

Deep Learning-based Prediction Model for Risk Factor of Atherosclerotic Cardiovascular Disease

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Abstract: With the development of medical digitization technology, artificial intelligence and big data technology, the medical model is gradually changing from treatment-oriented to prevention-oriented. In recent years, with the rise of artificial neural networks, especially deep learning, great achievements have been made in realizing image classification, natural language processing, text processing and other fields. Combining artificial intelligence and big data technology for disease risk prediction is a research focus in the field of intelligent medicine. Blood lipids are the main risk factors of cardiovascular and cerebrovascular diseases. If early prediction of abnormal blood lipids in iron and steel workers can be carried out, early intervention can be carried out, which is beneficial to protect the health of iron and steel workers. This project around the steel workers dyslipidemia prediction problem for further study, firstly analyzes the influence factors of the steel workers dyslipidemia, discusses the commonly used method for prediction of disease, and then studied deep learning related theory, this paper introduces the two deep learning algorithms of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Use the basic principle of Python language and the TensorFlow deep learning framework, establishes a prediction model based on two deep learning networks, and makes an example analysis. Experimental results show the LSTM prediction effect is superior to traditional RNN network, it provides scientific basis for the prevention of iron and steel dyslipidemia.

Keywords: Dyslipidemia, deep learning, recurrent neural networks, long short-term memory.

1. Introduction

As the pillar industry of the secondary industry, iron and steel industry has made an indelible contribution in the period of China from agricultural economy to industrial economy. The contribution of front-line steel workers in the processing and production of steel is even more obvious. Therefore, the physical health of front-line steel workers is directly related to the economic benefits of each steel production unit, the financial revenue of the entire city and the comprehensive strength of the country [1]. Along with the advancement of society and technology, the working environment of steel workers has also been greatly improved, which has gradually been transformed from mechanical work to manual operations [2]. However, there are still some jobs that require workers to be under high temperature conditions and pay attention for a long time to ensure the successful completion of production work, such as the temperature control of molten iron in front of the furnace, the casting machine, etc., and require workers to concentrate on standing or sitting for a long time in high temperature and noise. Hence, in addition to occupational diseases, there are also a series of chronic non-infectious diseases in the course of work [3], [4]. Dyslipidemia is one of the major risk factors for a variety of chronic non-infectious diseases, and a major cause of stroke and heart disease [5]. A series of physiological reactions will occur in the human body during high-temperature operation, mainly including changes in body temperature regulation, water and salt metabolism, circulatory system, neuroendocrine system, and urinary system. The mechanism of noise on blood lipids and glucose is not noticeably clear, but there are reports suggesting that noise stimulation can not only damage hearing, but also be introduced into the cerebral cortex and autonomic nervous center through hearing, triggering a series of reactions in the central nervous system. Changes in neuroregulatory functions have led to disturbances in central regulation of vascular movement, resulting in disorders of lipid metabolism [6]. In the noise environment for a long time, the auditory nerve would activate the upward activation system of the brain stem network structure, excite the cerebral cortex, increase the activity of the sympathetic nervous system, and increase the secretion of catecholamines. Epinephrine and norepinephrine can increase the synthesis of light methyl glutaramide coenzyme A reductase in liver, thus promoting the synthesis of cholesterol. High temperature workers tend to be irritable and nervous, which can also increase TC (Total Cholesterol) [7].

The health of steel workers is related to the healthy development of the industry. The prediction of blood lipid and early intervention can effectively reduce the prevalence of cardiovascular disease in steel workers and ensure the health of steel workers and the healthy development of steel enterprises. Therefore, this project focuses on the prediction of blood lipid risk for steel workers. At present, disease prediction mainly uses the traditional machine learning method, which requires the establishment of prediction model for data. However, with the increase of data types and complexity, the establishment of model becomes more difficult, so the deep learning method emerges [8–10]. Nowadays, deep learning has been widely accepted and successfully applied to many fields in daily life, such as natural language processing, face recognition, target tracking, video parsing, etc., [11]. In the medical field, there are also successful applications of deep learning, such as image segmentation in medical imaging, based on a large amount of medical image data, to help doctors quickly find disease pathology and perform accurate classification [12], and the use of deep learning for disease risk prediction, based on the medical data, as a diagnostic tool to assist doctors diagnose [13]. Therefore, the application of deep learning in medical big data can mine useful information in medical big data to assist doctors in diagnosis, improve the accuracy of pathological diagnosis and the quality of medical service.

Neural network experts Jordan, Pineda, Williams, Elman are equivalent to a RNN (Recurrent Neural Network) proposed in the late 1980s [14]. The essential characteristic of this kind of network is that there are both internal feedback connections and feedforward connections between processing units. It is a feedback dynamic system, which reflects the dynamic characteristics of the process in the calculation process and has stronger dynamic behavior and computing capacity than the feedforward neural network. Thus, it has become one of the important research objects of neural network experts in the world. In 1997 Sepp Hochreiter and Jurgen Schmidhuber proposed the LSTM network (Long Short-Term Memory) [15], which is a special RNN network. This article introduces the basic principles of two deep learning algorithms: RNN and LSTM. By using Python language and TensorFlow deep learning framework, a prediction model based on two kinds of deep learning networks is built, and an example is analyzed and studied to compare the prediction effects of the two models.

1.1. Influencing factors

Cholesterol (TC) and triglyceride (TG) are the main lipid components in plasma, accounting for about one third of the total plasma fat. Most cholesterol is synthesized by the body, and a fraction of it comes from food. Triglycerides, which account for about a quarter of the total plasma fat, are obtained mostly from food and a small part from the body. Phospholipids (PL) are mainly lecithin, encephalin, serine phospholipids, neuro-lipids, etc., accounting for about one third of the total plasma fat. Free fatty acid (FFA), also known as non-esterified fatty acid, accounts for about 5% to 10% of total plasma lipids. It is the main source of energy for the body [16]. Blood lipid is an important indicator for monitoring health status. Dyslipidemia, also known as hyperlipidemia, is caused by an increase in total cholesterol and triglyceride levels in the plasma and a decrease in low-density lipoprotein. It may cause complications such as hypertension, fatty liver, and atherosclerosis. If the blood lipid level of steel workers can be accurately predicted and intervened in advance, the occurrence of these conditions will be greatly reduced. At present, the detection of dyslipidemia has been realized medically. The data of TC, TG, high-density protein (hdl-c), low-density protein (ldl-c) and other data can be collected to check the level of dyslipidemia in workers and to intervene in workers with dyslipidemia [17]. However, if workers do not undergo frequent physical examinations, it cannot make early predictions, leading to blood lipid accumulation in the body, which will undoubtedly have a great impact on the health of steel workers. Recent studies have shown that behavior-based dyslipidemia prediction and early intervention are cost-effective interventions to reduce cardiovascular morbidity [18]. Dyslipidemia, a few are systemic diseases, and most are the result of interactions between genetic defects and environmental factors. Studies have shown that genetic and environmental factors play an important role in the etiology of dyslipidemia. It can be a component of the metabolic syndrome and is closely related to a variety of diseases such as obesity, type 2 diabetes, hypertension, coronary heart disease, and stroke. Long-term dyslipidemia can lead to atherosclerosis and increase the morbidity and mortality of cardiovascular vessels. With the improvement of living

standards and lifestyle changes, the number of dyslipidemia patients has increased significantly [19]. According to reports, the prevalence of dyslipidemia in Chinese adults is about 18.6%, and it is estimated that the number of patients can be as high as 160 million. Therefore, preventing and treating dyslipidemia is of great significance for prolonging life and improving quality of life [20], [21]. Prediction of blood lipids and early intervention can effectively reduce the prevalence of cardiovascular and cerebrovascular diseases in steel workers and ensure the health of steel workers and the healthy development of steel companies.

2. Literature Survey

Measurement of chlorine concentration on steel surfaces via fiber-optic laser-induced breakdown spectroscopy in double-pulse configuration.

AUTHORS: X. Xiao, S. Le Berre, D. G. Fobar, M. Burger, P. J. Skrodzki, K. C. Hartig, A. T. Motta, and I. Jovanovic

The corrosive environment provided by chlorine ions on the welds of stainless-steel dry cask storage canisters for used nuclear fuel may contribute to the occurrence of stress corrosion cracking. We demonstrate the use of fiber-optic laser-induced breakdown spectroscopy (FOLIBS) in the double-pulse (DP) configuration for high-sensitivity, remote measurement of the surface concentrations of chlorine compatible in constrained space and challenging environment characteristic for dry cask storage systems. Chlorine surface concentrations as low as 5 mg/m² have been detected and quantified by use of a laboratory-based and a fieldable DP FOLIBS setup with the calibration curve approach. The compact final optics assembly in the fieldable setup is interfaced via two 25-m long optical fibers for high-power laser pulse delivery and plasma emission collection and can be readily integrated into a multi-sensor robotic delivery system for in-situ inspection of dry cask storage systems.

Unusual effect of temperature on direct fluorination of high temperature vulcanized silicone rubber and properties of the fluorinated surface layers.

AUTHORS: Z. An, F. Shan, L. Yang, R. Shen, X. Gu, F. Zheng, and Y. Zhang

In order to investigate the effects of fluorination temperature on surface layer characteristics (chemical composition and structure, morphology, and thickness) and surface layer properties, high temperature vulcanized silicone rubber samples were fluorinated in a laboratory vessel using a F₂/N₂ mixture with 12.5% F₂ by volume, at 0.1 MPa and the different temperatures of 25, 55, and 85 °C, for the same time of 30 min. ATR-IR analysis indicates that the substitution of fluorine atoms for hydrogen atoms of methyl groups is dominant for the fluorination at the different temperatures, while a substitution for methyl groups cannot be excluded. SEM cross-section and surface images show the fluorinated layers with nanostructured surfaces. The surface layer fluorinated at 55 °C appears to have the lowest degree of fluorination, but it clearly has the largest thickness and surface nanostructure size among the fluorinated layers. This unusual phenomenon is caused by two competing effects, the thermal activation of the substitution reaction and fluorine diffusion through the surface layer and the steric hindrance by the fluorinated methyl groups to the fluorination and fluorine diffusion. Contact angle measurements reveal that the fluorinated surfaces have high hydrophobicity and oleophobicity and thus an extremely low surface energy. Surface potential decay measurements show a much more rapid decay of potential on the fluorinated samples, compared to the unfluorinated sample. There is no significant difference in surface hydrophobicity or surface conduction between the fluorinated samples, due to the combined effect of compositional and structural changes. The difference in surface oleophobicity between the fluorination at 55 °C and the fluorination at 25 or 85 °C provides further evidence for the difference in their surface chemistry, because surface geometry of the fluorinated samples has little effect on the oleophobicity.

Comprehensive genotyping in dyslipidemia: Mendelian dyslipidemias caused by rare variants and mendelian randomization studies using common variants.

AUTHORS: H. Tada, M.-A. Kawashiri, and M. Yamagishi

Dyslipidemias, especially hyper-low-density lipoprotein cholesterolemia and hypertriglyceridemia, are important causal risk factors for coronary artery disease. Comprehensive genotyping using the 'next-generation sequencing' technique has facilitated the investigation of Mendelian dyslipidemias, in addition to Mendelian randomization studies using common genetic variants associated with plasma lipids and coronary artery disease. The beneficial effects of low-density lipoprotein cholesterol-lowering therapies on coronary artery disease have been verified by many randomized controlled trials over the years, and subsequent genetic studies have supported these findings. More recently, Mendelian randomization studies have preceded randomized controlled trials. When the on-target/off-target effects of rare variants and common variants exhibit the same direction, novel drugs targeting molecules identified by investigations of rare Mendelian lipid disorders could be promising. Such a strategy could aid in the search for drug discovery seeds other than those for dyslipidemias.

Stress, health, noise exposures, and injuries among electronic waste recycling workers in Ghana

AUTHORS: K. N. Burns, S. K. Sayler, and R. L. Neitzel

Background Electronic waste (e-waste) recycling workers in low and middle-income countries have the potential for occupational injuries due to the nature of their work at informal e-waste sites. However, limited research exists on stress, noise, occupational injuries, and health risks associated with this work environment. This study evaluated injury experience, noise exposures, and stress risk factors among e-waste workers at the large recycling site in the Agbogbloshie market, Accra, Ghana. **Methods** Participants completed a survey addressing their work, health status, stress, exposures to several occupational hazards (including noise), use of personal protective equipment at work, and injury experience. This study identified a large number of injuries among informal e-waste recyclers, and we found that higher levels of perceived stress and perceived noise were associated with an increased number of occupational injuries, even after controlling for other injury risk factors.

Risk assessment of hypertension in steel workers based on LVQ and Fisher-SVM deep excavation

AUTHORS: J.-H. Wu, W. Wei, L. Zhang, J. Wang, R. Damasevicius, J. Li, H.-D. Wang, G.-L. Wang, X. Zhang, J.-X. Yuan, and M. Wozniak

The steel industry is one of the pillar industries in China. The physical and mental health of steel workers is related to the development of China's steel industry. Steel workers have long been working in shifts, high temperatures, noise, highly stressed, and first-line environments. These occupational related factors have an impact on the health of steel workers. At present, the existing hypertension risk scoring models do not include occupational related factors, so they are not applicable to the risk score of hypertension in steel workers. It is necessary to establish a risk scoring model for hypertension in steel workers. In this study, the learning vector quantization (LVQ) neural network algorithm and the FisherSVM coupling algorithm are applied to estimate the hypertension risk of steel workers, and the microscopic laws of the "tailing" phenomenon of the two algorithms are analyzed by means of graphics analysis, which can describe the influence trend of sample size change in different intervals on the classification effect. The results show that the classification accuracy of the algorithm depends on the size of the sample space. Through the example's verification, the accuracy rate of the scale is 90.50% and the effect is very good. It shows that the established scoring system can effectively assess the risk of hypertension in steel workers and provide an effective basis for primary prevention of hypertension in steel workers.

3. Proposed System

The essence of dyslipidemia risk prediction based on physical indicators and working environment factor parameters is to build a model that reflects a mapping relationship, that is, the mapping relationship between the probabilities of dyslipidemia of workers in the future and workers' physical indicators, as well as working-environment factor parameters. This mapping relationship changes over time. The RNN model is characterized in that it can use its internal memory to process input sequences of arbitrary timing, with internal feedback connections and feedforward connections between its processing units. Compared with the traditional prediction method, the input data of RNN adds the change factor of time, thus achieving better prediction effect. Dyslipidemia is a chronic

disease caused by long-term poor diet, living habits and the environment, which is a problem in this category. In summary, this paper proposes a risk prediction model for dyslipidemia based on RNN and LSTM as shown in Fig.1.

3.1. LSTM neural network

Deep learning is a new research direction in the field of artificial intelligence. It is developed on the basis of shallow neural networks with the improvement of computer hardware levels and the explosive growth of the current data volume. Deep learning and shallow neural network structure are both layered. Each layer will process the data input to the model and combine low-level features into potential high-level features by learning data rules. Compared with shallow models, deep learning can express complex high dimensionality such as high-variable functions and find the true relationships within the original data better. In the 1980s, artificial neural network back propagation algorithm was born. This method can automatically learn data rules from a large amount of training data without manual intervention. At present, deep learning is the most concerned research direction in the field of artificial intelligence, which completely subverts the shallow model in traditional machine, proposes a deep learning network model, and elevates it to a new height from theory to application. CNN (convolutional neural network) and RNN are two types of classical deep learning network structures now.

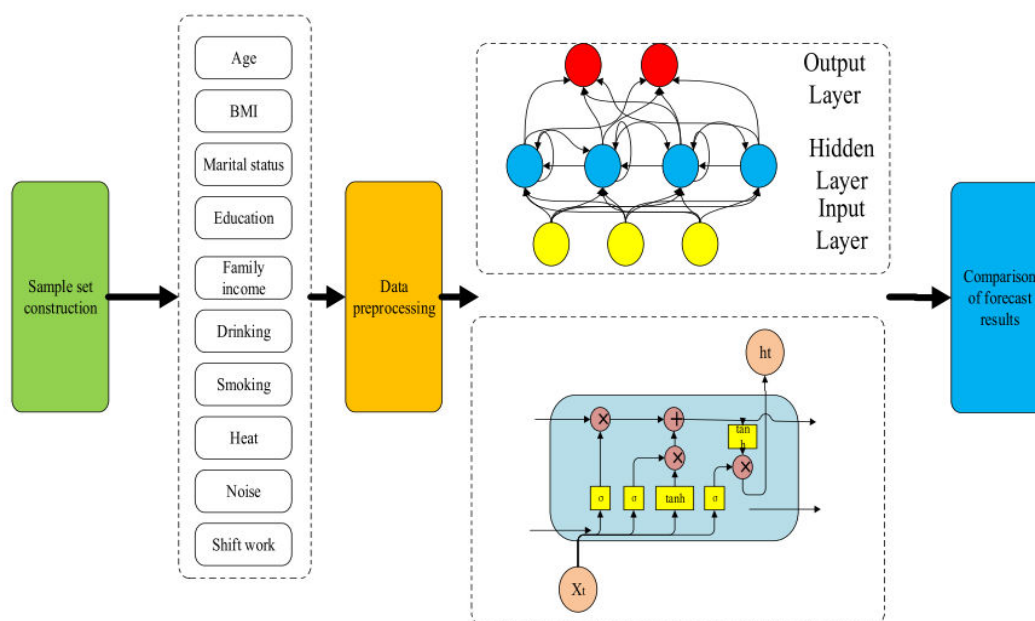


Fig. 1: Risk prediction model for dyslipidemia based on RNN and LSTM.

3.2. RNN model structure

Deep neural networks are a network with automatic adjustment of network parameters, which can iteratively calculate data according to the set coordinates and models. The training process of deep learning model is a process of constantly tuning the ownership values of nodes which are all used as tools to describe data features. The key to whether the model can describe the features of things lies on the final training results of each weight. The deep neural network takes the neural network as the carrier and focuses on the depth. It can be said to be a general term, including the recurrent neural network with multiple hidden layers, the all-connected network and the convolutional neural network. Recurrent neural networks are mainly used for sequence data processing and have a certain memory effect. The long-term and short-term memory networks derived from them are better at processing long-term dependencies. Convolutional neural networks focus on spatial mapping. And image data is particularly suitable for feature extraction of various networks. When the input data is dependent and sequential, the results of CNN are generally not good. There is no correlation between the previous input of CNN and the next input. The RNN network appeared in the 1980s. It is designed a different number of hidden layers. Each hidden layer stores information and selectively forgets some

information. In this way, the data characteristics of the sequence changes of the data can be extracted. RNN has not only achieved many results in the fields of text processing and speech processing, but also been widely used in the fields of speech recognition, machine translation, text generation, sentiment analysis, and video behavior recognition. Therefore, this paper will use RNN modelling to predict the risk of abnormal blood lipids in steel workers. RNN is good at processing time series data and can describe the context of the data on the time axis. The RNN structure is shown in the Fig. 2.

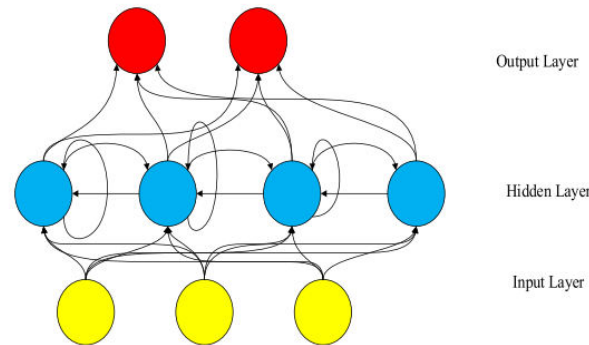


Fig. 2: Structure of RNN.

As can be seen from the figure above, the RNN structure is relatively simple. It mainly consists of an Input Layer, a Hidden Layer, an Output Layer, and an arrow in the Hidden Layer represents the cyclic update of data, which is the method to realize the time memory function. The input levels of this paper were: age, BMI, marital status, education level, family income, alcohol consumption, smoking, exposure to high temperature, noise, shift work. The 10-dimensional data were normalized and input into the RNN model. After the extraction of hidden layer depth features, the output layer output the sequence of lipid health status, in which 1 represented normal lipid status and 0 represented abnormal lipid status.

3.2.1. Forward propagation of RNN

Fig. 3 shows the hierarchical expansion of the Hidden Layer. $T-1$, t , $t+1$ represent the time series. X represents the input sample. S_t represents the memory of the sample at time t . W represents the weight of the input. U indicates the weight of the input sample at this moment, and V indicates the weight of the output sample.

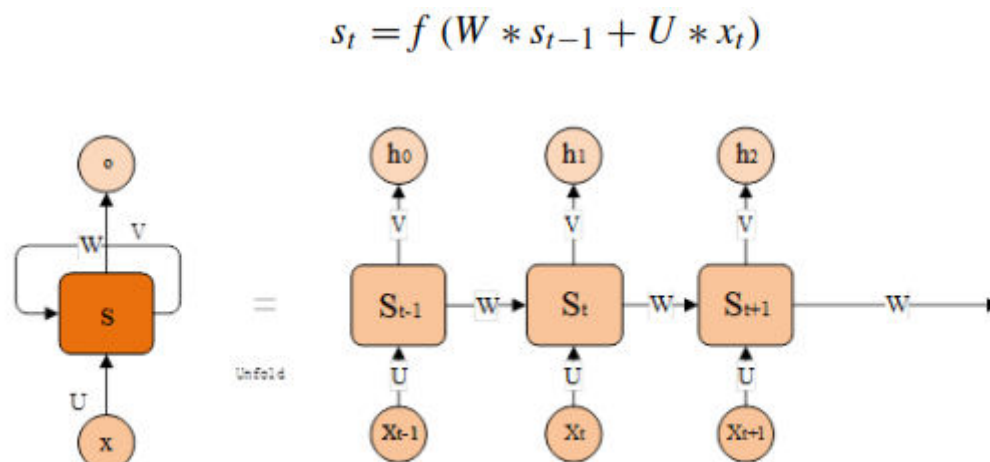


Fig. 3: Forward propagation of RNN.

At time $t = 1$, generally initialize the input, randomly initialize W , U , V , and perform the following formula calculation:

$$h_1 = Ux_1 + Ws_0$$

$$s_1 = f(h_1)$$

$$o_1 = g(Vs_1)$$

Among them, f and g are activation functions, where f can be activation functions such as tanh, ReLU, sigmoid. G is usually a SoftMax function. Time advancing, the state s_1 as the memory state of time 1 will participate in the prediction activity of the next time, that is:

$$h_2 = Ux_2 + Ws_1$$

$$s_2 = f(h_2)$$

$$o_2 = g(Vs_2)$$

And so on, the final output value can be obtained as:

$$h_t = Ux_t + Ws_{t-1}$$

$$s_t = f(h_t)$$

$$o_t = g(Vs_t)$$

Here, W , U , and V are equal at every moment which is weight sharing.

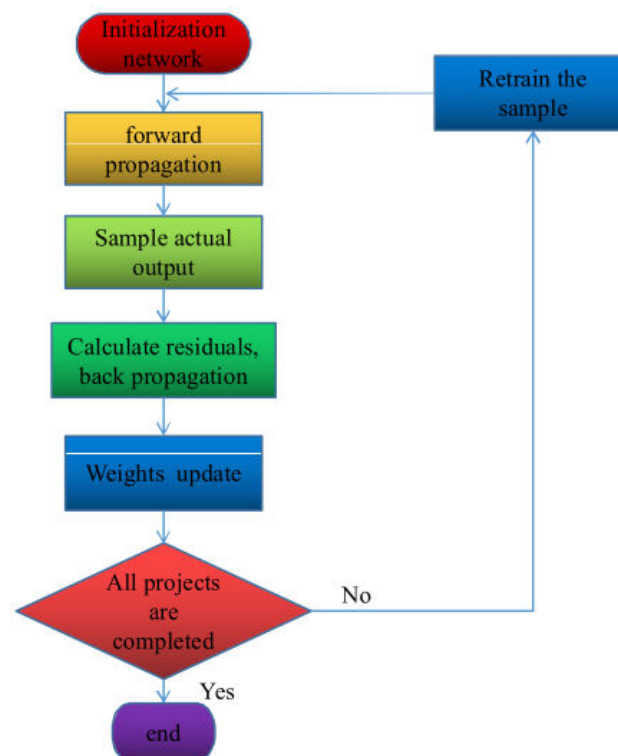


Fig. 4: RNN training process.

3.2.2. Back propagation of RNN

The back propagation process of RNN is the updating process of weight parameters W , U , and V . Each output value o_t will produce an error value E_t , tanh the total error value can be expressed as: Since the output of each step depends on not only the network of the current step but also the state of the previous steps, the Backpropagation Through Time (BPTT) algorithm is used to pass the error value at the output back, and the gradient descent method is used to perform the weight update.

$$\nabla U = \frac{\partial E}{\partial U} = \sum_t \frac{\partial e_t}{\partial U}$$

$$\nabla V = \frac{\partial E}{\partial V} = \sum_t \frac{\partial e_t}{\partial V}$$

$$\nabla W = \frac{\partial E}{\partial W} = \sum_t \frac{\partial e_t}{\partial W}$$

The model training process of RNN is shown in Fig. 4.

3.3. LSTM model structure

Because there are connections between neurons in the RNN layer, the network can learn the change law of sequence data before and after, and the internal sequence rules of data is easy to be mined. Thus RNN is widely used in the field of sequence data processing such as speech recognition and machine translation. However, this structure also has some problems. When data is transmitted backward, the problem of gradient disappearance or gradient explosion is unavoidable, which limits its processing of long-term dependencies. The LSTM network changes the way of gradient transmission during backpropagation by adding multiple special computing nodes in the hidden layer of RNN, which effectively slows the problem of gradient disappearance or gradient explosion. Its model structure is shown in Fig.5.

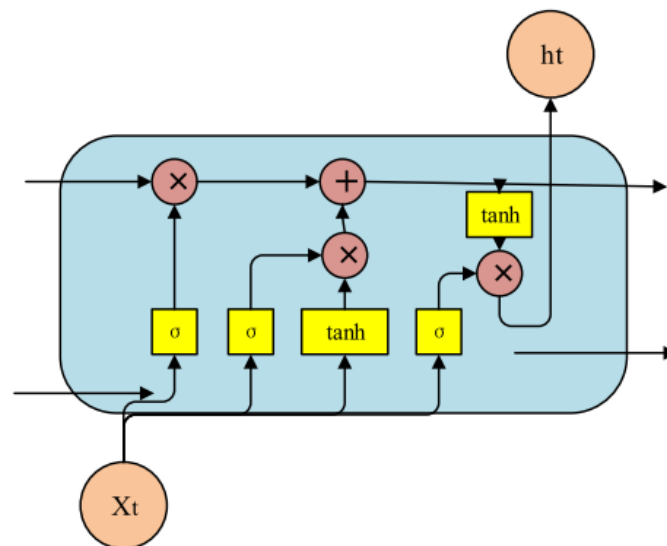


Fig. 5: LSTM model structure.

Where h_{t-1} represents the output of the previous cell, and x_t represents the input of the current cell. σ represents the sigmoid function. The difference between LSTM and RNN is that it adds a “processor” to the algorithm to determine the usefulness of the information. The structure of this processor is called a cell. Three gates are placed in a cell, which are called *Input gate*, *Forget gate*, and *Output gate*. A piece of information enters the LSTM network, and it can be judged whether it is useful according to the rules. Only the information that meets the algorithm authentication will be left, and the non-conforming information will be forgotten through the *Forget gate*.

3.3.1. Forget gate

The first step for data entering the LSTM is to decide what information should be lost and what retained. This decision is made by the Forget gate, which reads h and x and outputs a value between 0 and 1, where 1 means “complete reserved”, 0 means “completely discarded”. Forget gate is calculated as:

$$f_t = \sigma (W_f * [h_{t-1}, x_t] + b_f)$$

In the formula, f_t is the calculation result of the Forget gate which is mainly used to control the retention of the information transmitted from the unit state at the previous moment to the unit state at the current moment. $[]$ indicates that the two vectors are spliced, h_{t-1} is the output of the unit at the previous moment, and are the weight and bias of Forget gate, W_f and b_f are Sigmoid activation functions.

3.3.2. Input gate

Input gate determines the addition of new information, and its operation process includes sigmoid layer and tanh layer. The sigmoid layer determines the information that needs to be updated. The calculation formula is:

$$i_t = \sigma (W_i * [h_{t-1}, x_t] + b_i)$$

In the formula, i_t is the calculation result of the input gate, and the input gate also has independent weight and bias. The role of the tanh layer is to generate a vector of candidate update information. Its calculation formula is:

$$\tilde{C}_t = \tanh (W_c * [h_{t-1}, x_t] + b_c)$$

\tilde{C}_t is the unit state of the current input, the unit state of the current moment is C_t , and its calculation formula is:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

3.3.3. Output gate

Output gate is roughly the same as the Input gate, and its operation flow includes sigmoid layer and tanh layer. The sigmoid layer determines the output part of the information, and the calculation formula is:

$$o_t = \sigma (W_o * [h_{t-1}, x_t] + b_o)$$

Finally get the output of the current moment h_t :

$$h_t = o_t * \tanh (C_t)$$

The forward propagation of LSTM calculates the cell state C_t and h_t the output of the current moment and completes the forward propagation calculation of the network. The backpropagation of LSTM is like the back-propagation principle of RNN. Finally, the weights and biases of all parts of the network are updated to complete the model training.

4. Results and Discussion

4.1. Sample set construction and data analysis

To better study the influence of working environment in steel mills on the lipid status of workers, this project selected 4000 male workers who worked in the stainless steel, hot rolling department, power department, cold rolling department and maintenance department of an iron and steel group for more than one year as the research object. The age, height, body quality, length of service, marital status, education level, economic level, alcohol consumption, smoking, workshop, type of work, shift type and exposure to high temperature and noise in the occupational environment were investigated by questionnaire.

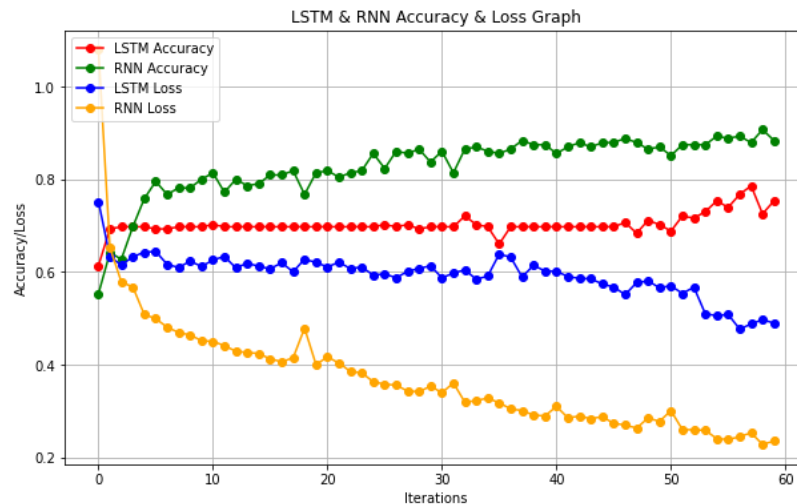


Fig. 6: Accuracy and loss comparison graph of both LSTM and RNN.

X=[50.	1.	14.	256.	215.
135.	32.	156.	116.	4.
0.6	1.	1.2	32.	28.
56.	2.	2.	1.	5.
2.	0.	78.	1.52	33.76038781
0.	1.	0.	0.], Predicted = Dyslipidemia disease detected

X=[45.	0.	13.6	316.	180.	110.
30.	189.	92.	4.5	0.4	1.
1.1	56.	45.	62.	3.	2.
3.	8.	3.	0.	74.	1.51
32.4547169	1.	0.	0.	0.], Predicted = No Dyslipidemia disease detected

X=[56.	1.	16.	54.	146.
47.	25.	43.	155.	2.82
1.6	1.1	2.6	25.	28.
163.	3.	1.	2.	6.
2.	2.	64.	1.43	31.29737395
1.	0.	0.	0.], Predicted = No Dyslipidemia disease detected

Fig. 7: Disease prediction output on test dataset.

5. Conclusion

In this project, a risk prediction model for dyslipidemia in steel workers based on RNN and LSTM networks was established. A survey was conducted on the long-term living habits and working environment of 4000 workers in a steel enterprise with ten key factors influencing dyslipidemia being extracted. Two prediction networks, RNN and LSTM, were established to predict the risk of dyslipidemia in steel workers. Disease risk prediction refers to the discovery of potential risks and trends of diseases, which plays an important role in the prevention, intervention, and management of diseases. In medicine, the ideal goal of disease risk prediction is to find the potential risks and trends of diseases before doctors diagnose diseases and take effective measures to prevent and intervene diseases. The work in this paper can better predict the risk of dyslipidemia in steelworkers, provide a scientific basis for protecting the health of steelworkers, and expand the application scope of deep learning theory in the field of medicine.

However, due to time constraints, we fail to obtain more sample data, which may reduce the robustness of the model. This content will be gradually improved in the future work.

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