	Standing	Walking	Jogging
DT	91.29%	90.90%	92.34%	**94.46%**
GBDT	**94.30%**	93.51%	**92.76%**	94.35%
SVM	92.53%	**94.10%**	90.68%	93.51%
RF	93.87%	93.87%	92.64%	93.34%
KNN	90.11%	89.54%	**88.93%**	**90.20%**
Accuracy smartwatch				
Algorithm	Sitting	Standing	Walking	Jogging
DT	**84.34%**	**89.41%**	92.29%	97.72%
GBDT	**91.84%**	**92.16%**	95.86%	98.38%
SVM	91.50%	91.56%	**97.06%**	**99.19%**
RF	89.95%	89.90%	94.56%	98.27%
KNN	91.62%	90.63%	91.62%	95.57%

Accelerometer data on smartwatches gave a high accuracy of over 91% with all five algorithms for walking and jogging activities, while smartphone data showed much worse results with the walking activity. Besides, two activities of sitting and standing were more accurate when using the dataset on the phone. DT algorithm gave the lowest accuracy with sitting (84.34%) and standing (89.41%) data from the watch. However, data of walking and jogging on the phone had the lowest accuracy with the KNN algorithm. The sensitivity was shown graphically in Figure 4.

The sensitivity of the algorithms for jogging was the highest on both datasets. The KNN has the slightest sensitivity for two activities of walking and sitting on the phone activities. Still, it was pretty good with two activities of standing (> 86%) and jogging (> 95%) on both datasets. The specificity of the algorithm is shown in Figure 5.

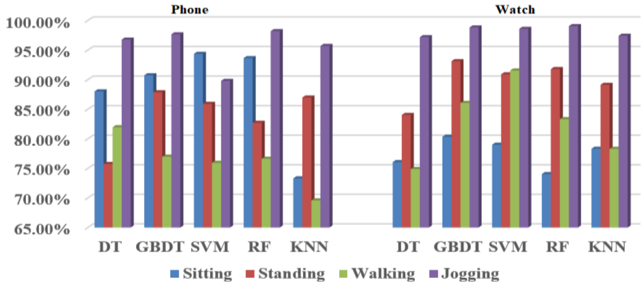

Fig. 4. The sensitivity in classifying four activities

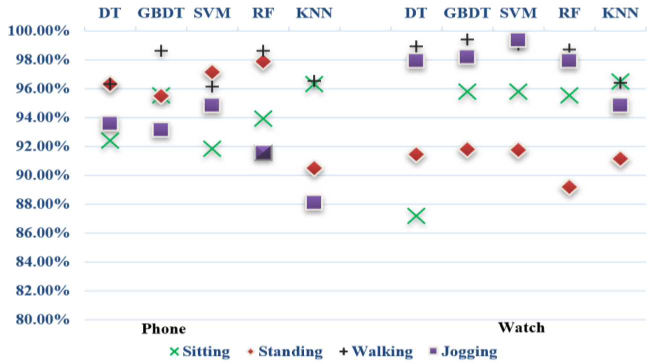

Fig. 5. The specificity in classifying four activities

The specificity of the algorithms reached over 90% on phone data, except for the KNN algorithm for jogging, which only achieved 88.11%. However, the data on the watch had the lowest specificity when using the DT algorithm with the activity of sitting (87.17%). GBDT algorithm has a good clarity of over 91 % with activities.

Overall, the Accelerometer dataset on smartwatches gave good results with walking, jogging, and standing compared to the dataset from smartphones. However, the sitting from the phone dataset had slightly higher metrics than the watch dataset.

B. *Five activities classification model*

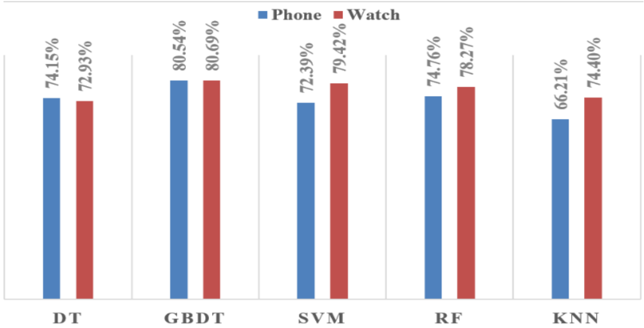

Fig. 6. Results for five activities classification model

When adding stairs to the classification model activity, results had changed clearly, as shown in Figure 6. The GBDT algorithm had the highest result, over 80%, for five activities on both datasets. In contrast, the KNN algorithm had the lowest result for the phone dataset with 66.21%, while the algorithm that gave the lowest result on the watch dataset was DT. Looking at the graph from left to right except for DT, the algorithms applied on the watch data tend to be slightly down. Besides, the classification results with algorithms applied on the dataset of phones fluctuated moderately. Similar to the results of the 4-action classification at part III-A, the watch dataset had good results with most of the applied algorithms except the DT algorithm.

Table VI showed the accuracy of the 5-activities classifier model on two datasets. In general, two activities of standing and sitting were classified quite well on the phone dataset. In comparison, the three activities of walking, jogging, and stairs were classified more stably on the watch dataset.

TABLE VI. THE ACCURACY IN CLASSIFYING FIVE ACTIVITIES

Phone					
Algorithm	Sitting	Standing	Walking	Jogging	Stairs
DT	91.94%	91.33%	82.63%	93.31%	81.11%
GBDT	**95.12%**	**94.80%**	85.94%	94.88%	86.24%
SVM	92.10%	91.85%	78.47%	93.33%	80.48%
RF	92.00%	91.84%	82.68%	91.80%	83.28%
KNN	**90.13%**	**88.65%**	**75.76%**	**86.01%**	**76.90%**
Watch					
Algorithm	Sitting	Standing	Walking	Jogging	Stairs
DT	90.49%	90.18%	78.18%	97.20%	81.95%
GBDT	92.32%	91.80%	**87.87%**	**97.73%**	87.35%
SVM	91.19%	91.39%	86.70%	95.29%	**88.91%**
RF	90.36%	90.74%	86.66%	96.95%	86.14%
KNN	91.83%	91.11%	83.42%	91.83%	82.36%

Figure 7 gave information about the sensitivity of the algorithms. With the activity of walking, five algorithms were applied on the phone dataset that had very low sensitivity (< 50%), but with the watch dataset, they had pretty good sensitivity (> 55%).

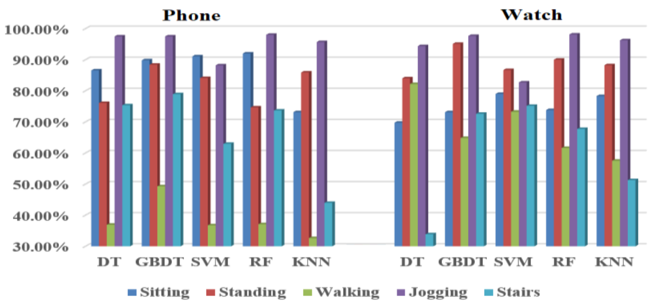

Fig. 7. The sensitivity in classifying five activities

The algorithms had relatively high sensitivity (>70%) with two datasets of standing and jogging activities, but there was a substantial variation on other algorithms (Figure 8). Besides, the specificity of the DT algorithm fastly changed when classifying actions.

Fig. 8. The specificity in classifying five activities

For example, the DT algorithm had the sensitivity of walking over 96% on the phone dataset but just over 75% on the watch dataset. Three algorithms GBDT, SVM, and RF, had better specificity over 85% when classifying activities on both datasets. Example: The SVM algorithm had the highest specificity (99.14%) for jogging activity on the watch dataset.

C. *DISCUSSION*

Within the methodological framework proposed in the present research, the acceleration datasets collected from smartphones and smartwatches were evaluated by combining five features and five machine learning algorithms. Five effective features are mean, median, standard deviation, root mean square, and range. They were extracted on all three axes X, Y, and Z. The training and classifying activities were implemented using five machine learning algorithms: decision tree, gradient boosted decision tree, support vector machine, random forest, and k-nearest neighbors.

The smartwatches dataset gave better classification results for standing, walking, jogging, and stairs activities than the phone dataset. GBDT, SVM, and RF algorithms were classified quite well. The sensitivity of these algorithms was over 89%, with the 4-activities model (standing, sitting, walking, jogging) on both datasets, but it was less than 50% with model 5-activities on the phone dataset. Besides, the sensitivity of the KNN algorithm in the five-activities classification model was less than 50% on the phone dataset but increased to more than 55% with the watch dataset. This difference occurred due to different ways of data collection, orientation, and phone location changed, but these things have never been done with the watch. Not only that, in a sedentary position (sitting and standing), the phone would be less sensitive to gentle hand movements. In contrast, the watch was worn on the hand, so it was sensitive to these activities. The sensitivity and accuracy of algorithms increased on watch data while a person was moving, arm flexibility rose in proportion to movement speed and intensity [18-21].

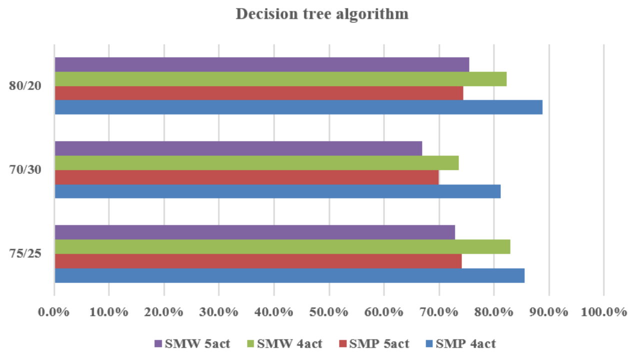

Fig. 9. Classification results with different rates with DT

The classification results on the 5-activities model changed significantly compared to the 4-activities model. For example, with the watch data, the SVM algorithm achieved 89.54% in model 1 but only 79.42% in model 2; KNN algorithm performance decreased by 15.1% (from 81.31% to 66.21%) when the classification model added activity of stairs. It happened because two activities of walking and (up/down) stairs had a great similarity, so they were easy to get confused. However, the confusion has improved more on the watch dataset. Figure 9-11 showed the comparison of classification results on each algorithm with different training and test split ratios. The 80/20 ratio on the datasets gives the best results, followed by the 75/25 ratio and the lowest with the 70/30 ratio. However, similar to the 75/25 scale, the 70/30 and 80/20 ratios give better results on the watches dataset.

Vavoulas et al., in a study [4], classified six activities (walking, jogging, sitting, up/downstairs and standing) for similar low results for two actions up to and downstairs from the dataset on the phone (Table VII). They used up to 64 features on the WISDM dataset to acquire the stairs accuracy less than 80%. Besides, Kwapisz [14] also on the WISDM dataset used 43 features, but the highest result with stairs activity was only 77.6%. In comparison, our research only used 15 features of accelerometer data on the X, Y, and Z-axis.

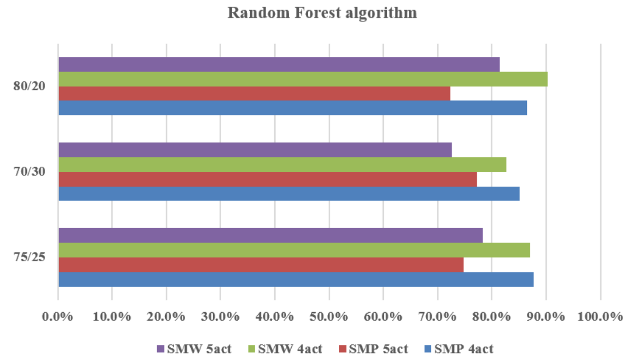

Fig. 10. Classification results with different rates with RF

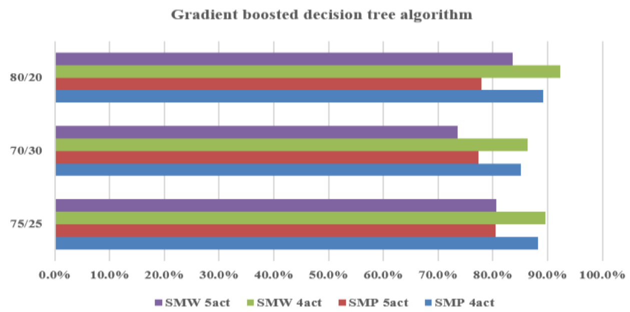

Fig. 11. Classification results with different rates with GBDT

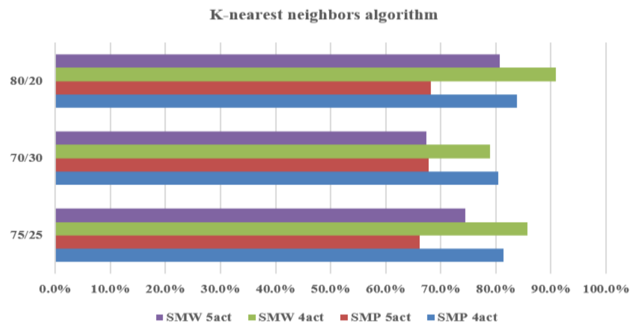

Fig. 12. Classification results with different rates with KNN

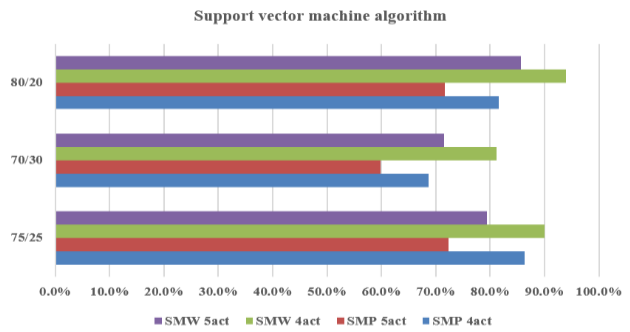

Fig. 13. Classification results with different rates with SVM

The research results evaluated the accuracy of the datasets on two mobile devices in classifying human activities. The data on the watch had a strong categorization of hand movements, while the information on the phone was sensitive to the activities in the static state. However, different hand movements would cause problems that affect the classification results. Besides, the activities of sitting and walking had many variations. Thus, it was challenging to distinguish if only with the data on a smartwatch or smartphone.

TABLE VII. CLASSIFICATION RESULTS WITH THE ACTIVITY OF STAIRS

Activity		Ours	Vavoulas [4]	Kwapisz [14]
Stairs	Upstairs	86.24% (Phone)	79.3%	77.6%
	Downstairs	89.1% (Watch)	69.4%	

IV. CONCLUSION

In this research, we evaluated accelerometer data collected from smartphones and smartwatches in classifying different human actions. First, we select machine learning features and algorithms to build 4 and 5 activities, classification models. We then review the classification results on these two models with five machine learning algorithms (DT, GBDT, SVM, RF, and KNN). The results showed the limitation of using the sensor from the smartphone and smartwatch. The smartphone was put in the pocket, and the smartwatch was fixed on the wrist. In this paper, our dataset was not uniform because it was surveyed 51 people with a sampling frequency of 20Hz, so there is a strong fluctuation. However, to evaluate the performance of two datasets collected from smartphones and smartwatches, the research team assessed the performance of algorithms applied to these datasets. Overall, the data collected from the watch achieves better performance classifiers than the data from the phone.

In the future, we will study the classification of more complex poses such as running up and downstairs, crawling with fielding, falling state, and survival states in many different contexts. These activities are essential in health care, search and rescue. Therefore, collecting data about these actions is essential, especially from smart devices such as phones and watches. The location monitoring will be also integrated to our system in the future development [22-24].

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