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Increasing Performance of Multiclass Ensemble Gradient Boost uses Newton-Raphson Parameter in Physical Activity Classifying

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Abstrak

Kecanggihan smartphone dengan berbagai sensor yang dimiliki, dapat difungsikan untuk mengenali aktivitas fisik manusia dengan menempatkan smartphone pada tubuh manusia. Klasifikasi aktivitas manusia, performa terbaik diperoleh saat menggunakan metode machine learning, sedangkan metode statistik seperti regresi logistik memberikan hasil yang kurang baik. Namun kelemahan metode regresi logistik dalam mengklasifikasikan aktivitas manusia dapat diatasi dengan menggunakan teknik ensemble. Penelitian ini mengusulkan untuk menerapkan teknik Multiclass Ensemble Gradient Boost untuk meningkatkan kinerja klasifikasi Regresi Logistik dalam mengklasifikasikan aktivitas manusia seperti berjalan, berlari, menaiki tangga, dan menuruni tangga. Hasil penelitian menunjukkan bahwa Multiclass Ensemble Gradient Boost Classifier dengan Estimasi Parameter Newton Raphson berhasil meningkatkan kinerja regresi logistik dari segi akurasi sebesar 29,11%.

Kata kunci*—Aktivitas Fisik, Klasifikasi, Multiclass Ensemble Gradient Boost, Newton Rapshon Parameter, Smartphone*

Abstract

The sophistication of smartphones with various sensors they have can be used to recognize human physical activity by placing the smartphone on the human body. Classification of human activities, the best performance is obtained when using machine learning methods, while statistical methods such as logistic regression give poor results. However, the weakness of the logistic regression method in classifying human activities is corrected by using the ensemble technique. This paper proposes to apply the Multiclass Ensemble Gradient Boost technique to improve the performance of the Logistic Regression classification in classifying human activities such as walking, running, climbing stairs, and descending stairs. The results show that the Multiclass Ensemble Gradient Boost Classifier by Estimating the Newton-Raphson Parameter succeeded in improving the performance of logistic regression in terms of accuracy by 29.11%.

Keywords— *Physical Activity, Classification, Multiclass Ensemble Gradient Boost, Newton Rapshon Parameter, Smartphone*

1. INTRODUCTION

Advances in motion sensor technology have experienced significant developments by successfully overcoming shortcomings in the past so that motion detection technology can be

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used for various purposes such as detecting. One of the uses of motion sensors is as a prop to produce information on human physical activity. Physical activity is any body movement caused by muscle work to increase energy and energy expenditure. This activity includes daily activities such as walking, running, climbing stairs, and descending stairs [1]–[3]. The using motion sensors as props by placing several sensors in the body causes discomfort with the sensors used in daily activities. So we need a tool that is more efficient so that it does not interfere with the daily activities of the exhibit.

Currently, the development of mobile phones is so rapid, where its use was only for calls and SMS, but now its use is wider, namely the internet, chat, e-mail, games, navigators, photos, videos, etc. [4]–[6]. The sophistication of smartphones with various sensors that have been embedded in them is now used to detect human physical activity [7], [8]. To be able to recognize the data generated by the sensor, a calculation process is used, namely analyzing a data set using an algorithm. [9]–[14].

Research [15], [16] evaluates the recognition of human activities using accelerometer and gyroscope sensors on smartphones to classify human activities, the KNN and NB methods are used. The results suggest that both sensors have a performance contribution when using branched data. Research [17] conducted an analyzed of human activity recognition using three sensors on smartphones to classify human activities, seven methods are used, namely Decision Trees, Logistic Regression, Rule-Based Classifiers, Naive Bayes, K Nearest Neighbors, Neural Networks, and Support Vector Machines. The results show that the best performance among all the proposed methods is Decision Trees and Neural Networks. This study also found that the accelerometer and gyroscope sensors complement each other in recognizing human activities. Research [18], [19] conducted an introduction to human activities using five classification methods, namely Decision tree, Random Forest, Logistics Regression, K-Nearest Neighbor, and Support Vector Machine. The best classifier performance obtained is the Support Vector Machine. Research [20] conducted the introduced of human activities to find the best overall performance and certain activities using seven classification methods, namely Naïve Bayes, Support Vector Machine, K-Nearest Neighbor, J48, Multilayer Perceptron, Bagging, and k-Star. The results obtained indicate that the classifier that has the best performance is KNN and k-Star. Based on research related to human activities, the best performance when using machine learning methods is compared to statistical methods, which give poor results. However, research [21]–[24] suggests that the weakness of statistical methods can be overcome using ensemble techniques. This is evidenced by research [25] which applies the ensemble bagging technique with a single classification using the Support Vector Machine method to classify human activities, namely walking and running, based on accelerometer and gyroscope sensors. The results show that the Bagging ensemble has succeeded in increasing the performance of the Support Vector Machine method by ± 2%. Research [7] applies the ensemble Gradient Boost technique with a single classification using the Logistic Regression method to classify human activities, namely going up and downstairs based on accelerometer, gyroscope, and gravity sensors. The results showed that the Gradient Boost ensemble succeeded in increasing the performance of the Logistic Regression method by ± 12.90%. Research [26] applies the ensemble stacking technique with a single classification using the Support Vector Machine method to classify human activities, namely walking and running, based on accelerometer and gyroscope sensors. The results show that the Stacking ensemble has succeeded in increasing the performance of the Support Vector Machine method by ± 1%. Research [27], [28] proposed to improve logistic regression algorithm using Gradient Boost to detect climbing stairs, descending stairs, running, and walking. The performance of the Gradient Boost algorithm provides an increase of 27.93%.

Based on these studies, we propose applying the Multiclass Ensemble Gradient Boost technique with a single classification using the Logistic Regression method to classify human activities, namely walking, running, climbing stairs, and descending stairs based on accelerometer, gyroscope, and gravity sensors on smartphones. This research contribution proposes the Multiclass Ensemble Gradient Boost method to improve the performance of logistic regression. This research also provides another contribution, namely improving the performance of the Multiclass Ensemble Gradient Boost algorithm by estimating the Newton-Raphson Parameters.

2. METHODS

The research stages are divided into several stages, where each stage is interconnected. The process of each stage can be seen in Figure 1.

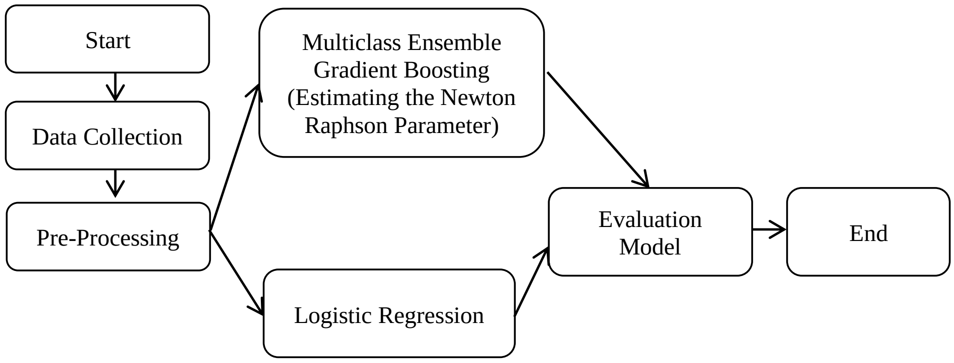

Figure 1 Research Stages

2.1 Data Collection

In data collection, three smartphone sensors were used, namely Accelerometer, Gravity, and Gyroscope. Accelerometers identify the phenomenon of acceleration weight which serves to measure acceleration precisely [29]–[31], However, the accelerometer has a weakness when measuring the accuracy of the coordinates in acceleration precisely [32]. The gravity sensor provides a three-dimensional vector indicating the direction and strength of gravity. Gravity sensors are usually used to determine the relative orientation of the device in space [33]–[35]. A gyroscope measures orientation based on angular momentum [18], [29], [36], [37].

2.2 Preprocessing

At the preprocessing stage, there are several techniques used before classifying objects using the multiclass ensemble Gradient Boosting method. The initial process is data cleaning, the data integration or data transformation, and the last process is data reduction.

2.3 Logistic Regression

Consists of 2 variables, namely response, and predictor. [38]–[40]. the equation is as follows:

$$\pi(x) = \frac{\exp\,(\beta_0 + \sum_{k=1}^{p} \beta_k x_k)}{1 + \exp\,(\beta_0 + \sum_{k=1}^{p} \beta_k x_k)} \tag{1}$$

Where: $0 \leq \pi(x) \leq 1$
Y has values 0 and 1

The function $\pi(x)$ is a non-linear function, so the logit transformation $\pi(x)$ is expressed as $g(x)$ by looking at the relationship between the response variable (y) and the predictor variable (x) to obtain a linear function.

$$g(x) = ln\left(\frac{\pi(x)}{1-\pi(x)}\right) \quad (2)$$

Where

$$ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (3)$$

There are two ways to estimate parameters, but in this study only one is used, namely Newton-Raphson. Newton Rhapson is a method for solving nonlinear equations such as solving likelihood equations in Logistic Regression models [41]. In the newton raphson equation, it is necessary to estimate the value obtained through the initial estimate of a polynomial equation of degree two. To determine the $\hat{\beta}$ value of β is the maximum function of $g(\beta)$ Suppose $q' = \left(\frac{\partial g}{\delta\beta_1}, \frac{\partial g}{\delta\beta_2}, \dots\right)$, and suppose H is denoted as a matrix with members $h_{ab} = \frac{\partial g}{\delta\beta_{1,\delta\beta_2}}$ suppose $q^{(t)}$ and $\boldsymbol{H}^{(t)}$ is a form of evaluation of $\beta^{(t)}$ estimate to t at $\hat{\beta}$. In step t in the iteration process *(t = 0, 1, 2, ...)*.

2.4 Gradient Boosting

The process of Combining a set of models with other models to get a more accurate model is called the ensemble technique. The process is carried out by training from various data sets and learning from the trained data. The wrong prediction will be compared with the correct prediction. Then the ensemble produces new classifiers that are better for predicting samples that have poor performance on the previous classifiers [42]–[45].

Algorithm Gradient Boosting:

$$F_0(\mathbf{x}) = \arg\min_\gamma \sum_{i-1}^{N} \Psi(y_i, \gamma).$$

for $m = 1$ to M do:

$$\tilde{y}_{im} = -\left[\frac{\partial\Psi(\mathrm{y}_i, F(\mathrm{x}_i))}{\partial F(\mathrm{x}_i)}\right]_{F(\mathrm{x})=F_{m-1}(\mathrm{x})}, i = 1, N$$

$$\{R_{lm}\}_1^L = L - \text{terminal node } tree(\{\tilde{y}_{im}, \mathbf{x}_i\}_1^N)$$

$$\gamma_{lm} = \arg\min_\gamma \textstyle\sum_{\mathbf{x}_i \in R_{lm}} \Psi(\mathrm{y}_i, F_{m-1}(\mathrm{x}_i) + \gamma)$$

$$F_m(\mathrm{x}) = F_{m-1}(\mathrm{x}) + v.\gamma_{lm} 1(\mathbf{x} \in R_{lm})$$

endfo

2.5 Performance Evaluation

Classification error is used to evaluate the method's performance by calculating the misclassification value based on accuracy. The assessment process can use a confusion matrix [46].

Table 1 Confusion Matrix

Actual	Prediction			
	Walk	Run	Walk Upstair	Walk Downstair
Walk	T_0	F_{01}	F_{02}	F_{03}
Run	F_{10}	T_1	F_{12}	F_{13}
Walk Upstairs	F_{20}	F_{21}	T_2	F_{23}
Walk Downstairs	F_{30}	F_{31}	F_{32}	T_3

Description:

T0 (True 0) = The actual value is zero, and the result of the prediction model is zero.
T1 (True 1) = The actual value is one, and the result of the prediction model is one.
T2 (True 2) = The actual value is two, and the result of the prediction model is two.
T3 (True 3) = The actual value is three, and the result of the prediction model is three.
F01 (False 01) = The actual value is zero, and the result of the prediction model is one.
F02 (False 02) = The actual value is zero, and the result of the prediction model is two.
F03 (False 03) = The actual value is zero, and the prediction model results are three.
F10 (False 10) = The actual value is one, and the result of the prediction model is zero.
F12 (False 12) = The actual value is one, and the result of the prediction model is two.
F13 (False 13) = The actual value is one, and the prediction model results are three.
F20 (False 20) = The actual value is two, and the prediction model result is zero.
F21 (False 21) = The actual value is two, and the result of the prediction model is one.
F23 (False 23) = The actual value is two, and the result of the prediction model is three.
F30 (False 30) = The actual value is three, and the prediction model result is zero.
F31 (False 31) = The actual value is three, and the result of the prediction model is one.
F32 (False 32) = The actual value is three, and the result of the prediction model is two.

Accuracy indicates the closeness of the measurement results to the actual value. Calculation of accuracy using equation 4 is as follows:

$$accuracy = \frac{\sum_j T_i}{N} \tag{4}$$

3. RESULTS AND DISCUSSION

Four human physical activities will be used as data, namely walking, running, climbing stairs, and descending stairs. Accelerometer, Gravity, and Gyroscope sensor data readings use an android-based system (.apk). The position of the smartphone is on the right thigh. Sensor data is stored on smartphone storage. Overall data representation representing each attribute can be seen in Figure 2.

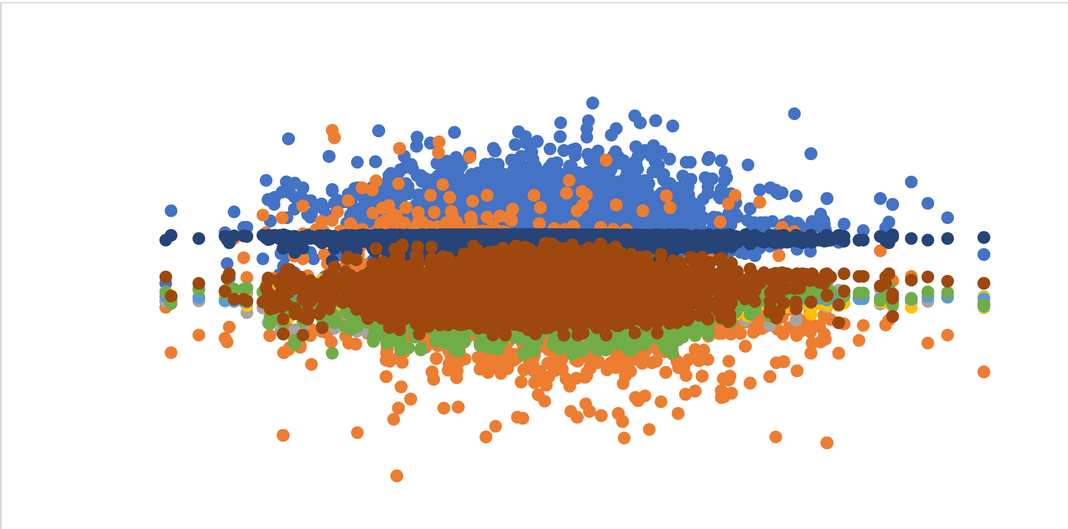

Figure 2 Overall Representation of Activity Data

Then the human physical activity data will be partitioned into several training and test sets, as shown in Table 2. The training data is used to train the algorithm, while the testing data is used to determine the performance of the previously trained algorithm.

Table 2 Data Partition

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

The classification process uses two methods. Namely the Logistic Regression method and the Multiclass Ensemble Gradient Boost method by Estimating the Newton-Raphson. To get the classification results, use python.

Table 3 Classification Results With 90:10 Data Partition

Classification	**Accuracy**
Logistic Regression	48.63 %
Ensemble Gradient Boost	75.46 %
Ensemble Gradient Boost by Newton-Raphson Parameters	76.75 %

Table 4 Classification Results With 80:20 Data Partition

Classification	**Accuracy**
Logistic Regression	46.45 %
Ensemble Gradient Boost	74.26 %
Ensemble Gradient Boost by Newton-Raphson Parameters	75.56 %

Table 5 Classification Results With 70:30 Data Partition

Classification	**Accuracy**
Logistic Regression	46.59 %
Ensemble Gradient Boost	74.52 %
Ensemble Gradient Boost by Newton-Raphson Parameters	75.68 %

Table 6 Classification Results With 60:40 Data Partition

Classification	**Accuracy**
Logistic Regression	46.34 %
Ensemble Gradient Boost	73.95 %
Ensemble Gradient Boost by Newton-Raphson Parameters	75.26 %

Table 7 Classification Results With 50:50 Data Partition

Classification	**Accuracy**
Logistic Regression	46.14 %
Ensemble Gradient Boost	72.91 %
Ensemble Gradient Boost by Newton-Raphson Parameters	74.32 %

Table 8 Classification Results With 40:60 Data Partition

Classification	Accuracy
Logistic Regression	45.77 %
Ensemble Gradient Boost	72.38 %
Ensemble Gradient Boost by Newton-Raphson Parameters	73.72 %

Table 9 Classification Results With 30:70 Data Partition

Classification	Accuracy
Logistic Regression	46.02 %
Ensemble Gradient Boost	71.95 %
Ensemble Gradient Boost by Newton-Raphson Parameters	73.25 %

Table 10 Classification Results With 20:80 Data Partition

Classification	Accuracy
Logistic Regression	45.85 %
Ensemble Gradient Boost	71.27 %
Ensemble Gradient Boost by Newton-Raphson Parameters	72.62 %

Table 11 Classification Results With 10:90 Data Partition

Classification	Accuracy
Logistic Regression	45.14 %
Ensemble Gradient Boost	69.52 %
Ensemble Gradient Boost by Newton-Raphson Parameters	70.86 %

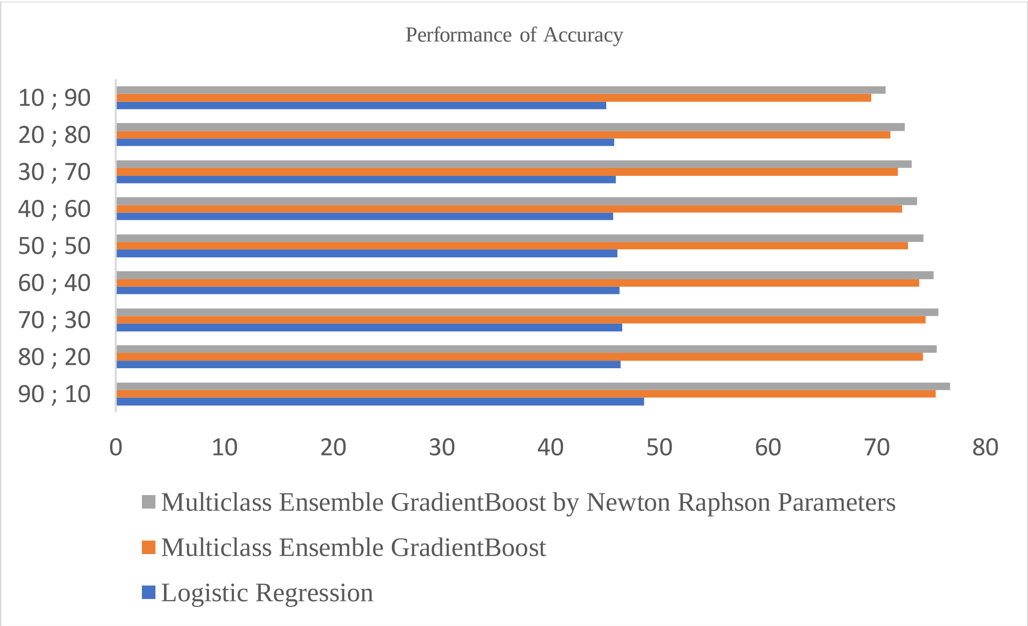

Figure 3 Classification method accuracy results

Based on Tables 3 to 11, it is found that the best accuracy is obtained when partitioning 90% of training data and 10% of test data with an accuracy value of 76.75%. However, the best performance of the Multiclass Ensemble Gradient Boost method uses the Newton-Raphson Parameter. Parameters for improving the performance of the logistic regression method were obtained when partitioning 80% of training data and 20% of test data with an increase in accuracy of 29.11%. While the lowest performance increase was obtained when partitioning 10% of training data and 90% of test data with an increase in accuracy of 25.72%. Based on the results obtained, it is found that the Multiclass Ensemble Gradient Boost method using the Newton-Raphson Parameter will have the best performance when the amount of training data is abundant. This study also compares the results obtained with related studies to see how far the performance of the Multiclass Ensemble Gradient Boost method is using the Newton-Raphson Parameter.

Table 12 Comparison of accuracy method

Author	Year	Method	Accuracy
Aziz Firman, et.al	2021	Ensemble Multiclass Gradient Boost	74.52
Propose method	2022	Multiclass Ensemble Gradient Boost by Estimating the Newton-Raphson Parameter.	76,75%

Based on Table 12, the proposed method has a superior performance compared to previous studies because the focus of improvement in this research is estimating Newton-Raphson Parameters.

4. CONCLUSIONS

The success of the proposed method is measured based on the increase in accuracy. Table 3-11, shows a very significant increase in accuracy from logistic regression after ensemble using gradient boost by utilizing the Newton-Raphson parameter. Based on the table, it is found that the increasing amount of training data affects the performance results of the proposed method. Ensemble Gradient Boost using Newton-Raphson parameters succeeded in increasing the accuracy of logistic regression with the best value of 29.11%. Improved accuracy based on correcting misclassification of logistic regression. As shown in Tables 3 until 11, the False Negative and False Positive values from the initial classification were reduced and succeeded in increasing the values of T_0, T_1, T_2, and T_3.

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