Implementation of fitness and health management system utilising deep learning neural network and internet of things technology

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Abstract: The purpose is to implement fitness and health management services more scientifically, enhance people's awareness of health management, prevent diseases caused by long-term sub-health, and comprehensively improve people's fitness and health status physically and mentally. Specifically, the data of people's health indicators are analysed, and a fitness and health management service system is established using deep learning and Internet of Things (IoT) technologies. First, people's fitness and health indicators are detected using IoT technology and integrated and pre-classified into text, number, and image. Afterward, the pre-classified data are input into the Convolutional Neural Network (CNN), their features are extracted for modelling and analysis, and the results are input into the constructed BP BackPropagation Neural Network (BPNN) model. Consequently, a preliminary prediction result about the user's fitness and health is obtained for the user's fitness and health status. The results show that the constructed fitness and health management system based on the proposed ensemble prediction model is more optimised than those constructed by a traditional simple model. With the proposed intelligent fitness and health management system composed of IoT devices, users can gain a better health status by self-monitoring, self-control, self-discovery, self-analysis and self-search.

Keywords: health management; backpropagation neural network; DS evidence theory; composite prediction model.

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1 Introduction

Health is the basis for all human activities. With social development, enriching material wealth, and rising living standards, health is becoming the focus of more and more people. Hyperlipidaemia, hypertension, hyperglycaemia, overweight, and obesity constantly appear among many social groups. In recent years, population ageing and sub-health are increasingly worsening. The elderly often suffer from chronic osteoporosis and cardiovascular disease, while cancers, such as lymphoma and gastric cancer are mostly found among young and middle-aged people, who generally get diagnosed in the middle and late stages of cancer, with mortality rate getting higher year by year. The national health status distribution of China shows that only 5% of the total population are enjoying health in a real sense with up to 80% sub-healthy people. Meanwhile, the age of the diseased is becoming younger and younger: the youth, middle-aged and young white-collar workers are facing various risks, new and strange, such as overwork, sudden death, cardiovascular diseases and cancer (Hatcher and Yu, 2018). Thus, the significance of health and fitness becomes particularly important. Fitness places may help people build up bodies, while hospitals may treat and cure their pains and disease. To prevent potential disease, people are increasingly participating in fitness exercises. It is believed that fitness can uplift people's physical strength, spiritual outlook, immunity function and compressive capacity, thereby promoting people's health, life quality, social skills and work efficiency. Consequently, many social problems caused by poor health may be alleviated, especially, the burden on hospital resources and treatment expenses. However, fitness exercises, if not properly guided, may cause injuries, which has been much magnified with the surging fitness population. The emergence of various intelligent devices and precision instruments has made it possible to record and digitally save people's actions data. Thanks to big data technology, once worthless data are now mined in-depth for practical utilisation. With a well-designed user-based fitness and health management system, user fitness information will be acquired in real-time and excavated to monitor and scientifically guide people's fitness exercise and health status, which is a feasible research direction, and the obtained research results can be spread among the public.

Many works have been conducted on health services based on deep learning. For example, Van Le Eenoo et al. (2018) identified and characterised the home-based care service modes within and across European countries and used the Principal Component Analysis (PCA) method to identify and summarise six health care service modes. Rathore et al. (2017) proposed a Hadoop-based Intelligent Nursing System (HICS), which demonstrated the information sharing based on the Internet of things (IoT) among all the health care system devices and could remotely, effectively and timely analyse data of the domiciliary elderly through high-speed sensors. Cair et al. (2017) designed a more reasonable solution plan by incorporating a neural network algorithm into the disease prediction system, which greatly improved the prediction accuracy. To provide more effective and systematic fitness and health management services and protect people's health, it was of great significance to explore a new model of fitness and health management through Artificial Intelligence (AI) and IoT technology (Ma and Pang, 2019). IoT technology could combine sensor personnel and terminal equipment to collect health data in real-time with communication technologies and local networks. Deep learning technology in AI was widely used in big data analysis scenarios and could classify and analyse the collected data and optimise the analysis results, thus forming a multi-level intelligent network system of remote management and control. Ultimately, human resources could be replaced by AI to protect human health. Intelligent devices and big data technology optimised the fitness guidance process with more accurate and scientific health management (Liu et al., 2018). Therefore, the fitness and health management system based on deep learning and IoT can greatly reduce possible hospitalisation time and fitness efficiency. Users can enjoy self-health monitoring and understanding of fitness and health knowledge anywhere and anytime Ma (2020).

Here, the health data are pre-classified and analysed utilising the deep learning theory, IoT and big data analysis to study intelligent fitness and health management services. Then, an ensemble prediction model is proposed. In the proposed prediction model, the feature extraction results of CNN are input into the BPNN, and the preliminary prediction result of the BPNN is input into the Dempster-Shafer (DS) evidence theory model for optimisation, namely, the CNN+BPNN+DS model. Thus, the prediction accuracy and the reliability of the evaluation results are improved. Finally, the fitness and health management system based on the proposed CNN+BPNN+DS model is established.

2 Method

2.1 Theory of IoT

The internet has changed the way people live, see the world, and communicate. At present, there are already abundant IoT devices connected to the internet. The concept of the IoT has been proposed in 1999. It is an internet network based on contemporary information, communication, and internet technology. Any item can be connected with the IoT (see Figure 1) through the Radio Frequency Identification (RFID), sensors and other information transmission equipment, and the intelligent identification and processing tools installed and set on a real object. The connected item can exchange information in IoT, thus realising an intelligent identification, positioning, monitoring and management (Zhou et al., 2021). The Health IoT: in the medical industry, sensors can be used to monitor the patient's vital physical signs (such as blood oxygen saturation and breathing) and can be used in emergencies and indicate the patient's everyday life. They can also improve the life quality of the disabled (Zhu et al., 2017). Underwater IoT can monitor human-inaccessible waters to explore and protect these underwater resources. Many more objects, such as cars, buildings, sensors, actuators, mobile phones, embedded electronic devices, software, sensors and networks, can be used to collect and exchange data to establish an intelligent system. People's work and life have been much simplified through these intelligent systems established with ultra-modernised technology (Zhang et al., 2020).

Fitness and health management system can be modularised and intellectualised with IoT technology. Intelligent fitness and health management system can recognise information, analyse data, and correct behaviour timely compared with the traditional system, thereby saving manpower in fitness and health management and can provide better services to users (Chen et al., 2020). Thus, users' health and fitness data can be predicted through neural network technology with high accuracy, and the results have high reliability.

2.2 BP neural network (BPNN)

The multilayer feedforward neural network trained by the error BP algorithm is often referred to as BPNN and has strong self-learning ability. BPNN involves forward signal propagation and error backpropagation (Pokkuluri and Nedunuri, 2018). The neural signal is unidirectional and cannot affect the upper layer. BPNN is featured by a downward propagation layer by layer until the output layer. The data obtained from the output layer and the expected value are compared to determine an output. If the obtained data are not the expected output, the error will be propagated backward, and the weights and thresholds will be changed according to the size of the error. The output results are optimised through multiple learning and training and get closer to the expected value.

Figure 2 shows that BPNN is a multilayer feedforward network. The input layer is the first layer, the output layer is the last, and the hidden layer is distributed in the middle layer. The data source is added to the neural network, and there is a buffer effect through the input layer. Thus, the input-output relationship presents a linear relationship in the neurons of the input layer, and the neurons of the hidden layer are generally non-linear functional relationships.

Figure 1 Application of IoT in fitness and health

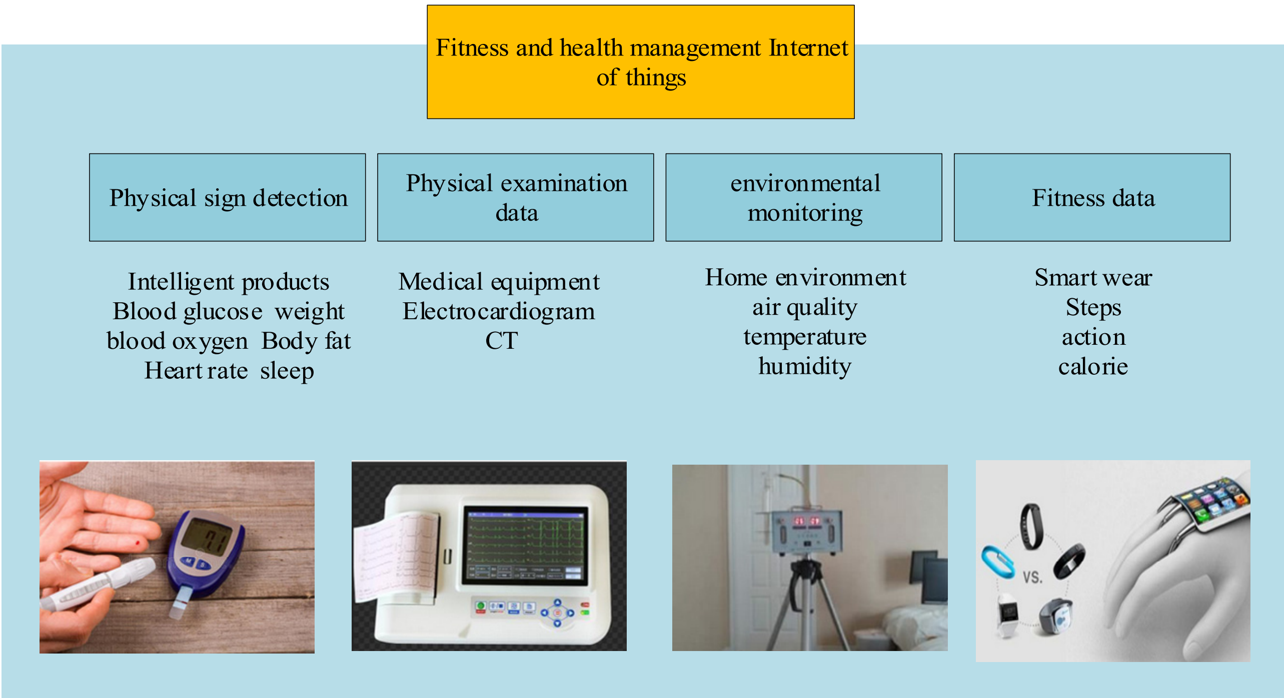
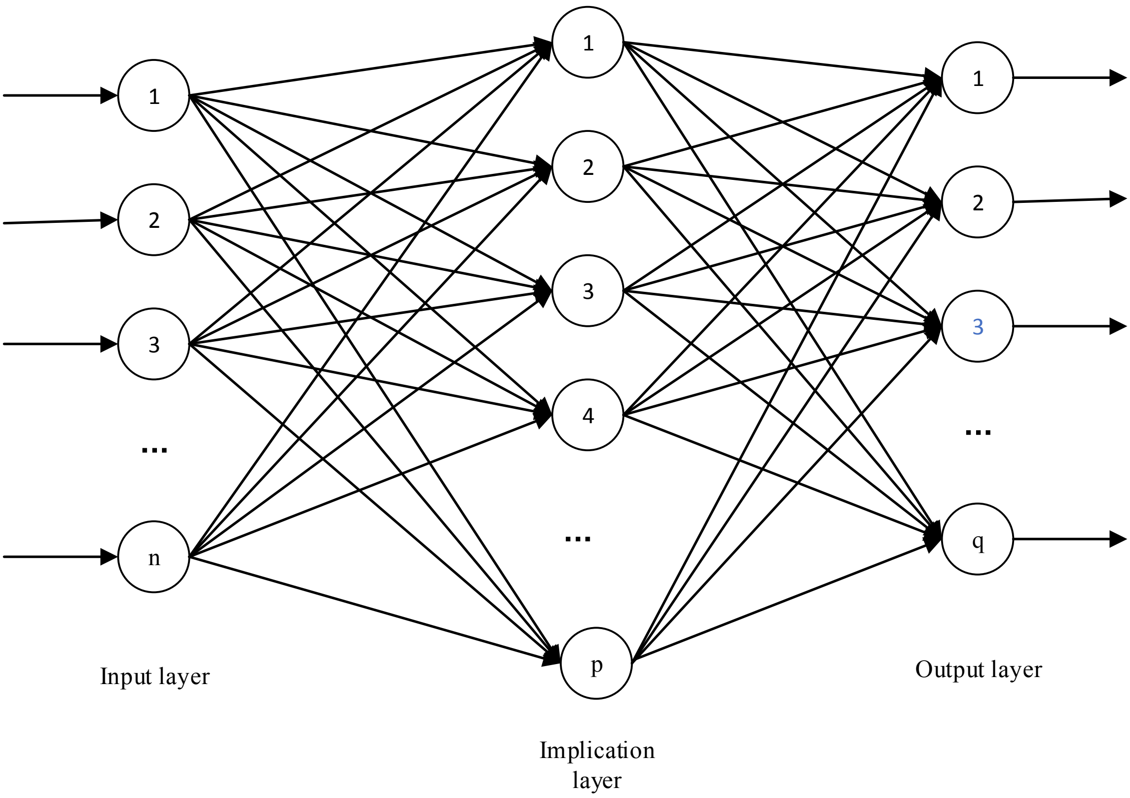


Figure 2 BPNN



Here, $fk(k = 2,\dots,m)$ denotes the non-linear input-output relationship between the hidden layer *k* and the neurons in the output layer. The connection weight between the *j* neurons in the $k-1$ layer and the *j* neurons in the *k* layer is w_{ij}^{k}. The sum of the input of the *i* neurons in the *k* layer is u_i^k, and the output is y_j^k. The relationship between the variables is:

$$y_i^k = f_k\left(u_i^k\right) \tag{1}$$

$$u_i^k = \sum_j w_{ij}^k y_j^{k-1}, \quad k = 2,\dots,m \tag{2}$$

The advantage of the BPNN lies in its superior learning ability. Theoretically speaking, a simple BPNN can approximate any function and achieve the highest possible accuracy.

The feature values calculated in CNN are input into the BPNN model to get a series of related parameters, and then the threshold value of each health state and the health management model can be obtained. Finally, the DS evidence theory is used to optimise the results of the BPNN to verify the health prediction effect of the ensemble prediction model.

BPNN is a feedforward neural network with multiple hidden layers. The data and error are transmitted in the opposite direction. The transfer function used is the Sigmoid function. When the output value of the model is far from the expected value, the error backpropagation is started. In the process of error propagation, the parameters between neurons in each layer of the hidden layer are modified according to the principle of error gradient decreasing. Each hidden layer has a regulation neuron b, to increase the efficiency of optimisation.

2.3 CNN

CNN is proposed by Professor Yang Lechun in the late 1990s with a biological inspiration. The basis of CNN deep learning is more like biological neural networks. Nowadays, CNN is one of the best neural networks and has become the focus of research. CNN includes one-dimensional, two-dimensional and three-dimensional neural networks. One-dimensional neural networks and two-dimensional neural networks can be used in simple data analysis and speech recognition technology. The three-dimensional neural network plays an important role in artificial intelligence such as image processing and machine vision (Pan et al., 2020).

The basic structure of CNN is partially similar to that of the ordinary neural network, which consists of neurons with relevant parameters that can learn and be trained. Generally, the main components of CNN include the input layer, convolution layer, pooling layer, fully connected layer and output layer, as shown in Figure 3.

Figure 3 shows the classical network structure of the CNN model. The convolution layer is essential, which extracts the high-level characteristics from low-level input information through the convolutional operation of the convolution kernel on the input matrix. The pooling operation is a downsampling process, which can reduce the number of parameters and characteristics of the next layer, and avoid overfitting. The fully connected layer deals with the extracted characteristics and is much like a classifier. Each node in the fully connected layer is connected to the upper node. The parameters are further decreased by the fully connected layer and classified (Vijayakumar et al., 2020). The output parameters are mainly obtained through the matrix multiplication operation of input parameters, and the non-linear characteristics are obtained through the activation function. The input-output equation is:

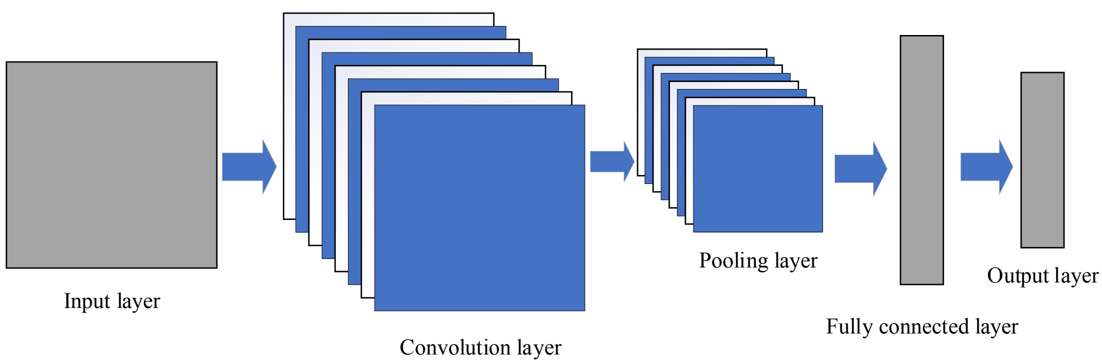
$$Y = f\left(W \cdot X + b\right) \tag{3}$$

In equation (3), X represents the input feature vector, Y is the output feature vector, W denotes the weight matrix, b represents the bias and $f(\cdot)$ stands for the activation function. First, all data are pre-processed by the input layer. Then, the data output from the input layer is locally correlated and compressed by the alternating part of the convolution layer and the pooling layer. Afterward, the output characteristics are processed by the fully connected layer. Finally, the characteristic input objective function is output through the output layer.

Because of the different importance of each word in the text, the words that play an important role in the text are selected through the maximum pooling operation. The largest word h_3 in h_2 is calculated using equation (4).

$$h_3 = \max_{1 \le n \le N}\left(h_2\right) \tag{4}$$

Figure 3 CNN



The neurons in the pooling layer and fully connected layer interact with each other through a complete connection. The specific interaction result h_4 is expressed as in equation (5).

$$h_4 = w_4 h_3 + a_4 \tag{5}$$

In equation (5), w_4 and a_4 represent the weight and deviation between the two layers of neurons, respectively. The output layer contains classifiers, which identify the health assessment results of users.

The parameters of the feature representation model of health text-data based on CNN are w_1, w_4, a_1, and a_4. w_1 represents the weight between the neurons in the convolution layer and the pooling layer; w_4 indicates the deviation of convolution layer calculation; a_1 and a_4, respectively represent the weight and deviation of the fully connected layer during feature fusion. Text information involves multimodal data, such as the user's identity information, inspection project results and life habits. During feature characterisation, multimodal data feature fusion will affect the accuracy of subsequent health status assessment.

When deep learning technology is used for NLP (Natural Language Processing), such data as medical orders and cases should be converted into numbers according to specific word-number conversion rules. Firstly, a text is decomposed into words, and each word can be represented by a unique vector in the word vector matrix. The *i*-th column of the word vector matrix represents the vector of the *i*-th word in the vocabulary. Therefore, the sample word vector representation can be realised through sentence decomposition into different words and word vectors. Here, the collected data are integrated into three categories: text, number and image, which are input into the CNN model to represent the characteristics of text-type health data.

When data are input into the convolution layer, they first go through tensor convolution coding, then enter the hidden layer and finally enter the output layer through tensor reconstruction. In the self-encoder, the weight parameters of each neuron between layers are adjusted by the greedy algorithm. A large number of unlabelled sample data can train the weight parameters in the network, and the input is reconstructed by forwarding propagation and backward propagation algorithms. The greedy algorithm can optimise the weight parameters after several iterations so that the reconstructed input data can get as similar to the initial input data as possible.

2.4 Dempster-Shafer (DS) evidence theory

The initial model of DS evidence theory is proposed by Dempster in 1967, and then, it is improved by Shafer. DS evidence theory has developed into a theoretical reference for uncertainty problem handling. DS evidence theory can be used to deal with more uncertain problems than Bayesian evidence theory, and its advantage is obvious. Presently, it is widely used in many fields, such as information fusion, decision analysis, and pattern recognition (Le et al., 2021).

Let the whole domain $U = \{x, xx,\}$ be a set of all propositions in a hypothetical space, and the elements in the set U are mutually exclusive, so U is called an identification framework. $2v$ represents the power set, which is composed of all subsets in the identification framework U. If the function m: 20 → [0,1] satisfies equations (4) and (5), then $m(A)$ denotes the degree of confidence in hypothesis A, which is the basic probability assignment (BPA) of A. Equation (4) means that there is no support for empty sets, and equation (5) means that the sum of all the assumed trust values must be 1. When $m(A) > 0$, A is called the focal element of m.

$$m(\varnothing) = 0 \tag{6}$$

$$\sum_{A \subseteq U} m(A) = 1 \tag{7}$$

Trust function *bel* and likelihood function *pl* are represented:

$$bel(A) = \sum_{B|B \cap A \neq A} m(B) \tag{8}$$

$$pl(A) = 1 - bel(\overline{A}) = \sum_{B|B \cap A \neq \varnothing} m(B) \tag{9}$$

Equations (8) and (9), and Figure 4 can conclude: the trust degree of hypothesis *A* is expressed as the trust function *bel (A)*, the sum of BPA of each subset *B* in *A*. The doubt degree of *A* is expressed as the likelihood function *pl (A)*, the sum of BPA of all the non-empty assumptions *B* that intersect with *A* (Qaisar and Usman, 2017). The uncertainty interval of an *A* is expressed as a closed interval [*bel (A)*, *pl (A)*] composed of a trust function and a likelihood function in an identification framework.

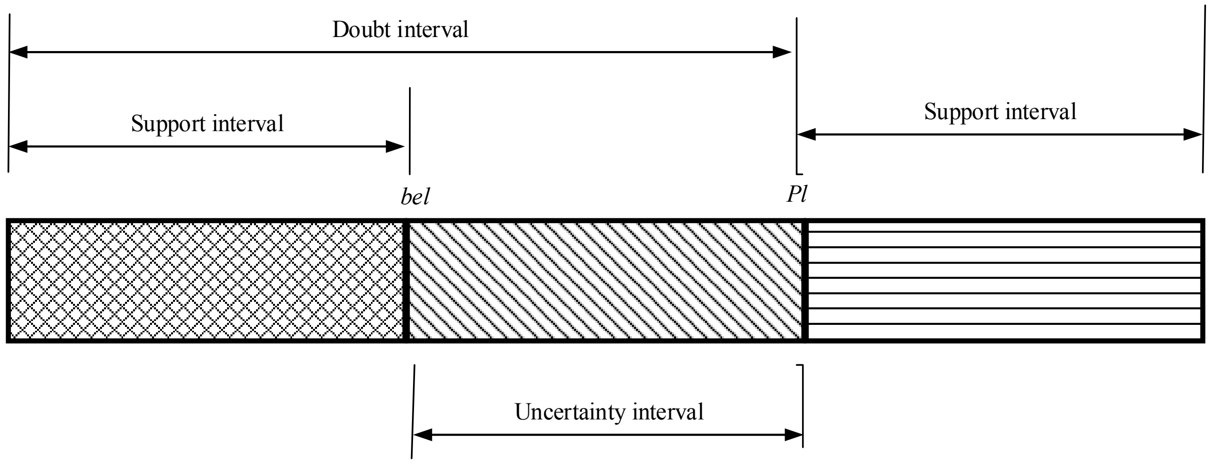
Equations (10) and (11) are the Dempster-Shafer (DS) evidence expressions: *m1* and *m2* denote the two-independent evidence of a hypothesis *A* in the recognition framework *U*. Here is the combination equation of m_1 and m_2:

$$m_{12}(C) = \begin{cases} (1-K)^{-1} \sum_{A \cap B = C} m_1(A) m_2(B), \forall C \subset U \Pi C \neq \varnothing \\ 0, \qquad C \neq \varnothing \end{cases} \tag{10}$$

$$K = \sum_{A \cap B = \varnothing} m_1(A) m_2(B) < 1 \tag{11}$$

DS combination equation conforms to the exchange law and combination law. A more accurate BPA can be obtained through the combination of several independent pieces of evidence. In the above equations, *K* represents the conflict coefficient, and its value is positively correlated with the evidence. The greater the *k*-value, the greater the conflict (Dimililer et al., 2021). Generally, the core of the DS evidence combination rule is to solve multiple evidence combinations in the same domain. The confidence function and plausibility function are formed based on the quality function. A consistent quality function can be obtained through quality function fusion on each evidence even with complex evidence from different fields and levels. Dempster proposed a rule to deal with two or more quality functions-orthogonalisation rules (Goyal et al., 2021).

Figure 4 Trust degree interval



3 The research model and framework

3.1 Architecture of fitness and health management system

Here, the heart disease data set is selected from the official website of the UCI standard data set for model verification. The data set includes attributes, such as age, gender, and type of chest pain. Table 1 lists the original data of some heart disease data sets, in which num represents the type of heart disease (0 represents no heart disease, and 1–4 represent four types of heart disease, respectively). The official website and references do not give the specific types of heart disease represented by 1–4, so in the follow-up experiment, Type 1 heart disease will be used to represent the type of heart disease when num = 1. Similarly, other types of heart diseases will be represented with different values of num.

Table 1 Data of some cardiac patients

age	*sex*	*trest*	*chol*	*fbs*	*rest*	*thalach*	*exang*	*oldpeak*	*ca*	*thal*	*num*
56	1	140	265	0	1	132	1	2	0	2	1
59	1	155	231	0	0	122	1	0	1	3	2
66	0	120	226	0	1	156	0	0	1	3	1
71	0	158	289	0	2	163	1	1	2	4	3
63	1	122	201	0	1	100	0	–1	1	6	0
72	0	134	205	0	0	110	0	2	3	7	2
55	1	170	177	0	1	86	1	2.5	0	7	4

Here, the research topic focuses on a fitness and health management system, in which user's basic body information, as well as daily monitoring and physical examination data, are collected and used to evaluate their fitness and health status. Then, users can timely understand their fitness and health condition, formulate targeted fitness training plans and prevent disease, thereby improving their life quality.

Specifically, intelligent devices can collect user data, such as fitness data, diet data, physical sign parameters and electrocardiogram (ECG) data. These data types are diverse and constantly changing, so they should be pre-classified before being input into the CNN model. Afterward, the output of the CNN model is input into the BPNN model and analysed combined with the scientific fitness and medical health theory and case analysis. However, in data prediction scenarios, the optimal network structure of the BPNN is difficult to be determined, and the prediction results easily fall into a local minimum (Le et al., 2021). Therefore, the BPNN algorithm is optimised utilising the DS evidence theory, that is, the output of the BPNN is input into the DS evidence theory model, thus improving the prediction accuracy. The prediction results can be used for users' fitness and health behaviours correction and guidance. Eventually, an ensemble prediction model is proposed, namely, the CNN+BPNN+DS model, and a fitness and health management system based on the proposed ensemble prediction model is constructed. The architecture of the constructed fitness and health management system based on the CNN+BPNN+DS model is shown in Figure 5.

The following is the specific process of the constructed fitness and health management system.

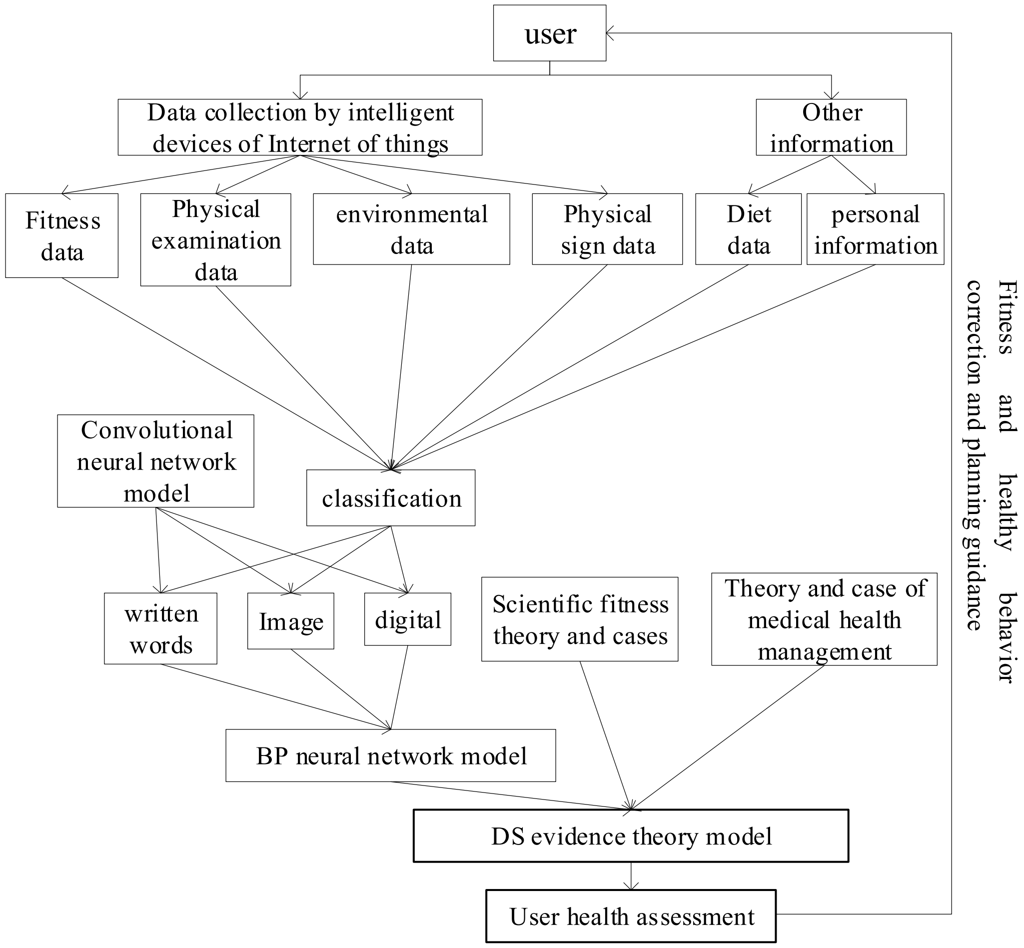
1) User information is collected, including data collection by intelligent IoT devices and other information. The data collection by IoT intelligent devices includes fitness data, physical examination information, environmental information (humidity, temperature, purification degree and noise) and physical sign data. Other information includes diet data, personal information (age, gender, and disease history).

2) The collected data are integrated and pre-classified into text, digit and image and then are input into the CNN model, respectively, thus forming three CNN models.

3) The results of the three CNN models are input into the BPNN model for prediction, and user fitness and health status are predicted preliminarily.

4) The preliminary prediction results are input into the DS evidence theory model combined with the scientific fitness and medical health management theory and case analysis for further optimisation. Finally, the user's fitness and health status prediction is obtained.

Figure 5 Architecture of the constructed fitness and health management system based on CNN+BPNN+DS model



5) The final results will be fed back to the users for fitness behaviour and health status correction or improvement and can warn them of some potential diseases.

6) The system can provide self-monitoring and self-discovery services to users accordingly. Under the guidance and diagnosis of the system administrator, the users can also enjoy an all-around health management service.

Wireless sensor technology connects many sensors through logical modes to form a wireless sensor network, which can intelligently collect and sense the data of the connected objects in actual applications and then transmit the results to the receiver at the other end of the network. In intelligent medical applications, users can transfer health care data to experts of medical institutions from home using intelligent devices while receiving feedback diagnosis and treatment guidance. Meanwhile, the application of positioning systems in intelligent medical treatment is associated with electronic tags and intelligent hardware. Positioning technology can ensure that the real-time position of patients is sent to the data platform of medical institutions so that doctors can visit patients timely for medical treatment in case of emergency.

3.2 The deep learning with the proposed system

1) The number of nodes, learning times, learning rate and error precision of each layer is determined.

2) The sample data are normalised and input to the proposed CNN+BPNN+DS model for training.

3) The process of results forwarding propagation and error backpropagation is repeated until the maximum training times or the set calculation accuracy is reached, and then the parameters of the proposed CNN+BPNN+DS model are saved for subsequent prediction.

3.3 Data set collection and pre-processing

An effective data mining and utilisation are the keys to the realisation of intelligent services. Data pre-processing is an important link to data analysis and is also the foundation for the scientificity and accuracy of research prediction. Here, the collected user data include fitness data, physical examination information, environmental information (humidity, temperature, purification and noise), and physical signs. Other information includes diet information and personal profile (age, gender and disease history). Data can be integrated and classified into three types: text, numbers, and images.

Numbers can be directly inputted into the model. The text needs to be converted to numbers through the corresponding associations in the word matrix, the text is disassembled and then the only corresponding vector is found in the word matrix, obtaining the vector representation of the text. The picture information is planar, so the picture processing can be transformed into the feature extraction, and features can be input into the neural network model.

4 Results and discussion

4.1 Test procedure and results

The testing procedure can be divided into model training and test sample validation. The proposed ensemble prediction model is trained with the features of text, digit and image. First, a group of people's fitness and health data are collected as data sets. In total, the fitness and health data of 1000 volunteers of different age groups are collected from hospitals and communities, in which 700 samples are selected randomly for model training, and the rest are kept for test sample validation. Afterward, the non-DS evidence theory prediction model, unclassified user information prediction model, and the single neural network model are selected as comparisons with the proposed CNN+BPNN+DS model.

Figure 6 shows that the accuracy of the proposed ensemble prediction model and the three comparison prediction models: the non-DS evidence theory model, the unclassified user information model, and the single neural network model are significantly different. In Figure 6, 1 represents the proposed ensemble prediction model, and 2, 3 and 4 represent, respectively the above-mentioned three models. Apparently, the prediction accuracy of the proposed ensemble prediction model is the highest, 88.5%. The non-DS evidence theory model follows right behind, with an accuracy of 75.3%. The prediction accuracy of the unclassified user information model and single neural network model is much lower, only 71.2% and 67.5%.

To verify the model's prediction accuracy for users of different ages, users are divided into four groups accordingly: people under 18, people who are 18–35, 36–55 and over 55. The accuracy of the model is verified in different age groups. The above three models are also used as a comparison. Figure 7 shows that when verified under different age-span, the overall accuracy of the model shows obvious advantages. Those under 18 lack fitness style, yet have better physical repairability and excellent functional indexes. The evaluation accuracy of the four models is relatively high, which is 90.1%, 85.4%, 79.6% and 77.9%, respectively. Users in 18–35 years and 36–55 years old groups share a relatively stable physical condition. However, the majority of them suffer from many unpredictable health-damaging factors, such as social pressure, psychological pressure, and irregular lifestyle, and the assessment accuracy is considerably reduced. The elderly people over 55 enjoy a comparatively simple physical condition since most of the encountered diseases are commonly found among this age of people. Thus, the prediction accuracy is relatively higher. The specific prediction accuracy is shown in Table 2.

Table 2 Fitness and health prediction accuracy of different age groups under the four models

	Under 18	*18–35*	*35–55*	*Over 55 years old*
Model 1	90.1%	85.4%	79.6%	77.9%
Model 2	85.5%	82.3%	75.8%	73.2%
Model 3	84.3%	81.6%	71.4%	72.7%
Model 4	87.5%	84.1%	78.9%	76.1%

Figure 6 Fitness and health status prediction of the four models

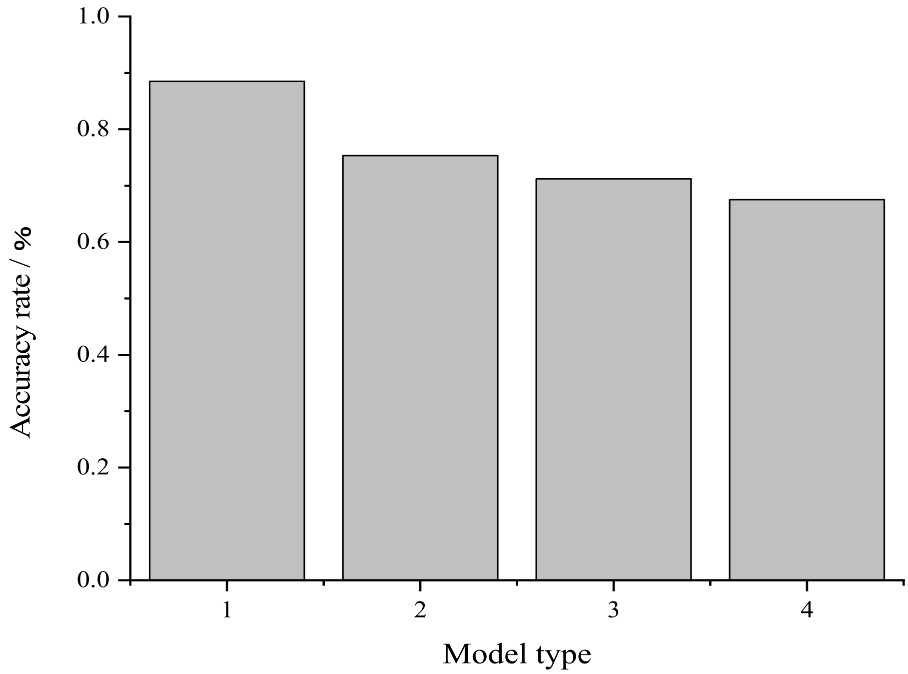
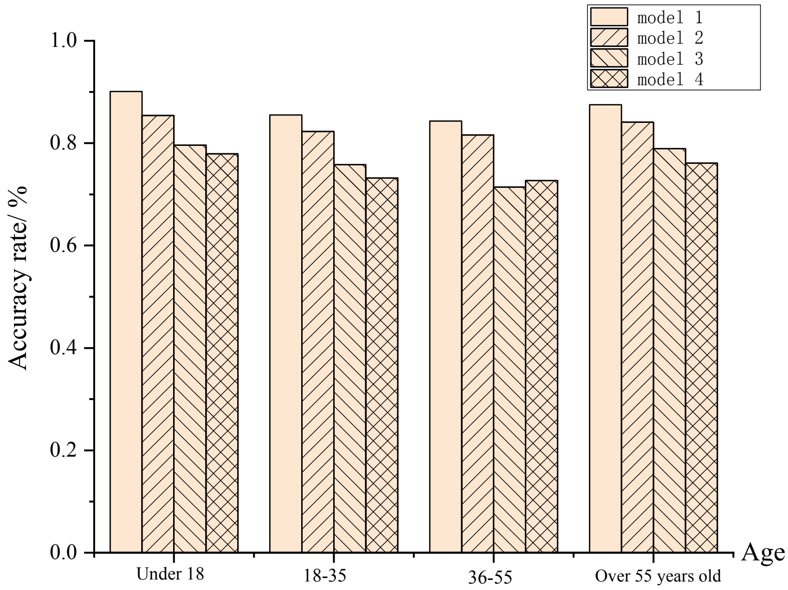


Figure 7 Fitness and health prediction accuracy of different age groups under the four models



4.2 Discussion

Here, fitness and health management are mainly studied. The proposed ensemble prediction model and the other three comparison models are verified through fitness and health data collection on survey subjects, which are divided into the sample set and the test set. The results show that the prediction accuracy of the proposed ensemble prediction model has obvious advantages over the comparison models: theory optimisation model without DS evidence, the prediction model without user information classification, and the single neural network model. Next, to verify the applicability of the model to people of different ages, users are divided into four stages: the under 18 years old, 18–35 years old, 36–55 years old and over 55 years old. Afterward, the accuracy of the model is verified at every stage. The final results indicate that the prediction accuracy of the proposed ensemble prediction model in different ages varies, while the overall prediction accuracy of the proposed composite prediction model is most superior.

5 Conclusions

According to features and types, fitness data are classified, analysed and predicted through the CNN algorithm model. Then, the BP neural network model is used to integrate, analyse and predict data. Finally, a composite prediction model is proposed based on BP neural network, DS evidence theory and scientific fitness and health management theory and cases, and the output of the BP neural network is input into the DS evidence theory model to improve the prediction accuracy. The proposed ensemble prediction model has several characteristics. (1) With the DS evidence theory model, it has a good measurement uncertainty. Compared with the traditional probability theory, DS evidence theory can reduce the uncertainty of the system effectively with the accumulation of evidence, improving the system's accuracy. (2) CNN, as a feedforward neural network, has strong recognition and accuracy in image processing and plays a great role in the prediction and analysis of users' health data images. (3) The composite prediction model is established. The composite prediction model contains many deep learning algorithms, which can complement each other. Different methods can be chosen to process data efficiently at different stages, improving the model accuracy. The fitness and health management system can help people understand their health status timely and accurately, warn against health crises, and improve people's health awareness.

Compared with other models, the proposed ensemble prediction model has high accuracy, proving its effectiveness and feasibility and laying a solid theoretical and practical foundation for fitness and health management system. However, there are still some shortcomings, specifically, three aspects: (1) the efficiency of the model under massive users and longer time needs to be further analysed; (2) meanwhile, the evaluation of user's fitness and health are focused on individual's physical signs, so more aspects, including psychological impact should be considered in the future research; (3) with the current level of IoT technology in China, the home-based management model cannot completely replace the hospital treatment methods for the time being. The proposed composite prediction model can only carry out routine monitoring and health management for patients, while specific treatments should be completed in hospitals. However, in the future, with the development of information technology, the change of domestic policy and the gradual improvement of the medical model, genuine home-based and intelligent fitness and health management will sure to be constructed. It is hoped that in future research, the proposed ensemble prediction model will be further improved.

Fitness and health is a huge systematic project. In future research, there are many challenges, and more work needs to be further studied. With the gradual establishment of health management systems and the development of high-end health wearable devices, health data will gradually become unified, shared and open information. To process larger scale and more complex data, deep learning model improvement, training efficiency and parameters optimisation still need further research, which is the way for transformation from weak AI systems to strong AI systems.

References

Cai, R. Zhu, B. and Ji, L. et al. (2017) 'An CNN-LSTM attention approach to understanding user query intent from online health communities', *International Conference on Data Mining Workshops*, Orleans, pp.430–437.

Chen, K., Zhang, D. and Yao, L. et al. (2020) 'Deep learning for sensor-based human activity recognition: overview, challenges, and opportunities', *ACM Computing Surveys*, Vol. 54, No. 4, pp.1–40.

Dimililer, K., Dindar, H. and Al-Tudjman, F. (2021) 'Deep learning, machine learning and internet of things in geophysical engineering applications: an overview', *Microprocessors and Microsystems*, Vol. 80. Doi: 10.1016/j.micpro.2020.103613.

Goyal, S.B., Bedi, P. and Yadav, D.K. et al. (2021) 'Internet of things information analysis using fusion based learning with deep neural network', *Journal of Physics: Conference Series*.

Hatcher, W.G. and Yu, W. (2018) 'A survey of deep learning: platforms, applications, and emerging research trends', *IEEE Access*, pp.24411–24432.

Le, D.N., Parvathy, V.S. and Gupta, D. et al. (2021) 'IoT enabled depthwise separable convolution neural network with deep support vector machine for COVID-19 diagnosis and classification', *International Journal of Machine Learning and Cybernetics*, pp.1–14.

Liu, Y., Ge, Z. and Lv, G. et al. (2018) 'Research on automatic garbage detection system based on deep learning and narrowband internet of things', *Journal of Physics: Conference Series*, pp.1–7.

Ma, H. and Pang, X. (2019) 'Research and analysis of sports medical data processing algorithms based on deep learning and internet of things', *IEEE Access*, Vol. 7, pp.118839–118849.

Ma, W. (2020) 'Analysis of anomaly detection method for internet of things based on deep learning', *Transactions on Emerging Telecommunications Technologies*, Vol. 31, No. 2.

Pan, Y., Fu, M. and Cheng, B. et al. (2020) 'Enhanced deep learning assisted convolutional neural network for heart disease prediction on the internet of medical things platform', *IEEE Access*, Vol. 8, pp.189503–189512.

Pokkuluri, K.S. and Nedunuri, S.U.D. (2018) *Internet of things with deep learning for societal applications*, Scholars' Press.

Qaisar, S.B. and Usman, M. (2017) 'Fog networking for machine health prognosis: a deep learning perspective', *International Conference on Computational Science and its Applications*, pp.212–219.

Rathore, M.M.U., Ahmad, A. and Paul, A. (2017) 'Hadoop-based intelligent care system: analytical approach for big data in IoT', *ACM Transactions on Internet Technology*, pp.1–24.

Van Le Eenoo, Van Der Roest, H. and Onder, G. et al. (2018) 'Organizational home care models across Europe: a cross sectional study', *International Journal of Nursing Stuswwqdies*, Vol. 77, pp.39–45.

Vijayakumar, R., Alazab, M. and Srinivasan, S. et al. (2020) 'A visualized botnet detection system based deep learning for the internet of things networks of smart cities', *IEEE Transactions on Industry Applications*, pp.1–1.

Zhang, J., Tian, T. and Wang, S. et al. (2020) 'Research on an olfactory neural system model and its applications based on deep learning', *Neural Computing and Applications*, Vol. 32, No. 10, pp.5713–5724.

Zhou, Y., Lu, Y. and Pei, Z. (2021) 'Intelligent diagnosis of alzheimer's disease based on internet of things monitoring system and deep learning classification method – ScienceDirect', *Microprocessors and Microsystems*. Doi: 10.1016/j.micpro.2021.104007.

Zhu, W., Yin, N. and Zhu, W. et al. (2017) 'Research on the mass sports fitness based on internet of things and intelligent system', *Revista De La Facultad De Ingenieria*, Vol. 32, No. 3, pp.376–382.