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An Improved Control Chart Pattern Classification using a Transfer Learning-Based VGG-16 Network

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Control chart pattern recognition is a crucial statistical process control tool used to determine whether a process operates within intended parameters or exhibits abnormal behavior. Accurate and automated recognition is essential for manufacturing companies to maintain high-quality production. Recent studies have combined machine learning with control chart pattern recognition, yet these methods often assume identical feature spaces and statistical distributions between training and test data—a condition rarely met in practice. Retraining models from scratch with new data is time-consuming. Transfer learning offers a more efficient alternative by leveraging knowledge from pre-trained models. This study employs the pre-trained VGG-16 deep convolutional neural network to classify control chart patterns, significantly improving recognition performance without extensive retraining. Through Monte Carlo simulations and a real-world case study, the proposed method achieved a recognition accuracy of 99.3%, outperforming conventional MLP, 1D-CNN, and CNN models. Sensitivity analysis demonstrated that the use of ReLU activation, batch normalization, and dropout techniques substantially enhanced accuracy and model robustness. The results confirm the potential of the proposed transfer learning-based recognizer to improve intelligent quality control in manufacturing processes by effectively handling limited training data and complex feature extraction.

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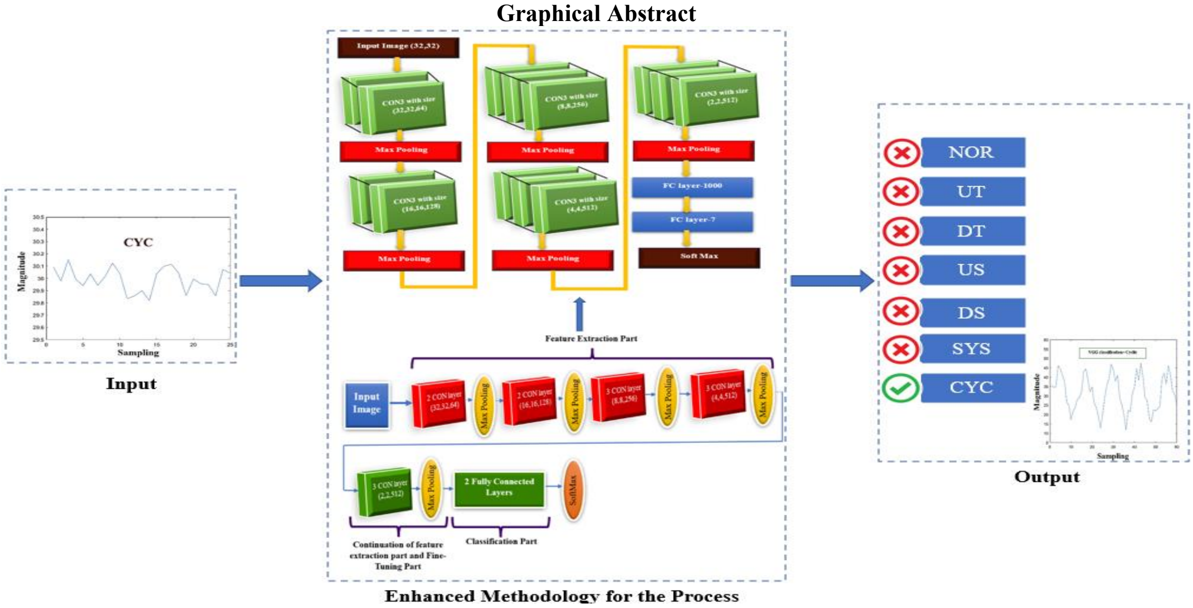
Graphical Abstract



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1. INTRODUCTION

Statistical Process Control (SPC) are some techniques that involve monitoring and evaluating different stages of the manufacturing process to maintain a stable and acceptable level, ensuring that products and services meet predetermined standards. Control charts are a crucial tool in SPC. When a control chart exhibits a natural pattern, it shows that the process is in-control state. Conversely, an unnatural pattern signals an out-of-control state due to at least an assignable cause. There are different types of non-random patterns that can appear in-control charts, and various analytical tools have been created to help identify these patterns and their underlying assignable causes. However, the accuracy of identifying unnatural patterns using run rules is dependent on the practitioner's experience and skill, and the identification rate is not satisfactory. Moreover, although these methods can identify abnormalities indicating out-of-control conditions, they do not provide information about the specific non-random pattern that occurred .

Traditional control charts in manufacturing processes have a significant limitation: they only utilize the information from the most recent plotted point, disregarding potentially valuable data about disturbances contained in previous samples. Incorporating pattern recognition into the control chart can address this challenge. By knowing the type of Control Chart Pattern (CCP) and the corresponding process factors that could cause it, the diagnosis search can be expedited. Hence, timely recognition of CCPs is crucial for identifying potential assignable causes (1). There are several common examples of assignable causes that can lead to the appearance of abnormal, non-random patterns in manufacturing control charts such as operator fatigue. Figure 1 illustrates seven common CCPs. A normal pattern is one where the control chart only includes common causes, showing that the process is in-control state.

Machine learning techniques, especially neural networks and deep learning models, offer powerful tools for automated control chart pattern recognition. They enable accurate classification of a wide range of patterns, including subtle and complex ones, and can adapt effectively to variable-length and multivariate data sequences. Additionally, these methods are robust in handling autocorrelation and dynamic changes in process behavior. As a result, they significantly enhance online monitoring capabilities, facilitating timely detection of assignable causes and improving overall process control. These advancements make machine learning-based control chart pattern recognition highly valuable in modern manufacturing and quality control, where automation and precision are essential.

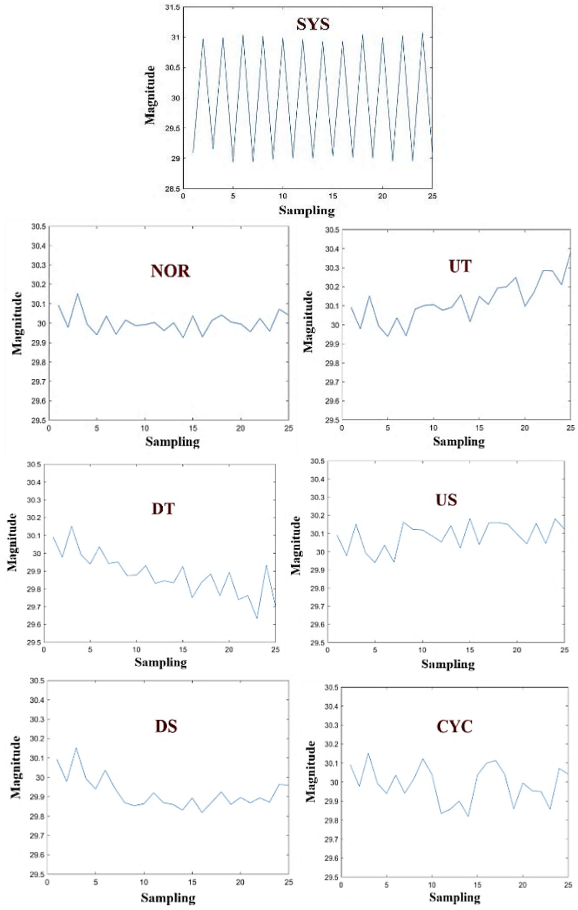

Figure 1. A sample for the well-known and typical CCPs

The remainder of the paper is structured as follows: Section 3 outlines the proposed methodology for the proposed intelligence classifier of control chart patterns in detail. Section 4 presents the comprehensive simulation results obtained. Section 5 applies the proposed intelligent CCP recognizer in a real-world data. The next section presents some managerial insights on this topic. Section 7 concludes the paper and offers suggestions for future research.

2. LITERATURE REVIEW

Due to the limitations of supplementary rules and the growing demands of intelligent manufacturing, there is an increasing interest in developing intelligent CCP recognition algorithms. As a result, the CCP recognition challenge is being addressed as a pattern recognition issue and addressed using machine learning methods (2). In this respect, a systematic literature review by Hachicha and Ghorbel (3) covered 120 research indexed papers until 2010. Moreover, Garcia et al. (4) presented a comprehensive taxonomic classification of studies focused on identifying concurrent patterns, with most papers relying on ANNs until 2021. There are various machine learning-based approaches to detect different types of unnatural CCPs, considering the autoregressive nature of the process observations.

As mentioned, literature reviews shown that most studies have initially focused on ANNs. As a pioneer, Cheng (5) proposed a neural network-based CCP recognizer in SPC scope. After that, several works have conducted on this subjectin recent years too. For example, Kadakadiyavar et al. (6) presented an approach to classify CCPs by developing an adaptive radial basis function neural network that uses a stochastic gradient method to map pattern features to their respective categories. Recently, Zaidi et al. (7) presented a pattern recognition tool using multilayer feed-forward neural networks to accurately recognize Compositional data patterns.

Recent advancements in CCP recognition have involved the adoption of more complex frameworks to enhance classification accuracy. In this regard, SVMs have been widely used, achieving good results. However, SVM models can be complex due to the need to choose the most suitable kernel function and hyperparameter settings. In this regard, optimization algorithms can be practical, including cuckoo optimization (8), Genetic (9), and particle swarm optimization algorithms (10). In another viewpoint, to enhance the recognition performance, Lee et al. (11) combined SVM with adaptive neuro-fuzzy inference and spectral clustering techniques, respectively. Additionally, some researchers have employed various techniques, including expert systems (12), fuzzy- methods (13) and decision trees (14), to recognize CCPs.

Convolutional Neural Networks (CNNs) have gained prominence in various domains due to their ability to train directly from raw inputs to classifier outputs, reducing the need for manual feature engineering. This shift towards CNNs is particularly relevant in CCP recognition, where they can learn discriminative features directly from data, making them well-suited for these applications. For example, a CCP classifier is introduced by Zan et al. (15) leveraging a 1D-CNN. This approach eliminates the need for manual feature extraction, as the 1D-CNN learns to identify the most relevant features directly from the raw data. This automated feature learning process enables the method to efficiently identify CCP. Additionally, a new method that leverages a multi-label CNN was presented by Cheng et al. (16) to show concurrent CCPs. They extended a multi-channel deep CNN model to involve 1D and 2D representations of control chart information for pattern recognition in multivariate processes. However, a major challenge with CNNs is that they require significant expertise to choose the proper parameters, such as the number of kernels, kernel sizes, and learning rates. These parameters are interdependent, making it difficult to fine-tune them. To address this issue, Golilarz et al. (17) employed the Harris Hawks optimization algorithm to optimize CNN parameters. Also, CNN and long short-term memory were integrated based on Genetic algorithm as a classifier for CCPs by Yu and Zhang (18). Cheng et al. (19) proposed control chart mixture pattern classification using multi-label CNN. Wu et al. (20) have developed a CNN-based technique to show CCPs in autocorrelated processes, which is a recent contribution to the field. Recently, Xue et al. (21) designed a method of recognition based on multi-feature fusion by using CNN for the automatic recognition of imbalanced CCPs.

2. 1. Research Gap The literature demonstrates how well CNNs perform complicated classification tasks and can extract features from unprocessed data. Nevertheless, in real-world circumstances, it might not be the case that training and test data have the same properties and distribution, as most research assume. Because of this limitation, models must be rebuilt from the ground up. We used a modified version of VGG-16 to address this CCP recognition difficulty (22). It can be applied to the process of transfer learning to extract characteristics. We explored the value of transfer learning in cross-domain fault detection and diagnosis tasks, similar to the approaches used by Go et al. (23). The pretrained VGG-16 is a potent model whose pre-trained layers may be adjusted to obtain high accuracy for particular tasks. It can be used as a base for various image categorization applications like CCP recognition. Consequently, this work proposes a transfer learning-based control chart recognition approach. To enhance the network model's capacity for generalization throughout the feature extraction process, the convolutional layer is simultaneously fine-tuned using the fine-tune approach. Subsequently, the classifier is trained based on the number of control chart categorization classes. To classify the CCP, the classifier uses the output of the feature extraction layer as its input. We evaluated the model's performance using Monte Carlo simulations and real-world case, comparing it to traditional classifiers. This approach has the potential to contribute to developing smart SPC systems.

3. METHODOLOGY

3. 1. Data Generation Despite the significant advancements in automatic production capacity, leading to a substantial accumulation of data. Garcia et al. (4) found that most studies (41 out of 44) still rely on simulated data to assess the performance of CCP recognition methods due to the limited availability of publicly accessible, thoroughly documented databases. Only three studies used real data. In this research, a significant number of CCP samples are generated using the Monte Carlo method, which is commonly employed for training and testing CCPs. The literature frequently referred to seven fundamental CCPs: NOR, UT, DT, US, DS, CYC and SYS. Based on Zan et al. (15), the process means and two noise components are utilized for the different patterns as follows:

$$y(t) = \mu + x(t) + d(t), \tag{1}$$

in which $y(t)$ shows the value of a sample gathered during sampling *t*. The *t* is the discrete-time in which the monitored process variable is gathered. $x(t)$ shows random noise at t^{th} time, and it follows a normal distribution with a mean of zero and a variance of σ^2. Note that μ and σ^2denote the mean and variance when process is in-control state, respectively. In addition, $d(t)$ demonstrates particular pattern due to assignable causes manufacturing process at t^{th} time.

Based on Equation 1, the simulation approach for CCPs is performed. For NOR pattern, we consider $d(t) = 0$, and for $d(t) = \pm v \times s$ in which v is responsible for the shift position such that it is equal to zero before the change and to one after the change. Moreover, *s* represents magnitude of shift, considering its direction. The UT and DT patterns are shown as Equation 2.

$$d(t) = \pm v \times d \times t, \tag{2}$$

in which v is responsible for the shift position similar to the concept of upward-and downward-shift patterns. Moreover, d shows the slope of a trend in which signs "+" and "-" are applied for the UT and DT patterns, respectively, and CYC pattern is shown by Equation 3.

$$d(t) = v \times a \times sin\left(\frac{2\pi t}{\omega}\right), \tag{3}$$

in which ω and a denote the period and amplitude of a cycle, respectively. On the other hand, when a systematic pattern has been observed in a control chart based on $d(t) = b \times (-1)^t$, it is commonly referred to as a SYS pattern. This type of pattern indicates that there is an underlying, consistent cause influencing the process, which requires further investigation and corrective action to maintain the desired level of quality and consistency.

3. 2. The Deep Neural Network for CCP Classification

CNNs can simplify the difficult feature extraction in the conventional recognition because they are feed-forward, weight-sharing neural networks. A common CNN consists of the following layers: input, convolutional, downsampling, fully connected, and output. The computation depending on input can be advantageous for the feature map. Equation 4 represents the output of channel *j* of the convolutional layer *l* as x_j^l, where $f(.)$ is the activation function.

When the output characteristic x_j^{l-1} of the previous layer is weighted and biased, it produces the net activation of channel j in the convolutional layer *l*, represented as u_j^l in Equation 5. The feature map input set denoted by M_j is utilized to obtain the convolution kernel matrix k_{ij}^l, which in turn yields u_j^l. The bias of the feature map is b_j^l.

$$x_j^l = f(u_j^l). \tag{4}$$

$$u_j^l = \sum_{i \in M_j} x_j^{l-1} * k_{ij}^l + b_j^l. \tag{5}$$

Computing the feature map's input is one method of figuring out the downsampling layer's output. In the down-sampling layer *l*, the net activation of channel *j* is obtained by biasing and weighting the output characteristic x_j^{l-1} of the previous layer represented by u_j^l in Equation 6. β represents the bias weight coefficient. The function for subsampling is down (.).

$$u_j^l = \beta_j^l down(\, x_j^{l-1}) + b_j^l. \tag{6}$$

The fully connected layer's output is calculated using the activation function and the weighted sum of the input. The completely linked *l* layer's net activation in Equation 7 obtained by biasing and weighting the output characteristic x^{l-1} of the layer that came before it.

$$u^l = w^l x^{l-1} + b^l. \tag{7}$$

The back propagation method computes the error based on the actual network output and expectation. Equation 8 shows the total error of training, where y_n is the sample training prediction value for the n^{th} sample and t_n is the true value of the label for the nth sample.

$$E(w, \beta, k, b) = \frac{1}{2}\sum_{n=1}^{N} \|t_n - y_n\|^2. \tag{8}$$

The primary applications of CNNs include semantic segmentation of scenes, object detection, face recognition and verification, and image categorization. Within this field, one of the main areas of research is image categorization. Picture classification can be significantly aided by using the ImageNet (24) dataset, which comprises 3200000 images, 5246 synonym sets, and 12 subtrees. Using a CNN, Krizhevsky et al. (25) developed the AlexNet model, and he took first place in the image categorization competition. The VGG16 model from Oxford University (22), GoogleNet from Google (26), ResNet from Microsoft (27), and so on are examples of common CNN models. The Visual Geometry group's VGG16 network model is currently regarded as a top-notch image categorization model. Thirteen convolutional layers, five downsampling layers, and three fully connected layers comprise the VGG16 network structure. The parameters in the 16-level network total 1380000000.

3. 2. 1. The Modified VGG 16 Architecture The suggested model (Figure 2) is a modified version of the VGG net. Because of the VGG's straightforward architecture, which makes result analysis easier, and the 32x32 input would not disappear via it, we decided to utilize it as the base net. Moreover, one of the strongest deep CNNs is the VGG net. The results in Section 4 will demonstrate how much more powerful our VGG-based deep model is in classifying the CCP dataset when compared to other types of convolutional networks. The modified VGG16 contains 13 convolution layers and two fully connected layers. The proposed model has five groups of convolution layers and 1 group of fully connected layers. Each convolution filter has a pooling zone of 2 by 2 without overlap and a kernel size of 3 by 3 with a stride of 1. It should be noted that we minimize the number of parameters greatly by shrinking the two 4096-dimension fully connected layers to one 1000-dimension fully connected layer.

3. 2. 1. 1. Batch Normalization Small modifications in earlier levels of very deep networks will amplify layer by layer until they become an issue. The term "internal covariate shift" refers to the problem that arises when the input distribution of a layer changes since the parameter must iteratively adjust to the new distribution (28). To address this issue, Ioffe et al. (28), a researcher at Google, presented Batch Normalization. This method normalizes the inputs of each layer, which accelerates network convergence, lowers error rates, and somewhat reduces overfitting. With adding Batch Normalization layers to GoogleNet, Ioffe et al. (28) beat human performance records in ImageNet classification tasks. Batch normalization, in our opinion, can also optimize extremely complex models like VGG. Before the VGG16 architecture and dense layers, we add the Batch Normalization layer. Our implementation differs slightly from the conventional one, though. We apply the same z-score-like function to the Batch Normalization layer's inputs.

$$\hat{x}^{(k)} = \frac{x^{(k)} - E(x^{(k)})}{\sqrt{var(x^{(k)})}}. \tag{9}$$

After that, perform the linear operation on $\hat{x}^{(k)}$:

$$y^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)}. \tag{10}$$

All operations are channelwise since k indicates the channel. Instead of using the fixed mean and variance, we utilize exponentially-weighted moving averages, where the subscript n denotes the number of iterations.

$$Mean_n = \begin{cases} BatchMean_1 & n = 1 \\ \alpha BatchMean_{(n)} + (1-\alpha)Mean_{n-1} & n > 1 \end{cases} \tag{11}$$

$$Mean_n = \begin{cases} BatchVar_1 & n = 1 \\ \alpha BatchVar_{(n)} + (1-\alpha)Var_{n-1} & n > 1 \end{cases} \tag{12}$$

The outcomes demonstrate that batch normalization greatly raises the accuracy of recognition. With the aid of dropout, which lowers the error rate, it can awaken the hidden power of extremely deep models.

3. 2. 1. 2. Dropout Setting The first thing we need to consider when applying a deep network to a limited dataset is how to lessen overfitting. Dropout is the most widely used technique to lessen overfitting. Dropout is typically used by setting it at the fully connected layers,

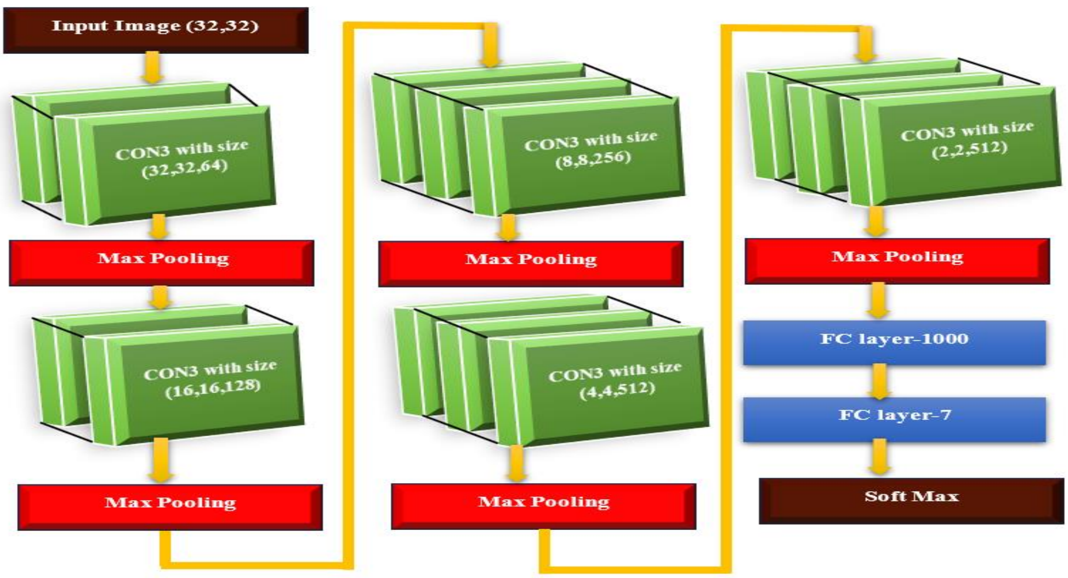

Figure 2. The VGG 16 network's architecture after modification

which contain most of the parameters. In this case, the fully connected layers' dropout rate was adjusted to 0.5 because the model is quite deep and the dataset is small. The overfitting of the deep model is considerably controlled by the dropout value, according to the results. The deep model's hidden power was unleashed in conjunction with the application of batch normalization, lowering the error rate.

3. 2. 1. 3. Training Acceleration While deep models can yield powerful representations, training a deep model is computationally demanding; that is, both the forward and backward passes are slower than with shallow models. For classification learning to be reliable, there must be an adequate number of training examples to guarantee the classification model's correctness, and the samples must be independent and uniformly distributed. Nonetheless, there exist specific issues such as a restricted quantity of training samples and unsatisfactory independence and distribution of samples. The researchers proposed a new machine learning technique called transfer learning (29). Transfer learning synchronous satisfies two fundamental difficulties of traditional machine learning, allowing for the application of current knowledge to a limited amount of labelled sample data in the target area without learning issues. At the moment, transfer learning is divided into three components: instance-based transfer learning in isomorphic space, transfer learning using features in isomorphic space, and transfer learning in heterogeneous space. This work uses the isomorphic space characteristic for transfer learning. There are four steps in the generic CNN method that are based on transfer learning.

The random starting parameters of the model are saved and trained using large data sets from related disciplines, which improves the network's generalization capacity. Second, features are extracted from the trained network model's convolutional and downsampling layers. Thirdly, samples from the target domain are used to train the pattern classifier. The target application of pattern classification is finished when the feature extraction layer's output is fed into a pattern classifier.

The processes of extracting VGG16 features, training classification models, and fine-tuning them are all part of the transfer learning-based control chart recognition principle. As illustrated in Figure 3, the whole network structure for control chart identification consists of the feature extraction part, fine-tuning section, and classification components of VGG16. Convolutional and downsampling layers are used in the VGG16 feature extraction step of the model, and the fully connected layer is removed from the modified VGG16 model. The feature extraction portion's weight parameters are equal to the VGG 16 weights when trained in ImageNet, which enhances the network's capacity to generalize and yield the best classification results, particularly in the absence of a large amount of training data. In the last stage of feature extraction, the fine-tuning portion includes three convolutional layers with size (2,2,512) and one downsampling layer. We selectively freeze the layers in the fine-tuning portion in addition to the feature extraction part's layers.

Freezing layers serves to prevent changing parameter values and maintain the network's capacity for generalization. None-freezing layers are used to increase the network's capacity for adaptive learning to the target samples. There are six different types of anomalous patterns that are the defined output results of the two completely connected layers that make up the categorization section.

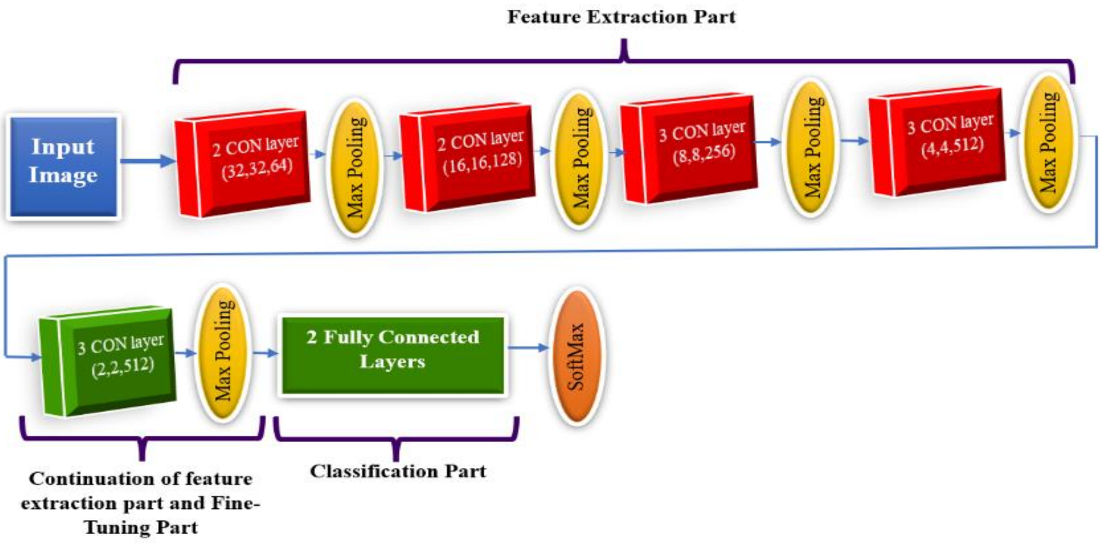

Figure 3. The principle of transfer learning in network architecture

4. SIMULATION AND VERIFICATION

4. 1. CCP Parameter Settings In this subsection, seven common CCPs were analyzed using the Monte-Carlo simulation method, which is described in Section 3, to generate datasets for the modified pretrained VGG16. In this respect, Table 1 presents the equations and parameter settings used in the simulation process.

In the real applications, the changes in quality characteristic are complex (30). To accurately simulate this, CCP parameters were generated from a uniform distribution. The μ and σ values are set to 30 and 0.05, respectively. Next, the slope d is randomly selected within the range of 0.1σ to0.3σ. The s value follows a uniform distribution between 1.5σ and 3σ. Furthermore, a uniformly distributed between $1.5\sigma$and 4σ. The ω value is respectively set to 4, 5, 6, 7, and 8. The responsible position of CCPs is in range of 4 to 9. Also, the data length for each pattern is 25. In contrast to VGG, comparing recognition rates across various sample sizes revealed that beyond 2000 samples, the recognition rate improvement becomes negligible for other models. Conversely, the recognition accuracy of VGG network is enough high with 750 samples per CCP, resulting in a total of 5250 unique samples. The dataset was categorized into two separate parts in a random manner. 4200 samples were used to train the VGG, while the remaining samples were reserved for testing.

4. 2. Expremental Setup To finish the experiment, Keras based on TensorFlow, serves as the experimental setting in this research. The input consists of 32*32 jpeg files produced by Keras' matplotlib module based on sample numerical data. The output vector has seven lengths and an element value of either 0 or 1. The output vector is represented by the expression $y = [y_1, y_2, y_3, y_4, y_5, y_6, y_7]$; $y_i = 1$ denotes if the output is the input pattern, while $y_i = 0$ denotes that it is not. As an illustration, [1, 0, 0, 0, 0, 0, 0] denotes a normal pattern. The data set is randomly divided into two subsections of training and test data, which are completely separate from each other. Typically, 80% samples are used for training and 20% samples are used for testing. In this work, there are 50 training iterations and a 4:1 ratio between training and test data.

TABLE 1. Parameters for generating the six CCPs

CCP	Formula	Parameters values
NOR	$y(t) = \mu + x(t)$	$\mu = 30, \sigma = 0.05$
UT	$y(t) = \mu + x(t) + v \times d \times t$	$d \sim U(0.1\sigma, 0.3\sigma)$
DT	$y(t) = \mu + x(t) - v \times d \times t$	$d \sim U(0.1\sigma, 0.3\sigma)$
US	$y(t) = \mu + x(t) + v \times s$	$d \sim U(1.5\sigma, 3\sigma)$
DS	$y(t) = \mu + x(t) - v \times s$	$d \sim U(1.5\sigma, 3\sigma)$
CYC	$y(t) = \mu + x(t) + v \times a \times sin\left(\frac{2\pi t}{\omega}\right)$	$d \sim U(1.5\sigma, 4\sigma)$, $\omega \in \{4,5,6,7,8\}$
SYS	$y(t) = \mu + x(t) + b \times (-1)^t$	$b = 1$

4. 3. Analysis of Classification Results

4. 3. 1. Optimizing the Feature Extraction Layers The sample size for each pattern in this paper is 25 points, and the total number of dataset samples is 5250, of which 600*7 is the training sample and 150*7 is the test sample. The experiment's goal is to optimize the pretrained, modified VGG16 network by freezing various layers and identifying the optimal layer to freeze based on the control chart's recognition accuracy. Table 2 displays the findings of the experiment. The modified pretrained VGG16 model's last three convolutional layers and one downsampling layer have been fine-tuned, according to the experimental data, and the control chart's overall classification accuracy is higher than 99%. When the modified pretrained VGG16 model has 13 frozen layers instead of 12, the overall recognition rate increases. On the control chart, the modified pretrained VGG16 network performs best for recognition with 14 frozen layers. Simultaneously, 99.3% of normal and aberrant patterns are recognized. To achieve the best recognition result, we therefore set the modified pretrained VGG16 model's number of frozen layers to 14 in the subsequent trials.

4. 3. 2. Improve the Performance of Training Batch normalization-also referred to as batch norm-using re-centering and rescaling the layer inputs allows artificial neural networks to be trained more quickly and steadily. Additionally, "dropout" in machine learning describes the technique of randomly ignoring some nodes in a layer when training. A regularization strategy called a dropout makes sure that no units are codependent on

TABLE 2. The network model's recognition outcomes for the various frozen layers

Frozen layer of the modified pretrained VGG16	Test Accuracy (%)
12	97.1
13	99.3
14	99.3
15	98.9
16	98.6
17	98.4
18	98.4

another, which inhibits overfitting. As a result, we create four models for the CCP dataset's classification to conduct comparison studies.

1. Baseline: The modified pretrained VGG16 network was used as a baseline. The training process was performed without modification.
2. The modified pretrained VGG16 for CCP classification based on BN: This model consists of Batch Normalization layer before the VGG16 architecture and dense layers in the structure is shown in Section 3.2.1.3.
3. The modified pretrained VGG16 for CCP classification based on DROPOUT: This model includes dropout on the structure is shown in Section 3.2.1.3.
4. The modified pretrained VGG16 for CCP classification based on DROPOUT and BN: This model use Batch Normalization + dropout on the structure is shown in Section 3.2.1.3.

Our models were trained using the CCP dataset. Our experiment's results are displayed in Table 3. We discovered that the accuracy gained by the very deep model was not particularly high when we used only Batch Normalization or the dropout option. However, compared to the other models, the modified pretrained VGG16 model with dropout and batch normalization gains greater accuracy. This table demonstrates that the extremely deep model achieves high accuracy when both the BN and dropout are used. We believe that depth provides a high accuracy opportunity, BN keeps the training process from being stuck in subpar local optima, and dropout greatly reduce overfitting. This demonstrates how the power of depth can even be used with tiny datasets.

4. 3. 3. Different Nonlinearity To determine the best activation function, a number of simulations was done, the results of which are displayed in Table 4. Scheme 1 used the Sigmoid function to activate the unfrozen layers of the modified pretrained VGG16 architecture; Scheme 2 used the Softmax function to activate the output layer and the Leaky ReLU function to activate the unfrozen layers. The Softmax function for the output layer and the ReLU functions for the unfrozen layers were Scheme 3's activation functions.

TABLE 3. The comparative studies comparing for effects of batch normalization and dropout on CCP categorization

Network architecture	Accuracy
Baseline	88.2
The modified pretrained VGG16 with batch normalization	90.1
The modified pretrained VGG16 with Dropout	86.7
The modified pretrained VGG16 + Dropout + Batch normalization	99.3

The network using the ReLU and Softmax activation functions outperformed the other activation function, as shown in Table 4. Results employing Leaky Relu and Relu nonlinearity indicate no discernible difference. It's possible that we didn't apply the ideal negative slope setting for Leaky ReLU. However, given they are all non-saturate nonlinearities, we think that there isn't much of a distinction between these nonlinearities.

4. 4. Comparison of CCP Recognition A comparative study of 1D-CNN, CNN, MLP, and a modified pretrained VGG16 network model was carried out to assess the efficiency of the suggested approach in more detail. We utilized the MLP in this work's comparison since it is a machine learning technique with exceptional performance that has been applied extensively in the CCP recognition and has shown positive outcomes (30). An ordinary three-layer neural network, or MLP, was employed in the experiment. It had 25 neurons that received the raw CCP data and nine neurons that received the feature set. Six neurons in the output layer and fifteen in the hidden layer represented the six common CCPs. The Sigmoid function served as each layer's activation function. Two convolution and pooling layers with a fully connected layer make up the 1D-CNN and CNN structure. The fully connected layer performs classification, while the convolution and pooling layers handle feature extraction. The input was split into four categories: raw data for the 1D-CNN, control chart image data (60 × 60 pixels), feature set or raw data for the MLP, and 32*32 pixels for the modified pre-trained VGG-16. The MLP feature set included the statistical and shape characteristics that have been demonstrated to be very successful in the CCP recognition introduced by Garcia et al. (4). You may get a thorough explanation of the characteristics defined by Zan et al. (15).

In this experiment, the modified pre-trained VGG16 network (MPVGG16) and other network models (MLP, 1DCNN, CNN) are compared for their ability to recognize a control chart using the same samples. The experiment has a sample size of 25 for each pattern, the training and test data are randomly selected from the dataset and their ratio is 4:1, and 14 frozen layer was considered in the modified pre-trained VGG16 network. Table 5 displays the findings of the experiment. The experimental results show that, firstly, both the

TABLE 4. Modified pretrained VGG16 accuracy comparison using various activation functions

Accuracy	Activation Function of the unfrozen layers
99.3	Relu + Soft max
99.1	Leaky Relu + Soft max
98.1	Sigmoid

MPVGG16 network model and other network models constantly improve their control chart identification rate with an increase in training data volume. Second, with low training data, the MPVGG16 network model achieves above 98% recognition accuracy. Thirdly, under varying sample data quantities, the MPVGG16 network model performs better overall than other network models in the classification accuracy of the control charts. This shows that, two-dimensional training data in the form of control chart image is a good input candidate for the modified pre-trained VGG16 model. Additionally, it shows that a pre-trained VGG16 network with low design and tuning complexity can classify the control chart more accurately, which has significance for research as well as practical applications.

Table 5 presents a comparison of the five deep network examples' performance based on varying numbers of samples per pattern. The number of training samples for each CCP was considered 200, 600, or 2,000, as Table V illustrates. It can be concluded from Table V that the suggested approach outperformed the conventional MLP network and the CNN method in terms of recognition accuracy.

The confusion matrix was considered to assess the classifier's performance in a more intuitive manner. The percentage of correctly identified patterns was indicated by the values on the diagonal of the confusion matrix. The percentage of misclassifications is represented by the other values in the matrix. The average value of every member on the matrix diagonal equaled the control chart recognition rate. Tables 6-10 display the confusion matrix, and it is evident that the modified pretrained VGG16 performed better than the other approaches. In particular, the modified pretrained VGG16 network model produced a lower mistake rate and improved recognition accuracy.

The suggested approach was contrasted with the techniques documented in the literature review to assess the efficacy of the modified pretrained VGG16 model even more. Several classifiers were utilized for the CCP

TABLE 5. Comparison findings for various sample of training and test patterns

Train sample	Test sample	MLP/raw data (15)	MLP/ feature (15)	1DCNN (15)	CNN (15)	This work
200 sample/pattern	50 sample/pattern	82.61	92	92.4	93.2	98
600 sample/pattern	150 sample/pattern	-	-	-	-	99.3
2000 sample/pattern	500 sample/pattern	85.93	93.27	98.33	96.33	99.5

TABLE 6. The CCP recognition confusion matrix for the modified pretrained VGG16, total accuracy with VGG=99.3%

	NOR	UT	DT	USS	DS	CYC	SYS
NOR	99.9	0	0	0	0	0.1	0
UT	0.1	99.2	0	0.7	0	0	0
DT	0	0	99.1	0	0.9	0	0
US	0	0.9	0	99	0	0.1	0
DS	0	0	1.1	0	98.9	0	0
CYC	1	0	0	0	0	99	0
SYS	0	0	0	0	0	0	100

TABLE 7. The CCP recognition confusion matrix the MLP and raw data reported by Zan et al. (15), total accuracy with VGG=85.93%

	NOR	UT	DT	US	DS	CYC
NOR	73.6	2.4	1.6	5.6	6	10.8
UT	4.8	92	0	2.8	0	0.4
DT	2.4	0	91.6	0.4	5.2	0.4
US	6.4	4.4	0	86..4	0	2.8
DS	3.2	0	5.2	0	91.6	0
CYC	18.8	0	0	0.4	0.4	80.4

TABLE 8. The CCP recognition confusion matrix for the MLP and feature set of data reported by Zan et al. (15), Total accuracy=93.27%

	NOR	UT	DT	USS	DS	CYC
NOR	97.6	0	0.4	0	0.4	1.6
UT	1.2	89.6	0	9.2	0	0
DT	0	0	96	0	4	0
US	0	8.8	0	91.2	0	0
DS	0.4	0	10.8	0	88.8	0
CYC	3.6	0	0	0	0	96.4

TABLE 9. The CCP recognition confusion matrix the 1D-CNN and raw data reported by Zan et al. (15), total accuracy=98.33%

	NOR	UT	DT	USS	DS	CYC
NOR	100	0	0	0	0	0
UT	0	97.6	0	2.4	0	0
DT	0	0	98	0	2	0
US	0	1.2	0	98.4	0	0.4
DS	0	0	3.2	0	96.8	0
CYC	0	0	0.4	0	0.4	99.2

TABLE 10. The CCP recognition confusion matrix for the CNN and image data reported by Zan et al. (15), total accuracy=96.33%

	NOR	UT	DT	USS	DS	CYC
NOR	99.2	0	0	0	0.4	0.4
UT	0.8	92.4	0	6.8	0	0
DT	0	0	97.2	0	2.8	0
US	0	2.8	0	97.2	0	0
DS	0	0	6.4	0	93.6	0
CYC	1.6	0	0	0	0	98.4

recognition, as indicated in Table VI, including the Multi-Layer perceptron (MLP), PNN, Fuzzy ARTMAP, SVM, and RBF. Either a feature set or raw data was used as the input. According to the results of Table VI, in neural networks other than convolution networks, the use of pre-extracted feature vectors in the input has a better performance than applying raw data as input. The performance was especially noticeable when statistical and shape features were combined. However, in convolution networks, due to the presence of convolution and pooling layers as feature extractors, raw data input is a suitable option. However, new learning transfer techniques can address the issue of convolution networks having too many parameters and requiring a large amount of training data for the training phase. Table 11 demonstrates the high accuracy of the suggested pre-trained network (99.3% classification accuracy) when compared to alternative approaches, despite using less training data.

Most of the literature used control chart samples with 60 or more sampling points each, which may guarantee a more significant difference between the various CCP kinds. Moreover, over time, the trend patterns might become more pronounced, aiding in achieving high classification accuracy. To identify irregularities in the manufacturing process more quickly and lower the loss of manufacturing companies, there were 25 sampling points per control chart sample in this work. But the patterns might grow remarkably similar, particularly the shift and trend patterns, making identification even more challenging.

5. A REAL APPLICATION

A control chart diagnostic system has been created and used to monitor an actual dataset from the production environment to better demonstrate the suggested technique. An instrument that measures three coordinates can be used to measure a part's diameter, which is thought to be the primary quality attribute. There were sixty sample points in all. As demonstrated in Figure 4 and Table 12, the modified pretrained VGG model can identify all five unnatural CCPs.

The Nelson rules are applied to control charts to identify patterns that deviate from a random, stable process, allowing manufacturers to investigate and address the underlying causes. In this regard, Figure 5 demonstrates Nelson rules for the first six sample in the real case. The numbers displayed within the circular markers in individual charts indicate the specific rules, based on Nelson's rules, that were violated and consequently triggered a warning signal.

Figure 5 shows that specific patterns that may indicate process instability or other issues for these samples based on Nelson rules method. However, it's essential to consider the rules in combination and the context of the specific process to draw accurate conclusions about potential causes of unnatural patterns. While, the proposed diagnostic method, which can

TABLE 11. Comparing the effectiveness of various techniques

Model	Number of patterns	Input representation	Approach	Test accuracy
Guh and Tannock (31)	4	Raw data	MLP	94.38
Hassan et al. (32)	6	Statistical features	MLP	96.80
Assaleh and Al-Assaf (33)	4	Frequency features	MLP	97.22
Cheng and Ma (34)	6	Raw data	PNN	95.58
Zan et al. (35)	6	Autoregressive (AR) spectrum	Fuzzy ARTMAP	95.00
Ranaee and Ebrahimzadeh (36)	6	Shape and statistical features	MLP	99.15
Kao et al. (37)	7	Independent component analysis (ICA)	SVM	98.94
Zhou et al. (9)	6	Shape and statistical features	FSVM	99.28
Addeh et al. (38)	8	Shape and statistical features	Bees-RBF	99.63
Zan et al. (15)	6	Raw data	1D-CNN	98.33
This work	7	Raw data	The modified pretrained VGG16	99.3

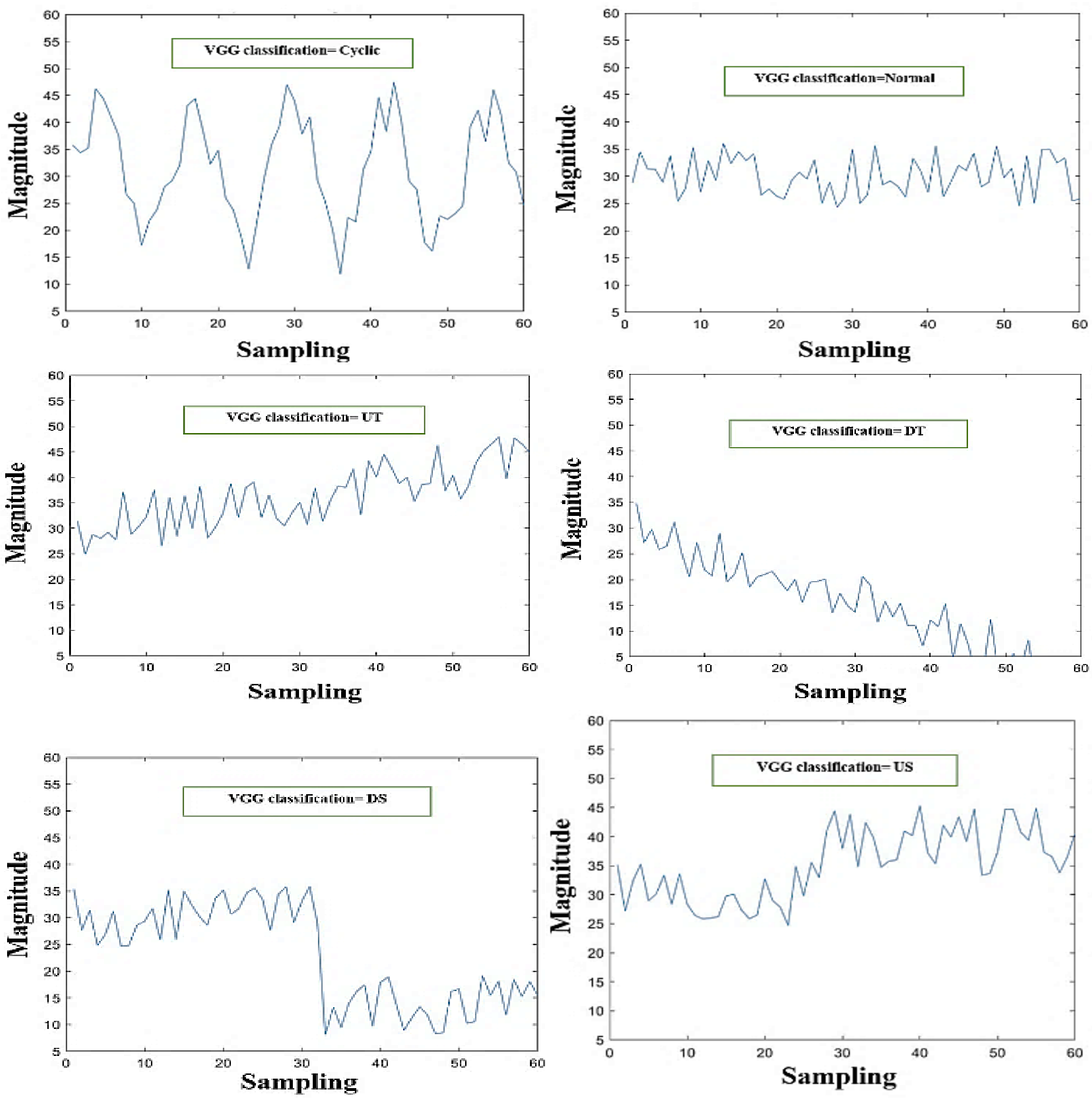

Figure 4. The suggested model's detection of normal and abnormal CCPs in the real data

TABLE 12. Accuracy of real data CCP recognition by the modified pretrained VGG16 (test sample: 100 samples/pattern)

	Real Data						Overall accuracy
Class	**NOR**	**UT**	**DT**	**US**	**DS**	**CYC**	
Accuracy	100	99.4	99.2	97	97.1	918	98.45

accurately predict the specific pattern, has the potential to significantly improve manufacturers' capacity to identify the root causes of process variations. By providing a more precise pattern classification, this approach enables manufacturers to more effectively pinpoint the reasons for unnatural patterns and take targeted corrective actions. As a result, the implementation of the proposed pattern recognition technique can lead to substantial savings in both time and costs associated with quality control and process improvement efforts. Hence, it was discovered via correspondence with enterprise engineers that the exchange of equipment and tool status could cause these abnormal CCPs to appear during processing. This indicates the model trained using a simulated dataset was still able to identify real datasets from the real-world setting with good accuracy. Furthermore, the recognition results of the suggested model and Nelson rules complement each other, and utilizing both can improve the recognition system.

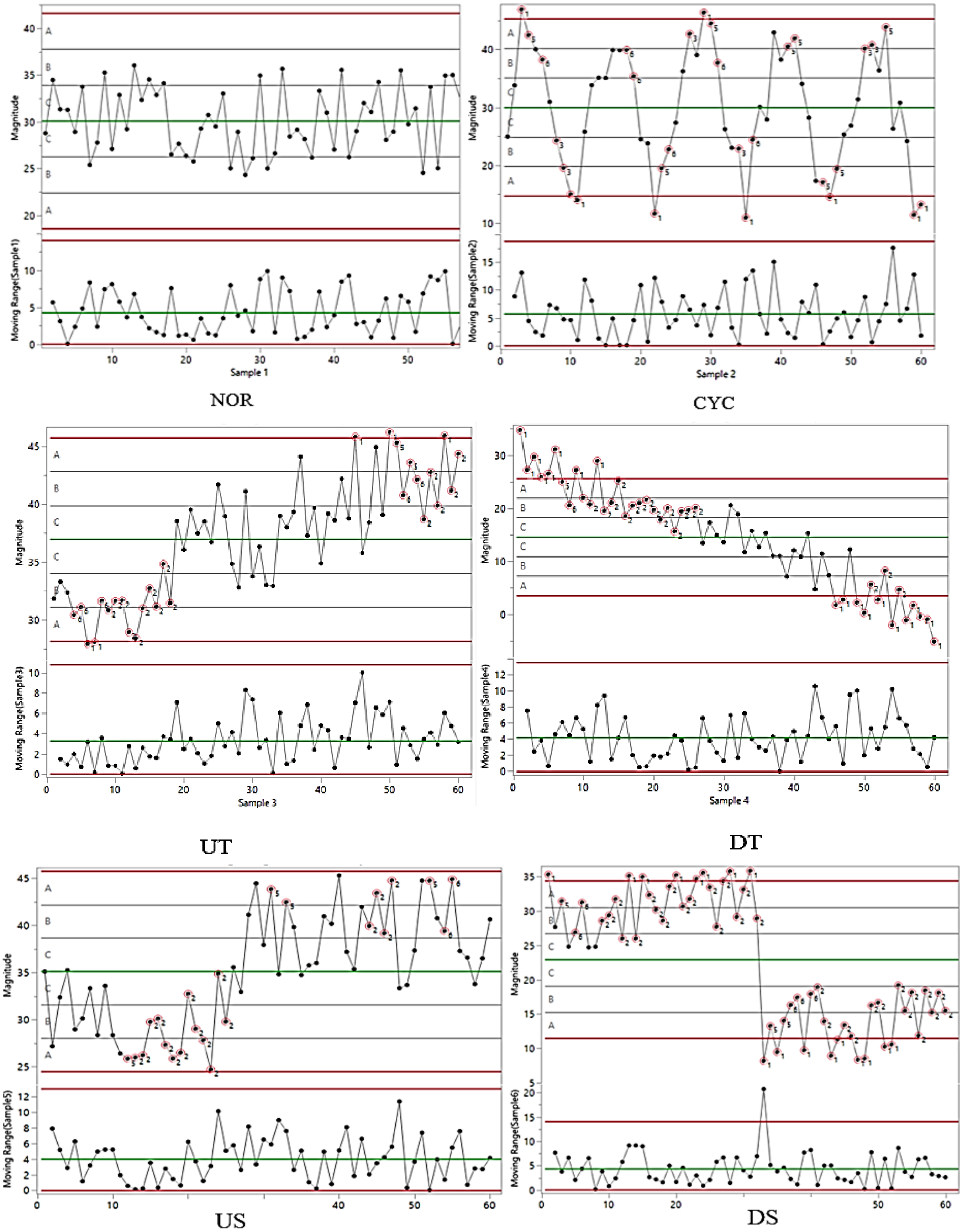

Figure 5. Nelson rules in Individual & Moving Range (IMR) chart in the real data

6. MANAGERIAL INSIGHTS

The findings of this study provide several important managerial implications for manufacturing and quality control professionals:

- Enhanced Quality Control through Advanced AI Techniques: By adopting transfer learning with pre-trained deep networks such as VGG-16, managers can significantly improve the accuracy and reliability of control chart pattern recognition. This leads to earlier and more precise detection of process abnormalities, minimizing defects and reducing waste (39).
- Cost and Time Efficiency in Model Development: The use of transfer learning reduces the need for extensive retraining and large volumes of labeled data. Managers can thus deploy intelligent quality control systems more rapidly and cost-effectively, even when historical data are limited or when processes change frequently.
- Improved Decision-Making with Robust Recognition: The integration of techniques like ReLU activation, batch normalization, and dropout enhances model robustness and consistency. This reliability supports confident, data-driven decision-making in production environments, helping managers maintain process stability and product quality.
- Scalability and Adaptability: The proposed approach's ability to generalize well across different control chart patterns and conditions means that manufacturing firms can scale their quality monitoring systems across multiple production lines or facilities without the need for rebuilding models from scratch.
- Strategic Investment in AI-Driven Quality Systems: Managers should consider investing in AI-powered quality control solutions as a strategic asset that not only improves operational efficiency but also strengthens competitive advantage by ensuring superior product quality and compliance with industry standards.

Overall, the study highlights how leveraging state-of-the-art machine learning techniques can transform traditional quality control practices into intelligent, adaptive systems that support proactive management and continuous process improvement.

7. CONCLUSION AND FUTURE RESEARCH

The accurate and automated classification of CCPs is crucial for manufacturing processes to maintain high-quality production processes. Recently, there has been extensive research and exploration into integrating CCP recognition with machine learning methods. This study proposes a modified pretrained VGG16 model for end-to-end CCP recognition realization and feature learning. The modified pre-trained VGG16 model was trained in this paper's unfrozen layers in the isomorphic space using the image of the CCP. The training set of control chart images is really used for fine-tuning which can enhance and satisfy the need for control chart recognition in complicated circumstances.

The results collected allow for the drawing of the following conclusions. 1) Despite the large number of network structure parameters in VGG16, this problem was resolved and the maximum recognition accuracy compared earlier deep networks was attained by applying the transfer learning technique. 2) The ReLU activation function significantly increased the recognition accuracy and was better suited for deep learning. 3) The accuracy of control chart recognition can be increased by using the batch normalization and dropout technique. 4) Using a pre-trained deep network improves the accuracy of CCPs' correct detection even with a low number of training sample. 5) The feature set recovered manually was of lower quality than the one that was acquired by the suggested modified pretrained VGG16 network. The suggested network identified the patterns properly with a 99.3% recognition accuracy when the image of control chart patterns was utilized as an input. This significantly improved identification accuracy over the conventional MLP model, 1DCNN, and CNN. In conclusion, the suggested model helps to increase the intelligence level of quality control in businesses by avoiding the challenge of extracting various complicated features. This makes it more suited to actual quality control.

Limitations: While the proposed model demonstrates excellent recognition accuracy under the tested conditions, it has certain limitations. First, the study primarily focused on individual control chart patterns under the assumption of normality and independence, potentially limiting its applicability to more complex, non-normal, or correlated processes. Second, the generalizability of the model to different types of control charts and industrial settings requires further validation. Third, the computational resources required for training and fine-tuning deep learning models like VGG16 may be a barrier to adoption for some smaller enterprises.

Recommendations for Future Research: Based on these limitations, future research can proceed in several directions. First, extending CCP recognition systems for non-normal data distributions, such as those belonging to the exponential family, is essential. Second, expanding the proposed method to recognize concurrent patterns would address more complex real-world scenarios. Third, developing this intelligence system for multivariate processes and exploring its applicability to different control chart types (e.g., EWMA, CUSUM) could broaden its practical utility. Finally, investigating techniques to reduce the computational demands of the model, such as model compression or efficient fine-tuning strategies, would make it more accessible to a wider range of users.

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Persian Abstract

چکیده

تشخیص الگوی نمودار کنترل، یک ابزار کنترل فرآیند آماری حیاتی است که برای تعیین اینکه آیا یک فرآیند در محدوده پارامترهای مورد نظر عمل می‌کند یا رفتار غیرعادی از خود نشان می‌دهد، استفاده می‌شود. تشخیص دقیق و خودکار برای شرکت‌های تولیدی جهت حفظ تولید با کیفیت بالا ضروری است. مطالعات اخیر، یادگیری ماشین را با تشخیص الگوی نمودار کنترل ترکیب کرده‌اند، با این حال این روش‌ها اغلب فضاهای ویژگی و توزیع‌های آماری یکسانی را بین داده‌های آموزشی و آزمایشی فرض می‌کنند – شرایطی که به ندرت در عمل برآورده می‌شود. آموزش مجدد مدل‌ها از ابتدا با داده‌های جدید زمان‌بر است. یادگیری انتقالی با بهره‌گیری از دانش مدل‌های از پیش آموزش‌دیده، جایگزین کارآمدتری ارائه می‌دهد. این مطالعه از شبکه عصبی کانولوشن عمیق VGG-16 از پیش آموزش‌دیده برای طبقه‌بندی الگوهای نمودار کنترل استفاده می‌کند و عملکرد تشخیص را بدون آموزش مجدد گسترده به طور قابل توجهی بهبود می‌بخشد. از طریق شبیه‌سازی‌های مونت کارلو و یک مطالعه موردی در دنیای واقعی، روش پیشنهادی به دقت تشخیص ۹۹.۳٪ دست یافت که از مدل‌های MLP معمولی، 1DCNN و CNN بهتر عمل می‌کند. تجزیه و تحلیل حساسیت نشان داد که استفاده از تکنیک‌های فعال‌سازی ReLU، نرمال‌سازی دسته‌ای و dropout، دقت و استحکام مدل را به طور قابل توجهی افزایش می‌دهد. نتایج، پتانسیل تشخیص‌دهنده مبتنی بر یادگیری انتقالی پیشنهادی را برای بهبود کنترل کیفیت هوشمند در فرآیندهای تولید با مدیریت مؤثر داده‌های آموزشی محدود و استخراج ویژگی‌های پیچیده تأیید می‌کند.