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LightGBM for Human Activity Recognition Using Wearable Sensors

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Abstract: With the popularization of information technology, a variety of embedded sensors have quietly entered our side, through these smart devices, can get our human body activity signals, so its life services, health monitoring, sports training and other fields play a vital role, and how to identify these signals for the focus of the study. In view of the development in the field of machine learning, especially the excellent performance of LightGBM (Light Gradient Boosting Machine) algorithm in handling large datasets and high-dimensional features, this study used HAR data collected based on smartphones and applied LightGBM algorithm on a publicly available dataset to achieve 94.40% accuracy rate. To enhance the persuasiveness, we also chose KNN (K-Nearest Neighbors) and Decision Tree as comparison experiments.

1. Introduction

With the continuous progress of science and technology in recent decades. Being in an era of information technology, the technology of Human Activity Recognition (HAR) has been advancing in line with the needs of the times. Human activity data is collected in a number of ways and then processed by algorithms to obtain labeled and visualized data. And this data will play a very important role in many fields, such as virtual reality, health monitoring, sports training and so on[1]. Then processing the collected data for identification becomes the most critical part of the research.

Currently the more mainstream human motion recognition is mainly based on two data acquisition methods, the first is image recognition technology, and the second is extracted from wearable sensors. In daily life, it is very inconvenient to acquire motion images relative to sensors. Due to the continuous development of sensor technology, it is easier and more accurate to extract data from sensors. In people's daily life, compared with wearing complex sensors, smartphones, as an essential tool for every person, are accompanied by people for a long time and have a high degree of portability. Therefore, smartphones with built-in sensors become an excellent data source. Therefore the research on data classification methods based on smartphones is constantly updated and iterative.

With the development of the computer field, machine learning as a way to process data has a significant advantage in speed and accuracy over manual screening of data. In the vast field of machine learning, there have been some difficult challenges, such as dealing with large datasets and high-dimensional features. The lightGBM algorithm has shown excellent results in dealing with these problems, and thus the algorithm has been widely used and recognized.

2. Classification Algorithm

The main methodological idea of GBDT (Gradient Boosting Decision Tree) is to construct a series of decision trees iteratively, each working with the intention of trying to minimize the error produced by the previous tree. His optimization model is achieved by using gradient descent such methods. LightGBM is an efficient gradient boosting framework developed and open-sourced by Microsoft[2]. It is based on the Gradient Boosting Decision Tree (GBDT) algorithm, but with several optimizations to make it more efficient in handling large-scale datasets while maintaining good accuracy.

The principle of LightGBM is based on the gradient boosting algorithm, and its core idea is to use the negative gradient of the loss function as a residual approximation of the current decision tree. In each iteration, LightGBM keeps the original model unchanged and then fits a new decision tree based on this negative gradient. This new decision tree will attempt to minimize the loss function so that the predicted values constantly approximate the true values[3]. As shown in Fig. 1. In this way, LightGBM can gradually optimize the model and improve the accuracy of the predition.

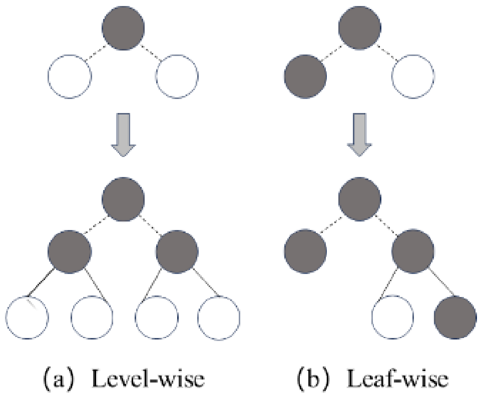

Figure 1: Level-wise strategy and Leaf-wise strategy

In building the decision tree, LightGBM adopts a leaf-wise strategy instead of the traditional level-wise strategy. This strategy helps to reduce the training time and memory usage, and improve the efficiency and accuracy of the model. Also, to prevent overfitting, LightGBM adds a maximum depth limit to ensure that the model does not overfit the training data. GOSS (Gradient-based one side sampling) is used to keep the instances with larger gradients and randomly sample the instances with smaller gradients.

GOSS is used to retain the instances with larger gradients and randomly sample the instances with smaller gradients to obtain accurate information gain estimation with a smaller amount of data. From the perspective of feature reduction, mutual EFB(Exclusive feature bundling) is used to combine mutually exclusive features within a certain conflict ratio to achieve the effect of dimensionality reduction without information loss.

The objective function of training is shown in (1) equation , where y_i is the true value of the label,$\hat{y}_i^{K-1}$ is the result of the K-1st learning, and $C^{K-1}$is the sum of the regularization terms of the first K-1 trees, and the meaning of the objective function is to find a suitable tree $f_k$to minimize the value of the function[4].

$$Obj^K = \sum_i L(y_i, \hat{y}_i^K) + \Omega(f_k) + C^{K-1} = \sum_i L\left(y_i, \hat{y}_i^{K-1} + f_K(x_i)\right) + \Omega(f_k) + C^{K-1} \quad (1)$$

A second-order expansion of the loss function is performed using Taylor's formula:

$$\sum_i L\left(y_i, \hat{y}_i^{K-1} + f_K(x_i)\right) = \sum_i \left[L(y_i, \hat{y}_i^{K-1}) + L'(y_i, \hat{y}_i^{K-1}) f_K(x_i) + \frac{1}{2} L''(y_i, \hat{y}_i^{K-1}) f_K^2(x_i)\right] \quad (2)$$

Denote the first order derivative of the i sample loss function by g_i and the second order derivative of the i sample loss function by h_i

$$g_i = L'(\, y_i, \hat{y}_i^{K-1}) \tag{3}$$

$$h_i = L''(\, y_i, \hat{y}_i^{K-1}) \tag{4}$$

The simplified objective function is expressed as: [5]

$$Obj^K = \sum_i \left[L(\, y_i, \hat{y}_i^{K-1}) + g_i f_K(x_i) + \frac{1}{2} h_i f_K^2(x_i)\right] + \Omega(f_k) + C \tag{5}$$

As a control group, two additional algorithms are used in this paper, the first one is KNN algorithm the second one is decision tree algorithm.

In order to find the suitable algorithmic parameters all the algorithms mentioned in this paper use GridSearchCV i.e. grid search and cross validation. By traversing the search, the method can find the optimal parameters by training within the required range.

3. Date Set

The datasets used in the experiments are from smartphones embedded with a three-axis accelerometer and gyroscope. The datasets were obtained from the public dataset UCI[6].A total of 30 experimenters participated in this experiment for the accuracy of the data. And two experimental approaches were designed during the experiment to be closer to the real life situation. The first time, the cell phone was worn on the waist, and the second time, the position was decided by the experimenters themselves. Finally, the signals obtained from the experiment were labeled. Table I shows several states of personnel activity in this experiment.

Table 1: HAR experimental activity plan

Mode	Duration time	Mode	Duration time
Start(Standing Pos)	0	Walk(1)	15
Stand(1)	15	Walk Downstairs(1)	12
Sit (1)	15	Walk Upstairs(2)	12
Stand(2)	15	Walk Downstairs(1)	12
Lay Down(1)	15	Walk Upstairs(2)	12
Sit(2)	15	Walk Downstairs(3)	12
Lay Down(2)	15	Walk Upstairs(3)	12
		Stop	0
Total			192

The smartphone embedded with a triaxial accelerometer used in the experiment was scanned to record the resulting velocity signals at a constant frequency of 50 Hz. It is clear that this frequency satisfies the conditions for acquiring HAR signals and is fast enough[7].

In the signal preprocessing stage, the signal was filtered using a filter, the experiment used median filtering and low-pass Butterworth filtering (cutoff frequency of 20 Hz). The clean denoised signal was then subjected to signal segmentation, which decomposed the sensor signal into two vectors (human activity acceleration and gravity acceleration). It was assumed that the gravity component only affects the lowest frequency and that 0.3 Hz is the optimal cutoff frequency for obtaining a constant gravity G. This cutoff frequency was used to determine the frequency at which a constant gravity G was obtained. This frequency is calculated as the difference between the filtered signal and the gravity constant in steps of 1/40 Hz during the process of raising the cutoff frequency from 0.0 Hz to 1.0 Hz[8].The frequency domain signal of the motion recognition sensor is shown in Table 2.

Facilitating experimental training was used to sample them with a 50% overlap and a fixed-width sliding window of 2.56s.

Table 2: Frequency domain signals from embedded sensors

Signal	Freq.
Body Acc	1
Gravity Acc	0
Body Acc Jerk	1
Body Angular Speed	1
Body Angular Acc	0
Body Acc Magnitude	1
Gravity Acc Mag	0
Body Acc Jerk Mag	1
Body Angular Speed Mag	1
Body Angular Acc Mag	1

4. Results

In this paper, the LightGBM algorithm has been used to analyze the signal data of HAR. The same also used control group KNN[9] with decision tree algorithm. After classifying this HAR dataset, the algorithm achieved a 94.40% correct classification rate, with a misclassification rate of only 6.60% for the same. The final result is shown in Fig. 2, which achieves more satisfactory classification data[10].

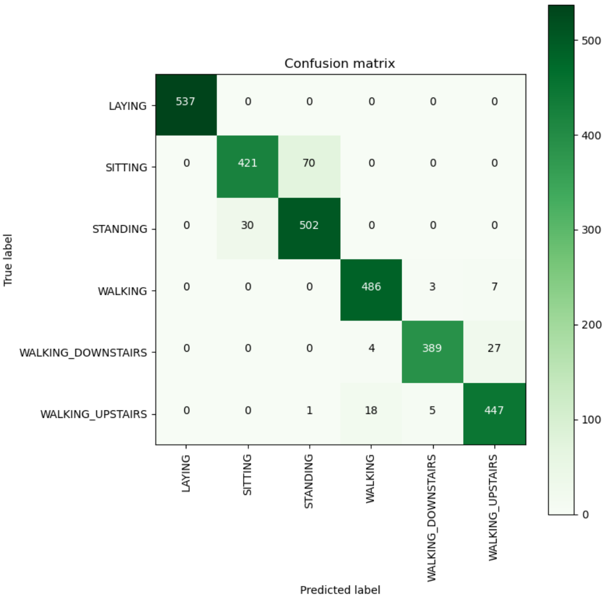

Figure 2: Algorithmic results for LightGBM

As a comparison experiment, this paper also adopts KNN and decision tree algorithms to process the dataset, and the experimental results show that the recognition accuracy of KNN algorithm is 90.77%, and the recognition accuracy of decision tree algorithm is 87.75%. The calculation results of these two algorithms are shown in Figure 3 and Figure 4.

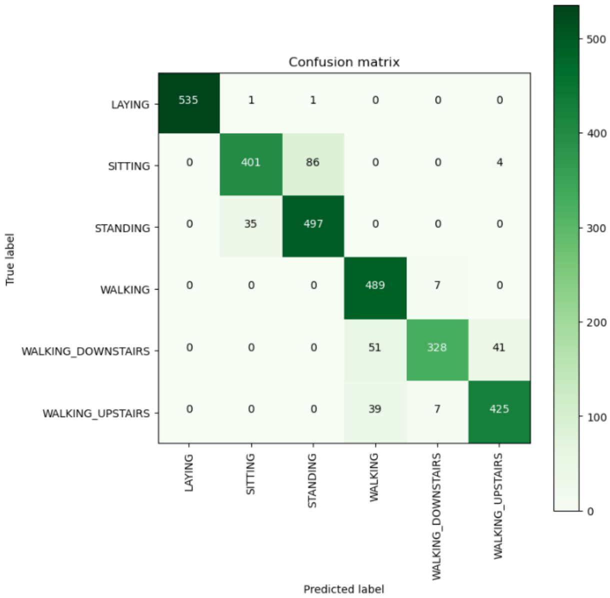

Figure 3: Algorithmic results for KNN

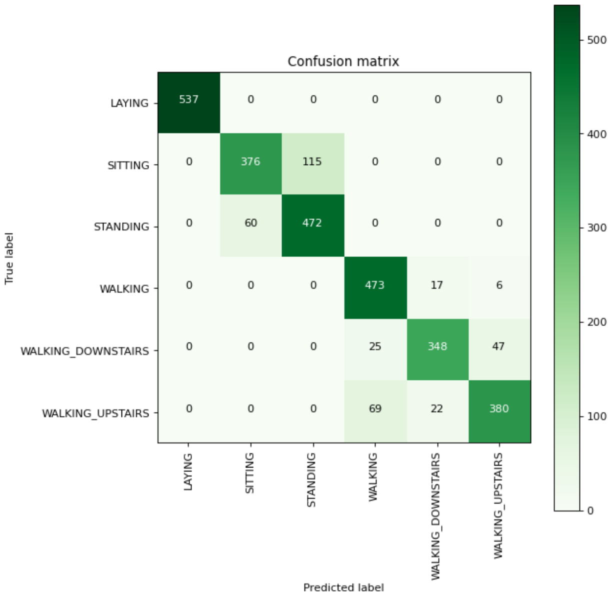

Figure 4: Results using the Decision Tree algorithm

The following Table 3 shows a comparison of the accuracy of the three algorithms, which have a very high degree of fit in the HAR signal recognition task. Being a lightweight algorithm, the algorithm also has the feature of fast training speed with low memory footprint, making it the most powerful tool for the task.

Table 3: Comparison of experimental results

Arithmetic	Accuracy	Error
LightGBM	94.40%	6.60%
KNN	90.77%	9.23%
Decision Tree	87.75%	12.25%

5. Conclusions

Through the experiments in this paper, LightGBM is an efficient and lightweight machine learning algorithm for solving human movement recognition tasks. The data used in this experiment are from embedded sensors and the device used is a ubiquitous smartphone. The signals are transformed to the frequency domain by sampling filtering and FFT so that we can observe from both sides. LightGBM algorithm shows good performance on feature labeling and human motion data training and recognition. The feasibility of using smartphones with embedded sensors for this class of problems is finally demonstrated. This experiment only set the overlap rate to 50% when dealing with the overlap problem, so there is still room for improvement of the method.

Acknowledgements

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