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Control Chart Pattern Recognition Method Based on Improved One-dimensional Convolutional Neural Network

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Abstract: The application of statistical process control (SPC) has promoted production quality improvement of many enterprises. As a core tool of SPC, control chart is used to reflect the production state. In addition to normal pattern, abnormalities in the production process can be summarized in seven basic control chart patterns (CCPs). The recognition of CCPs is helpful to identify quality failures and find root abnormal causes in time. Convolutional neural network (CNN) is a classical model in the field of deep learning. CNN can automatically extract features from the raw data, so the operation of constructing manual features can be omitted. In this paper, the one-dimensional CNN is applied to the recognition of CCPs and achieves 98.96% average recognition accuracy in 30 tests. What's more, even if there is a deviation between the distribution of test data and training data, the model still shows excellent generalization performance.

Keywords: Statistical process control, Control chart, Pattern recognition, Convolutional neural network, Monte Carlo simulation

1. INTRODUCTION

Product quality is a key factor in the market competition of enterprises. Statistical process control (SPC) has brought significant improvements to the production quality of many enterprises, covering the industries of machining, chemical, electronic, etc. The fundamental idea of SPC is to use mathematical statistics methods to monitor various stages of production process, so the production anomalies can be detected timely and measures can be implemented to eliminate potential hazards.

Control chart is a core tool of SPC. Western Electric Company (1956) has summarized 15 control chart patterns (CCPs), including 8 basic patterns, while others such as freaks, grouping or bunching, instability, interaction mixture, etc. are a mixture or special case of these basic patterns. The 8 basic patterns are normal (NOR), cyclic (CYC), systematic (SYS), stratification (STA), uptrend (UT), downtrend (DT), upward shift (US), and downward shift (DS) patterns (Gauri et al., 2009). Fig. 1 shows an example of 8 basic CCPs. A brief introduction of the 8 basic CCPs is stated below.

(1) Normal pattern: The normal pattern indicates the production process is in-control.

(2) Systematic pattern: The systematic pattern appears as a high point always follows a low point and vice versa, so the point-to-point fluctuations can be predicted (Zhou et al., 2018).

(3) Stratification pattern: The stratification pattern shows that the data is more concentrated and the variance of data becomes smaller. STR pattern may be caused by computational errors (Zaman et al., 2018).

(4) Cyclic pattern: Periodic occurrence of peaks and troughs can be found in cyclic pattern (Addeh et al., 2018). CYC pattern may be related to system cycle changes such as voltage fluctuations, periodically executed tasks, etc.

(5) Trend pattern: In trend patterns, the data shows a continuous rise or fall, named upward trend and downward trend respectively. The emergence of trend patterns may be related to tool wear, operator fatigue, lack of effective supervision, etc.

(6) Shift pattern: The shift patterns appear as a sudden rise or fall in the mean of data, named upward shift and downward shift respectively. Shift patterns may be caused by the introduction of new operators, materials, methods, minor faults of devices, etc.

The abnormal CCPs in the production process are usually correspond to some specific causes. Hence, the recognition of abnormal patterns can not only help to find the problems in time, but also narrow the scope of abnormal causes.

In the early period of control chart applications, human experience is required to judge whether the production process is abnormal and find the corresponding cause. With the development of industrial automation, the rule-based discriminant system partially replaces the role of manual observation. The discriminant rules of control chart are based on small probability events and can be easily implemented. However, it is difficult to cover all abnormal patterns with rules due to the complexity of production process.

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In response to the problems of rule-based discriminant systems, researchers attempt to mine the specific features of different CCPs. The advent of the era of big data provides a data foundation for the CCPs recognition. At the same time, the development of information technology and artificial intelligence technology provides a technical basis.

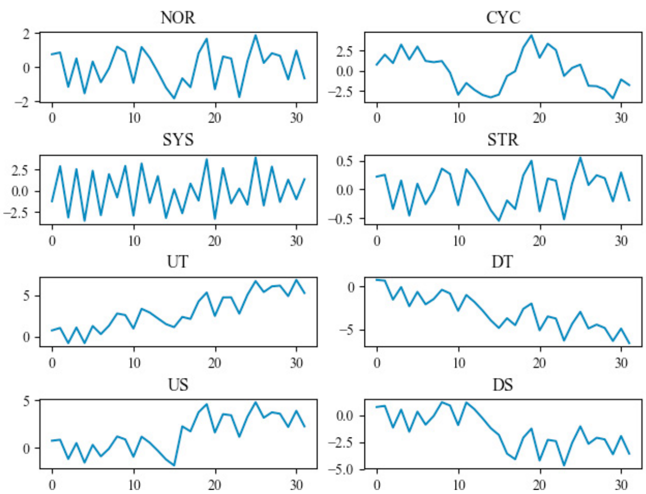

Fig. 1. Basic control chart patterns.

The rest of this paper is organized as follows. The existing CCPs recognition methods are reviewed in section 2. Section 3 introduces the data simulation method. The model of the improved one-dimensional convolutional neural network (1D-CNN) proposed in this paper is presented in section 4. Section 5 shows the recognition accuracy and generalization ability of the improved 1D-CNN model. The conclusion is showed in section 6.

2. RELATED WORK

Many methods have been applied to the recognition of CCPs. Some methods directly feed the raw CCPs data into the recognition model, while others first use statistical knowledge to extract features from raw data, such as mean square amplitude, standard deviation, peak, average, etc. Then these extracted features are fed into the model.

Pham et al. (1997) propose that different CCPs have different geometric characteristics, so it is helpful to improve CCPs recognition accuracy by constructing features. However, there are lots of different features that can be constructed, making it a challenge to select the appropriate feature subset so as to reduce the computational complexity and improve the classification accuracy of the model. Gauri et al. (2007) have applied classification and regression tree (CART) to select feature subset. Addeh et al. (2018) apply the association rules (AR) to select the best feature subset. But some of the features selected by these methods are still highly correlated, leading to redundancy. Thus, some dimension reduction methods such as independent component analysis (ICA) (Lu et al., 2011) and principal component analysis (PCA) (Tai-Fu et al., 2012) are used to reduce redundancy between features.

After determining the input form of data, whether it is raw data or extracted feature data, a model will be built to realize accurate recognition of different CCPs. Some classical methods such as fuzzy inference system (FIS), support vector machine (SVM), artificial neural network (ANN) have been applied in CCPs recognition systems.

Gulbay et al. (2007) propose a fuzzy method for recognition of unnatural CCPs. Zaman et al. (2018) combine the fuzzy c-mean (FCM) with adaptive neuro-fuzzy inference system (ANFIS) to realize the CCPs recognition and get comparable classification accuracy. Ebrahimzadeh et al. (2011) apply SVM method to CCPs recognition for its excellent generalization performance. However, it is difficult to select appropriate parameters for SVM. Therefore, some optimization algorithms such as genetic algorithm (GA) (Zhao et al., 2017) and particle swarm optimization (PSO) (Yongman et al., 2013) are used to automatically optimize the parameters of SVM model. In addition, many studies have introduced ANN into the CCPs recognition. Cheng et al. (1997) construct a modular neural network using a multilayer perceptron (MLP) trained by back-propagation (BP) algorithm and realize the recognition of two kinds of CCPs. The CCPs recognition module designed by Ghomi et al. (2011) combines two types of neural network, one is learning vector quantization (LVQ) and another is MLP. Considering the continuity of control chart data over time, Awadalla et al. (2012) apply the spiking neural network (SNN) to the CCPs recognition.

Based on existing researches, it can be found that the CCPs recognition method based on feature extraction usually have better performance. But the construction of features depends on human experience, thus, feature screening methods are needed to select the best feature subset.

Deep learning has been extensively studied for its outstanding performance. Deep learning establishes a mapping from inputs to outputs by a network structure (Zhang et al., 2018). As a multi-level representation learning method, the deep learning model is composed by simple but non-linear modules of which can transform a lower level representation to a higher and slightly more abstract level representation (Lecun et al., 2015). The structure of deep learning makes it can automatically extract features from raw data. There are many typical deep learning methods such as deep belief network (DBN), deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN) and etc. CNN is a classical deep learning model and has been applied in many fields, such as image recognition (Krizhevsky et al., 2012), speech recognition (Hinton et al., 2012), fault diagnosis (Zilong et al., 2018) and so on.

In recent years, CNN has been used to recognize one-dimensional (1D) signals. Kiranyaz et al. (2016) apply the 1D-CNN to the real-time classification of patient-specific electrocardiogram (ECG). Malek et al. (2017) propose a new method to analysis the chemometric data based on 1D-CNN. Wen et al. (2018) convert one-dimensional bearing vibration signal into two-dimensional (2D) image format, and use 2D-CNN for bearing fault diagnosis. The literatures above show that CNN can extract features from raw data and has great advantages in the processing of complex classification problems. It is the reason why this paper attempts to use CNN for recognition of CCPs.

3. DATA SIMULATION

Data simulation technology is the most widely used method in the field of recognition of CCPs. With the improvement of automatic production capacity, enterprises have accumulated a lot of data. However, it is difficult to train models with these data for it takes lots of efforts to classify and label the data. Fortunately, once enough data of an in-control production process have been collected, some information such as the distribution, mean estimate, and variance estimate of data can be obtained. Then the data simulation process can be carried out to generate data of various patterns.

In this paper, Monte Carlo method is used for data simulation. Table 1 shows the formulas and parameter settings of the simulation process. Here, μ and σ are the mean and standard deviation estimate of the controlled production process, respectively, $r(t)$ represents the inevitable accidental fluctuation which subject to gaussian distribution $N(0,1)$, d indicates the degree of system state departure, a is the amplitude of cyclic pattern, T is the period of the cycle, g is the gradient of data trend, P represents the time point when the shift anomaly occurs, and s is the amplitude of shift pattern. The setting range of the above parameters is referred to Gauri et al. (2006). The sequence length of simulation data L should not be too long, because longer window width of data means larger lag of anomaly recognition. Generally, the window length is set to be 16-64 sampling points.

Table 1. Parameters and formulas of data simulation

Class	Description	Equations	Remarks
0	Normal, NOR	$y_t = \mu + r(t) \times \delta$	$\mu = 0, \sigma = 1$
1	Cyclic, CYC	$y_t = \mu + r(t) \times \delta + a\sin(2\pi t/T)$	$r(t) \sim N(0,1)$
2	Systematic, SYS	$y_t = \mu + r(t) \times \delta + d \times (-1)^t$	$\delta = 1\sigma$
3	Stratification, STR	$y_t = \mu + r(t) \times \delta'$	$\delta' \in (0.2\sigma, 0.4\sigma)$
4	Upward Trend, UT	$y_t = \mu + r(t) \times \delta + t \times g$	$d \in (1\sigma, 3\sigma)$
5	Downward Trend, DT	$y_t = \mu + r(t) \times \delta - t \times g$	$a \in (1.5\sigma, 2.5\sigma)$
6	Upward Shift, US	$y_t = \mu + r(t) \times \delta + k \times s$ $k = 1\ if\ t \geq P, else\ k = 0$	$T = 16$ $g \in (0.05\sigma, 0.25\sigma)$
7	Downward Shift, DS	$y_t = \mu + r(t) \times \delta - k \times s$ $k = 1\ if\ t \geq P, else\ k = 0$	$P \in (10, 20)$ $s \in (1\sigma, 3\sigma)$ $t = 1,2, \dots, L$

4. METHODS

4.1 A brief Introduction of CNN

The structure of CNN can be divided into two parts. The first part is composed of convolutional layers and pooling layers to realize feature extraction, and the second part is composed of full connection layers for final classification.

Each convolutional layer contains several filters to extract local features from the feature maps of previous layer, respectively, and followed by an activation unit to generate the output feature maps. The weights of filters to calculate each unit of a feature map are same, which is called weight sharing. The depth of feature maps is determined by the number of filters. The performance of CNN is affected by the size and number of filters in per layer, so the setting of the filters in convolutional layer needs to be well designed to adapt to specific problems.

The pooling layer is usually set after the convolutional layer, which is used to reduce the size of extracted feature maps. Max pooling and average pooling are two most widely used pooling methods.

The fully connected layer and the softmax layer are usually set at the end of network structure to output the probability that the input sample belongs to each category.

The typical characteristics of CNN can be summarized as follows, local connection, weight sharing, pooling operation and multi-layer structure (Lecun et al., 2015). Local connection and weight sharing greatly reduce the number of training parameters in the network, leading to lower complexity and better generalization ability. While pooling operation reduces the number of neurons in the model and enhances the robustness.

4. 2 Architecture of the Improved 1D-CNN

The network structure proposed in this paper is shown in Fig. 2. The first layer of the network is an input layer. The length of simulation data is set to 32, which means that the dimension of the input layer is 32.

Next comes a triple parallel convolutional module, known as 'inception' (Szegedy et al., 2015). The filter sizes of three parallel convolutional structures are 1*1, 1*3, 1*5, respectively. The stride of the filters in each convolutional structure is 1 and the number of filters is 5. Filters of different sizes can extract multi-scale information from raw data. It should be noted that if these three parallel convolutional structures are fed with the same input, the size of output feature maps will be different because of various filters. Therefore, paddings are needed to keep the output in the same size. For convolutional structure with filters of size 1*3, it is necessary to add one zero before and after the input sequence. Similarly, two zeros need to be padded in the convolutional structure with the filters of size 1*5.

Then, all the feature maps obtained in 'inception' layer need to be concatenated and be fed into an averaging pooling layer. Feature maps obtained after pooling are fed into the next convolutional layer which has 10 filters of size 1*1 and the stride is 1. Then another pair of averaging pooling layer and convolutional layer with the same parameters is followed.

The activation function used in convolutional layers is the Rectified Linear Units (RELU) function which has showed great performance in recent years. The action mode of RELU can be expressed as follows, the neuron's output f can be calculated from the input x by formula $f(x) = max(0, x)$. As a non-saturating nonlinearity function, RELU has been proved to achieve faster convergence rate than other activation function such as sigmoid and tanh (Krizhevsky et al., 2012).

The convolutional layers showed above mainly realize the function of automatically extracting the features from raw data, and then the fully connected layer is set to realize classification. Before connecting to the fully connected layer, the feature maps need to be flattened by a flatten layer so that the feature maps can be fed into the fully connected layer which is set at the end of the network structure. The softmax function is used as the activation function of the output layer to implement multi-category output.

The CNN structure proposed in this paper introduces an 'inception' structure to extract information of different scales and the model is named as improved 1D-CNN.

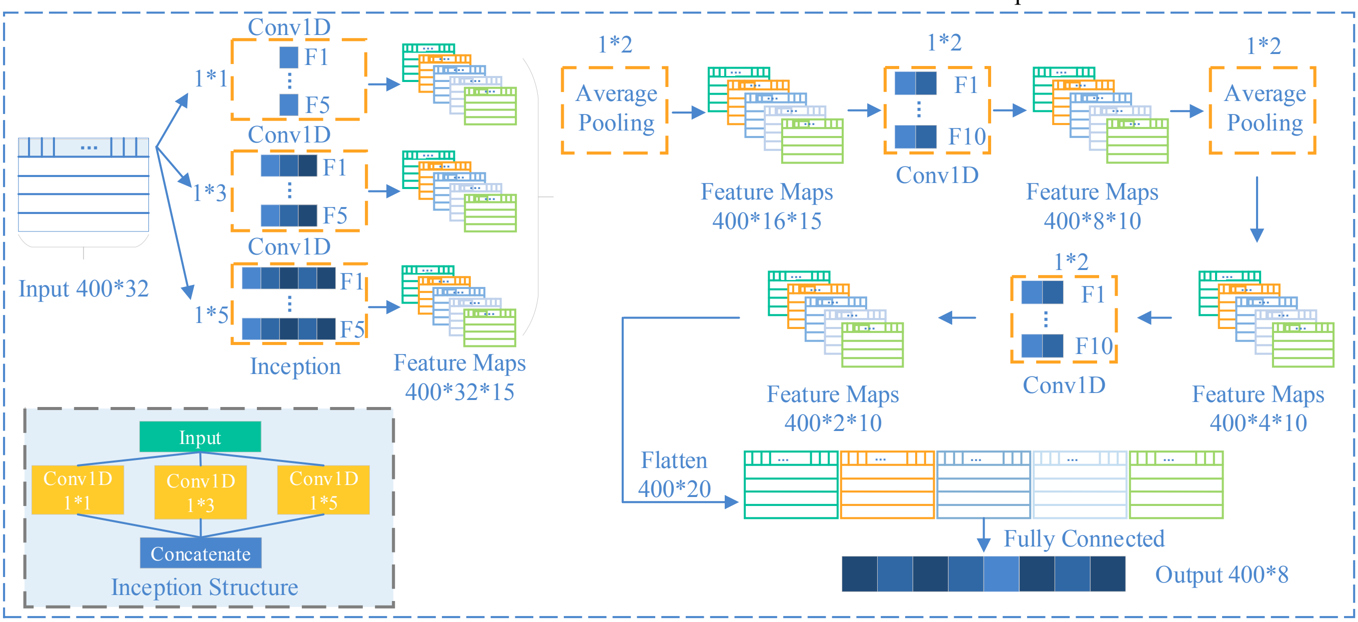

Fig. 2. Architecture of the improved 1D-CNN model.

5. EXPERIMENTS

Two experiments are carried out to verify the effectiveness of improved 1D-CNN model for CCPs recognition. What's more, several different neural network models, which are presented in Table 2, have been used for comparative experiments. The recognition effects of different models are compared in experiment I and the generalization performance of improved 1D-CNN is tested in experiment II.

5. 1 Experiment I: Recognition effects of different models

The data of 8 kinds of CCPs used in this experiment are generated by the simulation method mentioned in section 3. Each sample length is 32, and 500 pieces of samples of each pattern are generated, 350 of which are used for training, 50 for validation and 100 for testing. Considering the randomness of data simulation, the experiments are repeated for 30 times to obtain the average recognition accuracy of each model. The recognition effects of various methods are summarized in Table 3.

Table 2. Structure of the models used for CCPs recognition

Model	ANN	1L-1D-CNN	2L-1D-CNN	3L-1D-CNN	Improved 1D-CNN		
Input	1*32	1*32	1*32	1*32	1*32		
Layer 1	Dense (40)	Conv 1D (1*2, 10)	Conv 1D (1*2, 10)	Conv 1D (1*2, 10)	Conv 1D (1*1, 5)	Conv 1D (1*3, 5)	Conv 1D (1*5, 5)
Layer 2	Dense (40)	Average Pooling (pool size=2)	Average Pooling (pool size=2)	Average Pooling (pool size=2)	Concatenate		
Layer 3	Dense (8)	Flatten	Conv 1D (1*2, 10)	Conv 1D (1*2, 10)	Conv1D (1*2, 10)		
Layer 4	-	Dense (8)	Average Pooling (pool size=2)	Average Pooling (pool size=2)	Average Pooling (pool size=2)		
Layer 5	-	-	Flatten	Conv 1D (1*2, 10)	Conv1D (1*2, 10)		
Layer 6	-	-	Dense (8)	Flatten	Average Pooling (pool size=2)		
Layer 7	-	-	-	Dense (8)	Flatten		
Layer 8	-	-	-	-	Dense (8)		
Parameters	3288	678	408	538	748		

Table 3. Recognition effects of various models

Model	ANN	1L-1D-CNN	2L-1D-CNN	3L-1D-CNN	Improved 1D-CNN
Accuracy (%)	96.32	98.64	98.37	98.34	98.96
Standard deviation	1.9	0.56	0.52	0.63	0.32

Compared with ANN model, CNN has higher recognition accuracy and fewer model parameters. All the models based on CNN show great recognition performance, while the improved 1D-CNN with 'inception' structure achieves the highest recognition accuracy, reaching 98.96%. What's more, the standard deviation of recognition accuracy of improved 1D-CNN is also smaller than other methods in 30 times tests, which shows the good stability of recognition. The result indicates that the 1D-CNN model combined with parallel 'inception' structure is more suitable for recognition of time series data for its ability of multi-scale information extraction. The confusion matrix of model recognition accuracy of the improved 1D-CNN is showed in Fig. 3.

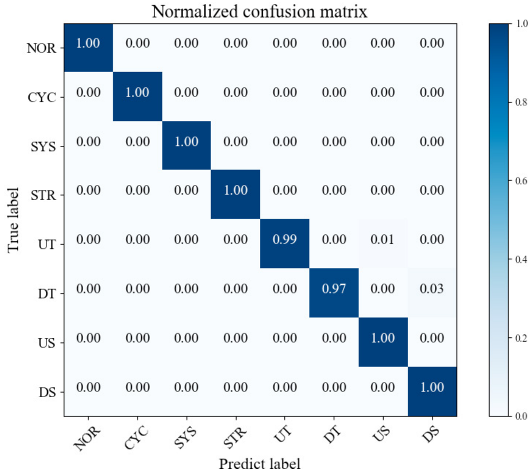

Fig. 3. Confusion matrix of recognition accuracy of improved 1D-CNN model.

5. 2 Experiment II: Generalization Performance of improved 1D-CNN Model

Even huge amounts of data are obtained, it is still impossible to get the true mean and true standard deviation of the process data. There must be a deviation between the estimate value and the true value. Therefore, experiment is carried out to measure the generalization ability of the model when the mean and standard deviation of the training data and the test data are inconsistent. According to the data simulation method provided in section 3, 500 pieces of data are generated for each CCP. The generating parameters of 400 pieces of data used for model training are set unchanged, that is, the estimate mean value is 0 and the estimate standard deviation is 1. While the mean value of test data is set to -0.5 to 0.5 with an interval of 0.1, the standard deviation value of test data is set to 0.5 to 1.5 with the same interval. Fig. 4 shows the test accuracy of improved 1D-CNN and ANN when the true mean value of test data is fixed as 0 and the true standard deviation value of test data is set between 0.5 and 1.5. Fig. 5 shows the test accuracy of improved 1D-CNN and ANN when the estimate standard deviation value of test data is fixed as 1 and the true mean value of test data is set between -0.5 and 0.5. 30 times repeated tests are implemented for different combination of parameters to get the average accuracy of CCPs recognition.

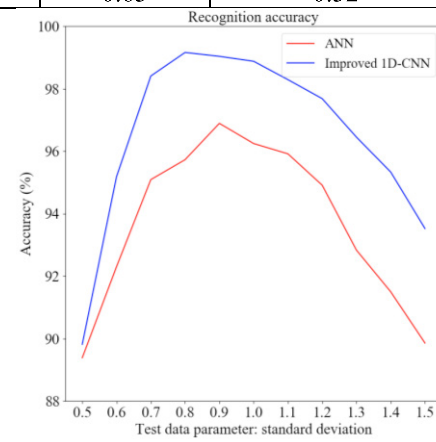

Fig. 4. Recognition accuracy of improved 1D-CNN and ANN when the standard deviation of training data and test data are inconsistent.

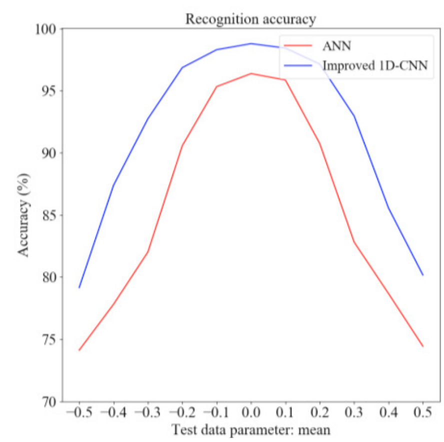

Fig. 5. Recognition accuracy of improved 1D-CNN and ANN when the mean of training data and test data are inconsistent.

The results showed in Fig. 4 and Fig. 5 indicate that when the test data and training data distribution are inconsistent, the prediction accuracy of the model will inevitably decrease. However, the prediction accuracy of the improved 1D-CNN model is still significantly better than that of ANN. It can be found that the model still has high recognition accuracy for different CCPs when the error between the mean or standard deviation estimates value and true value is small, which indicates the excellent generalization performance of the improved 1D-CNN model.

6. CONCLUSIONS

The model of improved 1D-CNN proposed in this paper has achieved an average recognition accuracy of 98.96% on the simulation dataset after 30 repeated tests, which is a satisfactory result. The result shows that CNN with an introduction of 'inception' structure achieves higher recognition accuracy than purely layer-by-layer CNN. Besides, the improved 1D-CNN model also has better generalization ability when there is an error between the estimate value and true value of mean or standard deviation.

Though many methods have been applied to the recognition of CCPs, different data simulation methods and parameter settings used in different studies reduce the significance of comparing these results. But in general, the improved 1D-CNN model obtains better recognition accuracy when compared with other models which based on raw data and reaches the same level of accuracy when compared with the model which based on artificial designed features. What's more, thanks to the function of automatic feature extraction of CNN, there is no need to design features by human experience.

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