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Exploratory Data Analysis of Human Activity Recognition Based on Smart Phone

WEIHENG KONG[1], LILI HE[1], AND HAILONG WANG[2]
[1]College of Information and Electronic Technology, Jiamusi University, Jiamusi 154007, China
[2]College of Physical Education, Jiamusi University, Jiamusi 154007, China

Corresponding authors: Hailong Wang (wang_hailong2021@163.com) and Lili He (jmshelili@163.com)

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ABSTRACT In a smart urban environment, providing accurate information about human activities is an important task. It is a trend to implement human activity recognition (HAR) algorithms and applications on smart phones, including health monitoring, self-management system, health tracking and so on. However, human activity recognition(HAR) is very complex, and it is important to use the best technology and machine learning to understand human activities. One of the main problems of the existing HAR strategies is that the classification accuracy is relatively low, and in order to improve the accuracy, it needs high computational overhead. The purpose of this paper is to use an exploratory data analysis method to deal with HAR, after the implementation of different data mining techniques, the results of dimensionality reduction and visualization are obtained. The HAR method based on smart phone and EDA proposed in this paper is a high precision method. Compared with other classifiers, its accuracy is 96.56%. This article will discuss computational prediction activities and the computational limitations of using exploratory data to analyze (EDA) on 564 feature data frames. The experimental results show that HAR-based exploratory data analysis is a common sensory signal processing technology. The GridSearchCV and LinearSVC algorithm can provide accurate automatic human activity recognition (HAR), for elderly and disabled patients in need of continuous care, and it is a decision-making tool to support sports coaches to make plans.

INDEX TERMS Activity identification, wearable sensor, data classifier, accelerometer, sports activities.

I. INTRODUCTION

Today, many healthcare applications will benefit from progresses information and communication technology, wireless networking technology, wearable devices and smartphones to analyze patient big data, medical images, videos and images based on data mining technologies that can also identify in daily life activities and in human activity recognition (HAR). Monitoring patient activities provide effective results, especially in the case of elderly and disabled patients in need of continuous care. Because of its great impact on human beings, especially on health care, HAR has become an important field in the computer field. In addition, the integration of smartphones in the field of health care has led to the launch of intelligent applications such as mobile medical and intelligent medical monitoring systems [1].

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As our social population aging and health risks increase, HAR has been shown to help detect cases of different health problems, such as Parkinson's disease, dyskinesia, tremor, dystonia or dyskinesia. There are several ways to provide activity recognition by different ‘‘classifications’’ that distinguish the types of recognition algorithms based on machine learning and logical modeling and reasoning. Davide Anguita *et al.* [2] The main concerns are HAR data sets and energy efficiency. It is believed that energy can be saved by using simple hardware-friendly computing methods. Based on smartphone technology, different data mining technologies have been used to detect human behavior [3].

In the literature, there are many HAR algorithms and schemes based on smart phones. The WISDM (Wireless Sensor data Mining) project aims to mine sensor data from mobile devices and build useful hardware applications to identify six activities [4]. The author extracts six basic features of the current frame: average, standard deviation, average absolute deviation, average composite acceleration, peak interval time and binary distribution [5]. Use a smartphone equipped with Android system to collect three accelerometer data of inactivity, running, walking, upstairs and downstairs activities. Then, five time-domain statistical features are extracted for each frame. Finally, the neural network is used to classify these activities in real time. Muhammad Shoaib *et al.* [6] Various features of the current frame are extracted, including mean, standard deviation, median, root mean square, spectral energy and so on. They then studied the performance of applications using different classification algorithms and performed multi-sensor data fusion, including data from accelerometers, gyroscopes, magnetometers and linear accelerometers. The results show that the performance of multi-sensor data is better than that of single sensor data.

These work simply use the classification methods in the field of data mining to complete the prediction task, resulting in low classification accuracy and efficiency. In recent years, some studies have tried to improve the overall performance of HAR systems by building hierarchical classifiers and developing context awareness. Specifically, N.A. Capela *et al.* [7] A hierarchical classifier including the transition phase of entering and leaving the sitting position is used to identify three kinds of activities, namely, sitting, standing and lying. However, the classifier is only suitable for predicting motionless state and can not be applied to more general scenarios. L.Zhang *et al.* [8] Zhang proposed to make use of context information based on adjacent frames. However, adjacent frame fusion brings computational overhead and computational complexity, so it is not suitable for real-time applications.

Different from the related work, which usually requires intensive computing (such as case selection, attribute selection, etc.), and is only suitable for part of the activity detection in HAR systems, this paper proposes a new exploratory data analysis method for human activity classification data mining. Different data mining techniques are used to evaluate the experimental results of HAR data in order to improve the classification efficiency. Using data obtained by the wearable sensor, the activity recognition is achieved successfully. Our contributions are as follows:

(1) In this work, a new exploratory data analysis method is used to deal with HAR. The exploratory data analysis method pays attention to the real distribution of the data and emphasizes the visualization of the data, so that the analyst's understanding of problem solving will progressing along with studying more and deeper, so as to help the analyst to find a model suitable for the data. ''exploratory'' means that the analyst's understanding of problem solving will change with the deepening of the study.

(2) Exploratory data analysis based on HAR is a general method of sensor signal processing, which realizes activity recognition. We use t-SNE dimensionality reduction technology to get the dataset results after dimensionality reduction and visualization. In this study, the gravity acceleration component and its position on the human body are used for classification, which has a positive impact on performance.

(3) The HAR method based on the smart phone and EDA proposed in this paper is a high precision method. Compared with the depth model based on transfer learning, this method achieves higher classification accuracy.

The rest of the paper is arranged as follows. The second section reviews the related work in the field of human activity identification and smartphone use. The third section introduces a new exploratory data analysis method to deal with HAR. The fourth section shows and discusses the experimental results after dimensionality reduction and visualization using t-SNE dimensionality reduction technology. The fifth part summarizes the work of this study, draws a conclusion, and puts forward some guiding ideology for the future work.

II. RELATED WORKS

HAR has become an active field in the research field and has been widely paid close attention by countries all over the world. Many researchers and research institutions have carried out HAR projects, ranging from building real-time HAR applications such as health monitoring, self-management systems and health tracking [10] to optimizing classification models to improve the overall performance of HAR systems.

As shown in FIGURE 1, the smartphone-based HAR system consists of the following key components: data sensing and preprocessing, feature extraction, and training and classification. First of all, the motion signal data are collected from the smart phone sensor, and then the collected data are preprocessed to reduce noise [11]. In general, the feature vector is extracted by dividing the sensing data into frames by sliding window, and its size is usually 1s [12] and 2.56s [2]. The frames of equal size are generally used, and consecutive frames overlap by 50%. The extracted features are mainly divided into two categories: time domain features, such as mean, standard deviation, correlation between axes, etc.; frequency domain features, such as information entropy, spectral energy, etc. [13]. Finally, these feature vectors are fed into the appropriate classifier, the classification model is established in the training phase, and the reasoning task is performed in the classification phase. As the classifier is the key and important part of the HAR system, the selection of the classifier has a great impact on the overall performance of the HAR system.

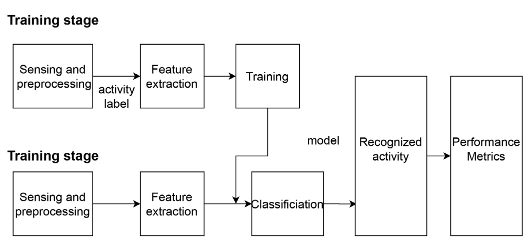

FIGURE 1. General framework of HAR system.

A. LITERATURE REVIEW

The popularity of mobile phones among the general public makes them an indispensable element in daily life. They can monitor our daily activities, learn from them and help them make decisions [14]. Smartphones are equipped with sensors that can recall daily activities, detect falls, assess health, and so on. These sensors can help with health care, by detecting a person's daily activities, assessing a person's health, and predicting when their health will change, which ultimately helps to identify possible diseases. Human activity recognition is a challenge because different people may behave differently when performing the same activity. Activity recognition systems on smartphones can be trained to use geometric templates to classify data in real time, while classifiers use support vector machines. Activity identification requires training phase and identification phase, in which the collected data is processed based on the activity model. As for the sensors connected to these smart devices, one advantage is that the data collected by these sensors for human activity identification can be analyzed offline using machine learning tools. Although it can now be implemented in online mode through the more powerful resources that smartphones now have, including processors, memory and batteries.

In the past decade, the research on sensor-based human activity recognition has exploded. Many methods have been proposed to identify human daily life. One of the studies [15], compares the deep learning methods of sensor-based activity recognition with traditional pattern recognition methods.Therefore, the latest development of deep learning methods has studied and explored the sensor-based activity recognition task from three aspects: sensor channel, deep model and application. Ye.Liu, at al. [16] Different algorithms are reviewed to identify time patterns in simple actions that present complex activities. Ignatov *et al.* [17] In this paper, a depth learning method for online human activity recognition using convolution neural network with statistical characteristics is proposed, which keeps the global attribute of accelerometer time series. Xu *et al.* [18] A multi-layer feature learning model based on a single human body wearable inertial sensor is proposed for sensor-based human activity recognition. The model is based on low-level, middle-level and high-level features. Liang Cao *et al.* [19] A wearable activity recognition system using multiple heterogeneous or homogeneous sensors to obtain effective information is proposed. Under this framework, the sensor-based activity recognition system realizes multi-sensor fusion, and an integrated pruning system is designed. Espinilla *et al.* [20] An intelligent environment with heterogeneous architecture is realized in a wide range of heterogeneous electronic devices. Lei Zhang *et al.* [21] A method combined with dynamic available context is proposed to improve the activity identification system in the dynamic environment. In the dynamic environment, the original data source may fail, while the new data source may be available. The experimental results show that the performance of activity recognition can be improved by using dynamically discovered data sources. Arif *et al.* [22] Use smartphones with accelerometers to monitor a person's physical activity, including walking, sitting, standing and going upstairs or downstairs. Martín *et al.* [23] Focus on exploration and using smartphones for HAR without affecting users' lifestyles. Guiry *et al.* [24] A method of using a smartphone to detect human activity is described, and it is concluded that HAR can be inferred using only five features of two accelerometers. Abdulhamit Subasi *et al.* [25] HAR based on Bagging and Boosting in smart phone is proposed.

Although a lot of work has been done to improve and optimize the classifiers in HAR systems, there are still the following shortcomings:

(1) The optimized classification model should be applicable to common human daily life activities (including fixed and mobile categories). However, in Ref. [7], the classifier only improves the accuracy of inference of motionless activities (standing, sitting, and lying), but not for determining dynamic activities (walking, going upstairs, etc.). We use a new exploratory data analysis method to deal with HAR, which can effectively and accurately classify the main activities of daily life.

(2) For most HAR systems, once a specific classifier is selected and embedded in the recognition system, the classifier can not be changed/replaced with the real environment alternation. However, the adolescent classifier with excellent performance may not perform well in the classification activities of the elders. For example, Ref. [7] points out that older people are more sensitive to sitting posture than young people, because older people transition from standing to sitting more slowly than young people. The HAR method based on EDA can find the most suitable classifier for the current data set.

(3) In this method, EDA is used to reduce classification errors, and t-SNE is used to reduce dimensionality, and higher classification accuracy is obtained.

B. UCI DATABASE

The data we used came from the University of California, Irvine. The experiments were conducted by 30 people between the ages of 19 and 48. Their task is to walk, walk up and down, sit, stand and lie down, while wearing smart phones (especially Samsung Galaxy phones) on their waists. The phone gets a built-in accelerometer and gyroscope to capture the three-axis linear acceleration and three-axis angular velocity of a uniform 50Hz. The data are manually marked, but randomly divided, so 70% of volunteers are selected to generate training [26].

Pre-processing sensor signals are provided by embedding accelerometers and gyroscopes. This is achieved by applying a noise filter and sampling in a sliding window of fixed width for 2.56 seconds and 50% overlap (128 readings/window). The acceleration signal of the sensor is divided into two parts: object acceleration and gravity by using Butterworthfilter, low pass. It is presumed that gravity has only a low frequency component, so a filter with a cut-off frequency of 0.3Hz is used. From each window, a feature vector is obtained by calculating variables.

III. METHODOLOGY

For our project, we wrote a Python3 code to process all the calculated data. We applied several existing packages referenced in this article and in the source code.

A. CHECK WHETHER THE DATA IS BALANCED

As showed in FIGURE 2, it can be clearly found that the data is more balanced, indicating that the data set can be better suitable for the development of this project. Moreover, it can be concluded from FIGURE 3 that the error range of the six activities is between 2% and 5%.

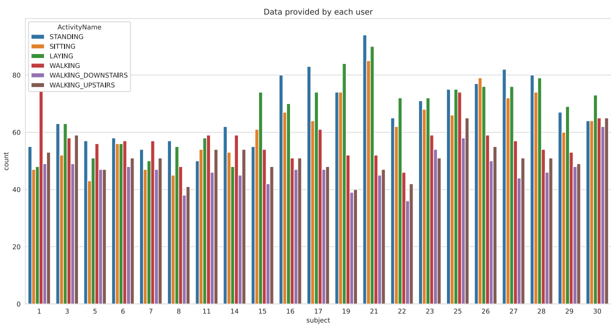

FIGURE 2. Data provide by each user.

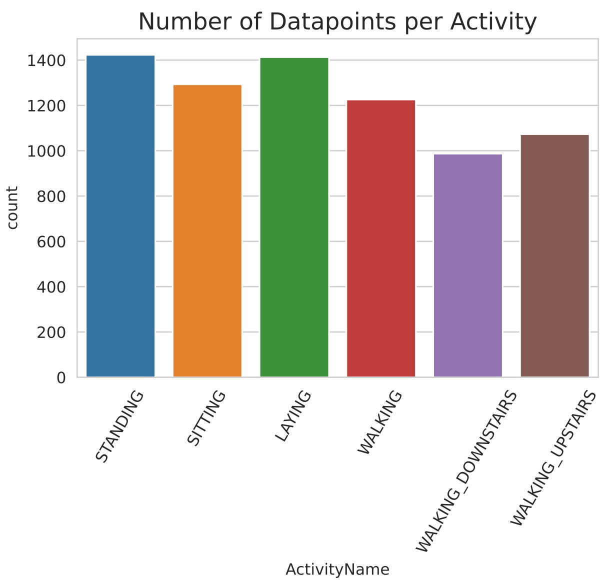

FIGURE 3. Number of data points per activity.

B. EXPLORATORY DATA ANALYSIS (EDA)

"Without domain knowledge EDA has no meaning, without EDA a problem has no soul."

The main work of exploratory data analysis (EDA) is to clean the data, describe the data (describe statistics, charts), view the distribution of the data, compare the relationship between the data, cultivate the intuition of the data, summarize the data, etc. [27].

Differences between EDA and traditional statistical analysis (ClassicalAnalysis):

The traditional statistical analysis method usually assumes that the sample obeys a certain distribution, and then applies the data into the hypothetical model for analysis. However, because most of the data can not meet the hypothetical distribution, the results of traditional statistical analysis are often not satisfactory.

The exploratory data analysis method pays attention to the real distribution of the data and emphasizes the visualization of the data, so that the analyst can clearly see the hidden rules in the data at a glance, thus get inspiration, so as to help the analyst to find a model suitable for the data. "exploratory" means that the analyst's understanding of problem solving will change with the deepening of the study.

C. FEATURING ENGINEERING FROM DOMAIN KNOWLEDGE

1) MOTIONLESS AND DYNAMIC ACTIVITIES

1) In motionless activities (sit, stand, lie down) motion information will not be very useful.
2) In the dynamic activities (Walking, WalkingUpstairs, WalkingDownstairs) motion info will be significant.

2) STATIONARY AND MOVING ACTIVITIES ARE COMPLETELY DIFFERENT

Based on the given data, the graphs of six active states are drawn, as shown in FIGURE 4. Then, the data are further distinguished, and the inactivity and dynamic curves are drawn, respectively, as shown in FIGURE 5 and FIGURE 6. Comparing the two pictures, we can find that motionless activities are more intensive, while dynamic activities are relatively less. This reason can explain to a great extent that in today's life, people may exercise very little because of the pressure of life, thus affecting their physical and mental health [28].

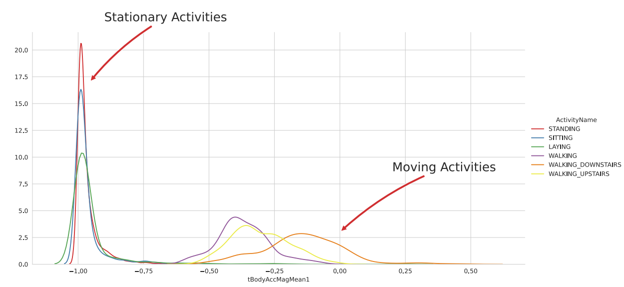

FIGURE 4. Stationary and Moving activities are completely different.

3) MAGNITUDE OF AN ACCELERATION CAN SEPARATE IT WELL

As shown in FIGURE 7:

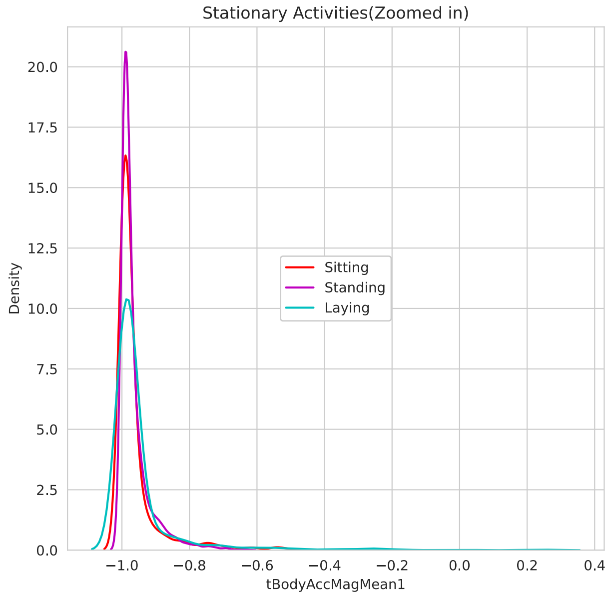

FIGURE 5. Stationary activities.

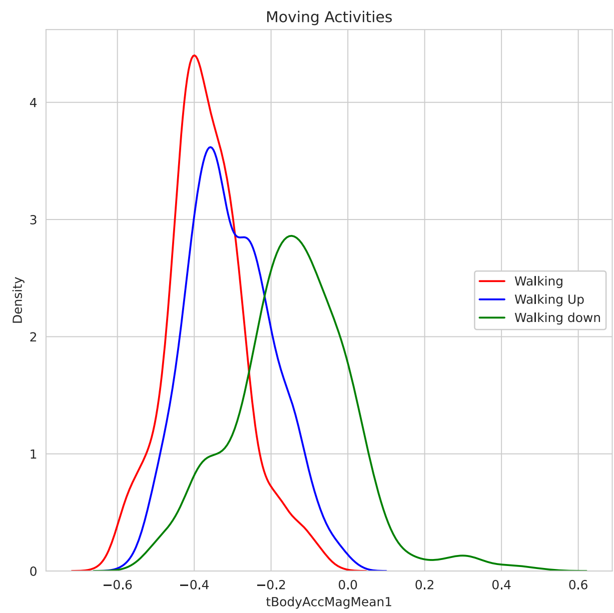

FIGURE 6. Moving activities.

1) If tAccMean is < -0.8 then the Activities are either Standing or Sitting or Laying.
2) If tAccMean is > -0.6 then the Activities are either Walking or WalkingDownstairs or Walking Upstairs.
3) If tAccMean > 0.0 then the Activity is Walking Downstairs.
4) We can classify 75% the Acitivity labels with some errors.

4) POSITION OF GRAVITY ACCELERATION COMPONANTS ALSO MATTERS

Looking at FIGURE 8 above, we can see that if angleX, gravityMean > 0.0, the action in progress is laying the groundwork

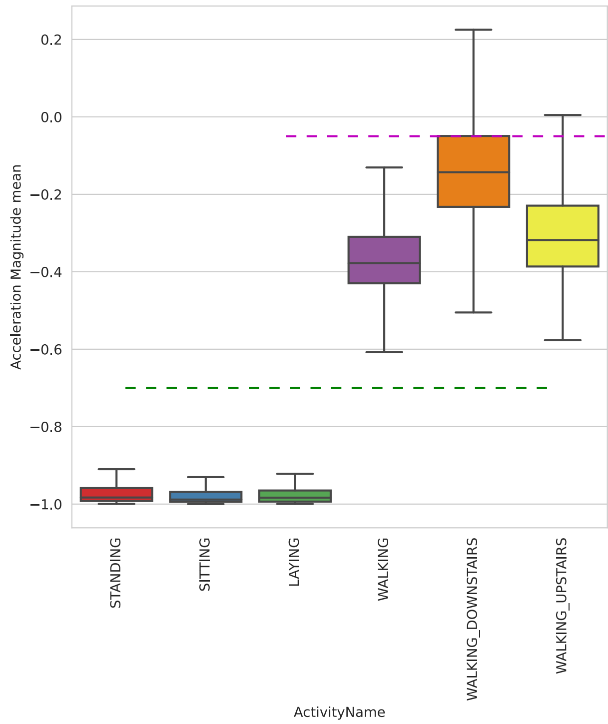

FIGURE 7. Magnitude of an acceleration can saparate it well.

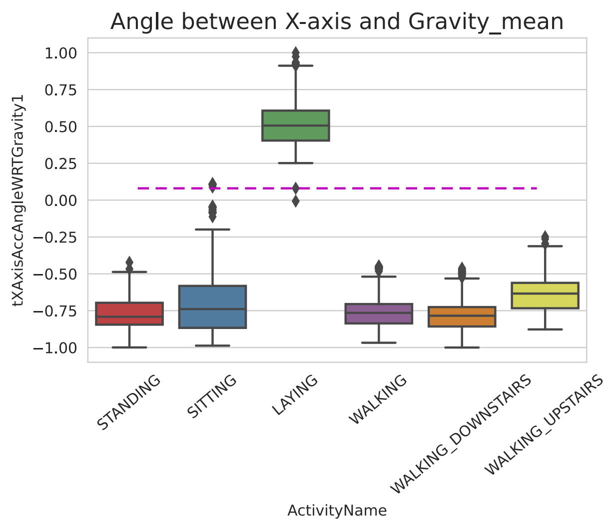

FIGURE 8. Position of Gravity Acceleration Componants also matters.

for the next action. Then, we only need to use an ifelse statement to classify all the data points that belong to the matting action, as showed in FIGURE 9.

5) APPLY T-SNE TO DATA

T DistributedStochasticNeighborEmbedding(t−SNE) is a dimensionality reduction technique used to visualize high-dimensional datasets in two-dimensional or three-dimensional low-dimensional space. Compared with other dimensionality reduction algorithms (such as PCA),

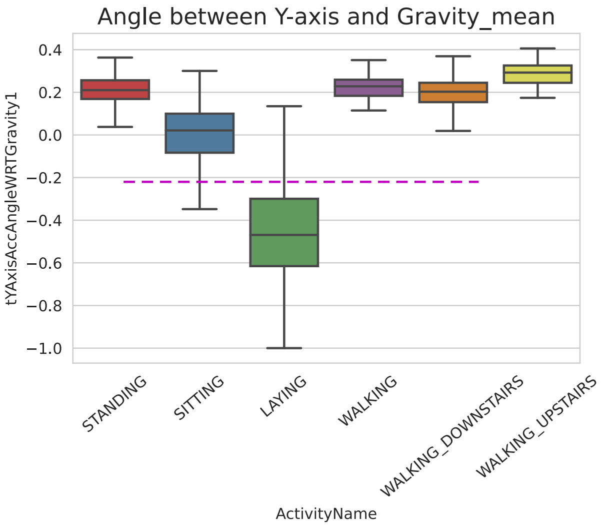

FIGURE 9. Classify all datapoints belonging to Laying activity with just a single if else statement.

t−SNE creates a reduced feature space, with similar samples modeled by nearby points and dissimilar samples modeled by high-probability distant points [29].

At a high level, t−SNE constructs a probability distribution for high-dimensional samples [30].

$$q_{ij} = \frac{\left(1 + \|\mathbf{y}_i - \mathbf{y}_j\|^2\right)^{-1}}{\sum_{k \neq l} \left(1 + \|\mathbf{y}_k - \mathbf{y}_l\|^2\right)^{-1}} \tag{1}$$

Next we calculate the KL divergence:

$$KL(P\|Q) = \sum_{i,j} p_{ij} \log \frac{p_{ij}}{q_{ij}} \tag{2}$$

Next calculate the gradient:

$$\frac{\delta C}{\delta y_i} = 2 \sum_j \left(p_{j|i} - q_{j|i} + p_{i|j} - q_{i|j}\right) \left(y_i - y_j\right) \tag{3}$$

Given by1,2,3, the degree of freedom $\frac{\delta C}{\delta f(x_i|W)}$ can be expressed as:

$$\frac{\delta C}{\delta f\ (x_i \mid W)} = \frac{2\alpha + 2}{\alpha} \sum_j \left(p_{ij} - q_{ij}\right) \times \left(f\ (x_i \mid W) - f\ \left(x_j \mid W\right)\right) \tag{4}$$

where α represents the degree of freedom of the s−t distribution.

Therefore, the possibility of similar samples being selected is very high, while the possibility of singular points being selected is very small. Then, t−SNE defines a comparable distribution for points in low-dimensional embedding. Finally, t−SNE minimise the Kullback Leibler (KL) divergence between the two distributions with respect to the location of the embedding point [31]. t−SNE is a technology that integrates dimensionality reduction and visualization. It is built on the improvement of SNE visualization and solves the characteristics of crowded sample distribution and unclear boundary of SNE after visualization. It is a useful visualization method for dimensionality reduction at present [32]. The confusion of executing t−SNE, is 5, 10, 20, 50 respectively, and the maximum number of iterations is 1000. The resulting image is illustrated in FIGURE 10.

D. MODELING WITH DATA

When writing the code, we set up a general function of the model that can run any specified model.

The algorithm inputs the selected model, training data set and test data set into the general function. Model fitting and prediction are carried out according to different models. According to different models, calculate the time used to fit the model, and calculate the time used to predict the model. Finally, the confusion matrix is output and normalized and output the class of 6 label parameter results.

IV. RESULT ANALYSIS

Utilising the model established by the above data to analyze the data, the confusion matrix of the GrdiSearchCV and Linear SVC model is obtained, and the thermal map of the normalized confusion matrix is obtained after normalizing it. For specific images, please see FIGURE 11. Comparing the six thermal maps, we can remove the following conclusions: (1) The correlation degree of Linear SVC model is higher. (2) The correlation degree of motionless activity is higher than that of dynamic activity.

After tuning with GridSearch, the table of model accuracy and model training time, best score is obtained (Table 2), where best score is the average cross-validation score of the best estimator. Compared with the table, we can find that the prediction accuracy of the: Logistic Regression, Linear SVC, Kernel SVM model is almost the same as the model training time, Best score, in which the accuracy of Kernel SVM is as high as 96.46% Random Forest, GradientBoosting DT. Although the prediction accuracy is also 91.82%, it takes about 5 hours to train the GradientBoosting DT model. And we also obtained the prediction accuracy, recall rate and F1 score, support table of inactivity and dynamic motion under different model states (Table 6, 8, 5, 4, 3, 7). Because there are too many details, please see Table 2 on page 73362. By comparing these tables, we can find that motionless exercise accounts for 1% more than dynamic exercise, which is the same as the result obtained by the confusion matrix above, which shows that most people in today's society belong to motionless work, which in disguise shows that a large number of people do not like exercise, which leads to some physiological diseases such as obesity, high blood pressure and so on [33].

The experimental results show that the exploratory data analysis method has better generalization performance than the traditional data analysis method no matter for different databases or different evaluation strategies. These conclusions provide guidance for the design of HAR systems using

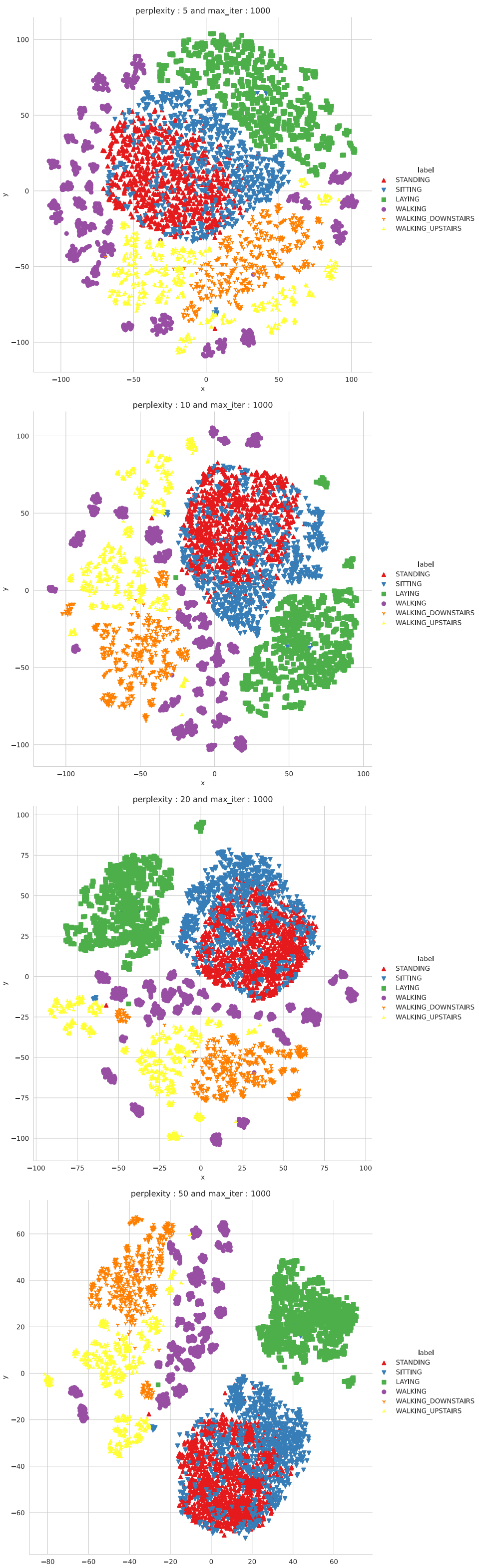

FIGURE 10. **The perplexity of executing TSNE, is 5, 10, 20, 50 respectively, the maximum number of iterations is 1000, and the resulting images are a, b, c, d respectively.**

smartphone sensors in the future. In this study, the experiment was carried out under the condition of completely offline. In this way, the implementation of the method in smartphones

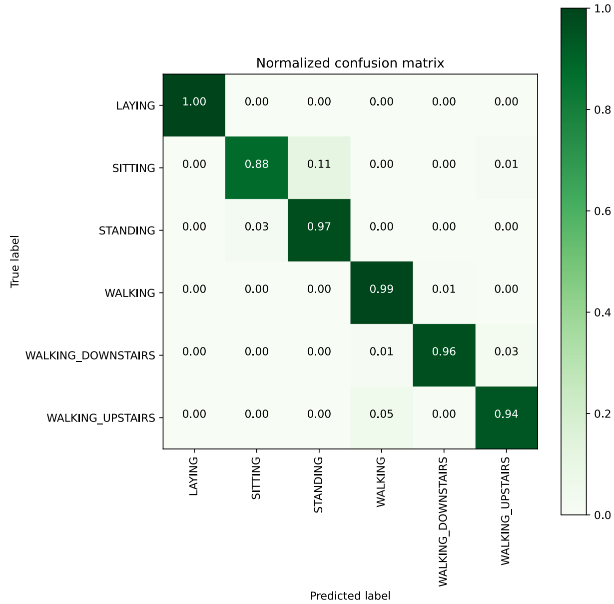

FIGURE 11. **Confusion matrix of GridSearchCV and Linear SVC model.**

TABLE 1. **Comparison with the latest research.**

The study reference	Method	Classification Accuracy%
Hassan et al.[27]	SVM	94.12
Ye Liu et al.[16]	SVM	80
Espinilla et al.[20]	k-NN	83.13
Liang Cao et al. [19]	C4.5	83.5
Xiaojie Wang et al. [34]	k-NN	81.4
Reem Al-Ghannam et al. [35]	Naive Bayes	91.3
Garcia-Gonzalez et al. [10]	RandomForest	89.6
Lu, D.N et al. [36]	RandomForest	91.31
Markstrom et al. [37]	Decision Table	88
This Study	**GridSearchCV and Linear SVC**	**96.56**

will be evaluated in the future, and the classification of activities will be evaluated in real time. Moreover, the solution can be extended to other classification or generalized tasks for the classification of multivariable time series. Therefore, the experimental evaluation of further application fields, such as the classification of physiological signals, makes it possible for future work.

V. COMPARISON WITH THE LATEST RESEARCH

Comparing the classifiers created in this study with similar studies, the diversity of classification techniques and their data sets is a challenging task. Compared with the examples in the literature, the results of this study are satisfactory, with a success rate of 96.56%. Some previous studies have been compared with the results given in the table. As can be seen from the table, Hassan *et al.* [27] The accuracy of 94.12% is obtained by using support vector machine. Ye Liu *et al.* [16]. Support vector machine classifier is also used to achieve 80% accuracy. Espinilla *et al.* [20]. The accuracy of 83.13% is obtained by using k-NN. Liang Cao *et al.* [19]. Using C4.5 decision tree classifier, the classification accuracy is 83.5%. We use the same data set with an accuracy of 96.56%. In order to promote the results of this study, we selected the data for evaluation and considered a large number of exercises of different types of activities. Therefore, different intensity and speed involve different combinations of body parts. In order to facilitate promotion, the HAR framework tested in this paper corresponds to the most widely used HAR framework in related work.

VI. CONCLUSION AND FUTURE WORK

The experimental results show that the HAR method proposed in this paper is successful. In addition, this method is lightweight, accurate and cognitive. In addition, by using the proposed exploratory data analysis framework, new activity monitoring and identification applications can be developed.

HAR based on sensor data is very challenging, especially when there are a variety of machine learning techniques. Despite the latest developments in health informatics, machine learning and data mining, we should not forget that human behavior is not only natural and spontaneous, but also that human beings may perform several activities at the same time, or even carry out some unrelated activities. Another problem is the challenge of predicting the speed of movement or activity. We believe that the future HAR should be designed to be able to predict and identify concurrent activities and to deal with uncertainties in order to achieve high accuracy and improve health care functionality, quality, and safety.

Good preliminary experimental results show that our proposed classification method has the potential to improve the performance of HAR applications. As the research is in progress, the application in real life has not been achieved.

For the future work, there are the following aspects for further in-depth study.

(1) It is also important to extend HAR to other activities such as sleeping or cycling, and to extract more features that help analyze human interactions and relationships.
(2) Use our proposed EDA to build and publish a real-time HAR system to promote a variety of intelligent Internet of things and network applications.
(3) HAR is designed to be able to predict and identify concurrent activities and to deal with uncertainties in order to achieve high accuracy and improve health care function, quality and safety.
(4) Develop the cloud network architecture [9], as shown in FIGURE 12. The network architecture is divided into three layers from top to bottom, which is cloud computing layer, computing layer and terminal user layer. The cloud computing layer consists of high-performance server clusters. The computing layer is composed of switches, routers and other network edge devices in the hospital. on the one hand, it provides network access channels for medical devices and users, and is responsible for data forwarding in the whole fog network, on the other hand, through active caching to pull computing services from the cloud computing layer to the local, task computing, the end-user layer is composed of many medical detection devices and target user terminals. Based on this architecture, medical big data does not need to be transmitted to the cloud for processing, but is sent directly to the target user through the hospital's fog network, and uses the pre-cached computing service on the data transmission path to gradually complete the big data task calculation. The data obtained by the target user are the result of pathological analysis.

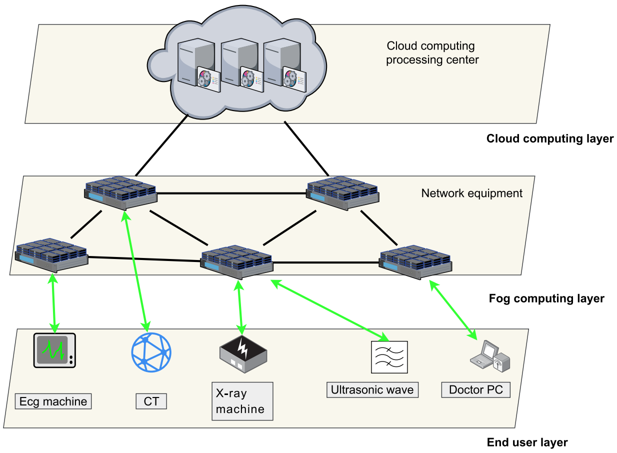

FIGURE 12. Cloud network architecture.

TABLE 2. Model accuracy, model training time, Best score.

Mode name	Accuracy	training time	Best Score
Logistic Regression	95.79%	0:00:20.143272	0.937
Linear SVC	96.66%	0:01:10.760986	0.943
Kernel SVM	96.46%	0:09:19.616294	0.947
Decision Tree	87.25%	0:00:10.421130	0.850
Random Forest	92.72%	0:05:39.268746	0.921
Gradient Boosting DT	92.72%	5:13:25.448262	0.913

TABLE 3. Logistic Regression with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.97	0.88	0.92	508
STANDING	0.90	0.97	0.93	556
WALKING	0.94	0.99	0.97	496
WALKING DOWNSTAIRS	0.99	0.96	0.97	420
WALKING UPSTAIRS	0.96	0.94	0.95	471
macro avg	0.96	0.96	0.96	2996
weighted avg	0.96	0.96	0.96	2996

TABLE 4. Linear SVC with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.97	0.90	0.93	508
STANDING	0.92	0.97	0.95	556
WALKING	0.95	1.00	0.97	496
WALKING DOWNSTAIRS	1.00	0.98	0.99	420
WALKING UPSTAIRS	0.98	0.95	0.96	471
macro avg	0.97	0.97	0.97	2996
weighted avg	0.97	0.97	0.97	2996

VII. DATA SOURCE

The data used to generate the results of this study can be downloaded from the following website: https://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions#

APPENDIX

TABLES MENTIONED IN THE ARTICLE

See Tables 2–8.

TABLE 5. Kernel SVM with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.97	0.90	0.94	508
STANDING	0.92	0.98	0.95	556
WALKING	0.96	0.99	0.97	496
WALKING DOWNSTAIRS	0.99	0.95	0.97	420
WALKING UPSTAIRS	0.95	0.97	0.96	471
macro avg	0.97	0.96	0.96	2996
weighted avg	0.97	0.96	0.96	2996

TABLE 6. Decision Trees with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.86	0.77	0.81	508
STANDING	0.81	0.88	0.85	556
WALKING	0.84	0.95	0.89	496
WALKING DOWNSTAIRS	0.89	0.82	0.86	420
WALKING UPSTAIRS	0.84	0.78	0.81	471
macro avg	0.87	0.87	0.87	2996
weighted avg	0.87	0.87	0.87	2996

TABLE 7. Random Forest with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.91	0.88	0.90	508
STANDING	0.89	0.92	0.91	556
WALKING	0.91	0.98	0.94	496
WALKING DOWNSTAIRS	0.97	0.85	0.90	420
WALKING UPSTAIRS	0.90	0.92	0.91	471
macro avg	0.93	0.92	0.93	2996
weighted avg	0.93	0.93	0.93	2996

TABLE 8. Gradient Boosted Decision Trees with Grid Search different activity precision, recall, f1-score, support.

Activity name	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	545
SITTING	0.91	0.83	0.86	508
STANDING	0.85	0.92	0.88	556
WALKING	0.93	0.98	0.95	496
WALKING DOWNSTAIRS	0.97	0.89	0.93	420
WALKING UPSTAIRS	0.92	0.93	0.92	471
macro avg	0.93	0.92	0.92	2996
weighted avg	0.93	0.93	0.93	2996

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REFERENCES

[1] G. Yuan, Z. Wang, F. Meng, Q. Yan, and S. Xia, "An overview of human activity recognition based on smartphone," *Sensor Rev.*, vol. 39, no. 2, pp. 288–306, Mar. 2019.

[2] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. R. Reyes-Ortiz, "Energy efficient smartphone-based activity recognition using fixed-point arithmetic," *J. Universal Comput. Sci.*, vol. 19, no. 9, pp. 1295–1314, Jan. 2013.

[3] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, "A survey of online activity recognition using mobile phones," *Sensors*, vol. 15, no. 1, pp. 2059–2085, Jan. 2015.

[4] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explor. Newslett.*, vol. 12, no. 2, pp. 74–82, Mar. 2011.

[5] E. T. Horta, I. C. Lopes, and J. J. P. C. Rodrigues, "Ubiquitous mHealth approach for biofeedback monitoring with falls detection techniques and falls prevention methodologies," in *Mobile Health: A Technology Road Map* (Springer Series in Bio-/Neuroinformatics), S. Adibi, Ed. Cham, Switzerland: Springer, 2015, pp. 43–75.

[6] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, "Fusion of smartphone motion sensors for physical activity recognition," *Sensors*, vol. 14, no. 6, pp. 10146–10176, Jun. 2014.

[7] N. A. Capela, E. D. Lemaire, and N. Baddour, "Improving classification of sit, stand, and lie in a smartphone human activity recognition system," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, May 2015, pp. 473–478.

[8] L. Zhang, X. Wu, and D. Luo, "Improving activity recognition with context information," in *Proc. IEEE Int. Conf. Mechatronics Automat. (ICMA)*, Aug. 2015, pp. 1241–1246.

[9] X. Zhang, Z. Ren, J. Hu, Y. Zhang, and H. Zhang, "A path computing scheme for low-latency requirement of medical big data task," *J. Xi'an Jiaotong Univ.*, vol. 54, no. 02, pp. 119–126, 2020.

[10] D. Garcia-Gonzalez, D. Rivero, E. Fernandez-Blanco, and M. R. Luaces, "A public domain dataset for real-life human activity recognition using smartphone sensors," *Sensors*, vol. 20, no. 8, p. 2200, Apr. 2020.

[11] M. A. Labrador and O. D. L. Yejas, *Human Activity Recognition: Using Wearable Sensors and Smartphones*. Boca Raton, FL, USA: CRC Press, 2013.

[12] T. Ploetz, N. Y. Hammerla, and P. L. Olivier, "Feature learning for activity recognition in ubiquitous computing," in *Proc. 22nd Int. Joint Conf. Artif. Intell. (IJCAI)*. Barcelona, Spain: AAAI Press, Jun. 2011, pp. 1729–1734.

[13] L. Zhang, D. Liu, M. Chen, H. Li, C. Wang, Y. Zhang, and Y. Du, "A user collaboration privacy protection scheme with threshold scheme and smart contract," *Inf. Sci.*, vol. 560, pp. 183–201, Jun. 2021.

[14] T. Tuncer, F. Ertam, S. Dogan, and A. Subasi, "An automated daily sports activities and gender recognition method based on novel multikernel local diamond pattern using sensor signals," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 12, pp. 9441–9448, Dec. 2020.

[15] A. Subasi, D. H. Dammas, R. D. Alghamdi, R. A. Makawi, E. A. Albiety, T. Brahimi, and A. Sarirete, "Sensor based human activity recognition using AdaBoost ensemble classifier," *Procedia Comput. Sci.*, vol. 140, pp. 104–111, Jan. 2018.

[16] Y. Liu, L. Nie, L. Liu, and D. S. Rosenblum, "From action to activity: Sensor-based activity recognition," *Neurocomputing*, vol. 181, pp. 108–115, Mar. 2016.

[17] A. Ignatov, "Real-time human activity recognition from accelerometer data using convolutional neural networks," *Appl. Soft Comput.*, vol. 62, pp. 915–922, Jan. 2018.

[18] Y. Xu, Z. Shen, X. Zhang, Y. Gao, S. Deng, Y. Wang, Y. Fan, and E. I.-C. Chang, "Learning multi-level features for sensor-based human action recognition," *Pervas. Mobile Comput.*, vol. 40, pp. 324–338, Sep. 2017.

[19] L. Cao, Y. Wang, B. Zhang, Q. Jin, and A. V. Vasilakos, "GCHAR: An efficient group-based context—Aware human activity recognition on smartphone," *J. Parallel Distrib. Comput.*, vol. 118, pp. 67–80, Aug. 2018.

[20] M. Espinilla, J. Medina, A. Calzada, J. Liu, L. Martínez, and C. Nugent, "Optimizing the configuration of an heterogeneous architecture of sensors for activity recognition, using the extended belief rule-based inference methodology," *Microprocessors Microsyst.*, vol. 52, pp. 381–390, Jul. 2017.

[21] L. Zhang, J. Li, S. Yang, and B. Wang, "Privacy preserving in cloud environment for obstructed shortest path query," *Wireless Pers. Commun., Int. J.*, vol. 96, no. 2, pp. 2305–2322, Sep. 2017.

[22] M. Arif, M. Bilal, A. Kattan, and S. I. Ahamed, "Better physical activity classification using smartphone acceleration sensor," *J. Med. Syst.*, vol. 38, no. 9, p. 95, Jul. 2014.

[23] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar, "Activity logging using lightweight classification techniques in mobile devices," *Pers. Ubiquitous Comput.*, vol. 17, no. 4, pp. 675–695, Apr. 2013.

[24] J. J. Guiry, P. van de Ven, J. Nelson, L. Warmerdam, and H. Riper, "Activity recognition with smartphone support," *Med. Eng. Phys.*, vol. 36, no. 6, pp. 670–675, Jun. 2014.

[25] A. Subasi, K. Khateeb, T. Brahimi, and A. Sarirete, "Human activity recognition using machine learning methods in a smart healthcare environment," in *Innovation in Health Informatics, Next Gen Tech Driven Personalized Med&Smart Healthcare*, M. D. Lytras and A. Sarirete, Eds. New York, NY, USA: Academic, Jan. 2020, ch. 5, pp. 123–144.

[26] J. J. A. van Boxtel, M. Dapretto, and H. Lu, "Intact recognition, but attenuated adaptation, for biological motion in youth with autism spectrum disorder: Reduced global biological motion adaptation in ASD," *Autism Res.*, vol. 9, no. 10, pp. 1103–1113, Oct. 2016.

[27] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, "A robust human activity recognition system using smartphone sensors and deep learning," *Future Gener. Comput. Syst.*, vol. 81, pp. 307–313, Apr. 2018.

[28] S. Ampamya, J. M. Kitayimbwa, and M. C. Were, "Performance of an open source facial recognition system for unique patient matching in a resource-limited setting," *Int. J. Med. Informat.*, vol. 141, Sep. 2020, Art. no. 104180.
[29] Y. J. Habib and Z. Zhang, "The involvement of crustaceans toll-like receptors in pathogen recognition," *Fish Shellfish Immunol.*, vol. 102, pp. 169–176, Jul. 2020.
[30] A. Batch and N. Elmqvist, "The interactive visualization gap in initial exploratory data analysis," *IEEE Trans. Vis. Comput. Graphics*, vol. 24, no. 1, pp. 278–287, Jan. 2018.
[31] X. Li, P. Zhao, M. Wu, Z. Chen, and L. Zhang, "Deep learning for human activity recognition," *Neurocomputing*, Nov. 2020.
[32] I. Rawtaer, R. Mahendran, E. H. Kua, H. P. Tan, H. X. Tan, T.-S. Lee, and T. P. Ng, "Early detection of mild cognitive impairment with in-home sensors to monitor behavior patterns in community-dwelling senior citizens in singapore: Cross-sectional feasibility study," *J. Med. Internet Res.*, vol. 22, no. 5, May 2020, Art. no. e16854.
[33] A. A. Mauracher *et al.*, "Erythropoiesis defect observed in STAT3 GOF patients with severe anemia," *J. Allergy Clin. Immunol.*, vol. 145, no. 4, pp. 1297–1301, Apr. 2020.
[34] X. Wang, V. C. C. Carlson, C. Studholme, N. Newman, M. M. Ford, K. A. Grant, and C. D. Kroenke, "In utero MRI identifies consequences of early-gestation alcohol drinking on fetal brain development in rhesus macaques," *Proc. Nat. Acad. Sci. USA*, vol. 117, no. 18, pp. 10035–10044, May 2020.
[35] R. Al-Ghannam and H. Al-Dossari, "Prayer activity monitoring and recognition using acceleration features with mobile phone," *Arabian J. Sci. Eng.*, vol. 41, no. 12, pp. 4967–4979, May 2016.
[36] D.-N. Lu, T.-T. Nguyen, T.-T.-T. Ngo, T.-H. Nguyen, and H. N. Nguyen, "Mobile online activity recognition system based on smartphone sensors," in *Advances in Information and Communication Technology*, vol. 538. 2016, pp. 357–366.
[37] J. L. Markström, H. Grip, L. Schelin, and C. K. Häger, "Dynamic knee control and movement strategies in athletes and non-athletes in side hops: Implications for knee injury," *Scand. J. Med. Sci. Sports*, vol. 29, no. 8, pp. 1181–1189, Aug. 2019.

WEIHENG KONG was born in 1999. He is currently pursuing the degree in computer science and technology with Jiamusi University, majoring in algorithms, mathematical models, and data analysis.

LILI HE was born in 1979. She received the B.E. degree from the College of Information Science and Electronic Technology, Jiamusi University, Jiamusi, China, in 2001, and the M.E. degree from the College of Software Engineering, Beijing University of Posts and Telecommunications, Beijing, China, in 2014. She is currently an Associate Professor of computer software with Jiamusi University. Her research interest includes software engineering.

HAILONG WANG graduated from Harbin Normal University, in 2007. He worked with Jiamusi University. His research interests include theory of physical education and training.