A Neural Network Method for Systematic Evaluation of Informatization Development Level in Smart Court Construction

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Abstract

The systematic evaluation of informatization development level (IDL) is an evaluation that follows the development trend of digitization, networking and intelligence, and focuses on the formation of business capabilities of informatization. Research on informatization evaluation methods has been extensively studied by both domestic and international academics over the years. However, traditional evaluation methods suffer from flaws like complex mechanism design, unreliable metric conversion, difficulty obtaining the relative importance of indexes, complex evaluation process, and high computational volume. This paper attempts to introduce the neural network method into the information system evaluation, and uses the Extreme Learning Machine (ELM) algorithm to establish the evaluation model. The evaluation of the smart court system is used as an example to simulate and test the model, and the results show that the neural network-based evaluation model of informatization system is more applicable to large-scale evaluation indexes, and by continuously increasing the learning samples, it objectively improves the accuracy of evaluation, effectively avoids human subjective factors, and has the advantageous features of advanced, accurate and convenient.

Keywords: Informatization, Systematic evaluation, Neural network, Model

1 Introduction

With the development of a new generation of information technology, informatization has gradually developed into a systemic stage, turning from a technical means tool into an indispensable mode of production and life for human beings, and endowing all walks of life with new business capabilities. The evaluation of the information system follows the development trend of digitization, networking, and intelligence, and places more emphasis on forming a business capability evaluation of the informatization. It focuses on the evaluation of the compatibility of business systems, the data sharing and integration, the in-depth applications, intelligent and flexible customized services, and information security capacity, with a stronger system, integrity, flexibility, operability [1].

At present, the more commonly used traditional informatization evaluation methods mainly include data envelopment analysis, analytic hierarchy process, gray fuzzy association, principal component analysis, factor analysis and cluster analysis [2]. Fu, Zhu and Liu employed principal component analysis for the study of enterprise informatization evaluation model, which uses the loadings of the original indexes and the common factor variance value to calculate the index weights to reflect the contribution of each index to the principal component [3]. Jing, Mao and Wang applied the grey correlation method to analyze the association degree between industrialization and information of Shanxi Province [4]. Zhang proposed the establishment principle of statistical informatization evaluation indexes, established a hierarchical statistical informatization evaluation index system, used analytic hierarchy process to determine the weight value of each evaluation index, and gave the specific index weight determination process and the calculation method of the quantitative results of comprehensive evaluation of statistical informatization [5]. Wang and Lin applied the Fuzzy Analytic Hierarchy Process (FAHP) and Association Rule Mining methods to evaluating e-Learning systems. A hierarchal structure of evaluation criteria was established [6].

Although all types of traditional evaluation methods have a relatively complete theoretical basis and can be used for informatization system assessment and evaluation, each method also has drawbacks and limitations of its own. The analytic hierarchy process relies more on experts for qualitative analysis, and experts' subjective judgments, choices, and preferences have a great impact on the results, and errors in judgment of objective laws are very likely to cause errors in decision-making [7]; the gray fuzzy association evaluation method makes extensive use of human subjective judgments, which is not suitable for application to complex problems and cannot solve the problem of duplication of evaluation information caused by correlation of indexes [8]; data envelopment analysis calls for large amounts of data, numerous calculations, clumsy operations, lacks horizontal comparability, and produces not very instructive results [9].

The neural network algorithm can reflect the pertinent features in the weights of the interconnection between neurons because it has nonlinear characteristics, strong fitting

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and prediction abilities, and only requires appropriate training data for model training in the application. Additionally, after inputting the actual problem feature parameters, the mapping relationship can be more accurately trained between the input index data and the final evaluation results, and is widely used in comprehensive evaluation methods for research [10]. This study designs a neural network-based assessment model of information technology system for evaluation scenarios with high data dimensionality and heterogeneous data. It aims to solve the shortcomings of traditional evaluation methods, including complex mechanism design, unreliable measurement conversion, difficulty determining the relative importance of indexes, complex evaluation process, and significant amount of calculation. With this skill, we may train the evaluation model flexibly using the experts' evaluation experience, thereby achieving the goal of autonomous and intelligent evaluation. When the model has been trained, it can be quickly deployed to the server, with low deployment cost and easy operation.

2 Evaluation Model Design

2.1 Systematic Evaluation Model Framework Design

The evaluation model is designed based on the hierarchy of the index system, assuming that the index system is two-level, with a total of m first-level indexes and n second-level indexes, and the high-dimensional second-level indexes are directly processed and the first-level index scores are output. After obtaining the scores of the first-level indexes, the final evaluation results are obtained by combining the traditional evaluation algorithm for weighted fusion. Using the neural network-based information system evaluation model, the model framework is shown in the following Figure 1, which primarily consists of two steps:

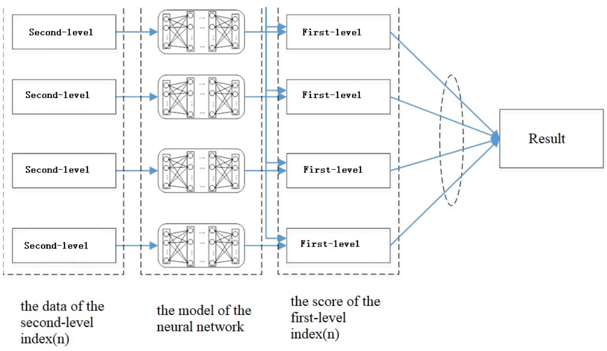


Figure 1. Evaluation model based on the neural network

The first step is based on neural network for the prediction of the first level index score. For each first-level index, the data of its second-level indexes are used as input data into the neural network and the score of the first-level index is output. For the evaluation scenario, there are m first-level indexes, n second-level indexes, and the number of second-level indexes in each first-level index, which is the data dimensions, are n_1, n_2 ......, n_m. When the number of n is large it is suitable for processing using neural networks.

The second step is based on weighted evaluation for first-level index fusion. After obtaining the scores of the first-level indexes, weighted fusion can be performed directly to obtain the final evaluation scores. The weight value can be given directly by experts based on the actual evaluation criteria, or can be obtained by a certain mechanism.

In the traditional scenario, the n-dimension data can be directly input into the neural network to get the final evaluation score directly. However, this study adopts predicting the first-level index scores first and then performing weighted fusion to obtain the final evaluation score results, the main reasons for which are:

(1) Each expert scores only one first-level index and then performs the fusion, which fully utilizes the experts' subjective professional experience and prevents the experts from producing evaluations that are inaccurate due to the intricacy of the data they must deal with. Additionally, it permits the fusion of the first-level indexes using objective assessment algorithms to obtain the results.

(2) The advantage of scoring only the first-level index is that when revising the evaluation system, only the part to be revised needs to be re-scored, and the scores of the first-level indexes of other parts are not affected, which significantly reduces the cost of model revision.

2.2 Evaluation Process Design

A neural network method for systematic evaluation of informatization mainly contains two processes: data collection and model training. The specific steps are shown in the Figure 2:

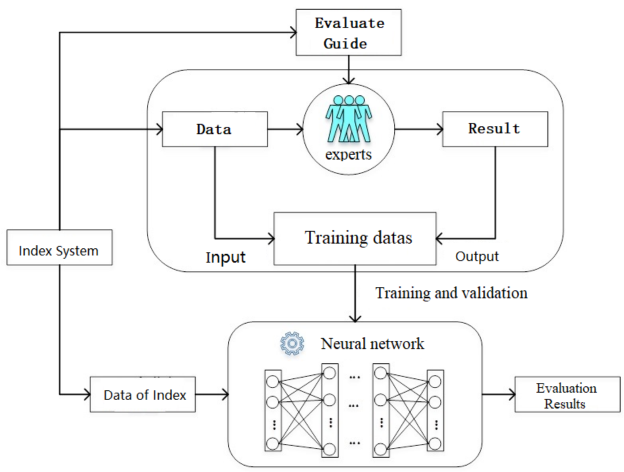


Figure 2. Evaluation flow based on the neural network

(1) Establishing the index system and collecting index data: A set of suitable IDL indexes is established according to the actual situation of the evaluation object. The index system serves as the foundation for the overall evaluation. Before the model training, a fundamental index system must be constructed and a substantial amount of index data must be gathered.

(2) Design of evaluation guidance: Before the experts conduct the evaluation, a certain process needs to be designed to standardize the evaluation process. The main contents

of the evaluation guide are: the necessary information description for each index, the accompanying index score calculation method, the corresponding index and the description of the index. At the same time, an evaluation flow chart is given to guide experts in scoring the indexes after the index data is given. When designing the evaluation guide, it is important to present fair and impartial justifications; no misleading information, circumstances that could skew the experts' opinions, etc., should be included.

(3) Training and validation of the neural network model: After obtaining more than sufficient training data, the neural network algorithm is trained using the gradient descent method to obtain the mapping relationship between indexes and evaluation results, and the model can automatically give output results after new inputs are given.

(4) Model revision: The evaluation model may not be set reasonably enough and needs to be adjusted according to the actual needs, so the evaluation model may need to be revised in the subsequent process. When the model is revised, the expert scores of the corresponding indexes need to be adjusted, and the overall evaluation results are further adjusted.

3 Design of the Systematic Evaluation Model Based on Neural Network

3.1 Data Collection and Pre-processing

The index data required for IDL are collected through various ways. Since the index dimensions are relatively large and the number of evaluation objects is large, the collected data must be pre-processed, which is primarily done in the links below.

(1) Data cleaning processing: According to the meaning of the IDL index to determine the valid range of its data, the data are cleaned item by item, and data that are not within the valid range, data collection with missing items and apparently without distinction are eliminated.

(2) Numerical conversion: Numerical conversion is performed for selective data and text data. When it is "Yes/No", it is converted to Boolean data, and when it is text data, it is converted to numerical data.

(3) Data normalization: The neural network is sensitive to the order of magnitude of the input data, and the data are normalized to the 0-1 interval to improve the reliability of the neural network model because of the large differences in the data levels of the second-level indexes.

3.2 Neural Network Algorithm Design

Traditional neural network learning algorithms (like the BP algorithm) require artificially setting a large number of network training parameters, which have the problems of easily falling into local extremes, slower speed of convergence, difficulty in determining the number of nodes in the hidden layer and difficulty in selecting the number of learning samples [11]. The Extreme Learning Machine (ELM) algorithm in neural networks was proposed by Huang et al. of Nanyang Technological University, Singapore, using a learning algorithm based on a single hidden layer feedforward network [12]. This algorithm uses a randomized method to determine the weights and biases between the input and hidden layers, and an analytical method to further determine the weights of the output layer. ELM algorithm overcomes many shortcomings on traditional neural network algorithms, such as getting into local extrema, inappropriate learning rate, and slow learning speed [13]. The advantage of the extreme learning machine algorithm is that only the number of nodes of the hidden layer of the network needs to be set, the input weights of the network and the bias of the hidden layer neuron do not need to be adjusted manually during the execution of the algorithm, and only one unique optimal solution is generated, avoiding the process of repeated iterations [14]. Therefore, compared with the traditional neural network model, the Extreme Learning Machine model has a faster training speed and better generalization ability [15].

The principle of the ELM is shown in the Figure 3.

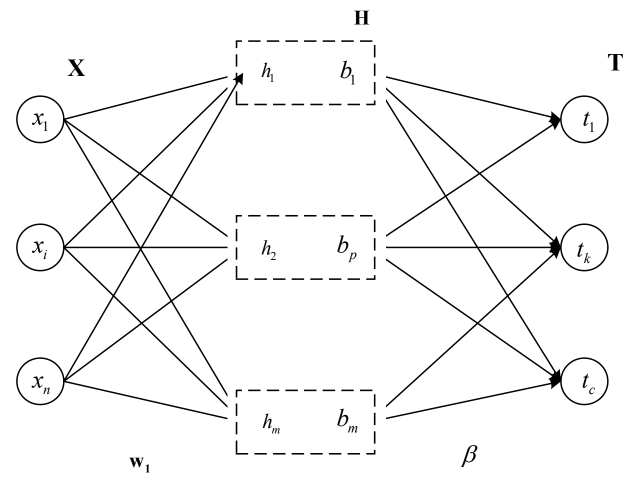


Figure 3. Principle of the ELM

The ELM learning model is shown in the figure. The learning process is as follows:

Step 1: Normalize the data. This research will normalize the data to the interval [0, 1].

Step 2: Determine the number of hidden layer neurons m. Randomly generate the input layer weights. The random number distribution is a uniform distribution with mean 0 and the interval of weights is [-1, 1].

Step 3: Calculate the output of the hidden layer of the network, by a nonlinear function. The expression of the hidden layer output is

$$H = h(Xw + b). \quad \textbf{(1)}$$

where X is the sample data, b is the bias, $h(\bullet)$ is the activation function, and the following sigmoid activation function is used in this study.

$$h(x) = \frac{1}{1+e^{-x}}. \quad \textbf{(2)}$$

Step 4: Add bias to the output of the hidden layer and calculate the output layer weights. The learning output layer weights are the following regularized learning model.

$$\min_{\beta} \|\beta\|^2 + C\|H\beta - T\|^2. \tag{3}$$

where β is the weight of the regularization constraint, the larger β is, the more obvious the constraint is, and C is the number of nodes in the output layer. In this application, the sample size is large. The solution for the output layer weights is

$$\beta = (\frac{1}{C} + HH^T)^{-1} H^T T. \tag{4}$$

Step 5: Calculate the output of the test data, the formula is

$$Y = h(x)\beta. \tag{5}$$

4 Simulation and Testing

4.1 Smart Court Systematic Evaluation Index Design

By using the smart court as an example, this study simulates and tests the evaluation model of the informatization system based on neural networks. Since 2017, Chinese Courts have deeply promoted the construction of the smart court, and the preliminary formation of the smart court featuring networking, publicity and intelligence has strongly promoted the modernization of the trial system and trial capacity [16]. Based on the principle of combining rationality, scientificity, purposefulness and operability, a set of comprehensive effectiveness evaluation index system has been designed. The system has included: foundation support (found), networking (net), publicity (pub), and intelligence (intel) with a total of 4 first-level indexes and 103 second-level indexes. The foundation support mainly covers the indexes of informatization infrastructure construction and operation; the networking mainly covers the indexes of trial, execution, letter and visit, judicial management and data management based on the network; the publicity mainly covers the indexes of judicial openness, litigation service and judicial publicity of court business for the parties, lawyers and the public; and the intelligence mainly covers the intelligent indexes of core business such as trial, execution and litigation.

4.2 Evaluation Model Test Training Experiments

In this experiment, the data of 97 courts were used as input data, and the corresponding first-level score data were used as output results to train their respective neural network models. The sample number of data was 97, and model training randomly selected 87 of the samples as training data and the remaining 10 samples as test data.

The model parameters were set as shown in the following Table 1:

Table 1. The model parameters of the first-level index

First-level index	Mix score	Model parameters
Found	6	$N = 500, C = 10$
Net	20	$N = 1500, C = 0.1$
Pub	19	$N = 1500, C = 0.1$
Intel	12	$N = 1000, C = 1$

The prediction performance of the model uses the mean-square error, which is used to measure the deviation between the observed and predicted values. The smaller the value of deviation, the better the accuracy of the prediction model in describing the experimental data. By using different sample numbers of training to train the neural network, the output samples are set to have errors of $y1$, ..., y_N, whose corresponding mean-square error is calculated as:

$$e = \frac{1}{N}\sum_{i=1}^{N}(y_i - \overline{y})^2. \tag{6}$$

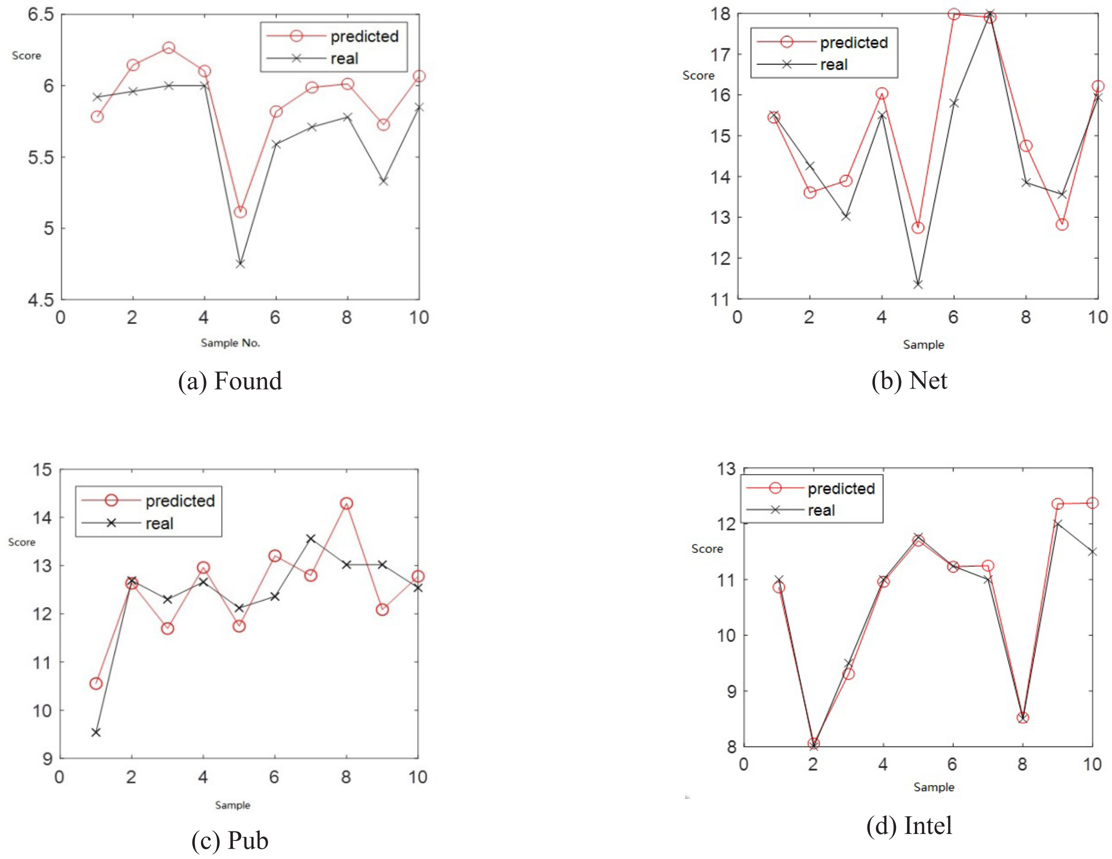
Where $\overline{y} = \frac{1}{N}\sum_{i=1}^{N} y_i$ denotes the mean of the sequence y_1, ..., y_N.

By using data from 87 courts in province F for model training and testing the model with sample data from another 10 courts, the mean-square error performance was calculated as shown in Table 2. According to the data in the Table 2, the intelligent index value, which is the most accurate model, is 0.3516. The networked index value, which is likewise a more accurate model, is 1.0778. (E value less than 2 can be considered as more accurate model). This demonstrates that the trained neural network-based smart court evaluation model has a certain accuracy.

Table 2. Mean-square error performance

Mean-square error	Found	Net	Pub	Intel
e	0.4820	1.1617	0.3619	0.1236

The following Figure 4 shows the simulation comparison of the performance test using the test sample data of 10 courts in province F. The four figures respectively correspond to the four first-level indexes, the red ones are the data predicted by the model, and the black ones are the real data in the actual court informatization evaluation, from which it can be seen that the smart court evaluation model has a good fitting effect.



(a) Found (b) Net

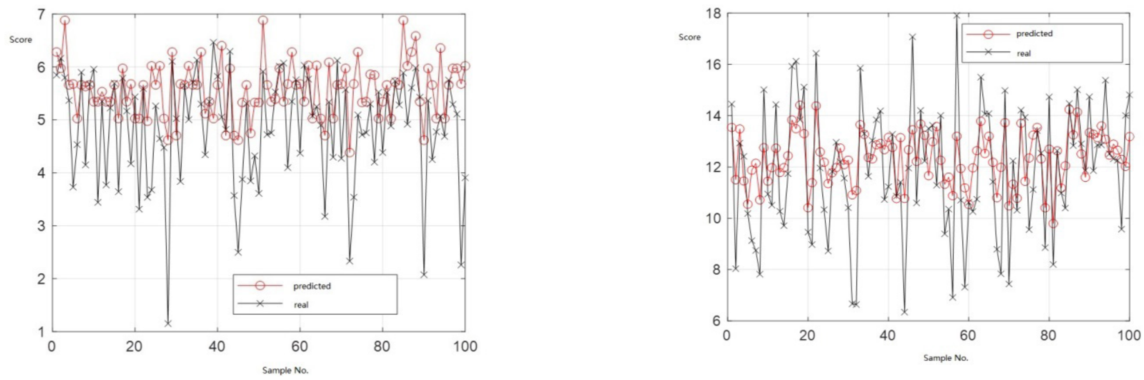
(c) Pub (d) Intel

Figure 4. Comparison between the real and the predicted result

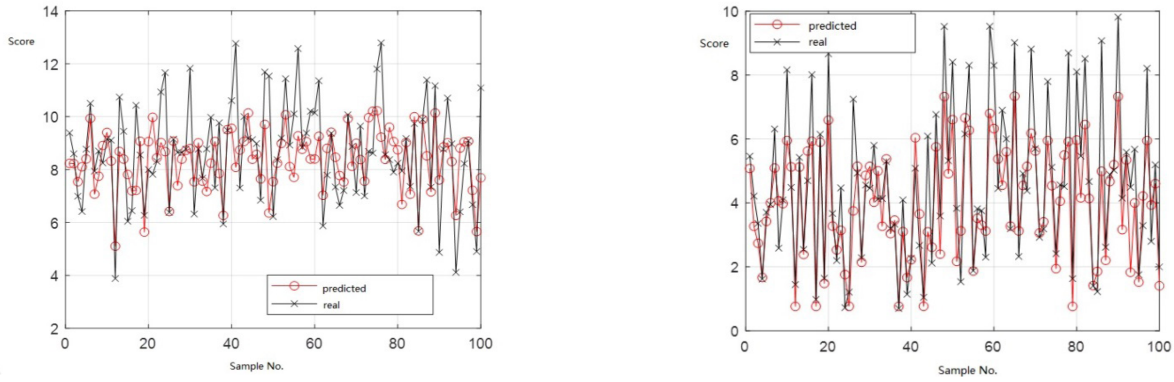
From the above 4 figures, it can be seen that the neural network model has good prediction ability and can achieve prediction results with less error when the training sample data size is less than 100.

4.3 Accuracy Validation of Neural Network-based Evaluation Model under Different Samples

By adjusting the number of training samples, the gap of model prediction accuracy is observed. Assuming the number of training samples N=10 and N=100, both test samples of 100 examples are equally selected to observe the prediction error values. When the number of training samples is 10, the prediction results of the four first-level indexes of basic support, networking, publicity and intelligence for 100 test samples are shown in the figure, and the mean-square errors are 0.862, 1.965, 1.536 and 1.160, respectively.The mean square error in Figure 5 is 0.699, 1.354, 0.932, and 0.737. The variability between the prediction results and the actual results is large, which shows that the prediction performance of the neural network is poor when the training samples are too small.



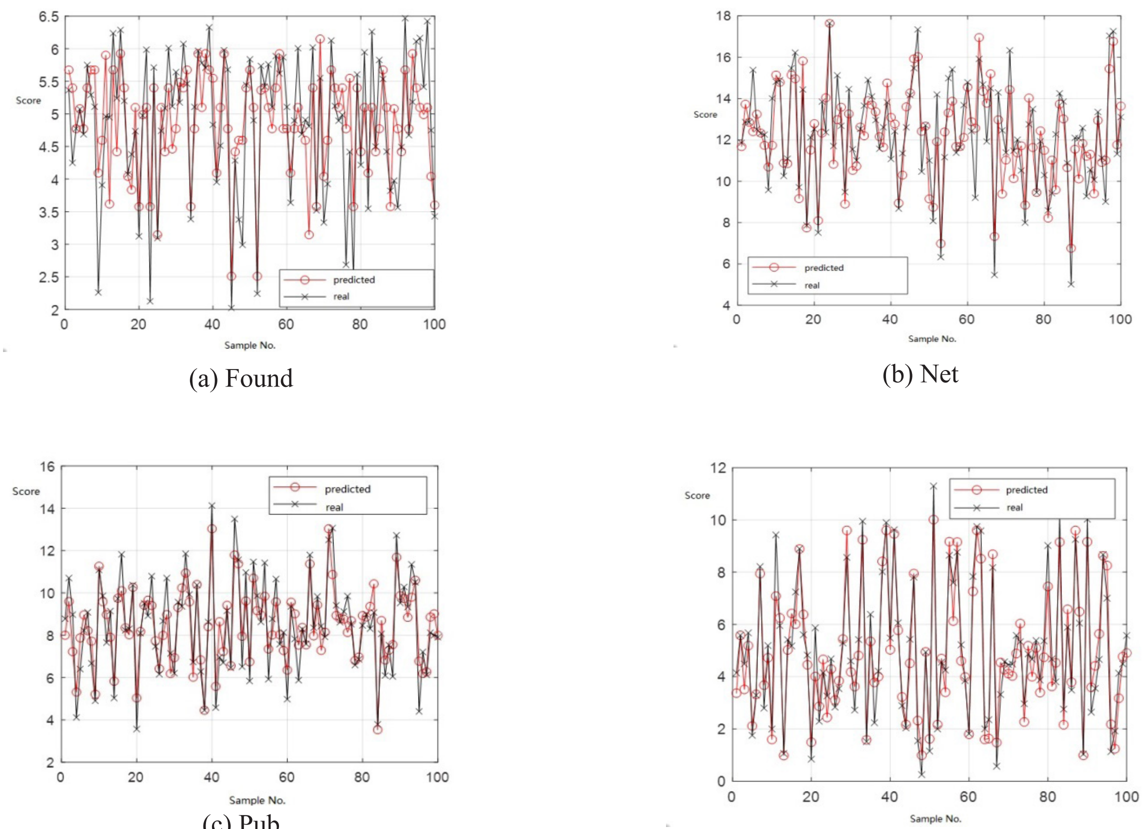
(a) Found (b) Net



(c) Pub (d) Intel

Figure 5. The prediction results of neural network for 100 samples (training samples N=10)

When the number of training samples is 100, the mean-square error of the four first-level indexes is 0.699, 1.354, 0.932, and 0.737. As Figure 6, it can be seen that when the number of training samples increases to 100, the prediction results are seen to be extremely near to the real index scores, indicating that the neural network already has good prediction performance at this time and is more practical.



(a) Found (b) Net

(c) Pub (d) Intel

Figure 6. The prediction results of neural network for 100 samples (training samples N=100)

In order to test the trend of the prediction performance of the algorithm under different training samples, the number of training samples is gradually increased from N=10 to N=200, and its prediction mean-square error change curve is shown in the Figure 7. It can be observed that with the increase of the number of training samples, the prediction ability of the neural network is gradually enhanced, as manifested by the gradual decrease of the prediction mean-squared error. And it can be observed that as the number of training samples gradually increases, the trend of decreasing mean-square error gradually weakens, indicating that the prediction model tends to be stable. In order to improve the prediction ability of the model, the number of training samples can be further increased. Overall, at N=200, the neural network model already has a smaller error and has a relatively strong practicality.

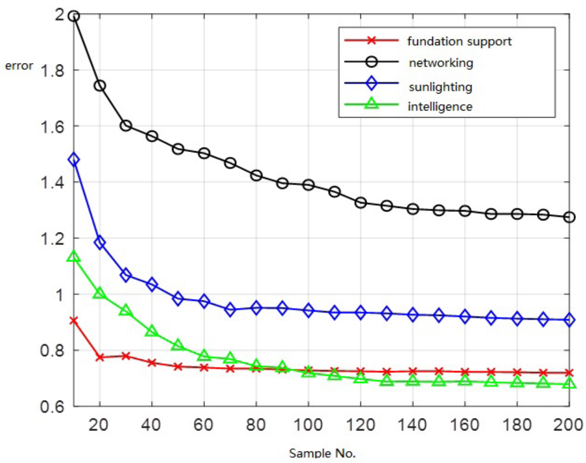


Figure 7. Curve of prediction mean square error

5 Conclusion

The study of smart court evaluation through neural network model has mainly drawn the following conclusions:

(1) The neural network-based IDL model is more applicable to the information technology evaluation with a large scale of index system and heterogeneous index data. The training process of the evaluation model is more convenient, and it can flexibly apply the evaluation experience of experts to train the model. The trained model can be quickly deployed to the server, which greatly reduces the workload, improves the evaluation efficiency and accuracy, and realizes the intelligence of the IDL.

(2) The neural network-based IDL model has strong prediction ability, the model can effectively avoid the human subjective factors in the evaluation process, and the error of the model keeps decreasing with the increase of the number of training samples of neural network. Objectively, the accuracy of the evaluation is improved, making the applicability of the evaluation model more extensive, and the prediction ability of the model can be improved by further increasing the number of training samples.

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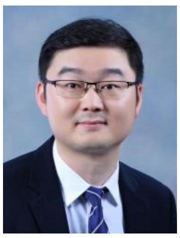

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