Research Article
Locating Defects and Image Preprocessing: Deep Learning in Automated Tobacco Production

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Deep learning is an emerging discipline developed in recent years, which is aimed at investigating how to actively obtain multiple feature representations from data samples, rely on data-driven methods, and apply a series of nonlinear transformations to obtain reliable research results. Combined with today’s development dynamics, the traditional way of cigarette production can no longer adapt to the current rate of economic development. Therefore, cigarette companies must achieve their own rapid and stable development through automation and automated management techniques for production and operation. In this paper, in the context of the research on deep learning and tobacco automation production, we focus on the application in tobacco automation production based on the management theory related to deep learning and the research method of deep convolutional neural network, mainly analyzing the application of distributed control system, production command system, logistics system, and quality control system in tobacco automation system, and conclude that the automated production system plays a role in tobacco production strengthen management and command, circumvent quality problems, save costs, and other conclusions, which hopefully have some reference.

1. Introduction

Deep learning is an emerging discipline that has been developed in recent years. Deep machine learning tools have been playing an increasingly important and unique role in various contemporary speech and video analysis techniques and various video image analysis and recognition algorithms, respectively, and are significantly changing those traditional machine learning methods in some traditional knowledge fields today, so that machines begin to mimic some visual and perceptual behavioral features inherent in the human brain itself. In recent years, the basic motivation for deep speech learning, a technological advancement in both intelligent speech recognition research and in many applications of computer vision information processing, is mainly to build a model to simulate the basic structure of neural networks in the human brain. In computer processing of various images, sound signals, and image text, the data are then interpreted by layering the semantic features of the data in multiple data transformation process stages and further illustrating with image data as an example. In the research method of the human vision system, the sequencing steps for processing these visual image signals are as follows: first, detecting image edges, initial shapes and then gradually learning to form more abstract or complex visual shapes, deep learning and combining visual low-level features so that representative features and attribute class features can be gradually learned to form complex abstract visual high-level features. As a result, deep learning has made progress in various fields, and a great technological breakthrough has been achieved in the automated production of tobacco sticks [1].

In recent years, with the rapid development of computer network communication technology and automation, companies are gradually turning to automatic production control to achieve more efficient production quality. As an important part of China’s economy, the production, production efficiency, and quality of the tobacco industry directly affect the development of the entire national economy of China, and the efficiency of the tobacco industry also affects the competitive position of the tobacco enterprises themselves.
in the industry. Combined with today’s development trend, the traditional production method of tobacco sticks can no longer adapt to the current economic development speed. Through the automation of production and operation, automated management technology can achieve the rapid and stable development of cigarette enterprises. Therefore, cigarette enterprises should have a deep understanding of all aspects of automated production management technology, master the principles of how to do a good job of automated production management, from the process, structure, and other aspects, to achieve the automation of tobacco industry production management control. The cigarette industry is an important part of the market economy that affects the national economy, and improving the efficiency and quality of the cigarette industry can better promote the development of the national economy. Automatic control technology, as an effective way to promote the cigarette industry to a modern enterprise, is gaining more and more attention and application; therefore, it is necessary to pay attention to the construction and improvement of the automatic control system to promote the development of the cigarette industry. In the competitive context of pursuing efficiency and development, cigarette enterprises urgently need to change the traditional production and operation mode through advanced information technology, with high-tech information technology as the core, in business transformation and integration in the age of high technology. Under the guidance of implementing the concept and method of tobacco automation, tobacco companies should strengthen management, master market information, standardize and expand the scale of operation, and promote the overall progress of the tobacco industry with advanced automation [2].

In summary, it is of great research significance to study the application of deep learning in the automated production of tobacco sticks, which can improve its competitiveness in the industry for the tobacco sticks enterprises themselves and promote the progress of the whole industry for the whole tobacco sticks industry, so as to improve its contribution to the national economy and promote the development of the national economy.

2. Research Background

2.1. Research Review of Deep Learning. The technical origin of deep cognitive learning methods is from artificial neural networks. Around the middle of the 20th century, due to many major theoretical breakthroughs in the field of cognitive neuroscience, researchers have started to learn to imitate the basic structure of human brain nerve cells and initially proposed new ideas to create the theory of artificial neural networks. As the field of machine research has gradually expanded further, researchers have begun to focus more on learning how to make these machines more intelligent like other human computers. The proliferation of perceptor networks as a very special form of human artificial neural networks, which were initially not understood and fully implemented by systematic constructions, has gradually caused to stimulate later high attention to the structural aspects of neural network research. However, further in-depth experimental studies showed that the two-layer structure of perceptual learning machine networks could only be applied to prefabricated feature learning linear functions and could not be used to solve the problem of nonanalyzable linear functions. Due to the huge limitations of various theoretical foundations and research techniques at that time, the state of the art of artificial perceptual neural network theory became increasingly unpromising [3]. It was not until the 1980s that the backpropagation properties of artificial neural network data were redefined to become the focus of increasing attention today. Compared with perceptrons, BP neural network sensors have more steganographic units and can build more complex data model structures and more flexible and powerful data feature expression and processing capabilities, etc. However, due to the significant increase in the number of sensor layers, learning becomes more difficult and easily falls into local minima, and the gradient of the lower layers of the network becomes weaker. Due to these drawbacks, BP neural networks can only construct shallow learning models, which affects their scalability [4]. In recent years, many computer researchers have paid special attention to the study of deep machine learning algorithms for pairs. Izhevsk et al. also applied the technical results of deep machine learning in the field of classification of computer images and other areas to improve to the computational accuracy of classification results of images. In the field of computer speech fast recognition algorithms, Jéremy et al. advocated the use of computer deep machine learning algorithm technical results to improve the algorithmic accuracy of computer speech fast recognition methods [5]. The use of unsupervised learning models and deep learning, not only to learn image data features from image data models that can be unlabeled but also to establish parallelized image models that can be massively parallelized, points out another new direction to explore for the systematic in-depth analysis and research development of deep machine learning algorithms [6]. Among them, the most advanced representative image network target recognition residual network model, whose recognition performance, at present, has significantly exceeded the human cognitive ability. The latest voice intelligent voice response system under development by Google Inc. can easily automate more than 10% of text message response responses on the cell phone screen; the intelligent voice recognition function is better than the input accuracy of a normal keyboard, and the voice error rate is currently continuing to slowly decrease; the automatic skin cancer recognition technology is as good as the automatic skin cancer recognition system of professional clinicians. The automatic neural machine learning translation system developed by Google, Inc. is also now widely available in more than 10 other computer language programs. There are many more examples of such applications. Such maturity models could eventually allow the application of these maturity models to a large number of corporate customers and to people’s lives in the future [7].

2.2. Review of Research on Automated Tobacco Production. In recent years, research on automated production has covered a wide range of areas, such as production planning
management, production scheduling management, and production management aspects of the cigarette industry as well. The details are summarized as follows: National Sun Yat-sen University, Chen Zhixiang thesis, based mainly on fuzzy control theory analysis, studied the fuzzy demand lead time theory and fuzzy demand-driven production process planning theory and production control theory model for tobacco automation, researched to how to improve the dynamic flexibility of the master production control plan management in MRPII system, and pointed out that the current master production. It is pointed out that the current MRPII system lacks the dynamic response of the system, and two main improvement measures are proposed to improve the dynamic response flexibility of the MRPII system by improving the flexibility of the MRPII system design, introducing the design concepts of both demand flexibility and supply response flexibility in the production planning system, and further giving a corresponding algorithm model [8]. The paper by Ruan et al. is based on an empirical study of the key strategic issues of how to effectively determine the strategic development of a modern tobacco enterprise that is developing in complex dynamic, stochastic, and fuzzy management environment conditions, to develop an effective and reasonable medium- and long-term planning plan, and to ensure the successful achievement of the overall long-term planning objectives. Using the theoretical analysis of dynamic stochastic and fuzzy development theory, a model of strategic multistage dynamic development of modern tobacco business operation was constructed and improved [9]. For the technical characteristics of centralized production and scheduling management in China’s continuous production tobacco and production industry, Rimam et al. proposed the establishment of a production management process structure that applies a network model for analytical modeling and solving, respectively, and further elaborated and improved the management strategy for the design and implementation of the scheduling automation system for continuous tobacco and production enterprises, based on the requirements of the basic production operation methods developed in the continuous production process industry at home and abroad and the technology market characteristics, proposed a summary of the four main basic models of continuous production control process optimization in enterprises [10]. On the other hand, Ding Feng from Tsinghua University used the optimization methods of “process optimization” and “system optimization” to systematically study the local optimization design problem of the design of the scheduling optimization system for the continuous tobacco production process, and tried to feed the simulation results of the whole system design optimization back to the process model in time to guide the optimization idea of the local equipment scheduling optimization system and explore the creation of another new design problem. The effective method of the problem opens up a new development of ideas for realizing the problem of comprehensive system scheduling optimization of large-scale industrial production system design, giving an analysis of the theoretical framework structure of production command scheduling large system design, the principle basis of system optimization technology for large system design and practical application design examples [11]. Xu Zhi and Han Bing, in Shanghai Jiaotong University, worked out a scheduling optimization problem of continuous production earliest completion time index with cigarette segment production task constraint and buffer constraint effects, which effectively and quickly converts an original complex scheduling problem into another linear production planning problem by integer form of constraint and continuous production time as the computation center form of constraint [12].

In summary, deep learning and automated tobacco production both have a lot of research content and research results, and this paper is developed based on the previous research.

3. Research Methods and Materials

3.1. Main Concepts and Theories

3.1.1. Deep Learning Concept. The principle of deep mining distributed machine learning is to extract some underlying data features by using multiple data hidden layers; each hidden layer is equivalent to only one data perceptron, which can obviously and effectively alleviate the minimum problem of underlying data locally. The depth of the extracted underlying data features can be obtained by using a data perceptron to extract some low-level features and then by recombinating all these underlying features to form some more complex and abstract representations of the high-level data, which is a representation of distributed deep learning features [13].

3.1.2. Classification Applications of Deep Learning. The model of deep learning can be said to be composed of several semantic level models together, which has many unique functional advantages of many kinds of deep semantic learning tools; that is, at the same time, it has a strong autonomous semantic autonomous learning ability, efficient and fast parallel massive data feature extraction and natural language expression and processing analysis ability. Therefore, the deep learning system can soon be widely recognized by domestic enterprises for applications in intelligent image feature recognition, speech recognition, face intelligence recognition, video semantic analysis, and data information mining and collation. Therefore, this deep learning system can be quickly applied to intelligent image feature recognition, speech recognition, face intelligent recognition, video semantic analysis, and data information mining and collation, etc., which are widely recognized by domestic enterprises [14].

(1) Speech Recognition. The hybrid Gaussian statistical model system (GMM) system has long been used as a probabilistic model to describe the Gaussian statistics among individual modeling units [15]. Due to the advantage of simplicity of estimation theory and the effective support of more mature and stable technical systems such as language recognition and training, this Gaussian model theory has long been kept in the leading position of international monopoly in the practical application technology of speech recognition. However, the hybrid Gaussian model is still
essentially structured as a shallow network, which cannot really describe the state space distribution among semantic features adequately and effectively [16]. In addition, in the process of GMM speech modeling, the feature model dimensional model is usually only a few tens of dimensions, and the deep neural network is used to simulate, human brain multilayer analysis results in the gradual extraction of various information features, forming a more complete and ideal information features suitable for pattern classification research. This human brain multilayer analysis structure has a considerable high degree of information similarity with the simulated human brain analysis in computer processing of various speech data and video image information. In the Baidu speech recognition system, DNN algorithm is used for speech recognition modeling, and compared with the traditional GMM speech recognition system modeling method currently used in China, the corresponding speech error rate is reduced to about 25%. In November 2012, the first enterprise speech information search and service application system based entirely on DNN technology was officially launched, becoming one of the first professional technology companies in the international industry that can formally use DNN information search service technology for enterprise speech information search service products [17]. The flow of speech recognition is shown in Figure 1 below.

(2) Image Recognition. Image recognition algorithm is one of the first typical applications of computer deep image learning theory proposed for the system. In this model called Hinton, the input object is only considered to be a single face pixel corresponding to a natural image feature, without considering any other kind of artificial features involved and used [18]. In 2012, Baidu Maps has successfully and innovatively tried to explore and apply mapping technology based on deep machine learning methods to achieve accurate recognition of real-time face pixels in the presence of natural image features and finally successfully launched a Baidu Maps search tool product based on its technology accordingly [19]. In 2013, deep machine learning, models, and computation have been successfully and effectively and widely applied to the study of deep recognition and understanding of natural language image data and advanced natural language analysis and understanding. The successful application of deep machine learning technology in computer image recognition algorithm analysis can not only directly and effectively improve the recognition and algorithm accuracy of computer images but also completely avoid sacrificing the huge consumption of time resources for manual computation due to the manual extraction process of large amount of manual image feature information, thus effectively and greatly improving. The efficiency of online image algorithms and computational analysis is greatly improved. The deep learning algorithm will probably replace the existing manual feature learning method and machine learning method in the future and become a mainstream development in the field of intelligent image feature recognition processing technology [20]. The process of face recognition is shown in Figure 2 below.

(3) Natural Language Processing. Another emerging application and area of deep machine learning research may be natural language analysis processing (NLP). In recent decades, artificial neural network models based on statistical analysis seem to have gradually become the mainstream of today’s neural network theory, but there has been very little systematic research on artificial neural network theory in the field of neural networks as such a statistical inference method alone. The world’s first work on deep machine learning for NLP problems was done entirely in the laboratory, and the research and development organization started to use embedded systems and multilayer one-dimensional convolutional structures to solve the most typical NLP problems simultaneously in 2008, including the same model they used for people of different backgrounds, which could achieve a very high accuracy rate. However, the great progress that has been made in the analysis of deep semantic learning of natural language based on NLP algorithms has not been as impressive as in the processing of audio images.

3.1.3. Common Deep Neural Networks. The neural network model mainly uses a deep machine learning model as the core of the hidden layer Markov model, and the input feature data information can be processed and extracted from multiple
hidden layer models layer by layer at the same time, so that a series of feature data mappings containing different levels of feature data can be generated, and then, these mappings can also be extracted from the underlying data of the network at the same time. The more general network feature information extracted from the underlying network data can then be connected or combined with some other mappings that require deeper abstraction to extract higher-level network features, thus enabling the network model itself to have another way to better learn to extract data and learn to express the feature mapping information. The classical deep neural network model with three hidden layers is shown in Figure 3 below.

Because the number of hidden layers involved in complex deep neural network layers is often too large, the number of parameters that need to be learned and processed in depth are larger, and there may even be new and old problems in the computational process and design practice of learning and training analysis, so now people are engaged in the analysis of modeling and construction of complex or deep complex neural network system layers. The deeper the neural network level, the more difficult it is to optimize and compute. Therefore, it is still very difficult and complicated to train from scratch until a deeper neural network model is created and finally to guarantee the good computational performance of the neuronal network model itself. Hinton et al. finally decided to divide the whole training process into two most important parts, the main process of previewing the training results and the fine-tuning process. Through the use of such networks and training, these problems have been solved by a very mature and effective technique, and since then, in-depth research has started and more and more senior researchers in the field are starting to use it, and a wave of research is coming. As the research related to computerized deep machine learning theory has been carried out in further stages in recent years, people have gradually developed various computerized deep neural network models including various types of different structural forms in the face of these complex problems that require multiple data types at different levels and cross depths between different technical fields for research verification.

3.2. Research Methodology. The following is a description of the convolutional neural network used on this paper.

The convolutional neural network role is mainly that it can significantly reduce the complexity of the algorithm for solving complex model problems, not only can effectively maintain a most complete deep and complete model structure of the model itself but also actually therefore greatly reduce the redundant some weight parameters in the model itself, so that the model can be more with a strong good generalization and analysis ability. The two major advantages are that the image CNN technology can simultaneously use all the individual pixels of an image as input, and at least one filter signal must be used between each pixel convolution layer signal to interact with other image input signals to help determine the image features needed after obtaining the original image input data. This allows the system to continuously and repeatedly extract and compute the basic image features needed for the image input and then to progressively extract and transform the subsequent image features into higher-order image features. The training process also makes use of a specially integrated image feature extraction engine and image classifier, which can easily and repeatedly extract various image features that can be effectively combined, avoiding a large amount of complex feature engineering. Therefore, the CNN structure can be generally regarded as a multilayer perceptron that refers to an image with a relatively stable special structure, allowing only the scaling, translation amplitude, and rotation direction of any point of the image to be relatively stable or constant. The simplest and most common CNN structure usually consists of a cascade of image hiding layers with different functional characteristics, which are first assumed to be just one image convolution layer, then an image pooling layer, repeated several times until the image output is reduced to a sufficiently narrow image size, and finally, an image cascade structure is usually added to help regain an image output that appears to be completely unconnected and unrelated. An image cascade structure that appears to be completely unconnected and unrelated is added to help regain an image output.

(1) Convolutional layers

Once the mapping of image features is quickly extracted by the convolutional layer method, in principle we can also
quickly use the mapping information as input information for further training of the image classifier function. However, there may still be a lot of redundant information in the image feature mapping process. In order to minimize these redundancies, a new pooling layer (downsampling layer) is added. Different convolutional kernels can extract different features of the image. In order to get the complete and effective features of the sample image, multiple convolutional kernels are usually chosen, such as 64, 128, and 256. The size of the convolution kernel determines the size of the feature image, and the step size of the convolution kernel determines the step size and the number of features. That is, when the input size of the convolution process is $W_1 \times H_1 \times D_1$, the output feature image size $W_2 \times H_2 \times D_2$ is, $P$ is the zero-complement size, stride is the kernel − size step size, is the size output of the filter, is the number of filters, calculated as follows:

$$W_2 = \frac{W_1 - \text{kernel} - \text{size} + 2P}{\text{stride}} + 1, \quad (1)$$

$$H_2 = \frac{H_1 - \text{kernel} - \text{size} + 2P}{\text{stride}} + 1, \quad (2)$$

$$D_2 = \text{output}. \quad (3)$$

(2) Pooling layer

After extracting image features through the convolution layer, in principle, these features can be directly used as input for classifier training. However, there may be redundant information in the feature mapping at this point. To reduce these interferences, we add a pooling layer (downsampling layer). The pooling layer reduces the dimensionality of the convolutional layer data and reduces the number of parameters and computation. It can effectively prevent overfitting. It also tolerates slight distortion of the model with translation invariance and rotation invariance. There are three types of pools: max pool, average pool, and random pool, also using windows to move through the input graph. The difference between the three convergence methods is in the calculation of the window values. The maximum pool is the maximum value, the average pool is the average of the fast subsampling elements, and the random pool is a random value calculated by its probability. Pooling is also a special kind of convolution kernel, but the difference is that the pooling layer acts on regions of the image that do not overlap. Given the convergence function under the direction, the whole process of the descent sampling layer can be described as follows:

$$X^{(l+1)}_k = f(\text{down}(R_k) + b^{(l+1)}). \quad (4)$$

(3) Activation function

Each layer in a CNN can have some kind of activation function that accepts the product of the input and the weights, except for the input layer. CNN uses the activation function to select the features extracted from the network in a nonlinear mapping way to avoid the problem of inadequate expression of linear operations. In practical applications, the common activation functions can be divided into saturated nonlinear functions and nonsaturated nonlinear functions.

(4) Softmax layer

After extracting the image features, to use these advanced features for classification, then a regression model is required, and the most commonly used is the Softmax regression model. It is improved on the basis of logistics and is mainly used to solve the problem of multiclassification of data.
4. Results and Discussion

4.1. Research Results. The following points were analyzed by deep learning theory algorithm and deep convolutional neural network.

(1) The scale of automated production of cigarettes gradually increases, as seen from the Figure, the scale of automated production of cigarettes in 2010 was 431 million times, 453 million times in 2012, 475 million times in 2014, 497 million times in 2016, 519 million times in 2018, 541 million times in 2020, and 563 million times in 2022, with the gradual increase of automated production, the scale of cigarette production and operation increases, and the production efficiency increases significantly, as shown in Figure 4.

(2) Compared with traditional cigarette production, the market share of automated cigarette production is also increasing year by year, with traditional cigarette production accounting for 63% and automated cigarette production accounting for 37% in 2010; traditional cigarette production accounting for 58% and automated cigarette production accounting for 42% in 2012; traditional cigarette production accounting for 50% and automated cigarette production accounting for 50% in 2014; and in 2016 Traditional cigarette production accounted for 44% and automated cigarette production accounted for 56%; in 2018, traditional cigarette production accounted for 38% and automated cigarette production accounted for 63%; in 2020, traditional cigarette production accounted for 31% and automated cigarette production accounted for 69%; in 2022, traditional cigarette production accounted for 25% and automated cigarette production accounted for 76%, it can be seen that in 2014, automated cigarette production and traditional production occupy the same market share, and after 2014, the scale of automated production exceeds the scale of traditional production of cigarettes, and the proportion of automation in the production of cigarettes gradually increases and occupies the main share, as shown in Figure 5.

(3) Distributed control system application in tobacco automation production: assuming a full score of 10 for employee efficiency and performance, it can be seen that 5.5 before and 7.51 after application of distributed control system in 2010, 5.7 before and 7.82 after application of distributed control system in 2012, 5.8 before and 8.13 after application of distributed control system in 2014, 2016 5.97 before and 8.44 after the application of distributed control system, 6.12 before and 8.75 after the application of distributed control system in 2018, 6.27 before and 9.06 after the application of distributed control system in 2020, and 6.42 before and 9.37 after the application of distributed control system in 2022; thus, the data shows that the efficiency and performance of employees are significantly improved after the application of distributed control system and nearly full score. The management system effectively connects the tobacco shop and the management center through the existing network technology and eventually achieves remote control, thus promoting more effective management of the tobacco shop. This requires computer processing technology, control technology, communication technology, computer technology, and control table technology as a whole to build the management system. This automated
system control model allows for timely and effective management of the production site through remote control supervision even when workers are not in the workshop, in order to reduce production costs, improve management efficiency, and enhance the quality of tobacco production and management, as shown in Figure 6.

(4) Production command system: the cost of tobacco production and operation in 2010 was 432 million yuan, the cost of tobacco production and operation in 2012 was 425 million yuan, the cost of tobacco production and operation in 2014 was 418 million yuan, the cost of tobacco production and operation in 2016 was 411 million yuan, the cost of tobacco production and operation in 2018 was 404 million yuan, and the cost of tobacco production and operation in 2020 was 397 million yuan. In 2022, the tobacco production and operation cost will be 390 million yuan, and the production cost will be reduced continuously, which can be applied to the production and management of the whole process of tobacco production control, to provide comprehensive tracking and management of each tobacco production workshop operation data, forming a complete report for guiding and optimizing tobacco production activities through the collection and analysis of tobacco production workshop site data, so as to accurately grasp the production process command system, reduce the occurrence of error rates, and ensure the productivity of the tobacco industry, as shown in Figure 7.

(5) Compared with the use of traditional production methods, such as agricultural mechanized production logistics system, automated agricultural logistics system can help more effective and low-cost efficient savings in farm human resources costs and labor costs and improve the utilization of agricultural land resources elements. The application of automated warehousing logistics system in cigarette enterprises can give full play to the advantages of networking, automation, intelligence, and informationization. In the traditional cigarette system, the supply of 230 million and the demand of 340 million exceed the demand, and the supply of 340 million and the demand of 340 million in the automated logistics system can reach the state of supply and demand balance, as shown in Figure 8.

(6) There are many competitors in the cigarette industry, and the competitive pressure is great. To develop in the severe environment, it is necessary to strictly...
control quality, ensure quality, and extend management automation to all aspects of quality control. Therefore, managers should set up tobacco quality evaluation standards in advance and put forward detailed requirements in terms of production process, standardization, institutionalization, networking, and strict enforcement. On the other hand, the automatic tobacco quality control network is established in factories and warehouses, forming a strong automatic control network that improves control transparency and provides real-time information on the quality of tobacco preparation, production, and logistics. For example, information can be collected, transmitted, processed, and fed back in a timely manner for special cases, such as loss of dried materials, damage to manually operated items, incomplete packaging, etc., so that managers can easily identify problems and make corresponding adjustments and treatments in a timely manner.

The number of quality accidents in cigarette production was significantly reduced after automation was added: 15 in 2010, 13 in 2012, 10 in 2014, 8 in 2016, 5 in 2018, 3 in 2020, and 1 in 2023, which shows that the addition of automation in the

**Figure 6:** Distributed control system before and after the application of the salt worker efficiency ratio and performance comparison chart.

**Figure 7:** Automation joined the change of production and operation cost of cigarette enterprises.
production process is more standardized and intelligent, which reduces the probability of quality problems and controls quality problems to each link, as shown in Figure 9.

4.2. Analysis of Results

(1) Current status of tobacco automation production: at present, tobacco automation has been widely used in China’s tobacco machinery. It is widely used in packing, silk making, leaf beating, rebaking, automation, and other machinery and equipment. Threshing and machinery of preloading is obtained and the packaging has fully realize automation operation, but the operation is obtained using air separation equipment, although many equipment manufacturers go through innovation, imitation, and mapping method to improve the technology and has a certain technical strength, but in self-control and wind separation technology level, there is still a gap with the international technology. The machine also adopts advanced production lines from Germany, Italy, and other countries to improve the automation degree of tobacco production machinery and equipment. YanZhi commonly used mechanical automation control technology, frequency conversion technology, servo technology and fieldbus technology, control equipment mainly includes the rich, Siemens, mitsubishi, panasonic, omron, etc., frequency conversion equipment is mainly including Siemens, danfoss mixer by yaskawa servo technologies such as controller, panasonic, Bosch company and Siemens equipment technology. In terms of bus, it is mainly used in man-machine interface, valve island technology, special language, image processing, and robot technology. In view of the automation YanZhi production machinery and equipment, advanced equipment and technology applied to YanZhi production, from relay logic controller to the PLC control, the centralized monitoring, to the integrated management and control of automatic control device, these changes fully embodies the YanZhi mechanical technology advances, formed with the core of robots, PLC, and servo automation infrastructure. The middle management has also realized information, and the upper decision-making has also realized intelligence, forming a three-layer intelligent network structure. Some tobacco enterprises apply advanced fine processing technology and equipment to realize the design of fine processing and product production, and realize intelligent control and cost saving.

(2) Existing problems: in recent years, the application of Profinet technology in the field of tobacco production has been promoted. With the progress of technology, Profinet technology is gradually developing towards the direction of high automation, wireless network, low cost, and low energy consumption. However, although China’s tobacco machinery and equipment technology continues to progress, but the application of tobacco automation in the production of tobacco enterprises is not extensive; some cigarette automation application is not mature, seriously affecting the intelligent and efficiency of tobacco production. Especially in automatic control equipment, sensor is the key technology, widely used in YanZhi production equipment, but the sensor technology in China is not very sensitive and cannot fast access to relevant information; therefore, YanZhi
production equipment parameters cannot be timely transferred to the control system of information transmission delay significantly reduces the effect of intelligent control. At the same time, its automatic control performance is relatively low, the selection of automatic control system is not consistent with the actual production, the stability of the actual operation of the monitoring system, and network communication system is relatively poor, prone to failure, resulting in cigarette production efficiency and quality decline, to bring huge economic losses to the enterprise. In addition, the automation industry continues to develop, the automation of tobacco production equipment to constantly upgrade and optimize. However, some tobacco production enterprises can not advance and can not properly upgrade and optimize the automatic control equipment, resulting in a low degree of automation of their technical equipment.

(3) Measures: tobacco production enterprises should attach importance to the application value of automation, timely introduce advanced automation technology, and improve the intelligent level of production. In particular, PLC and Profinet technology should be actively introduced and applied to improve the level of equipment intelligence. At the same time, it is necessary to optimize the production process and the design of several production lines, especially the automatic control device in the production line, to ensure the stability of its operation, and to carry out comprehensive management of all links of tobacco production, to achieve real-time monitoring of production. In the automatic equipment of the tobacco production system, the internal structure should be optimized constantly, and the quality of equipment, process, and products should be tested regularly to improve the production quality. Of course, this operation and quality inspection is mainly carried out through the use of sensors, detectors, and other automatic devices. The control system of tobacco production equipment can complete various operations according to the instructions of sensing information to ensure that the production quality meets the production requirements. Optimize the internal structure, improve the sensitivity and accuracy of detectors, sensors, and other equipment, and effectively improve the quality and efficiency of production, saving production costs. In addition, we should pay more attention to the training of technicians so that they can operate the relevant technical equipment effectively. With the progress and development of automation technology, its application in YanZhi production equipment is changing, needs regular training of operating personnel and management personnel, makes them master relevant technical knowledge and management, and improves the level of operation, to ensure that YanZhi production equipment automation function can timely and effectively deal with the problems existing in the equipment operation. In a word, the application of automation in tobacco production equipment can effectively improve its production efficiency and quality and effectively reduce the production cost of enterprises. However, tobacco production enterprises should pay attention to the application of automation and personnel training to ensure the smooth progress of automation.

5. Conclusion

Based on the correlation tube theory of deep learning and deep convolutional neural network, this paper focuses on the application of tobacco automatic production and draws the following conclusions:
In the process of automatic control design of tobacco industry, we should start from the standards of system design to ensure the communication between automation system and various business systems and external systems. Generally speaking, the specification of automatic control system for tobacco production management needs to be realized from the aspects of internal and external interface, internal program design, module interface, and system user interface.

The principle of flexibility and expansibility of the automatic control system of production management in tobacco industry is mainly aimed at the function and performance of the system. The application of the automation system can be adapted to different production operators and facilitate the development and expansion of other production systems. As long as the production management control system of the cigarette industry always ensures the principle of flexibility and scalability, the scale expansion of the cigarette enterprise in the development process will not be limited by the system, thus providing a guarantee for the development of the cigarette enterprise.

The design of the production management automation control system in the tobacco industry should adhere to the principles of reliability and operability. In the production and management process of tobacco industry, the automatic control system should have strong stability, safety, and reliability, and each functional module to realize its own process, with certain tolerance according to the requirements of each functional module, which will not cause problems for each functional module with other functional modules. In addition, the system should be easy for operators to manage, the system operation interface automation, application system clear and concise, and easy to manage and use.

**Data Availability**

The dataset can be accessed upon request.

**Conflicts of Interest**

The authors declare no conflicts of interest.

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