Risk Prediction of Dyslipidaemia in Steel Workers using Recurrent Neural Network Framework

Mohammed Khan, Yadaiah Vaspari, Rajini Akula

Department of Electronics and Communication Engineering

Sree Dattha Group of Institutions, Hyderabad, Telangana, India.

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 dyslipidaemia prediction problem for further study, firstly analyses the influence factors of the steel workers dyslipidaemia, 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 RNN prediction effect is superior to traditional LSTM network, it provides scientific basis for the prevention of iron and steel dyslipidaemia.

Keywords: Dyslipidaemia, Recurrent Neural Network, Long Short-Term Memory, Deep Learning.

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]. Dyslipidaemia 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 glutarbamide 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 analysed and studied to compare the prediction effects of the two models.

2. LITERATURE SURVEY

Xiao, et al. [16] 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.

z.an, et al. [17] 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 F 2 /N 2 mixture with 12.5% F 2 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.

H.Tada, et al. [18] 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 dyslipidaemias.

K.N. Burns, et al. [19] 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. A subset of participants also completed personal noise dosimetry measurements. Poisson regression was used to evaluate the association between the number of injuries experienced by participants and various factors evaluated in the survey. Results Forty-six male e-waste workers completed the survey, and 26 completed a noise dosimetry measurement. Participants experienced an average of 9.9 ± 9.6 injuries per person in the previous 6 months (range: 1–40). The majority of injuries were lacerations (65.2%), and the most common injury location was the hand (45.7%). Use of personal protective equipment was rare. The mean time-weighted average noise level was 78.8 ± 5.9 dBA. Higher perceived stress, greater age, poorer health status, not using gloves, and involvement in dismantling activities were associated with an increased number of injuries. After controlling for each of these risk factors, perceived stress level and perceived noise exposure were associated with a significantly greater number of injuries. Conclusions Our 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.

J.-H. Wu, et al. [20] 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 hypertensions 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. When the sample size $n \leq 30 * (k + 1)$, the Fisher-SVM coupling intelligent algorithm is more applicable. Because its average accuracy rate is 90.00%, the average accuracy of the LVQ algorithm is only 63.34%. When the sample size is $n > 30 * (k + 1)$, the LVQ algorithm is more applicable. Because its average accuracy rate is 93.33%, the average accuracy of the Fisher-SVM coupling intelligent algorithm is only 76.67%. The sample size of this paper is 4422, and the prediction of LVQ neural network model is more accurate. Therefore, based on the relative importance of each risk factor obtained by this model and to establish a steel worker hypertension risk rating scale, the score greater than 18 is considered as the high risk, 12-18 is considered as the medium risk, and less than 12 is considered as the low risk. 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 dyslipidaemia 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 below Fig. 1.

3.1 Dataset

The steel workers under test had fasted overnight or for at least 12 hours. Then in the morning, their 2 to 3 ml of forearm venous blood would be collected and centrifuged for 10 minutes (1500 r / min). The serum was measured on the same day. Total cholesterol and triglyceride were digested by enzyme method. Apolipoprotein A, apolipoprotein B, high-density lipoprotein and low-density lipoprotein were determined by direct method. The instrument test parameters were set in strict accordance with the specification of each indicator. Before testing the serum samples, the laboratory quality control should be done first. And the samples can be tested after the quality control was qualified. The instrument is a Hitachi-7020 automatic biochemical analyzer, with TC > 6.2 mmol or TG > 2.3 mmol as anomalies.

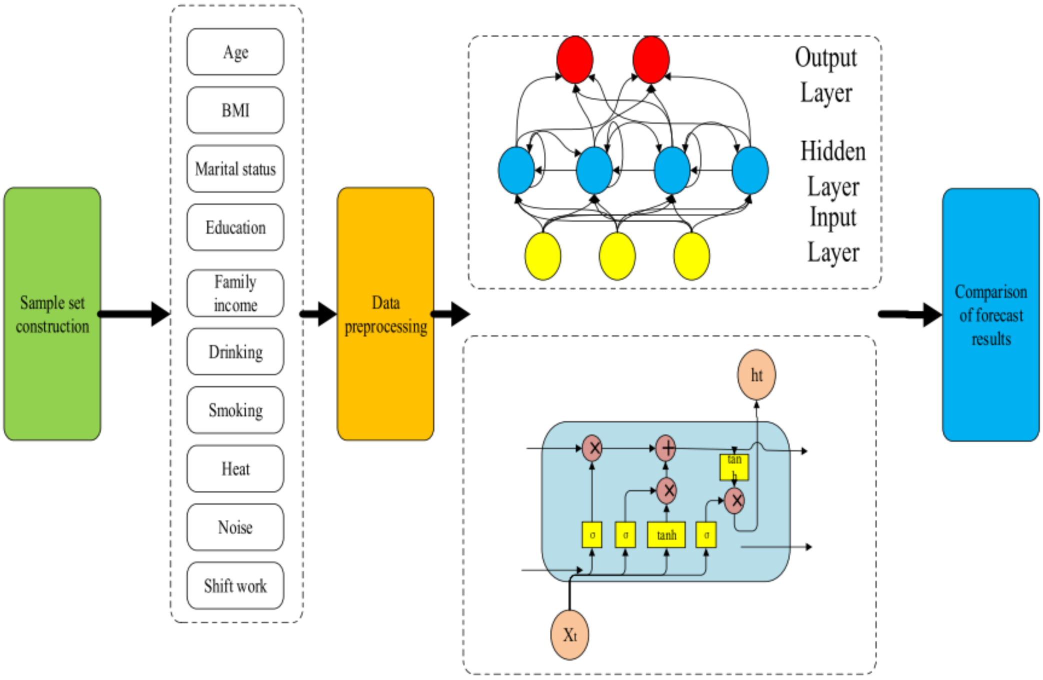

Fig. 1. Risk prediction model for dyslipidaemia based on RNN and LSTM.

In this study, smoking was defined as smoking 1 > a day for 6 months or more. Drinking referred to those who drink more than once a week for more than 6 consecutive months. Tea drinking referred to those who drink tea more than once a week for more than 6 consecutive months. Body mass index (BMI) = body mass (kg) / height (m) 2. BMI 28.0 is obesity The statistical results are shown in the table1: From the table 1, it can be seen that the rate of dyslipidaemia in workers exposed to high temperature, high noise and long-term shift work is significantly higher than that of other workers, and the age, height, weight, length of service, marital status, education level, economic level, alcohol consumption, smoking and other factors of workers also have a certain impact on the blood lipid.

3.2 Dataset pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

3.3 Splitting the Dataset

In machine learning data preprocessing, we divide our dataset into a training set and test set. This is one of the crucial steps of data preprocessing as by doing this, we can enhance the performance of our machine learning model. Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models. If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance

3.4. RNN

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 actually 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 behaviour 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.

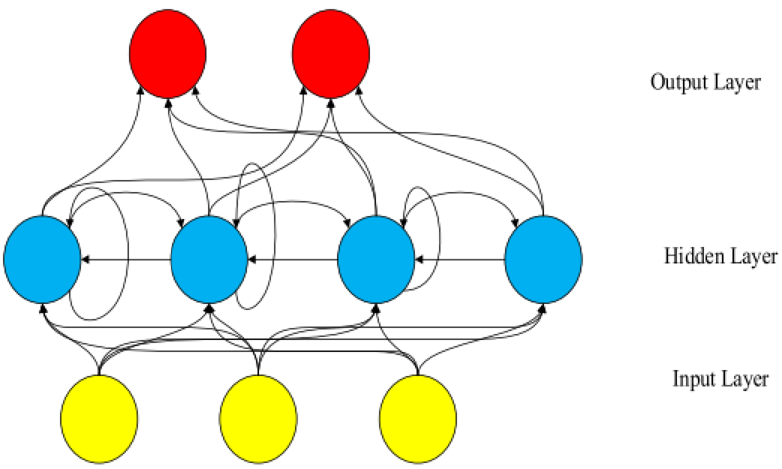

Fig. 2. Structure of RNN.

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.

4. RESULTS

This section gives the detailed analysis of simulation results implemented using "python environment". Further, the performance of proposed method is compared with existing methods using same dataset. Fig. 3 compares the performance of proposed method with existing methods. Here, Proposed RNN resulted in superior Accuracy with reduced loss as compared to existing LSTM method. Fig. 4 shows the predicted outcomes using proposed method.

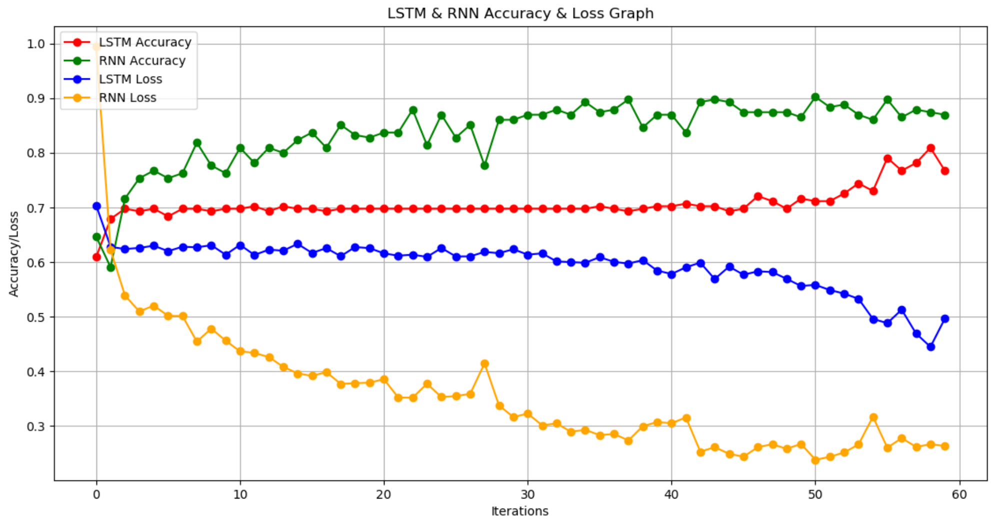

Fig. 3. LSTM & RNN Accuracy & loss graph.

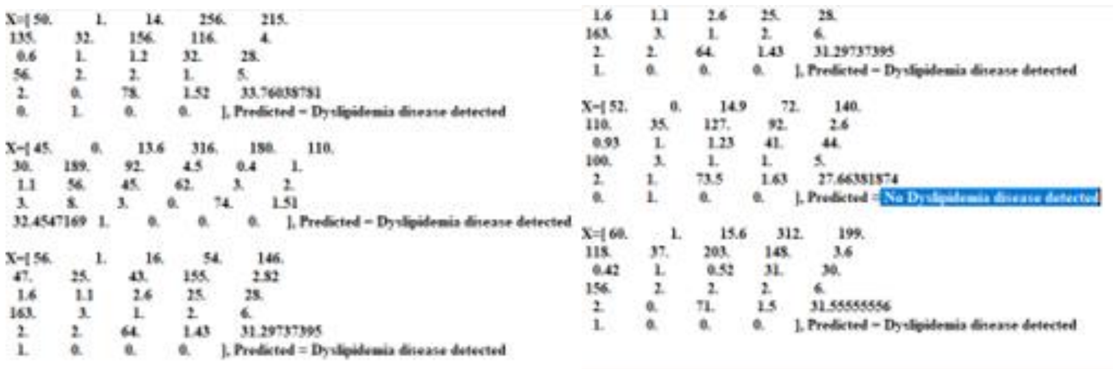

Fig. 4. Predicted outcomes.

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. Experimental results showed that the prediction effect of LSTM is significantly better than that of traditional RNN network, with an accuracy of more than 95%. 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.

REFERENCES

[1] X. Xiao, S. Le Berre, D. G. Fobar, M. Burger, P. J. Skrodzki, K. C. Hartig, A. T. Motta, and I. Jovanovic, ''Measurement of chlorine concentration on steel surfaces via fiber-optic laser-induced breakdown spectroscopy in double-pulse configuration,'' Spectrochimica Acta B, Atomic Spectrosc., vol. 141, pp. 44–52, Mar. 2018.

[2] Z. Huang, L. Li, G. Ma, and L. C. Xu, ''Local information, and commanding heights: Decentralizing state-owned enterprises in China,'' Amer. Econ. Rev., vol. 107, no. 8, pp. 2455–2488, 2017.

[3] Z. An, F. Shan, L. Yang, R. Shen, X. Gu, F. Zheng, and Y. Zhang, ''Unusual effect of temperature on direct fluorination of high temperature vulcanized silicone rubber and properties of the fluorinated surface layers,'' IEEE Trans. Dielectrics Electr. Insul., vol. 25, no. 1, pp. 190–198, Feb. 2018.

[4] S. M. Kopeikin, ''Millisecond and binary pulsars as nature's frequency standards - II. The effects of low-frequency timing noise on residuals and measured parameters,'' Monthly Notices Roy. Astronomical Soc., vol. 305, no. 3, pp. 563–590, May 1999.

[5] H. Tada, M.-A. Kawashiri, and M. Yamagishi, ''Comprehensive genotyping in dyslipidemia: Mendelian dyslipidemias caused by rare variants and mendelian randomization studies using common variants,'' J. Hum. Genet., vol. 62, no. 4, pp. 453–458, Jan. 2017.

[6] K. N. Burns, S. K. Sayler, and R. L. Neitzel, ''Stress, health, noise exposures, and injuries among electronic waste recycling workers in ghana,'' J. Occupational Med. Toxicol., vol. 14, no. 1, Jan. 2019, pp. 77–80.

[7] S. Hur, B. Min, K. Nam, E. Lee, and D. Ahn, ''Effect of dietary cholesterol and cholesterol oxides on blood cholesterol, lipids, and the development of atherosclerosis in rabbits,'' Int. J. Mol. Sci., vol. 14, no. 6, pp. 12593–12606, Jun. 2013.

[8] P. Schulam and S. Saria, ''A framework for individualizing predictions of disease trajectories by exploiting multi-resolution structure,'' in Proc. Adv. Neural Inf. Process. Syst., 2015, pp. 1145–1170.

[9] 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, ''Risk assessment of hypertension in steel workers based on LVQ and Fisher-SVM deep excavation,'' IEEE Access, vol. 7, pp. 23109–23119, 2019.

[10] N. An, H. Ding, and J. Yang, ''Deep ensemble learning for Alzheimers disease classification,'' Mach. Learn., vol. 5, pp. 583–590, May 2019.

[11] S. Khan and T. Yairi, ''A review on the application of deep learning in system health management,'' Mech. Syst. Signal Process., vol. 107, pp. 241–265, Jul. 2018.

[12] E. Gibson, W. Li, C. Sudre, L. Fidon, D. I. Shakir, G. Wang, Z. Eaton-Rosen, R. Gray, T. Doel, Y. Hu, T. Whyntie, P. Nachev, M. Modat, D. C. Barratt, S. Ourselin, M. J. Cardoso, and T. Vercauteren, ''NiftyNet: A deep-learning platform for medical imaging,'' Comput. Methods Programs Biomed., vol. 158, pp. 113–122, May 2018.

[13] A. Maxwell, R. Li, B. Yang, H. Weng, A. Ou, H. Hong, Z. Zhou, P. Gong, and C. Zhang, ''Deep learning architectures for multi-label classification of intelligent health risk prediction,'' BMC Bioinf., vol. 18, no. S14, pp. 523–525, Dec. 2017.

[14] K. K. Sarma and A. Mitra, ''A class of recurrent neural network (RNN) architectures with SOM for estimating MIMO channels,'' in Advances in Computing and Communications (CCIS), vol. 192. Berlin, Germany: Springer, 2011.

[15] G. Jain, M. Sharma, and B. Agarwal, ''Optimizing semantic LSTM for spam detection,'' Int. J. Inf. Technol., vol. 11, no. 2, pp. 239–250, Apr. 2018.

[16] O. A. Ismaiel, R. G. Jenkins, and H. Thomas Karnes, ''Investigation of endogenous blood lipids components that contribute to matrix effects in dried blood spot samples by liquid chromatography-tandem mass spectrometry,'' Drug Test. Anal., vol. 5, no. 8, pp. 710–715, Oct. 2012.

[17] A. Mohammadbeigi, E. Moshiri, N. Mohammadsalehi, H. Ansari, and A. Ahmadi, ''Dyslipidemia prevalence in iranian adult men: The impact of population-based screening on the detection of undiagnosed patients,'' World J. Men's Health, vol. 33, no. 3, p. 167, 2015.

[18] J. S. Khan, J. M. Hah, and S. C. Mackey, ''Effects of smoking on patients with chronic pain: A propensity-weighted analysis on the collaborative health outcomes information registry,'' Pain, vol. 160, no. 10, pp. 2374–2379, Oct. 2019.

[19] P. Bramlage, S. T. Azar, O. Okkeh, P. Brudi, B. M. Ambegaonkar, H. A. Hantash, S. Jambart, M. El Zaheri, R. Rachoin, A. Chafoun, and L. Lahoud, ''Factors influencing dyslipidemia in statin-treated patients in Lebanon and Jordan: Results of the dyslipidemia international study,'' Vascular Health Risk Manage., vol. 10, p. 225, Apr. 2014.

[20] Y. Jiao, G. Li, Y. Xing, D. Nie, and X. Liu, ''Influencing factors of hemorrhagic transformation in non-thrombolysis patients with cerebral infarction,'' Clin. Neurol. Neurosurg., vol. 181, pp. 68–72, Jun. 2019.

[21] N. R. Balian, C. B. Alonzo, and M. C. Zurrú, ''Clinical predictors of hemorrhagic transformation in non-lacunar ischemic stroke,'' Medicina, vol. 77, no. 2, pp. 100–104, 2017.

[22] Y. L. Guo and L. I. Jian-Jun, ''Highlights of the guidelines for prevention and treatment of dyslipidemia in Chinese adults (revised edition 2016),'' Chin. J. Frontiers Med. Sci., vol. 31, pp. 937–953, Jul. 2017.

[23] N. Demirel, S. Özbay, and F. Kaya, ''The effects of aerobic and anaerobic training programs applied to elite wrestlers on body mass index (BMI) and blood lipids,'' J. Edu. Training Stud., vol. 6, no. 4, p. 58, Mar. 2018.

[24] X. Yu, H. Lu, and D. Wu, ''Development of deep learning method for predicting firmness and soluble solid content of postharvest korla fragrant pear using Vis/NIR hyperspectral reflectance imaging,'' Postharvest Biol. Technol., vol. 141, pp. 39–49, Jul. 2018.

[25] K. Cui and X. Qin, ''Virtual reality research of the dynamic characteristics of soft soil under metro vibration loads based on BP neural networks,'' Neural Comput. Appl., vol. 29, no. 5, pp. 1233–1242, Jan. 2017.

[26] Y. Sun, J. Xu, H. Qiang, and G. Lin, ''Adaptive neural-fuzzy robust position control scheme for maglev train systems with experimental verification,'' IEEE Trans. Ind. Electron., vol. 66, no. 11, pp. 8589–8599, Nov. 2019.

[27] S. Hussain, J. Keung, A. A. Khan, A. Ahmad, S. Cuomo, F. Piccialli, G. Jeon, and A. Akhunzada, ''Implications of deep learning for the automation of design patterns organization,'' J. Parallel Distrib. Comput., vol. 117, pp. 256–266, Jul. 2018.