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Classification of Multiclass Ensemble SVM for Human Activities based on Sensor Accelerometer and Gyroscope

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Abstract

Human Activity Recognition is technology introduced to recognize human activities. Several technologies that have been applied are Accelerometer sensors, Gyroscope sensors, Cameras, and GPS. The selection of the Support Vector Machine algorithm is due to its capabilities to minimize errors in training data sets and the Curse of dimensionality which can estimate parameters as well as its ability to find the best hyperplane that separates two classes. The SVM algorithm was originally developed for the classification of two classes. Problem raised if there are more than two classes. In addition, the performance will not optimal for the large-scale data. Therefore, modification the current design is needed. An ensemble technique can be used to combine the Support Vector Machine algorithm with the bagging algorithm. This study proposes the application of an ensemble SVM algorithm to classify human activities based on accelerometers and gyroscope sensors on smartphones. The total data is 13725 records with 4575 representatives of each class. From the results of the overall data partition carried out in the calcification process using the ensemble SVM algorithm, the best performance was generated when comparing datasets with 80% training data and 20% test data from a total of 13725 records because it succeeded in increasing accuracy, precision, and sensitivity.

Keywords: Classification; Human Activity Recognition; Ensemble; Bagging; Support Vector Machine

Introduction

Human Activity Recognition is an introduction technology that allows a system to detect activities carried out by humans [1]. The introduction is grouped into two activities, namely simple activities and complex activities. The former includes activities such as walking, climbing stairs, going down stairs, jogging while the latter is long-term activities such as waiting for the bus, driving etc [2]. With the rapid development of technology, human activities can be recognized using Accelerometer sensors, Gyroscope sensors [3], Camera [4], and GPS [5].

The accelerometer sensor and gyroscope sensor are classified as wearable device technology [6] that is worn on several parts of the user's body. However, the use of wearable devices causes inconvenience and the battery runs out more quickly [7]. The Accelerometer sensor and Gyroscope sensor that has been embedded in smartphone make its use very efficient to be used on collecting human activity data. This system produces hundreds or even thousands of records which in turn requires data mining methods to classify human activities based on these outputs. Data mining is a computational process that shows patterns in a data set using methods such as artificial intelligence, machine learning, statistics etc [8], [9].

Research [10] utilized accelerometer sensors on smartphones to recognize some simple human activities such as; sit, stand, walk and run. The K-Nearest Neighbor algorithm was used to classify the accelerometer sensor output. The results showed that the accuracy rate was 100%. The study was limited to two human activities namely standing and sitting with small amounts of data. Research [11] proposed a Multiclass Support Vector Machine (SVM) to classify human activities. The lowest performance was 88% for sensitivity and 90% for precision. However, there was an overlap between "sitting" and "standing" activities related to the location of the device so that it is difficult to determine the activity. Research [12] proposed a method of introducing human activity based on CNN 1D. The results indicated an accuracy of 92.71%. The dimensions of input vectors affected performance in distinguishing signals from "walking" activities. Research [13] employed four accelerometer sensors placed on several different body parts, namely the waist, left thigh, right ankle and right arm. The accelerometer sensor output was classified using the random forest method and decision tree. The study resulted in an accuracy of 99.8% and 99.9% for five different activities. However, the method requires a long computing time. Research [14] proposed a classification of human activity based on the accelerometer sensor and gyroscope. The sensor device was attached on the human thigh as it provides the best accuracy as suggested by previous studies. It applied the SVM ensemble method to classify human activities [13]. Overall, the application of SVM ensemble algorithm in data partition would generate best performance when comparing the dataset with 70% of training data and 30% of test data because it succeeded in increasing accuracy and sensitivity as well as reducing specificity. However, this research is merely limited to two classes. Research [15]–[17] proposed a classification of human physical activity using accelerometer sensors, gyroscopes, and gravity sensors. The ensemble technique was employed by combining logistic regression as initial classification and gradient boost to correct misclassified logistic regression [18], [19]. The results showed that the performance of the ensemble method resulted in an accuracy of 81.82%, sensitivity of 86.11% and specificity of 77.50%. This research, however, applied one data partition and was limited to two classes. Research [20] applied the ensemble Stacking method to assess the performance improvement of the Support Vector Machine method. The proposed method obtained results of 99.2% accuracy, 99.6% sensitivity and 98.7% specificity. Similarly, this research was limited to two classes which were walking and running. Based on the abovementioned studies, the state of the art is as shown in the following **Table 1**:

Table 1. State of The Art

Author/Year	Title	Method	Activity	Results
Kaghyan, S. and Sarukhanyan, H., 2012.	Activity recognition using k-nearest neighbor algorithm on smartphone with tri-axial accelerometer.	K Nearest Neighbor	Multiclass : Sitting, standing, walking, running	100% accuracy rate but limited to two human activities namely standing and sitting and small amounts of data
Anguita, Davide, Alessandro Ghio, Luca Oneto, Xavier Parra, and Jorge Luis Reyes-Ortiz. 2013	A public domain dataset for human activity recognition using smartphones.	Support Vector Machine	Multiclass : Sitting, standing, walking, running	the lowest performance is 88% for sensitivity and 90% for precision. However, there is overlap between “sitting” and “standing” activities regarding the location of the device, making it difficult to define which activity.
Zubair, Muhammad, Kibong Song, and Changwoo Yoon. 2016	Human activity recognition using wearable accelerometer sensors	Random Forest and Decision Tree	Multiclass : Sitting, standing, walking	The results show 99.8% and 99.9% accuracy for five different activities. However, this method requires a long computational time.
Wannenburg, Johan, and Reza Malekian. 2016	Physical activity recognition from smartphone accelerometer data for user context awareness sensing	Support vector machines, Multilayer Perceptron, Naive Bayes, K Nearest Neighbor, Bagging, J48, and kStar	Multiclass : Jogging, lying down, sitting, standing, walking	Best method using K Nearest Neighbor and kStar
Rakesh, Y. Joy, R. Kavitha, and J. Julia. 2021	Human Activity Recognition Using Wearable Sensors	Decision tree, Random Forest, Logistics Regression, K-Nearest Neighbor, and Support Vector Machine	Multiclass : Standing, sitting, walking, running, climbing stairs, and descending stairs	The results show that the best classifier performance is Support Vector Machine.
Hardiyanti, Nurul, Armin Lawi, and Firman Aziz. 2018	Classification of Human Activity based on Sensor Accelerometer and Gyroscope Using	Support Vector Machines, and Ensemble	Twoclass : Walking and running	SVM ensemble method produces 99.1% accuracy, 99.6% sensitivity and 98.7% specificity when the data partition is 70% training data and

Author/Year	Title	Method	Activity	Results
	Ensemble SVM method	Support Vector Machines		30% test data.
Lawi, Armin., Firman Aziz, and Supriyadi. La Wungo. 2019	Increasing accuracy of classification physical activity based on smartphone using ensemble logistic regression with boosting method	Logistic regression, and Ensemble GradientBoost	Twoclass : up and down the stairs	The ensemble GradientBoost method produces an accuracy of 81.82%, a sensitivity of 86.11% and a specificity of 77.50%.
Firman Aziz 2021	Klasifikasi Aktivitas Manusia menggunakan metode Ensemble Stacking berbasis Smartphone. Classification of Human Activities using the Smartphone-based Ensemble Stacking method	SVM, and Ensemble Stacking	Twoclass : Walking and running	The results show that the Stacking ensemble has succeeded in increasing the performance of the Support Vector Machine method by ± 1%.
Firman Aziz, Syahrul Usman, and Jeffry. 2021	Klasifikasi Physical Activity berbasis sensor Accelorometer, Gyroscope, dan Gravity menggunakan Algoritma Multi-class Ensemble GradientBoost Classification of Physical Activity based on Accelorometer, Gyroscope, and Gravity sensors using the Multi-class Ensemble GradientBoost Algorithm	Logistic regression, and Multiclass Ensemble GradientBoost	Multiclass : Walks, runs, climbs and descends stairs.	The results obtained show that the Multi-Class Ensemble Gradientboost algorithm has succeeded in increasing the logistic regression performance by 27.93%.
Supriyadi La Wungo and Firman Aziz. 2022	Increasing Performance of Multiclass Ensemble Gradient Boost uses Newton-Raphson Parameter in Physical Activity Classifying	Logistic Regression, Ensemble Gradient Boost and Ensemble Gradient Boostby Newton-RaphsonParameters	Multiclass : Walks, runs, climbs and descends stairs.	The results showed that the Multiclass Ensemble Gradient Boost Classifier with Newton Raphson Parameter Estimation succeeded in increasing the performance of logistic regression in terms of accuracy by 29.11%.

This study proposes the application of the Support Vector Machine algorithm to classify human activities based on the accelerometer and gyroscope sensors on smartphones that are attached on human thighs because they provide the best accuracy. The selection of Support Vector Machine algorithm is based on its generalization capabilities. Firstly, it can minimize errors in training-sets and Curse of dimensionality which can estimate parameters. Secondly, it is able to find the best hyperplane that separates two classes. Basically, the Support Vector Machine algorithm was developed for classification problems with two classes. Modifications need to be made for the case of more than two classes and the amount of large-scale data. Therefore, an ensemble technique is required to combine the Support Vector Machine algorithm with the bagging algorithm.

Method

A. Data Collection

This study uses primary data obtained from recordings of human activity movements detected by the Accelerometer sensor and Gyroscope sensor on an Android Smartphone. 8 subjects were used to perform movements with several repetitive activities for each subject. The android smartphone was placed on the human's right thigh with a duration of ±12 seconds. Accelerometer and gyroscope sensor data were automatically stored in the smartphone's storage space in *.xls format. The system design as shown in **Figure 1** below:

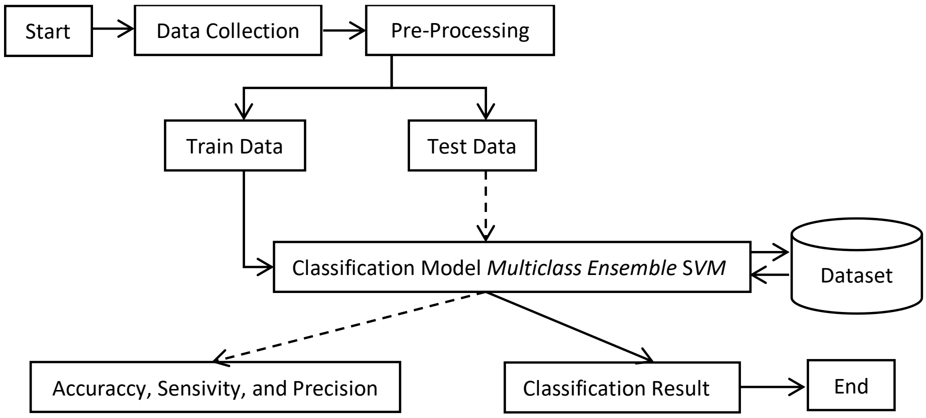

Figure 1. System design

B. Pre-Processing

The entire class data process (walking, running and walking upstairs) went through a data reduction process which was minimizing the number of data sets in order to achieve a balanced class representation between walking, running and walking upstairs. The results of the data representation were then partitioned into several training sets and test sets as shown in **Table 2** below:

Table 2. Training Set and Test Set

Training Set	Test Set
10%	90%
20%	80%
30%	70%
40%	60%
50%	50%
60%	40%
70%	30%
80%	20%
90%	10%

C. Ensemble SVM with Bagging Method

This study proposes ensemble SVM algorithm using bagging technique. The purpose of this algorithm is to improve the performance of the single SVM classification. The proposed model has the following systematic stages:

- Load Dataset
- Identification of Label Attributes, classes and amount of data.
- Determine the amount of training data and test data.
- Form a classification
- Determine the value of C, Kernel, Gamma, Sigma etc.
    - Variable initialization and initial weight.
    - Training set model
    - Input sequence from the training set model for each class
    - Initialize the overall probability of the training set
    - The looping process to get a hypothesis

- The final hypothesis of the ensemble SVM
- Output model

D. Performance Evaluation

Performance evaluation of the classification method can be seen from the level of error classification. To calculate the misclassified value, confusion matrix, commonly called the contingency table, can be used and [21]. The performance results of each classification are evaluated based on three measurements namely Accuracy, Sensitivity, and Precision.

Table 3. Contingency Table

Actual	**Prediction**		
	Walk	***Run***	***Walk Upstair***
Walk	T_0	F_{01}	F_{02}
Run	F_{10}	T_1	F_{12}
Walk Upstair	F_{20}	F_{21}	T_2

Description of Table 3 is given as follows :

T_0 (True0) = The true value is zero and the prediction model results are zero

T_1 (True1) = The actual value is one and the results of the prediction model are one

T_2 (True2) = The actual value is two and the results of the predictive model are two

F_{01} (False01) = The true value is zero and the results of the prediction model are one

F_{02} (False02) = The true value is zero and the results of the predictive model are two

F_{10} (False10) = The actual value is one and the prediction model results are zero

F_{12} (False12) = The actual value is one and the results of the prediction model are two

F_{20} (False20) = The actual value is two and the prediction model results are zero

F_{21} (False21) = The actual value is two and the results of the prediction model are one

Accuracy is defined as the rate of true value of a model in grouping data.

$$accuracy = \frac{\sum_j T_i}{N} \quad (1)$$

Sensitivity is the ratio of positive observations that are predicted correctly for all observations in the actual class.

$$Sensitivity_i = \frac{T_i}{T_i + \sum_j F_{ji}} \quad (2)$$

Precision is the ratio of positive observations that are predicted correctly to the total predictions of positive observations.

$$Precision_i = \frac{T_i}{T_i + \sum_j F_{ij}} \quad (3)$$

Results and Discussion

The data collected for the whole class was 15191 records comprising of 6010 records for the 'walk' class, 4606 records for the 'run' class and 4575 records for the 'walk upstairs' class. The data reduction process was carried out by reducing the size of the data set to achieve a balanced class representation between 'walking', 'running' and 'walking upstairs' classes. The total data after this process was 13725 records making it 4575 representatives for each class. Next, the data was partitioned into several training and test sets as shown in Table 4 below:

Table 4. Training Set and Test Set

Data Partition	**Training Set**	**Test Set**
10% : 90%	1372	12353
20% : 80%	2745	10980

Data Partition	Training Set	Test Set
30% : 70%	4117	9608
40% : 60%	5490	8235
50% : 50%	6862	6863
60% : 40%	8235	5490
70% : 30%	9607	4118
80% : 20%	10980	2745
90% : 10%	12352	1373

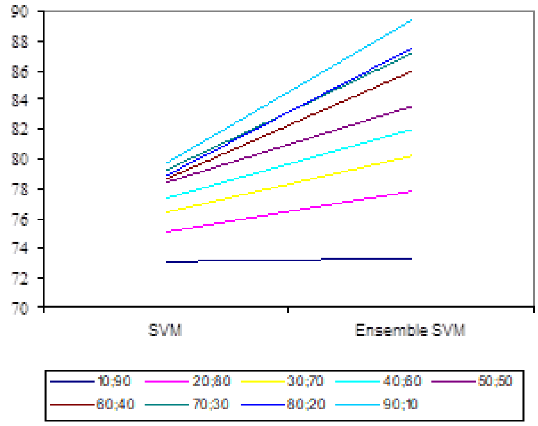

Figure 2. The accuracy of SVM employing the Ensemble method.

This study deployed the Python 2.7 programming language to obtain the overall results of the classification of the proposed method. **Table 4** up to Table XI depicts the performance of SVM and SVM Ensemble in the entire data partition. The amount of test data correctly classified is shown in numbers diagonal thickness. Meanwhile, the overall accuracy of each method is shown in the lower right corner of each confusion matrix. In the entire data partition, the ensemble SVM (10 : 90 = 73.39%, 20 : 80 = 77.97%, 30 : 70 = 80.28%, 40 : 60 = 82%, 50 : 50 = 83.66%, 60 : 40 = 86.01%, 70 : 30 = 87.17%, 80 : 20 = 87.50%, and 90 : 10 = 89.43%) has successfully improved the SVM performance (10 : 90 = 73.12%, 20 : 80 = 75.10%, 30 : 70 = 76.46%, 40 : 60 = 77.43%, 50 : 50 = 78.55%, 60 : 40 = 78.72%, 70 : 30 = 79.35%, 80 : 20 = 78.79%, and 90 : 10 = 79.82%).

Figure 2. illustrates the accuracy of both SVM and ensemble SVM method. Data partitioning in several sets does not affect the performance of the SVM ensemble algorithm. The proposed method has succeeded in increasing the performance of the SVM method throughout the data partition with an average increase in accuracy of around 5.5%. The highest increase in SVM performance using the SVM ensembles was around 9.6% in 90 : 10 data partitions. Overall, the performance of SVM ensemble in recognizing human activities can be increased if the amount of training data input increases which in turn will produce a high level of accuracy.

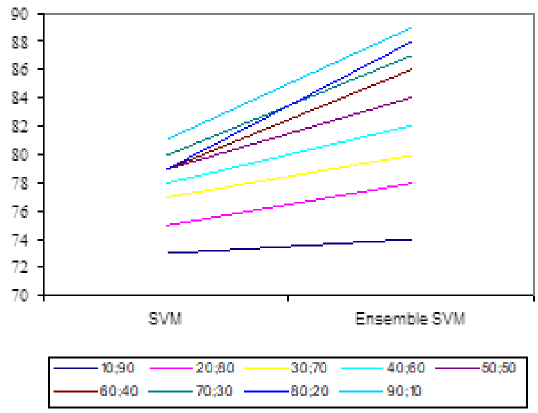

Figure 3. Improved Precision of SVM using Ensemble method.

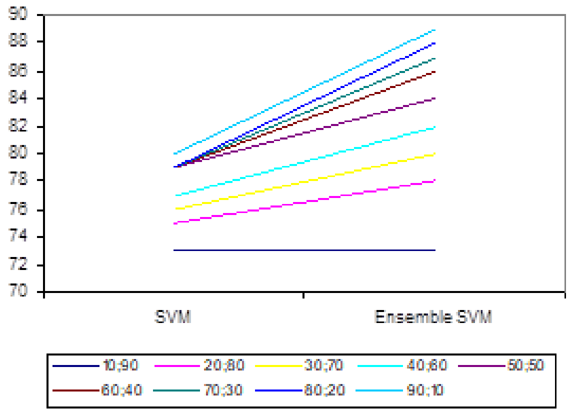

Figure 4. Improved sensitivity of SVM using Ensemble method.

Precision and sensitivity measurements should be increased to prove the success of the proposed SVM Ensemble method. **Figure 3** and **Figure 4** display SVM precision and sensitivity using the ensemble method. The precision and sensitivity values of each class are used to obtain the average value of the precision and sensitivity of each method. The SVM ensemble method has successfully enhanced the precision and sensitivity of SVM in the entire data partition as see in **Table 5-13**.

Table 5. SVM vs Ensemble SVM using Data Partition 10 : 90

SVM		**Predicted Class**			**Sensitivity**
	Activity	***Walk***	***Run***	***Walk Upstairs***	
Actual Class	***Walk***	2978	271	859	72%
	Run	455	3208	470	78%
	Walk Upstairs	851	414	2847	69%
Precision		70%	82%	68%	73.12%
Ensemble SVM		**Predicted Class**			**Sensitivity**
	Activity	***Walk***	***Run***	***Walk Upstairs***	
Actual Class	*Walk*	3199	240	669	78%
	Run	509	3205	419	78%
	Walk Upstairs	1008	442	2662	65%
Precision		68%	82%	71%	73.39%

Table 6. SVM vs Ensemble SVM using Data Partition 20 : 80

SVM		**Predicted Class**			**Sensitivity**
	Activity	***Walk***	***Run***	***Walk Upstairs***	
Actual Class	***Walk***	2783	224	654	76%
	Run	377	2872	422	78%
	Walk Upstairs	775	282	2591	71%
Precision		71%	85%	71%	75.10%
Ensemble SVM		**Predicted Class**			**Sensitivity**
	Activity	***Walk***	***Run***	***Walk Upstairs***	
Actual Class	***Walk***	3052	180	429	83%
	Run	351	2922	398	80%
	Walk Upstairs	763	297	2588	71%
Precision		73%	86%	76%	77.97%

Table 7. SVM vs Ensemble SVM using Data Partition 30 : 70

SVM		**Predicted Class**			**Sensitivity**
	Activity	***Walk***	***Run***	***Walk Upstairs***	
Actual Class	***Walk***	2476	170	578	77%
	Run	310	2506	393	78%
	Walk Upstairs	597	213	2365	74%
Precision		73%	87%	71%	76.46%
Ensemble SVM		**Predicted Class**			**Sensitivity**

SVM		Predicted Class			Sensitivity
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	2476	170	578	77%
	Run	310	2506	393	78%
	Walk Upstairs	597	213	2365	74%
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	2680	163	381	83%
	Run	264	2649	296	83%
	Walk Upstairs	556	234	2385	75%
Precision		77%	87%	78%	80.28%

Table 8. SVM vs Ensemble SVM using Data Partition 40 : 60

SVM		Predicted Class			Sensitivity
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	2160	128	481	78%
	Run	252	2177	316	79%
	Walk Upstairs	506	175	2040	75%
Precision		74%	88%	72%	77.43%
Ensemble SVM		**Predicted Class**			**Sensitivity**
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	2318	142	309	84%
	Run	162	2337	246	85%
	Walk Upstairs	442	181	2098	77%
Precision		79%	88%	79%	82%

Table 9. SVM vs Ensemble SVM using Data Partition 50 : 50

SVM		Predicted Class			Sensitivity
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	1838	86	383	80%
	Run	209	1848	239	80%
	Walk Upstairs	425	130	1705	75%
Precision		74%	90%	73%	78.55%
Ensemble SVM		**Predicted Class**			**Sensitivity**
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	1991	95	221	86%
	Run	161	1981	154	86%
	Walk Upstairs	331	159	1770	78%
Precision		80%	89%	83%	83.66%

Table 10. SVM vs Ensemble SVM using Data Partition 60 : 40

SVM		Predicted Class			Sensitivity
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	1476	68	296	80%
	Run	168	1488	188	81%
	Walk Upstairs	335	113	1358	75%
Precision		75%	89%	74%	78.72%
Ensemble SVM		**Predicted Class**			**Sensitivity**
Actual Class	***Activity***	***Walk***	***Run***	***Walk Upstairs***	
	Walk	1631	57	152	89%
	Run	111	1621	112	88%
	Walk Upstairs	224	112	1470	81%
Precision		83%	91%	85%	86.01%

Table 11. SVM vs Ensemble SVM using Data Partition 70 : 30

SVM		Predicted Class			Sensitivity
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	1140	52	179	83%
	Run	124	1106	144	80%
	Walk Upstairs	270	81	1022	74%
Precision		74%	89%	76%	79.35%
Ensemble SVM		**Predicted Class**			**Sensitivity**
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	1226	38	107	89%
	Run	73	1216	85	89%
	Walk Upstairs	154	71	1148	84%
Precision		84%	92%	86%	87.17%

Table 12. SVM vs Ensemble SVM using Data Partition 80 : 20

SVM		Predicted Class			Sensitivity
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	744	35	124	82%
	Run	83	731	103	80%
	Walk Upstairs	185	52	688	74%
Precision		74%	89%	75%	78.79%
Ensemble SVM		**Predicted Class**			**Sensitivity**
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	808	26	69	89%
	Run	42	820	55	89%
	Walk Upstairs	110	41	774	84%
Precision		84%	92%	86%	87.50%

Table 13. SVM vs Ensemble SVM using Data Partition 90 : 10

SVM		Predicted Class			Sensitivity
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	377	16	61	83%
	Run	41	377	54	80%
	Walk Upstairs	87	18	342	77%
Precision		75%	92%	75%	79.82%
Ensemble SVM		**Predicted Class**			**Sensitivity**
	Activity	*Walk*	*Run*	*Walk Upstairs*	
Actual Class	*Walk*	408	14	32	90%
	Run	19	432	21	92%
	Walk Upstairs	41	18	388	87%
Precision		87%	93%	88%	89.43%

Conclusion

This study proposes the use of an accelerometer sensor and a gyroscope sensor using the ensemble SVM method to classify human activities. The initial stage was the design of a smartphone-based program for data retrieval. The data collection process employed an accelerometer sensor and gyroscope sensor on an Android smartphone with 8 subjects placed on the human right thigh with a duration of ± 12 seconds for each movement. The next step, x, y, z coordinate data from the accelerometer sensor and gyroscope sensor were used as dataset attributes for the classification process. The proposed ensemble SVM method classified human activities and their performance results (Accuracy, Precision, and Sensitivity) were compared with the SVM method. From the entire data partition performed on the calcification process using the ensemble SVM method, the best performance was generated when comparing datasets with 80% training data and 20% test data from a total of 13725 records as it increased accuracy, precision and sensitivity compared to SVM. The overall performance of the ensemble SVM method may overcome the problem for the condition of more than two classes by increasing the accuracy, precision, sensitivity of the SVM method. However, this study found that the ensemble SVM method lacks a higher specificity than the SVM method. In the future, further research will be carried out to overcome this.

References

[1] M. Labrador and O. Yejas, *Human activity recognition: Using wearable sensors and smartphones*. 2013.

[2] X. Su, H. Tong, P. J.-T. science and technology, and undefined 2014, "Activity recognition with smartphone sensors," *ieeexplore.ieee.org*, Accessed: Jun. 15, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6838194/.

[3] S. Ranakoti *et al.*, "Human fall detection system over IMU sensors using triaxial accelerometer," *Adv. Intell. Syst. Comput.*, vol. 798, pp. 495–507, 2019, doi: 10.1007/978-981-13-1132-1_39.

[4] J. Chaochuan *et al.*, "Human activity recognition using support vector machine for automatic security system," *iopscience.iop.org*, doi: 10.1088/1742-6596/1192/1/012017.

[5] D. James, J. Lee, and K. Wheeler, "Introduction to wearable sensors," *SpringerBriefs Appl. Sci. Technol.*, pp. 1–6, 2019, doi: 10.1007/978-981-13-3777-2_1.

[6] L. Chen and C. D. Nugent, "Sensor-Based Activity Recognition Review," *Hum. Act. Recognit. Behav. Anal.*, pp. 23–47, 2019, doi: 10.1007/978-3-030-19408-6_2.

[7] L. Cao, Y. Wang, Q. Jin, J. M.-2017 I. C. on, and undefined 2017, "ActiRecognizer: Design and implementation of a real-time human activity recognition system," *ieeexplore.ieee.org*, Accessed: Jun. 15, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8250368/.

[8] M. Chen, J. Han, P. Y.-I. T. on Knowledge, and undefined 1996, "Data mining: an overview from a database perspective," *ieeexplore.ieee.org*, Accessed: Jun. 15, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/553155/.

[9] D. Zhang, "Wavelet Transform," pp. 35–44, 2019, doi: 10.1007/978-3-030-17989-2_3.

[10] S. Kaghyan, … H. S.-J. of I. M. and A., and undefined 2012, "Activity recognition using k-nearest neighbor algorithm on smartphone with tri-axial accelerometer," *foibg.com*, Accessed: Jun. 15, 2022. [Online]. Available: http://www.foibg.com/ijima/vol01/ijima01-2-f.pdf#page=46.

[11] D. Anguita, A. Ghio, … L. O.-P. of the, and undefined 2013, "A public domain dataset for human activity recognition using smartphones," *upcommons.upc.edu*, Accessed: Jun. 15, 2022. [Online]. Available: https://upcommons.upc.edu/handle/2117/20897.

[12] S. Lee, S. Yoon, … H. C. on big data and smart, and undefined 2017, "Human activity recognition from accelerometer data using Convolutional Neural Network," *ieeexplore.ieee.org*, Accessed: Jun. 15, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7881728/.

[13] M. Zubair, K. Song, C. Y.-2016 I. International, and undefined 2016, "Human activity recognition using wearable accelerometer sensors," *ieeexplore.ieee.org*, Accessed: Jun. 15, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7804737/.

[14] N. Hardiyanti, A. Lawi, Diaraya, and F. Aziz, "Classification of Human Activity based on Sensor Accelerometer and Gyroscope Using Ensemble SVM method," *Proc. - 2nd East Indones. Conf. Comput. Inf. Technol. Internet Things Ind. EIConCIT 2018*, pp. 304–307, Nov. 2018, doi: 10.1109/EICONCIT.2018.8878627.

[15] A. Lawi, F. Aziz, and S. L. Wungo, "Increasing accuracy of classification physical activity based on smartphone using ensemble logistic regression with boosting method," *J. Phys. Conf. Ser.*, vol. 1341, no. 4, p. 042002, Oct. 2019, doi: 10.1088/1742-6596/1341/4/042002.

[16] F. Aziz, S. Usman, J. J.-J. M. INFORMATIKA, and undefined 2021, "Klasifikasi Physical Activity Berbasis Sensor Accelorometer, Gyroscope, dan Gravity menggunakan Algoritma Multi-class Ensemble GradientBoost," *stmik-budidarma.ac.id*, Accessed: Jun. 15, 2022. [Online]. Available: http://stmik-budidarma.ac.id/ejurnal/index.php/mib/article/view/3222.

[17] F. Aziz, *Klasifikasi Physical Activity Berbasis Sensor Accelorometer, Gyroscope Dan Gravity Menggunakan Algoritma Multi-Class Ensemble Gradientboost*. 2021.

[18] A. Lawi, F. Aziz, and S. Syarif, "Ensemble GradientBoost for increasing classification accuracy of credit scoring," *Proc. 2017 4th Int. Conf. Comput. Appl. Inf. Process. Technol. CAIPT 2017*, vol. 2018-January, pp. 1–4, Mar. 2018, doi: 10.1109/CAIPT.2017.8320700.

[19] F. A.-I. (Indonesian J. of C. and, "Increasing Performance of Multiclass Ensemble GradientBoost Classifier

by Estimating the Newton Raphson Parameter in Physical Activity," *journal.ugm.ac.id*, Accessed: Nov. 15, 2022. [Online]. Available: https://journal.ugm.ac.id/ijccs/article/view/73179.

[20] F. A.-J. of S. and C. E. (JSCE) and undefined 2021, "Klasifikasi Aktivitas Manusia menggunakan metode Ensemble Stacking berbasis Smartphone," *journal.unpacti.ac.id*, vol. 1, no. 2, p. 53, 2021, Accessed: Jun. 15, 2022. [Online]. Available: http://journal.unpacti.ac.id/index.php/JSCE/article/view/171.

[21] F. Provost, R. K.-M. LEARNING-BOSTON-, and undefined 1998, "On applied research in machine learning," *Citeseer*, Accessed: Jun. 16, 2022. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.32.9924&rep=rep1&type=pdf.