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Bioinformatics-Based Modeling and Prediction of the Effects of Heavy Metal Drugs on Acute Liver Toxicity

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Abstract: - Heavy metal pollution can cause a series of diseases, especially the liver, which becomes the main target of toxicity. In order to be able to accurately predict the effects of heavy metals on the liver, this paper is based on bioinformatics firstly, the pollution level of heavy metals and the effects on the liver were analyzed, and the relationship between the characteristics of heavy metals and the liver was derived. Secondly, the toxicity of heavy metals was tested to get the toxicity content in different heavy metals. Finally, a toxicity prediction model was established based on the toxicity data to facilitate the analysis of the effects of heavy metals on the liver and to reduce the hazards of heavy metals on the human body. The analysis was carried out in three parts: prediction accuracy, prediction model performance and the effect of heavy metals on the liver, and it was concluded that the prediction ability of the model was better, and the values of the mean squared error and the root squared error were smaller, around 0.483 and 0.161, which indicated that the actual value was similar to the test value, and the comparison found that the heavy metal Cd had a greater effect on the function of the liver, and the value of the alanine aminotransferase was increased to 0.47, which can show the complete the concentration of toxicity and the effect on the liver.

Keywords: Heavy metal contamination; Bioinformatics; Liver; Toxicity testing; Predictive modeling

1. INTRODUCTION

In the field of chemistry, heavy metals are unique existences, which are used in various fields due to their own characteristics and efficacy, but as the heavy metal environment continues to aggravate, it has a certain impact on human health and causes a series of diseases [1-2]. The liver is an important organ for metabolism and detoxification in the human body, and is often used to eliminate toxins from the body, thus becoming a major target for heavy metal substances. In order to reduce the toxicity of heavy metals to the liver, bioinformatics is used to predict and model the toxicity of heavy metals [3-4]. Bioinformatics is mainly a collection of data such as proteomics, transcriptomics and genomics, which is used to study the toxicity and performance of drugs through machine learning and other methods, and to show the relationship between drugs and organisms. Simulating and predicting the effects of heavy metals on the liver through bioinformatics technology can not only reduce the cost of experiments, but also find out the threat of heavy metals to the liver in time, avoid the human body from being harmed by heavy metals, and provide the direction for the treatment of liver diseases, which is of high research value and practical value [5].

In analyzing the treatment effect of hip fracture, Sun, Y. et al. collected samples containing heavy metals and tested their contents to obtain heavy metal data. According to the content of heavy metals, a light gradient was designed to predict the relationship between heavy metals and liver, and according to the experiments, the results of the toxicity prediction model were more accurate and in good agreement with the actual measurements,

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which can be used in real life to remind people of heavy metals and improve the safety of people's lives [6]. Algarni, S. et al. collected soil or other materials with heavy metals and used reflectance spectroscopy and artificial intelligence to calculate the results of heavy metals. The concentration and content of heavy metals were calculated using reflectance spectroscopy and artificial intelligence methods. Based on the calculated concentrations, artificial neural networks were used to predict the toxic effects of heavy metals on the liver and to protect people in time. From the experimental analysis, the constructed model analyzed better and reduced the effects of heavy metals on people [7]. Sang, L. et al. collected liver cells and samples containing heavy metals, combined liver cells and heavy metals together to obtain the toxic effects of heavy metals on liver cells. Using machine learning algorithm to build a prediction model to evaluate the toxicity effect on the liver, according to the test concluded that the model can complete the analysis of the toxicity of heavy metals, and the results are more comprehensive [8]. Kong, M. et al. studied the toxicity of heavy metals to the liver in different environments and developed a model to predict the effects of heavy metal toxicity on the liver, and the results showed that the model can better alert people to the levels of heavy metals and reduce the threat to people's lives [9]. Ju, Y. et al. collected substances containing heavy metals and evaluated the toxicity of heavy metals to obtain the toxicity content of heavy metals. Based on the toxicity content, a model was developed to assess the effect of heavy metals on liver toxicity and analyzed to obtain the effect of heavy metals on the liver. The performance and effect of the model was tested by using multiple linear regression, and it was concluded that the prediction results of the model were more accurate and suitable to be widely used to reduce the risk of people [10]. Roy, J. et al. collected heavy metal substances and used the collected heavy metals on liver cells to observe the effect of heavy metals on liver cells, and based on the results obtained, the toxicity prediction model was constructed by using integrated learning to obtain the adverse effects of heavy metals on the liver, so as to remind people to pay attention to heavy metal substances and reduce the harm of heavy metals to people [11]. Wang, X. et al. carried out research and analysis of heavy metals to obtain the content of toxicity in heavy metals, and the effects of heavy metals in different concentrations and under different conditions. Based on the obtained data, a model was established for analyzing the effect of heavy metals on the liver, predicting the content of toxicity, and at what concentration it causes disease to the liver, affecting human health and life safety, the model is more effective and the results are more comprehensive, providing a new direction and idea for analyzing heavy metals [12].

In this paper, firstly, the concepts and sources of heavy metals were analyzed to obtain the contamination of heavy metals and the effects of heavy metals on the liver. Secondly, the toxicity of heavy metals was tested to obtain the concentration of heavy metal toxicity and related elements for subsequent modeling. Finally, based on the toxicity concentration of heavy metals, a prediction model of the toxicity of heavy metals was established, which was used to evaluate the amount of toxicity in heavy metals and the effect on human liver. The damage and harm of heavy metals to the liver and the effects of different concentrations of heavy metals on the liver can be fully demonstrated, reminding people to pay attention to the emission of heavy metals and avoiding the threat of heavy metals to human health. It can provide new treatment directions and ideas for patients suffering from liver diseases and enhance the cure rate of liver diseases.

2. CHARACTERISTICS AND HAZARDS OF HEAVY METALS

2.1 Concept of heavy metals

In general, heavy metals are metallic substances with a density of about 4.0 or 5.0, and are categorized into more than 60 different types, including mainly metallic elements such as Pb, Hg, Ag, Cd and As, as well as elements that contain toxic substances. Although heavy metals contain toxic substances, they are also micronutrients for biological activities. Can, in recent years, pollutants of heavy metal substances have gradually spread into the environment, contaminating soil and rivers with heavy metals, thus posing a threat to human health [13-14].

In the daily environment, the source of heavy metals can not be separated from two ways, one is naturally occurring, the other is generated in human production and life, and the anthropogenic generation of heavy metal pollution is the highest degree. Heavy metals produced by human factors mainly include domestic waste, metal smelting and ore mining, etc. The pollution of heavy metals is long-lasting, wide-ranging and highly toxic. If it reaches a certain value in the human body, it will cause harm to the human body, causing anemia, nerve tissue anomalies, Parkinson's syndrome, muscle stiffness, and even cancer. Heavy metals have and amplify biological effects and are easily bioconcentrated, both heavy metals in the environment at low concentrations, but also have a certain impact on crops, thus posing a threat to human life and health, affecting people's daily life and diet.

At present, heavy metal pollution is more serious, the soil and rivers have been threatened by heavy metals, according to the survey, there have been thousands of meters of farmland has been contaminated, resulting in a substantial loss of nutrients in the land, its own purification capacity declined. The crops cultivated on the polluted land are consumed and absorbed by the human body, which puts people's health at risk, resulting in a large number of diseases. According to the data show that the economic loss due to heavy metal pollution has reached 20 billion yuan, food pollution reached more than 10 million tons, in the harm to the economy and food at the same time, but also on the human body caused specific harm. The heavy metal testing of the rivers shows that the internal pollution rate of the rivers is around 80%, the heavy metals in the Yellow River system and the main stream of the Huaihe River have exceeded the standard by 16.7%, and the heavy metals in the Suzhou River have exceeded the standard by 75%. This proves that heavy metal pollution has reached a very serious level, which has a serious impact on human health.

2.2 Effectiveness of heavy metals

The degree of contamination or the form of reaction of heavy metals with organisms is called bioefficacy, which is usually used to indicate the degree of uptake of heavy metals by organisms and the toxic effect of heavy metals on organisms [15-16]. The effect of heavy metal release and enrichment in the sediment environment is caused by a variety of factors, including the stability of the environment, the substance of the sediment and the pH of the environment, etc. In addition, the factors affecting heavy metals are as follows:

(1) Heavy metals in precipitates usually have different chemical forms, and the forms of heavy metals are generally closely related to potential toxicity, biological effectiveness and migration. The exchange and carbonate states of heavy metals are more easily absorbed and are subject to environmental influences. The organic form is difficult to be absorbed and cannot be utilized, being present only in precipitates, while the ferromanganese oxidation state is more sensitive to potential. Under certain conditions, the various metal states can transpire with each other into non-toxic or more toxic states.

(2) The chemical properties of the precipitates contain substances such as sulfides, clay minerals and organic carbon that can be volatilized, which can affect the toxic effect of heavy metals by regulating the content of these forms, so the chemical properties of the precipitates affect the toxicity concentration.

(3) The equilibrium relationship of heavy metals is related to the metal concentration of particles in the interstitial water and the concentration of dissolved heavy metals, and the interstitial water solution in the precipitates will unfold the change of the toxic content of heavy metals in the precipitates, which affects the toxicity concentration and the effectiveness in heavy metals.

(4) Due to the different varieties between plants and their own characteristics, there are differences in the absorption capacity of heavy metals, even for the same type of plant, the effect of heavy metal absorption is not the same, and the effectiveness of heavy metals will be affected. At the same time, the environment of the plant

also has an effect on heavy metals, the molecules secreted in the root system of the plant have soluble organic acids, which can activate the trace heavy metal elements in the sediments and enhance the effectiveness of heavy metals.

2.3 Relationship between heavy metals and liver

In recent years, due to the increasing heavy metal pollution, the effects on the human body, especially the liver, have become more and more severe, causing irreversible damage. More and more attention has been focused on the role of trace elements in the formation of liver cancer. According to research findings, heavy metals and liver cancer development have a great relationship, in the absence of other viral infections, people's daily life if the concentration of heavy metals in drinking water is more than 300g/L, will cause people to develop cirrhosis of the liver and hepatitis and other diseases, causing damage to the liver. If a large number of people in the population are infected with hepatitis virus, heavy metal concentration of 100g/L or more will cause cirrhosis of the liver. And if humans consume water containing heavy metals for a long period of time, it increases the lethality of liver cancer [17]. Meanwhile, according to the research, among heavy metals, heavy metal manganese is an element needed in human body, and high manganese intake in diet will reduce the prevalence of liver cancer. According to the data, liver cancer patients have lower levels of iron and zinc in their bodies, which indicates that iron and zinc have a preventive effect on liver cancer and reduce the chance of developing liver cancer. It can be seen that heavy metals have serious effects on the liver.

3. HEAVY METAL TOXICITY PREDICTION MODEL

3.1 Heavy metal toxicity test

In today's era, there are many ways to test the toxicity of heavy metals, mainly including chronic toxicity test, algal toxicity test and luminescent bacteria acute toxicity test, according to the analysis of several ways can be concluded that the luminescent bacteria acute toxicity test for testing the toxicity of the test has a more sensitive and accurate results for the purpose of testing toxicity, which is more sensitive to the contamination of heavy metals [18].

Luminescent bacteria mainly belong to Gram-negative and anaerobic bacteria, with length and width between 0.4 and 1.0 and 1.0 and 2.5 respectively, and the types of luminescent bacteria are shown in Table 1. Under normal circumstances, luminescent bacteria can emit blue-green light around 450 to 490 nm if their physiological conditions are normal, and their luminescence is relatively stable. In the natural environment, there are many types of luminescent bacteria, but the luminescence mechanism is similar, the light emitted by the luminescent bacteria is its own metabolism produced by oxidation reaction, which is caused by long-chain aliphatic aldehydes and flavin mononucleotides. In the presence of oxygen molecules and oxidizing enzymes in the environment, flavin mononucleotide and long-chain aliphatic aldehydes will produce oxidation reaction, and emit fluorescence. After contacting with toxic substances, the intensity of light emitted by the luminous bacteria will change, which is related to the concentration of toxicity. Therefore, the luminous bacteria can test the toxicity of heavy metals, and determine the concentration of toxicity of heavy metals according to the size of the light emitted.

Table 1 Types of luminescent bacteria

Genus (taxonomy)	Habitat	Name
Vibrio	Marine	Vibrio harveyi
		Vibrio fischeri
	Non-marine	Vibrio vulnificus
Luminescent bacilli	Marine	Vibrio brilliantus

		Vibrio fischeri
		Vibrio mandaricus
Heterobacillus	Non-marine	Vibrio luminescens

3.2 Heavy metal toxicity prediction modeling

Based on the above process, the amount of toxic substances in heavy metals can be measured accurately, and this can be used to build a toxicity prediction model to test the effects of heavy metals on the liver.

The deep network approach is utilized to build a model for predicting toxicity as a way to reduce the threat to the human body. The main process of modeling in the deep network approach is to construct a learning model with gate control units and add a noise penalty term to the loss function of the model using the regularized damage function to reduce the noise of the data, train the data in the model, and obtain the final results [19-20].

3.2.1 Application of the GRU model

The GRU model in regular loss function has good effect and performance for prediction, which can be divided into two gates in GRU, which are reset gate and update gate. Figure 1 shows the GRU process, the reset gate is used to control the degree of forgetting of the previous moment, and the update gate is mainly used to control the degree of state information from the previous moment to the current state.

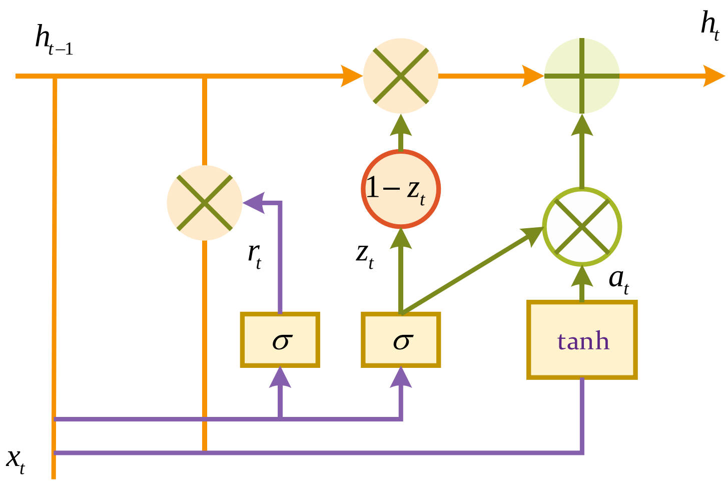

Figure 1 GRU flow

The forward propagation calculation is unfolded for the parameters in the cell according to the GRU structure as follows:

$$z_t = \sigma\left(W_z x_t + h_{t-1}U_z + b_z\right) \tag{1}$$

$$r_t = \sigma\left(W_r x_t + h_{t-1}U_r + b_r\right) \tag{2}$$

$$a_t = \tanh\left(W_a x_t + U_a\left(h_{t-1} * r_t + b_a\right)\right) \tag{3}$$

$$h_t = \left(1 - z_t\right) * h_{t-1} + z_t * a_t \tag{4}$$

where x_t represents the input value at moment t, r_t represents the decay function of the reset gate, h_{t-1} represents the state vector at moment $t-1$, h_t represents the state vector at moment t, z_t represents the decay function of the update gate, W_r, U_r represents the weight of the reset gate. W_a, U_a represents the weight of a_t, W_t, U_z represents the weight of the update gate, * represents the multiplication, σ represents the activation function, tanh represents the activation function of tan, and b_z, b_r, b_a represents the bias vector.

The GRU model will overfit linearly with the elements in the heavy metals when training is launched on the data, which reduces the generalization ability of the model and has an impact on the prediction results of the model, so the overfitting phenomenon needs to be avoided [21]. The GRU model is mainly designed to limit the parameters in the model, so the overfitting phenomenon will be avoided as long as a noise-smoothing loss function is added to the model as in the following equation:

$$\min\left|\frac{1}{N}\sum_{i}^{N}\left|y_i-\hat{y}_i\right|^2+\beta\left\|P_y\right\|\right| \tag{5}$$

Where, y_i is used to represent the predicted value, $\hat{y}_i$ represents the true value, P_y is the matrix used to measure the smoothing of the data, N represents the amount of input data, β is used to represent the regularization and $\min$ is used to represent the minimum value.

The added noise smoothing loss function consists of two parts, a measure of how well the data are fitted and a measure of how well the data are smoothed, where the fit is expressed using the form of the mean error, and the smoothing is expressed as a P_y -parameter, with β representing regularization, which can be used in-between the fit and the smoothing.

Expanding the computation for P_y is a key step in setting up the smoothing loss function, which is preceded by determining the matrix P, which is given by the following equation:

$$P=\begin{bmatrix} -1 & 2 & -1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & -1 & 2 & -1 \end{bmatrix} \tag{6}$$

Where the dimension of matrix P is related to the value of the input data, if the length of the input data is T, the dimension of matrix P is (T,T). Using matrix P and the input data can be formed into matrix P_y to get the paradigm of the degree of data smoothing.

3.2.2 Forecasting model optimization

When training the data in the model, the loss function is set to reduce the phenomenon of overfitting, reduce the influence of noise on the model, and provide the predictive ability of the model.

In order to make the performance of the prediction model more stable, the parameters in the deep network are optimized, which mainly include the neural elements, the number of training times and the optimizer.

The Bayesian optimization method is used to optimize the model parameters, selecting the appropriate evaluation points according to the fitting results, defining the objective function $g(w)$, and according to the objective function, finding the appropriate parameters for optimization, the specific equation is:

$$g(w)=\sqrt{\frac{\sum_{i=1}^{m}\left(y_i(w)-\hat{y}_i\right)^2}{m}} \tag{7}$$

Where, $g(w)$ represents the objective function, $\hat{y}_i$ represents the true value, m represents the amount of input data and $y_i(w)$ represents the predicted value.

The function for Bayesian optimization is as follows:

$$w^* = \arg\min_{w\in W} g(w) \tag{8}$$

where w represents the input parameters, W represents the multidimensional parameter space, and w^* represents the optimal parameters.

The Bayesian optimization is divided into two parts, one is to estimate and update the Gaussian process using step $t+1$, and the other is to sample the parameters using the maximizing proxy function, setting the Gaussian distribution of the objective function $g(w)$ as:

$$g(w) - GP\left(\mu(w), K(w,w')\right) \tag{9}$$

where $\mu(w)$ represents the mean of the objective function, $K(w,w')$ represents the variance matrix of the objective function, GP represents the distribution of the Gaussian, and the initial $K(w,w')$ is as follows:

$$K=\begin{bmatrix} k(w_1,w_1) & \cdots & k(w_1,w_i) \\ \vdots & \ddots & \vdots \\ k(w_i,w_1) & \cdots & k(w_i,w_i) \end{bmatrix} \tag{10}$$

where K represents the variance matrix, i represents the number of parameters w, and $k(w_1,w_1)$、$k(w_1,w_i)$、$k(w_i,w_1)$、$k(w_i,w_i)$ represents different combinations of parameters of the matrix.

When the parameters of the model are optimized using Bayesian optimization, the variance matrix of the Gaussian process changes according to the iterations, and let the input parameter of step $t+1$ be w_{t+1}, the variance matrix is as follows:

$$K'=\begin{bmatrix} K & k^T \\ k & k(w_{t+1},w_{t+1}) \end{bmatrix} \tag{11}$$

where K represents the initial covariance matrix, k represents the combinatorial matrix of parameters w, K' represents the covariance matrix at the moment of $t+1$, w_{t+1} represents the parameters at the moment of $t+1$, k^T represents the transpose of k, and the combinatorial subequation of k is $k=\left[k(w_{t+1},w_1),k(w_{t+1},w_2),\cdots,k(w_{t+1},w_t)\right]$ to obtain the a posteriori probability of the function P as:

$$P\left(g_{t+1} \middle| \theta_{t+1}, w_{t+1}\right) - N\left(\mu_{t+1}(w), \sigma_{t+1}^2(w)\right) \tag{12}$$

where θ_{t+1} represents the observed data in step $t+1$, $N(a,b)$ represents the Gaussian noise, $\mu_{t+1}(w)$ represents the average value of the objective function in step $t+1$, w_{t+1} represents the parameters in step $t+1$, and $\sigma_{t+1}^2(w)$ represents the variance of the objective function in step $t+1$.

After completing the a posteriori probability, the parameter search method is utilized to find the optimal parameters as follows:

$$w_{t+1} = \arg\max S\left(w \middle| \theta_t\right) = \arg\max \mu_t(w) + \zeta_{t+1}^2 \sigma_t^2(w) \tag{13}$$

Where w_{t+1} represents the parameter of step $t+1$, $S\left(w \middle| \theta_t\right)$ represents the acquisition function, ζ_{t+1} represents the constant, $\mu_t(w)$ represents the mean of the objective function, and $\sigma_t^2(w)$ represents the variance of the objective function.

According to the above process, the prediction of heavy metal toxicity can be accomplished, and the effects of heavy metal toxicity on the liver can be analyzed to reduce the damage of heavy metals to the human body.

4. BIOINFORMATICS-BASED IMPACT MODELING AND PREDICTION

4.1 Preparation of the study

In order to be able to more intuitively see the model prediction of heavy metal toxicity and analyze the impact of heavy metal toxicity on liver disease, it is necessary to carry out the test. The test instruments are shown in Table 2, and the main instrument ultra-clean bench was selected from Hangzhou Purification Instrument Company.

Table 2 Test Instruments

Instrument Name	Affiliated Companies
Ultra-clean bench	Hangzhou Purification Instrument Company
Electrothermal constant temperature water bath	Beijing Changfeng Instrument Factory
vulgar centrifuge	Hunan Xiangyi Instrument Equipment Company
Fluorescence microscope	Japan Olympus
Micro pipette	Eppendorf, Germany
Automatic Enzyme Labeler	Thermo Forma, USA
Microshocker	Beijing Haidian Electronic Medical Instrument Factory
Electronic Analytical Balance	Beijing Sartorius Instrument Systems Inc.

The reagents are shown in Table 3, 8.5 g of NaCI, 0.5 ml of pure acetic acid, 1000 ml of distilled water, 4% paraformaldehyde, 1.5% agarose gel, 0.01 M citrate buffer, blocking solution, TBS buffer, TBST buffer, 10% SDS solution, and protein electrophoretic transfer solution are required to be prepared prior to the experiment.

Table 3 Reagents

Name	Company
Hanks Powder	Hyclone Corporation of America
Fetal Bovine Serum	Gibco USA, Inc.

Trypsin	Gibco, USA
Goat Anti-Rabbit Secondary Antibody	Abcam UK
Rabbit Anti Monoclonal Antibody	Abcam, UK
Cadmium Oxide	Sigma, USA
Paraformaldehyde	Tianjin Damao Chemical Reagent

4.2 Toxicity prediction analysis

The analysis of toxicity prediction is mainly used to measure the accuracy of the model for the prediction of toxicity, the predicted toxicity and the actual toxicity values are very consistent, whether it can accurately predict the effects of heavy metal toxicity on the human liver. Whether the generalization ability of the model is accurate, if the predicted value of the model and the real value are almost the same, then it proves that the toxicity prediction model's prediction results are more accurate and comprehensive, and can meet the actual needs, so it is necessary to carry out a test of the model's prediction ability, and the performance of the prediction model is shown in Figure 2. Nineteen heavy metal elements were selected as research objects, and 16 of them were ranked according to the model. According to the results, it can be seen that the predicted and actual values of the model are almost the same, and the prediction results of the real and predicted values are on a line, and even when both the real and predicted values are 50, the two kinds of overlap, and the accuracy of prediction is high. The analysis of the effect of toxicity on the liver can be accomplished to reduce the probability of people's exposure to heavy metals, which provides a therapeutic way to treat liver diseases and ensure the health of the human body.

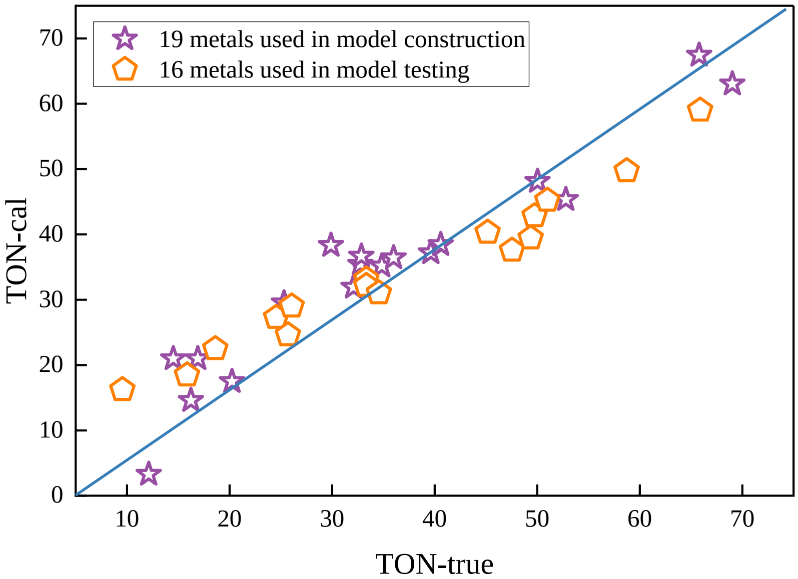

Figure 2 Predicting model performance

4.3 Model performance analysis

The performance analysis of the prediction model is mainly used to measure the performance and level of the prediction model, responding to the error value of the model and the stability of the model prediction, and whether it can get a more accurate prediction value under any conditions, so as to reduce the harm of heavy metals to the human body and improve human health. The prediction performance of RNN model, LSTM model and deep network model is analyzed, and Table 4 shows the prediction model performance. The prediction performance of the deep network model is better, and the values of the mean squared error and root squared error are smaller, around 0.483 and 0.161. It proves that the deep network prediction model has less error and is similar to the actual measurements, and can accomplish the prediction of toxicity with high stability. And because the noise smoothing function is added to the deep network model, it has the function of reducing the noise, so that the model will have more accurate results no matter what environment. While RNN model and LSTM model have higher values of root variance and mean squared error, which are 0.541 and 0.924, 0.362 and 0.567, respectively.It shows that the two models have higher error, the prediction results are not accurate, and the stability of the model is poor, which will be affected by the environment, resulting in the results of the test are different.

Table 4 Predictive model performance

Models	Statistics	Roots Variance	R-value
RNN Models	0.924	0.541	0.852
LSTM Models	0.567	0.362	0.993
Deep network model	0.483	0.161	0.998

4.4 Effects of heavy metals on the liver

The Heavy Metals on Liver Test can be used to measure the abnormalities caused by heavy metals on the liver, assess the extent of liver damage by heavy metals, and the accumulation of heavy metals in the body. At the same time, it provides new ideas and directions for treating liver diseases and improving the cure rate of liver diseases. Table 5 shows the effects of heavy metals on the liver, heavy metal Cr has low damage to the liver, but heavy metal Cd has a greater impact on the function of the liver, resulting in the value of alanine aminotransferase is elevated to 0.47, which will affect the health of the human body, resulting in the decline of liver function and cirrhosis of the liver and other diseases, which are harmful to the human body. Heavy metal Cr has a greater correlation with the total bilirubin of the liver, with a correlation value of 0.59, which proves that it has a greater impact on the total bilirubin of the liver, which has a certain impact on the human body, thus causing a series of diseases and affecting the human body's health.

Table 5 Effects of heavy metals on the liver

Name	Heavy metal Cr	Heavy metal Cd
Alanine aminotransferase (ALT)	-0.67	0.47
Aspartate transaminase (AST)	1.14	-0.43
Albumin (ALB)	-0.72	-1.12
Globulin (GLB)	0.43	-0.02
Total Bilirubin (TBIL)	0.00	0.59

5. CONCLUSION

This paper analyzes the concepts and hazards of heavy metals, obtains the main sources of heavy metals and the current situation of heavy metal pollution, and the effects of heavy metals on the liver. Toxicity tests were conducted on heavy metals and a toxicity prediction model was developed from the test results to predict and simulate the effects of heavy metals on the liver. The prediction effect, prediction performance and the effect of heavy metals on the liver were analyzed to analyze the accuracy of the model prediction, and it was found that the prediction ability of the model was better, and the values of the mean squared deviation and the root squared deviation were smaller, around 0.483 and 0.161, which proved that the prediction results of the model were similar to the actual results. And because the model kind of noise smoothing parameter is used, 19 kinds of heavy metal elements are selected as the research object, and the toxicity of 16 kinds of them are ranked, and the two kinds of overlap when both the real value and the predicted value are 50. So the stability of the model is better and can be predicted in any environment without affecting the predicted results. The establishment of the toxicity prediction model reduces the effects of heavy metals on human beings, ensures the safety of human lives, and provides a new way to treat liver diseases.

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