Classification of Human Activity based on Sensor Accelerometer and Gyroscope Using Ensemble SVM method

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***Abstract*—Rapid technological development at this time is not only recognized by humans, now sensors embedded in smartphones can also recognize human activity using an accelerometer sensor and gyroscope sensor that has been embedded in it by producing hundreds or even thousands of records. accelerometer sensor and gyroscope sensor is one feature that serves to read the rate of change of acceleration from a smartphone but has a different function and requires data mining methods to group based on that output. Data mining methods that have better performance than other methods are Support Vector Machine (SVM) but are sensitive to parameter settings and sample training that cause undefined performance to overcome the shortcomings of the Support Vector Machine method by performing SVM ensembles, which are ensemble used is bagging. This research proposes the application of svm ensemble technique to perform human activity classification based on accelerometer sensor and gyroscope sensor. The results show that the best performance of SVM ensemble technique when comparing datasets with 70% training data and 30% test data with 99.1% accuracy, sensitivity 99.6% and specificity 98.7%.**

Keywords—human activity, sensor accelerometer, sensor gyroscope, SVM, ensemble, bagging

I. INTRODUCTION

Human Activity Recognition is an introduction to human activity technology that allows a system to detect simple activities by humans, such as sitting, standing, walking, running, jumping, climbing stairs, going down stairs and others using a camera or sensor. As technology progresses more rapidly, human activity can be identified with an accelerometer sensor and gyroscope that has been embedded in a smartphone.

The accelerometer and gyroscope sensors produce hundreds or even thousands of records and require a data mining method that can group human activities based on these outputs. Data mining is a computational process to show unknown patterns of knowledge from a large set of databases [1].

Research [2], clustering using the K-Means algorithm by utilizing the accelerometer sensor and gyroscope on a smartphone to identify some simple activities carried out by humans such as; sit, stand, walk and run. To be able to recognize human activity, data is needed on the sensor which is placed on the part of the body that performs a movement. Research [3], Other studies also carried out the concept of introducing activities such as types of activities and sensors located on smartphones and in this study reviewing data mining techniques behind activity recognition algorithms and introducing several applications that can be developed for activity recognition. The result of introducing sensor-based activities on smartphones leads to more possibilities for future research such as new ways that can complement applications on smartphones to replace traditional devices such as traffic control, remote control, and applications that can recognize user movements to perform commands in electronic homes.

Research [4], using 4 accelerometer sensors placed on 4 different body parts, namely waist, left thigh, right ankle and right arm and using the Random forest method and decision tree as a classification but this method requires a long computation time. Research [5], similar research is also directed specifically in the field of activity recognition that uses inertial sensors in the body. This study takes the example of educational problems in different hand movements due to the accuracy of overall performance and introduces the best practice methods. Research [6], using two-stage continuous markov model (CHMM) on the introduction of human activity using the accelerometer sensor data sensor and gyroscope. CHMM consists of two levels for coarse classification and fine classification and random forests are used in each classification. The results show competitive performance compared to other classification algorithms and achieve an overall accuracy of 91.76%.

This study proposes a human activity classification based on an accelerometer sensor and gyroscope mounted on the human thigh because it provides the best accuracy in previous studies and applies SVM ensemble method to classify human activities. Support Vector Machine was chosen because it is one of the machine learning methods that have better performance than other machine learning methods. Even though it has better performance, Support Vector Machine is sensitive to parameter settings and sample training which causes not optimal performance. Then using ensemble is the right choice to improve the performance of the Support Vector Machine [7]. The ensemble used in this research is bagging algorithm.

II. Methodology

A. Human Activity

The introduction of human activities is grouped into two types. First, there are simple activities carried out by humans such as; walking, climbing stairs, going down stairs, jogging, and so on. Second, there are complex activities that usually combine activities into activities for a long time, such as; waiting for the bus, driving and others. An activity can also be done only with a few limbs such as; typing, waving and others [3]. Human activities can be identified using sensors such as; Accelerometer, Gyroscope, Camera, and GPS. At present, smartphones have Accelerometer and Gyroscope sensors that can be used to collect data from activities carried out and have sufficient performance.

B. Sensor Accelerometer

Accelerometer is a device that functions to measure precise acceleration. Accelerometer does not have coordinate accuracy (rate of velocity change) when measuring precise acceleration [8]. But accelerometer identifies acceleration associated with severe phenomena experienced by the test mass on the reference frame of the accelerometer device [9].

The Accelerometer sensor on the smartphone functions to determine the degree of tilt of the smartphone that reads three axes from different directions.

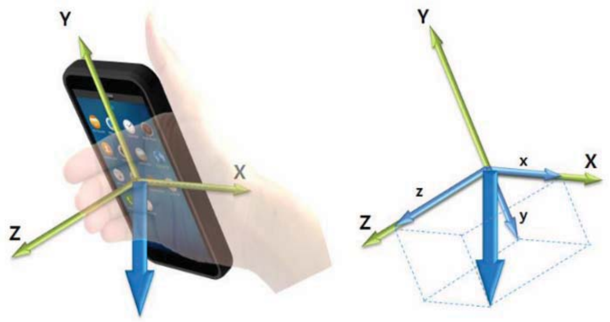

Fig. 1. Illustration of an accelerometer sensor on a smartphone

C. Sensor Gyroscope

Gyroscope is a tool to measure and determine the motion according to gravity which is carried out based on angular momentum [10]. Gyroscope has a working basis if the z axis rotates clockwise then the output voltage will decrease (-Z), whereas if the Z axis rotates counter-clockwise then the output voltage will increase (+ Z) and if it does not rotate or remain silent then the output voltage will correspond to the Gyro-sensor offset value. Fig. 2 Shows illustrations of gyroscope sensors on a smartphone.

D. Support Vector Machine

Support vector machine is one method of solving problems in pattern classification. SVM has been developing since the 1960s, but was only introduced by Vapnik in 1995 [11]. SVM finds the optimal hyperplane that categorizes training data input into the class. Fig. 3 shows the basics of SVM [11].

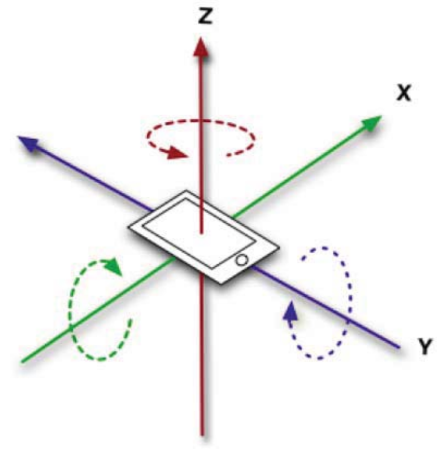

Fig. 2. Illustration of gyroscope sensor on a smartphone

E. Ensemble

Ensemble technique is a combination of several sets of models to solve problems so that they get a more accurate model. Ensemble techniques can effectively reduce classification errors and improve predictive performance from several standard models [12]. In contrast to single classification only testing and training in a data set, ensemble testing classifiers and training of various original data sets, so that it will build a series of hypotheses from the results of data that has been trained [13].

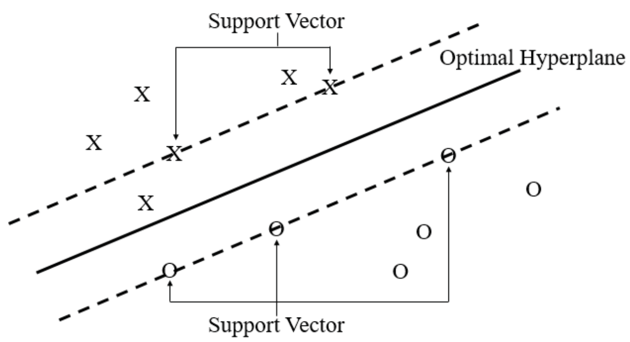

Fig. 3. Base of Support Vector Machines

F. Bagging

Bagging algorithm stands for aggregating bootstrap, making sample M bootstrap samplesT_1, T_2, ..., T_M randomly drawn from the original training set T of size n [14]. Each bootstrap sample T_i of size n is then used to train a base classifier Ci. Predictions on new observations are made by taking the majority vote of the ensemble C^* built fromC_1, C_2, ..., C_M [15].

Algorithm for ensemble Bagging

Given training set of size n and base classification algorithmC_t(x).

1) Input sequence of training samples $(x_1: y_1), \ldots\ (x_n: y_n)$ *with labels* $y \in Y = (-1,1)$

2) Initialize probability for each example in learning set $D_1(i) = \frac{1}{n}$ *and set* $t = 1$.

3) Loop while $t < B = 100$ *ensemble members*

a) Form training set of size n by sampling with replacement from distribution D_t

b) Get hypothesis $ht: X \rightarrow Y$

c) Set $t = t + 1$

d) End of loop

4) Output the final ensemble hypothesis

$$C^*(x_i) = h_{final}(x_1) = argmax \sum_{t=1}^{B} I(C_t(x) = y).$$

G. Performance Evaluation

The level of error in the classification can be seen in the performance evaluation of the classification method. Calculating the error value in the classification can use the confusion matrix/contingency in Table I [16].

TABLE I. CONFUSION MATRIX/ CONTINGENCY TABLE

Actual/Prediction	Path	Run
Path	TP	FN
Run	FP	TN

To determine the performance of each classification method that is evaluated can be seen from accuracy, specificity, sensitivity. The measurement uses the following equation:

$$accuracy = \frac{TP+TN}{TN+FP+FN+TP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

III. EXPERIMENTAL RESEARCH

A. Dataset

The data taken in this study is an accelerometer sensor and gyroscope that has been embedded in a smartphone using an Android-based system that has been designed to read the sensor. Android smartphones are placed on the right foot of a human with a duration of ± 30 seconds. Accelerometer and gyroscope sensor data will be directly stored in the smartphone storage room with * .xls format (path = 0, run = 1). Data in the form of x, y, z coordinates from the accelerometer sensor and gyroscope. The data consists of 6 attributes with the following description:

- Accelerometer x: The x-axis reading on the accelerometer sensor.
- Accelerometer y: Y-axis reading in the accelerometer sensor.
- Accelerometer z: reading the accelerometer sensor on the z axis.
- Gyroscope x: Reading of the gyroscope sensor on the x axis.
- Gyroscope y: Reading of the gyroscope sensor on the y axis.
- Gyroscope z: Reading of the gyroscope sensor on the z axis.

B. Implementation

This study focuses on proposing and looking at the performance of SVM algorithms and SVM ensembles and a single classification on the Support vector machine that can be improved. The data reduction process is done by reducing the size of the data collection to achieve the same class representation between the 'walk' and 'run' classes so that the total data is 3600 records with 1800 class representatives each. Then the data will be partitioned into several sets of 50% data train and 50% test data, 60% training data and 40% test data, 70% training data and 30% test data, 80% training data and 20% test data, 90% training data and 20% test data.

IV. RESULTS AND DISCUSSION

In this section, the overall results are obtained from experiments using python programming language. Table II explains the performance of SVM and Table III explaining the performance of the SVM ensemble.

Fig. 4 Shows the accuracy of the two proposed algorithms where the SVM ensemble manages to improve the accuracy of SVM. Data partitions that are divided into several sets do not affect the performance of the SVM ensemble. Fig. 5 shows the sensitivity of SVM and SVM ensemble. High sensitivity measurement is needed to detect human activity and SVM ensemble successfully gives high sensitivity value and successfully improves SVM performance.

TABLE II. PERFORMANCE OF SVM METHOD

Comparison of training data and test data	Performance measurement SVM		
	Accuracy	*Sensitivity*	*Specificity*
50 :50	98.5	97.5	99.6
60 : 40	98.8	98.2	99.4
70 :30	98.8	98.3	99.3
80 : 20	98.8	98.6	98.9
90 : 10	99.2	98.8	99.5

TABLE III. PERFORMANCE OF ENSEMBLE SVM METHOD

Comparison of training data and test data	Performance measurement ensemble SVM		
	Accuracy	*Sensitivity*	*Specificity*
50 :50	99.4	99.2	99.6
60 : 40	99	98.9	99
70 :30	99.2	99.6	98.7
80 : 20	99.6	100	99.2
90 : 10	100	100	100

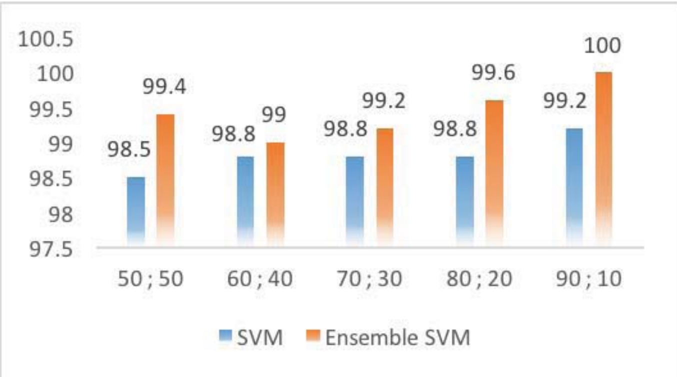

Fig. 4. Improved Algorithm Accuracy

Fig. 6. shows the specificity of SVM and SVM ensemble. Low specificity measurements are needed to detect human activity. The specificity value generated by the SVM ensemble varies depending on the data partition. When compared between SVM and SVM ensemble, the decrease in value from specify only occurs in two data partitions and the rest increases. This proves that the SVM ensemble is very

dependent on selecting the right data partition to produce a low specify value.

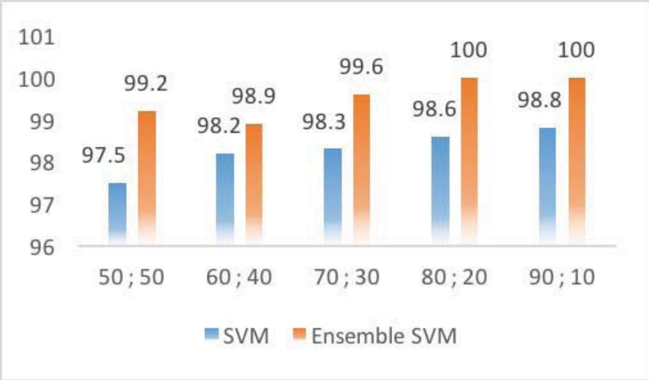

Fig. 5. Comparison of algorithm sensitivity

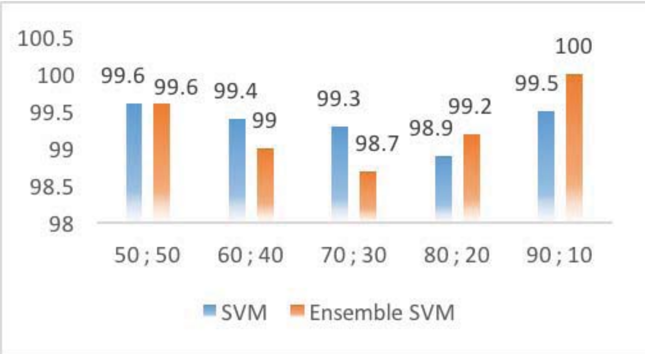

Fig. 6. Specifity algorithm comparison

V. CONCLUSION

This study proposes a classification of human activities using accelerometer and gyroscope sensors with SVM ensemble method. Retrieval of data using the help of a program that has been designed to read the accelerometer and gyroscope sensors on an Android smartphone that is placed on the right foot of the human being with a duration of ± 30 seconds. Data in the form of x, y, z coordinates from the accelerometer sensor and gyroscope. Data will be processed using the SVM ensemble algorithm to classify human activities. Then, it will be compared with a single SVM method to see the accuracy, sensitivity, and specify of the proposed method. From the entire data partition using SVM ensemble algorithm, the best performance is generated when comparing datasets with 70% training data and 30% test data because it successfully increases accuracy and sensitivity and decreases specify. The overall performance of the SVM ensemble has succeeded in increasing the accuracy and sensitivity of SVM, but it is different from specify whose value varies depending on the data partition done where there should be a decrease in the value of the specify. The decrease in specify only occurs on 2 data partitions, namely ‘60% of the training data; 40% of the test data 'and ‘70% of the training data; 30% of test data. Other data partitions have increased and require further research.

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