

Retraction

Retracted: The Effect of Temperature on Intestinal Flora Imbalance Based on Time Series Prediction Model

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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Research Article

The Effect of Temperature on Intestinal Flora Imbalance Based on Time Series Prediction Model

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A series of effects caused by temperature change are the biggest problems faced by biological systems. These irregular environmental characteristics have brought new challenges to people and even animal groups. The immune function of human intestinal flora has a great protective effect on other organs and the body environment. It can help the human body carry out intestinal digestion, food absorption, nutritional metabolism, and so on. Based on the above situation, this paper uses the time series prediction model to study the factors affecting the imbalance of intestinal flora in the process of temperature change. Firstly, biological experiments are carried out with animals to simulate the human environment. Based on the sequence information of historical temperature change parameters, a temperature prediction device based on time series model is proposed. The effects of air factors and carbon dioxide content on the prediction results are evaluated by statistical analysis. Secondly, in order to ensure the accuracy of the experimental data, the neural network algorithm is used to optimize the model, and the white blood cell count is used to analyze the influence of temperature change on the intestinal flora structure of the two organisms. Finally, the experimental results are applied to the human environment to analyze the research results. The results showed that with the irregular change of temperature, the number of intestinal flora and internal colony structure also changed. The richness index in the normal temperature environment is relatively large, which can effectively explain the high richness of intestinal microflora in the experimental population. Further analyze the subjects and distinguish the animals according to sex. The number of Bacteroides in the intestinal flora of male animals was higher than that of female animals, but this phenomenon disappeared immediately after physical ligation. In addition, the intestinal flora abundance of female animals is higher than that of male animals, and the metabolic level is faster.

1. Introduction

The internal environment of the human body is composed of various flora. Intestinal flora can ensure the digestion and absorption of food and the promotion of metabolism in daily life [1]. With the irregular change of external temperature, climate poses a great threat to the survival and development of organisms. How to explore the influence of temperature on the number, structure, and state of flora is a common research topic for scholars all over the world [2]. Therefore, based on the above situation, the time series prediction model has become one of the means to solve the current problems. It can calculate and process massive data, obtain effective information, and accurately predict the development trend of the research object [3]. At present, the generated data exist in the form of a certain sequence, and the conventional sequence reflects the prediction function in the statistical model. According to the development process of time series, this quantitative estimation can solve the problem of information diversity [4]. However, the data processed by the time series model is relatively large, and the internal structure of the system is relatively complex; so, the prediction function needs to be continuously improved [5].

The time series prediction model has two forms: single structure and combined structure. According to the attribute division, it can be determined as combined and noncombined

state [6]. Each prediction model has its own obvious problems, which need to be further optimized and improved in combination with various big data technologies. The first thing to be solved is the accuracy of the model processing data. Whether the prediction results are accurate or not can directly affect the effectiveness of the experimental results [7]. We can select data and restructure the model structure for different experiments. Secondly, as for the noncombinatorial prediction model, the improvement of fuzzy time series algorithm mainly tends to the establishment of fuzzy matrix [8]. Finally, whether the prediction model is reasonable and effective and whether it can be directly applied to solve problems. We found that the multiangle parameter representation of the data can judge the prediction level and then complete the detection of the prediction model [9]. According to the above analysis of the time series prediction model, we also need to combine various biological experimental data in the study of intestinal flora imbalance. The temperature environment simulation scene is used to control the external humidity, internal humidity, temperature supercooling, temperature overheating, and other conditions during the experiment [10]. Liu et al. explore the changes of food intake and physical fitness data of the subjects in the animal experimental group with each degree of temperature rise. Environmental elements such as oxygen content and carbon dioxide content in the environment are added to the prediction model to study their impact on the temperature prediction curve [11]. Sheng et al. use the time series prediction model to simulate the experimental environment, create irregular changes in temperature under various conditions, and analyze the internal correlation of the experimental data. Thus, the experimental environment is changed to ensure the accuracy and effectiveness of the research results [12]. Huaixiang and Kai using the spotted lizard and mouse as the two-way comparative data of animal experiments and the effects of temperature changes on the number, structure, and state of intestinal flora were explored, respectively [13]. Finally, combine the experimental results with the characteristics of human intestinal flora, further sort out and analyze the research results, and judge the specific factors affecting the imbalance of intestinal flora.

2. Application Status of Time Series Prediction Model in Various Countries

The field of time series research is proposed by British scientists, which is transformed from the regression variable model [14]. Subsequently, Swedish scholars made targeted improvements to the automatic regression mobile operation to form a time series average model in a flat mode, which can basically realize the decomposition and classification of data calculation [15]. With the increasing number of research papers on this discussion, the time series model also became a hot research content in various countries at that time [16]. Among them, the average moving time series that can process dynamic data has become a representative in the prediction model because of its wide application [17]. Zeng et al. proposed a modular temperature prediction method based on the autoregressive moving average model. The ARMA method requires historical and current temperature

data of IGBT module, obtains temperature time series through uniform sampling, and constructs the autoregressive (AR) model [18]. With the advent of the era of big data, the proportion of data in the experiment is increasing. The complexity of the time series structure in the process of processing dynamic disordered data makes the experimental results change more. However, the traditional time series model has computational defects due to the increase of data [19]. Therefore, we optimize the structure of the model, and the combined prediction model gradually replaces the original sequence. The combined forecasting model is to integrate multiple calculation methods into the same structure. Analyze and predict the sample set by using the function vertical and horizontal expansion [20]. The improved calculation results of this combination mode have a significant improvement in performance. That is to discretize the data calculation process of the experimental object, obtain the best solution of the calculation steps, and finally form a complete combination.

The time series prediction technology is applied to the observation of historical objects, and the historical development law is captured and inferred according to the time change. The prediction model has no requirements for the background environment of information; so, it can be applied to any object analysis process. The applicability of the time series prediction model is also widely used in river trend, transportation, population migration, urban power consumption, consumption level, etc. [21]. In the economic field, researchers use time series models to judge the trend of capital curve and amount index and use the characteristics of these data to determine the next investment direction of enterprises [22]. According to the different problems to be solved, the long-term and short-term time series prediction models are established. For the same stage, different objects, and environments, the scope of long-term prediction is different from that of short-term prediction. Taking the economic field as an example, the long-term forecast is only for changes with a cycle of more than two years. The short-term prediction model can be applied to power consumption [23]. In order to predict the residential power consumption of the city at the same time, the length of this time period is usually between a few minutes and a few hours. Some scholars have different requirements for prediction application. They divided the model into point structure and interval structure and used probability calculation to assist the prediction model [24]. Point structure is to combine the behavior track after machine training with the dynamic change of time, analyze the change of the sample object at a certain time in the future, and carry out certain control and guidance according to the analysis results. However, the point structure will be unstable in practical application, and it is easy to be disturbed by many factors, which makes the experimental results difficult to convince the public [25]. Then, in the application of interval structure, the calculation range is extended, and the activity interval of the sample object at a certain time is obtained, so as to calculate the reliability of the data. Based on the above research status, this paper uses the time series prediction model to predict the development trend of temperature environment.

Then, the imbalance of intestinal flora under different temperature environment was studied.

3. Influencing Factors and Correlation Analysis of Intestinal Flora Imbalance

3.1. Construction of Experimental Temperature of Intestinal Flora Based on Time Series Prediction Model. The human environment contains many kinds of cells and flora. Flora participates in the normal activities of organs and human body and plays an important role in texture health. Intestinal flora is one of the main factors affecting human dietary behavior. With people's daily intake of different nutrients and foods, intestinal flora will also be affected accordingly and then begin to adapt to the internal environment. Over time, the internal structure and species of intestinal flora have changed greatly. Many young people's daily eating habits are often too cold and overheated. Doctors believe that the alternation of cold and hot food is easy to harm gastrointestinal health. This habit of eating too cold and overheating will always lead to the imbalance of human spleen and stomach. From the perspective of temperature, the root cause is the imbalance of intestinal flora caused by the rapid change of the intestinal environment with temperature. In view of the above situation, we use the time series prediction model to simulate an environment suitable for biological feeding and study the regulation of internal temperature.

The integrated biological food room is a complex simulation scenario, and the temperature of the whole room can be regulated and monitored. In the process of biological experiment, both supercooling and overheating of the environment will cause different changes. The traditional model uses the combination of statistics and algorithm to predict the temperature, but without the help of natural wind, the experimental temperature change will produce an irregular state. Because it is based on the feedback principle, for the process with large delay, such as temperature control, the stability time is too long. On the other hand, many modern control algorithms need to build models in advance. This is costly for high-dimensional and multivariable industrial processes. Considering all kinds of interference, it is difficult to obtain ideal results. In addition, some scholars use humidity series for temperature analysis, and the calculation result curve is static, which cannot effectively calculate the dynamic data. This vector regression prediction method can only judge the humidity value of the next stage and estimate the experimental temperature according to the humidity. Although this method shows the linear transformation of the data, the accuracy of the experimental results is not properly controlled, and the accuracy is relatively poor. In this paper, the time series model is used to dynamically predict the time change of the experimental environment. The optimization of the neural network algorithm is added to the condition of multi module, and the influence of various characteristics in the experimental environment on the results is studied. The data series of experimental temperature are affected by space, geographical environment, relative humidity, oxygen content, carbon dioxide

As can be seen from Figure 1, first, process the temperature data sequence, use the neural network model and data processing technology, and judge the reliability index of the model. Finally, the experimental results are evaluated according to the single variable of the missing function. In the data acquisition and processing, the multisource remote monitoring system is used to collect the values of humidity, oxygen content, and carbon dioxide content in the experimental environment, preprocess the data, and remove the wrong data. The experiment also adds the cyclic unit network algorithm, that is, the improved neural network algorithm. Compared with the data disappearance problem of traditional algorithms, it increases the efficiency of the training model and reduces the decline of parameter accuracy and too complex problems caused by too much data. The internal structure and expansion structure of the cyclic element algorithm are as follows:

As can be seen from Figure 2, the state of each midway transformation of transmission data will be recorded. The judgment conditions can be updated according to the input results of the current node, and the calculated data can be reset by using the cyclic control structure. Finally, it can reduce the data participation and the complexity of the prediction model. The specific application formula of cyclic unit network is as follows:

r

$$\mathbf{r}(t) = \operatorname{sigmoid}[U_r h(t-1) + W_r x(t)], \quad (1)$$

$$z(t) = \operatorname{sigmoid}[U_z h(t-1) + W_z x(t)], \qquad (2)$$

$$\tilde{h}(t) = \operatorname{ReLU}\{U[r(t) \odot h(t-1) + Wx(t)\},$$
(3)

$$h(t) = \left[1 - z(t)h(t-1) + z(t)\tilde{h}(t)\right].$$
 (4)

In the formula, U_r and W_r , respectively, represent the hidden state of each control condition and the weight value of input data. Hide and reset the changes at each time in the future. In the data processing stage, association rules are combined to calculate and extract the correlation of each feature in the sample data. Variance or least square fitting is used in regression, which has the disadvantage of unstable scoring of correlation characteristics. The average accuracy is reduced by disrupting the order of features to see the impact on the accuracy of the model. Stability selection is a new method based on the combination of quadratic sampling and selection algorithm. The principle is to run the feature selection algorithm on different data subsets, repeat constantly, and finally summarize the feature selection results. The effect is generally good. The number of feature points contained in the set and association rules jointly construct the spatial region. The proportion of valid data is calculated as follows:

$$support(X \Longrightarrow Y) = \frac{|T; X \cup Y \subseteq T, T \in D|}{|D|}.$$
 (5)

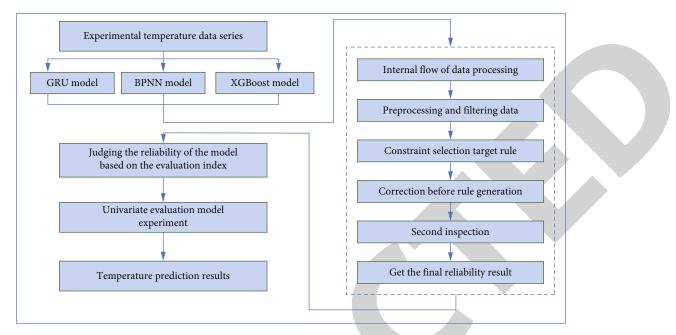


FIGURE 1: Flow chart of the prediction model.

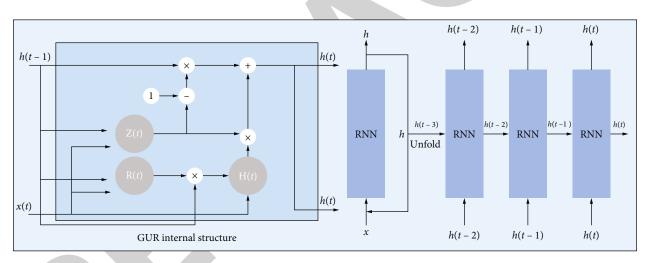


FIGURE 2: Internal structure and expanded structure diagram of the cyclic element algorithm.

In the formula, |D| represents the length of the sample set, which can express the correlation strength of association rules. The credibility of association rules in the object set is expressed as

$$\operatorname{confident}(X \Longrightarrow Y) = \frac{|T; X \cup Y \subseteq T, T \in D|}{|T; X \subseteq T, T \in D|}.$$
 (6)

When a key sample is specified, the function of data processing is to find the calculation result with the highest reliability. Therefore, we can also divide the experimental data into two parts for interpretation. The first part is to find the minimum confidence position of all data in the set and mark this part as the preferred area. The second part is to use the rules generated by the preferred region to find all nonempty sets for each sample subset. If the following formula is satisfied, the calculation result is the best credible:

$$\frac{\sup \operatorname{port}(M)}{\sup \operatorname{port}(m) \ge \min \operatorname{conf}}.$$
(7)

The generated rule tree can also be represented by the decision tree algorithm. The decision tree algorithm with gradient rise is used to optimize the performance of the system and further improve the effectiveness of calculation speed. This improved algorithm can realize the processing of parallel computing in the structure of the time series prediction model and establish relevant branch and leaf nodes for exclusion calculation in the part with scarce data.

The sample object function is expressed as

$$Obj(\Psi) = \sum_{i=1}^{n} l\left(\widehat{\gamma}\,i,yi\right) + \sum_{k=1}^{g} \Omega(f_k),\tag{8}$$

$$\Omega(fk) = \Upsilon T + \frac{1}{2}\lambda w^2 \tag{9}$$

In the formula, $\hat{y}i$ represents the predicted value of data, yi represents the actual value, and l represents the loss change in the calculation process. The child nodes in each tree structure can be expanded and calculated by mathematical formula:

$$L^{(t)} = \sum_{i=1}^{n} [l(y_i, \hat{y}_i) + f_t(x_i)] + \Omega(f_t)$$
(10)

Make a second-order expansion of the above formula:

$$L^{(t)} \cong \sum_{i=1}^{n} \left[l \left(yi, \hat{y} \, i^{(t1)} \right) + gif_t(xi) + \frac{1}{2} gif_t^2(xi) \right] + \Omega(f_t),$$
(11)

which is further simplified as

$$gi = \partial_{y}^{(t-1)} l\left(yi, \hat{y}_{i}^{(t1)}\right)$$
(12)

Finally, we predict the actual results based on the time series prediction theory. Assuming that there are relevant rules for several influencing factors, the node function responsible for the input data is as follows:

$$O_1^i = \mu_{Ai}(x_1), i = 1, 2.$$
 (13)

Multiply the predicted results:

$$W_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2), i = 1, 2.$$
 (14)

Finally, all rules are output uniformly to simulate the prediction data:

$$y = \frac{\sum_{i} W'_{i} f_{i} = \sum_{i} w_{i} f}{\sum_{i} w_{i}, i = 1, 2}.$$
 (15)

We compare the experimental data from the processing speed of the traditional prediction method, adding cyclic neural network and association rule decision tree algorithm, as shown in Figure 3.

It can be seen from Figure 3 that the calculation speed of the traditional method is significantly reduced in the face of complex space-time conditions. Finally, the prediction model using cyclic network combined with the decision tree algorithm can simplify the computational complexity and improve the computational speed in the overall data processing. Next, according to the above calculation process, we can get a combined time series prediction model based on neural network algorithm and related rules. The internal structure and basic structure of the model are shown in Figure 4.

It can be seen from Figure 4 that after the rules are obtained by the combined prediction model, the spatiotemporal correlation is first established to arrange the relationship and influence of the areas near the sample. Then, the number of units is obtained in the input layer and the competition calculation layer, the association rule algorithm is used to normalize, and finally, the experimental prediction data is obtained. In the environmental construction, cooling and warming instruments are also prepared. Before the experiment, the number and distribution position of animal intestinal flora are recorded in detail. The experimental time is three days, and the total test perimeter is 72 hours. The time consumed by replacing the power supply is not included in the cycle. Finally, more than 17000 effective data were collected as experimental samples. It includes indoor temperature, oxygen, relative humidity, carbon dioxide, and number of intestinal flora in animal samples. Upload the data to the prediction model to further explore the state of animal intestinal flora within three days.

3.2. Analysis of the Relationship between Temperature and Animal Intestinal Flora Based on Thermometer Imaging and Sample Control. The climate disorder is largely caused by human beings. The energy consumption and pollution emissions in people's daily life have an impact on the law of temperature change. The concentration of carbon dioxide in the air is increasing, and the greenhouse effect and sudden cooling affect all fields. The sudden rise or fall of temperature does great and irreversible harm to human beings and even biological groups. Many wildlife researchers have found that with the change of temperature, the warm season and frequent precipitation season have migrated, and the growth law of many animals has been in an uncoordinated state. At the same time, temperature also affects the reproduction and alternation of flora in human body and animals. Among them, intestinal flora can protect human gastrointestinal absorption, promote digestion, and improve people's immunity. We monitored and studied the number, structure, and state of intestinal flora under extreme temperature changes. At first, the culture method was used to set the control conditions for the number of microorganisms, so as to obtain the numerical changes. However, most microorganisms cannot be effectively analyzed, resulting in the final results are not convincing. Subsequently, it was found that using the time series prediction model to build the experimental environment, using temperature imaging to judge the changes of animal body temperature, and analyzing the structure of intestinal flora according to flux sequencing technology had a significant effect. Therefore, we only need to design different animal control groups to expand the credibility of the research results.

In this experiment, 30 female experimental rats were selected, with an average weight of about 200 grams and an error of no more than 5 grams. The equipment selects infrared temperature imaging instrument and uploads it to the computer for image comparison. The temperature changes of stomach and intestine of experimental rats were

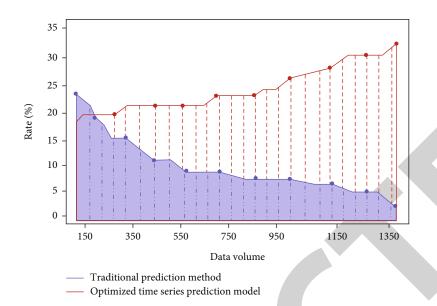


FIGURE 3: Comparison of processing speed between traditional prediction method and optimized time series prediction model.

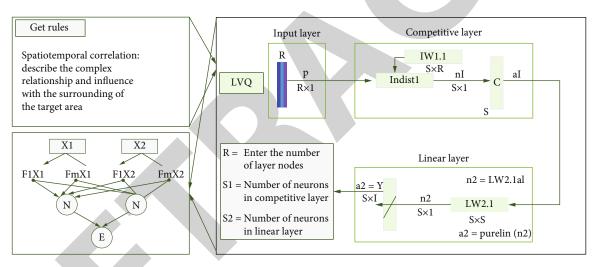


FIGURE 4: Internal structure and basic structure of the model.

recorded every hour according to the experimental cycle. The rats were divided into warm water group and cold water group. The experimental group was perfused with warm water every three hours, and the control group was perfused with cold water. Then, the change of the average body weight of the experimental rats was recorded in a cycle of three days, as shown in Figure 5.

As shown in Figure 5, the body weight of the experimental rats in the warm water experimental group did not change significantly after one cycle, while the average body weight of the experimental rats in the cold water control group decreased significantly, and the body fat rate increased slowly. From the observation of behavioral activity area, it is known that the rats in the cold water group have a small amount of activity and often gather for heating. Next, the spotted lizard samples were numbered and recorded in the same environment. Measure the length, weight, body fat rate, and other data of each object. First, maintain constant

temperature for two days and nights and then conduct temperature control experiment. The experimental group was in a constant temperature state and maintained the normal activities of the spotted lizard under the maintenance conditions. The warm group was heated with a heating lamp and set as the control group. During this period, the temperature was monitored for 24 hours with one week as the experimental cycle. The excreta of the lizard was collected and analyzed daily. The relevant results were obtained according to the temperature of the excretion place of the spotted lizard and the changes of intestinal flora and immune ability collected from the excreta. After flux sequencing of all samples, 546178 pieces of data were obtained, and the sequence information with a similarity of more than 97% was classified and processed at the same time. Count the types of intestinal microflora microorganisms in the experimental samples and annotate all types into the ranking to obtain the following statistical chart.

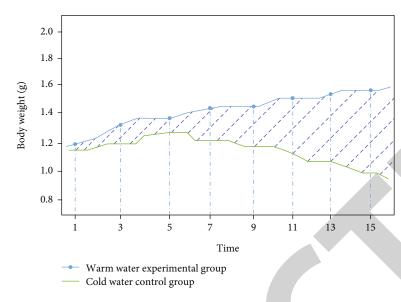


FIGURE 5: Comparison diagram of average weight change of experimental rats.

It can be seen from Figure 6 that in the six boundary method of biological classification, we only use the first five, the horizontal represents the number of each spotted lizard, and the vertical represents the biological classification attribute of the flora. The experimental subjects of spotted lizard showed impatience after the continuous increase of temperature, and the number of activities changed from initial increase to decrease. In the subsequent capture of experimental subjects, it was found that the spotted lizard in the warming control group had weak resistance and low spirit. There is also a surplus of food put in a fixed amount every day. The experimental results further showed that temperature had an effect on the number, structure, and distribution area of intestinal flora.

4. Analysis of Research Results on the Construction of Temperature Environment and Its Impact on Intestinal Flora Imbalance

The construction of the experimental environment adopts the plane roof design, the floor adopts the nonventilated full seam type, and the ventilation port is the mechanical air supply equipment. The wireless monitoring system is used as a data acquisition tool. Record the quantity, number, body shape, weight, and other data of each experimental object in detail. There are several abnormal information in the time series prediction model. It may be missing during the collection process. This includes data loss caused by sudden change of power supply, equipment instability, and other factors. The anomaly detection problem of time series is usually expressed as outliers relative to some standard signals or common signals. Although there are many exception types, we only focus on the most important types from the business perspective, such as unexpected peak, decline, trend change, and grade conversion. Generally, the anomaly detection algorithm should mark each time point as abnormal/non abnormal. Or predict the signal of a certain point and measure whether the difference between the real value of this point and the predicted value is large enough, so as to treat it as an anomaly. Using the latter method, we can get a visual confidence interval, which is helpful to understand why exceptions occur and verify. We know that this information is invalid; so, we use mathematical interpolation to predict and fill the abnormal results. According to the characteristics of temperature time series, the effectiveness of time series is detected by the cyclic unit neural network algorithm. Firstly, the mathematical statistics method is used to detect the running stability of the sequence, and the neural network model is added to predict the temperature change law to select the final result. We compare the average error index of the actual observation value and the observation value before and after the optimization of the time series prediction model, as shown in Figure 7.

It can be seen from Figure 7 that with the increase of prediction time, the optimized time series model can basically match the actual observation values with less error. Therefore, in the experimental temperature prediction, the time series prediction model optimized by the neural network algorithm can improve the effectiveness of the calculation results. The data collected from the experimental rats and lizards were stored in their respective databases. The sequencing screening method is used to check one by one from top to bottom. The experimental rats are selected as an example, and the infrared imaging of animal body temperature is dynamically represented by multimedia animation software, as shown in Figure 8.

It can be seen from Figure 8 that compared with the experiment on the first day, the body surface temperature of the experimental mouse control group showed obvious blue at the end of monitoring. In the normal temperature group, the temperature imaging is normal, indicating that there is no error in the experimental process, which is consistent with the actual expected results. Next, the number of intestinal flora of the sample object is detected. The flora abundance index and average size index were used to judge

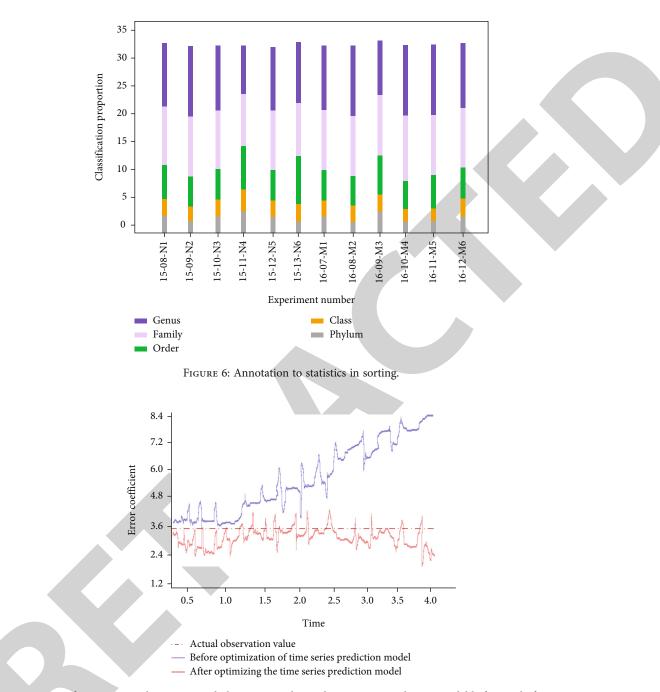


FIGURE 7: Variation of average error between actual observation value and time series prediction model before and after optimization.

whether there was imbalance. The excretion test samples of two animals under normal temperature can be classified into 32 to 35 families and genera, and the low-temperature control group and high-temperature control group can only be allocated to 30 species. According to the statistics of microbial diversity, under normal conditions, the mouse flora is mainly composed of 29.6% Corynebacterium, 46.4% Bacteroides, and 12.3% dauricum. After cooling with cold water in the experimental cycle, the number of Corynebacterium, Bacteroides, and dauricum in mice decreased to 7.7%, 13.6%, and 80%, respectively. Under normal conditions, the flora of lizard is mainly composed of 46.9% Bacteroides, 20% Proteus, and other flora. After warming, the content of Bacteroides decreased to 43%, and Proteus increased to 25%. The intestinal tract of mice inhabits a complex and dynamic microbial community, in which bacterial groups dominate. The intestinal normal indigenous flora of adult mice is very similar to that of mammals at the high classification level. The intestinal microorganisms of mice are mainly facultative anaerobes, including Strepto-coccus, Lactobacillus, and Escherichia coli. The microbial flora of mice is composed of a mixture of microorganisms from different partitions of the gastrointestinal tract. There are four dominant microbial system groups in feces, two of

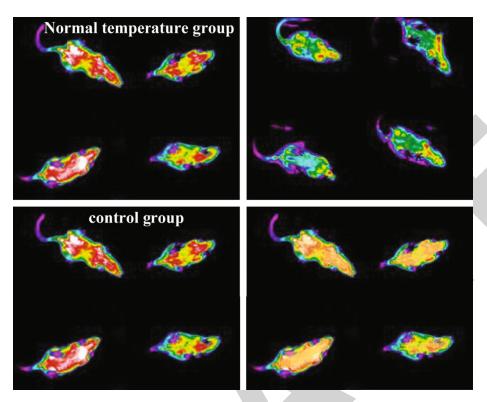


FIGURE 8: Infrared imaging of body temperature of experimental animals.

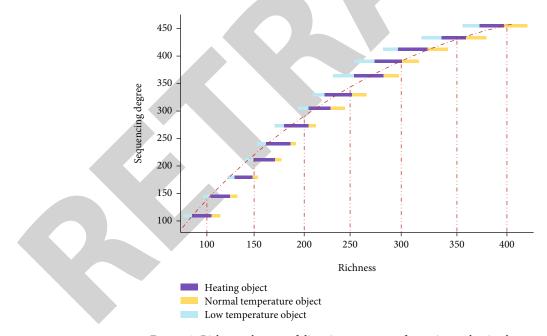


FIGURE 9: Richness changes of diversity sequences of experimental animals.

which are related to intestinal flora. Fecal sample analysis can obtain the diversity of most microorganisms in the cecum. The composition of microbial flora in fecal samples and cecal contents of mice is similar in nature but different in quantity. Cecal contents can reflect cecal microorganisms of chicken, while fecal samples cannot. The calculation results show that the number and structure of animal intestinal flora are relatively stable at room temperature, in which Bacteroides and actinomycetes account for a high proportion. It shows that the bacteria detected above are the core flora in the intestine. With the change of temperature into supercooled and overheated state, the intestinal microbial content of the experimental subjects changed significantly. Among them, the soft membrane flora of mice and the deformable flora of spotted lizard all increased too much. It can be directly determined that the intestinal flora of animals is in a state of imbalance. In order to judge whether the sequence richness change of the diversity contained in the tested object can meet the research needs, we use sparse curve for detection. The optimized data sequences of mice and lizards are randomly selected. The abscissa represents the degree of sequencing, and the ordinate represents the richness, as shown in Figure 9.

As can be seen from Figure 9, the objects in the heating experiment are marked with red, the normal temperature group is marked with yellow, and the low temperature group is marked with blue. With the increase of the sequencing degree of sample data, the similarity of each group of data is very high, showing a gentle development trend, indicating that the range and quantity of experimental objects meet the detection standards. Among them, the richness index in the normal temperature environment is relatively large, which can effectively explain that the richness of microbial content of intestinal flora in the experimental population is high, which meets the conditions of routine experimental research. The experimental subjects were further analyzed, and the animals were distinguished according to gender. The number of Bacteroidetes in the intestinal flora of male animals was higher than that of female animals, but this phenomenon disappeared directly after physical ligation. In addition, the abundance of intestinal flora of female animals is higher than that of male animals, and the metabolic level is also faster.

5. Conclusion

The human intestine contains abundant colony groups, which participate in normal physiological activities and play an important role in diet, exercise, and metabolism. Intestinal flora can promote the human body's absorption of food nutrition, help the metabolic cycle, improve immune function, and improve health indicators. Because people's eating habits are gradually irregular and often eat in the state of temperature imbalance, they often have symptoms of gastrointestinal discomfort. In this paper, the time series prediction model is used to study the effect of temperature on the imbalance of intestinal flora. Firstly, neural network algorithm and association rule algorithm are used to optimize the traditional time series prediction model and change the internal complex structure of the model, so as to simplify the prediction process and improve the operation speed. Secondly, the temperature infrared imaging instrument was used to monitor the body surface temperature of experimental rats and lizards, and the experimental group and control group were set up in the simulated experimental environment. Explore the changes of animal behavior and the number of intestinal flora in excreta under normal temperature, low temperature, and high temperature. Flux sequencing was used to detect the richness index of intestinal flora and judge the structural components of intestinal flora at various temperatures. Finally, the specific effects of temperature changes on the diversity of animal intestinal flora were studied under the condition of microbial richness. Under the condition of high temperature, the behavior of Corynebacterium increased first and then decreased. The results showed that the appetite of animals decreased under the condition of high temperature. It shows that the change of temperature has an obvious effect on the number and internal structure of intestinal flora. The human environment is similar to the environment of the experimental object, which can directly affect the experimental results in the study of human intestinal flora, and has a certain credibility. However, the research still has some limitations. Due to the lack of simulation verification, this paper only discusses the simulation results of mouse experiments. The human environment is similar to the environment of the experimental object, which lacks certain scientificity. Therefore, further research and analysis are needed in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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