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RESEARCH ON RISK MANAGEMENT METHODS IN BIG DATA BASED ON STATISTIC PROCESS CONTROL AND DEEP LEARNING

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Abstract. *The data redundancy and interference brought by the era of big data make it more difficult to extract useful information for analyzing and controlling the process or systems. To more precisely distinguish valid information helpful for process analysis from big data, this paper proposes a two-stage technology based on statistical process control and deep learning. In the first stage, according to the patterns of anomalies which are set rigorously based on small-probability events and the historical information in the same period, the valid information can be isolated statistically from interference and invalid information. In the second stage, deep learning models are proposed to learn suspicious patterns of statistical anomalies, and find underlying risks and problems in reality. In addition, realistic data is used to carry out the experiment to verify the utility of the proposed integrated technology. The observations and results of the experiment indicate that the proposed models perform better than the traditional LSTM and GRU in data anomaly identification, processing and control.*

Keywords: Data anomaly, Deep learning, Risks management, Big data, Statistic process control

1. Introduction.

In all kinds of fields, risks management has become an essential task to keep the system from being out of control. In spite of the divergences and inconsistencies in different fields about what constructs risk management, a consensus about the core elements of the risk management has arisen gradually. Generally, risk management is the process that helps managers to exclude the operational issues and accidents in the system and achieve mission capacity. Effective risks management can reduce the running interference and increase the stability and sustainability [1]. Statistical process control (SPC) was originally developed for the quality control in manufacture process, and recently has been widely applied in data anomaly analysis in many other fields. Besides, artificial intelligence technology has shown great power in solving nonlinear problem, where deep learning (DL) is a representative one. Scholars have proved that the combination of

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the two technologies can bring great benefits from theoretical research and application research. Zan et al. used multilayer bidirectional long short-term memory network to identify the histogram pattern and control chart pattern in SPC, and the results showed that this network had enormous advantages over other method in recognition accuracy [2]. Darem et al. proposed an adaptive behavioral-based incremental batch learning malware variants detection model based on concept drift detection and sequential deep learning (AIBL-MVD) for facing the emerging threats of malware variants and used SPC technology to control the update of the model [3]. Yang and Zhang developed a deep joint variational auto-encoder to calculate the reconstruction errors of the behavior parameters that could reflect the gearbox abnormality, and utilized SPC chart to monitor the reconstruction errors [4]. Biegel et al. introduced a deep auto encoder-based monitoring approach and computed Hotelling's T^2 and Squared Prediction Error monitoring statistics, which provided a huge potential in prompting the performance of current multivariate SPC approaches [5]. Yeganeh et al. proposed a novel ensemble model which used an evolutionary artificial neural network as an underlying reasoning scheme combining with multiple intelligent algorithms to handle with the problem of change point estimation [6]. Zhang et al. proposed a hybrid method based on SPC and DL to analyze the abnormal information in big data and verify the effectiveness of the proposed method through comparison experiments [7]. Most current researches on risk management are to establish intelligent model to solve nonlinear problems, which expanded the original qualitative research methods. However, these studies neglected the theoretical analysis of the screening and discrimination of information. This will inevitably increase the difficulty of information processing, reduce the efficiency of information analysis and adversely affect the accuracy of judgment and decision. In the environment of rapid information increment, the extraction and screening of information seems to be more important.

In big data era, data information occupies a dominant position in decision-making and analysis, and risk management gradually increases its dependence on data. This puts forward higher requirements for data information processing. Diverse historical data can help researchers analyze the process from different levels and dimensions [8]. However, the increment in data brings new challenges to traditional qualitative and quantitative research methods. On the one hand, the increase in the amount of data inevitably brings redundancy and interference, which hinders the risk judgment of the process. On the other hand, the original method is difficult to adapt to the huge changes in the size and nature of data. At the same time, reasonable pattern recognition is a prerequisite for effective data extraction. Due to the dynamic changes of data over time, the abnormality of data often needs to be determined jointly according to the sample arrangement and the historical distribution trend, rather than a unilateral factor. To best of our knowledge, there are few studies on the effective extraction of information in the big data environment in the field of risk management, which is difficult to meet the demand for effective information under the current circumstances. Besides, the significance of history information is usually being ignored. Some data fragments in the current time periods may have certain correlation and similarity with the data fragments in the previous time step, which may lead to wrong judgement on the seemingly abnormal information. In other words, the data in many different periods rather than a piece of period follows a skewed distribution, it is supposed to be recognized as normal data.

In this paper, aiming at the research gap that existing studies have, a two-stage approach based on SPC and DL was proposed. We innovated horizontal and vertical identification method in SPC, which guarantees the rationality of the extraction and identification of abnormalities. We also introduced a deep network to tackle with the nonlinear relationship between the data and practical problems. Because of the distinctions in the distribution and characteristics of data generated by different processes, the applied approach may vary in detail for different research objects. For example, Electrocardiogram (ECG) records changes in the electrical activity of the heart during each cardiac cycle, so regularity and periodicity can be an important basis for the detection of ECG abnormalities. However in this study, key performance indicators (KPI) of hospital are chosen as the research subjects for targeted research. Unlike ECG, the indicators in hospital have no obvious tendency, so it is improper to take regularity and periodicity as the basis of judgement. On the contrary, it may be more reasonable to take normality and randomness into consideration for the abnormalities detection.

The rest of this paper is organized as follows. Section 2 introduces horizontal identification method based on small probability events, and then vertical identification method, as an auxiliary detection tool, is further proposed. Section 3 introduces a novel deep learning model. Section 4 shows the experimental results. The conclusions and future work are presented in Section 5.

2. **Data Identification Based on SPC.**

The essence of SPC is a method of analyzing the data feature based on statistics and mathematics, which aims at keeping the whole process or system under control in order to reduce the adverse impact of interference and deviance. As a consequence, SPC may play an important part in executing modern risk management, which can offer managers feasible selection of decision and keeping the whole process as steady as possible.

In order to routinely detect quality, outlier-based control chart detection is a hot topic in the field of SPC recently owing to its efficiency in monitoring shifts in the process parameters. Jean-Claude proposed a new distribution-free double exponentially weighted moving average (DEWMA) control chart, which improved the ability to monitor small to large process mean alterations [9]. Tahir et al. presented progressive mean and double progressive mean charting structures based on generalized linear model to be more effective in detecting mounting variation in the process mean [10]. Theoretically, historical information can be used to calculate the permitted and reasonable range and measurements are examined to judge if their population are the same. If the points are scattered from the limits or the assumption that the measurements come from the same population as the observations is rejected, the process will be considered out of control.

However, the permutation of the points within the limits should be also valued since they may disclose the morbidity of the process. The processes without evident regularity may abound in risk management, which are not as easy to identify and analyze as ECG. As a result, normality can be substituted for the random that risk management process may present due to many social factors. For this kind of processes, some mechanisms are set up for horizontal and vertical anomaly detection of data. Figure 1 shows the proposed mechanism of SPC.

On the one hand, within the reasonable control limits, four patterns of anomalies are set for horizontal detection. By this mean, abnormal arrangement of data in the sequences can be found. Figure 2 shows how the reference lines in the control chart are used to judge whether the data is abnormal, where CL is the centerline, UCL and LCL are the upper and lower control limits respectively, and WUL and WLL are upper and lower sub-limits respectively.

Table 1 shows the proposed four patterns of anomalies. These patterns are set based on the arrangement that is unreasonable and less common in hospital performance data. Anomaly A presents the data points distribute on one side of the centerline. Anomaly B means the data points are monotonically increasing or monotonically decreasing. Anomaly C signifies the aggregation of the data points near the centerline. Anomaly D reflects the

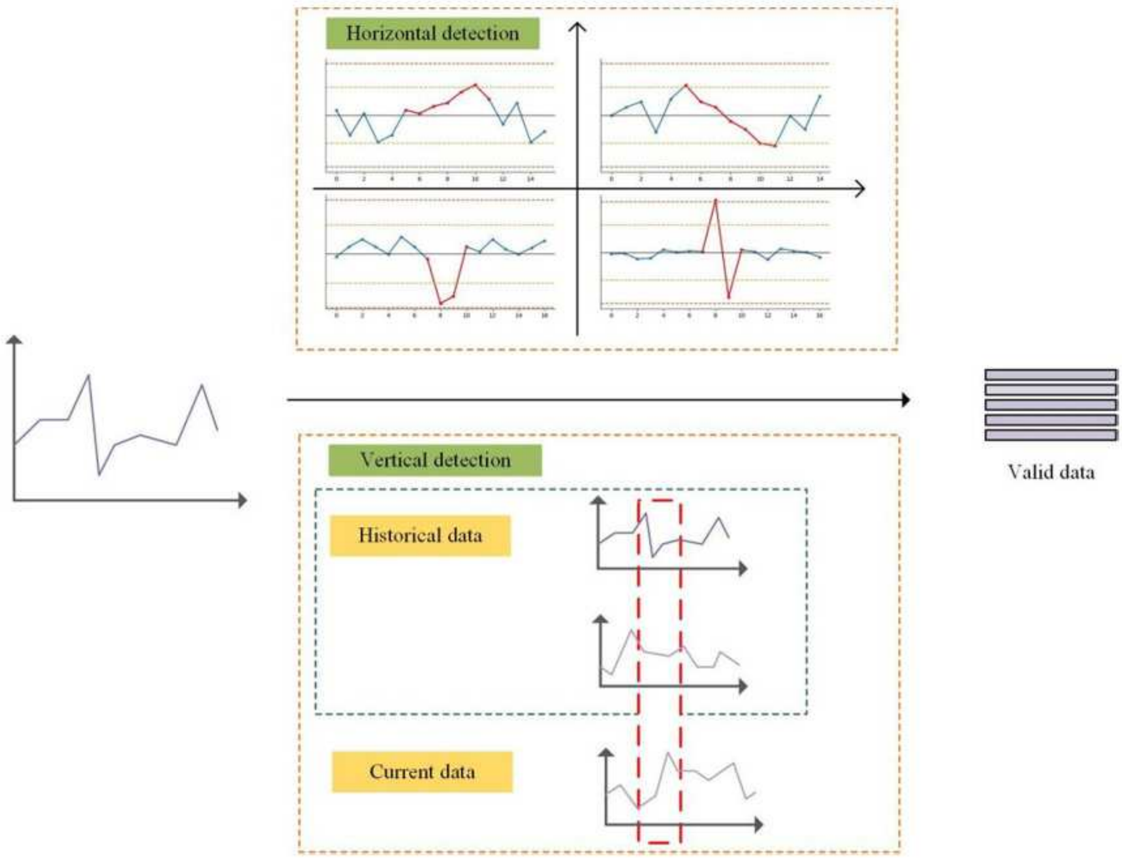

FIGURE 1. SPC detection mechanism

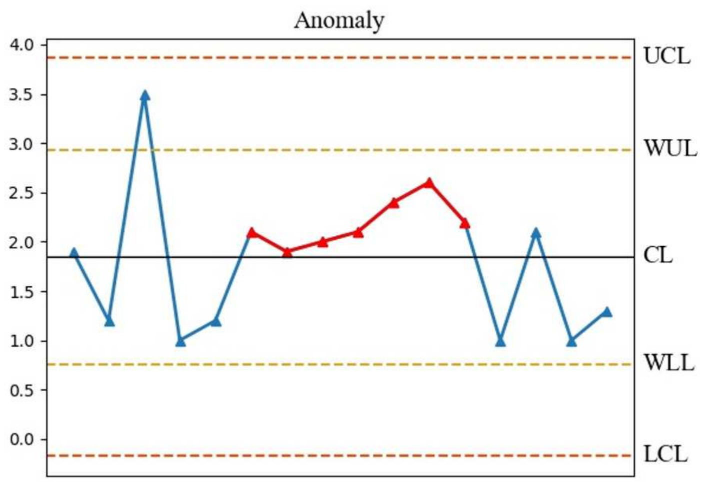

FIGURE 2. A sample of control chart

excessive variation of adjacent data points. The visualization of horizontal detection can be seen in Figure 2.

The above patterns of anomalies actually are the representatives of special small probability events that may occur in the statistic process. The anomaly patterns can be finely subdivided into concrete judgment criteria, as shown in Table 2. The selection and formulation of judgement criteria depend on the characteristics the process possesses. According to the nature of process, SPC can mine different and idiosyncratic sequence patterns.

Table 1. Specific rules for anomalies

Code	Anomaly pattern
A	The points display one-side tendency
B	The points display monotonous tendency
C	The points display skewness
D	The points present drastic change

Table 2. Judgement criteria for anomalies

Anomaly	Probability	Concrete criteria
A	$P_A^{(6,6)} = 0.0307$	6 consecutive points
	$P_A^{(10,8)} = 0.0855$	More than 8 of 10 consecutive points
	$P_A^{(12,10)} = 0.0312$	More than 10 of 12 consecutive points
	$P_A^{(14,12)} = 0.0125$	More than 12 of 14 consecutive points
B	$P_B^5 = 0.0164$	5 consecutive points
	$P_B^8 = 0.00004$	8 consecutive points
C	$P_C^{(3,2)} = 0.0053$	More than 2 of 3 consecutive points
	$P_C^{(7,3)} = 0.0024$	More than 3 of 7 consecutive points
D	$P_D = 0.0036$	2 consecutive points

On the other hand, nonlinear social factors abound in this process, and have a significant impact on the process. For example, seasonal changes may lead to significant periodic changes in annual data. Normal as it is, it may be detected by the horizontal detection mechanism. Therefore, historical data can be used as an important reference for anomaly identification. In this paper, Euclidean distance is used for vertical anomaly detection, which is one of the methods commonly used in similarity calculation.

Set two time series are respectively $X_T = \{x_1, x_2, \ldots, x_T\}$, $Y_T = \{y_1, y_2, \ldots, y_T\}$. The Euclidean distance L^p can be used to represent the similarity of two time series, and the calculation formula of L^p is shown as the following Equation (1).

$$d_{L^p}(X_T, Y_T) = \left(\sum_{t=1}^{T} |x_t - y_t|^p\right)^{1/p} \tag{1}$$

where the value of p needs to be determined according to the targeted process and repeated experiments. As an auxiliary tool, it takes account of the valuable information in the historical data, which make the anomaly screening mechanism more reasonable.

3. **Data Anomaly Identification Based on Deep Learning.** In the field of risk management, many problems mapped from the data information have multiple influence factors, which is very complex and problematic for traditional machine learning methods. The problem is that traditional measures are highly hypothetical and are not an expert at dealing with non-linear and high-dimensional data.

Compared with traditional ways, although the concrete learning process of DL model is unknown for people, the big power of the black box of DL model is the ability to learn the feature of data autonomously. As the classical learning tool, recurrent neural network

(RNN) and convolutional neural network (CNN) have been developed very comprehensively to be applied in data with sundry characteristics. RNN has been proved to have good performance and general applicability on the analysis of time series. Among all kinds of variants of RNN, long short-term memory (LSTM) and the gate recurrent unit (GRU) are the most widely used in many fields. These models have potential to extract better representations to create more accurate models. They can capture precisely the patterns of the sequences and learn the correlation of the sampling points so as to grasp the regularity of sequences. As the most classical types of RNN, it will be reasonable and persuasive to choose GRU and LSTM as comparison subjects.

3.1. **LSTM.** LSTM is a modified type of RNN. The most remarkable characteristic of LSTM is that LSTM introduces gates mechanism to capture the long-term dependencies to tackle with the gradient problems of RNN [11]. Figure 3 shows the typical structure of LSTM, which consists of a forget gate f_t, an input gate i_t, and an output gate o_t.

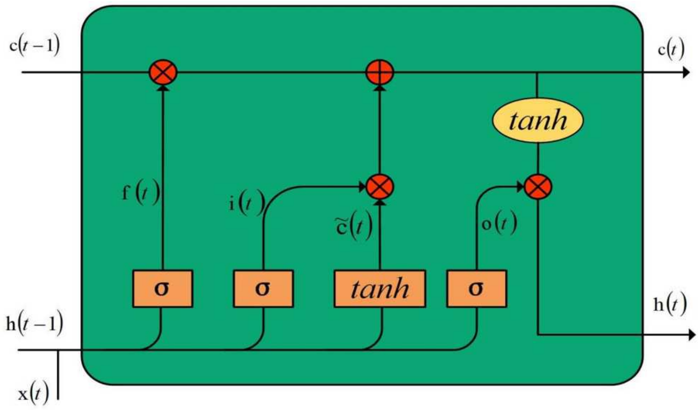

FIGURE 3. LSTM structure

The forget gate decides what kind of information needs to be abandoned on the basis of previous states information. The input gate can selectively retain useful information. The output gate controls the output information [12]. More specifically, the mathematical expressions of LSTM are shown as the following Equation (2).

$$
\begin{aligned}
f_t &= \sigma\left(W'_f x_t + W'_{hf} h_{t-1} + b_f\right) \\
i_t &= \sigma\left(W'_i x_t + W'_{hi} h_{t-1} + b_i\right) \\
\tilde{c}_t &= \sigma\left(W'_{\tilde{c}_t} x_t + W'_{h\tilde{c}_t} h_{t-1} + b_{\tilde{c}_t}\right) \\
c_t &= i_t \otimes \tilde{c}_t + f_t \otimes c_{t-1} \\
o_t &= \sigma\left(W'_o x_t + W'_{ho} h_{t-1} + b_o\right) \\
h_t &= \tanh(c_t) \otimes o_t
\end{aligned} \tag{2}
$$

where W'_f, W'_i, $W'_{\tilde{c}_t}$, W'_o are the weights which connect input vector, W'_{hf}, W'_{hi}, $W'_{h\tilde{c}_t}$, W'_{ho} are the weights of the previous state, and b_f, b_i, $b_{\tilde{c}_t}$, b_o are bias.

3.2. **GRU.** GRU is another type of RNN, whose structure is similar to LSTM. Both LSTM and GRU can selectively reserve useful information, and generate the current output through the non-linear transformation using the current input and previous information. However, the simpler gates mechanism of GRU allows more complex calculations with fewer resources and less time [13]. Figure 4 shows the typical structure of GRU, which consists of a reset gate r_t and an update gate z_t.

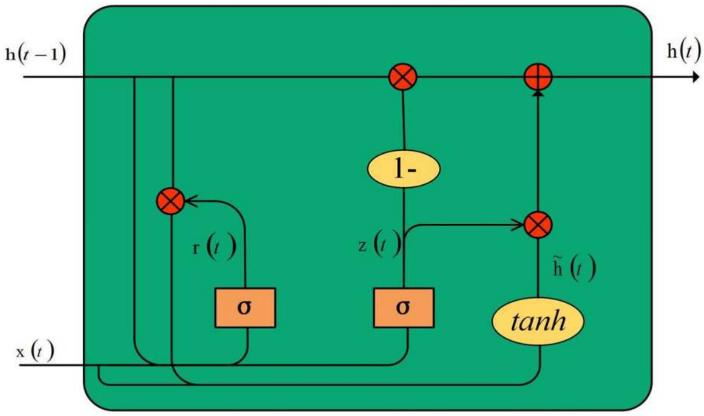

FIGURE 4. GRU structure

The current data point and previous hidden states make up the input of GRU. The reset gate can filter out useless information from the input through nonlinear activation function. The update gate then performs mathematical operations according to the processed data and makes preparation for updating the hidden states. Throughout the whole training stage, these processes are repeated. More concretely, the mathematical expressions of GRU are shown as the following Equations (3).

$$\begin{aligned}
r_t &= \sigma\left(W_r' x_t + W_{hr}' h_{t-1} + b_r\right) \\
z_t &= \sigma\left(W_z' x_t + W_{hz}' h_{t-1} + b_z\right) \\
\tilde{h}_t &= \tanh\left(W_{\tilde{h}}' x_t + W_{h\tilde{h}}' \cdot \left(h_{t-1} \otimes r_t\right) + b_{\tilde{h}}\right) \\
h_t &= h_t \otimes \left(1 - z_t\right) + \tilde{h}_{t-1} \otimes z_t
\end{aligned} \tag{3}$$

where W_r', W_z', $W_{\tilde{h}}'$ are the weights which connect input vector, W_{hr}', W_{hz}', $W_{h\tilde{h}}'$ are the weights of the previous state, and b_r, b_z, $b_{\tilde{h}}$ are bias.

3.3. **CNN.** CNN was first designed as a productive tool to identify the features in images, which was proved afterwards to be effective for time series signal processing [14]. The core of CNN is the convolutional kernel. In this way, the deep feature of data will be excavated with the model getting deeper. As shown in Figure 5, data can be processed in different channels and high levels of features can be generated. The features generated from different channels will be downsampling to get more distinctive features and finally be concatenated as one feature. Then the features will be fed into linear layers to finish feature classification [15].

3.4. **CNN-RNN.** In risk management, the spatiotemporal characteristics of sequence data are important basis for identifying underlying risk. In this study, a new DL model is proposed, as shown in Figure 6. The first two layers are the CNN layers, the middle two layers are the RNN layers, and the last layer is the fully connected layer. RNN layers are built respectively in the form of GRU and LSTM. The proposed model consists of forward propagation and backward propagation. Forward propagation takes the responsibility of calculating the output value, and backward propagation takes the responsibility of passing residuals which are accumulated to optimize the weights. The statistical anomalies that represent some realistic problems are considered as the input of the proposed model. In CNN layers, the convolutional kernels traverse the sample and create the deep features. The deep features are viewed as the inputs of RNN and then go through the RNN cells. The residuals obtained from the output of RNN are imperative to update the hidden weights. The updated hidden weights are treated as the output of RNN and ultimately

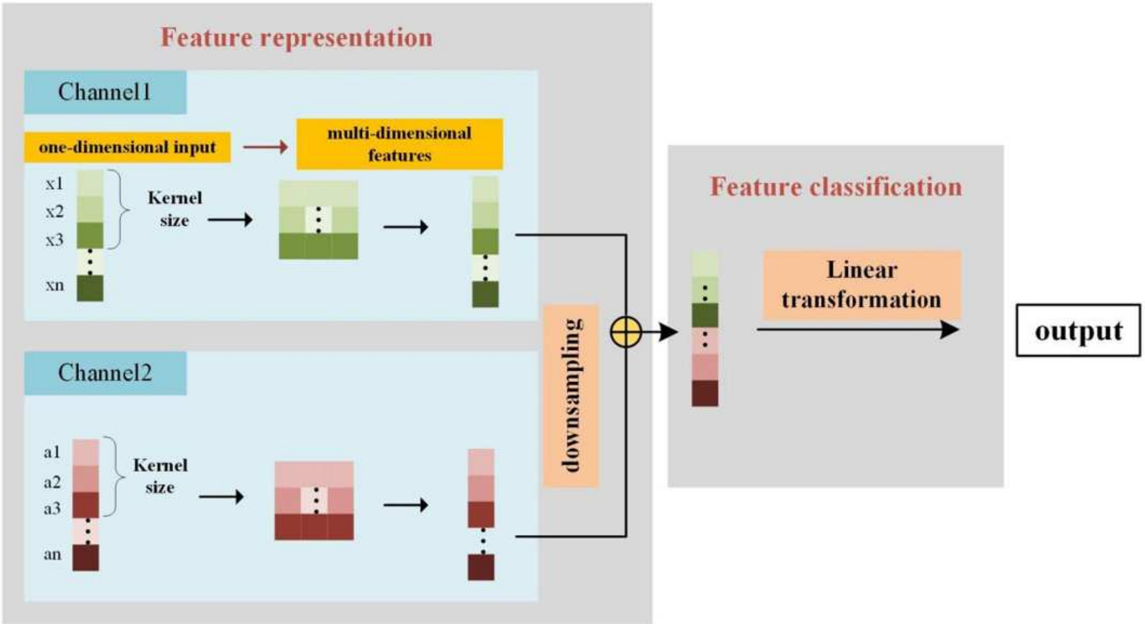

FIGURE 5. CNN structure

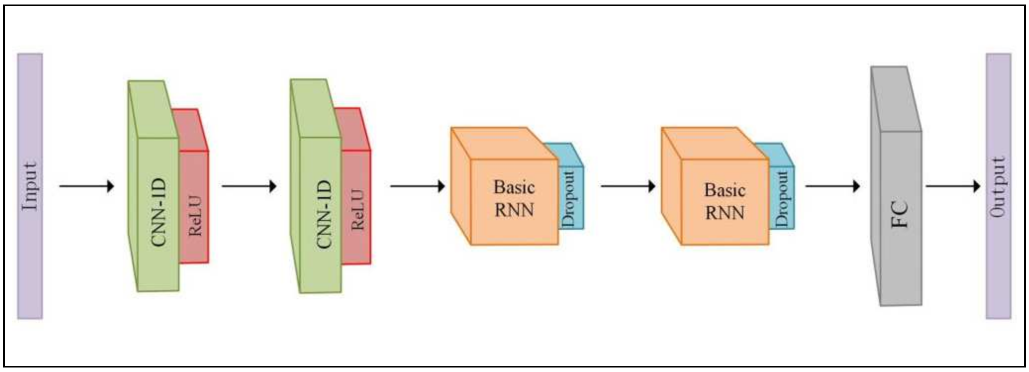

FIGURE 6. The proposed CNN-RNN network

they are to be classified through fully connected (FC) layer. Theoretically, this model will be able to extract the spatiotemporal features of the sequences, and then understand the way spatiotemporal features distribute.

4. **Simulation Experiment.** Figure 7 shows the overall description of the proposed approach. SPC acts as a data filter, whose function is to separate statistically abnormal information from initial data. DL is used for deep mining the potential information features of data. First valid data is marked from original data by the proposed rules of SPC, that is, statistically abnormal data. However, theoretically abnormal data does not mean risks and accidents in the system, and professionals need to deal with these seemingly abnormal data to narrowing down the data. This is to ensure that unnecessary distracting information is excluded. After that, we get the data that represents the real running problem of the process. Last, these data is learnt by the proposed DL models and hidden relationship between real problems and abnormal data can be excavated.

4.1. **Experimental environment and setting.** The experiment was on a private computer with i7-9750 HF CPU, 8GB RAM and GTX 1650 GPU. Python 3.9.5 and PyCharm 2020.1.5 were used. The experiment data came from The People's Hospital of Panjin City,

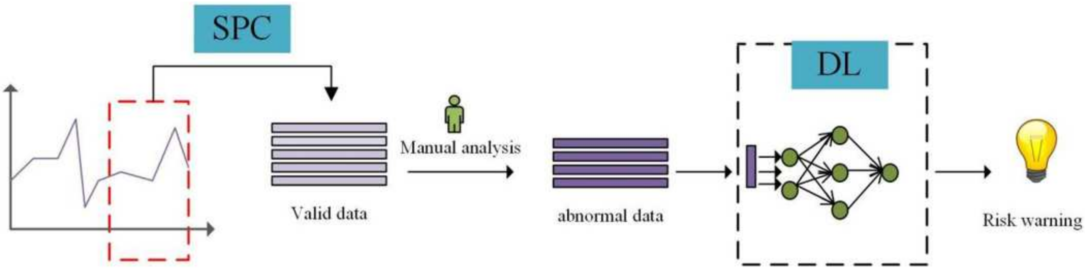

Figure 7. The overall description of the proposed approach

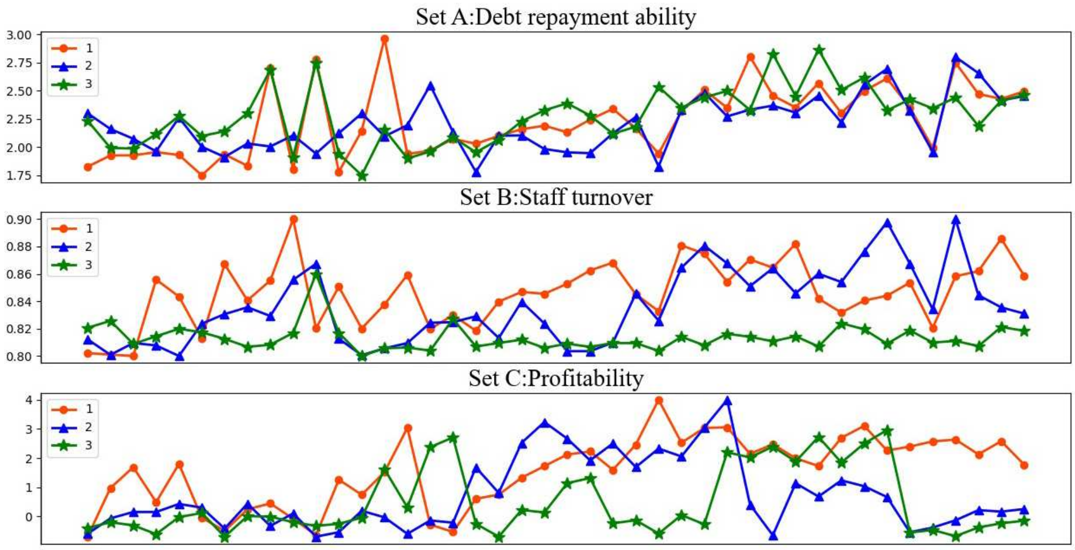

Figure 8. The visualization of experimental data

Panjin, China. We selected three sets of data from the hospital's debt repayment ability, staff turnover and profitability, which were referred to as groups A, B and C, with three samples in each set. These data are collected from January of 2019 to December of 2021. As shown in Figure 8, data in group A ranges approximately from 1.73 to 3. The higher the value, the better the hospital's ability to repay its debts. Data in group B ranges nearly from 0.78 to 0.92, which represents a hospital's ability to take care of patients. The higher the value, the better the ability. Data in group C ranges probably from -0.7 to 4 and the high value means the profit increases.

To demonstrate the effectiveness of the proposed model, comparative experiments were carried out. The CNN-LSTM and CNN-GRU models were built, and GRU and LSTM as the comparative model. In the experiment, GPU was applied to speeding up the training. All models applied the Adam optimizer and the cross-entropy loss function. The hyperparameter setting was shown in Table 3, which was adapted to all experimental models. The hyperparameters are determined according to the result of repeated experiments.

4.2. **Results and discussion.** The total of 510 records identified statistically from original data were at random separated into training set and test set. The parameters of the model are updated through the minimization of training loss. Hence, the training loss manifests, to some extent, if the model meets expectation. The accuracy is another key performance indicator for measuring the quality of models. Take the experimental result of the proposed CNN-LSTM model on real data set as an example. Figure 9 shows the convergence of training loss of the model. Figure 10 shows the accuracy of the training

TABLE 3. The hyperparameter setting

Hyperparameter	Value
The size of CNN kernel	3
The input channel	1
The output channel	120
The step size of CNN kernel	1
Size of CNN pooling layer	3
The number of RNN layers	2
The size of hidden layer	180
Epoch	200
Dropout rate	0.5

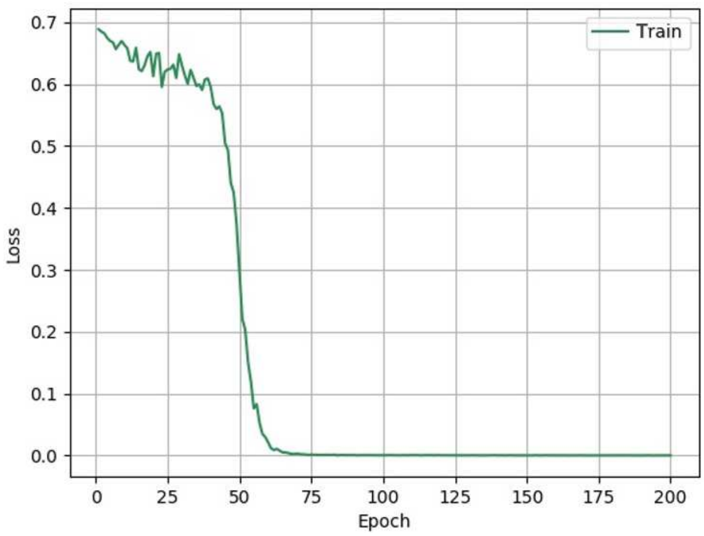

FIGURE 9. The loss of the training process of the proposed model

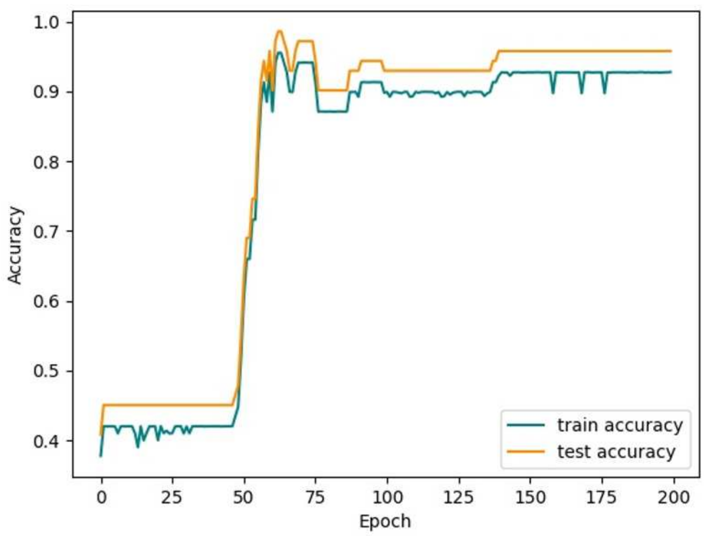

FIGURE 10. The accuracy of the model on real data set

process and test process. Apparently, both of them come to be stable at a high level after a certain number of iteration times. Besides, test accuracy obviously is close to the training accuracy, which means the effectiveness of training is good.

Figure 11 shows the accuracy of the test process and the test process was performed after each training epoch. For debt repayment ability, the accuracy of the proposed model ranges approximately from 95% to 97%, but the classical models ranged from 89% to 93%. For staff turnover, the accuracy of the proposed model ranges from 97% to 99%, but the classical models perform unstably with the final accuracy about 71%, which means the model presumably going overfitting. For profitability, the proposed model performs very well, while there is a huge gap between the proposed model and classical models. Consequently, the proposed models have higher performance than the classical.

We also tested the effect of batch size on the accuracy. Table 4 shows the reported overall classification accuracy of all models. Clearly, the accuracy of all models with the batch size of 30 is higher, compared with batch size of 15. More specifically, with the batch size of 30, the minimum accuracy is 85.63%, and the maximum accuracy is 96.45%. However, with the batch size of 15, the minimum accuracy is 75.66% and the maximum accuracy is 91.96%. In addition, the proposed models apparently outperformed

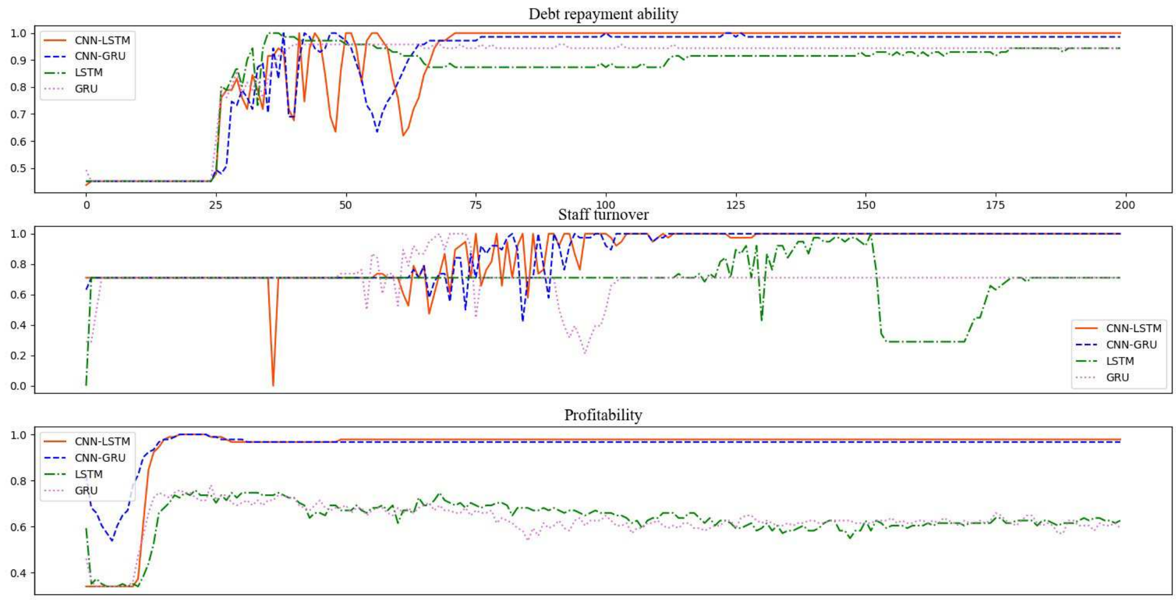

FIGURE 11. Test accuracy of three indicators on respectively CNN-LSTM, CNN-GRU, LSTM, and GRU

TABLE 4. The experimental result

Type of model	Batch size	Accuracy (%)
CNN-LSTM	30	95.73
	15	91.78
CNN-GRU	30	96.45
	15	91.96
LSTM	30	88.42
	15	75.66
GRU	30	85.63
	15	79.42

conventional models. The classification accuracy of the proposed CNN-LSTM and CNN-GRU models ranges from 91.78% to 96.45% whereas the accuracy of traditional models ranges from 75.66% to 88.42%, which means the LSTM and GRU models might have an over-fitting problem.

5. **Conclusion.** This paper is dedicated to providing a new digitized analysis technic about how to effectively analyze and identify risk information in big data. Statistic process control and deep learning are used to extract statistical anomalies and map realistic problems. Real data set is used to carry out experiment and the results show the effectiveness of the proposed technique. Our study is managed to develop a new solution for the identification and management of risk information in big data. In the future, abnormal patterns in other industrial engineering fields can be explored to provide risk warning methods for processes in other industries. At the same time, new control limits are needed to be developed according to statistics which conform to the distribution characteristics of data in the process. Furthermore, more complex situations can be included in the study, such as high-dimensional data anomaly judgment and the impact of multivariate data correlation on anomaly criteria.

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