Research on intelligent analysis of running sports training performance based on artificial intelligence

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Abstract

With the increasing awareness of human beings in the pursuit of human health, running in sports has become a fashionable and healthy first choice. The research uses artificial intelligence technology to conduct intelligent analysis when running training, and aims at the use of artificial intelligence technology. Artificial intelligence technology can accurately analyze and predict the application requirements of sports training postures. We proposed a set of sports posture analysis and predict system to design in this paper. It uses the running training record data in the watch heart rate and GPS smart sports watch, and uses Recurrent Neural Network (RNN), Long and short-term memory (LSTM) and Gate recursive unit (GRU) that three types of neural network models to predict whether the road race can be in the conference. And confirm it will be completed within the scheduled closing time, and it will also perform intelligent analysis of physical fitness (heart rate, pace) and running technology (cadence, pace). The training and test data for this study are the running training records from (Running distance, time, heart rate, stride frequency, stride length, pace, calories, altitude and other characteristic values) as input parameters to test and compare the running completion time trend of RNN, LSTM, GRU neural network models in the exercise table predictive power. The results show predict accuracy is the best is GRU method, and the worst is LSTM method. After the hidden layers are added to the three predict models, RNN is slightly regressive, LSTM has a significant trend of improvement, and GRU is less obvious.

1. Introduction

In recent years, the popularity of road running sports has also produced more and more amateur runners participating in training that is more advanced and close to the level of professional runners. Compared with sports watches, more training functions are provided. Training the data is becoming more complete. What is important that for general beginner runners, as long as a sports wrist optical watch can analyze and record the current status and values of running training, more advanced or professional trainers will also in addition, the heart rate belt and cadence motion detector are used for more precise running numerical analysis. After training, as long as you connect to your smartphone via Bluetooth, it can connect to the cloud and immediately analyze the current running training status. Runners can use these physical data and running values to modify or improve their training process [1].

In recent years, artificial intelligence-like neural networks have been continuously applied in various professional fields, and the performance and computing speed of computers have also been continuously evolving. Therefore, it is hoped that normal running training data can be used by neural networks. The technology is used to predict the results of road races, as a reference for runners. However, most of the road running sports are nothing more than the hope that their body can be healthier, or to seek a breakthrough in the performance of the road running field that has been invested, but the advancement of science and technology that the functions of smart watches and bracelets, it is also becoming more complete. In addition to using GPS to measure running distance, it also records heart rate, oxygen uptake, calories, stride frequency, stride length, pace, altitude, weather temperature, etc. to monitor physiological data during training, in addition to providing complete physiological data during training, you can also use the cloud platform interface to create a training menu to prepare yourself for your next road race. On running-related websites at home and abroad, you can find and use your latest running results, enter the running time and distance into the online forecast program to calculate the end time of the 10 km, 21 km, and 42 km road runs. Most of the online forecasting programs like use David F Cameron's model, Peter Riegel model, Purdy point model, VO2 MAX four forecasting models. The main purpose of this research is not only to predict using running time and distance, but also to use smart wearable technology to record running training process data, and to integrate more

running-related feature value data through Recurrent Neural Network (RNN) [2], Long and short-term memory (LSTM) and gate recursive unit (GRU) models are used to analyze and predict the next road running event to achieve whether it can be completed within the closing time of the conference and break through individual road running results, and predict running techniques (step frequency, pace). To analyze and adjust the most suitable mechanical benefits for running, or by predicting the heart rate, plan the next pace training intensity and weight loss effect [3] [4].

Section one, introduction summarizes the research background, purpose and motivation. The section two, literature discussion and neural networks such as cyclic neural network (RNN), long short-term memory (LSTM), gate recursive unit (GRU). The section three, research design and method. The section four, experimental results and analysis. Section five, is conclusion and future work.

2. Literature Relative Work

2.1 Quantitative running training data

Mentioned that there are three elements of scientific training, namely: quantification, personalization and periodicity. Among them, quantification is the most important, because if you cannot quantify the results of your training and competition, the other two cannot be implemented in detail. Quantification is the original abstract training results and subjective feelings are digitized, as if we can only feel thin or fat when it visually observe a person's posture, without telling a standard or actual value[5][6]. For example, the BMI value can be calculated based on the height and weight, or use body weight to measure standard data such as the correct weight in kilograms, body fat and muscle mass ratio. With the rapid advancement of science and technology, in addition to all kinds of wearable technology or smart phones on the market, you can collect and record your own running training data [11]. There is also a cloud platform for analysis and calculation that can be used as a reference basis after training. This research is used the training data of the running watch as reference data for forecast [7][8].

2.1.1 Heart rate

Heart rate refers to the frequency of heart contraction and beats and the number of beats per minute (bpm). The heart rate of a normal person is 60 to 100 beats per minute when it is at rest. The heartbeat will start to accelerate during exercise, but the heart and lungs athletes with better functions will have a slower heart rate than normal people. The heart rate is controlled by the autonomic nerve [3]. When the sympathetic nerve activity increases, the heart rate will increase; when the vagus nerve activity increases, the heart rate will also slow down. The main fluid factors that affect the heart rate are adrenaline and norepinephrine in the circulating blood, and thyroxine. In addition, the heart rate is also affected by body temperature. If the body temperature rises by 1℃, the heart rate will increase by 12 to 18 times. The heart rate provides a lot of information [3] [9][10][12]. With correct information, you can evaluate your body's responsiveness, adaptability, energy consumption, and the suitability of your training plan. Using the heart rate monitor, plus the correct record data, you may get the following information:

- Exercise suitable intensity when establishing aerobic and anaerobic systems
- The correct length of time to stay in the appropriate training interval
- Interval training and appropriate recovery time between the two training events
- Effective evaluation of training courses
- Anticipate the occurrence of overtraining, heatstroke and physical exhaustion in advance

- Long-distance race pace strategy setting

When talking about how to use the heart rate during running to determine the intensity of running training, it must be understood that the intensity of running does not always directly correspond to the pace. Factors such as weather and terrain will affect the heart rate. When using the heart rate to monitor the training intensity, the most It is important to know what your maximum heart rate is. The maximum heart rate can be calculated using formulas to calculate the predicted value, or you can wear a heartbeat watch to increase the number of runs and speed measurements on the uphill section and in the playground[13][14].

Some coaches and athletes discuss how to effectively use heart rate in training. Nowadays, heart rate-based training is so common that athletes are too confident that the rate is a decisive factor reflecting their training and competition conditions. From another perspective, good use of a heart rate monitor can improve physical fitness and competition performance. When morale is low, over-excited, competing, inattentive and improper judgments, it will hinder wise training. At this time, the heart rate monitor is like a coach will accompany you to practice together. Understand how the heart rate works and use it with other tools for assessing intensity, plus some common sense gained from experience, the heart rate monitor can help determine whether such training is too much or not enough, whether recovery is complete, and physical progress. Increasing age is beyond the physiological irreversible factors that make the maximum heart rate slowly decrease [15] [16]. There are also situations where the maximum heart rate is getting higher and higher. In addition to the influence of age, each person's maximum heart rate may also change after training. It is not necessary to measure the maximum heart rate, but it can also be seen from the maximum heart rate data that your physical condition is a good or bad reference benchmark. After all, measuring the maximum heart rate can cause injuries in addition to the original exercise posture. For long-distance aerobic endurance sports events such as marathon, middle and long distance running, triathlon, swimming, cycling, heart rate has become an indispensable and important, and one of the basic monitoring data for these sports. In sports, it is most common to measure the resting heart rate and maximum heart rate, and use the method of monitoring heart rate to increase the intensity of training. It is very dangerous for athletes to break through the limits of the body during training or competitions, so using this data, the trainer or athlete can clearly understand the state of their body. However, heart rate monitoring has become one of the most important data indispensable in wearable technology [17] [18].

2.1.2 Cadence and stride length

Cadence is the frequency of steps, the number of times the legs alternate per unit time during running, and the pace per minute (ppm) of the soles of the feet (step per minutes, spm). Simply put, the faster the cadence, the faster the movement. However, the higher the efficiency in mechanics, the more the load on physical fitness. Also, because everyone's physical condition is different, each runner needs to find a pace that suits him at different distances, and basically wants to run. Accelerating speed, increasing stride frequency or increasing stride length (running speed = stride frequency × stride length) is one of the important factors that determine running speed. "Moving your feet quickly" sounds like a good way to increase speed, but it is actually a skill that must improve aerobic capacity while allowing neuromuscular training. This kind of double training, for more important than modifying the running posture [30] [32]. The average leisure runner's stride frequency is between 150–170 steps per minute, and the number evolution may depend on factors such as leisure running, racing or fitness. Many well-trained runners, regardless of the heel or forefoot landing, too large or moderate span, each runner may have a different running style, but most of the steps can be maintained at more than 180 steps. Stride length is the distance of one step, calculated at the center of the foot. After taking a step, the distance between the centers of the feet is the stride. However, the stride length in running will vary according to different running styles, which is generally related to

height [19] [20]. If it is a short-medium run, the stride length is about 80% of your height. For example, if your height is 170, then the short and medium running width is about 136 cm (the short and medium running generally refers to 3000 meters or less). Because the marathon is a long-distance running (mostly 10KM/21KM/42KM), the stride is between 55% and 70% of the height. Speed = cadence × stride length. This formula is quite easy to understand. When you want to increase your running speed, you can increase the frequency that you can step out per minute. The so-called "step frequency 180" means that you can take 180 steps per minute. And stride length is the distance you can cross each step, the product of the two is equal to speed [6][7].

The relationship between stride frequency and stride length can be described as a complementary relationship. In a 100-meter sprint, stride length is more important than stride frequency, because short distances require more muscle power and do not need to adjust physical fitness [37–39]. On the contrary, marathon steps are used. The importance of frequency is much greater than stride length, and the adjustment of rhythm and physical fitness is very important. An increase in stride means a reduction in possible stride frequency, and an increase in stride frequency may also mean a shortened stride length [33] [35]. The point is not to increase the efficiency of the stride frequency or stride length, but the degree of attenuation of the other after the efficiency is improved, and the degree of durability. The reason why stride frequency is more efficient than stride length is that the increase in stride length makes it difficult to extend the joints, while stride frequency is the room for improvement through muscle and nerve training. Speaking of triathletes, try to increase the stride length and reduce the stride frequency to speed up the running speed. In order to increase the stride length, the center of gravity must be increased by tens of centimeters every time you step. Such a long-stride running method will have some undesirable effects. In addition to consuming extra unnecessary energy, the runner will also reduce the running speed due to the influence of gravity [34] [36]. The last effect is the long-stride running method. When the footsteps fall back to the ground, a great impact will be generated, and such impact will accumulate day after day and year after year of running, causing one of the chronic sports injury factors for runners. It is also mentioned that whether it is a general amateur runner or a long-distance runner, when participating in a long-distance running competition, the faster the running speed, the increase rate of running stride will be significantly higher than the increase rate of stride frequency. The rate is five times the rate of cadence increase. However, running stride length is proportional to long-distance running performance and optimal running speed. Increasing stride length to increase running speed in long-distance competitions seems to be more important than increasing stride frequency [8].

2.1.3 Pace

Pace is one of the key factors in the regulation of physical fitness and running technology in road running. It is used in long-term endurance sports such as 10 km, half marathon or full marathon, road racing, and even triathlon. In the event, the pace is appropriate. In addition to completing the event, you can even get better results after training. In the spring, the coach will adjust the training to a week on the track and a week to practice the fartlek run; in summer [29] [31]. All speed schedules are changed to train on the track. Such training can force the runners to focus on their actual race pace, speed up or decelerate according to the situation, and the turning points and lines on the track can help you increase the competition [5]. If the physical fitness is strong, even if the pace is wrong, you can withstand a certain degree of error performance in the game. If you add various factors such as fierce confrontation in the competition, extremely challenging track, and difficult external environment. It may be impossible to overcome the mistakes caused by the wrong pace. So pace is the key skill necessary to win, if and when you set high goals for yourself. The mentioned heart rate monitoring is actually a bit similar to monitoring pace. According to different running distances and training intensity, both are important data for observing physical fitness and adjusting. The

slower Easy Pace (EP) and Threshold Pace (TP), Interval Pace (IP), Repeat Pace (RP), four marathon pace training [10].

2.1.4 Calories

For a person who is losing weight or losing weight, how many calories you burn and reduce your intake of calories. Calories is a data that is easy to understand. More and more wearable technology is based on the time distance of exercise or heart rate. Multi-advanced data to calculate how the calories burned after exercise trains the body's ability to burn fat is a very important thing for long-distance runners, and it is even more important for people who want to use running to lose weight [25][27]. The unit of calories is calories. Fat burn refers to the grams of fat consumed by runners. The meaning of fat burn rate is the percentage of energy derived from fat. The meanings of these three are very different. Although high-intensity exercise consumes more calories per unit time, the fat-burning rate is far less than that of long-distance jogging. In long-distance sports events such as running and cycling, you can often see the setting of food replenishment stations [26][28]. This kind of long-term aerobic endurance exercise means that a lot of energy will be consumed, and the water and fat in the body Carbohydrates (sugars) need to be supplemented in a timely manner to maintain the continuous energy supplement of the game [11].

2.2 Recurrent Neural Network

RNN also be called recursive neural network. It is the most commonly used neural network model in the field of natural language processing. It is a neural network that processes sequence data such as sound, language, and video. The network is a kind of neural network with short-term memory ability [15] [16]. Because the front input value and the back input value of RNN are related, it is most suitable for practical applications such as language translation, sentiment analysis, and weather forecasting. One of the characteristics of RNN is that the output of each layer in the multi-layer neural network is directly added to the layer itself. The input is derived from the loop (Self-Loop). With this network memory structure, it is possible to think about the previous input of the desired data [18] [19]. The meaning of the data, the following Fig. 1 is the basic structure of RNN. In Fig. 1, x is the input vector, y is the output vector, and h is the state vector that preserves the internal RNN [13–15]. Figure 2 is the expanded architecture flow of the RNN, t is the time step parameter, t-1 is the previous step, and t + 1 is the next step.

Figure 3 is a simple RNN calculation model method. The input vector x_t at time point step t is connected with the internal state vector h_t−1 before the update to become a longer vector in the form of [x_t, h_t−1], which is taken as the input excitation function σ, its output is the internal state vector h_t.

$ht = \sigma(Wh \times [ht-1, xt])$ (1)

The new internal vector h_t, when passed through the internal loop in the next step, becomes the input vector of the fully connected layer of the second layer. In the fully connected layer of the second layer, use the excitation function σ to get the output vector y_t at the time point of step t.

$yt = \sigma(Wh \times ht)$ (2)

The values of h_t are arranged horizontally, indicating that the previous x_t information has been consolidated. RNN uses this method to memorize past information.

Figure 3 RNN internal calculation structure

2.3 Long Short-Term Memory (LSTM)

LSTM is improved from RNN. This is a neural network with long-term memory ability. In order to solve the problem of disappearing gradient of recurrent neural network, it was developed a kind of cyclic neural network structure, because RNN will produce gradient disappearance in structure, causing long-term memory to be hidden by short-term memory. The most important feature of LSTM is that it can transfer the internal state vector stably for a long time. In order to solve the problem of RNN, LSTM adopts an improved memory management architecture [12] [13] [16][18]. The internal state vector h uses a simpler calculation method to transfer. Even after a long time step, the transfer vector can be stabilized h. But the LSTM operation situation mentioned above as shown in Fig. 4.

From Fig. 4, we can clearly see that the LSTM activation function has become more, and the element-wise multiplication and element-wise addition are also used. There are three more gates in it, which is LSTM, it is an important factor for better memory function, and these three gates are forget gate (f_t) input gate (i_t) output gate (o_t), the following is the calculation formula of LSTM three gates.

$$f_t = \sigma(W_f \times [y_{t-1}, x_t]) \quad (3)$$

$$i_t = \sigma(W_i \times [y_{t-1}, x_t]) \quad (4)$$

$$o_t = \sigma(W_o \times [y_{t-1}, x_t]) \quad (5)$$

LSTM is a technology to update the internal state vector h_t in a long time step. The choice of forgetting or additional information is determined by the forgetting gate f_t and the input gate i_t. Forgot to read f_t decides to memorize part of the message, and the input gate i_t adds the repeated message here. Then the LSTM neural network can temporarily retain part of the information [17].

2.4 Gated Recurrent Unit (GRU)

LSTM also has a brother neural network called gate recurrent unit (GRU) neural network, GRU, which is an updated version of LSTM, a simpler version than LSTM, which can provide faster execution speed and reduce memory usage. In GRU, no explicit internal state transition is required. It is because the internal state is combined with the output vector y_t. In step t, the GRU neural network calculates the binary vector called Update Gate z_t, and the binary vector called Reset Gate r_t These gates are in Update Gate Layer and Reset Gate Layer are calculated [12].

From Fig. 5, it use of element product, element sum, and activation function, except that the activation function σ and the internal state vector h_t are missing. The following are the calculation formulas for Update Gate, z_t and Reset Gate r_t.

$zt = \sigma(Wz \times [yt-1, xt])$ (6)

$rt = \sigma(Wr \times [yt-1, xt])$ (7)

Compared with the forget gate and input gate of LSTM, the update gate action of GRU is simpler. Consider that for one value output by the GRU, remember the original value or replace it with a new value. Since the update gate z_t does not update or touch a part of the memory, it can be memorized within a long step like LSTM, so the memory mechanism of GRU is more efficient than RNN.

3. Research Methods

The computer equipment used in this research is equipped with Intel Core quad-core 1.8GHz processor, 32 GB DDR4 memory, Intel UHD Graphics display chip and 1024 GB SSD solid state drive. The research collected data is a wrist-type heart rate GPS smart sports watch running record. In terms of program calculations, Python and tensorflow packages are used as neural-like calculation models.

3.1 Data preprocessing

This study uses the running training data of our own wrist heart rate watch, and exports the running training data from 2019/3/3 to 2020/2/28 from the cloud analysis platform. Feature data set (Feature) will be the original data fields, Distance, Calories, Time, Avg HR, Max HR, Avg Run Cadence, Max Run Cadence, Avg Pace, Best Pace, Elev Gain), Avg Stride Length. Because the fields Time and Pace of the running data are strings, the fields are standardized to avoid large differences in data values during forcast, and data with a running distance of less than 3 kilometers are also eliminated [21][23].

3.2 Parameter setting

There are 12 features in this study, Distance, Calories, Time, Avg HR, Max HR, Avg Run Cadence, Max Run Cadence, Avg Pace, Best Pace, Elev Gain, Elev Loss, Avg Stride Length. Time, Avg HR, (Max HR, Avg Run Cadence, Max Run Cadence, Avg Pace, Best Pace do Label output forecast results. The model uses RNN, LSTM, and GRU respectively, and sets 256 neurons and adds 2 layers of 256 neuron hidden layers for comparison, and an output layer as the output of the forecast result. Refer to Table 1 and Fig. 6 for detailed parameter setting and model forecast process flow.

Table 1
Model parameter setting

Three layer	
Feature	Distance, Time, Calories, Avg Heart Rate, Max Heart Rate, Avg Run Cadence, Max Run Cadence, Avg Stride LengthAvg Run Pace, Max Run Pace, Elev loss, Elev Gain
Label	Time, Avg Heart Rate, Max Heart Rate, Avg Run Cadence, Max Run Cadence, Avg Run, Pace, Max Run Pace
Epoches	200
Batch_size	100
RNN, LSTM, GRU,	Units = 256, input_shape(10,1), unroll = False
Dense	Units = 256, kernel_initializer='uniform', activation='relu'
Dense	Units = 256, kernel_initializer='uniform', activation='relu'
Dense	Unit = 1

3.3 Experimental framework

Use running data as input parameters, divide the data into training period (90%) and test period (10%), and use Python to input the test period data into RNN, LSTM, and GRU neural network models as training data [22][24]. Modeling. Finally, the training period data is input into the model to simulate the trend of future running performance (running time, heart rate, cadence, pace), and compare the predicted value of the running performance with the actual value. The experimental architecture of the forecast model is shown in Fig. 7.

3.4 Accuracy of predict model

Use the following three formulas as a tool for this study to evaluate the accuracy of the forecasting model:

mean absolute deviation (MAD)

$$MAD = \frac{\sum(\text{Actual value}_t - \text{Forecast value}_t)}{n}$$

mean squared error (MSE)

$$MSE = \frac{\sum(\text{Actual value}_t - \text{Forecast value}_t)^2}{n-1}$$

mean absolute percent error (MAPE)

$$MAPE = \frac{\sum \frac{(\text{Actual value}_t - \text{Forecast value}_t)}{\text{Actual value}_t} \times 100}{n}$$

4. Results And Analysis

4.1 Running time forecast results

This section predicts running time for RNN, LSTM, and GRU models, and analyzes and compares the forecast results of the three models.

4.1.1 RNN

Table 2 shows the results of running time forecast by the RNN model. The Time field is the actual value, RNN-1Layer is 1 hidden layer, RNN-2Layer is 2 hidden layer, and RNN-3Layer is 3 hidden layer. Table 2 is a line chart comparing actual value Time and RNN1 ~ 3 layer predicted value.

Table 2
RNN running time forecast results

Time	RNN-1Layer	RNN-2Layer	RNN-3Layer
31.50	31.72	32.08	33.24
30.43	30.61	30.15	30.07
30.02	30.24	29.53	29.42
18.73	18.68	18.66	18.44
17.48	17.38	16.95	17.91
24.40	24.48	24.08	24.77
17.43	17.32	17.56	17.86
29.27	29.48	29.53	30.30
17.70	17.56	18.09	18.02
24.48	24.58	24.50	25.44
18.35	18.26	17.99	18.65
24.78	24.87	24.79	25.84

4.1.2 Comparison of running time results

Table 3 shows the average running time forecast results of the three models, the field Time is the actual value, RNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of the forecast results of 1 ~ 3 layers, and GRU is the average value of the forecast results of 1 ~ 3 layers., Fig. 8 is a line chart comparing the actual value of Time and the three models.

Table 3
Average value of running time forecast results of the three models

Time	RNN	LSTM	GRU
31.50	32.35	23.30	26.21
30.43	30.28	26.05	28.45
30.02	29.73	25.15	24.93
18.73	18.59	24.94	24.74
17.48	17.41	22.87	20.75
24.40	24.44	20.92	19.58
17.43	17.58	20.94	21.59
29.27	29.77	21.61	21.95
17.70	17.89	22.54	23.30
24.48	24.84	23.00	22.73
18.35	18.30	22.33	21.43
24.78	25.17	23.14	23.69

4.2 Average heart rate forecast results

This section uses RNN, LSTM, and GRU models to predict the average heart rate, and analyzes and compares the forecast results of the three models.

4.2.1 RNN model forcast

Table 4 shows the results of the average heart rate predicted by the RNN model, the field average heart rate is the actual value, RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, and RNN-3L is 3 hidden layer.

Table 4
RNN average heart rate forecast results

average heart rate	RNN-1L	RNN-2L	RNN-3L
138	137.50	136.49	136.07
177	176.16	175.09	174.65
165	164.07	163.10	162.50
171	170.15	169.22	168.56
174	173.25	172.47	171.74
158	157.26	156.392	155.42
144	143.96	143.29	142.55
150	149.84	149.04	148.58
127	127.34	126.75	125.93
174	173.93	172.80	172.50
128	127.74	126.94	127.00
159	158.67	157.64	157.43

4.2.2 Comparison of forecast results

Table 5 is the average of the heart rate forecast results of the three models, the field average heart rate is the actual value, RNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of the forecast results of 1 ~ 3 layers, and GRU is the forecast result of 1 ~ 3 layers. Average value. Figure 9 shows the comparison of average heart rate and the three models.

Table 5
Average heart rate forecast results of the three models

average heart rate	RNN	LSTM	GRU
165	163.55	160.04	152.67
138	136.68	162.81	153.27
177	175.30	165.18	158.44
165	163.22	168.06	164.09
174	172.49	175.12	169.67
158	156.36	168.25	163.21
144	143.26	157.33	154.82
150	149.15	153.20	151.48
127	126.68	154.65	152.83
174	173.08	153.00	153.93
128	127.229	156.629	152.994
159	157.917	158.529	151.102

4.3 Maximum heart rate forecast results

This section uses RNN, LSTM, and GRU models to predict the maximum heart rate, and analyzes and compares the forecast results of the three models.

4.3.1 RNN model forcast

Table 6 shows the results of the maximum heart rate predicted by the RNN model, the field maximum heart rate is the actual value, RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, and RNN-3L is 3 hidden layer. Figure 10 is a line chart comparing maximum heart rate and RNN 1 ~ 3 layer forecast value.

Table 6
RNN maximum heart rate forecast results

maximum heart rate	RNN-1L	RNN-2L	RNN-3L
163	162.95	163.24	164.30
198	197.92	198.31	199.59
192	191.67	192.44	193.69
194	193.51	193.83	194.64
192	191.48	191.85	192.85
165	165.06	165.14	166.15
188	187.85	187.59	189.26
198	198.07	198.07	199.07
173	173.39	173.38	173.60
148	148.34	148.45	149.34
189	189.33	188.76	189.93
190	189.78	190.12	190.64

4.3.2 Maximum heart rate forecast result comparison

Table 7 shows the average maximum heart rate forecast results of the three models, the field maximum heart rate is the actual value, RNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of forecast results of 1 ~ 3 layers, and GRU is the forecast results of 1 ~ 3 layers.

Table 7
Comparison average maximum heart rate forecast results of the three models

maximum heart rate	RNN	LSTM	GRU
163	163.50	184.66	181.75
198	198.61	187.93	185.96
192	192.60	191.36	191.26
194	193.80	188.59	189.05
192	192.06	186.50	185.43
165	165.45	183.83	185.54
188	188.23	179.28	182.38
198	198.41	176.44	177.28
173	173.46	175.89	177.35
148	148.71	173.74	174.73
189	189.34	173.76	171.88
190	190.75	172.18	169.79

4.4 Average cadence forecast results

This section predicts the average step frequency for RNN, LSTM, and GRU models, and analyzes and compares the forecast results of the three models.

4.4.1 RNN model forcast

Table 8 shows the average cadence result of the RNN model forcast, the field average cadence is the actual value, RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, RNN-3L is 3 hidden layers.

Table 8
RNN average step frequency forecast results

Average step frequency	RNN-1L	RNN-2L	RNN-3L
171	171.69	170.96	170.68
175	175.38	175.00	174.56
172	171.70	171.83	171.48
176	176.19	175.86	175.52
167	167.72	167.01	166.80
170	170.45	169.98	169.69
174	174.41	174.02	173.79
172	172.39	172.09	171.77
173	173.21	172.94	172.50
172	172.39	171.93	171.60
170	169.71	169.93	169.57
172	172.57	171.96	171.72

4.4.2 Average cadence comparison of forecast results

Table 9 shows the average cadence forecast results of the three models, the field average cadence is the actual value, SimpleRNN is the average forecast result of 1 ~ 3 layers, LSTM is the average forecast result of 1 ~ 3 layers, and GRU is 1 ~ 3 layer. The average value of the forecast results. Figure 11 shows the average cadence and the comparison line chart of the three models.

Table 9
Average cadence forecast results of the three models

Average step frequency	RNN	LSTM	GRU
171	171.115	171.743	171.919
175	174.983	171.887	171.996
172	171.674	171.401	171.336
176	175.861	170.935	170.737
167	167.179	170.740	170.696
170	170.044	170.910	171.061
174	174.07	171.61	171.90
172	172.08	171.84	172.11
173	172.88	171.85	171.92
172	171.97	171.80	171.76
170	169.73	171.00	170.91
172	172.08	170.94	170.85

4.5 Maximum cadence forecast results

This section predicts the maximum step frequency for RNN, LSTM, and GRU models, and analyzes and compares the forecast results of the three models.

4.5.1 RNN model forcast

Table 10 shows the results of the maximum step frequency predicted by the RNN model. The maximum step frequency in the field is the actual value. RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, and RNN-3L is 3 hidden layers.

Table 10
RNN maximum step frequency forecast results

maximum step frequency	RNN-1L	RNN-2L	RNN-3L
190	190.01	190.01	190.01
188	187.98	188.04	188.04
190	189.99	189.76	189.62
210	210.33	210.13	210.29
182	181.90	182.29	182.08
188	187.96	187.85	188.07
189	188.98	188.86	189.01
188	187.97	188.06	188.15
184	183.89	183.67	184.01
188	187.96	187.91	187.98
190	190.01	190.01	190.04
188	187.99	188.05	188.01

4.5.4 Maximum stride frequency comparison of forecast results

Table 11 shows the average value of the maximum step frequency forecast results of the three models, the field maximum step frequency is the actual value, RNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of the forecast results of 1 ~ 3 layers, and GRU is the 1 ~ 3 layer. The average value of the forecast results. Figure 12 is a line chart comparing the maximum step frequency and the three models.

Table 11
Average value of forecast results of maximum step frequency of the three models

maximum step frequency	RNN	LSTM	GRU
190	190.01	189.88	189.84
188	188.00	187.32	187.12
190	189.79	195.29	190.87
210	210.25	201.15	206.99
182	182.09	184.70	181.73
188	187.96	187.88	186.46
189	188.95	189.52	189.50
188	188.06	187.14	188.12
184	183.85	186.44	184.79
188	187.95	188.16	187.25
190	190.02	189.97	189.93
188	188.01	187.31	187.72

4.6 Average pace forecast results

This section predicts the average pace for RNN, LSTM, and GRU models, and analyzes and compares the forecast results of the three models.

4.6.1 RNN model forcast

Table 12 shows the average pace predicted by the RNN model. The average pace in the field is the actual value. RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, and RNN-3L is 3 hidden layers.

Table 12
RNN average pace forecast results

Average pace	RNN-1L	RNN-2L	RNN-3L
5.33	5.33	5.33	5.32
5.12	5.12	5.11	5.11
4.85	4.84	4.85	4.85
4.95	4.95	4.96	4.95
5.15	5.15	5.14	5.15
5.08	5.08	5.07	5.08
5.30	5.30	5.29	5.30
5.15	5.15	5.14	5.15
4.85	4.84	4.85	4.85
5.13	5.13	5.12	5.13
5.18	5.18	5.18	5.18
5.10	5.10	5.09	5.10

4.6.4 Average pace Comparison of forecast results

Table 13 shows the average of the average pace forecast results of the three models, the field average pace is the actual value, RNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of the forecast results of 1 ~ 3 layers, and GRU is the 1 ~ 3 layer. The average value of the forecast results. Figure 13 is a line chart of the average pace and the comparison of the three models.

Table 13
Average speed forecast results of the three models

Average pace	RNN	LSTM	GRU
5.33	5.33	5.30	5.32
5.12	5.11	5.10	5.12
4.85	4.85	4.86	4.85
5.08	5.08	5.04	5.07
4.95	4.95	4.96	4.95
5.15	5.15	5.13	5.14
5.08	5.08	5.09	5.08
5.30	5.30	5.29	5.29
5.15	5.15	5.16	5.15
4.85	4.85	4.87	4.85
5.18	5.18	5.17	5.18
5.10	5.10	5.11	5.10

4.7 The best pace forecast results

This section predicts the best pace for RNN, LSTM, and GRU models, and analyzes and compares the forecast results of the three models.

4.7.1 RNN forcast

Table 14 shows the results of the best pace predicted by the RNN model, the field best pace is the actual value, RNN-1L is 1 hidden layer, RNN-2L is 2 hidden layer, and RNN-3L is 3 Hidden layer.

Table 14
RNN Best Pace forecast Results

Best Pace	RNN-1L	RNN-2L	RNN-3L
4.43	4.42	4.52	4.42
4.15	4.25	4.25	4.15
4.28	4.32	4.38	4.28
4.55	4.49	4.64	4.55
4.38	4.39	4.47	4.37
4.28	4.32	4.38	4.29
4.18	4.26	4.28	4.19
4.55	4.48	4.64	4.54
2.83	3.44	2.92	2.84
4.22	4.15	4.32	4.24
4.38	4.36	4.48	4.40
4.57	4.46	4.65	4.56

4.7.4 Comparison of the best pace forecast results

Table 15 is the average value of the best pace forecast results of the three models, the field best pace is the actual value, SimpleRNN is the average value of the forecast results of 1 ~ 3 layers, LSTM is the average value of the forecast results of 1 ~ 3 layers, and the GRU is 1 ~ The average value of the three-layer forecast results. Figure 14 is a line chart of the comparison between the best pace and the three models.

Table 15
Average value of the best pace forecast results of the three models

Best pace	RNN	LSTM	GRU
4.43	4.456	4.389	4.419
4.42	4.458	4.389	4.419
4.15	4.221	4.331	4.199
4.28	4.330	4.318	4.293
4.55	4.563	4.369	4.517
4.53	4.548	4.400	4.516
4.38	4.415	4.391	4.397
4.25	4.307	4.355	4.284
4.28	4.332	4.337	4.299
4.18	4.246	4.303	4.215
4.4	4.424	4.325	4.389
4.55	4.560	4.374	4.523
4.2	4.270	4.334	4.246
2.83	3.073	3.998	3.107
4.22	4.242	4.064	4.139
4.38	4.420	4.141	4.342
4.5	4.495	4.228	4.471
4.57	4.563	4.310	4.546

4.8 Analysis and comparison of model forecast accuracy

This section uses three forecast accuracy methods: mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percent error (MAPE) to calculate the forecast accuracy of RNN, LSTM, and GRU models. The calculated value is the smaller the better, and compare the numerical results of the final accuracy of the three models.

4.8.1 MAD forecast accuracy

Table 16 uses the average absolute deviation (MAD), RNN, LSTM, GRU three models to calculate the accuracy of the forecast results of the 1 ~ 3 layers, and compare and analyze the accuracy values of the last three models, Fig. 15 It is a bar graph comparing MAD's forecast accuracy of the three models.

Table 16
Comparison of forecast accuracy of three models using MAD

MAD									
Project/Model	RNN -1L	RNN -2L	RNN -3L	LSTM -1L	LSTM -2L	LSTM -3L	GRU -1L	GRU -2L	GRU -3L
Time	0.13	0.25	0.61	4.64	4.42	4.36	3.91	4.60	3.99
Average heart rate	0.44	1.23	1.82	12.25	12.33	12.67	12.75	12.35	12.81
Maximum heart rate	0.31	0.32	1.10	11.93	12.01	11.09	11.93	11.92	12.13
Average Run Cadence	0.43	0.05	0.34	1.44	1.70	1.62	1.46	1.58	1.74
Max Run Cadence	0.04	0.11	0.10	2.11	2.53	1.46	0.78	0.80	0.90
Average pace	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00
Best pace	0.08	0.10	0.01	0.20	0.18	0.17	0.13	0.01	0.01
Average value	0.20	0.29	0.57	4.65	4.74	4.48	4.42	4.47	4.51

4.8.2 MSE forecast accuracy

Table 17 shows the accuracy of the forecast results of the 1 ~ 3 layers of the mean squared error (MSE), RNN, LSTM, and GRU models, and compares and analyzes the accuracy values of the last three models. Figure 16 shows The forecast accuracy of MSE on the three models is compared with histogram.

Table 17
Comparison of forecast accuracy of three models using MSE

MSE									
Project/Model	RNN -1L	RNN -2L	RNN -3L	LSTM-1L	LSTM-2L	LSTM-3L	GRU-1L	GRU-2L	GRU-3L
Time	0.02	0.097	0.56	35.11	25.39	25.89	22.75	25.91	23.67
Average heart rate	0.29	1.83	3.82	255.50	265.10	259.74	251.47	238.05	251.43
Maximum heart rate	0.15	0.20	1.45	247.24	246.29	272.16	253.55	246.35	253.967
Average Run Cadence	0.23	0.00	0.13	3.97	4.91	4.84	4.03	4.59	5.07
Max Run Cadence	0.01	0.03	0.038	12.73	15.25	4.97	2.04	1.39	1.55
Average pace	0.01	0.02	0.04	0.03	0.02	0.03	0.07	0.04	0.04
Best pace	0.02	0.01	0.00	0.13	0.09	0.08	0.053	0.00	0.00
Average value	0.10	0.31	0.86	79.24	79.57	81.10	76.27	73.75	76.52

4.8.3 MAPE forecast accuracy

Table 18 uses the mean squared error (MSE), RNN, LSTM, GRU three models to calculate the accuracy of the forecast results of the 1 ~ 3 layers, and compare and analyze the accuracy values of the last three models. Figure 17 is a histogram of the comparison of MSE's forecast accuracy for the three models.

Table 18
Comparison of forecast accuracy of three models using MAPE

MAPE									
Project /Model	RNN -1L	RNN -2L	RNN -3L	LSTM -1L	LSTM -2L	LSTM -3L	GRU -1L	GRU -2L	GRU -3L
Time	0.57%	1.132%	2.55%	22.05%	20.43%	18.43%	17.82%	20.06%	19.35%
Average heart rate	0.27%	0.76%	1.13%	8.13%	8.33%	8.16%	8.17%	8.09%	8.22%
Maximum heart rate	0.16%	0.19%	0.61%	6.90%	6.98%	6.74%	7.01%	6.99%	7.10%
Average Run Cadence	0.25%	0.02%	0.19%	0.83%	0.99%	0.95%	0.85%	0.92%	1.01%
Max Run Cadence	0.02%	0.06%	0.05%	1.10%	1.32%	0.76%	0.41%	0.42%	0.47%
Average pace	0.01%	0.04%	0.02%	0.33%	0.33%	0.25%	0.13%	0.11%	0.05%
Best pace	2.43%	2.35%	0.19%	5.71%	4.91%	4.72%	3.70%	0.17%	0.14%
Average value	0.53%	0.65%	0.68%	6.44%	6.18%	5.71%	5.44%	5.25%	5.19%

4.8.4 Comparison and analysis of accuracy results

According to the above numerical results of MAD average absolute deviation, MSE average square error, and MAPE average absolute percentage error, RNN is better than LSTM and GRU in all forecast items, but in terms of predicting average pace and optimal pace, Although the numerical performance of RNN is still relatively good, the three models have little difference in the numerical value of forecast accuracy. However, the three models add 1 ~ 2 hidden layers to the forcasts. From the numerical results of the forecast accuracy, we can see that the average value of the RNN forecast accuracy is slightly degraded. The LSTM value has a relatively significant decrease, and the GRU value is The reduction is relatively small. Table 19, 20, and 21 show the upward and downward trend of forecast accuracy values.

Table 19
After the model increases the number of layers, the MAD forecast accuracy value increases and decreases

Project/Model	RNN-2L	RNN-3L	LSTM-2L	LSTM-3L	GRU-2L	GRU-3L
Time	increase	increase	decrease	decrease	increase	increase
Average heart rate	increase	increase	increase	increase	decrease	increase
Maximum heart rate	increase	increase	increase	decrease	increase	increase
Average Run Cadence	decrease	decrease	increase	increase	increase	increase
Max Run Cadence	increase	increase	increase	decrease	increase	increase
Average pace	increase	increase	decrease	decrease	decrease	decrease
Best pace	increase	decrease	decrease	decrease	decrease	decrease

Table 20
After the model increases the number of layers, the MSE forecast accuracy value increases and decreases

Project/Model	RNN-2L	RNN-3L	LSTM-2L	LSTM-3L	GRU-2L	GRU-3L
Time	increase	increase	decrease	decrease	increase	increase
Average heart rate	increase	increase	increase	increase	decrease	decrease
Maximum heart rate	increase	increase	decrease	increase	decrease	increase
Average Run Cadence	decrease	decrease	increase	increase	increase	increase
Max Run Cadence	increase	increase	increase	decrease	decrease	decrease
Average pace	increase	increase	increase	decrease	decrease	decrease
Best pace	decrease	decrease	decrease	decrease	decrease	decrease

Table 21
After the model increases the number of layers, the MAPE forecast accuracy value increases and decreases

Project/Model	RNN-2L	RNN-3L	LSTM-2L	LSTM-3L	GRU-2L	GRU-3L
Time	increase	increase	decrease	decrease	increase	increase
Average heart rate	increase	increase	increase	increase	decrease	increase
Maximum heart rate	increase	increase	increase	decrease	decrease	increase
Average Run Cadence	decrease	decrease	increase	increase	increase	increase
Max Run Cadence	increase	increase	increase	decrease	increase	increase
Average pace	increase	increase	decrease	decrease	decrease	decrease
Best pace	decrease	decrease	decrease	decrease	decrease	decrease

5 Conclusion

This study understands the importance of heart rate for observing physical fitness. Training intensity and pace depend on which heart rate zone. The adjustment of cadence and stride is the key to affecting running speed. It hopes to consider more characteristics and time series. And further use artificial intelligence RNN, LSTM and GRU to predict running time, and also predict and analyze other key characteristic values of heart rate, cadence, and pace. The results of this experiment found that the average MAD values of RNN 1 ~ 3 layers were 0.20, 0.29, 0.57, the average MSE values were 0.10, 0.31, and 0.86, and the average MAPE values were 0.53%, 0.65%, 0.68%, respectively. RNN has an overall effect on running data. The average result of project forecast accuracy, GRU is the best, and the worst is LSTM. After the hidden layers are added to the three forecast models, RNN is slightly regressive, LSTM has a significant trend of improvement, and GRU is less obvious. The contributions are used to analyze and predict the next road running event to achieve whether it can be completed within the closing time of the conference and break through individual road running results, and predict running techniques (step frequency, pace). To analyze and adjust the most suitable mechanical benefits for running, or by predicting the heart rate, plan the next pace training intensity and weight loss effect. Since this research is based on the training data of amateur runners. The future work, in addition to having more complete planning information on sports training records, we also hope that the data of professional runners or runners who use smart wearable devices for a long time can be included. The further research on the correlation of eigenvalues on running data.

Declarations

Ethical approval

No need ethical approval.

Funding details

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Conflict of 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.

Informed Consent

No need informed consent.

Authorship contributions

Cairu Yang: Conceptualization, Methodology, Validation, Investigation, Writing.

Yanhua Liu: Funding acquisition, Formal analysis, Software, Resources, Visualization.

Xuzhong Zhang: Funding acquisition. Methodology, Validation, Writing -Review & Editing, Supervision.

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Figures

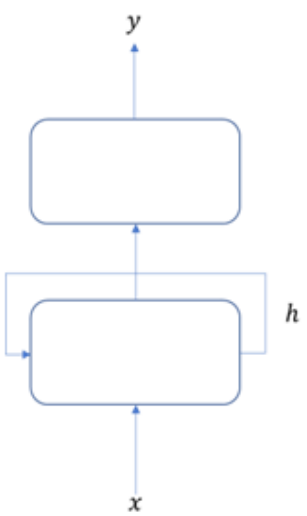

Figure 1

RNN basic architecture diagram

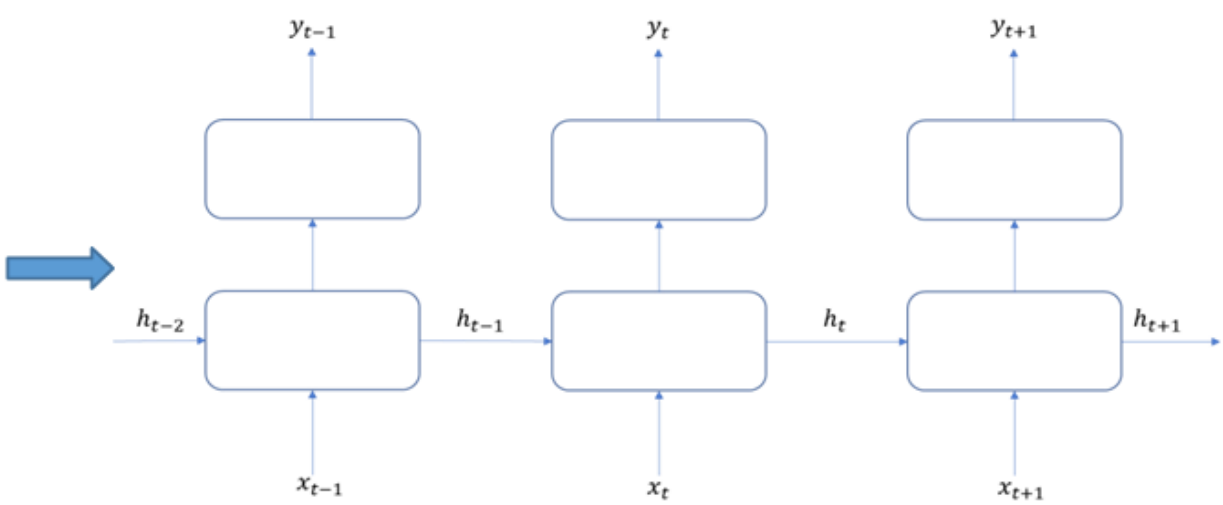

Figure 2

RNN expanded view

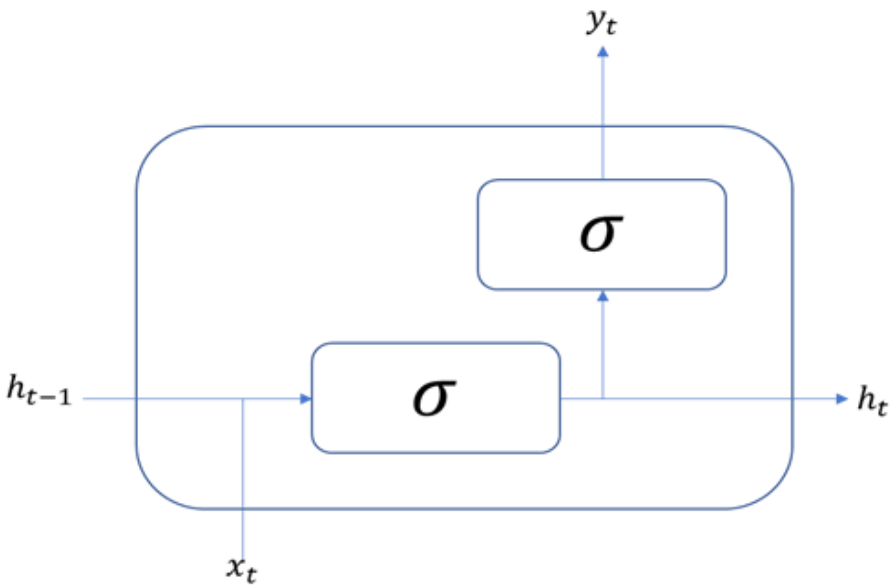

Figure 3

RNN internal calculation structure

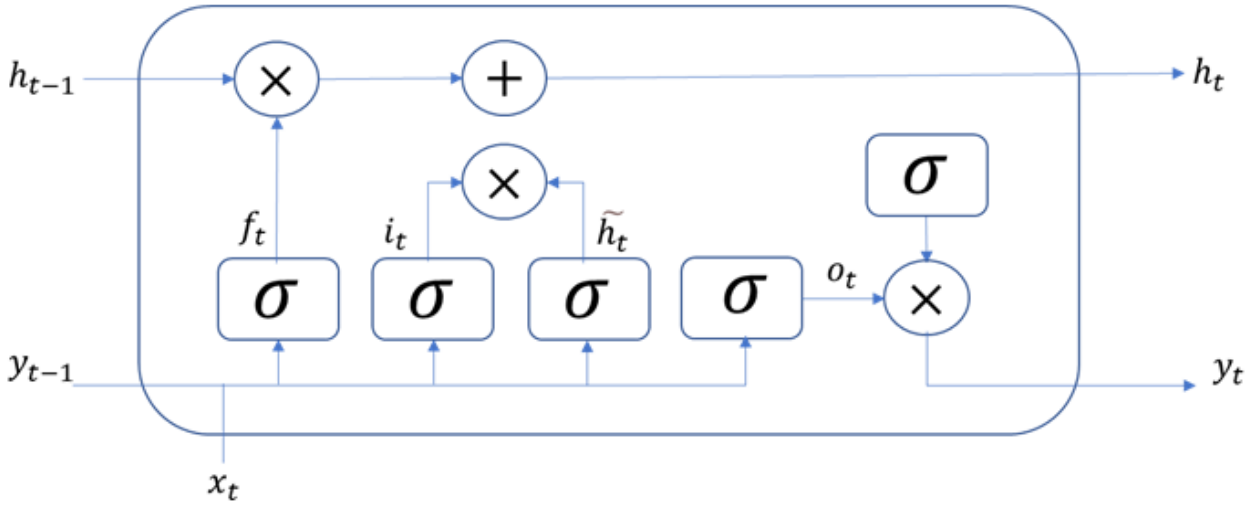

Figure 4

LSTM internal calculation structure

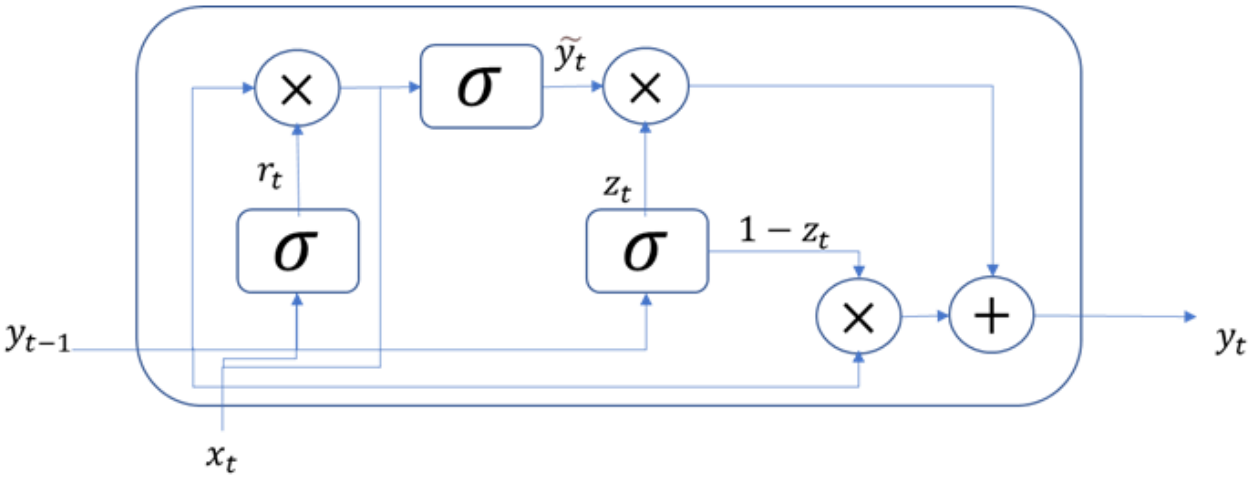

Figure 5

shows the operation of the GRU neural network.

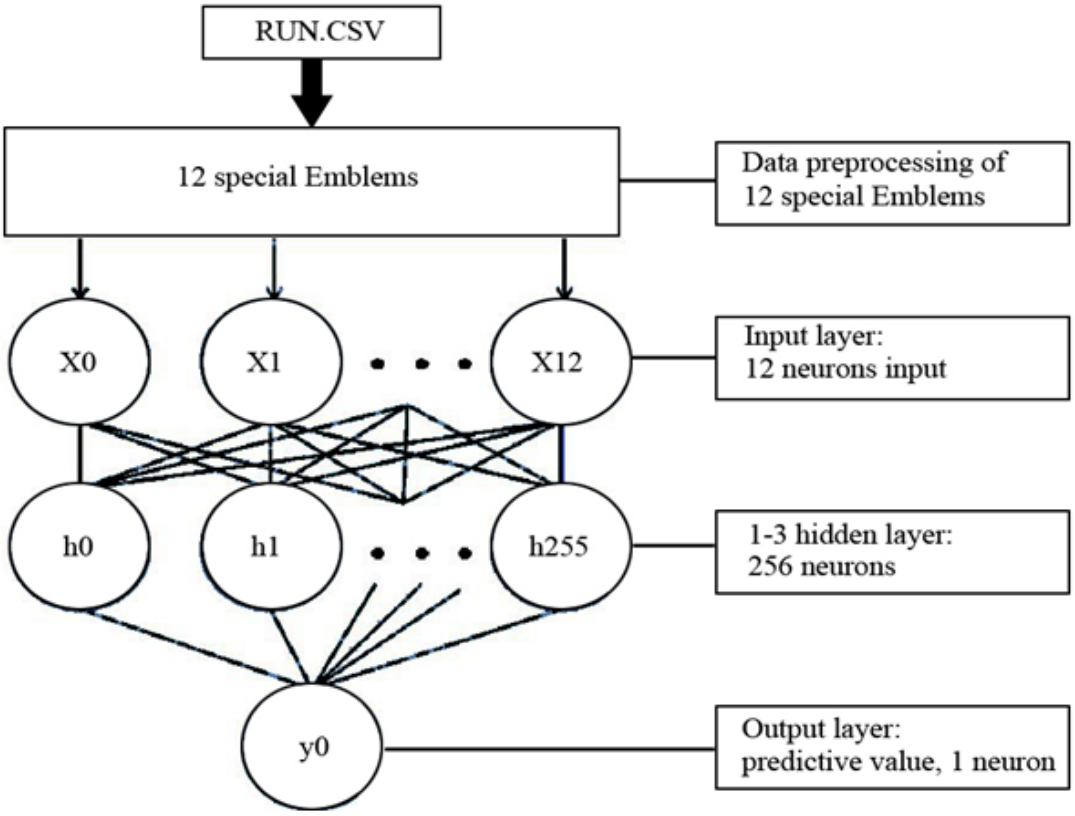

Figure 6

Model forecast process

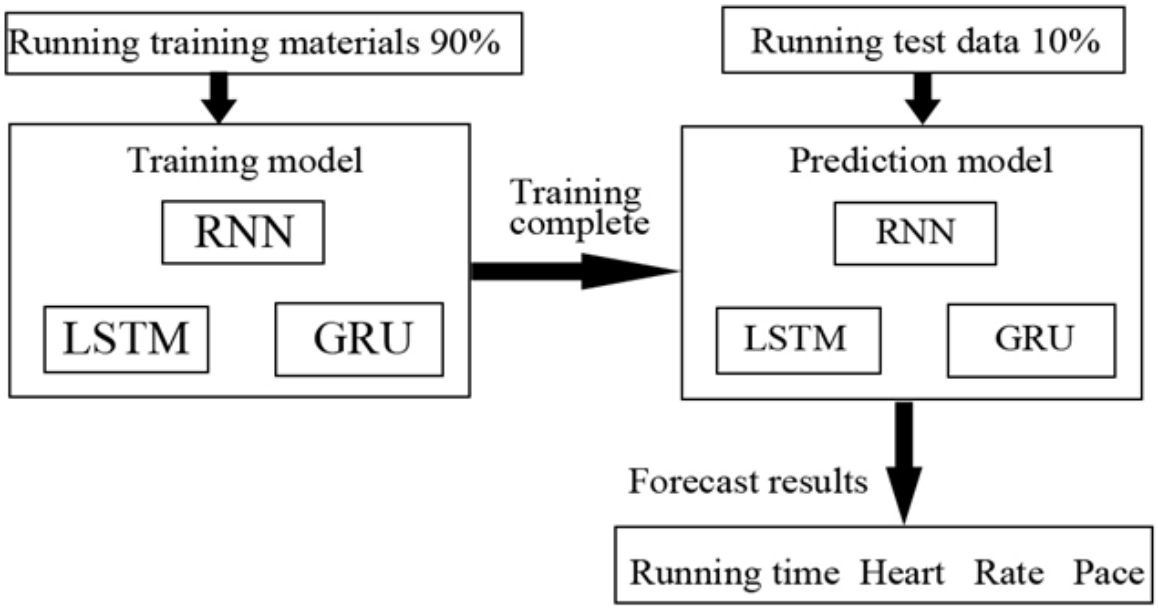

Figure 7

Predictive model experiment architecture

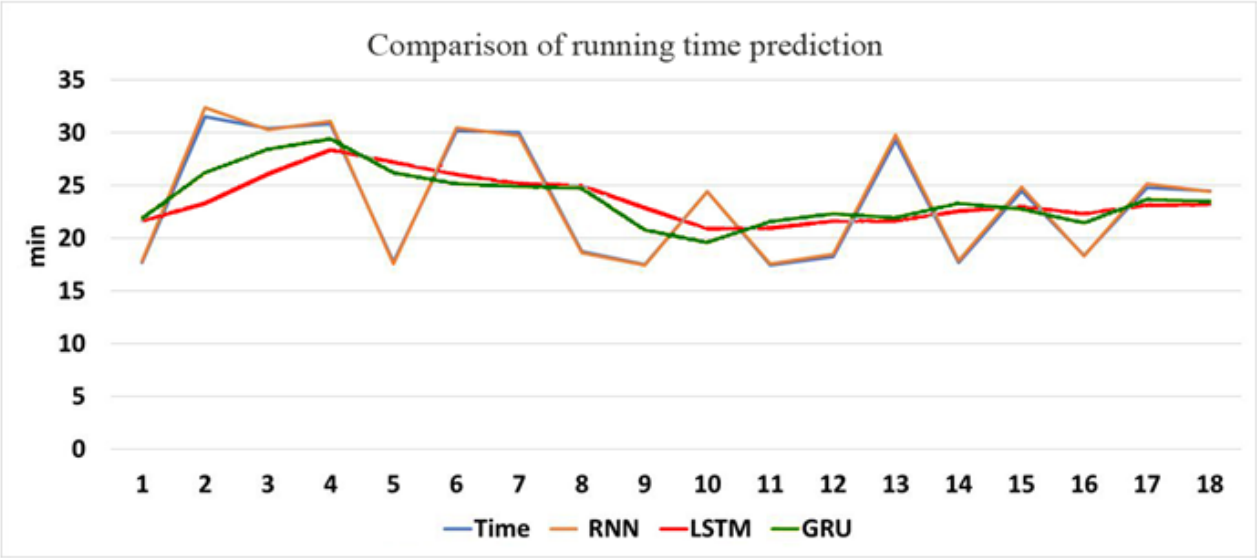

Figure 8

Comparison of running time forecast of three models

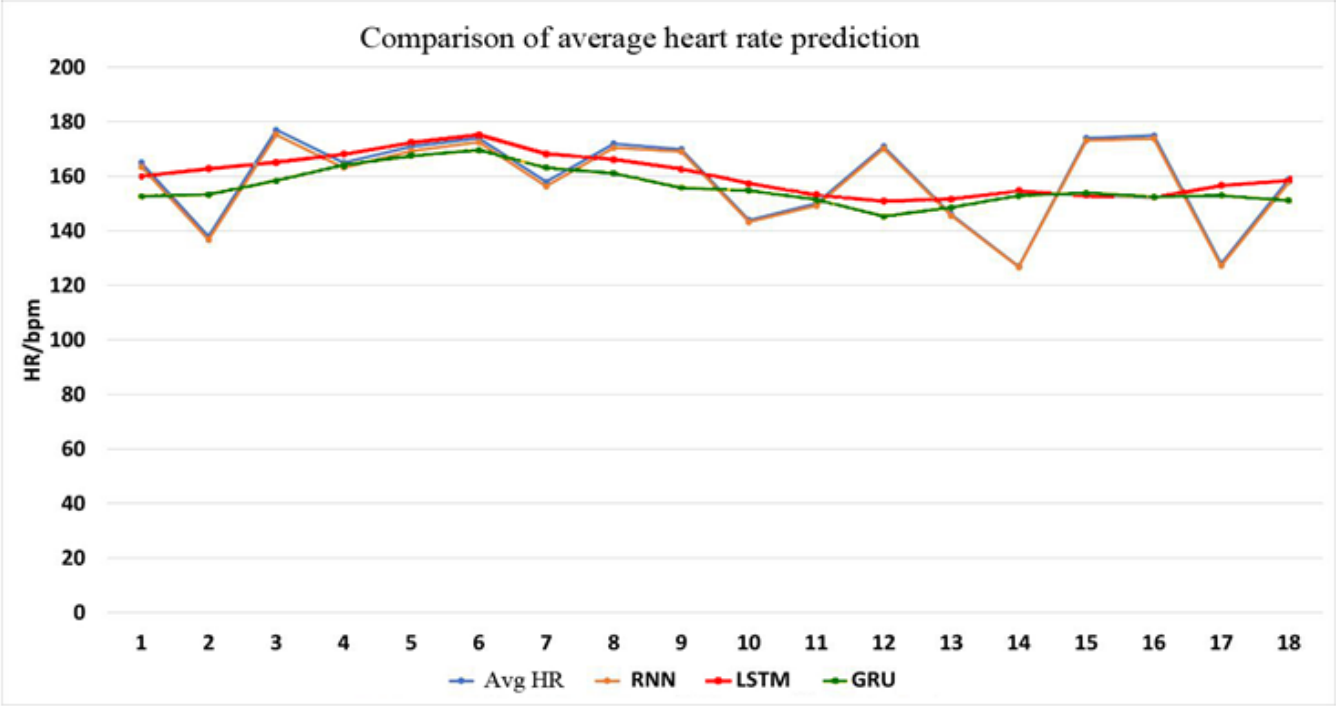

Figure 9

Comparison of average heart rate forcasts of the three models

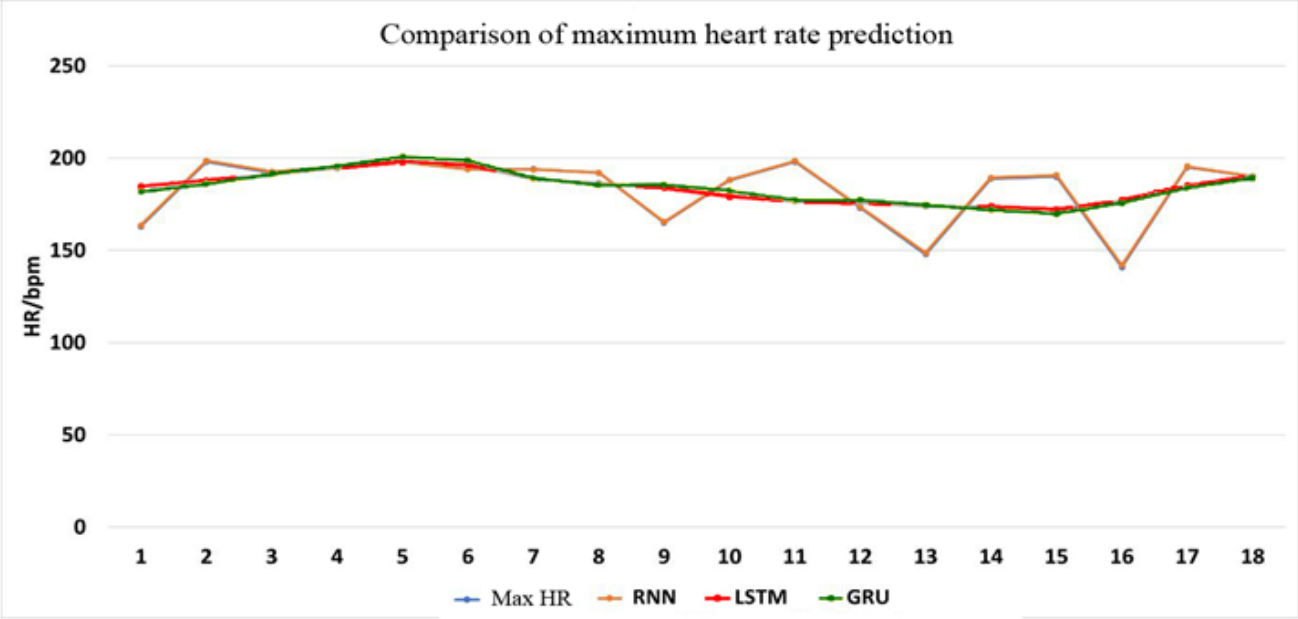

Figure 10

Comparing maximum heart rate and RNN 1~3 layer forecast value.

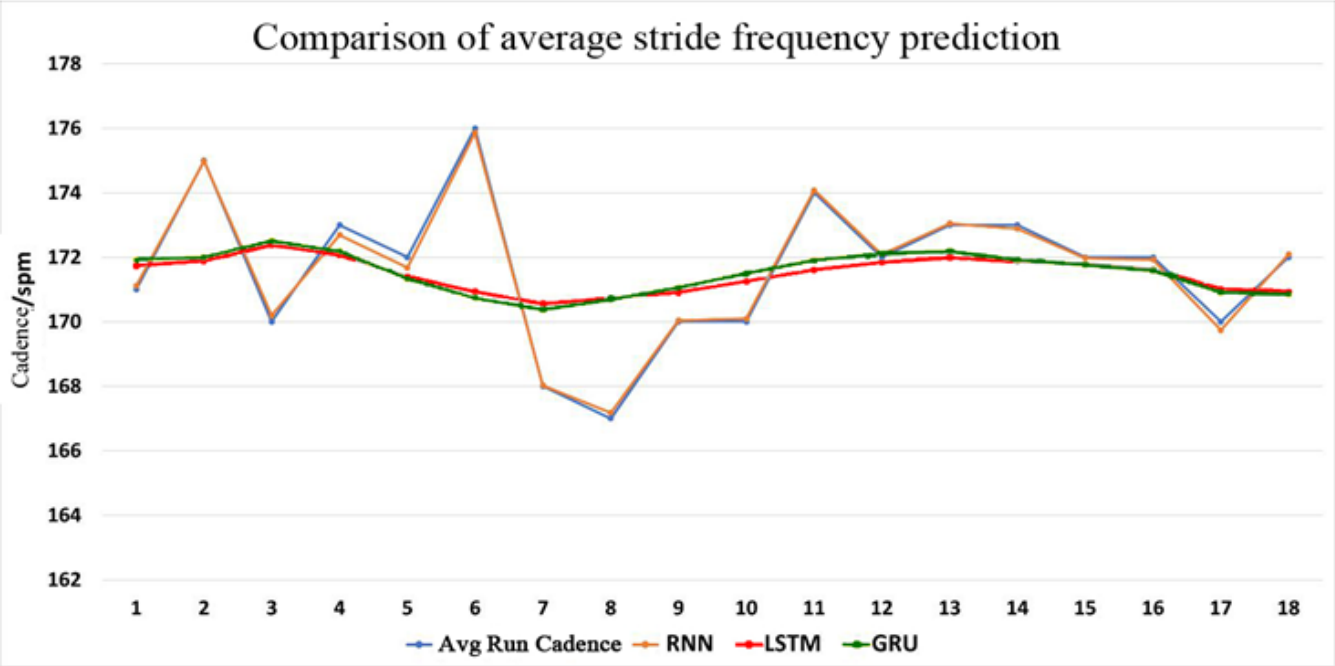

Figure 11

Comparison of average cadence forecast of three models

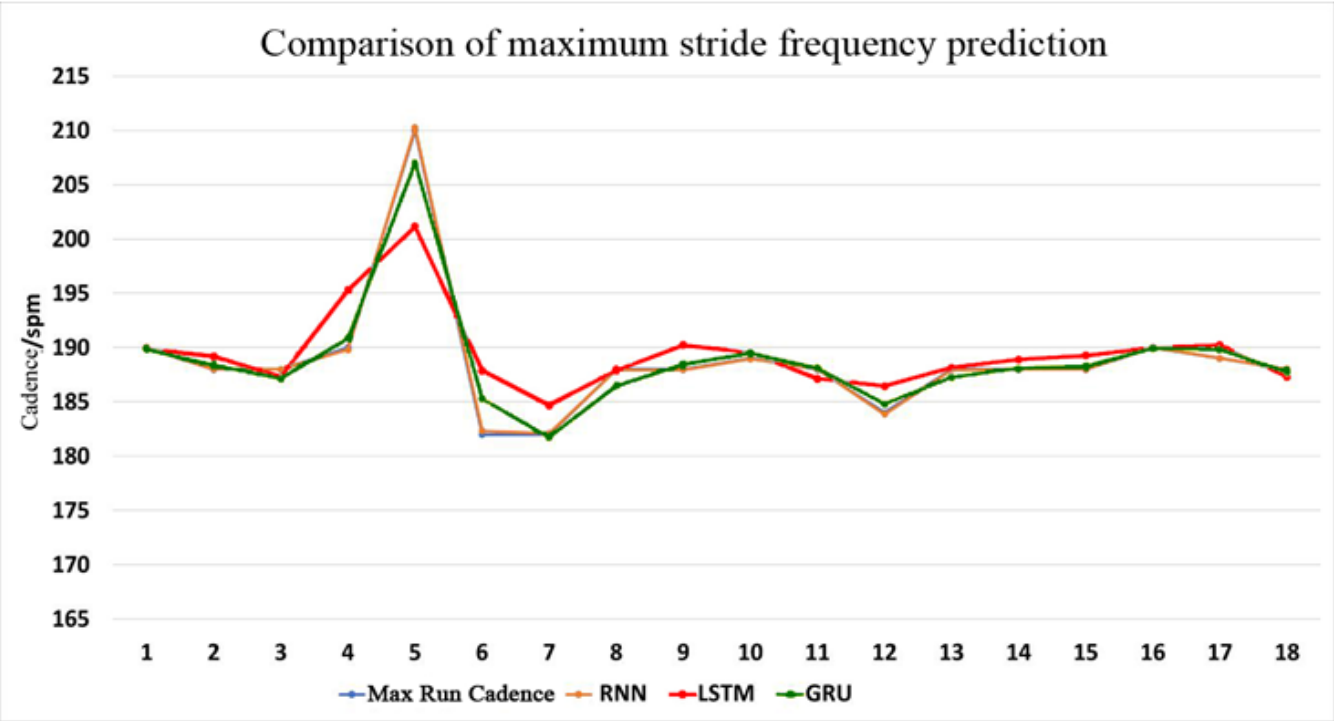

Figure 12

Comparison of the maximum step frequency forecast of the three models

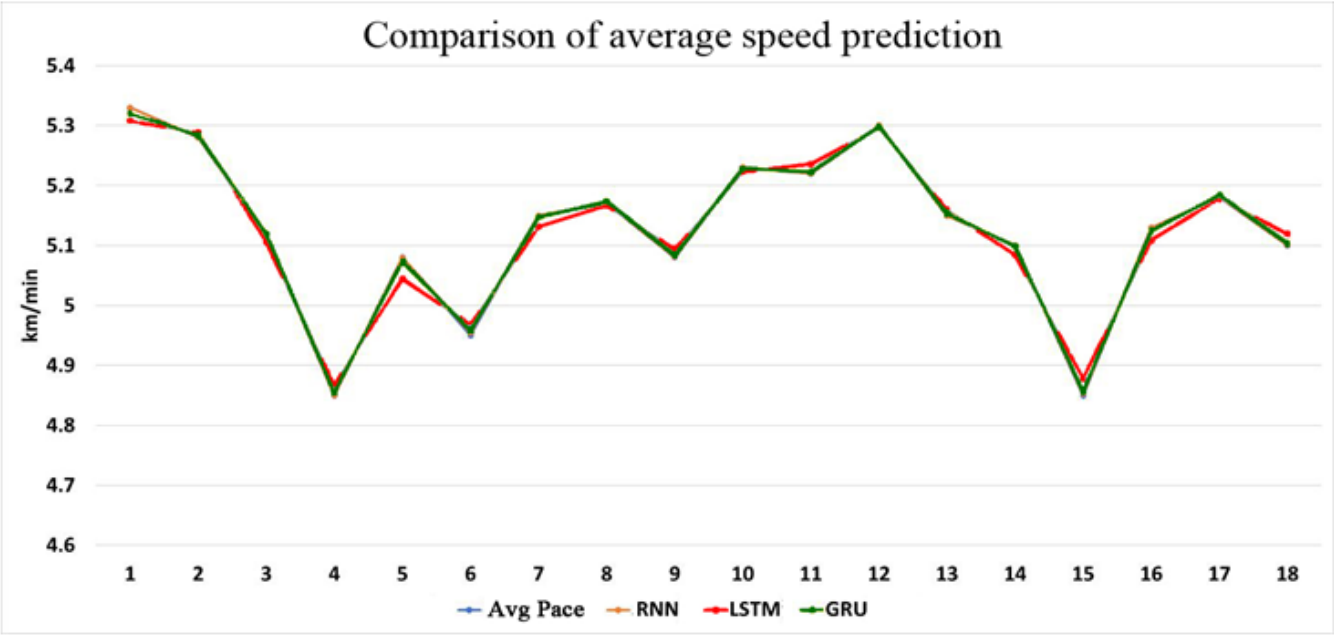

Figure 13

The average pace forecast comparison of the three models

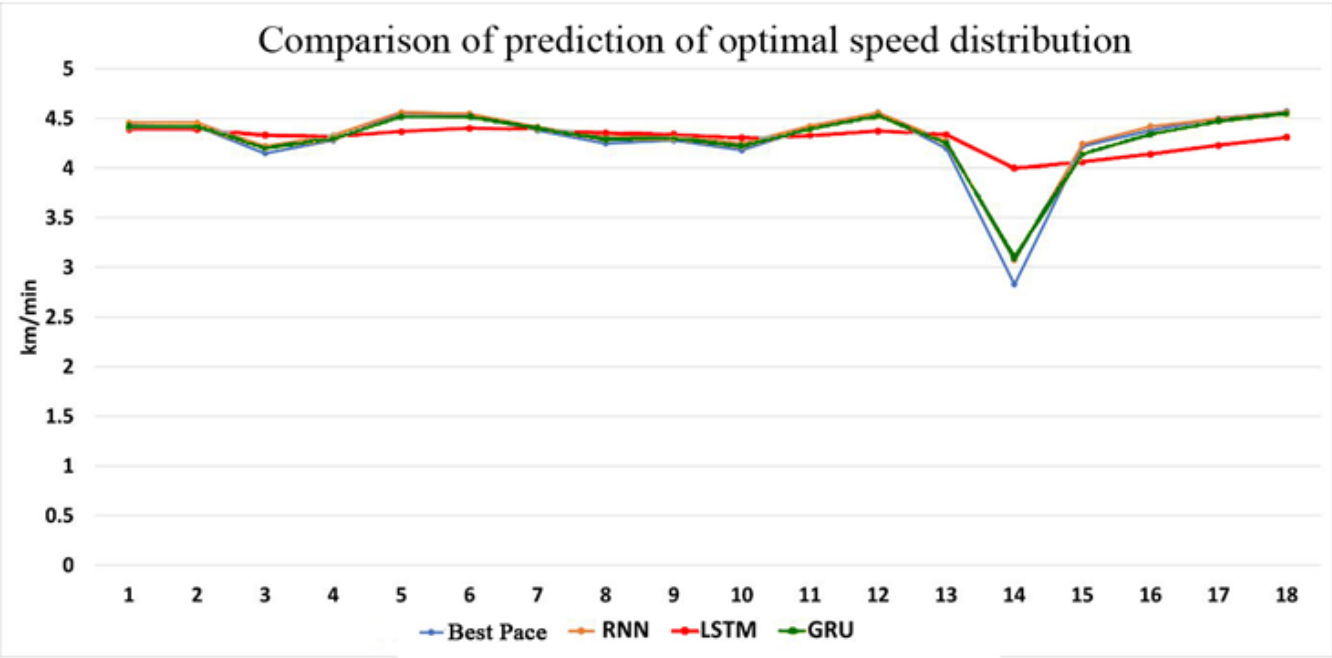

Figure 14

Comparison of the best pace forcasts of the three models

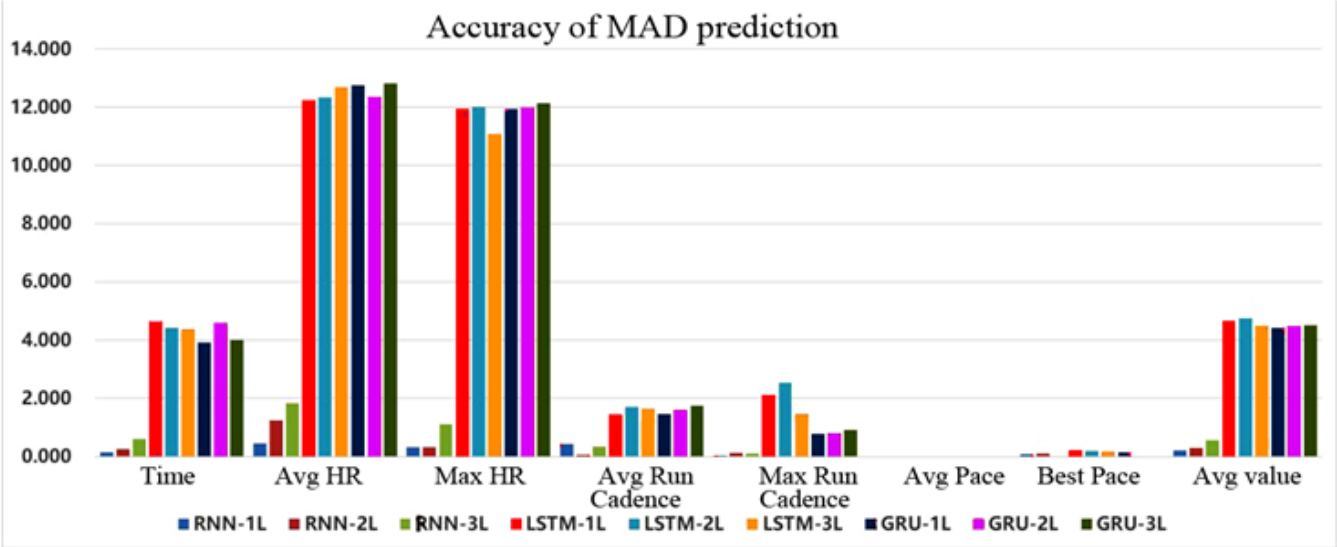

Figure 15

Comparison of forecast accuracy of three models using MAD

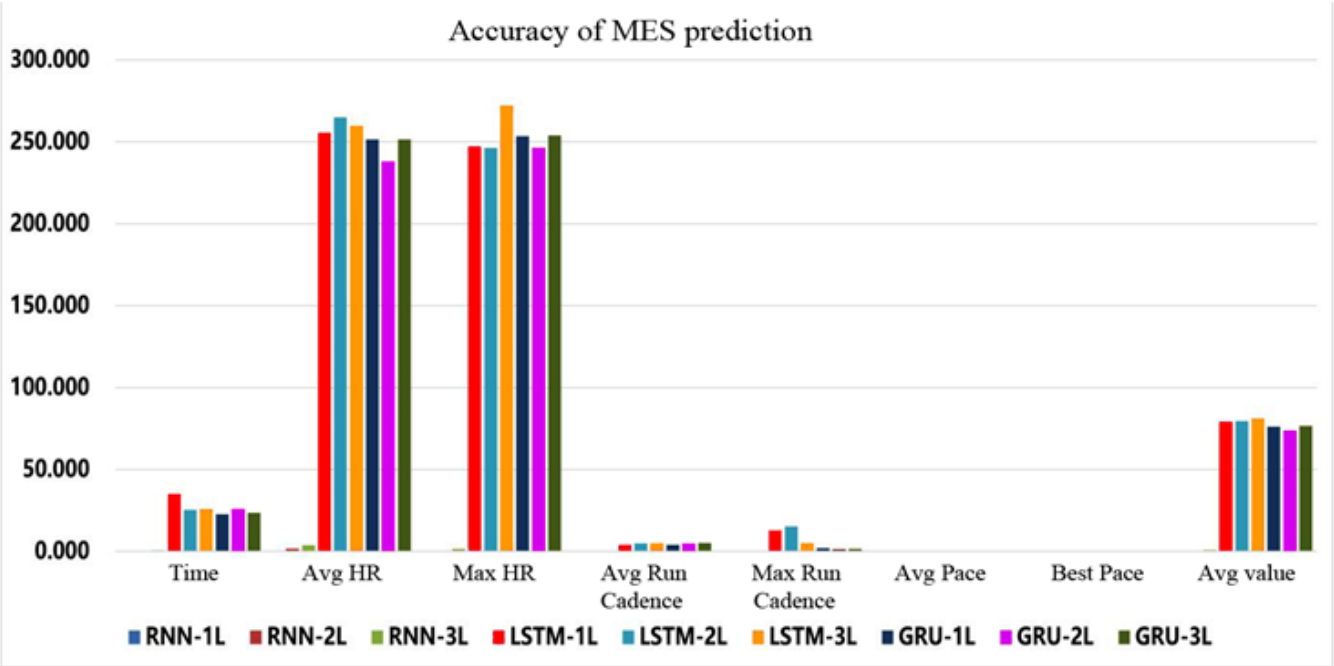

Figure 16

Comparison of forecast accuracy of three models using MSE

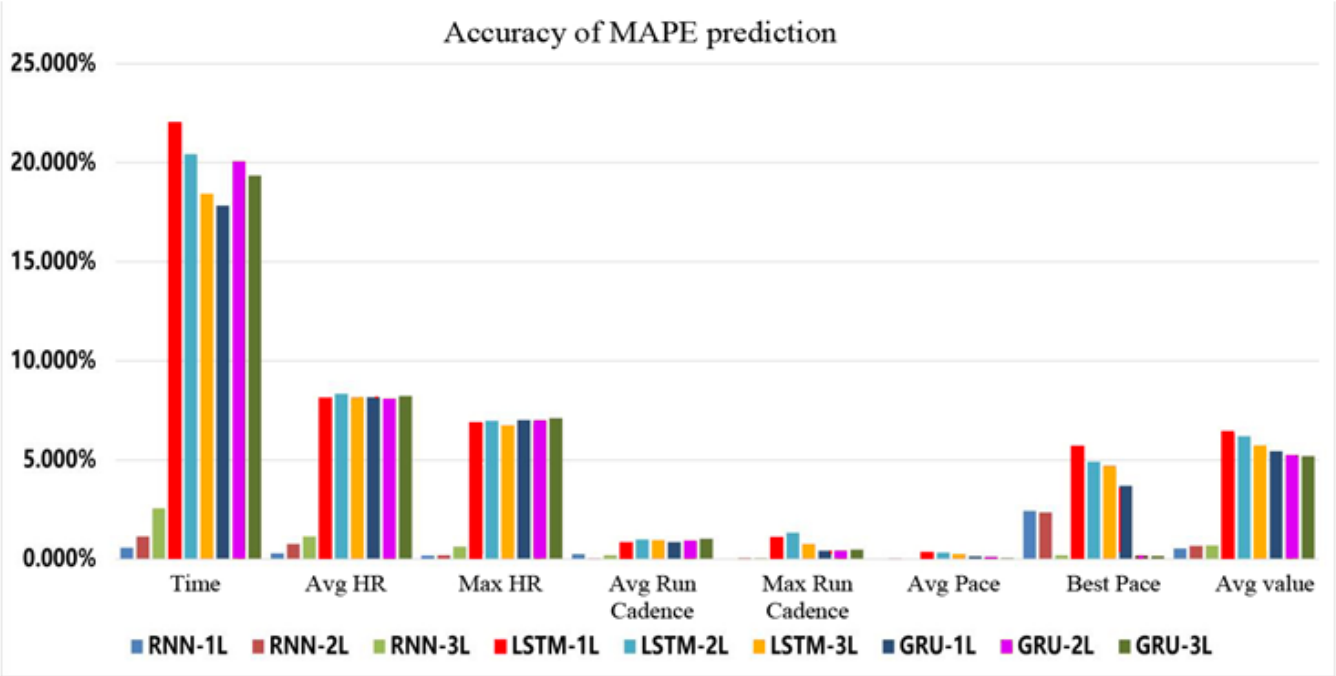

Figure 17

Comparison of forecast accuracy of three models using MAPE