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Artificial Intelligence Recommendation System of Cancer Rehabilitation Scheme Based on IoT Technology

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ABSTRACT Based on the advantages of Internet of things, this paper focuses on the research of intelligent recommendation model for cancer patients' rehabilitation, and designs a user-friendly intelligent recommendation system of cancer rehabilitation scheme. In view of the uncertainty of the cause and time of recurrence of cancer patients, the convolutional neural network algorithm was used to predict both of them. The prediction results of the model showed that the prediction accuracy was high, reaching 92%. To solve the problem of the optimal nutrition program for the rehabilitation of cancer patients, we took the recurrence time as the objective function, and established the recommendation model of the optimal nutrition support program for the rehabilitation by using BAS algorithm. Finally, under the framework of Internet of things technology, the intelligent recommendation model of cancer rehabilitation prediction model and nutrition support program was integrated to realize the recommendation system of intelligent recommendation of rehabilitation nutrition support program for cancer rehabilitation patients according to their different characteristics. After the system simulation experiment, it was found that under the condition that the predicted recurrence location was almost unchanged (49% of simulation results and 50% of actual results), the nutritional support scheme recommended by the intelligent recommendation system could extend the postoperative recurrence time of patients by more than 95%. This recommendation system can help doctors select personalized nutrition and rehabilitation programs suitable for patients in the later stage of rehabilitation treatment according to different cancer patients, and has certain guiding significance for the field of cancer rehabilitation.

INDEX TERMS IoT, CNN, BAS, cancer recovery, artificial intelligent recommendation system.

I. INTRODUCTION

Internet of things medicine is the application of IoT theory in medicine. It contains three basic processes of perception, transmission, and intelligent processing, as well as ten functions of online monitoring, positioning and tracing, alarm linkage, plan management, hidden safety hazards, and statistical decision-making [1]. The development trend of the medical industry is smart medical, which is to realize the interaction between patients, medical personnel, medical institutions and medical drugs by building a regional medical information platform for health records and utilizing the most advanced Internet of things technology, and gradually achieve informatization [2]. With the increasing incidence of human cancer, How to prolong progression-free survival and precision rehabilitation become the most concerned problems for cancer patients. Therefore, under the framework of Internet of things medical technology, the establishment of an intelligent recommendation system for cancer rehabilitation integrating prediction and optimization model will be a blessing for cancer patients.

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Cancer is the most difficult problem in the field of medicine, and its postoperative recovery has become the most concerned problem for cancer patients. The two most critical steps in cancer rehabilitation are recurrence time and nutritional support program [3]. With the gradual increase of the incidence of cancer, the traditional cancer rehabilitation forecast and the nutritional program of cancer rehabilitation provided by doctors based on their own experience can no longer meet the needs of patients. In today's Internet of things, data mining, artificial intelligence and deep learning conditions are ripe, a cross-fusion intelligent recommendation system for cancer rehabilitation will become the desire of cancer patients [4]. In this paper, based on the historical data and data-driven modeling of cancer rehabilitation, the process of cancer rehabilitation was cross-fused with mathematics, statistics, operation and intelligent algorithms to establish a cancer rehabilitation prediction model and an intelligent recommendation model for the best rehabilitation nutrition program [5]. Common cancer prediction model algorithms include artificial neural network (ANN), generalized regression neural network (GRNN), support vector machine (SVM), etc., [6]. ANN simulates biological neural network in structure and has strong learning ability, but ANN modeling needs a large number of samples and has shortcomings such as over-learning. GRNN has strong nonlinear mapping ability and learning speed, and finally the network generally converges to the sample size to accumulate more optimized regression surfaces. However, its disadvantages are the small learning sample size and the lack of parameters in the model. The SVM algorithm can solve the high-dimensional problem with a relatively sound theoretical basis. However, the prediction effect is good only when the number of samples is small. In the era of big data in cancer medicine, the advantages of this algorithm cannot be better demonstrated. This study will combine the advantages of Convolutional neural network (CNN) in training, learning and prediction accuracy to construct a cancer rehabilitation prediction model [7].

Beetle Antennae Search (BAS) algorithm is a biological-inspired intelligent optimization algorithm, which was developed in 2017 inspired by the foraging principle of longo longo. The algorithm program is simple and portability, with few artificial operation parameters and fast convergence speed [8]. The Internet of things is the entry point for the integration of medical intelligence and informatization, which has spawned many intelligent devices, intelligent software and intelligent systems with the characteristics of ''computing, regulation, recommendation, decision-making and autonomy'', realizing the transformation from traditional medical treatment to intelligent medical treatment. This transformation process requires the establishment of the tangible terminal entity of original medical data collection and the communication platform of intangible virtual medical network, and the construction of the medical network architecture, so as to realize the integration of long-term and stable accurate control, reliable perception, trusted service and real-time transmission [9]. In order to meet the intelligent demand of the recommendation system for cancer medical intelligent rehabilitation, Internet of things technology is needed to continuously strengthen in heterogeneous network transmission, automatic acquisition of multi-source objects and intelligent processing of mass information [10].

Based on the above research conditions, In this paper, BAS algorithm is introduced into the intelligent recommendation system of cancer rehabilitation medical plan. An intelligent recommendation model of nutritional support program was developed to effectively improve the time of cancer recurrence after surgery. Combined with the expert scoring system, the integrated cancer rehabilitation prediction model and recommendation model are coupled under the Internet of things technology framework to realize an intelligent recommendation of the Internet of things system for the nutritional support program of cancer rehabilitation. This system can effectively deal with the recurrence of cancer after surgery and the risk of recurrence, and indirectly improve the quality of life of patients.

II. RELATED WORK

A. APPLICATION OF IoT IN MEDICAL FIELD

At present, the IoT has entered a new stage of in-depth integration and development with traditional medicine. The transformation and upgrading of the IoT technology and the emergence of 5G network have become an important driving force for the development of IoT medicine and a necessary technical system to support intelligent medical care [11].

IoT medicine is mainly applied to the intelligent medical treatment of patients and the intelligent management of things in hospitals, supporting the digital collection, processing, storage, transmission and sharing of internal medical information, equipment information, drug information, personnel information and management information in hospitals. The realization of material management visualization, digitization of medical information, digitization of medical process, scientific medical process and humanized service communication can meet the needs of intelligent management and monitoring of medical health information, medical equipment and supplies, and public health security [12]. The basic architecture is shown in Fig.1. Compared with traditional medicine, Internet of things medicine, with its fine granularity, new concepts, omni-directional, multi-channel, full-cycle, high-tech and other characteristics, has rapidly become a favored medical instrument in the medical field and patients [13].

Medical Internet of things services in the field of health care, a comprehensive use of optical technology, pressure sensitive technology and RFID technology. It combines a variety of sensors to exchange information with the help of mobile terminals, embedded computing devices and medical information processing platforms through sensor networks and in accordance with agreed protocols. Its structure can be divided into four levels: perception acquisition layer, transmission access layer, support management layer and service application layer [14].

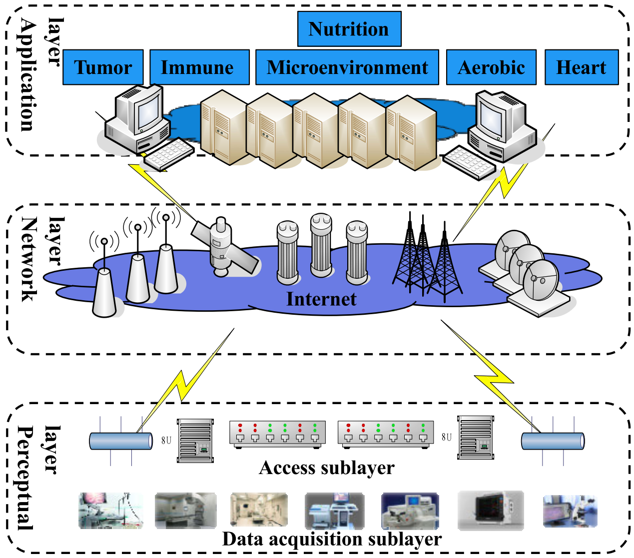

FIGURE 1. Basic framework of medical Internet of things.

The perception acquisition layer is divided into two sub-layers: data acquisition sub-layer and access sub-layer. The data acquisition sub-layer USES various technical means and equipment to transform the objects involved in the network into CPS nodes. Access sub-layer is to transmit the collected data and access to the network layer. Although there are various access modes of access sub-layers, appropriate access modes must be selected according to different needs of different objects [15]. Cancer rehabilitation medical data include a large number of medical CT images, (Pathology, Immune Cells, Genes and Proteomics,) cancer rehabilitation nutrition program data information, and cancer tumor score monitoring grades. Large amount of information transmission, high quality requirements, response speed is suitable for coaxial cable or cable access. Community health service centers usually deal with common diseases and transmit less data at fixed locations, which is suitable for fixed broadband access.

The network layer is divided into three sub-layers: active CPS network, middleware and cloud data center. Active CPS network is based on communication network, information center and network center to realize interconnection between active CPS nodes and other CPS nodes, while ensuring the reliability and accuracy of signals. Based on the active CPS network system, the user management, node monitoring, information processing and other functions of active CPS nodes are designed and realized, and then a middleware of Internet of things for a specific application is established [16]. The application middleware of Internet of things mainly realizes the unification of various data formats and the integration of information, and builds a service support platform on this basis to provide open interfaces for various services in the application layer for the development of applications by the third party [17].

The service application layer is divided into two layers, the cloud data center and the application system. The cloud data center processes the data passed by the middleware and provides various services. On this basis, various applications have been formed to construct an intelligent cancer rehabilitation medical recommendation system [18].

The core is application-specific systems that use cloud data centers for data mining to provide cancer patients with recovery plans and medical decisions. On the one hand, the intelligent recommendation system for cancer rehabilitation always pays attention to patients' medication status and nutritional support status. On the other hand, the intelligent recommendation system keeps track of a cancer patient's tumor status at any time, and predicts the time and location of his future cancer recurrence based on the patient's historical characteristics. Finally, adaptive regulation of nutritional programs in cancer patients.

In summary: the medical Internet of things has the typical characteristics of intelligent perception, service application, precise control, real-time analysis and adaptive regulation. The cognitive control technology, network communication technology and adaptive control technology in the intelligent recommendation system of cancer rehabilitation medicine designed in this study have been developed and matured. However, the deep mining of medical data and data processing technology of cancer patients still need to be improved. Therefore, the coupling between the recurrence prediction model of cancer rehabilitation and the intelligent recommendation model of nutrition program of cancer rehabilitation is the key to the intelligent recommendation system.

B. APPLICATION OF CNN IN MEDICINE

CNN was proposed by Yann LeCun of New York university in 1998. CNN is essentially a multi-layer perceptron, and the key to its success lies in its local connection and sharing of weights. On the one hand, reducing the number of weights makes the network easy to optimize, and on the other hand, reduces the risk of overfitting [19]. CNN is a kind of neural network. Its weight sharing network structure makes it more similar to biological neural network, reducing the complexity of network model and the number of weights. The model structure of CNN is shown in Fig.2.

With the increasing incidence of cancer, the difficulty of finding early cancer and the uncertainty of postoperative rehabilitation, cancer has become the first killer of human health. In view of this difficulty and uncertainty, CNN algorithm has been widely used in the detection of cancer CT images and the prediction of cancer recurrence after surgery due to its strong recognition ability and high prediction accuracy. American artificial intelligence AI makes use of deep science (CNN) to diagnose and treat cancer [20]. By letting artificial intelligence algorithm learn CT images of cancer that far exceed the lifetime number of visits by human doctors, it trains a deep convolutional neural network model to detect the canceration of normal cells, so as to achieve the purpose of early detection and treatment.

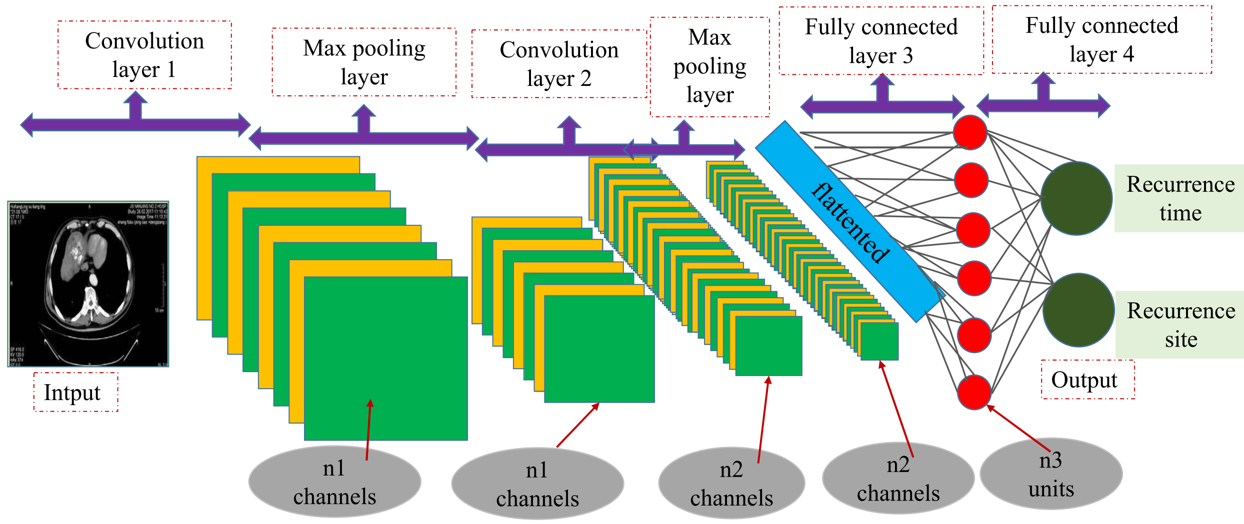

FIGURE 2. CNN structure diagram.

In addition to its high performance in identifying cancer CT images, CNN also shows a strong side in cancer prediction. Prostate cancer is known to be the most common and second-deadliest cancer in American men, and classification of prostate cancer based on the Gleason histological image is important in patient risk assessment and treatment planning. To solve this problem, the regional convolutional neural network model was used to detect epithelial cells and predict the risk of cancer. After model training and experimental testing, the accuracy rate reached 99.8% [21].

To sum up, CNN is one of the deep learning algorithms. It has a mature theoretical basis and experimental cases for both the detection and identification of cancer CT images and the prediction of cancer incidence. It provides theoretical guidance for the cancer rehabilitation medical recommendation system designed in this paper.

As early as 2004, an intelligent assessment model for cancer patient rehabilitation was developed by the interdisciplinary study of medicine and mathematics at Stanford university, and has shown great promise in clinical applications for hundreds of thousands of American cancer patients. In China, our team and STERIS cancer data analysis laboratory evaluated and followed the progress of thousands of liver cancer patients in China. Analyzed their clinical data and rehabilitation data, and established the system model suitable for Chinese patients.

III. MODEL

A. REHABILITATION TIME PREDICTION MODEL BASED ON CNN

CNN is an artificial neural network with high recognition ability. In CNN, there are multiple neuron connections between each layer of network. The convolution kernel is actually a user-defined size and weight matrix, which ACTS on the local perception domain in different regions of the same image, extracts the features of each local perception domain, and generates input values for the next layer of neurons. The convolution layer convolved the input features, and the pooling layer reduced the size of the feature map by means of spatial invariance averaging or maximization operations. In the softmax layer, the softmax activation function is used to classify the input feature maps as class values [22]. The main advantage of CNN is that they are easier to train and have fewer parameters than fully connected networks with the same number of hidden units. The characteristic diagram is shown in formula (1). The pooling layer performs the secondary extraction of input features through specific pooling rules, and the feature diagram is shown in formula (2).

$$H_i = f(H_{I-1} \otimes \omega_i + b_i) \tag{1}$$

$$H_j = f(pooling(H_{I-1}) + b_i) \tag{2}$$

where is the feature graph, is A nonlinear excitation function, is the convolution operation of convolution kernel and feature map, is the weight vector is the bias, pooling is a pooling rule, such as average pooling layer, maximum pooling layer and random pooling layer.

The convolutional neural network structure designed in this paper considers that the sample data is 6 indexes. The convolutional layer is $6 \times 7 \times 3$, $5 \times 5 \times 96$, $3 \times 3 \times 256$, $3 \times 3 \times 512$, $3 \times 3 \times 512$, and the pool layer is uniformly designed to be 2×2.

(1) convolutional layer: the j feature image of the first layer is expressed as:

$$X_j^l = g(\sum\nolimits_{x_i^{j-1} \in Mj_j} x_i^{l-1} * k_{ij}^l + b_j^l) \tag{3}$$

where, the nonlinear activation function g. The set of feature graphs connected to the j feature graph of layer $l-1$ and layer l is denoted as M_j, that's the set of input feature images. The offset value is M_j. The convolution kernel connecting the i

feature graph in layer $l-1$ and the j mapping graph in layer l is denoted as.

(2) Pooling layer: Pooling layer is denoted as layer l, and the j characteristic graph of layer l is denoted as:

$$x_j^l = g(w_j^l pool(X_j^{l-1}) + b_j^l) \tag{4}$$

where, the weight coefficient is denoted as, and real numbers are generally taken in the experiment. Offset value is expressed as, pooling function is expressed as, with maximum pooling, average pooling and random pooling, LP pooling, etc.

(3) Full connection layer: output vector x^l of the full connection layer:

$$x^l = g((\beta^l)^T v^{l-1} + b^l) \tag{5}$$

where, the vector generated by the feature graph of the pooling layer of layer $l-1$ or the output vector of the feature graph of the convolutional layer is represented as v^{l-1}. The offset value is b^l. The weight coefficient matrix is expressed as β^l.

B. AN INTELLIGENT RECOMMENDATION MODLE BASED ON THE BAS

In this paper, the maximum recurrence time of postoperative liver cancer patients was taken as the objective function, and the best nutrition plan was recommended to the patients by using the longhorn beard algorithm (The market mainstream nutrition products for cancer patients were selected as the library). Beetle antennae search (BAS) algorithm, also known as beetle antennae search algorithm, was proposed in 2017 as an efficient intelligent optimization algorithm suitable for multi-objective function optimization based on the principle of longo foraging [23]. The important biological characteristic of longhorned beetles is their extremely long antennae, which are usually longer than their body length. Its two antennae act as two-way olfactory sensors to recommend the best routes for foraging or mating. Longhorns use two whiskers to detect the nearby area in real time. When one side detects a stronger smell, the longhorns will move to that side to correct the walking route in real time. Fig. 3 shows this process.

Similar to genetic algorithm, particle swarm optimization, simulated annealing and other intelligent optimization algorithms. The BAS algorithm can achieve efficient optimization without knowing the specific form of the function or gradient information [24]. Compared with particle swarm optimization (pso), BAS algorithm requires only one individual, namely one longhorn, and the computation is greatly reduced. The algorithm flow is as follows:

1. Create a random direction vector of longhorn beard and standardize

$$\vec{b} = \frac{\text{rnd}(n,1)}{\|\text{rnd}(n,1)\|} \tag{6}$$

where rnd is a random function. n is the dimension of the parameter to be optimized.

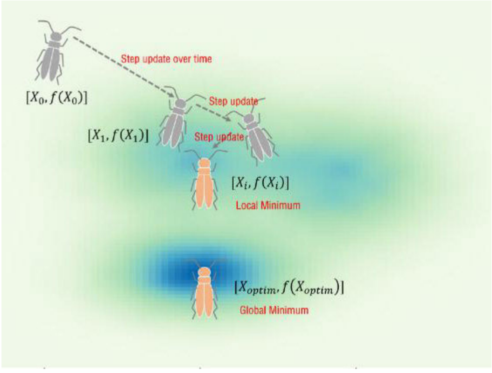

FIGURE 3. Schematic diagram of BAS optimization process.

2. Calculate the left and right necessary coordinates

$$\begin{cases} x_r = x^t + d^t\vec{b} \\ x_l = x^t - d^t\vec{b} \end{cases} \tag{7}$$

where, x^t represents the position coordinate of the right side of longhorn at the time of the t iteration. x_{lt} represents the position coordinates of longhorn left at the t iteration. x^t represents the centroid coordinates of longhorn at the t iteration. d_0 represents the distance between the whiskers.

3. According to the corresponding function values of the two whiskers, determine the position of the longhorn at the next moment.

$$x^t = x^{t-1} + \delta^t\vec{b}\text{sign}(f(x_r) - f(x_l)) \tag{8}$$

where, δ^t represents the step size factor in the t iteration. f is the objective function to be optimized.

4. Step size and search distance update

$$\begin{cases} d^t = 0.95d^{t-1} + 0.01 \\ \delta^t = 0.95\delta^{t-1} \end{cases} \tag{9}$$

where, d_0 is the constant of artificial distance, η_d and η_δ are the update attenuation coefficients of search distance and step length respectively. The algorithm flow is shown in **Fig. 4**.

IV. SYSTEM DESIGN

In order to facilitate the understanding of the recurrence time, location and recurrence probability of liver cancer rehabilitation patients and the correlation between immune index, tumor index, microenvironment index, psychological index, nutritional index and (exercise and advanced exercise), the system designed a simple and friendly system structure interface. The interface is shown in Fig. 5. Based on the analysis of intelligent recommendation system and medical Internet of things system architecture of liver cancer rehabilitation patients, the key is to analyze six related indicators of liver cancer rehabilitation patients, such as immune index and tumor index. The first interface of the liver cancer prediction system designed in this paper is composed of three modules:

Algorithm 1: BAS algorithm for global minimum searching

Input:Estabish an objective function $f(x^t)$, where variable $x^t=[x^1,\ldots,x^i]^T$, initialize the parameters x^o, d^o, δ^o.
Output: x_{bst}, f_{bst}.
While (t<Tmax)or(stop crierion)do
  Generate the direction vector unit **b** according to(1);
  Search in variable space with kinds of antennae according to (2);
  Update the state variable x^t according to (3);
  If $f(x^t)<f_{bst}$ then
  L$f_{bst}=f(x^t)$, $x_{bst}=x^t$.
  Update sensing diameter d and step size δ with decreasing functions (4) and (5)respectively,Which could be further studied by designers.
 return x_{bst}, f_{bst}.

FIGURE 4. Flow chart of BAS algorithm.

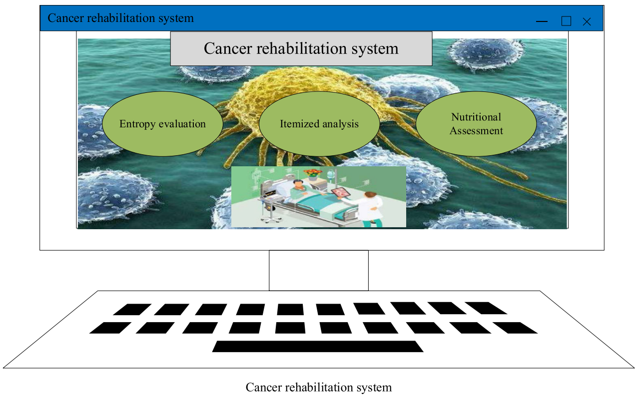

FIGURE 5. System interface.

entropy state assessment, itemized analysis and nutritional assessment. After the input of the six index signs corresponding to the recovered patients with liver cancer, the system will realize the corresponding recurrence probability value and the predicted recurrence location.

The key link of cancer rehabilitation intelligent recommendation system is recommendation engine [25]. The convolutional neural network model of cancer recovery prediction is recommended for the engine. Based on the convolution neural network model to predict the recurrence time of a patient's cancer, it can assist the doctor in charge of diagnosis and give reasonable treatment suggestions at the same time. At the same time, the biological culture data of cancer cells (or tissues) in the laboratory is used as the system sample input (The growth rate of cancer cells and the time of angiogenesis in different nutrient medium). Then, we build a data model of cancer cells in a certain patient, predict the growth rate and angiogenesis time in different culture components, and put forward constructive suggestions for the follow-up nutrition supply of patients. The recommended system architecture and interface are shown in Fig. 6.

Component 1 is responsible for obtaining the behavioral data of the original index of the liver cancer rehabilitation

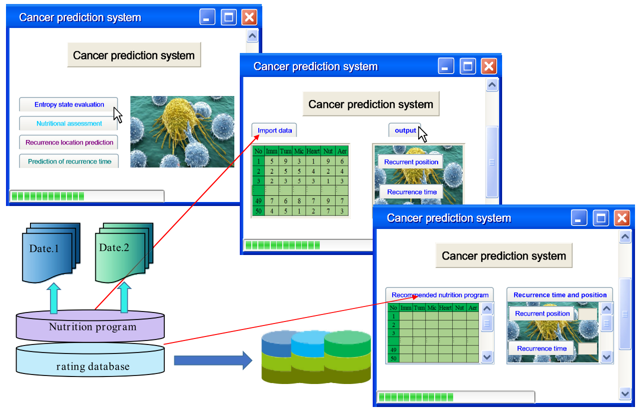

FIGURE 6. Architecture and interface presentation of cancer rehabilitation recommendation system.

TABLE 1. Data storage format in SQL server.

src_id	dst_id	weight
Feature vector ID	Patient Primitive Behavior Indications ID	Intelligent recommendation model weights for cancer rehabilitation

patient from the database or the medical library storage. By analyzing the patient's immune indications and basic indications, it is concluded that the recovery of cancer patients is related to their physical conditions, daily activities, dietary intake, environmental conditions and psychological factors. Correlation analysis is performed on many factors related to the rehabilitation of cancer patients, and finally six indicators are selected to generate the feature vector $\{x_1, x_2, x_3, x_4, x_5, x_6\}$ of the current user. In the prediction process of the cancer rehabilitation intelligent diagnosis system, the original behavior data of the patient can be directly used as the feature vector in the input system model sample. The feature vector is mainly obtained from various index indicators of cancer patients.

Component 2 is responsible for in-depth analysis and mining of various index behavior data of cancer patients to find quantitative relationships with human physiological and psychological indicators and cancer recurrence time and probability. The offline recommendation table can be obtained according to the offline correlation table (based on the relationship between the cancer rehabilitation intelligent recommendation system and the patient behavior data feature vector to obtain the offline correlation table). Offline related tables can be stored in SQL Server [26], and its storage format is shown in Table 1.

Component 3 is responsible for filtering, ranking and other serial processing of the patient's initial indications, and then generating the final intelligent recommendation scheme. This part is the most critical part of the intelligent recommendation in the whole system. In this paper, the beast search algorithm is used as the core algorithm of intelligent recommendation.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Recurrence after treatment of liver cancer is the bottleneck that affects the long-term survival of patients with liver cancer. Exploring practical and effective clinical intervention strategies for recurrent liver cancer is the key to improve the long-term survival rate of patients. Whether the recurrence of liver cancer after surgery is unicentric or multicentric. After the occurrence of polycentricity, that is, the radical resection of liver cancer, new tumors occur because of the continued growth of the liver cancer (cirrhosis) and other pro-cancer factors. In the case of a single center, central cancer cells spread through the portal vein before the original resection of the lesion, and intrahepatic recurrence and extrahepatic metastasis occurred. It has very important guiding significance for the clinical treatment of liver cancer. The source of cell clones for recurrence of liver cancer after surgery is different, which is reflected in the time of recurrence of liver cancer. There are also obvious differences.

The relationship between the source of relapsed cancer cell clones and the time of recurrence: 6 cases of recurrence occurred unilaterally, and the recurrence time was 3 to 13 months from the first operation. The average was (6.5 $\pm$ 3.25) months (X $\pm$ SD), and the recurrence of 9 cases of polycentricity was 7 to 54 months, with an average of (33.8 $\pm$ 17.8) months. After statistical processing, there are very significant differences. Within 2 years after the first operation, there were 9 cases of recurrence, including 3 cases of multicenter recurrence (33%), and 6 cases of recurrence 2 years after surgery, all of which were polycentric recurrence (100%). The examination showed that the recurrence within 2 years after surgery could be either a unicentric recurrence or a polycentric recurrence. The recurrence after 2 years was a multicentric recurrence, that is, the second primary cancer. Most patients had recurrence at a single center within 2 years, and all had recurrence after 2 years.

According to the recurrence of liver cancer patients after surgery, a recurrence prediction model based on various indications of liver cancer patients was established in this paper. Based on the patient's specific situation, and taking the maximum relapse time as the objective function, an intelligent recommendation rehabilitation model model based on the beetles algorithm (BAS) was established.

A. SAMPLE INFORMATION

For immune-related monitoring items, weighting is a weight given based on the experience of the doctor. According to this weight, it is converted into nine score segments, with 9 scores being the best and 1 score being the worst. The formula for the Immune Index term is as follows:

$$I = \frac{\sum_{i=1}^{6} x_i w_i}{\sum_{i=1}^{6} w_i} \tag{10}$$

TABLE 2. Immune finger evaluation form.

Immune Index	Weights
CD3+CD4+CD8+/CD45+	1
CD3+CD4+/CD45+	0.8
CD4+/CD8+	0.8
CD3+CD16+CD56+/CD45+	0.5
Exercise ECG (X±SD)	1.5
Sports Leather (X±SD)	1.5

TABLE 3. Microenvironment index evaluation form.

Microenvironment index	Weighted (tenths)
O2	0.5
PH value	0.2
Interstitial pressure	0.2
Inflammatory response	1
Vascular permeability	0.3
CTC value	3
Proteomic analysis	2

where x_i is the value of the i-th item and w_i is the weight of the i-th item. Immune index score ranges from 5-37 points, and is divided into nine score segments according to the score, with 9 points being the best and 1 being the worst.

For microenvironment-related monitoring items, weighting is based on the weight given by the doctor's experience. According to this weight, it is converted into nine score segments, with 9 scores being the best and 1 score being the worst. Similarly, the psychological index mainly evaluates depression and anxiety of patients with liver cancer, with 9 being the best and 1 being the worst. Nutrition support mainly evaluates basic intake, balanced intake, special needs nutrition and contraindications. 9 points is the best and 1 point is the worst. Aerobic exercise and advanced work The performance of the human body under the condition of sufficient oxygen supply.

We performed correlation analysis on each index to explore whether there is a correlation between each index. Table 4 shows the correlation matrix list of the six index indicators.

It can be seen from Table 4 that there is a positive correlation between tumor fingers and immune fingers. This indicates that the stronger the immune finger, the weaker the tumor finger. In addition, there is a negative correlation between psychological indications and tumor indications. Box diagrams of various index indicators and recurrence time of patients with liver cancer are shown in Fig. 7.

It can be seen from **Fig.7** that the box indicators of each index and the recurrence time of liver cancer patients can be seen. Nutrition index, tumor index and immune index are related to the recurrence time. The more ideal these indicators are, the longer the patient will relapse.

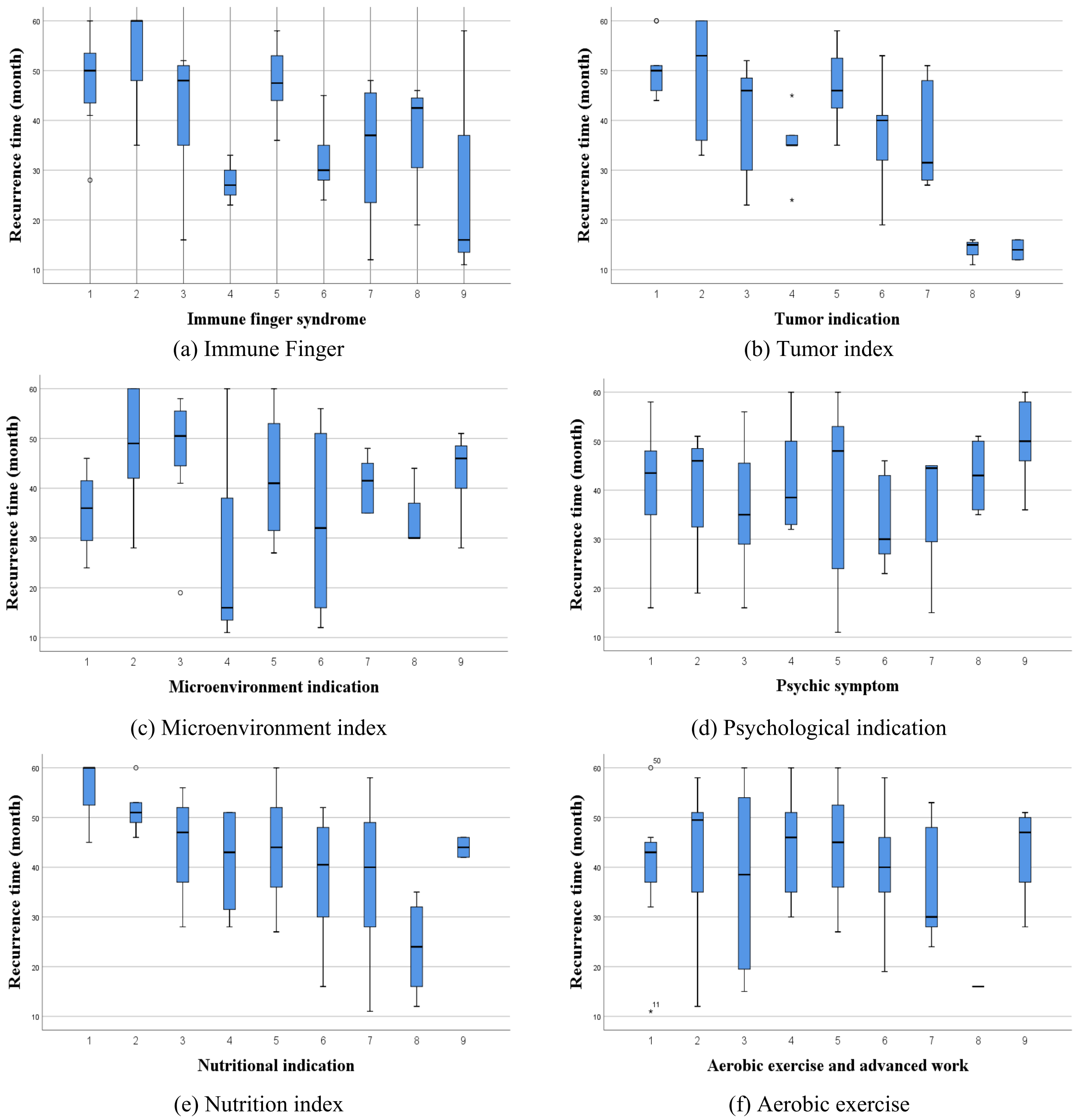

FIGURE 7. Box diagram of each index and recurrence time of patients with liver cancer.

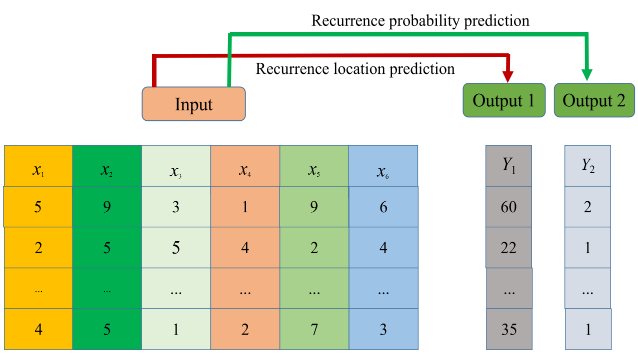

FIGURE 8. Sample input-output relationship diagram.

This paper selects 1000 sets of liver cancer data sets as the training set for the prediction model and recommendation model in this paper. Then select 100 sets of data from the data set to test the prediction model and recommendation model. The 1000 training sample sets used in this paper are shown in **Table 5**.

B. RESULTS ANALYSIS

According to the evaluation criteria of each index described above, we performed prediction simulation on 100 groups of data (100 liver cancer patients), and first established input and output vectors. Sample input and output: Take the six major symptoms of immune index, tumor index, microenvironment index, psychological index, nutrition index, aerobic exercise and advanced operation as input ($x_1, x_2, x_3, x_4, x_5, x_6$). Take the predicted recurrence time and the recurrence position as the output (Y_1, Y_2). As shown in Fig. 8.

TABLE 4. Correlation analysis table for each index.

	Pearson-cor/Sig.	Imm	Tum	Mic	Heart	Nut	Aer
Imm	Pearson-cor	1	0.304*	0.038	0.167	0.213	-0.068
	Sig.		0.032	0.793	0.246	0.138	0.641
Tum	Pearson-cor	0.304*	1	0.088	-0.378**	0.103	0.025
	Sig.	0.032		0.544	0.007	0.476	0.864
Mic	Pearson-cor	0.038	0.088	1	0.209	-0.195	-0.003
	Sig.	0.793	0.544		0.144	0.175	0.985
Heart	Pearson-cor	0.167	-.0378**	0.209	1	-0.145	-0.015
	Sig.	0.246	0.007	0.144		0.315	0.919
Nut	Pearson-cor	0.213	0.103	-0.195	-0.145	1	-0.188
	Sig.	0.138	0.476	0.175	0.315		0.192
Aer	Pearson-cor	-0.068	0.025	-0.003	-0.015	-0.188	1
	Sig.	0.641	0.864	0.985	0.919	0.192	

*. At 0.05 level (Sig.), The correlation is significant, **. At 0.01 level (Sig.), The correlation is significant.

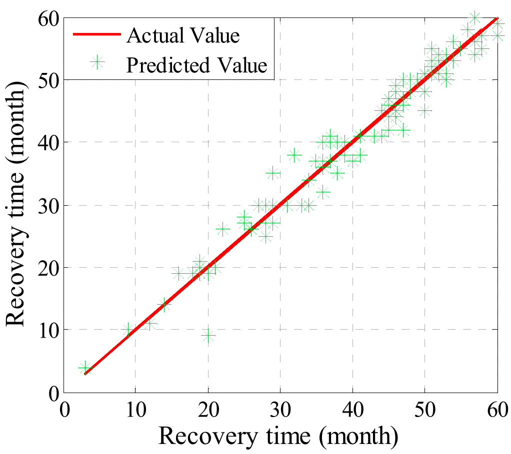

FIGURE 9. Comparison of predicted value and actual value of liver cancer recurrence time.

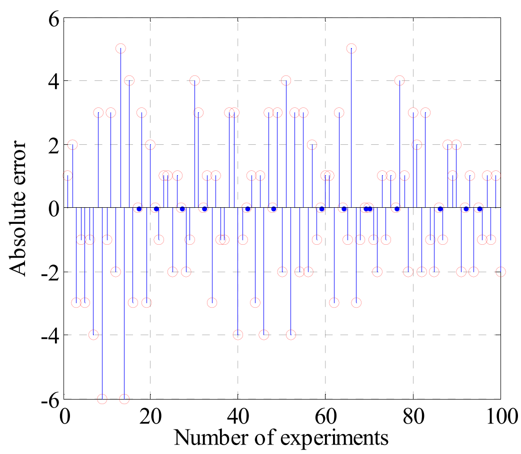

FIGURE 10. Error of prediction of livercancer recurrence time.

We will use the prediction model simulation for the 100 selected samples. The sample simulation output is available. The comparison between the predicted value of liver cancer recurrence time and the actual value is shown in Fig.9. The forecast error of recurrence time is shown in Fig10.

It can be seen from **Fig 9** that the recurrence time of liver cancer predicted based on CNN is distributed near the actual recurrence time, and almost coincides, indicating that the CNN-based cancer rehabilitation prediction model in this paper has good prediction accuracy. As can be seen from **Fig 10**, the prediction error range of cancer recurrence time is ±6 months. Therefore, the CNN-based cancer recurrence time prediction model has excellent prediction performance and prediction accuracy on the cancer nutrition program sample set. It can be generalized to the cancer rehabilitation intelligence in this paper Recommendation system.

TABLE 5. Some sample data.

No	Imm	Tum	Mic	Heart	Nut	Aer	Re-time (month)	Situ.1/Other.2
1	5	9	3	1	9	6	60	2
2	2	5	5	4	2	4	22	1
3	2	3	5	3	1	3	24	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
999	7	6	8	7	9	7	60	1
1000	4	5	1	2	7	3	35	2

100 sets of data samples are applied to the BAS intelligent algorithm. The results of system intelligence recommendation in the variable space of the algorithm are shown in **Table 6**. The algorithm has a longest iteration time of 137s

TABLE 6. System recommendation results.

No	x_1		x_2		x_3		x_4		x_5		x_6		IT	ORT	PT	SST
	Ori	Sim	Ori	Sim	Ori	Sim	Ori	Sim	Ori	Sim	Ori	Sim				
1	2	8	1	6	5	8	5	4	1	9	3	1	101	57	60	58
2	1	9	3	4	8	9	3	5	8	6	7	5	75	51	58	53
3	1	6	1	7	9	7	8	9	8	7	2	7	87	49	56	46
4	5	2	5	4	9	3	8	1	2	2	9	1	137	51	51	50
5	5	9	1	9	4	8	9	9	7	7	4	9	67	19	21	16
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
96	6	6	2	4	4	8	9	2	2	2	4	3	132	37	47	36
97	2	6	6	3	6	1	9	7	2	2	8	8	127	45	46	46
98	4	9	2	6	4	6	9	1	4	3	9	6	96	52	57	51
99	3	6	4	6	7	3	8	6	5	9	5	4	87	57	60	58
100	3	2	2	1	7	7	1	3	5	9	1	7	103	30	31	28

Note: Due to the large data, this table only shows some representative data.

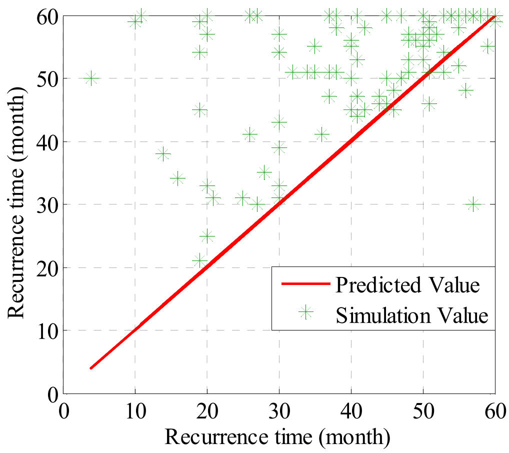

FIGURE 11. Comparison of predicted recurrence time and simulated relapse time.

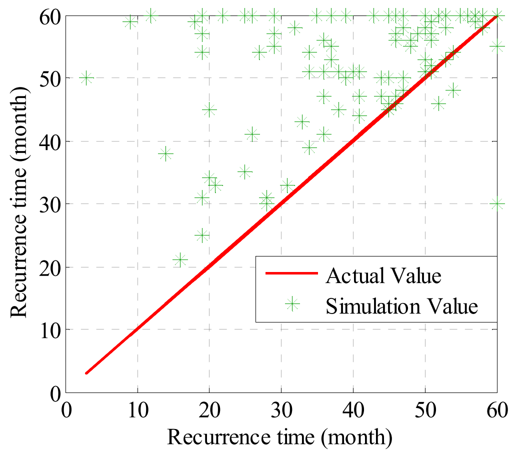

FIGURE 12. Comparison of actual relapse time and simulated relapse time.

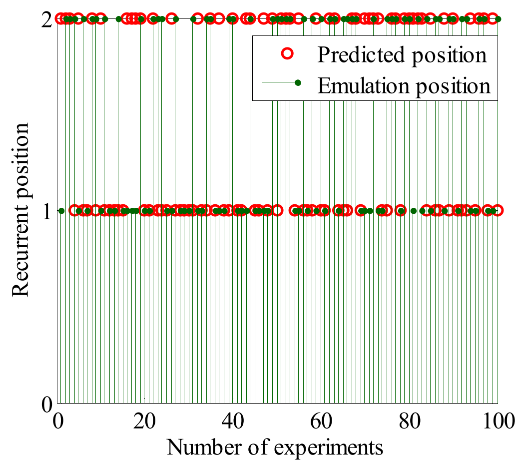

FIGURE 13. Comparison of predicted recurrence position and simulated recurrence position.

and a shortest iteration time of 67s. The convergence speed is very fast.

It can be seen from **Table 6** that the recommended nutrition support plan of the recommendation system is obtained through algorithm calculation and weight allocation. Not the higher the recommended score for each indication, the longer the relapse time of cancer patients, the deeper analysis of cancer rehabilitation The recommendation results of the intelligent recommendation system. Table 6 is visualized, and Fig. 11 to Fig.14 are obtained.

It can be seen from Fig. 11 and Fig. 12 that the recurrence time of the system simulation is significantly better than that of actual liver cancer patients and the time predicted by the prediction model. Among them, 92% of the simulation time exceeded the time predicted by the liver cancer prediction model, and 95% of the simulation time exceeded the actual liver cancer recurrence time. Through experiments, the performance of the intelligent recommendation system for cancer rehabilitation was verified. As can be seen from Fig. 13 and Fig. 14, the actual situation is that 50% of cancer patients relapse in situ. After prediction, 50% of cancer patients still relapse in situ. Finally, the results of system simulation show that 49% of liver cancer patients relapse in situ. From a certain perspective, the intelligent recommendation system has prolonged the recurrence time

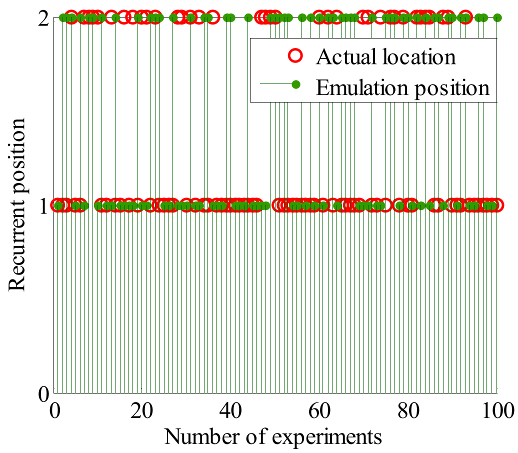

FIGURE 14. Comparison of actual recurrence position and simulated recurrence position.

of patients with liver cancer, and at the same time it has little effect on the location of cancer recurrence. Therefore, it is further affirmed that the intelligent recommendation system is of great significance to prolong the life of cancer patients.

VI. CONCLUSION

In this paper, the CNN algorithm and the BAS algorithm are coupled under the framework of the Internet of Things technology and embedded into the intelligent recommendation system. Based on the historical rehabilitation data provided by cancer patients, experimental simulation tests verify that the intelligent recommendation system has better recommendation performance. Among them, in the case where the predicted recurrence position is almost unchanged (49%), more than 95% of the nutritional support programs recommended by the intelligent recommendation system can prolong the recurrence time of patients. The intelligent recommendation system for cancer rehabilitation based on the Internet of Things technology is an optimal matching system for the rehabilitation nutrition plan needed by cancer patients. This platform can accurately recommend the nutrition support plan required for cancer patients for postoperative recovery. It has certain guiding significance in the field of medical cancer rehabilitation. In the future, we will continue to work on the research of cancer rehabilitation recommendation scheme, combining with more advanced mathematical models, to find the best scheme for cancer patients.

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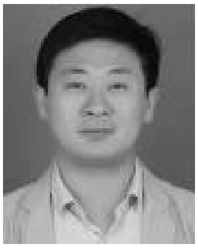

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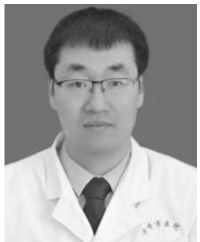

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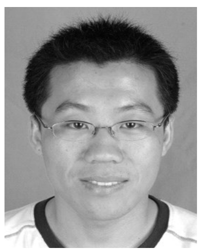

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