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A fitness training optimization system based on heart rate prediction under different activities

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ABSTRACT

Heart rate can be considered as an indicator of the exercise intensity in people's daily physical activities. Five heart rate zone theory is commonly adopted by individuals and professional athletes during their exercises and training. These heart rate zones are based upon percentages of people's maximal heart rate, which indicate different exercise intensities. The aim of paper is to propose an optimization training system based on dynamic heart rate prediction, which can predict people's heart rate under three different types of exercises: walking, running and rope jumping. The system can help people optimize their exercise by advising them to adjust the speed or workload to reach their predetermined training intensity under different activities. Four Long Short-Term Memory (LSTM) neural networks are deployed, one for human activity recognition (HAR) and three for heart rate prediction.

1. Introduction

Exercise intensity refers to how hard the body is working during physical activity. Different levels of exercise intensity will bring different effects on individuals' health during fitness training. For example, according to the heart rate zone theory, the moderate activity zone is low-intensity training and provides primarily metabolic and emotional health benefits [17]. The aerobic zone improves fitness by increasing mitochondrial density and enhancing fat utilization, resulting in more calories expended per exercise minute. Keeping in a pre-determined exercise intensity during people's fitness training can help to improve exercise performance and efficiency [22]. In addition, staying in a high-intensity training status for a long time increases the chance of heart-related disease [4]. Hence, to improve the performance and safety of exercise and training, it is critical to monitor exercise intensity during daily training and exercise for providing instructions for people.

Many studies have investigated the indicator of fitness training intensity. Glutamine is an amino acid essential for many critical homeostatic functions and the optimal functioning of several tissues in the body. Researchers measured glutamine level during different training periods and identified the glutamine's feasibility as an indicator of training intensity [21]. Besides, renal blood flow (RBF) has also been proven to be a good indicator because the increasing of exercise intensity will reduce RBF [13]. Although these studies can provide high accuracy indicators for exercise, professional devices are required.

Heart rate is one of the most commonly used physiological parameters. The rhythm of heart rate affected by exercise mode and duration has been investigated recently [15,12]. Heart rate data nowadays is widely used to monitor and analyze exercise training for athletes [7]. A considerable numbers of studies [19,26] suggest that real-time heart rate monitoring requires less requirement than other indicators we mentioned above. In addition, a heart rate zone theory was proposed to measure exercise intensity, which identifies the corresponding relationship between the percentages of maximal heart rate (HRmax) and exercises intensity [6]. With the help of the heart rate zone theory and heart rate monitoring, people's real-time exercise intensity can be easily acquired. However, gaining real-time exercise intensity still can not make a promise to help people stay in their pre-determined intensity zone. Studies on heart rate recovery after exercise show that when people lower their training intensity, heart rate will not start to decrease immediately [1]. This situation may bring the risk of stroke to some

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patients who have a heart-related disease and cannot exercise in high intensity zone [4]. The delayed reaction of heart rate to training intensity changing drives the need for a new heart rate-based training intensity optimization scenario, which can predict when the heart rate reaches higher or lower exercise intensity zone and make an alert in advance.

To overcome the limitations mentioned above, a Long Short-Term Model (LSTM) based activity recognition model and three heart rate prediction models under three kinds of activities are designed and implemented in this paper. Three types of commonly used sensor data: heart rate, tri-axial acceleration, and tri-axial gyroscope are served as input of the LSTM prediction. These sensor data can be collected from most brands of off-the-shell smart watches, which lower the equipment threshold for heart rate prediction. In the experiment, we collect sensor data from Tic Watch3 pro. LSTM is an artificial recurrent neural network architecture to train and predict time sequence sensor data. Moreover, the feature of LSTM model, "gate units", can help to remember the information from the past and make more accurate predictions. The trained LSTM model is embedded into a fitness training optimization smartwatch application. The notification system of android is utilized to provide exercise instructions for users in advance when the boundary of the heart rate zone is detected. The contributions of this paper are summarized as follows:

1. We proposed an LSTM-based heart rate prediction pipeline network under three common physical activities. The input of the LSTM from three types of sensor: heart rate, tri-axial acceleration and tri-axial gyroscope. The heart rate prediction and physical activity recognition are conducted simultaneity.
2. We developed a fitness training optimization system based on heart rate zone and heart rate prediction. The system provides instructions for subjects when a trend of reaching the border of heart rate zone is detected.
3. We deployed the fitness training optimization system on a smartwatch. With the help of the TensorFlow Lite, the trained LSTM model can run on android platform. The notification function of android will be utilized when instructions need to be provided for optimizing fitness training.

2. Related work

With the development of technologies, many studies explore to optimize training and daily exercise for athletes and regular people. Measuring the training intensity is one of the efficient methods to improve the performance of exercise and training [24,8]. Several physiological indices have been investigated and proven to be a reliable indicator for monitor exercise intensity. David et al. presented the relationship between glutamine level of blood and the training intensity [21]. Glutamine is a neutral amino acid, found in relatively high levels in many human tissues and is also the most abundant amino acid in human muscle and plasma. The functions of glutamine are reflected in the fact that it fulfills many important roles in the tissue and organs of the body, including transferring of nitrogen between organs, maintenance of acid-base balance, a fuel of gut mucosal cells and so on. Hence, Measuring the glutamine level during training period can make an exercise intensity prediction. However, the level of glutamine can only be analyzed from subjects' blood, which means it is impossible to monitor training intensity base on glutamine in real-time. Similarly, renal blood flow (RBF) has also proven to be a good indicator for training intensity [13]. RBF decreases simultaneously with exercise intensity rising, but collecting RBF needs ultrasound echo, which is a professional device and makes it difficult to carry on for real-time monitoring.

Unlike the indicator mentioned above, heart rate is a very commonly measured physiological index. Numerous studies identified the possibility to monitor real-time heart rate using a wearable device with minimal efforts. For example, Pankiewicz et al. proposed a time-domain heart rate measurement algorithm based on a high accuracy photoplethysmographic sensor [26]. The photoplethysmographic sensor is widely embedded in most brand of smart watches in nowadays market. The advancement of wearable technologies and detection algorithms expand the range of the applications. Edwards proposed a heart rate zone theory for measuring training intensity, which indicates the corresponding relationship between the percentages of maximal heart rate (HRmax) and exercises intensity [6]. Based on the different percentages of HRmax, the heart rate range during training is divided into five zones. Every intensity zone brings different benefits and functions for people during exercise as described in Table 1.

The heart rate zone theory attracted considerable recent research interests. Jill et al. presented that recording the heart rate during exercise can help to quantify the training load, the training response and the effect on performance [3]. However, even though the heart rate record can provide helpful information and instructions for training, the subjects cannot get any advice for optimizing their current training intensity. In addition, since the latency of heart rate reaction to the exercise intensity changing exists, it will lead to the situation that even if the subjects are informed their heart rate reaches or excesses their predetermined heart zone and start to lower down their training strength, the heart rate will still take some time to recovery to the pre-determined zone. For the patients who have heart disease, long time staying in a high training intensity will increase the chance of sudden death [11]. Several researchers have investigated the prediction of heart rate during physical activities. For example, a heart rate prediction model for cyclist training optimization system was developed [14]. However, this prediction may cause low accuracy under some activities, as it was specially designed for bicycle sport and different activities have different effect on heart rate vibration [15]. Xiao et al. [27] designed a feedforward neural network by using collected ECG and accelerometer signal. Even though more information and signals were considered in the network, the "memory' size of feedforward neural network is limited, which will decrease the accuracy when long-term heart rate prediction is required.

This paper proposed an optimization training application under three different activities based on heart rate prediction to overcome the shortcomings mentioned above. To fill the gap that limits the high accuracy of heart rate prediction under different activities in a long period, the human activity recognition method and LSTM were explored to realize the heart rate zone training optimization system.

3. System overview

In this section, the system of the training optimization system is discussed. It can be mainly separated into three phases: Setting up before training, recognizing training type and optimization for training based on heart rate prediction, as shown in Fig. 1. The entire system is

Table 1
Benefits and functions of the heart rate zone.

Intensity Zone	% HRmax	Benefit & Function
Moderate activity	50–60%	Low-intensity training and provide primarily metabolic and emotional health benefits.
Weight management	60–70%	Burn more calories from fat and more calories; conversations can still be easily carried out without any difficulty.
Aerobic	70–80%	Help people to train the endurance capacity- the ability rightarrow sustain exercise over a long period of time without fatigue.
Anaerobic threshold	80–90%	Help people to improve speed for fitness training performance and aerobic capacity.
Red-Line	90–100%	Consume almost all the energy of an individual and can only be sustained for a short period of time; Reserved for very fit persons and athletes.

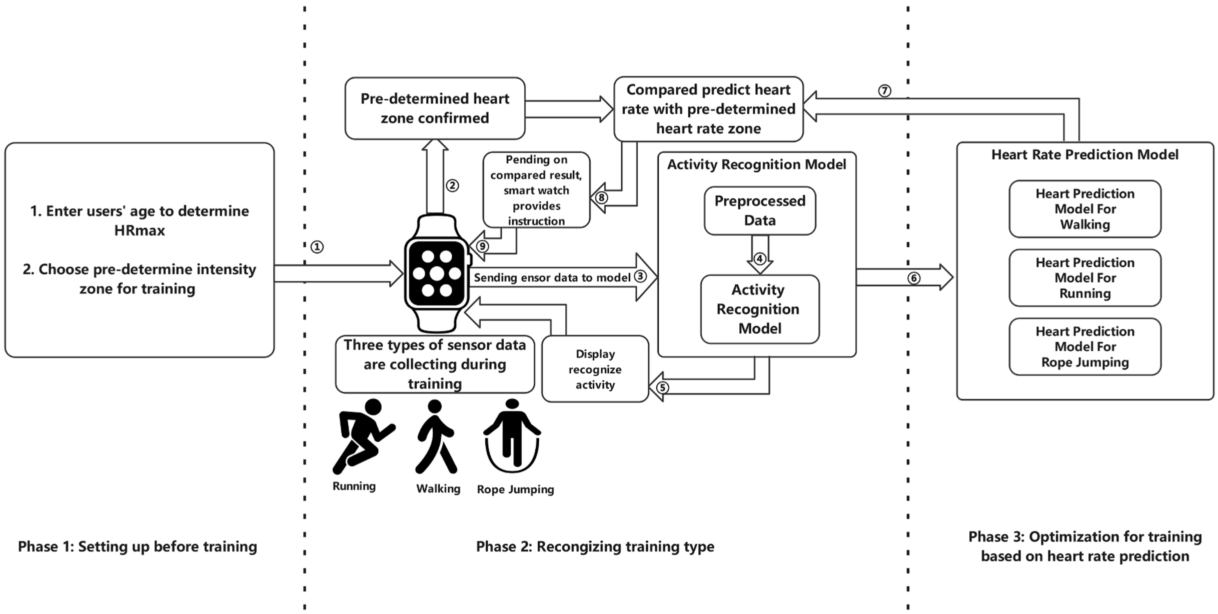

Fig. 1. The fitness training optimization system flowchart.

embedded into an android application and deployed on a smartwatch.

3.1. Setting up before training

In the first phase, the system will remind users to choose their account or register as a new user. The application will record every user's age in the back end. Since the maximal heart rate has a strong relationship with age, we consider the age as a predictor of the maximal heart rate [25]. Hence, once the user logins in their username and age, the maximal heart rate can be calculated. The maximal heart rate function is defined by:

$$HRmax = 208 - 0.7 * Age. \quad (1)$$

Another necessary step in the first phase is to choose a training intensity level. According to heart rate zone theory, every training intensity level can be indicated by different heart rate zone, as shown in Table 1.

The application interface of this phase is shown in Fig. 2.

3.2. Recognizing training type

After setting up a personal training profile, the user can start their exercise. Three sensors of smartwatch: heart rate, accelerator, and gyroscope will start to collect sensor signals simultaneously. The collected data will be imported into two neural network models in phase two and three to recognize current activity and predict heart rate. The prediction of activity will also be displayed on the application interface. In the following phase, the result from the heart rate prediction will be used to compare with pre-determined heart zone.

3.2.1. Dataset

The database we adopted for training the neural networks in this system is the dataset from UC Irvine machine learning repository. The sensor recordings are from 9 participants who are instructed to conduct 12 lifestyle activities [20], including a variety of exercise activities (walking, running, playing soccer, etc.). Accelerometer, gyroscope, magnetometer, temperature and heart rate data are recorded by inertial measurement units located on the wrist, chest and ankle over 10 h. The recordings has 52 dimensions. We choose heart rate, accelerometer and gyroscope sensor data on wrist inertial measurement unit to train our LSTM neural network pipeline, which can fully simulate the situation on smartwatch. The chosen sensor data has seven dimensions. The data is segmented using a sliding window of 5.12 s with a step size of 1 s. Note that, we also use the same setting in our experimental data collection as mentioned in Section 4.1. In total, we collect around 16000 samples of standing, walking, running, and jumping. For one subject, we achieve around 300∼320 standing samples, 640∼650 walking samples, 320∼330 running samples, and 330∼340 jumping samples. We perform nine fold cross validation to examine the performance of our system. Eight of the subjects are in the training set and the other one subject is in the test set. The confusion matrix shows the cross-validation activity recognition performance of nine subjects.

3.2.2. LSTM nueral network

Several previous works have presented their methods to recognize activity and predict heart rate with machine learning tools. Xiao et al. proposed an evolutionary neural network model to predict heart rate under different activities [27]. A feedforward neural network based model for heart rate prediction was also designed [18]. Although these

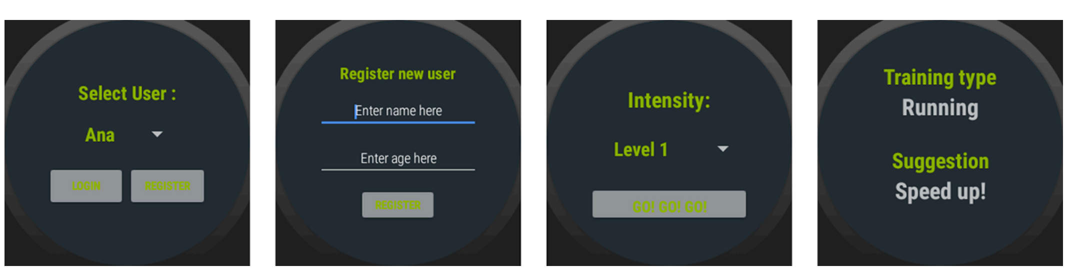

Fig. 2. The user interface of fitness training optimization application.

systems can accomplish a pretty good accuracy in a short time heart rate prediction, when the requirement of prediction time is enlarged, the prediction accuracy will decrease because of the small memory size of the model. In addition, the heart rate is vulnerable to be influenced by different human activities. Hence, to achieve high accuracy of heart rate prediction in a long period under different activities, a large memory size of the prediction model is necessary.

Long Short-Term Memory network is an artificial recurrent neural network architecture, proposed in 1997 by Schmidhuber. The original purpose of the LSTM was to store information over extended time intervals [10]. The structure of the LSTM was developed and improved by many researchers later. Graves and Schmidhuber proposed the bidirectional LSTM that outperforms unidirectional ones [9]. Cho et al. presented a new structure of LSTM called gated recurrent unit (GRU), which combines the forget gates and input gates into the update gates [5]. In this article, we adopted the original LSTM structure to build neural networks.

The structure of LSTM is shown in Fig. 3. The procedure of the LSTM network can be considered as a series of cells. Every cell contains three types of gates: forgot gate, input gate and output gate. With these unique gates, cells could determine which part of information from past is useless and forget it, then combine helpful information with the remaining and pass to the next cell. Fig. 3 shows the gate structure of the LSTM cell. The forgot gate f_t can be formulated as:

$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f), \tag{2}$$

where sigmoid is the sigmoid function. The forgot gate f_t determines what should be abandoned from the past. W_f and b_f are the weights and biases of the forgot gate layer. h_{t-1} and X_t are the previous output of the cell and the current cell's input, respectively. The input gate i_t is another layer of the LSTM similar to forget gate f_i, which can be formulated as:

$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i), \tag{3}$$

where the weight and bias here are different with forget gate f_i. The candidate value $\widetilde{C}_t$ can be represented as the combination of h_{t-1} and X_t, where:

$$\widetilde{C}_t = \tanh(W_c[h_{t-1}, X_t] + b_c). \tag{4}$$

After getting the candidate value $\widetilde{C}_t$, the new cell state C_t can be updated by multiplying the last cell state C_{t-1} with forget gate f_t and multiplying the input gatei_t with the candidate state $\widetilde{C}_t$, given by:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t. \tag{5}$$

At last, the output of the cell h_t combines the output gate o_t and cell state C_t, given by:

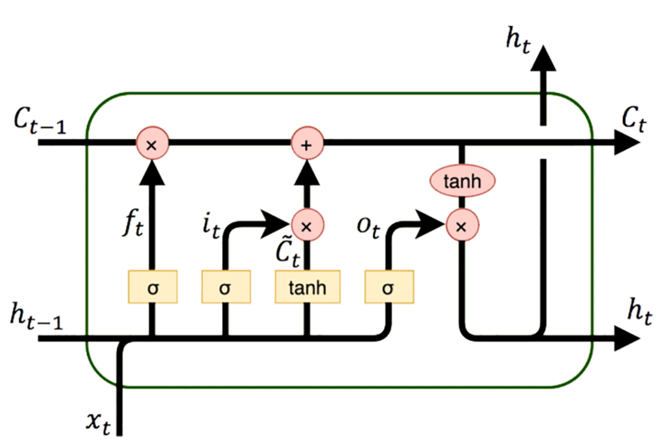

Fig. 3. LSTM cell.

$$\begin{aligned} o_t &= \sigma(W_o[h_{t-1}, X_t] + b_o), \\ h_t &= o_t * \tanh(C_t). \end{aligned} \tag{6}$$

All the parameter of the LSTM are trained by back propagation through time algorithm. The details of the neural network pipeline will be introduced in the following two sections.

3.2.3. Human activity recognition model

The architecture of the human activity recognition model contains one LSTM layer and three fully connected layers, as shown in Fig. 4. Since over-fitting is a severe problem in a deep neural network with a large number of parameters, three dropout layers are added in the heart rate prediction networks. The key idea of dropout layer is to randomly drop units from the neural network during training, which can prevent unit from co-adapting too much [23]. Besides, layer weight regularization is applied to the layers, which can also help to reduce the over-fitting problem. The input of the networks is in 2D dimensions. The first dimension contains two kinds of sensor data from smartwatch sensors, which are 3D acceleration sensor and 3D gravity sensor. Note that the gravity sensor is a software-based sensor and can be obtained by an API based on the calculation of accelerometer and gyroscope. Totally six types of data were in the first dimension. The second dimension is the time sequence length of one period. The 2D dimensions input data provides the motion information during activities. The function of the fully connected layer is to reshape the output of the LSTM into the predicted heart rate. 31,554 parameters are trained in the human activity recognition network. The optimizer of the system is Adam, which is also commonly chosen by other prediction and classification neural networks [2].

The loss function of the activity recognition is categorical cross-entropy from Keras API. The categorical cross-entropy computes the cross-entropy loss between labels and predictions. The formula of categorical cross-entropy loss is formulated as: $-\sum_{c=1}^{M} y_{o,c} * log(p_{o,c})$,

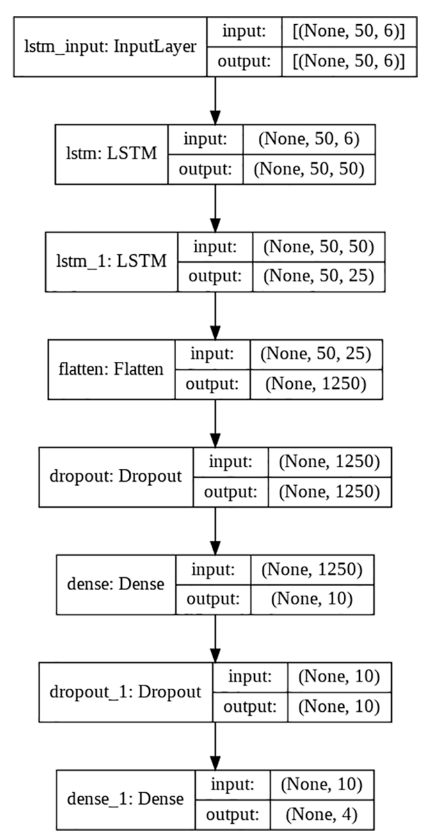

Fig. 4. Human activity recognition network structure.

where M is the number of classes, y represents the binary indicator (0 or 1) determined by whether the class label c is the correct classification for observation o, and p is the predicted probability that observation o belongs to class c.

The training process can be described by the decreasing of training loss and validation loss as shown in Fig. 5. The evaluation metric chosen for training is Kera's Accuracy API. After 48 echoes, the training and validation loss become stable and change little. The accuracy of human recognition model reached to 98.54%, and the performance of the model under four activities is shown in Fig. 6.

3.3. Heart rate prediction and training optimization

To lower the influence of the different training types on heart rate prediction, three heart rate prediction models for walking, running and rope jumping are developed. After the activity recognition model makes a prediction, the sensor data will be fed into the specific heart rate prediction model during the third phase. The training optimization scenario will be described later in this section.

3.3.1. Heart rate prediction model

The architecture of the heart rate prediction model contains one LSTM layer and three fully connected layers as shown in Fig. 7. To avoid over-fitting problem, dropout layer and layer weight regularization are applied in this model as well. The input of the LSTM layer is 2D dimensions. The first dimension contains heart rate, 3D acceleration sensor and 3D gravity sensor, and the second dimension is time sequence. The networks' input describes the variation of the heartbeats, acceleration and gravity during the activities. The fully connected layer reshapes the output of LSTM layer into the result we want. 11,651 parameters are trained in the heart rate prediction network, and Adam is also chosen for training optimizer here.

The loss function for the heart rate prediction model training is mean absolute percentage error. The mean absolute percentage error is a measure of prediction accuracy of forecasting method. The formula of mean absolute percentage error is given by:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \quad (7)$$

where A_t is the actual value and F_t is forecast value. Their difference is divided by the actual value A_t. The absolute value in this ratio is summed for every forecasted point in time and divided by the number of fitted points n.

In order to improve the prediction accuracy, we trained three models for walking, running and jumping rope separately. The accuracy has reached to 96.24%, 97.71% and 94.22%. The performance of heart rate prediction during three activities is shown in Fig. 8–10.

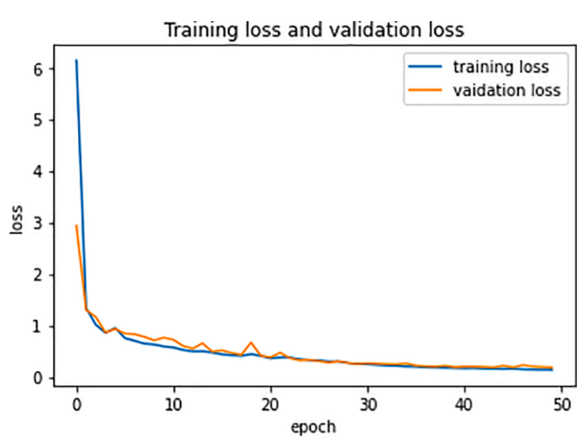

Fig. 5. Training and validation loss.

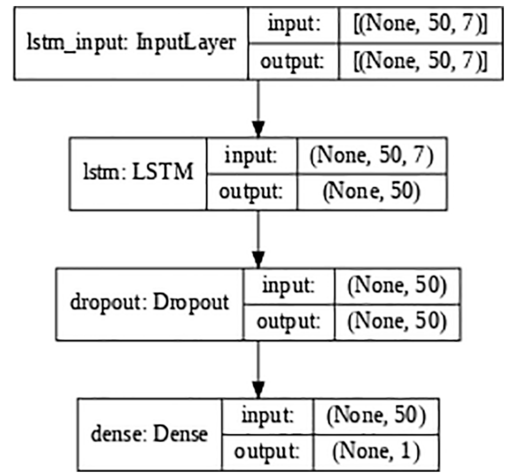

Fig. 6. The confusion matrix of human activity recognition.

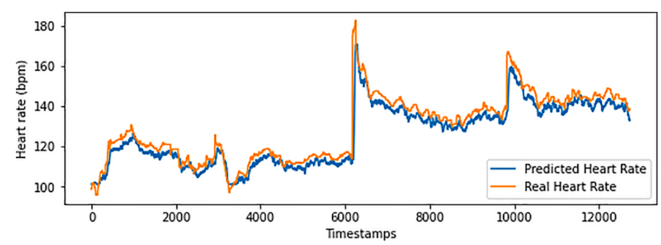

Fig. 7. Heart rate prediction network structure and parameters.

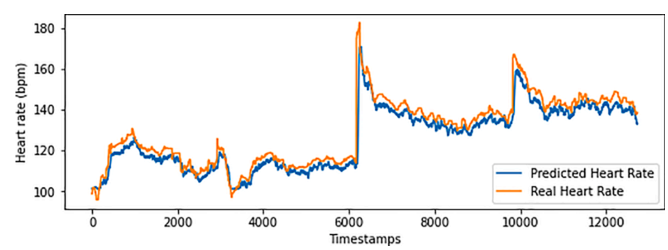

Fig. 8. The performance of heart rate prediction during walking.

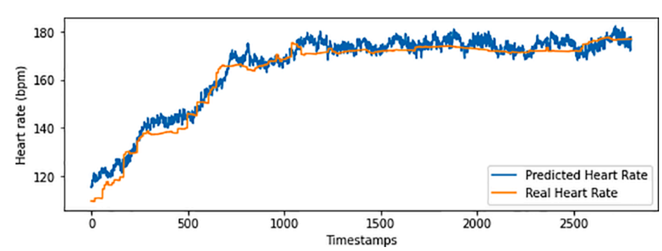

Fig. 9. The performance of heart Rate Prediction during running.

3.3.2. Training optimization scenario

The training optimization is based on the activity recognition, heart rate prediction and Android notification service. After the user enters their age and pre-setting heart rate zone. The application starts to collect sensor data during user's training. The activity type result detected by activity recognition model will be recorded, which can be used for subsequent training analysis. Based on the different activity type results, the selected heart rate prediction model will start to obtain sensor data and make predictions. Once the prediction results are out of the range user set in second step, an Android notification will be made to notify

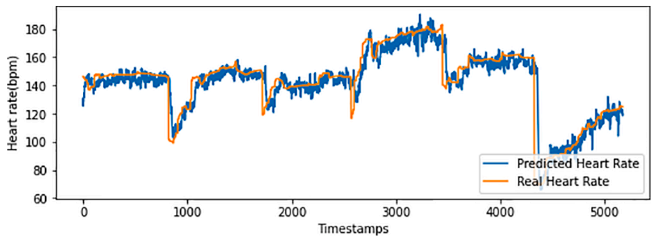

Fig. 10. The performance of heart rate prediction during rope jumping.

user to adjust their training strength. We provide multiple recommendation strategies for fitness training based on the predicted heart rate. Specifically, if the predicted heart rate is in the intensity zone of moderate activity and weight management, our app will provide suggestions“ try to speed up”. If the predicted heart rate is in the intensity zone of aerobic and anaerobic threshold, our app will recommend users adjust their breath. When the red-line is approached, our app will send an alert and suggest users slow down and have a rest. One example is shown in Fig. 2.

3.4. Deploy models on mobile platform

The four neural networks we introduced before were trained on PC platform. In order to deploy the models on smartwatch, the TensorFlow Lite tools are adopted. lthough smartwatch has limited memory and computational power, the model optimization of TensorFlow Lite can help to reduce the storage size and memory usage.

4. Experiment and result

4.1. Experiment design

The increasing trend of sensor data usage allows many customers and professional players to use a variety of sports-based smart watch such as Moto360, Garmin, Apple Watch and others. The experiment is conducted on TicWatch pro3 with Wear OS 2.29 system and Snapdragon 4100 wearable device chip. 1 GB RAM and 8 GB ROM is provided by TicWatch pro3, which can avoid Java GC collection clear necessary memory data automatically and offer more space for recording data. The sampling frequency of accelerometer, and gyroscope sensor are set as 99 Hz and the heart rate sensor’s sampling frequency is set as 10 Hz, which is the same as the sampling frequency of the training dataset [20]. The aim of the experiment is to check the performance of the trained model and application under real-time situations.

Nine subjects are invited to do the experiment. The subjects are requested to wear the TicWatch pro3 perform four kinds of activities as described in Table 2. We perform 9-fold cross-validation to examine the heart rate prediction performance, similar to the activity recognition part.

There is no requirement for the sequence of activities. When the subject is entering exercising mode of the application, the heart rate sensor, accelerometer sensor and gyroscope sensor are registered to collect data constantly during the experiment. The collected data from sensor is prepossessed and imported into the activity recognition model and heart rate prediction. After that, the recognized activities, current heart rate and predicted heart rate will be recorded with time stamp.

Table 2
Activities and corresponding instructions.

Activity Name	Instructions
Standing	Standing still and sometimes talking.
Normal walking	Walking outside with moderate to brisk pace in a speed of 4–6 km/h.
Running	Jogging outside with a suitable speed that the subject prefers.
Rope jumping	rope jumping in a suitable manner that the subject prefers.

4.2. Result and analysis

Each subject conducts six activities in the experiment, as shown in Fig. 11. The whole experiment lasted 785 s, and 157 predictions were made, as every 5 s the application sends the sensor data into the activity recognition model. The recognition performance of these 157 activities is presented in Table 3. As observed, we can achieve high levels of accuracy. The overall activity recognition prediction reached up to 98.72%. Only in the phase of walking after rope jumping phase, we got two false predictions. After the rope jumping activity, a small amount of walking activities was recognized as running. It is because the subject’s walking gait and speed are affected after rope jumping. The abnormal gait information may cause the false prediction when the model analyzes the sensor data.

The real heart rate (ground truth) and predicted heart rate are illustrated in Fig. 12. With the assistance of the timestamp, the six phases in the experiment are straightforwardly displayed in the figure. For the sake of analyzing the difference between predicted heart rate and ground truth in every exercise phase, mean absolute percentage error (MAPE) and mean absolute error (MAE) was selected as metrics. Table 4 shows the overall 100%-MAPE of predicted heart rate under 9-fold cross-validation. Table 5 summarizes the heart rate prediction performance in different activities.

As observed in Fig. 12, the first two phases, walking and running, achieved higher-level accuracy to predict heart rate. It suggests that during these two periods, the subject’s walking and running speed and gait are comfortable to him. Thus, the variation of heart rate here is more smooth than other phases, which reduces the difficulty for the prediction model to make the prediction. The prediction accuracy during these two periods achieved 97.36% and 97.89%. On the other side, the walking after running phase and walking after the rope jumping phase are the periods that the subject’s heart rate recovered from the higher heart rate zone to lower. The recovery speed may be influenced by age, heart rate, stamina and etc. Therefore, all of these factors probably increases the prediction difficulty. The heart rate prediction accuracy in these two phases drop slightly to 96.36% and 96.39%. The rope jumping phase is the most intense period for the subject during this experiment. Besides, rope jumping requires more skill and stamina. The subject can reach to highest heart rate in few seconds. For those people who have bad sense of balance and rope jumping skill, they are more likely to get tripping on the rope, which also lead to a lower prediction accuracy (i.e., 95.77%) in this phase. Considering all the phases of the experiment, the overall prediction accuracy is around 96.76%.

The LSTM heart rate prediction method in this paper outperforms the previous studies. Luo et al. proposed a feed-forward model for heart rate prediction with a 93.4% prediction accuracy [16]. Kusprasapta et al. proposed an improved feed-forward prediction for cyclists with 3.02 MAE [18]. A multi-step heart rate prediction model presented by Feng et al. reached 3.05 MAE when predicting the heart rate under normal daily activities [27]. Even though, some of the previous methods can achieve to higher-level prediction accuracy, their methods become ineffective when the activity type or intense changes.

In a word, the trained LSTM based activity recognition model and heart rate prediction model both achieve a high-level prediction accuracy, which is the core of the training optimization application. The prediction of the activity recognition model can not only be used to record exercise type for professional training analysis, but also help to increase to the prediction accuracy of heart rate prediction. Once the predicted heart rate is out of range of the required heart rate zone, the android notification function will notify user to increase or lower the exercise intensity.

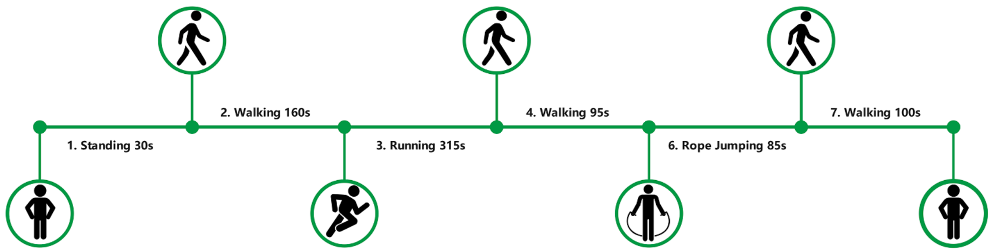

Fig. 11. Six phases in the experiment.

Table 3
The recognition performance of 157 activities.

Activities	Total number	True Prediction
1. Standing	6	6
2. Walking	32	32
3.Running	63	63
4. Walking	19	19
5. Rope Jumping	17	17
6. Walking	20	18

5. Discussion

Ahead of time prediction. Our system can predict the heart rate ahead of 5 s in average for each HR zone while the user is in an unchanged activity state. If we use the previous data point as the prediction of next data point, it will accumulate the error and is not robust to gradual HR changes. The ahead of time decreases slightly when HR zone goes to higher intensity level. We also study the heart rate performance with different ahead of time. As shown in Table 4, the average prediction accuracy (100%-MAPE) is below 90% when we expand the prediction range to more than 10 s ahead, and it continuously drops to 76.51% if ahead of 25 s for prediction. We plan to add self-attention module to study the relationship between the heart rate across time to make earlier and more accurate prediction. (See Table 6).

Activity type. Our system mainly focuses on the heart rate prediction for walking, running, and rope jumping in the current stage. We consider these three activities because they are more representative and very common among users. The heart rate prediction model for other activities (e.g., biking, yoga) can be adapted from our current model. We will investigate noise removal of sensor data to include some sports (e.g., playing basketball, playing football) in our system.

Recommendation strategy. Our app provides fitness training recommendation strategy based on the predicted heart rate intensity zone. In the future works, we plan to consider users' demographic information and health history to recommend more detailed and scientific strategies. We will also cooperate with clinicians to develop risk estimation model for myocardial infarction during fitness training.

Table 4
9-fold cross-validation results in terms of heart rate prediction.

Trial Number	100% – MAPE
1	96.31%
2	96.16%
3	97.23%
4	96.78%
5	96.24%
6	95.95%
7	97.8%
8	96.56%
9	97.81%
Average	96.76%

Table 5
The heart rate prediction performance in different activities.

Exercise Phase	100% – MAPE	MAE
1. Walking before running	97.36%	3.5
2. Running	97.89%	3.26
3. Walking after running	96.63%	5.72
4. Rope Jumping	95.77%	6.79
5. Walking after rope jumping	96.39%	6.04
Summary	**96.76%**	**4.53**

Table 6
Heart rate prediction performance with different ahead of time.

Ahead of time	100% – MAPE
5 s	96.76%
7 s	94.23%
10 s	90.72%
15 s	83.95%
20 s	78.89%
25 s	76.51%

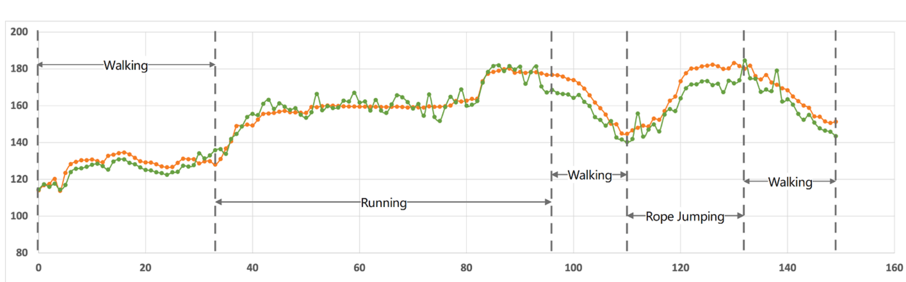

Fig. 12. The illustration of predicted heart rate and real heart rate (ground truth).

6. Conclusion and future work

In this paper, we successfully designed a training optimization application based on heart rate prediction under different activities. Four LSTM models are trained and deployed in the application. The function of activity recognition model is to detect current users' exercise type and record it with a timestamp. The result of the activity recognition helps to choose the specific model among three heart rate prediction models designed for different activities. In the experiment, the prediction accuracy of the activity recognition model and heart rate prediction reach 98.72% and 96.76%, respectively. As a result, once the user's predicted heart rate is out of the desire heart rate zone, the Android notification will remind the user to adjust their exercise intense to avoid stepping into the other heart rate zone. The assistance of the training optimization system of this study can help user to record their physical training process and maintain a stable intensity. In the future research, more exercise types will be considered, such as basketball, cycling, tennis and so on. Providing high accuracy heart rate prediction under more activities can make the training optimization application more intelligent and compatible in real training situations.

CRediT authorship contribution statement

Zetao Zhu: Methodology, Software, Writing - original draft. **Huining Li:** Writing - review & editing, Visualization. **Jian Xiao:** Resources, Investigation. **Wenyao Xu:** Conceptualization, Supervision. **Ming-Chun Huang:** Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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