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Pattern recognition of control chart with variable chain length based on recurrent neural network

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Abstract: The existing control chart pattern recognition method exhibits limitations in discriminating control charts with variable chain lengths, and it demonstrates poor generalization. This study introduces an innovative Recurrent Neural Network (RNN) control chart pattern recognition method designed to enable intelligent recognition of control charts with varying chain lengths and different patterns. In this study, control charts with six different chain lengths are generated through the Monte Carlo simulation method. Prior to processing the raw data, expected values are introduced as padding. Subsequently, an RNN model is established. The trained network model is then deployed to discriminate patterns in control chart data characterized by variable chain lengths. Simulation experiments and engineering applications show that the proposed method achieves a remarkable recognition accuracy of 99.06% and demonstrates robust generalization capabilities. The outcomes of this study bear direct practical relevance to the manufacturing industry and advanced manufacturing technologies. By enhancing pattern recognition accuracy under variable chain lengths, we can more effectively monitor the production process, reduce defect rates, and elevate production efficiency.

Keywords: Control chart; pattern recognition; variable chain lengths; recurrent neural networks; deep learning

1. Introduction

Statistical process control (SPC) constitutes a crucial component of comprehensive quality management, serving as an effective means for enterprises to guarantee the quality of products or services. Its impact extends to enhancing the core competitiveness of enterprises within product or service markets. The primary instrument within SPC, the control chart, is widely employed to assess the stability of the processing process, representing the predominant tool for monitoring quality fluctuations in manufacturing processes [1]. When the early control chart is applied, its effectiveness relies on the observations of quality management personnel. The identification effect depends on the relevant knowledge and experience of these personnel, rendering it susceptible to subjective factors [2]. The currently prevalent rule-based judgment methods face limitations in accurately describing various abnormal patterns within processes. This limitation results in issues such as missed alarms and delayed warnings stemming from abnormal fluctuations. The rise of artificial intelligence technology has reshaped the identification of abnormal patterns in control charts, eliminating the dependence on the experience or judgment rules of management personnel. Both academic and industrial communities have conducted extensive research in this field. Early control chart pattern recognition mostly adopted rules-based expert system (Expert System, ES) [3]. And numerous scholars [4-6] have proposed various non-natural pattern detection methods based on supplementary rules. Shewhart [7] conducted a comparative analysis between machine learning methods and expert system approaches in the application of control chart identification. Notably, machine learning exhibit greater convenience, efficiency, and accuracy compared to expert system. Pham *et al* [8] extracted shape features from control charts and developed a knowledge base to identify the belonging pattern using traditional expert system methods. This approach partially enhanced the recognition accuracy of the expert system. However, challenges persist in abnormal identification due to incomplete feature extraction. Le [9] proposed a locally supervised feature mapping network for control chart pattern recognition, characterized by a simple network structure, fast convergence speed, and notably enhanced recognition accuracy. Chen [10] employed an enhanced BP algorithm for control chart identification. This involved the application of the dynamic gradient descent method, adaptive adjustment of learning rate gradient method, and standardized co-gradient drop algorithm for network training. The results underscore the significant positive impact of the enhanced BP neural network on recognition rate improvement. However, noteworthy changes in recognition rates are not observed with a continued increase in the number of samples. Wang *et al.* [11] proposed a fuzzy self-adaptive resonance theoretical neural network with incremental learning capability, an unsupervised algorithm able to perform pattern clustering analysis. This method demonstrates superior recognition efficacy compared to the traditional multi-layer perceptron (MLP). Zan *et al.* [12] utilized an adaptive modification learning rate BP network and probability neural network to identify abnormal patterns in control charts. The analysis highlights the effectiveness of combining neural network identification with rule-based recognition methods, addressing the limitations associated with single-method approaches. Ata Ebrahimzadeh [13] innovatively applied the entropy of the small wave bag for feature extraction, providing an entropy-based standard that accurately represents pattern information. This approach exhibits robust generalization capabilities compared to other neural networks. Hou [14] proposed a method involving wavelet decomposition of the original signal, selecting response coefficients to reconstruct abnormal signals of different frequencies, and fitting the reconstruction signal to obtain a new feature number. This approach demonstrates effective recognition of uncertain abnormal patterns characterized by an upward trend and periodic abnormalities. However, improvements are needed to enhance its applicability to other types of uncertain abnormal patterns. Li *et al.* [15] proposed hybrid intelligent algorithms for control chart identification, integrating wavelet transform, principal component analysis, and particle swarm algorithms. This approach overcomes the limitations of traditional models, resulting in an improved recognition rate for control chart patterns. Zhang *et al.* [16] proposed a method that combines improved sequential forward selection with extreme learning machines for control chart pattern recognition. By selecting features to reduce redundancy and employing extreme learning machines for pattern recognition, a substantial improvement in recognition accuracy is achieved. However, it is important to note that this method only considers linear relationships between features and overlooks nonlinear relationships. Wang [17] presented a mixed abnormal pattern recognition algorithm based on wavelet analysis for control charts. This method utilizes the reconstructed detail signals and approximation signals after wavelet decomposition as fundamental patterns for the original mixed abnormal pattern, serving as inputs for a neural network, resulting in a high network recognition rate. However, the algorithm is limited to recognizing mixed abnormal patterns characterized by upward trends and cycle patterns, lacking generalization to other mixed patterns. Hou [18] applied the Bayesian rule to compute the confidence level for each pattern, making judgments on control chart patterns based on the statistical values of the decision points in each sample. Basic control chart patterns exhibit good applicability in terms of recognition rate and sensitivity. The evolution of artificial intelligence technology has seen the widespread adoption of methods such as Artificial Neural Network and Support Vector Machine in the domain of control chart pattern recognition. Liu [19] integrated time-domain features and shape features with wavelet decomposition to obtain an enhanced feature set, employing SVM as a classifier to improve the accuracy and efficiency of quality abnormal pattern recognition. This indicates the significance of feature selection, yet there is a limitation in addressing the information loss resulting from wavelet decomposition. Wang [20] proposed a control chart pattern recognition method based on principal component analysis, combining high-dimensional data into a linear combination and projecting it into a low-dimensional space to reduce the input dimensions for the classifier. Subsequently, SVM is employed for multi-classification recognition, effectively reducing the false negative rate and false positive rate. However, the method encounters challenges in extracting features from raw data with nonlinear relationships, leading to potential feature loss. The emergence and development of deep learning methods have expedited the utilization of low-level features to form more abstract high-level representations of attribute categories, facilitating the exploration of distributed features in data for control chart pattern recognition.

T.T. El-Midany *et al.* [21] proposed a framework for control chart recognition, employing an artificial neural network (ANN) to identify multi-variable abnormal patterns, obtaining high-precision recognition results. However, its performance diminishes notably in cases where multiple non-natural patterns coexist, such as transitions with cyclic patterns. Medhat H.A. Awadalla *et al.* [22] proposed a control chart identification method based on the Spike neural network and an enhanced SpikeProp learning algorithm, providing additional learning rules for synaptic delay, time constant, and neuron threshold. The resulting overall recognition rate reached 98.61%. Nevertheless, converting all data features into numbers and transforming reasoning into numerical calculations may lead to information loss. Héctor De La Torre-Gutiérrez *et al.* [23] proposed a control chart identification system for feedback control, utilizing raw data as input to generate patterns and demonstrating the capability to recognize various types of patterns to some extent. The choice of controller significantly influences recognition accuracy, and there is a notable need for deep learning techniques to enhance precision. Tao *et al.* [24] proposed a control chart identification method based on a one-dimensional convolutional neural network (1D-CNN), addressing the challenge of manually extracting complex features from traditional methods. By employing a one-dimensional CNN for optimal feature set acquisition through feature learning from raw control chart data, the trained model performed well in recognizing real data from production environments. Miao *et al.* [25] extracted statistical and shape features from raw data of control charts and utilized them as inputs to train a Convolutional Neural Network (CNN) for control chart pattern recognition. While this method yielded well recognition results, it still relied on manually extracted expert features as input, failing to fully exploit the potent feature learning capabilities of deep learning algorithms. Tao *et al.* [26] employed a multi-layer bidirectional Long Short-Term Memory network (Bi-LSTM) to learn optimal features from raw data, which showed substantial advantages in recognition accuracy. However, this approach necessitates retraining the network for control chart data with variable chain lengths and lacks robust generality. Wu *et al*. [27] proposed a control chart identification method based on bidirectional Long Short-Term Memory networks, utilizing the time-series prediction characteristics of the LSTM algorithm to theoretically detect process abnormalities earlier. Nonetheless, this method has not undergone validation in actual production scenarios and lacks practical engineering value. Chen *et al*. [28] utilized a deep recursive neural network model to represent process variables under different time lags, establishing a residual chart for detecting average shifts in auto-correlated manufacturing processes, demonstrating strong performance. Janssens *et al*. [29] employed CNNs to extract vibration signal features for rotating machinery fault diagnosis, achieving excellent results. Furthermore, Probabilistic Neural Network (PNN) [30], Spiking Neural Network (SNN) [31], and Learning Vector Quantization (LVQ) [32-34] are widely utilized in control chart pattern recognition. However, these approaches suffer from issues such as convergence difficulties, susceptibility to local minima, and challenges in determining network structure, constraining their further development in this field.

Table 1. Performance comparison of different methods.

Reference	Input Form	Method	Length Of Control Chart	Distance
Pham *et al*	Shape features	Expert system	Fixed length	Incomplete feature extraction
Chen	Raw data	BP algorithm	Fixed length	The recognition rate changes are not obvious
Wang	Raw data	Fuzzy theoretical	Fixed length	Low recognition efficiency
Hou	Control chart picture	Wavelet decomposition reconstruction	Fixed length	Intelligent online monitoring is not implemented
Liu	Characteristics of time-domain features and shape features	SVM	Fixed length	Wavelet decomposition results in information loss
Tao *et al*	Raw data	1D-CNN	Fixed length	Failure to achieve online prediction and diagnosis
Wu *et al*	Raw data	Bi-LSTM	Fixed length	Lack of actual verification of the feasibility of the method
This work	Raw data	RNN	Variable chain length	Variable chain length control chart

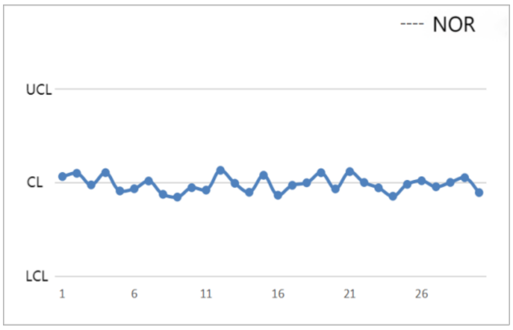
The aforementioned studies have addressed issues such as subjective factors and low discrimination efficiency in the control chart anomaly recognition process. However, it is observed that multiple Neural Network models must be trained to identify control charts with variable chain lengths, which is not conducive to early warning of abnormal patterns and impeding practical enterprise applications. Thus, there is a critical need to develop a concise and efficient approach for swift pattern recognition in control charts of different lengths. Currently, RNNs are not extensively studied in the domain of control chart pattern recognition, particularly concerning variable chain length control chart data. RNNs possess a notable advantage in extracting dynamic data features, making them suitable for handling time-series data like control chart information. In this study, we propose a novel pattern recognition method for control charts with variable chain lengths, employing the RNN model. The feasibility and effectiveness of this method are validated through simulation experiments and engineering applications.

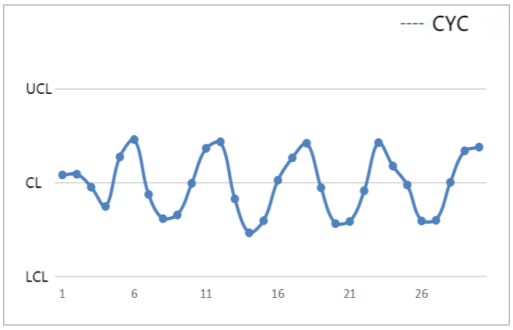
2. Methods

2.1. Control chart recognition principle

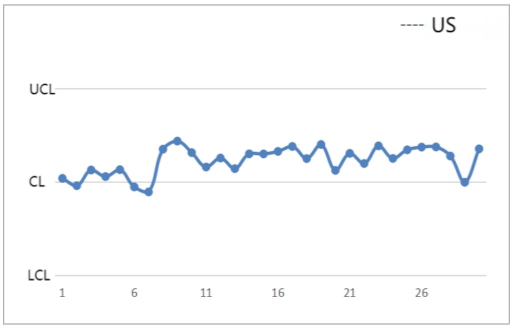
Control charts play an important role in enterprise quality control, serving as a widespread tool for monitoring the controlled state of processing processes [35]. During the production process, sample data typically follows a normal distribution. Integral calculation of the normal distribution's density function enables the determination of the probability within different quality eigenvalue intervals. Rule-based control charts employ two discriminant criteria categories: points exceeding boundaries and points within limits but not randomly arranged. Currently, judgment criteria for utilizing control charts in enterprises primarily adhere to the eight situations given by ISO 8258:1991. However, this method can not fully describe various abnormal patterns in the process, often leading to issues such as missed alarms and delayed alerts due to abnormal fluctuations. To address these limitations, experts and scholars enhance the rule-based discriminant method by identifying and summarizing typical abnormal patterns in control charts.

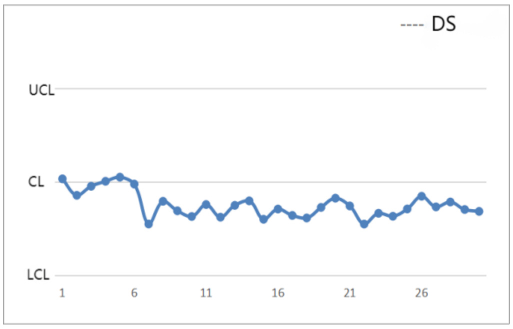
Based on the fluctuation distribution characteristics of product quality within the production process, researchers have summarized six characteristic control chart patterns, depicted in Figure 1. These patterns include Normal (NOR), Upward trend (UT), Downward trend (DT), Upward shift (US), Downward shift (DS), and Cycle (CYC).



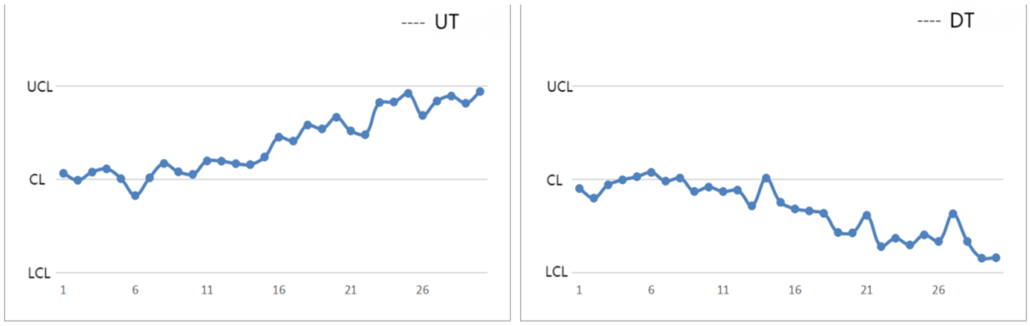


(a)Normal pattern (b)Cycle pattern





(c)Upward trend pattern (d)Downward trend pattern



(e)Upward shift pattern (f)Downward shift pattern

Figure 1. Typical patterns of control charts.

Training recognition models typically demands a sufficient supply of training samples, yet acquiring real production data proves challenging. Consequently, simulation data becomes a prevalent choice for replacing experiments data, with the Monte Carlo simulation algorithm acknowledged by scholars in the field as a reliable method for simulating product quality data [36]. The general formula for simulation is presented below.

$$y(t)=\mu+x(t)+d(t) \qquad (1)$$

Where t represents the sampling time of production data. y(t) represents the observed values of the production process. μ represents the expected value of quality characteristics when production is stable; x(t) represents the normal fluctuation caused by random factors and follows the normal distribution $x(t)\sim N(0,\sigma^2)$; d(t) represents abnormal fluctuations caused by exceptional factors. In the normal mode, the machining process is under control, d(t)=0. When a trend-type anomaly occurs, $d(t)=\pm\rho\times d\times t$, "+" represents an upward trend, "-" represents a downward trend; and d is the slope; ρ is 0 before the trend appears and 1 after it appears. When a step-type anomaly occurs, $d(t)=\pm\rho\times s$, "+" represents an upward step, and "-" represents a downward step; ρ is 0 before the trend appears and 1 after it appears; s represents shift magnitude.

When a periodic anomaly occurs, $d(t)=a\times\sin(2\pi t/\omega)$, where a is the amplitude of the fluctuation and ω is the period of the fluctuation.

In contrast to other traditional machine learning algorithms like MLP or CNN, RNN exhibits a flexible architecture that can be tailored and optimized according to the characteristics and complexity of the data. This adaptability allows it to accommodate different types of control chart data. Notably, RNN features a distinctive recurrent connection structure, enabling it to learn inter-sequence features during training. This process facilitates the saving and updating of relevant information, thereby achieving a "memory" function and resolving issues related to "forward and backward dependency relationships." RNN is particularly suitable for modeling data with time series changes, offering advantages such as parameter sharing, processing variable-length data series, and efficient long and short-term memory. Furthermore, in the context of control chart pattern recognition, where dynamic changes in data must be distinguished, RNN's ability to consider past states for predicting future situations is advantageous. For control chart data with variable chain lengths, RNN can effectively extract original features, giving inherent advantages in the field of control chart pattern recognition.

2.2. RNN model

RNN is a type of deep neural network [37], representing by the network structure illustrated in Figure 2. On the basis of the fully connected neural network, RNN incorporates time sequence relationships, enhancing its capacity to address temporal-related challenges, such as those encountered in machine translation. The calculation formula for RNN is outlined as follows:

$$O_t=g(V\cdot S_t) \qquad (2)$$

$$S_t=f(U\cdot X_t+W\cdot S_{t-1}) \qquad (3)$$

Where X_t is the input value at the current time, W and U are the weight matrices, g and f are the activation functions, S_t is the output of the hidden layer at the current time, and O_t is the output at the current time.

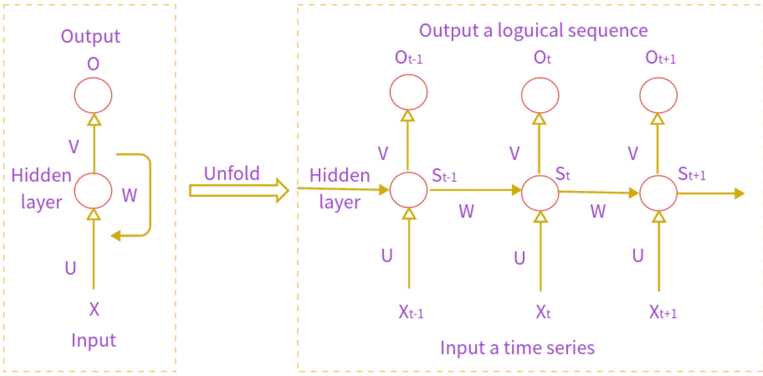


Figure 2. RNN structure diagram.

2.3. Variable chain lengths data processing

To achieve pattern recognition of data with variable chain lengths within a unified network model, it is imperative to process one-dimensional quality data into the same length by pre-filling values before the raw data sequence. This study introduces three data processing methods: padding with 0 values, padding with expected values, and padding with the mean value of the sequence, denoted in the following formulas, where 'i' represents the i-th control chart data sequence. Experimental results reveal that padding with the expected values proves to be more effective.

As the input control chart data sequence:

$$x(t)=y_1、y_2、y_3 \cdots y_{n-1}、y_n \qquad (4)$$

At a certain time in the control chart data sequence:

$$y(i)=y_1、y_2、y_3 \cdots y_{n-1}、y_n \qquad (5)$$

Where m>n, it is necessary to normalize the data sequence first. The three methods for data processing are as follows:

Padding with zero values, The number of supplemental 0 values is (m-n).

$$y(i)'=0、0 \cdots 0 \cdots y_1、y_2、y_3 \cdots y_{m-1}、y_m \qquad (6)$$

Padding with expected values (a is the expected value), The number of supplemental a value is (m-n).

$$y(i)''=a、a\cdots a\cdots y_1、y_2、y_3\cdots y_{m-1}、y_m \quad (7)$$

Padding with the mean values of the sequence (b is the mean values of the sequence), The number of supplemental b values is (m-n).

$$y(i)'''=b、b\cdots b\cdots y_1、y_2、y_3\cdots y_{m-1}、y_m \quad (8)$$

To mitigate the impact of different units of measurement on the analysis results, the control chart data undergoes normalization prior to training. The normalization formula is expressed as follows. This process significantly enhances the model's convergence speed and accuracy. In the formula, 'x' represents a specific data point in the control chart sequence, x_{min} and x_{max} denotes the minimum and maximum values of the control chart data, and x^* represents the normalized data.

$$x^* = \frac{x-x_{min}}{x_{max}-x_{min}} \quad (9)$$

3. Experiments and results

3.1. Simulation

This study considers six common control chart patterns: normal, upward trend, downward trend, upward shift, downward shift, and cycle patterns. Employing a uniform distribution method, simulation parameters for these patterns are randomly selected within a specified range, characterized by an expected value of 30 and a standard deviation of 0.05. Abnormal pattern occurrences are randomly chosen within the range [4,9], with a set period length of 8 and an amplitude value fixed at 1.5. The Monte Carlo simulation algorithm is applied to generate training and testing datasets, encompassing control charts with variable chain lengths ranging from 25 to 30, amounting to a total of 43,200 samples. The training set includes 6,000 samples for each pattern, summing up to 36,000 samples, while the testing set comprises 1,200 samples for each pattern, totaling 7,200 samples.

To closely approximate complex production data in simulation, we employ a uniform distribution method to randomly select Monte Carlo simulation parameters for various control chart samples within a specified range. The simulation parameters are detailed in Table 2.

Table 2. Simulation parameters of six control chart patterns.

Mode category	Formula	Parameter Value/Range
NOR	$y(t) = \mu + x(t)$	$\mu = 30, \sigma = 0.05$
UT	$y(t) = \mu + x(t) + v \times d \times t$	$d \epsilon [0.15\sigma, 0.3\sigma]$
DT	$y(t) = \mu + x(t) - v \times d \times t$	$d \epsilon [0.15\sigma, 0.3\sigma]$
US	$y(t) = \mu + x(t) + v \times s$	$s \epsilon [1.5\sigma, 3\sigma]$
DS	$y(t) = \mu + x(t) + v \times s$	$s \epsilon [1.5\sigma, 3\sigma]$
CYC	$y(t) = \mu + x(t) + v \times a \times sin\,(2\pi t/\omega)$	$a \epsilon [1.5\sigma, 4\sigma], \omega \epsilon \{4,5,6,7,8\}$

3.2. Experiments

To determine the optimal structure of RNNs and assess their performance under varying network parameters, two sets of experiments were conducted on the same dataset. The first set aimed to optimize the number of layers and neurons in the RNN, while the second set focused on optimizing the type of activation function and optimizer. The experimental results are presented in Tables 3 and 4, with the final network parameters summarized in Table 5. Subsequently, under the established network parameters, a comparative analysis of the three previously described data preprocessing methods was performed, as outlined in Table 6.

Table 3. Performance of RNN under different network parameters.

Experiment	Layer	Number of Neurons	Accuracy(%)	Loss(%)	Time(ms/epoch)
1	3	32	0.8014	0.3902	9.0667
2	3	32	0.8181	0.3415	8.3200
3	3	64	0.9737	0.0637	5.6667
4	3	64	0.8901	0.0219	6.4333
5	4	32	0.8015	0.3751	8.0667
6	4	32	0.8930	0.1017	8.2154
7	4	64	0.9930	0.0216	6.3000
8	4	64	0.9937	0.0234	6.3012

Table 4. Performance of RNN under different network parameters.

Experiment	Optimizer	Activation Function	Accuracy(%)	Loss(%)	Time(ms/epoch)
1	Adam	SoftMax	0.9359	1.1066	13.1000
2	Adam	SoftMax	0.9798	1.0640	14.1667
3	Adam	ReLU	0.9766	0.0645	12.8400
4	Adam	SoftMax	0.9069	0.0874	10.8000
5	SGD	SoftMax	0.4110	1.6309	11.4333
6	SGD	SoftMax	0.8064	1.3029	11.0667
7	SGD	ReLU	0.8506	0.2430	10.5333
8	SGD	ReLU	0.8652	0.2293	11.2653

Table 5. Final network parameters.

Experiment	Layer	Optimizer	Number of Neurons	Activation Function	Accuracy(%)	Loss(%)	Time(ms/epoch)
1	4	Adam	64	ReLU	0.9359	1.1066	13.1000
2	4	Adam	64	ReLU	0.9798	1.0640	14.1667

Table 6. Comparison of data processing methods in different windows.

	Padding with zero value	Padding with expected value	Padding with mean value
Accuracy (%)	0.9405	0.9765	0.9751
Loss (%)	1.1104	0.0608	0.0677
Time(ms/epoch)	9.3333	6.1333	5.7333

As depicted in Table3, Table4, and Table 5, following the 16 comparative experiments, the finalized selection for the RNN architecture comprises 4 layers with 64 neurons, utilizing the Adam optimizer and the Rectified Linear Unit (ReLU) activation function. The trained model achieved an impressive accuracy of 99.06%, showcasing optimal results for both the loss function and training time. The training process of the RNN model is illustrated through the convergence curve of the loss and accuracy in Figure 3. The results indicate that utilizing the Adam optimization function as the optimizer for RNN classification models led to the convergence of training error after 150 iterations.

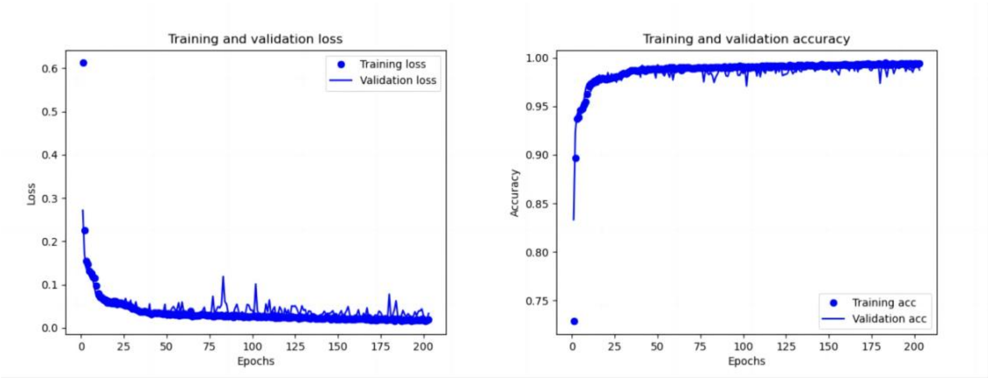


Figure 3. Loss vs accuracy curve during training.

Conducting a detailed analysis of the pattern recognition performance of the control chart utilizing the RNN model, a confusion matrix of recognition results was generated, as illustrated in Figure 4. The RNN-based pattern recognition method for control charts with variable chain lengths demonstrated some confusion, particularly in distinguishing between the normal pattern and the cycle pattern, while it exhibited accurate predictions in other patterns, resulting in an impressive overall accuracy rate of 99.06%.

Figure 4. Control chart pattern recognition confusion matrix.

3.3. Comparison of RNN and other methods

To further assess the proposed method's performance, a comparative experiment involving RNN, MLP, and Deep Belief Network (DBN) was conducted [38-39]. The test set was utilized to validate each network model's performance, and the confusion matrix of the recognition effect is presented in Figure 5. The results reveal a tendency of confusion, particularly from the normal pattern to the cycle pattern in abnormal patterns, as illustrated in Figure 6. This study extracted and analyzed two types of recognition confusion patterns. Among the three compared methods, MLP exhibited the most severe confusion, possibly due to the similarity between the normal pattern and the cycle pattern. The occurrence of false alarms during the control chart pattern recognition process can hinder a company's quality management efforts [40-41]. In the dataset comprising 7200 samples, the RNN-based control chart pattern recognition method with variable chain lengths achieved an impressive overall recognition rate of 99.06%, demonstrating significant advantages in accurate pattern recognition over other methods.

Figure 5 depicts the error classification of the MLP and DBN algorithms. In the DBN algorithms, the total recognition rate is 98.97%, with particularly advanced recognition results for the DT and US patterns, reaching respective recognition rates of 99.91% and 99.83%. However, MLP's total recognition rate is 85.33%. The experimental results indicate that although the DBN's recognition rate is higher than that of MLP, the two methods exhibit distinct advantages in identifying different patterns.

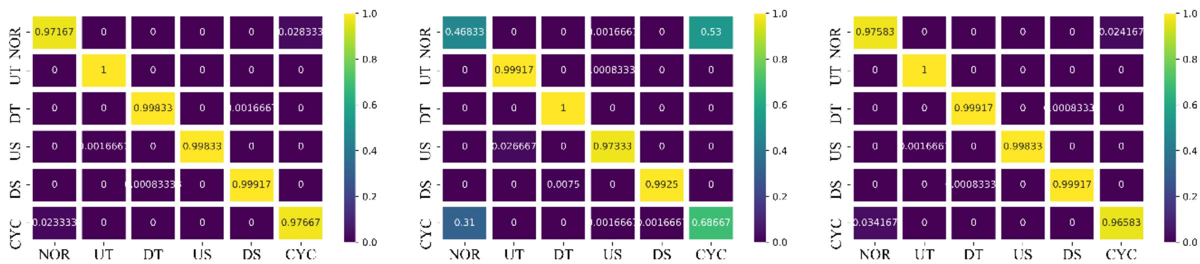


Figure 5. RNN、MLP、DBN networks confusion matrices compare.

To further validate the feature learning capability of the proposed method for control chart patterns, we conducted a comparison between the features extracted from raw data and those extracted using RNN. The results were visualized using the t-distributed stochastic neighbor embedding (t-SNE) [42] algorithm, which reduces the dimensions of feature sets for data visualization in a two-dimensional space, as illustrated in Figure 7.

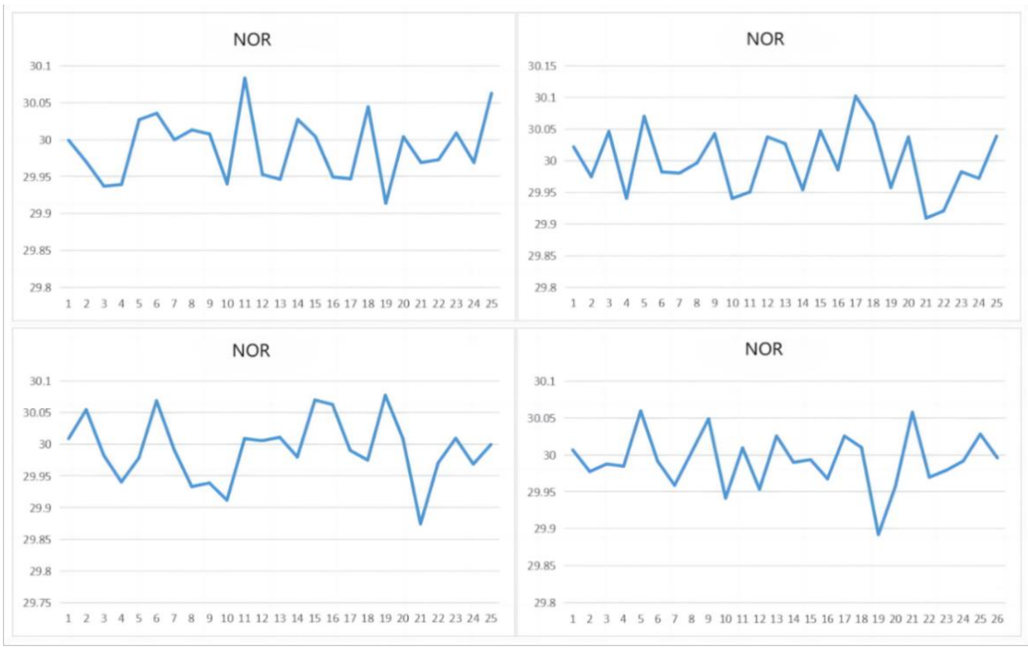


Figure 6. Cycle pattern and normal pattern recognition are confused.

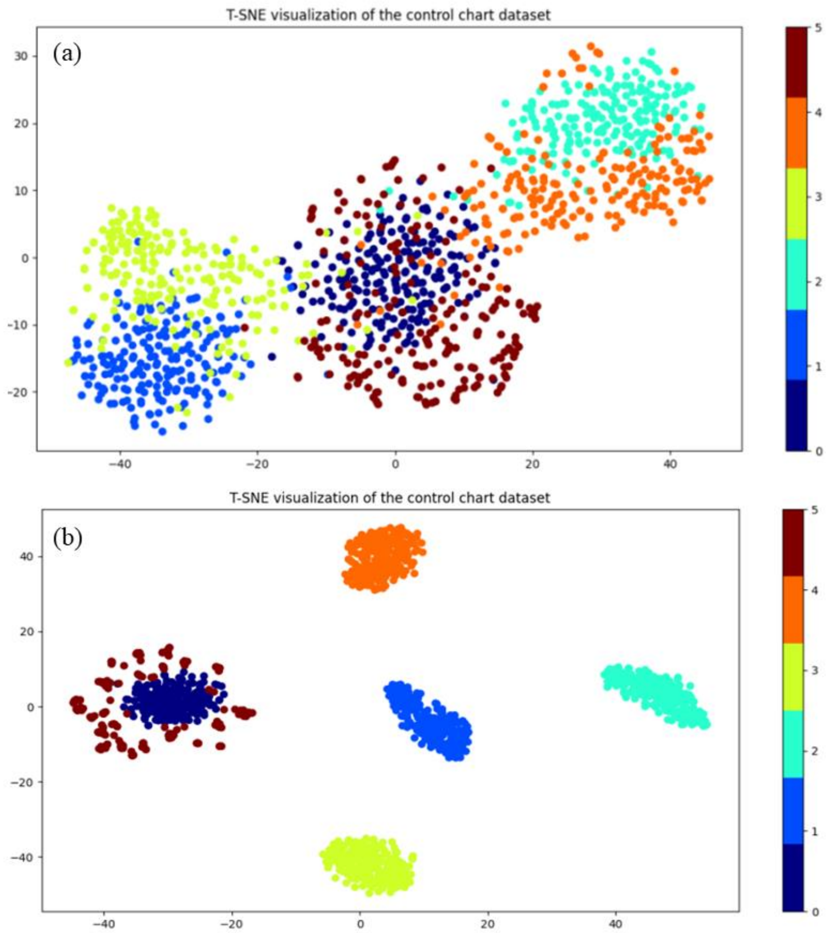


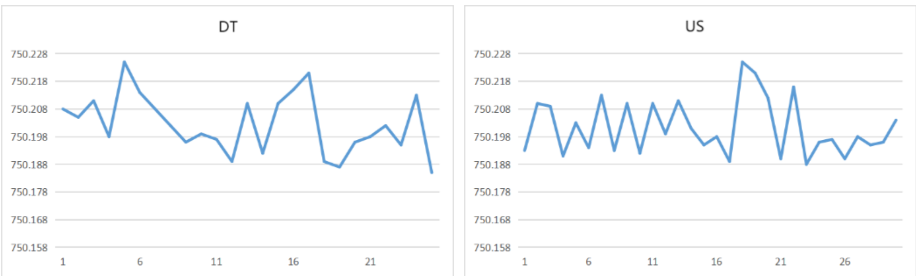
Figure 7. The feature visualization results for **(a)** the expert features, and **(b)** the features extracted by RNN.

In the field of pattern recognition, particularly in pattern classification, the feature set is expected to exhibit a clustered distribution in the feature space. A high quality feature set manifests as smaller distances within the same class and greater distance between different classes, signifying superior quality for classifier classification. As depicted in Figure 7a, raw data features exhibit a tendency toward a clustered distribution, but confusion between different patterns is evident. Conversely, in Figure 7b, features extracted by the RNN display a distinct and clear clustered distribution in the feature space, highlighting a notable clustering effect. Despite the close distance between the cycle pattern and the normal pattern due to the inherent data characteristics, the RNN-extracted features effectively distinguish between different patterns. This indicates that the RNN has successfully learned superior features from the raw control chart data.

4. Application in production environment

The methodology in this study has been effectively implemented for monitoring production quality data in a specific enterprise. Taking the quality indicator of a crucial process for axle components as an example, where the process size is $\varphi 750^{+0.235}_{+0.158}$ mm, the aforementioned method is employed for analyzing the quality data. The level of detail provided aligns with the confidentiality requirements of the involved companies. To validate the efficacy of the variable chain lengths control chart pattern recognition method, data with chain lengths of 25 and 30 are specifically chosen for comparative analysis.

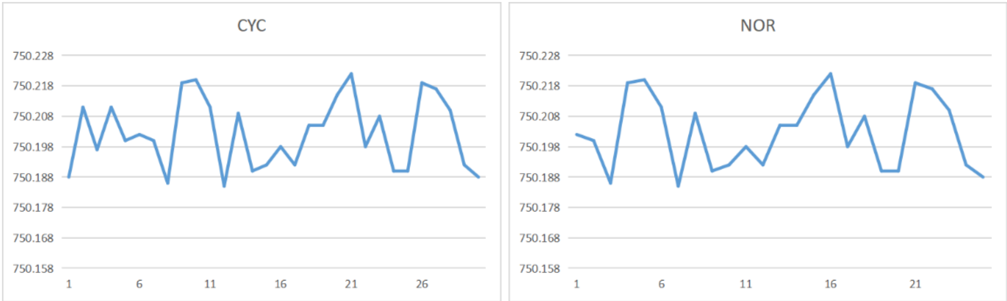
Both chain lengths demonstrated excellent recognition performance for typical control chart patterns, as depicted in Figure 8. The downward trend pattern and the upward shift pattern were promptly and accurately identified. Subsequent analysis and on-site investigation revealed that these anomalies were attributed to tool wear and batch variations in raw materials. Timely interventions were then implemented to rectify the anomalies. The identification results indicate that the production state of the enterprise is fundamentally under control.



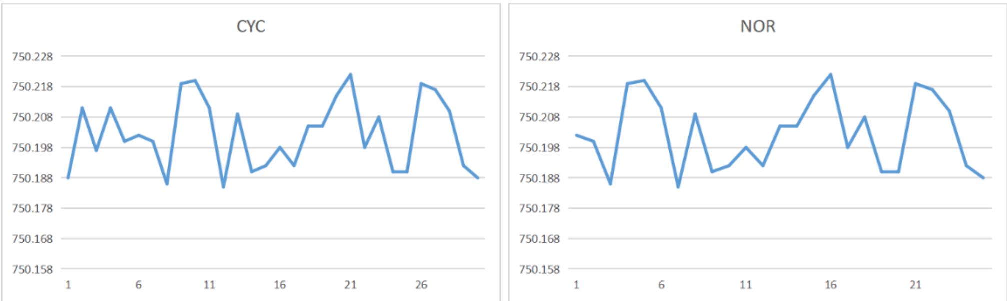
(a) (b)

Figure 8. Downtrend and upward step pattern control charts.

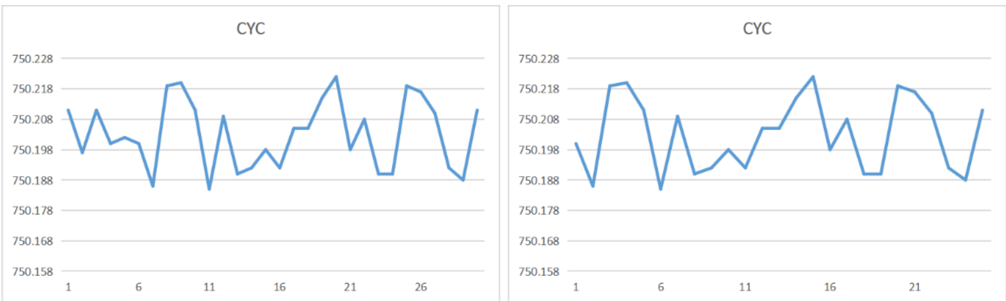
Compared to traditional control chart pattern recognition methods, the variable chain lengths method can help enterprises detect control chart pattern anomalies and quality fluctuations at an earlier stage. As illustrated in Figure 9. In Figures (a) and (b), depicting control charts of the latest quality data for axle components at a specific moment, both with chain length 30 and chain length 25, the charts are determined to be in a normal mode. However, when new quality data is collected, the control chart with a chain length of 30 is identified as a cycle pattern, while the control chart with a chain length of 25 is still identified as a normal pattern, failing to timely detect the pattern anomaly, as shown in Figures (c) and (d). With the continuous addition of more data, both control charts of different chain lengths are identified as cycle patterns, as shown in Figures (e) and (f). The application results indicate that the use of control charts with different chain lengths to analyze the quality data of the same production process, combined with the application of RNN to identify control chart patterns, can effectively detect production anomalies, reduce economic losses, and improve the level of production quality management.



(a) (b)



(c) (d)



(e) (f)

Figure 9. Variable long control chart pattern recognition.

5. Conclusion

In this study, a control chart pattern recognition method with variable chain lengths based on RNN was developed, demonstrating intelligent recognition of abnormal patterns across different control charts. Findings lead to the following conclusions:

(1) The proposed RNN-based method for pattern recognition in control charts enhances the capture of underlying feature relationships within the data through the inherent recurrent structure of RNN. Addressing the limitations of pattern recognition in traditional control charts. This method ensures recognition accuracy, significantly enhancing the model's generalization. The proposed approach enables early detection of abnormal patterns, thereby improving the overall quality management in the manufacturing process.

(2) The introduction of a data preprocessing method, involving padding with expected values before the raw data sequence, exhibits favorable applicability and generalization in recognizing anomaly patterns in control charts with varying lengths.

(3) The RNN-based variable-length control chart pattern recognition method, as proposed in this study, outperforms the traditional MLP model in terms of recognition accuracy, convergence speed, and iteration time, achieving an accuracy rate of 99.06%. Validated through engineering applications, the methodology proves effective in the timely and accurate detection of control chart anomaly patterns.

In summary, the proposed methodology overcomes the shortcomings of traditional methods, significantly improving the accuracy of control chart anomaly detection. It plays a crucial role in optimizing practical quality control, enhancing the intelligence and automation levels of enterprise quality management. The industrial Internet's increasing prevalence and the exponential growth in computer processing capabilities have highlighted the advantages of big data. The proposed method in this study offers a novel approach for further research in this expanding field, promising improved automation and intelligence for enterprise quality management. In future endeavors, we will continue our research on pattern recognition in control charts under mixed modes and explore mechanism studies. We aim to integrate pattern recognition problems with probability calculations, leading to more generalized and effective pattern recognition methods.

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Conflicts of Interest

The authors declare no conflicts of interest.

Authors contribution

Conceptualization, T.Z. and J.C.; methodology, J.C.; software, J.C.; validation, M.W., T.Z.; formal analysis, X.G.; investigation, X.G.; resources, Z.L.; writing—original draft preparation, J.C.; writing—review and editing, T.Z and W.L.; visualization, P.G.; supervision, Z.S.; project administration, M.W.; funding acquisition, M.W. All authors have read and agreed to the published version of the manuscript.

References

[1] Zhu B. Research on quality control methods for automatic machining processes based on support vector machines. Chongqing University.
[2] Saghir A. Flexible and robust control charts in statistical process monitoring. Zhejiang University, 2014.
[3] Evans JR, Lindsay WM. A framework for Expert System development in statistical quality control. *Comput. Ind. Eng.* 1988, 14(3):335-343.
[4] Roberts SW. Properties of Control Chart Zone Tests. *Bell Syst. Tech. J* 2012, 37(1):115-134.
[5] Nelson LS. Interpreting Shewhart X-bar control charts. *Qual Technol Quant M.* 1985, 17:114-116.
[6] Klingst A. Quality Control and Industrial Statistics - *Duncan, Acheson* 1959.
[7] Shewhart M. Interpreting statistical process control (SPC) charts using machine learning and expert system techniques. *Aerospace; Electronics Conference. IEEE Xplore*,1992.
[8] Pham DT, Wani MA. Feature-based control chart pattern recognition. *Int. J. Prod. Res.* 1997, 35(7):1875-1890.
[9] Yue QH, Gao XH, Hao J, Zhu MQ. A novel neural network for pattern recognition. *Comp Engineering* 2004 (17):17-18+35.
[10] Chen P, Huai CJ, Luo J. Improved BP algorithm for control chart pattern recognition. *M&E* 2005 (03):42-44.
[11] Wang M, Zan T, Fei R. Intelligent Statistical Process Control Using Fuzzy ART Neural Networks. *Front. Mech. Eng. in China* 2010, 5149-156.
[12] Zan T, Wang H, Liu ZH, Wang M, Gao XS. Rolling bearing fault diagnosis model based on multi input layer convolutional neural network. *Vib. Shock* 2020, 39(12):142-149+163.
[13] Ebrahimzadeh A, Ranaee V. Control chart pattern recognition using an optimized neural network and efficient features. *ISA Trans.* 2010, 3(49):387-393.
[14] Hou SW, Zhu HM, Li R. Pattern recognition of uncertain anomalies in quality control charts based on Simulink simulation. *CA* 2012, 32(10):2940-2943.
[15] Li C, Zhang HL, Zhao X. Simulation research on control diagram pattern recognition of hybrid intelligent algorithm. *Computer Simulation* 2013, 30(10): 345-349+437.
[16] Zhang YB, Lin XN. Pattern recognition method of SPC control chart combined with improved sequence forward selection method (ISFS) and extreme learning machine (ELM). *Journal of Qingdao University of Science and Technology* (Natural Science Edition), 2015, 36(03): 322-326.
[17] Wang H. Research on mixed abnormal pattern recognition of control charts based on wavelet analysis. *Central North University* 2017.
[18] Hou SW, Zhu HM. Quality control chart anomaly pattern recognition based on Bayesian theory. *Stats and Decision* 2017 (10):18-21.
[19] Liu YM, Zhao ZY. Quality anomaly pattern recognition based on Feature selection and SVM. *Stats and Decision* 2018(10):5.
[20] Wang HY, Zhuo YJ. Pattern recognition method of statistical process control chart based on principal component analysis. *Stats and Decision* 2020, 36(24):20-24.
[21] El-Midany TT, El-Baz MA, Abd-Elwahed MS. A proposed framework for control chart pattern recognition in multivariate process using artificial neural networks. *Expert Syst Appl* 2010, 2(37):1035-1042.
[22] Medhat HA, Awadalla M, Abdellatif Sadek. Spiking neural network-based control chart pattern recognition. *Alex. Eng. J.* 2012, 1(51):27-25.
[23] De la Torre-Gutiérrez H, Pham DT. A control chart pattern recognition system for feedback-control processes. *Expert Syst Appl* 2019, 138:112826.

[24] Zan T, Liu Z, Wang H, *et al*. Control chart pattern recognition using the convolutional neural network. *J. Intell. Manuf.* 2020, 31:703–716.
[25] Miao Z, Yang M. Control chart pattern recognition based on convolution neural network. In: Panigrahi, B., Trivedi, M., Mishra, K., Tiwari, S., Singh, P. (eds) Smart Innovations in Communication and Computational Sciences. *Adv. Intell. Syst. Comput* 2019, 670.
[26] Zan T, Liu Z, Su Z, Wang M, Gao X, Chen D. Statistical process control with intelligence based on the deep learning model. *Appl. Sci.* 2020, 10(1):308.
[27] Wu CL. Research and development of LSTM based quality control chartical model pattern recognition. *Kunming University of Science and Technology* 2020.
[28] Chen S, Yu J. Deep recurrent neural network-based residual control chart for autocorrelated processes. *QREI* 2019, 35(8):2687-2708.
[29] Janssens O, Slavkovikj V, Vervisch B, Stockman K, Loccufer M, *et al.* Convolutional neural network based fault detection for rotating machinery. *JSV* 2016, 377:331–345.
[30] Cheng Z, Ma YZ. A Research about pattern recognition of control chart using probability Neural Network. In Proceedings of the Isecs International Colloquium on Computing, Communication, Control & Management, Guangzhou, China, 3–4 August 2008; IEEE: Piscatway, NJ, USA.
[31] Awadalla MHA, Sadek MA. Spiking neural network-based control chart pattern recognition. *Alex. Eng. J.* 2012, 51:27–35.
[32] Gauri SK. Control chart pattern recognition using feature-based learning vector quantization. *Int. J. Adv. Manuf. Technol.* 2010, 48:1061–1073.
[33] Guh RS. Real-time recognition of control chart patterns in autocorrelated processes using a learning vector quantization network-based approach. *Int. J. Prod. Res.* 2008, 46:3959–3991.
[34] Yang WA, Zhou W. Autoregressive coefficient-invariant control chart pattern recognition in autocorrelated manufacturing processes using neural network ensemble. *J. Intell. Manuf.* 2015, 26:1161–1180.
[35] Shi Y. Technical research on spc based data collection and quality monitoring system. *Shenyang University of Technology* 2017.
[36] Wang K, Yang H, Tian J, *et al.* Comparison of the effectiveness of completely random missing data processing methods based on Monte Carlo simulation. China Health Statistics 2020, 37(2):4.
[37] Liu C, Liu C. A topic trend prediction method combining recurrent neural networks and convolutional neural networks. Industrial Control Computer 2022, 35(08):102-104.
[38] Zhao R, Yan R, Wang J, Mao K. Learning to monitor machine health with convolutional Bi-directional LSTM networks. *Sens.* (Basel, Switzerland). 2017, 17(2):273.
[39] Al-Assaf Y. Recognition of control chart patterns using multiresolution wavelets analysis and neural networks. *CAIE* 2004, 47:17–29.
[40] Ranaee V, Ebrahimzadeh A. Control chart pattern recognition using a novel hybrid intelligent method. *Appl. Soft Comput.* 2011, 11:2676-2686.