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REMOTE INTELLIGENT MEDICAL MONITORING DATA TRANSMISSION NETWORK OPTIMIZATION BASED ON DEEP LEARNING

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Abstract. A hospital operating status evaluation data analysis system was established based on the autoencoder's network. The Gibbs sampling method is used to obtain the approximate distribution of RBM. In addition, the Autoencoder neural network can also select feature dimensions that can better characterize the characteristics of financial operation data from a large amount of financial operation data. Deep learning methods are used to study the redundant information elimination method and the generation mechanism of multi-source heterogeneity in multi-source heterogeneous networks. The principle of intrinsic compression is used to reduce the dimensionality of the redundancy in the network and obtain the compression redundancy objective function. This article sets thresholds for information classification on the Internet. The approach was tested using financial data from a medical institution. Use smart encoders to extract 17 financial indicators from financial data that can be used for modeling. The evaluation results are used as the output vector of the model. Comparative experiments show that the AUC value and accuracy of the method proposed in this article can be improved by 0.84 and 83.33% compared with the AUC value of shallow logistic regression and BP neural network. This algorithm has apparent improvements.

Key words: Deep learning; DBN; RBM; Autoencoder; Network data; Redundant information; Optimization elimination; Medical data mining

1. Introduction. With the advent of the fourth industrial revolution, information on the Internet has also exploded. With the rapid development of big data, medical financial research will also face various challenges. As the scale of data continues to expand, higher requirements are placed on data processing technology. Rapid identification and processing of large amounts of data can efficiently extract useful information from these data. It can improve the efficiency of the financial system operation of medical institutions and provide a robust data basis for the operation and management of medical institutions. Computer processing capabilities have improved dramatically in recent years. The computing speed of classic machine learning methods can no longer meet the needs of practical applications. Due to their better computing power, deep neural networks are increasingly used in industrial fields. Due to the low degree of data structure, high feature dimension, and missing data of current medical financial data, it is challenging to directly apply deep neural networks to medical financial data. Literature [1] proposes a method for eliminating redundant information in network data transmission. This approach is based on grouping data in the network. A dynamic analysis of bimodality and packet characteristics in the network is performed. An algorithm based on sliding windows is proposed to realize the positioning of data grouping boundary points. In network data transmission, the data that is transmitted repeatedly is encoded. However, this method can easily cause the system's operating efficiency to decrease. Literature [2] provides a method to eliminate redundant information based on dynamic lookup tables during network data transmission. In network data transmission, the first-byte value of a data block with a high redundancy rate is selected as a mark. Update dynamic query tables promptly during network data transmission. Select data blocks based on tags in the lookup table. Blocks of redundant information are encoded in the network data that has been sent. Replace redundant information fragments in the original network data transmission with encoded data. This algorithm can effectively improve the average of the data, but it will cause data loss. This paper builds an intelligent analysis and identification system for medical imaging data. The system's data analysis capabilities were tested and analyzed using a hospital's relevant financial data set as an example.

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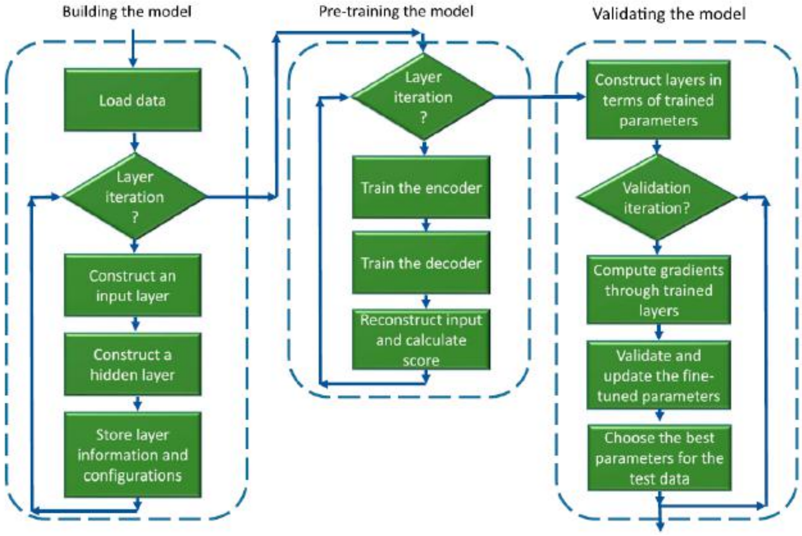

Fig. 2.1: Autoencoder method flow.

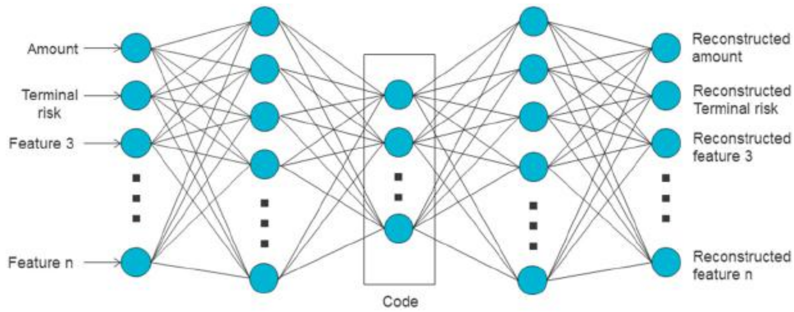

Fig. 2.2: Network architecture of autoencoder.

2. Autoencoder network feature extraction method. This paper uses an automatic encoding machine network for feature extraction. The network extraction process is given in Figure 2.1 (the picture is quoted from A deep learning method for lincRNA detection using auto-encoder algorithm).

Autoencoders can be thought of as unsupervised learning networks. It translates input data into passwords. Finally, the signal is decoded to obtain the final output decoding result [3]. Then, the encoding and decoding parameters are continuously adjusted according to the deviation between the input and the output, and finally, the required output is obtained. Its network structure is shown in Figure 2.2.

Determines the input quantity U with dimension m and the output quantity Y with dimension n. Determine the excitation functions h and f.

$$\begin{aligned} \rho = h(u) = s_h(\kappa u + \alpha) \\ v = f(u) = s_f(\bar{\kappa} u + \chi) \end{aligned} \tag{2.1}$$

where κ is the weight input to the hidden layer. α is the compensation matrix output to the hidden layer. $\bar{\kappa}$ is the weight of the hidden layer and output layer. $\chi$is the bias matrix of the hidden layer and output layer. The activation functions s_h and s_f used in this article are both Sigmoid functions [4]. Ideally, the output layer of Y should be a reproduction of the U data. So the relationship of κ is expressed as follows (2.2):

$$\bar{\kappa} = \kappa^T \tag{2.2}$$

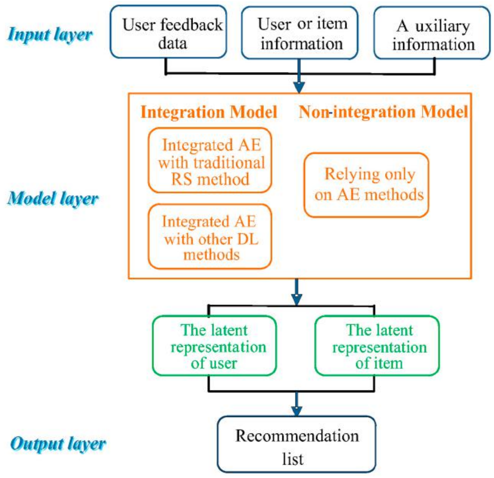

Fig. 2.3: System algorithm flow chart.

To reduce the deviation between input and output, the error distance $\Omega(u, v)$ must be determined. Determine$\Omega(u, v)$ as follows when using the Sigmund function.

$$\Omega(u, v) = -\sum_{i=1}^{n} [u_i \log v_i + (1 - u_i) \log(1 - v_i)] \tag{2.3}$$

The loss function can be determined in terms of $\Omega(u, v)$ in the automatic encoding process. If the training set has the following formula (2.4):

$$D = \{U^1, U^2, \cdots, U^N\} \tag{2.4}$$

Then, the loss function is expressed as (2.5).

$$l(\beta) = \sum \Omega(u, f(h(u))) \tag{2.5}$$

This paper uses the hidden layer of the self-organizing network obtained based on the gradient method. This method can be used as input to a deep learning network [5]. This article combines the DBN and Autoencoder self-encoding networks to construct the system algorithm flow shown in Figure 2.3 (picture cited in Mathematics 2023, 11(8), 1777). First, the required relevant medical data needs to be reprocessed. The Autoencoder method is used to realize automatic extraction of data. The extracted features are used for the training of deep neural networks. Finally, experiments were conducted on the established neural network, and the experimental results were verified.

3. Application of optimization removal principle in redundancy in network data transmission. A random sampling method based on wavelet transform is proposed [6]. It reflects the sample point distribution u_i and its uncertainty λ_i during the data transmission process in the network. Q^+, Q^- represents the average of the positive and negative values of the data sampling set D during network data transmission. $\beta^T = Q^+ - Q^-$ is the average vector of positive and negative values in the data sampling set during the network data transmission process, then the hyperplanes passing through the two categories of Q^+, Q^- can be expressed by formula (3.1)

$$\begin{cases} \beta^T (u_i - Q^+) = 0 \\ \beta^T (u_i - Q^-) = 0 \end{cases} \tag{3.1}$$

Use equation (3.2) to calculate the distance s_{i+}, s_{i-} between the sampling points in the positive and negative classes of data sampling in network data transmission and the hyperplane in the corresponding class.

$$\begin{cases} s_{i+} = \beta^T(u - Q^+)/||\beta|| \\ s_{i-} = \beta^T(u - Q^-)/||\beta|| \end{cases} \tag{3.2}$$

$S_+ = \max\{s_{i+}\}$ and $S_- = \max\{s_{i-}\}$ represent the farthest distance between the sample points in the positive class and the sample points in the corresponding class during the network data transmission process. β represents the standard vector element. Equation (3.3) can be used to determine the fuzzy coefficient

$$\lambda_i = \begin{cases} -1 + 2e^{-In2/(S_+ + \xi s_{i+})} \\ -1 + 2e^{-In2/(S_- + \xi s_{i-})} \end{cases} \tag{3.3}$$

ξ is the conversion factor. Because each feature of the data sample in the analyzed network data transmission contributes differently to the classification accuracy, it is necessary to use the feature validity h_t^iin the network data transmission to classify each feature of the sample [7] accurately. Quantify the correlation of rates. The data training sample set in the network data transmission under test is denoted as C. The total number of data samples in network data transmission is represented by $|D|$. Assume that there are m types of data sample sets in network data transmission $\sigma_i (i = 1, 2, \cdots, m)$, then $|\sigma_1| + \cdots + |\sigma_m| = |D|$. In any network data transmission, if the possibility that a sample is related to class σ_i is $P_i = |\sigma_i|/D$, then the information entropy of the data sample set D in network data transmission is:

$$Info(D) = -\sum_{i=1}^{m} P_i \log_2(P_i) \tag{3.4}$$

Assume that feature t_i in any network data transmission can divide the data training sample set D in network data transmission into $D = \{D_1, D_2, \cdots, D_q\}$. During network data transmission, D_i contains the number of samples $|D_i|$. Then, equation (3.5) can express the conditional entropy of t_i line classification in network data transmission.

$$Info_{t_i}(D) = \sum_{i=1}^{m} |D_i|/|D| Info(D) \tag{3.5}$$

Use the information of characteristic t_i in network data transmission to increase by $Gain(t_i)$ to represent the change in entropy:

$$Gain(t_i) = Info(D) - Info_{t_i}(D) \tag{3.6}$$

In the process of network data transmission, the feature vector $F = (Gain(t_1),\ Gain(t_2), \cdots, Gain(t_n))$ reflects the effectiveness of each feature. The feature validity in network data transmission can be defined by formula (3.7)

$$h_i' = (Gain(t_i)/\sum_{i=1}^{n} Gain(t_i))e^{Gain(t_i)} \tag{3.7}$$

$e^{Gain(t_i)}$is the conversion factor. On a specific network, when attribute t_i has a more considerable amount of information, it has a more significant impact on category $Gain(t_i)$. The feature validity matrix P in network data transmission describes the feature validity of n features of the sample.

$$P = (h_t^1 \cdots h_t^n) \tag{3.8}$$

h_i' represents the characteristic effect of the data characteristic when the i network data is transmitted. Among them, Z is the core function of FSVM. P is the $n\prime$ class characteristic performance matrix for network data transmission. The kernel function for the effectiveness of data characteristics in the network is

$$Z\prime(u_i, u_j) = Z(u_i^T P, u_j^T P) \tag{3.9}$$

$u_i^T P$ is the representation of the eigen normal vector matrix at the i transmission. $u_j^T P$ represents the eigen normal vector matrix at node j. This paper chooses the radial basic kernel function. where η is the characteristic concentration of the kernel function. Equation (3.10) can be used to express the characteristic effectiveness kernel function $Z\prime$ in network data transmission:

$$Z\prime(u_i, u_j) = \exp(-\eta||u_i^T P - u_j^T P||^2) = \exp\{-\eta(u_i - u_j)P \cdot h_t^i\} \tag{3.10}$$

Feature validity h_t^i is low during network data transmission, the $i$bit characteristics of data sampling have a lower impact on the performance kernel during network data transmission [8]. This shows that the intrinsically valid kernel function can avoid the influence of features with strong correlations or redundant features in some network data transmission processes.

4. Optimal method to remove redundant information in network data transmission.

4.1. Reconstruction based on phase space and feature extraction of network redundant information. i'^{th}represents the i' packet sent by the network. Its essence is to segment the packets transmitted by the block data chain in a static state. Data of various sizes can be obtained through this method. Map redundant data in the network into a high-dimensional space. t_0 represents the initial value processing of boundary characteristics in the network. t_f is the number of steps iteratively processing boundary features in the network in high dimensions. This article will reconstruct the phase space of the redundant information in this network [9]. Assume that the length of the information flow time series during the transmission of network redundant information is N. The limited network data set U is divided into σ categories. The reconstruction of network structure redundant information in phase space is expressed as follows:

$$\begin{aligned} &U = [u(t_0), u(t_0 + (Z-1)\Delta t)] = \\ &[u(t_0) \cdots u(t_0 + (1 + (\bar{m} - 1)l)\Delta t) \cdots u(t_0 + (N-1)\Delta t)] \end{aligned} \tag{4.1}$$

$u(t_0)$is the redundant data pattern of the timing-based network structure. l represents the space partitioning scale, which is used to reconstruct the redundant information of the network in phase space. $\bar{m}$represents the network redundant information reconstruction embedding dimension. This project intends to perform feature extraction on the constructed high-dimensional phase space. $U = (u_1, u_2, \cdots, u_{\breve{n}}) \subset R^s$ is a restricted set of vectors obtained when processing redundant information in the network [10]. Network information is obtained in U by shape vectors spanning network data. The information of the network is a finite element group containing $\breve{n}$ sample values. Using u_i as the sampling point, the network is sampled for redundant information. Use (4.2) to express the high-dimensional eigenvectors in the state space

$$u_i' = (u_{i1}, u_{i2}, \cdots, u_{is},)^T \tag{4.2}$$

The method based on entropy value is used to process the redundant information of multi-dimensional data. Redundant information encoding vectors are classified into category σ. Obtain the data's clustering center by characterizing and compressing the data.

$$B = \{b_{ij\prime} | i = 1, 2, \cdots, \sigma, j\prime = 1, 2, \cdots, s\} \tag{4.3}$$

$b_{ij\prime}$ is the processing of the disturbance vector $j\prime$ when processing the redundancy information. A multi-source data clustering method based on SVD is proposed. The obtained decomposition results are expressed as follows

$$A = \{\mu_{ik} | i = 1, 2, \cdots, \sigma, k = 1, 2, \cdots, n\} \tag{4.4}$$

μ_{ik} stands for decomposed elements. Determining the network redundancy indicator function based on sparse representation

$$l(A, B) = \sum_{k=1}^{n} \sum_{i=1}^{\sigma} \mu_{ik} (c_{ik})^2 \tag{4.5}$$

$\ddot{m}$ represents the weighted weight. μ_{ik} represents the weight of the split factor μ_{ik}. $(c_{ik})^2$ represents the Euclidean distance between network sampling points u_k and $b_{ij\prime}$ that contain redundant data. (4.1) is analyzed in the case that $\sum_{i=1}^{\sigma} \mu_{ik} = 1$ is satisfied. The objective function is maximized to obtain the compression of the feature space of network redundant information.

$$\begin{cases} \mu_{ik} = 1/(\sum_{j=1}^{\sigma} (c_{ik}/c_{jk})^{(2/m-1)}) \\ b_{ij\prime} = (\sum_{k=1} (\mu_{ik}) u_k)/(\sum_{k=1}^{n} (\mu_{ik})) \end{cases} \tag{4.6}$$

Initial values with perturbation vectors are given. A data extraction method based on a fuzzy index c_{jk} is proposed.

4.2. Eliminate redundant information during data transmission. s refers to the number of categories of redundant information in the network. $\{c_1, c_2, \cdots, c_s\}$is a set of network redundant information feature types [11]. The redundant information characteristic coefficient in the network is obtained through equation (4.8)

$$\begin{aligned} JH(u) = &\sum_{k=1}^{s} P(c_k) InP(c_k) + P(u) \sum_{k=1}^{s} P(c_k|u) InP(c_k|u) \\ &+ P(\bar{u}) \sum_{k=1}^{s} P(c_k|\bar{u}) InP(c_k|\bar{u}) \end{aligned} \tag{4.7}$$

$P(c_k)$ is the proportion of type c_k network data in all network data. $P(\bar{u})$ is the proportion of all network materials with characteristic u. $P(c_k|u)$ is the proportion of redundant information containing attribute u in class c_k. Set up the feature matrix. A represents the characteristics of redundant information in the network, which can be calculated using equation (4.9).

$$Y = (y_{\omega k})_{N\prime \times Q} \times p_{\omega} \tag{4.8}$$

$y_{\omega k}$ is the weight of attribute ω in the redundancy data set of network data. Q represents the number of samples in the redundancy data. $N\prime$ represents the data characteristics in the network redundant information sampling set [12]. Set the probability that a redundant information feature ω is included in a network data sample k to $f_{\omega k}$. The value of $y_{\omega k}$ can be solved by equation (4.10)

$$y_{\omega k} = \begin{cases} 1 & f_{\omega k} > 0 \\ 0 & f_{\omega k} = 0 \end{cases} \tag{4.9}$$

The weighting of the redundant information characteristics of the network can be obtained by Equation (4.10). The corresponding weights describe the impact of different network redundant information characteristics on the classification of redundant information. First, standardize the redundant information properties in the network

$$\delta = f_{\omega k} \times In(Q/c_k) \Bigg/ \sqrt{\sum_{k=1} [f_{\omega k} \times In(Q/p_{\omega})]^2} \tag{4.10}$$

p_{ω} is the probability occupied by the network redundancy information characteristic B of the sample group. Therefore, accurate classification parameters for network redundant information can be obtained according to the processing result of equation (4.11).

5. Method implementation.

Table 5.1: Model input characteristics.

Feature name	Input variables	Feature name	Input variables
current ratio	x1	cash flow ratio	x10
cash ratio	x2	Assets and liabilities	x11
Assets and liabilities	x3	Equity Multiplier	x12
Tangible net worth debt ratio	x4	debt service coverage ratio	x13
Fixed asset turnover rate	x5	Interest coverage ratio	x14
Sub-asset turnover rate	x6	Inventory turnover	x15
Current asset turnover ratio	x7	revenue growth rate	x16
return on assets	x8	total assets growth rate	x17
return on equity	x9		

Table 5.2: Influence of the number of nodes in the first hidden layer and the second hidden layer.

h1 number of nodes	Accuracy (%)	h2 Number of nodes	Accuracy (%)
27	62.7	15	69.0
25	64.0	14	72.7
23	66.0	13	70.9
21	65.8	11	74.6
19	64.8	10	78.6
17	64.6	8	71.8
15	65.9	7	71.0
13	64.5	6	70.1

5.1. Data preprocessing. This project plans to integrate deep learning and autoencoding networks to build a new deep learning system. And use it to conduct intelligent analysis of medical financial information. This article takes a large hospital as an example to verify this method. Our goal is to evaluate the performance of this system for data analysis [13]. This data collection contains 154,688 financial data for a certain period. The hospital's operating status is evaluated through the analysis of financial data during each unit period. The evaluation is divided into two categories: good operation and poor operation. This article adopts an evaluation method based on weekly financial statement data of each hospital. The autoencoder neural network was used to classify 17 image features by analyzing the original data. Feature categories are listed in Table 5.1.

The 17 economic indicators listed in Table 5.1 can reflect the financial indicators of the hospital. The evaluation system covers operating costs, profitability and prospects for future development.

5.2. Simulation results. Corresponding parameter selection must be made before conducting simulation experiments. Among them, the number of input, input, and hidden layer nodes are the most critical parameters [14]. In this algorithm, the number of nodes in the input layer is related to the eigenvalues. The number of hidden layers and the number of nodes in each layer are the main factors affecting network performance. Too many layers and nodes in the network will significantly impact processing performance when the network's depth is insufficient. This method will have over-adaptation problems during learning, which will have a particular impact on the generalization ability of experimental data. This paper uses hierarchical experiments to calculate the number of nodes in each network layer. Table 5.2 and Table 5.3 illustrate the impact of different numbers of hidden layers and the number of hidden layer nodes on the modeling results.

In the case of 22 nodes, the model can achieve the best accuracy of 66.04%. When the number of nodes is 10, the system can obtain the best accuracy of 78.65%. When adding the third hidden layer, the optimal solution of the algorithm dropped from 83.33% to 81.98%. The network structure is relatively complex, and over-adaptation can occur during learning [15]. The network's performance combined with the autoencoder was evaluated through comparative experiments. Detailed results are listed in Table 5.4.

Table 5.4 shows the data results obtained by several shallow machine learning methods. Compared with the

Table 5.3: Influence of the number of nodes in the third and fourth hidden layers.

h3 number of nodes	Accuracy (%)	h4 number of nodes	Accuracy (%)
11	77.3	9	77.3
10	76.3	8	76.3
9	78.2	7	80.9
8	83.3	6	82.0
7	75.2	5	75.4
6	76.1	4	72.1
5	77.1	3	77.3
4	74.1	2	76.3

Table 5.4: Network parameters.

Network parameters	AUC	Accuracy (%)
LR	0.60	63.75
Random Forest	0.74	77.40
BP Network	0.74	64.90
The algorithm of this article	0.84	83.33

shallow method, the AUC value of the method proposed in this article is increased to 0.84, and the Accuracy value is increased to 84.38%. However, the random distribution model that currently performs best in shallow machine learning has an AUC value of only 0.74 and an Accuracy value of 77.40%. The algorithm in this article has improved by 0.10 in AUC and 5.94% in accuracy. Both indices have improved significantly.

6. Conclusion. This project proposes an automatic extraction method for financial big data based on autoencoding networks. Comparative experiments show that the medical financial data processing method based on deep neural networks and redundant data elimination has achieved significant results.

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