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Sports Physiological Health Monitoring with Onenet IoT Cloud Platform and Deep Learning

Xin-Yu Tang*

School of Computer
Guangdong Business and Technology University
Zhaoqing 526040, P. R. China
36894625@qq.com

Zhi-Cai Zheng

St. Paul University Philippines
Tuguegarao City, Cagayan 3500, Philippines
57408943@qq.com

*Corresponding author: Xin-Yu Tang

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Abstract. *Traditional physiological state monitoring often relies on manual recordings or non-real-time devices, which limits the ability to assess and analyse the physiological state of an athlete or individual in real time at different exercise intensities. With advances in sports science and personal health management, there is a growing need for devices that can remotely monitor, store large amounts of data and perform sophisticated analyses. To address these two issues, this work proposes an exercise physiological health monitoring system based on the OneNet IoT cloud platform and deep learning. Firstly, through IoT technology, the monitoring device is able to collect and transmit physiological signals (e.g., heart rate, blood pressure, and body temperature) to the OneNet cloud platform in real time, which ensures the continuity and real-time monitoring, thus enabling timely detection and response to health problems. Secondly, after uploading the data on the OneNet cloud platform via the wireless data communication module, deep learning algorithms (CNN-LSTM) are applied to the collected data to automatically identify abnormal patterns and provide a more accurate assessment of health status. In addition, the performance of the deep learning model can be further improved by combining optimisation algorithms such as Particle Swarm Optimisation (PSO). Experimental results show that the CNN-PSO-LSTM model improves the classification of physiological signals by 3.8% compared to the benchmark experimental model. The designed system enables coaches, athletes and medical professionals to access and analyse data regardless of their location, enabling remote monitoring and assessment of athletes' physiological status, thus solving the problems of data silos and resource sharing in traditional methods.*
Keywords: internet of things; OneNet; physiological signals; health monitoring; CNN; PSO; LSTM

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1. **Introduction.** Traditional methods for monitoring physiological status often rely on regular physical examinations or data collection using bulky equipment, which is not only inefficient but also difficult to achieve real-time monitoring and analysis [1, 2, 3]. In addition, the processing and analysis of large amounts of physiological data is beyond the capabilities of traditional methods [4]. With the development of exercise science and personal health management, there is an increasing demand for the ability to remotely monitor, store large amounts of data and perform complex analyses. Therefore, how

to realise real-time and accurate monitoring of the physiological status of athletes and fitness enthusiasts using state-of-the-art technology has become a hot topic for research and application [5, 6].

With the rapid development of Internet of Things (IoT) technologies and deep learning algorithms, unprecedented opportunities and challenges have emerged in the field of exercise physiological health monitoring. OneNet, as a representative of the IoT cloud platform, provides powerful data collection, storage, and processing capabilities, which make remote monitoring and analysis possible [7, 8]. In addition, the introduction of deep learning techniques, especially the application of Convolutional Neural Networks (CNN) [9, 10] and Long Short-Term Memory Networks (LSTM) [11, 12], has greatly improved the ability to extract features and identify abnormal patterns from complex physiological signals. After collecting a large amount of physiological data, it is a challenge to process them effectively and extract useful health information from them. Deep learning models, especially CNNs and LSTMs, excel in processing complex physiological signals and recognising patterns. By applying deep learning algorithms to the collected data, the system is able to automatically identify abnormal patterns and provide a more accurate assessment of health status.

The aim of this study is to develop a system capable of monitoring and analysing physiological signals of an individual in an exercise state in real time by integrating the OneNet IoT cloud platform [13, 14] and an advanced deep learning model. The system combines the remote data collection and transmission capabilities of IoT and the efficient data processing and analysis capabilities of deep learning, aiming to improve the accuracy and real-time performance of physiological state monitoring. By monitoring key indicators such as heart rate, blood pressure and body temperature, the system is able to detect abnormal physiological signals in a timely manner, providing a scientific basis for health management and training optimisation of athletes. In addition, this study also explores how to further improve the performance of deep learning models in physiological signal analysis by particle swarm optimisation (PSO) algorithm [15, 16]. By implementing this comprehensive system on the OneNet cloud platform, we expect to provide an efficient and reliable technical solution for sports science research, athlete health monitoring and personal health management, as well as to open up new paths for research and application in related fields.

1.1. Related work.

Over the past few years, the application of IoT and deep learning technologies in the field of health monitoring has made significant progress. Much research has focused on the development of systems that can monitor and analyse physiological signals in real-time in order to detect health problems and intervene in a timely manner.

Augustyniak [17] proposed a wearable device-based heart rate monitoring system that assesses exercise intensity and health status by analysing heart rate data in real time. The study showed that wearable devices have potential for real-time monitoring, but there is still room for improvement in terms of accuracy and user compliance. Chandrasekaran et al. [18] proposed a smartphone-based blood pressure monitoring method that remotely monitors blood pressure by analysing sphygmomanometer readings taken by the user. Although this method is convenient and easy to deploy, it relies on the accuracy of user inputs and may be affected by subjective factors. Rai et al. [19] proposed a deep learning-based method for detecting electrocardiogram (ECG) abnormalities. By training a CNN model, the study successfully identified arrhythmia from ECG signals. This work demonstrates the effectiveness of deep learning in processing physiological signals and identifying health problems. Rabby et al. [20] presented the application of LSTM in predicting changes in blood glucose levels in diabetic patients. The ability of LSTM models to capture the long-term dependence of blood glucose levels provides a new tool for diabetes management. Dang et al. [21] proposed a comprehensive health monitoring system for the elderly by combining IoT technology and cloud computing. The system not only monitors physiological parameters but also provides health management recommendations by analysing the data. Elmasry et al. [22] proposed the application of particle swarm optimisation (PSO) algorithm in optimising hyperparameters of deep learning models. It was shown that the PSO algorithm is effective in selecting the optimal network structure and parameters to improve the performance of the model. Hanif et al. [23] proposed a deep learning-based face recognition technique for monitoring sleep apnoea. The technique provides a new approach for the diagnosis of sleep disorders by analysing facial expressions and small movements to detect breathing patterns. Mohammed et al. [24] proposed an IoT-based smart sports monitoring system that tracks athletes' performance and physiological responses in real time. By analysing the collected data, the system provides personalised training recommendations to the athletes.

1.2. **Motivation and contribution.** These studies show that IoT technologies, deep learning algorithms and cloud computing platforms have great potential for application in exercise physiological health monitoring. However, how to effectively combine these technologies to improve the accuracy, real-time performance and user-friendliness of monitoring remains an issue worthy of further research. The work in this paper is based on these related studies and proposes an integrated solution that aims to address the limitations of existing approaches and to advance the development of health monitoring technologies. The main innovations and contributions of this work include:

(1) A physiological health monitoring system based on IoT and OneNet is designed with data acquisition modules for temperature measurement, blood pressure measurement and pulse measurement. A wireless data communication module supporting Wi-Fi communication and cellular network communication is designed to ensure data transmission from the exercise physiological health monitoring device to the OneNet cloud platform.

(2) A CNN-PSO-LSTM deep learning model is proposed to conduct in-depth analysis of heart rate, blood pressure, body temperature and other data stored in the OneNet cloud to automatically and accurately detect abnormal physiological signals, providing a scientific basis for health management and training optimisation of athletes.

2. Analysis of relevant principles.

2.1. **Convolutional neural networks.** CNN is a deep learning architecture that has achieved remarkable success in areas such as image recognition, video analytics, and natural language processing. The core idea of CNNs is to use convolutional layers to automatically learn spatial hierarchical features from the input data, which makes them well suited for processing data with a lattice topology, such as images and time-series signals. In exercise physiological health monitoring, CNNs can be used to extract useful features from physiological signals. For example, real-time monitoring of abnormal states can be achieved by training a CNN model to recognise abnormal patterns in pulse signals. CNNs typically consist of the following layers:

(1) Convolutional Layer: Local features of the input data are extracted by means of a convolutional kernel (or filter). Convolutional operations capture the spatial dependence of the data while reducing the number of parameters and the risk of overfitting. To make full use of the local features of an image, a neuron is usually described as a $M \times N \times D$ neural layer consisting of D feature maps of size $M \times N$. The 3D structure of the convolutional layer is shown in Figure 1. Z^p denotes the output of the p-th neuron in the

Z layer, W^p denotes the weight matrix of the neuron, b^p denotes the bias of the neuron, and P denotes the number of neurons, that is, the number of output features.

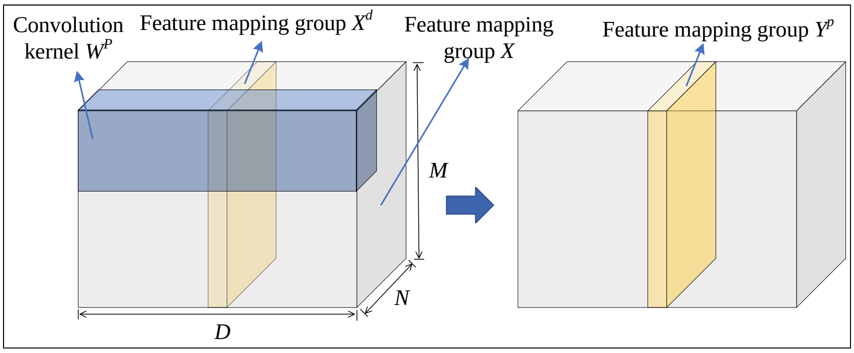

Figure 1. Three-dimensional structure of convolutional layers

(2) Activation Function: Usually followed by a convolutional layer that introduces nonlinear factors to enable the network to learn more complex features. reLU (Rectified Linear Unit) is one of the most commonly used activation functions.

(3) Pooling Layer: also known as the down-sampling layer, used to reduce the spatial size of the data, improve computational efficiency, and provide a certain degree of spatial invariance.

(4) Pooling Layer: also known as the down-sampling layer, used to reduce the spatial size of the data, improve computational efficiency, and provide a certain degree of spatial invariance.

Each neuron in the convolutional layer focuses on only one local region of the input data, which mimics the local receptive field in the biological visual system. In the convolutional layer, the weights of the same convolutional kernel are shared over the entire input data, which greatly reduces the number of parameters in the model. Through pooling operations, the CNN is able to remain invariant to small translations, rotations and scaling in the input data.

2.2. **Recurrent neural networks.** RNN is a neural network for processing sequence data that is able to capture the dynamics of the information at each time point in the sequence by using the output of the previous time point as part of the input of the current time point [25]. The core of the RNN is a hidden layer that stores the information from the previous time points in the sequence. This structure allows RNNs to excel in tasks such as speech recognition, natural language processing and time series analysis.

The state update method for the RNN hidden layer can be represented as [26]:

$$h_t = f\left(W_{hh}h_{t-1} + W_{xh}x_t + b_h\right) \tag{1}$$

where h_t is the hidden state at the current time step; h_{t-1} is the hidden state at the previous time step; x_t is the input at the current time step; W_{hh}, W_{xh} are the weight matrices from the hidden layer to the hidden layer and from the input to the hidden layer, respectively; b_h is the hidden layer bias; f is usually a nonlinear activation function such as tanh or ReLU.

The RNN output layers are

$$y_t = W_{hy}h_t + b_y \tag{2}$$

where y_t is the output of the current time step; W_{hy} is the weight matrix from the hidden layer to the output layer; b_y is the output layer bias.

LSTM is a special type of RNN designed to solve the long-term dependency problem during RNN training. It regulates the inflow, retention, and outflow of information by introducing three control gates (forgetting gate, input gate, and output gate) to enable the network to better learn long-term dependencies in sequential data.

The Oblivion Gate determines which information is discarded.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

where σ is the sigmoid activation function; W_f is the weight matrix of the forgetting gate; h_{t-1} is the hidden state of the previous time step; x_t is the input of the current time step; b_f is the bias term of the forgetting gate.

Input gates determine which new information is stored in the cell state.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{4}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{5}$$

where i_t is the activation value of the input gate; $\tilde{C}_t$ is the candidate cell state; W_i and W_C are the corresponding weight matrices; b_i and b_C are bias terms.

The way to update the cell state is shown below:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

The cell state C_t is updated by weighting the previous cell state C_{t-1} with a forgetting gate and adding the new input weighted candidate cell state.

The output gate determines the next hidden state.

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{7}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{8}$$

The output gate o_t determines how much information from the cell state C_t will be output to the hidden state h_t. The hidden state is the output of the LSTM network, which contains information from the current time step and context information from previous time steps.

These core principles and formulations form the theoretical basis for the application of recurrent neural networks and their variant LSTM in the field of exercise physiological health monitoring. LSTM is able to efficiently transfer information in long sequences and maintain long-term dependencies by means of well-designed gating mechanisms. LSTM is able to efficiently process and predict time-series data in applications such as exercise physiological health monitoring, e.g., heart rate, through the above mechanisms, step frequency and other dynamically changing physiological signals. It is able to recognise abnormal patterns, such as abnormal heart rate, and thus provide early warning of potential health problems.

2.3. **Physiological signalling theory.** Physiological signals play a key role in exercise physiological health monitoring, particularly blood pressure and pulse signals. These signals can provide important information about an individual's cardiac function and circulatory status.

Body temperature is an indication of the body's internal heat balance and is usually measured through the mouth, armpit or rectum. Abnormal changes in body temperature may indicate disease or other health problems. Blood pressure is the pressure exerted by blood against the walls of blood vessels and is usually expressed as Systolic BP and Diastolic BP. Measurement of blood pressure is essential for assessing cardiovascular health. Pulse signals, on the other hand, are closely related to the body's circulatory system and can provide information about vascular function and blood flow status. The normal quiet heart rate in adults is 60 to 100 beats per minute, and the ideal heart rate is 55 to 70 beats per minute.

In exercise physiological health monitoring, by analysing the above physiological signals, an individual's exercise response, fatigue level and recovery status can be assessed.

3. Design of a physiological health monitoring system based on IoT and OneNet.

3.1. Overview of system hardware design. The proposed exercise physiological health monitoring system aims to achieve real-time monitoring and analysis of physiological signals, such as body temperature, blood pressure, and body temperature, of individuals during exercise. The hardware system must be designed to ensure that these physiological signals can be accurately and stably captured, and the data can be transmitted and processed through the OneNet IoT cloud platform in order to realise the remote monitoring and early warning functions.

In the physiological health monitoring system based on the OneNet cloud platform, hardware design is the basis for physiological parameter acquisition and wireless data transmission. The main goal of the system hardware design is to ensure the accuracy, real-time and reliability of data acquisition, while maintaining the low power consumption and portability of the system. The system hardware is mainly composed of the following parts:

(1) Physiological signal acquisition modules: responsible for collecting physiological parameters such as body temperature, blood pressure and pulse. These modules usually include various sensors and signal conditioning circuits, such as infrared temperature sensors, pressure sensors and photoelectric pulse sensors.

(2) Data storage and processing module: the collected analogue signals need to be processed by amplification, filtering and analogue-to-digital conversion, and then the microcontroller (MCU) will process and store the digital signals.

(3) Wireless communication module: the processed data is sent to the OneNet cloud platform through the wireless module. The wireless module adopts Wi-Fi technology.

Through the comprehensive consideration of the above core components and design points, our goal is to build an efficient, accurate and portable exercise physiological health monitoring system, which can not only provide users with real-time health monitoring services, but also achieve long-term data storage, analysis and remote medical consultation through the cloud platform, providing powerful support for users' health management. The specific design and implementation of each hardware module will be described in detail next.

3.2. Temperature measurement module design. There are two main methods of temperature measurement, contact and non-contact. Contact measurement methods, such as using a mercury thermometer or an electronic thermometer, require direct contact with the human body, while non-contact measurement, such as an infrared ear thermometer, does not require direct contact with the human body. For sports physiological health monitoring systems, non-contact measurement methods are more appropriate because they are not only fast and convenient, but also reduce the risk of cross-infection. Considering that real-time monitoring of an athlete's body temperature during training or competition is crucial to avoid health risks associated with overheating, this module uses non-contact infrared temperature sensing technology to ensure a non-invasive and continuous measurement process.

Non-contact infrared temperature sensors are a widely used technology for body temperature monitoring today. It is based on the principle that the energy of infrared radiation emitted by an object is proportional to its surface temperature, and measures body temperature by capturing infrared radiation emitted from the surface of the human body (e.g. forehead). Infrared thermometry is mainly based on the blackbody radiation law.

M. Planck's theorem gives the relationship between the spectral radiant power and the absolute temperature, T. The theorem is based on the blackbody radiation law.

$$P(\lambda T) = \frac{c_1}{\lambda^5} \cdot \frac{1}{e^{c_2/\lambda T} - 1} \tag{9}$$

where $P(\lambda T)$ denotes the radiation outgoing degree of the blackbody; λ denotes the wavelength; T denotes the absolute temperature; c_1, c_2 denote the radiation constants. According to Planck's theorem, the relation curve in Figure 2 can be obtained.

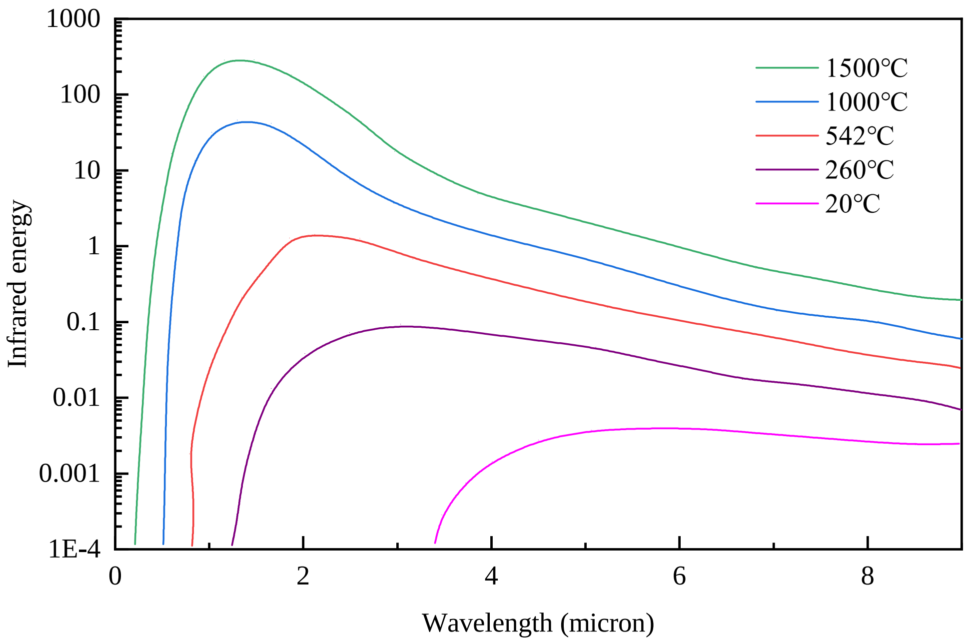

Figure 2. Spectral analysis of black body radiation

As can be seen from the figure, the higher the temperature T, the greater the degree of radiation emission, that is, the stronger the energy of radiation. The higher the temperature T, the more to the left of the peak of the radiant energy appears, that is, the direction of the short wavelength. According to the theorem, the blackbody radiance is proportional to the fourth power of the temperature T.

$$P(T) = \sigma T^4 \tag{10}$$

where $P_b(T)$ denotes the total radiance, i.e., the total radiant energy radiated from the unit area of the blackbody when the temperature is T; σ denotes the Stefan-Boltzmann constant.

$$\varepsilon = \frac{P(T)}{P_b(T)} \tag{11}$$

where ε is the emissivity, which characterises the ratio of radiances.

$$P(T) = \varepsilon P_b(T) = \varepsilon \sigma T^4 \tag{12}$$

The temperature of the measured object is.

$$T = \left(\frac{P(T)}{\varepsilon\sigma}\right)^{\frac{1}{4}} \tag{13}$$

The human body mainly radiates infrared waves at a wavelength of 8∼11 μm, and to accurately measure the body's temperature it is sufficient to pass through the body's radiant energy. In temperature measurement, the sensor needs to be calibrated to the specific emissivity of the body, which is usually assumed to be 0.98. The infrared radiation captured by the sensor is calculated and converted by the inbuilt microprocessor and the final output is the Celsius temperature value.

The MLX90614, an infrared temperature sensor with high accuracy and fast response characteristics, was chosen to provide medical-grade temperature measurement accuracy (± 0.2 °C). The signal captured by the infrared sensor needs to be processed by analogue-to-digital converter (ADC) and digital filtering technique to remove possible noise interference to ensure the accuracy of the data.

3.3. **Design of the blood pressure measurement module.** Blood pressure measurements are usually made using the oscillometric method, a method that indirectly measures blood pressure by detecting vibrations caused by blood flow as the cuff pressure changes. When the cuff is inflated beyond the patient's systolic pressure, blood flow is blocked. As the cuff pressure is gradually released, blood begins to flow again and vibrates against the vessel walls with each heartbeat. These vibrations are detected by the pressure sensor and converted into electrical signals, which are subsequently analysed by signal processing algorithms to determine systolic and diastolic blood pressures.

The vibration signals captured by the pressure transducers are fed into a signal processing module which analyses the changes in intensity and frequency of the signals to determine the systolic and diastolic pressures. The relationship between blood pressure and vibration frequency is shown below:

$$f = \frac{v}{d} \tag{14}$$

where f is the vibration frequency, v is the blood flow rate, d is the diameter of the artery.

The blood pressure measurement module uses the MPX5050GP blood pressure measurement sensor, an integrated pressure sensor from NXP Semiconductors designed to measure a wide range of pressures and ideally suited for implementing blood pressure measurements. The MPX5050GP sensor provides a stable and reliable pressure measurement solution for non-invasive blood pressure monitoring systems. blood pressure monitoring systems. The sensor's linear voltage output simplifies the interface with microcontrollers, making signal reading and processing more efficient. This, combined with its fast response time and wide operating temperature range, ensures measurement accuracy and reliability in a variety of environments and sporting conditions. In the blood pressure measurement module, the MPX5050GP can be installed in the trachea tube connected to the cuff for real-time monitoring of pressure changes inside the cuff. The main performance parameters of the MPX5050GP are shown in Table 1.

Table 1. MPX5050GP Main Performance Parameters

Parameters	**Descriptions**
Model number	MPX5050GP
Producers	NXP Semiconductors
Pressure range	0 kPa to 50 kPa
Output signal	Linear voltage output, 47 mV/kPa
Supply voltage	4.75V to 5.25V
Accurate	±2.5% maximum error (temperature range 0 °C to 85 °C)
Response time	Not more than 1 ms
Operating temperature range	-40°C to +125°C

3.4. **Pulse Measurement Module Design.** To implement the design of the pulse measurement module, Maxim Integrated's MAX30102 was selected as the key component. The MAX30102 is an integrated pulse oximetry and heart rate monitoring sensor that combines PPG and heart rate monitoring. The PPG technology utilises the principle of absorption or reflection of light to detect changes in the volume of blood that This results in a pulse waveform. When the heart contracts, blood is pumped into the arteries, resulting in an increase in the volume of blood in the vessels, which accordingly absorbs more light; when the heart diastoles, the volume of blood decreases and less light is absorbed. By monitoring the change in light intensity through the skin, the pulse waveform can be obtained and the heart rate calculated.

The MAX30102 has built-in red and infrared LEDs for emitting different wavelengths of light suitable for oximetry and pulse measurements. The MAX30102 supports an I^2C interface for easy communication with a wide range of microcontrollers (MCUs). The MAX30102 detects light passing through the user's skin through its built-in LEDs and photosensitive detectors, enabling monitoring of pulse fluctuations and blood oxygen levels. This process does not require direct contact with the blood, providing a safe and comfortable way for users to monitor. By analysing the captured PPG signal, heart rate and blood oxygen saturation can be calculated, providing important data for sports physiological health monitoring.

Analysis of the pulse waveform can provide important information such as heart rate (HR). Heart rate can be calculated by measuring the time interval (TT) between two consecutive pulse waveform peaks in the PPG waveform as shown below:

$$HR = \frac{60}{TT} \tag{15}$$

where HR is the heart rate (beats per minute) and TT is the time interval (in seconds) between two consecutive pulse wave peaks.

3.5. **Wireless Data Communication Module Design.** This work designs an efficient, stable and low-power wireless data communication module to ensure delay- and loss-free data transmission from the exercise physiological health monitoring device to the OneNet cloud platform. The module needs to support Wi-Fi communication and cellular network communication to facilitate applications in different environments, including outdoor sports, gym training, etc. The wireless module should be able to automatically adapt to different network environments, such as automatically switching to cellular networks when the Wi-Fi signal is weak, to ensure the continuity of data transmission.

The low-cost Wi-Fi module uses the ESP8266 manufactured by Espressif Systems. The ESP8266 has a built-in TCP/IP stack that allows easy connection to the Internet and supports multiple encryption modes to ensure secure data transmission. The ESP8266 pins are illustrated in Figure 3. The cellular network modules use SIM800L, which supports GSM/GPRS networks and can provide stable data transmission capability in areas lacking Wi-Fi coverage. They are equipped with a small SIM card slot that enables remote data communication. The data collected from the sensors is packaged into a JSON format suitable for transmission so that it can be parsed and processed by the cloud platform. Finally, the data packets are sent to the OneNet cloud platform via protocols such as HTTP/HTTPS or MQTT.

3.6. **OneNet Cloud Platform Application Design.** The OneNet cloud platform application design is the core of the entire exercise physiological health monitoring system, which is responsible for collecting, storing, processing and analysing data from the hardware devices and providing a user interface for medical personnel and users to access and

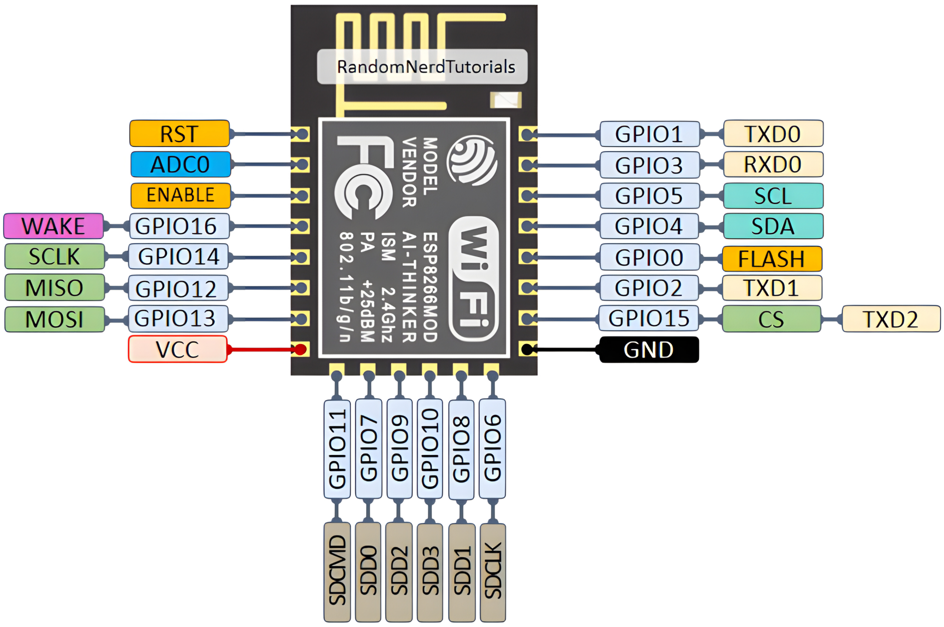

Figure 3. Description of ESP8266 Pins

interpret the data. The OneNET cloud platform provides rich API interfaces, which can be invoked via HTTP/HTTPS. The OneNET cloud platform The resource model diagram is shown in Figure 4.

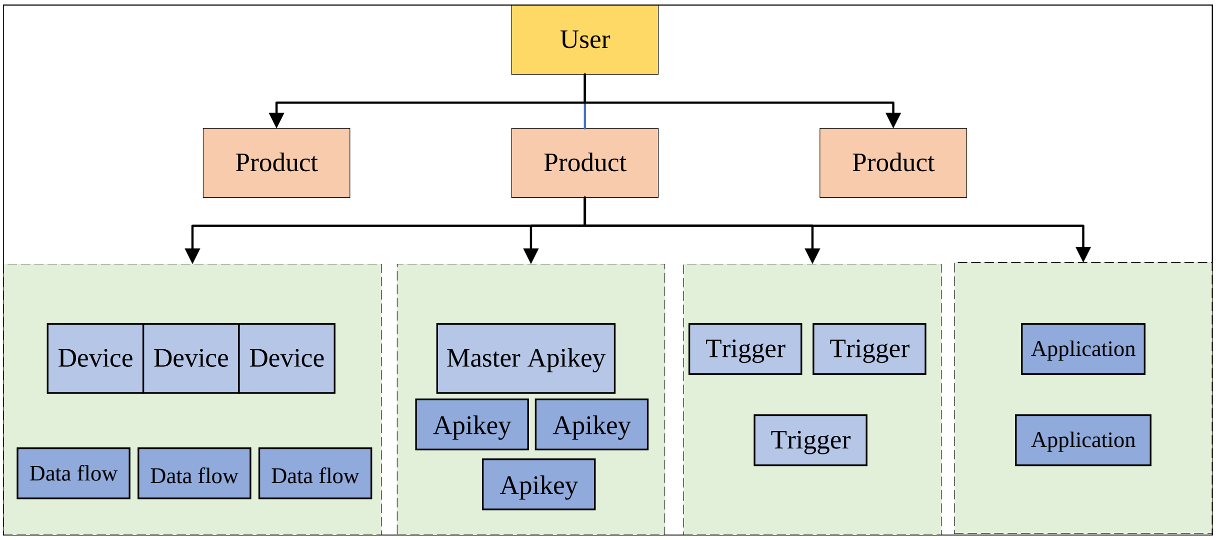

Figure 4. OneNET Cloud platform resource model diagram

The core functions of the OneNet cloud platform application include data storage, data processing and analysis, and alarm mechanism. Firstly, a stable and reliable database is established through MySQL for storing the collected physiological data, such as heart rate, blood pressure, and body temperature, as well as timestamps and device information. The data model and indexing strategy are optimised according to the data type and access frequency. Then, data analysis and machine learning model development were performed using integrated open source tools (Python's Pandas and Scikit-learn libraries). Data preprocessing includes data cleaning, formatting and outlier handling. The machine learning based time series anomaly detection model will be described in detail subsequently. Finally, alerts are generated based on preset thresholds or analysis results, and users or healthcare professionals are notified in a timely manner via email, SMS, or in-app notifications. SSL encryption, authentication and authorisation mechanisms are implemented to protect user data and privacy.

4. Model for monitoring abnormal physiological signals during exercise.

4.1. CNN-PSO-LSTM model. The main objective of designing the CNN-PSO-LSTM model is to utilise the feature extraction capability of CNN, the time series data processing capability of LSTM, and the optimisation mechanism of the PSO algorithm in order to achieve efficient monitoring of abnormalities of physiological signals (e.g., heart rate, blood pressure, and body temperature) during exercise.

CNN part: used to automatically extract features from physiological signal data. The CNN layer captures local features in the signal through convolutional operations and reduces the number of parameters and computational complexity through pooling layers to obtain higher level abstract features. PSO algorithm: used to optimise the parameter selection of the LSTM model. PSO is an optimisation algorithm based on group intelligence, which simulates the social behaviour of a flock of birds to find the optimal solution. In the CNN-PSO-LSTM model, PSO is used to optimise the hyperparameters of the network to improve the performance of the model. LSTM part: processes the feature sequences extracted through CNN [27, 28]. LSTM effectively processes and remembers the long-term dependent information through its special gating mechanism, and is suitable for analysing the dynamic changes in the time-series data and predicting the future state.

CNNs are used to automatically extract spatial features from raw physiological signals. Suppose there is an input data $X \in \mathbb{R}^{d\times n}$, where d is the feature dimension and n is the sequence length. The CNN extracts the features by means of a convolution kernel.

$$(X * W) + b = Z \tag{16}$$

where $*$ denotes the convolution operation, W is the weight of the convolution kernel, b is the bias term, Z is the output of the convolution layer.

PSO is used to optimise the hyper-parameters of the LSTM network such as the learning rate and the number of neurons in the hidden layer. The PSO algorithm iteratively updates the position and velocity of the particles:

$$v_{i,j}^{(t+1)} = wv_{i,j}^{(t)} + c_1 r_1 \left(pbest_{i,j}^{(t)} - x_{i,j}^{(t)}\right) + c_2 r_2 \left(gbest_j - x_{i,j}^{(t)}\right) \tag{17}$$

$$x_{i,j}^{(t+1)} = x_{i,j}^{(t)} + v_{i,j}^{(t+1)} \tag{18}$$

where $v_{i,j}$ is the velocity of the i-th particle in the j-th dimension; w is the inertia weight; c_1 and c_2 are the learning factors; r_1 and r_2 are the stochastic factors; $pbest_{i,j}$ is the personal best position of the particle i in dimension j; $gbest_j$ is the global best position.

4.2. Monitoring of physiological signal abnormalities. Before training the model, the physiological signal data first need to be preprocessed to ensure the data quality and adapt to the model input requirements. Then, based on the characteristics of time series, the data are partitioned into training set, validation set and test set for model evaluation and selection.

The preprocessed data were trained using CNN-PSO-LSTM model. Time series features of physiological signals are extracted by CNN layer. The combination of convolution operation and activation function helps to capture local features and nonlinear relationships. Particle swarm optimisation algorithm is applied to tune the hyperparameters of the LSTM layer including learning rate, number of neurons in the hidden layer. Sequential learning of features using LSTM layer and optimisation of network weights by back propagation algorithm:

$$\Delta W = -\alpha \cdot \frac{\partial L}{\partial W} \tag{19}$$

where W is the network weight; α is the learning rate; L is the loss function.

$$L = -\sum \left(y \log\left(h_t\right) + (1-y) \log\left(1-h_t\right)\right) \tag{20}$$

where y is the true label; h_t is the output of the model at time t.

After training, the model is used to detect anomalies in the new physiological signal data. Let y_t be the physiological signal value predicted by the model, and y_t^{actual} be the actual observation, the anomaly detection can be defined as: $D_t = \left|y_t - y_t^{actual}\right|$, if D_t exceeds the preset threshold, the anomaly is considered to be detected at time t.

Through the above steps, the CNN-PSO-LSTM model combines the advantages of the three, which can not only effectively extract the features of the physiological signals, but also adaptively optimise the model parameters and accurately analyse the time-series data, so as to realise the efficient monitoring of abnormal physiological signals in the exercise state.

5. Experimental results and analyses.

5.1. Benchmark experimental model.

In order to further validate the experimental performance of the proposed new model, this paper sets up a benchmark experiment based on the traditional simple CNN and establishes a benchmark model [29]. The CNN model adopts the alternation of convolutional layers and pooling layers, and the model base includes four convolutional layers, three pooling layers and a fully connected layer containing 128 nodes, and ultimately achieves classification. As shown in Table 2, a list of parameters of the baseline model is shown. The model construction process kind of uses the tfkeras high-level interface, with a total of 30 training rounds, a batch size of 128, and a share of the test set of 0.3.

Table 2. CNN Baseline Model Parameters

Storey	**Convolution Number**	**kernels size**	**Output size**
Convolutional layer 1	4	21*1	300*4
Pooling layer 1	4	3*1	150*4
Convolutional layer 2	16	23*1	150*16
Pooling layer 2	4	3*1	75*16
Convolutional layer 3	32	25*1	75*32
Pooling layer 3	4	3*1	38*32
Convolutional layer 4	64	27*1	38*64

5.2. Verification of PSO optimisation effect.

In the initialisation process of PSO parameters, it is necessary to set the relevant parameters, mainly including the number of particles in the population, the learning factor, the maximum number of iterations and the inertia weights of the four parameters [30], the PSO algorithm initialisation parameter settings are shown in Table 3.

The fitness curves can be used to evaluate the search performance and result quality of PSO algorithm and provide reference for the hyper-parameter adjustment during the

Table 3. Initialisation parameter Settings of PSO algorithm

Population size	Maximum number of generations	Learning factor	Inertial weights
10	10	[1.5, 1.5]	[0.9, 0.4]

optimisation process. The results of the fitness curves of PSO algorithm to optimise the LSTM model are shown in Figure 5.

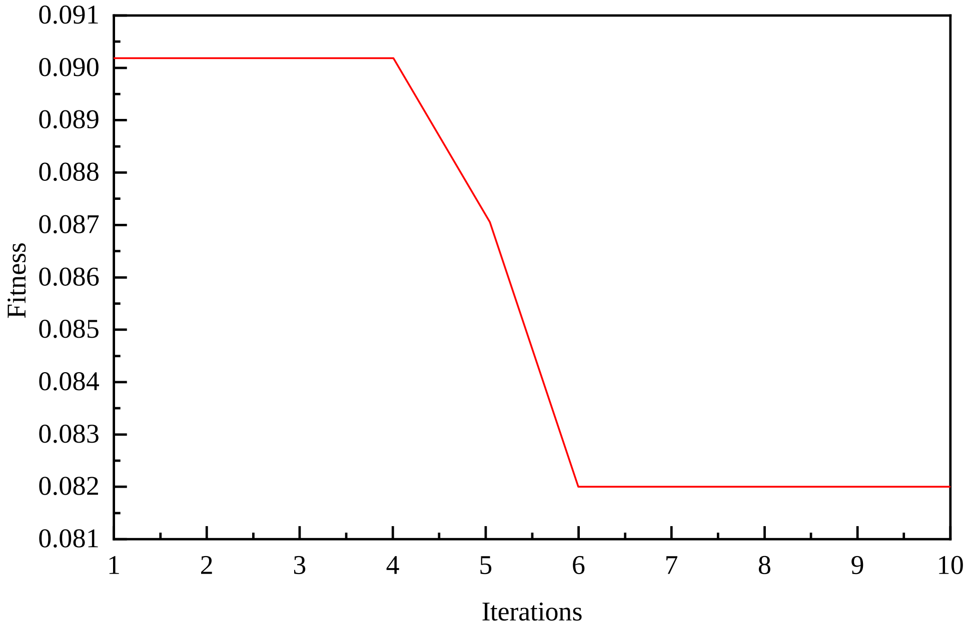

Figure 5. Fitness curve results of LSTM model optimised by PSO

It can be seen that when iterating to the 4th generation, the algorithm converges rapidly, and when iterating to the 6th generation, the fitness value is close to 0.071, which is already in a converged state, and no more substantial changes occur, and the algorithm is close to the optimal solution, which indicates that the PSO optimisation algorithm has significant effect and stability for optimising the hyperparameters of the LSTM model.

5.3. **Model comparison.** Based on the test results of the two models, Accuracy, Precision, Recall and Micro-F1, a total of 4 evaluation indexes were calculated, as shown in Table 4. It can be seen that the direct processing of physiological signals through the CNN model has obtained a very high accuracy rate, with an average accuracy rate of 92.8%. And the improved model still has some improvement for the classification of physiological signals, with an improvement of 3.8%. Overall, the new model has significantly enhanced the recognition ability for physiological health signals, and there is also some improvement in the overall recognition rate.

Table 4. Model evaluation indicators

Evaluation indicators	CNN	CNN-PSO-LSTM
Accuracy	0.9127	0.9443
Precision	0.9269	0.9691
Recall	0.9169	0.9509
Micro-F1	0.9267	0.9599
Average value	0.9208	0.95605

6. **Conclusions.** In this work, an IoT system based on OneNet and CNN-PSO-LSTM is proposed to provide real-time and accurate exercise physiological health monitoring. A physiological health monitoring system based on IoT and OneNet is designed with data acquisition modules such as temperature measurement, blood pressure measurement and pulse measurement. A wireless data communication module supporting Wi-Fi communication and cellular network communication is designed to ensure data transmission from the exercise physiological health monitoring device to the OneNet cloud platform. Secondly, a CNN-PSO-LSTM deep learning model is proposed to deeply analyse the heart rate, blood pressure, body temperature and other data stored in the OneNet cloud to automatically and accurately discover abnormal physiological signals. The experimental results show that the PSO optimisation algorithm has significant effect and stability for optimising the hyperparameters of the LSTM model. For the classification of physiological signals, the average evaluation index of CNN-PSO-LSTM is improved by 3.8% to 95.61% compared with the CNN model. As the number of IoT devices increases, edge computing provides an effective way to alleviate the pressure on the cloud and reduce the latency of data transmission. Follow-up research plans to deploy deep learning models to edge devices for local data processing and analysis, which can enable more real-time health monitoring and alerting.

REFERENCES

[1] R. Paradiso, T. Faetti, and S. Werner, "Wearable monitoring systems for psychological and physiological state assessment in a naturalistic environment," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 2011, pp. 2250–2253.

[2] R. Matthews, N. J. McDonald, P. Hervieux, P. J. Turner, and M. A. Steindorf, "A wearable physiological sensor suite for unobtrusive monitoring of physiological and cognitive state," in *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 2007, pp. 5276–5281.

[3] K. B. Konstantinov, "Monitoring and control of the physiological state of cell cultures," *Biotechnology and Bioengineering*, vol. 52, no. 2, pp. 271–289, 1996.

[4] P. K. Chrysanthopoulos, C. T. Goudar, and M. I. Klapa, "Metabolomics for high-resolution monitoring of the cellular physiological state in cell culture engineering," *Metabolic Engineering*, vol. 12, no. 3, pp. 212–222, 2010.

[5] G. Tartare, X. Zeng, and L. Koehl, "Development of a wearable system for monitoring the firefighter's physiological state," in *2018 IEEE Industrial Cyber-Physical Systems (ICPS)*, IEEE, 2018, pp. 561–566.

[6] R. Matanguihan, K. Konstantinov, and T. Yoshida, "Dielectric measurement to monitor the growth and the physiological states of biological cells," *Bioprocess Engineering*, vol. 11, pp. 213–222, 1994.

[7] O. Henry, A. Kamen, and M. Perrier, "Monitoring the physiological state of mammalian cell perfusion processes by on-line estimation of intracellular fluxes," *Journal of Process Control*, vol. 17, no. 3, pp. 241–251, 2007.

[8] V. Behringer and T. Deschner, "Non-invasive monitoring of physiological markers in primates," *Hormones and Behavior*, vol. 91, pp. 3–18, 2017.

[9] L. O. Chua, "CNN: A vision of complexity," *International Journal of Bifurcation and Chaos*, vol. 7, no. 10, pp. 2219–2425, 1997.

[10] T. Kattenborn, J. Leitloff, F. Schiefer, and S. Hinz, "Review on Convolutional Neural Networks (CNN) in vegetation remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, pp. 24–49, 2021.

[11] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: LSTM cells and network architectures," *Neural Computation*, vol. 31, no. 7, pp. 1235–1270, 2019.

[12] T.-Y. Wu, L. Wang, and C.-M. Chen, "Enhancing the Security: A Lightweight Authentication and Key Agreement Protocol for Smart Medical Services in the IoHT," *Mathematics*, vol. 11, no. 17, 3701, 2023.

[13] T.-Y. Wu, Q. Meng, Y.-C. Chen, S. Kumari, and C.-M. Chen, "Toward a Secure Smart-Home IoT Access Control Scheme Based on Home Registration Approach," *Mathematics*, vol. 11, no. 9, 2123, 2023.

[14] T.-Y. Wu, F. Kong, Q. Meng, S. Kumari, and C.-M. Chen, "Rotating behind security: an enhanced authentication protocol for IoT-enabled devices in distributed cloud computing architecture," *EURASIP Journal on Wireless Communications and Networking*, vol. 2023, 36, 2023.

[15] F. Marini and B. Walczak, "Particle swarm optimization (PSO). A tutorial," *Chemometrics and Intelligent Laboratory Systems*, vol. 149, pp. 153–165, 2015.

[16] M. Jain, V. Saihjpal, N. Singh, and S. B. Singh, "An overview of variants and advancements of PSO algorithm," *Applied Sciences*, vol. 12, no. 17, 8392, 2022.

[17] P. Augustyniak, "Wearable wireless heart rate monitor for continuous long-term variability studies," *Journal of Electrocardiology*, vol. 44, no. 2, pp. 195–200, 2011.

[18] V. Chandrasekaran, R. Dantu, S. Jonnada, S. Thiyagaraja, and K. P. Subbu, "Cuffless differential blood pressure estimation using smart phones," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 4, pp. 1080–1089, 2012.

[19] H. M. Rai, A. Trivedi, and S. Shukla, "ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier," *Measurement*, vol. 46, no. 9, pp. 3238–3246, 2013.

[20] M. F. Rabby, Y. Tu, M. I. Hossen, I. Lee, A. S. Maida, and X. Hei, "Stacked LSTM based deep recurrent neural network with kalman smoothing for blood glucose prediction," *BMC Medical Informatics and Decision Making*, vol. 21, pp. 1–15, 2021.

[21] L. M. Dang, M. J. Piran, D. Han, K. Min, and H. Moon, "A survey on internet of things and cloud computing for healthcare," *Electronics*, vol. 8, no. 7, 768, 2019.

[22] W. Elmasry, A. Akbulut, and A. H. Zaim, "Evolving deep learning architectures for network intrusion detection using a double PSO metaheuristic," *Computer Networks*, vol. 168, 107042, 2020.

[23] U. Hanif *et al.*, "Estimation of apnea-hypopnea index using deep learning on 3-D craniofacial scans," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 11, pp. 4185–4194, 2021.

[24] K. Mohammed, M. Abdelhafid, K. Kamal, N. Ismail, and A. Ilias, "Intelligent driver monitoring system: An Internet of Things-based system for tracking and identifying the driving behavior," *Computer Standards & Interfaces*, vol. 84, 103704, 2023.

[25] M. Abumohsen, A. Y. Owda, and M. Owda, "Electrical load forecasting using LSTM, GRU, and RNN algorithms," *Energies*, vol. 16, no. 5, 2283, 2023.

[26] H. V. Dudukcu, M. Taskiran, Z. G. C. Taskiran, and T. Yildirim, "Temporal Convolutional Networks with RNN approach for chaotic time series prediction," *Applied Soft Computing*, vol. 133, 109945, 2023.

[27] I. E. Livieris, E. Pintelas, and P. Pintelas, "A CNN–LSTM model for gold price time-series forecasting," *Neural Computing and Applications*, vol. 32, pp. 17351–17360, 2020.

[28] G. Swapna, S. Kp, and R. Vinayakumar, "Automated detection of diabetes using CNN and CNN-LSTM network and heart rate signals," *Procedia Computer Science*, vol. 132, pp. 1253–1262, 2018.

[29] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, pp. 1–74, 2021.

[30] H. Zhu, Y. Wang, K. Wang, and Y. Chen, "Particle Swarm Optimization (PSO) for the constrained portfolio optimization problem," *Expert Systems with Applications*, vol. 38, no. 8, pp. 10161–10169, 2011.