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# CNN algorithm for dual-modal acquisition and intelligent recognition of motion and health indicators

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**Abstract** Aiming at the demand for precise regulation of exercise intensity due to individual differences in sports health management, this paper proposes a data acquisition device for sports health signs based on the MICNN model. The device collects data through a combination of multiple sensor modules and relies on data filtering for data processing. The MICNN model is used to construct a multi-sensor feature parallel extraction architecture, and the exercise heart rate prediction is realized through feature aggregation. The designed device is put into experiments, and a Butterworth low-pass filter is used to process the skin electrical signals and extract the time-domain features containing SCR and SCL. The heartbeat signals are normalized and the validity of respiratory signal acquisition is verified using polysomnography. Exercise heart rate was predicted by the MICNN model, and its performance was evaluated by a combination of Bland-Altman analysis and comparative experiments. The mean value of model-predicted heart rate deviation was 0.03, the 95% agreement range ( $\pm 1.96$  times standard deviation) was +4.52bpm and -4.46bpm, and the RMSE, MAE, and MAPE were 0.73, 0.52, and 7.25%, respectively, which were significantly lower than those of other control models.

**Index Terms** exercise data acquisition, MICNN model, Butterworth low-pass filter, Bland-Altman analysis, heart rate prediction

## I. Introduction

Relevant studies have shown that reasonable exercise and sports can not only improve physical fitness, but also enhance attention and memory, and moderate exercise also helps to enhance immunity, which in turn improves the efficiency of learning and work [1], [2]. However, excessive exercise may cause a series of problems, including excessive fatigue, reduced immunity, increased heart burden, and may even lead to symptoms such as myocardial ischemia, hypoxia, chest tightness, and in extreme cases, fainting due to insufficient blood supply [3]-[5]. In addition, long-term lack of exercise will also cause various adverse effects on physical health, such as tissue and organ function decline, basic muscle atrophy, as well as decreased respiratory and circulatory functions [6], [7]. Therefore, reasonable exercise workouts are crucial for physical health [8]. Based on this, when exercisers exercise, if they can acquire an exercise duration that matches their own state according to their own physical condition, they can effectively prevent excessive or insufficient exercise, and then realize better exercise effects [9]-[11]. Reasonable advice can be provided to exercisers by collecting and analyzing their health signs during exercise, including real-time heart rate, blood oxygen saturation, and energy expenditure, to ensure that they can have a more efficient and beneficial exercise experience [12]-[14].

Traditional health monitoring methods for sports often rely on coaches' intuitive observation and athletes' self-feedback, which are not only limited by human subjectivity and experience, but also difficult to monitor athletes' health status continuously and comprehensively [15]-[17]. Meanwhile, due to the lack of accurate data support, it is difficult for coaches to make targeted adjustments and optimization of training programs [18], [19]. By deploying a variety of sensors and equipment, using intelligent algorithms to collect real-time data from athletes in the process of exercise, conducting in-depth analysis of the collected sports training data, and carrying out in-depth mining and extraction of its features to achieve optimized output of real-time data on sports training [20]-[24]. Being able to minimize the interference of the external environment and lower packet loss rate when transmitting monitoring data, it can help athletes better improve their sports level [25], [26].

A large number of scholars are trying to develop targeted sports health monitoring systems to meet a wider range of sports training needs. Literature [27] developed a fitness monitoring method based on sports health big data, which can effectively collect and recognize the human heart rate, body temperature and other vital characteristics, helping users to understand their own health status during sports in real time. Literature [28] applies wearable technology and recurrent neural network in the field of athletes' health monitoring, and by analyzing the collected

sports data, the depth characteristics of the athletes can be obtained, which provides a reference for data-driven health monitoring and training. Literature [29] established a sports health monitoring system consisting of wearable devices, cloud computing and deep learning technology, which can collect various physiological parameters of athletes in real time and transmit the data to a cloud server for training, providing athletes with reports reflecting their health status. Literature [30] designed an artificial intelligence based sports health monitoring and management system, which collects and analyzes the user's health status in different scenarios through different monitoring modules and sends health alerts to users in risky conditions with high effectiveness. Literature [31] combines wearable technology and Internet of Things (IoT) technology to establish a sustainable health monitoring system for athletic populations, which collects and tracks users' health characteristics through wearable sensors and introduces machine learning technology to analyze them, which effectively reduces the health risks of athletes. Literature [32] proposes the use of mobile big data to provide resource support for user sports health evaluation, introduces a graph neural network model to evaluate the collected sports big data, and makes an accurate evaluation of the sports health level of real users after simulation analysis. Literature [33] constructs an Internet of Things framework for sports health management, collects a large amount of physiological characteristic data through wearable devices, and analyzes the user's health status using big data analysis and convolutional neural network methods, which is conducive to improving the personalized level of sports health management. Literature [34] uses a convolutional neural network-based sports health monitoring system to track, analyze, and evaluate the physical exercise performed by exercisers in real time, so that they can adjust a personalized sports strategy based on real-time feedback, and then improve their health and exercise effects.

In this paper, the overall framework of the device is firstly designed to realize the multidimensional simultaneous acquisition of exercise physiological parameters by integrating multimodal sensor hardware devices. Kalman filter and Butterworth low-pass filter are used to effectively remove motion noise and standardize the collected physiological data. The features of the sensor are extracted based on the MICNN model to improve the accuracy and overfitting resistance of the model. ER-SCR is extracted by Butterworth low-pass filtering, and a four-dimensional feature system containing delay, peak amplitude, and rise/recovery time is established. Synchronized comparison of polysomnography was introduced to verify the accuracy of respiratory signal acquisition. Heart rate prediction was achieved by joint modeling of respiratory-heartbeat signals, and Bland-Altman test was used to test the prediction results. Comparison experiments are conducted between the MICNN model and three mainstream models to examine the performance level of model prediction.

## II. MICNN-based sign data acquisition and recognition device

Different people are stimulated differently by their organisms when performing the same physical activities. This is due to individual variability resulting in the body's ability to tolerate these activities differently, so physical activities need to be adjusted according to the individual's actual situation. Exercise intensity is an important measure for the normal implementation of exercise prescription, and is one of the important factors whether the exercise prescription can be continued or whether it is adjusted.

Therefore, in this paper, an exercise health signs data acquisition device is designed to monitor multiple physiological information of the human body in real time, such as skin electricity, heartbeat, respiration and so on. The device develops drivers for different functional modules to realize the collection, storage and data communication of information such as skin electricity, heartbeat and respiration.

### II. A. Overall structure of the hardware acquisition device

The hardware system framework of the sports health signs data collection device is shown in Figure 1.

As can be seen from the figure, the hardware system on the device side of the monitor is mainly composed of 5 modules, which are:

#### (1) Data Acquisition Module

Used to realize the acquisition and digitization of various physiological and movement parameters of the human body, it consists of physiological signal measurement module ADS1294R, digital infrared temperature sensor MLX90615, and six-axis motion processing component MPU6050. The outputs of each module are converted to digital signals by the internal ADC, so the master control unit can realize data communication directly through the corresponding interface.

#### (2) Memory Module

The hardware of storage module is micro SD card, which has the characteristics of small size, fast read/write speed, etc. After using FAT file system to write to the SD card, it can meet the needs of reading data files in the upper computer.

#### (3) Communication module

The wireless communication module of the monitor is selected from the consideration of power consumption, size, and communication requirements, and the ESP32 chip produced by Loxin, which integrates 2.4GHz Wi-Fi and Bluetooth LE v4.2, and the master control unit can realize Bluetooth communication with the host computer through the serial port. In addition, a USB port is integrated within the MINIHDMI interface, which can be connected to the host computer via a USB cable.

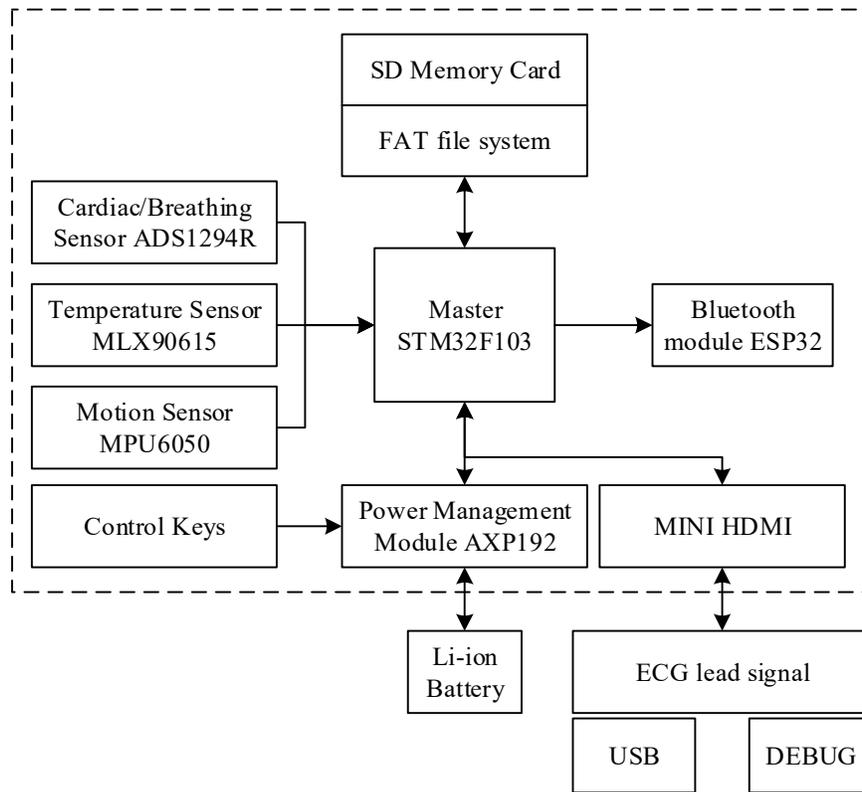


Figure 1: Overall hardware structure of the monitor

#### (4) Main control unit

The main control unit selects the STM32F103RCT6 microcontroller produced by STMicroelectronics, the controller kernel is Cortex-M3, the main frequency can reach up to 72MHz, built-in 48KB RAM and 256KB Flash, as well as a series of commonly used peripherals such as DMA, 11C, SPI, and so on, which can satisfy the needs of the functional design of the monitor. Functional design needs.

#### (5) Power Management Module

The power supply of the device system is provided by a 450mAh, 3.7V high-temperature lithium battery, and the AXP192 power chip is responsible for power control. The power management module not only realizes the provision of 3V-3.3V power supply to the main control/sensor/SD card and other chips, but also meets the monitoring of the power status of the main control unit, such as residual power, instantaneous power consumption, charging time, etc., through the internal ADC and the two-wire serial communication interface.

## II. B. Data pre-processing

### II. B. 1) Data filtering

The data collected by the inertial sensor is not stabilized before each stage of motion, and in order to minimize the noise effect of the motion data, the motion data of the first 40 seconds of the intensity of each stage of motion will be deleted. The Vet Intelligent Inertial Sensor has a built-in algorithm of Kalman filtering, which is able to filter out some mechanical noises and drift effects etc. Research has shown that in the process of movement, the individual clothing artifacts, etc. will produce high-frequency noise, the frequency of most of these noises is higher than 25 Hz. Butterworth low-pass filter is more widely used in speech signal processing, image processing, biomedical and other fields. It can maximize the response at frequencies in the passband and vice versa. It makes the response curve smoother and has greater smoothness in the passband without causing distortion in the phase of the signal. The mathematical function expression is shown in equation (1):

$$H(w) = 1 / \left[ 1 + (w / w_c)^{2N} \right] \quad (1)$$

In Eq. (1),  $H(w)$  denotes the frequency response,  $w$  denotes the corner frequency,  $w_c$  denotes the cutoff frequency, and  $N$  denotes the order of the filter, which also determines the steepness of the filter response curve.

Due to its good filtering effect on high-frequency noise and high fidelity effect on low-pass signals, the data from the inertial sensor will be further filtered in this paper by a low-pass filter with the cutoff frequency set to 25 Hz.

### II. B. 2) Data standardization

Included in the collected dataset are age, sex (male=1, female=2), height, weight, resting heart rate, triaxial acceleration, triaxial angular velocity, and heart rate. They do not have the same magnitude as each other, so some features may be particularly large and some have small values, making it difficult to obtain a high-performance model when modeling. In order to eliminate the effects when modeling the data and to improve the performance of the algorithm as well as the comparability of the data, it is necessary to process the data. Data normalization is a method of scaling the data to a mean of 0 and a standard deviation of 1. It ensures that the importance of each feature in the analysis is balanced, and it improves the speed of gradient descent optimization to find the optimal solution quickly. The mathematical expression of standardized processing is shown in equation (2):

$$X_{standardized} = \frac{x - \mu}{\sigma} \quad (2)$$

$X$  represents the original data,  $\mu$  represents the mean in the original data, and  $\sigma$  represents the standard deviation in the original data.

### II. C. Multihead Convolutional Neural Network-based Data Acquisition Model for Exercise Health Signs

The multi-head convolution technique is mainly used to solve the problem of feature loss in the traditional convolutional neural network sports health signs data acquisition model. The traditional CNN model is mainly based on the time window to extract the features of its local area, and it will lose some effective features when extracting the features of the time window composed of multiple IMU signals. In this paper, we mainly extract hierarchical features from different channels from local to whole by using multi-head convolution module, which can not only enhance the feature extraction ability of the model, but also prevent the model from overfitting phenomenon on the basis of ensuring the sparsity of the network.

The experimental procedure of deep learning based on multi-head convolutional neural network (MICNN) is as follows: first, after data preprocessing, the data are normalized. Second, a separate CNN extraction network is designed for each sensor, which mainly uses the original accelerometer or gyroscope signals based on a single time window as the model input, with a window size of  $1024 \times 3$ . Taking the hip accelerometer as an example, the accelerometer sensor signals are firstly subjected to two convolutional and pooling operations, so as to obtain the signal features of the sensors. Different feature vectors are obtained for each sensor after the convolution operation. Then, pooling and aggregation operations are performed on the output of the convolution layer of each sensor. Finally, the prediction results are output after two layers of fully connected operations.

In the experiments, stochastic gradient descent (SGD) is used as the optimizer with an initial learning rate of 0.01 and a stumble learning rate. The loss function is mean square error loss (MSE).

$$MSE(x) = \frac{1}{n} \sum_1^n (g(x^i) - y^i)^2 \quad (3)$$

where  $x$  is the overall sample,  $n$  is the number of samples.  $g(x^i)$  is the target predicted value, and  $y^i$  is the target measured value. We set Early Stopping to prevent the model from overfitting, and the model is also trained with LOSOCV for cross-validation. All the above parameters are locally optimized by grid search method.

## III. Evaluation of the performance of the MICNN-based data collection model for sports health signs

### III. A. Collection of data on physical signs

The data collection is carried out by utilizing the data collection device for sports health signs proposed in this paper. The device is powered by TypeC interface and can also be powered by Li-ion battery, and the battery life of the collection device can reach more than 6 days with 8 hours of data collection per day. The collection device connects to the network through Wi-Fi and sends the collected data in real-time to the background in the format of data

packets for saving. Before the experiment, make sure that all the devices have been installed and calibrated correctly, and make sure that the contact between the devices and the experimenter's body is good. After checking that there is no error, the experimenter starts to perform the scheduled exercise program and monitors his/her physiological indexes in real time. The equipment will record the physiological data of the exerciser in real time, and in order to ensure the accuracy and completeness of the data, the experimenter should avoid too many interruptions during the exercise.

### III. A. 1) Acquisition of electrical skin signals

A Butterworth low-pass filter was used to filter each group of 10 adjacent ADC signal values to effectively eliminate noise and jitter. The skin electrical curve is shown in Fig. 2, from which it can be seen that there is noise in the original signal at about 10000ms, and the final smooth skin electrical signal curve is obtained after the filtering process.

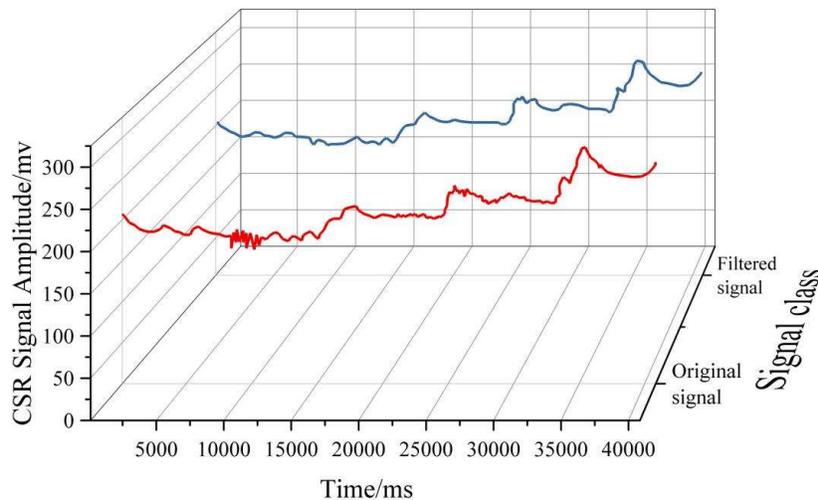


Figure 2: Skin electrical signal curve

During the analysis of the skin electrical profile, it is important to note that the skin electrical signal consists of two main components, the skin conductance response SCR and the conductance level SCL. The conductance level SCL is a relatively stable quantity that varies slightly over tens of seconds to several minutes. It rises and falls depending on the physical state of the experimenter, e.g., moisture and autoregulation of the skin. In contrast, changes in skin conductance response will be more pronounced. Among them, ER-SCR is sensitive to specific emotional stimulus events, with data spikes occurring within one to five seconds of the emotional event. In contrast, the nonspecific skin conductance response NS-SCRS occurs autonomously in the body without any provoking stimulus.

The most important aspect in the analysis of galvanic skin data is the analysis of event-related skin conductance responses, which can be used to detect the degree of emotional engagement and arousal of the subject. Each skin conductance response can be represented by four metrics: latency, peak amplitude, rise time, and recovery time. Latency indicates the time from the onset of the event stimulus to the onset of the burst of the ongoing event. Typically, the skin conductance response occurs within one to five seconds of the start of the event stimulation, and the point at which the skin electrical profile begins to rise is labeled as the start point. Peak amplitude indicates the difference in amplitude between the start point and the peak. Rise time indicates the duration from the start point to the peak. Recovery time indicates the duration from peak to 100% recovery. The typical activity curve of skin electricity is shown in Fig. 3. When the collected skin electricity curve of the experimenter produces a steady peak, it can be determined that the experimenter has entered the exercise state.

### III. A. 2) Heartbeat signal acquisition

Since the acquired signal is mixed with high frequency signal noise, it needs to be normalized to get a cleaner signal. The pre-processed heartbeat signal is shown in Figure 4. The red part of the figure is the original heartbeat signal. The blue part is the pre-processed heartbeat signal. The band-pass filtering eliminates the noise higher than the heartbeat frequency range and retains the main components of the heartbeat signal.

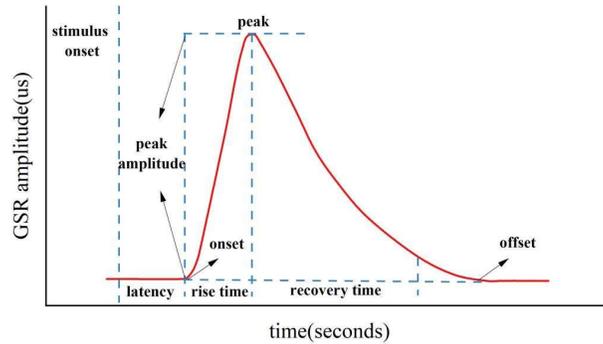


Figure 3: Typical curve of skin electrical activity

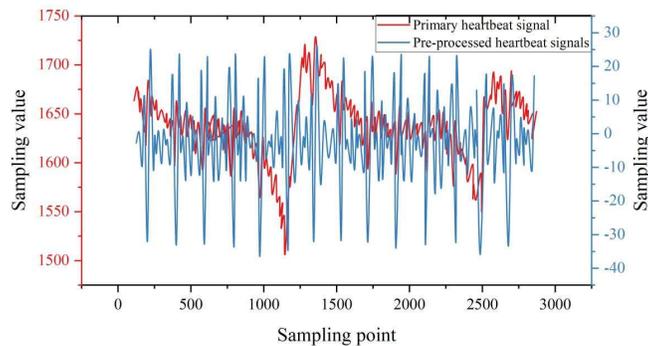


Figure 4: Heartbeat signal

### III. A. 3) Respiratory signal acquisition

In order to verify the validity of respiratory signal acquisition by the acquisition device, the designed hardware acquisition device is synchronized with the medical device to collect data. Polysomnography (PSG) is an instrument used to monitor physiological signals such as cerebral, cardiac, and thoracic and abdominal movements during sleep. It usually consists of multiple sensors that are placed in different parts of the body, such as the scalp, heart, chest and abdomen, to capture multiple physiological signals. Usually the cardiac electrical signals are used to record heart information and the chest and abdomen bands to record respiratory information. A comparison of the respiratory signals captured by the polysomnograph and the device designed in this paper is shown in Figure 5. The filtered and processed signals show the movement of the chest and abdomen, i.e., breathing, from which the corresponding respiration rate can be calculated. It can be seen that the vibration intensity of respiration is relatively large, and the designed device can easily and accurately capture the respiration situation. The respiration waveform after filtering has the same periodicity as the signals captured by the chest and abdominal belts of the polysomnograph, and each cycle contains about 500 sampling points.

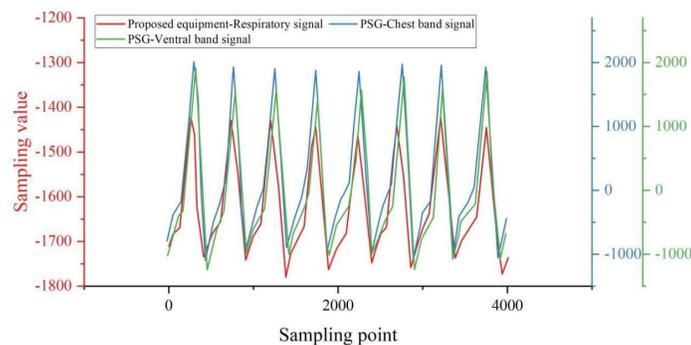


Figure 5: Comparison of respiratory signals collected

### III. B. Evaluation of model heart rate prediction performance

Breathing and heartbeat are two of the most basic physiological signals in the human body, and they are closely

related to each other. Under normal circumstances, the cycle of breathing is usually 12-20 times per minute, while the cycle of heartbeat is usually 60-100 times per minute. However, since the control centers for both respiration and heartbeat are located in the brainstem, they interact with each other. When respiration speeds up, the heart rate also speeds up; and when respiration slows down, the heart rate also slows down accordingly. Therefore, the device in this paper adds respiratory signal features for extracting heart rate from cardiac shock signals. The features of respiration and heartbeat signals are extracted using the MICNN model, pooled and aggregated to output the predicted heart rate values after two fully connected layers.

In order to evaluate the performance of the model, two commonly used evaluation metrics, namely mean absolute error, standard deviation of absolute error (SDAE), are used to assess the accuracy of the model in predicting heart rate. The mean absolute error MAE reflects the error between the predicted heart rate and the heart rate value calculated from ECG, and the SDAE is used to reflect the degree of dispersion of the error.

The Bland-Altman results for heart rate calculated from ECG and BCG are shown in Figure 6. The mean value of 0.03 indicates that the mean deviation of the heart rate predicted by the model is very small, but it should be noted that the Bland-Altman plot can only show the mean deviation not the absolute deviation, so the distribution of the absolute deviation needs to be further analyzed. The 95% concordance ranges ( $\pm 1.96$  times the standard deviation) were +4.52bpm and -4.46bpm, which is in the AAMI recommended accuracy standard of  $\pm 5$ bpm for heart rate measurements.

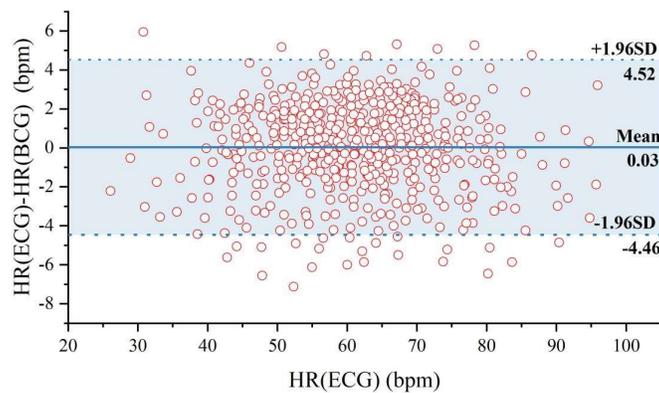


Figure 6: Bland-Altman results of ECG and BCG calculation of heart rate

Finally, this paper also selected some mainstream heart rate prediction models for comparison and validation, and took the average value of each prediction model index, and the test results are shown in Table 1. The RMSE, MAE, and MAPE of the MICNN model are 0.73, 0.52, and 7.25%, respectively, which are significantly lower than those of the other models, indicating that its prediction error is smaller and the overall accuracy is higher. The  $R^2$  of the MICNN model is close to that of the RF model, indicating that both can explain the data variation better, but the MICNN model significantly reduces the error while maintaining high explanatory power, with the RMSE and MAE reduced by 17.0% and 23.5%, respectively. By comparison, the model in this paper outperforms various models commonly used in heart rate prediction in all indicators.

Table 1: Model performance comparison

Model	RMSE	MAE	$R^2$	MAPE/%
SVM	0.94	0.74	0.69	30.25
RF	0.88	0.68	0.80	11.84
CNN	0.91	0.66	0.66	11.93
MICNN	0.73	0.52	0.78	7.25

#### IV. Conclusion

In this paper, we designed an exercise health sign data collection device based on the MICNN model, and conducted experiments to collect sign data and predict heart rate to explore the feasibility of its application.

The Bland-Altman analysis model predicted heart rate with a mean deviation of 0.03 and a 95% agreement range ( $\pm 1.96$  times standard deviation) of +4.52bpm and -4.46bpm, which were within the AAMI recommended accuracy standard of  $\pm 5$ bpm for heart rate measurements. The MICNN model had a RMSE, MAE, and MAPE of 0.73, 0.52, and 7.25%, respectively, which were significantly lower than those of other control models, indicating that its

prediction error was significantly lower than the other control models, and that its prediction error was significantly lower than the other control models. which were all significantly lower than the other control models, indicating smaller prediction errors and higher overall accuracy. The  $R^2$  of the MICNN model was close to that of the RF model, indicating that both explained the data variability better, but the MICNN model significantly reduced the errors while maintaining high explanatory power, with a reduction of 17.0% in the RMSE and 23.5% in the MAE, respectively. The experimental results indicate that the MICNN model performs better and that neural networks can significantly improve existing techniques in predicting heart rate for continuous real-time monitoring of exercise health.

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