Quality Control System in Cigarette Manufacturing Based on Employee Portrait

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Abstract: How to improve product quality has always been a pain point and difficult problem that plagues the tobacco industry. Employee behaviour is an important factor affecting product quality. In this sense, we propose one method for quality control in cigarette manufacturing based on employee portrait. Quality Control System is composed of behaviour recognition system, evaluation system and early warning system. The employee behaviour is recognized by recognition system and behaviour data is obtained. Combining with the equipment operating parameters, evaluation system calculates employee behaviour score based on the proposed evaluation index system. Behaviour data and behaviour score compose the employee portrait. The early warning system issues warnings to the employees and the managers when abnormal behaviour is recognized, quality inspection is not carried out within the specified time, and the behaviour score is below the threshold. Its application had improved product quality and efficiency.

1 INTRODUCTION

Consumer goods industry is an important civilian industry and traditional industry in China, which has the advantages of wide coverage and complete structure. However, it is far behind the international level in terms of variety, quality and brand. In order to promote the international competitiveness of consumer goods industry, China has implemented variety, quality and brand strategy since 2016 and has achieved good results in recent years (MIIT, 2020). In recent years, with the development of the new generation of information and communication technology(ICT), the United States, Canada, the United Kingdom, Germany, France, Russia, Japan and other major countries in the world have implemented digital strategies (U.S. Department of State, 2020; Canadian Industry, 2020; European Commission, 2021; DCMS, 2020; BMBF, 2020; MFIDS, 2020; Cabinet Office, 2021; MOEF, 2020). The technology of artificial intelligence (AI), big data, blockchain and etc are developed and are used to promote the digital transformation of traditional industries. China also attaches great importance to digital transformation and accelerates the high-quality development of various industries through digital transformation (SCPRC, 2021).

As one kind of consumer goods industry, the tobacco industry has always been confused by improving product quality. According to statistics, the quality defect rates of Qujing Cigarette Factory from April to December 2020 keep 0.1%, which means that there may be 1 pack with quality problems for every 1000 packs. Employee, equipment, raw material, process, environment and management system are all the risk factors of quality error. In order to improve cigarette product quality, Poka-yoke technology is studied to control the risk of quality error (Ye, 2021). Advanced equipment is applied and industial internet paltform in cigarette manufacturing was constructed to realize production monitoring, diagnosis, evaluation and optimization (Qiying et al., 2020). Cigarette manufacturing process parameters

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are intelligently optimized based on big data (Yang et al., 2020). Cigarette product quality supervision and inspection management system is optimized (Shan et al., 2020). The method of quality control level is improved (Guo et al., 2020). All the measures are to achieve the control of process, equipment, environment and management in cigarette manufacturing. The operation personnel are not mentioned.

Although many automation equipment and intelligent means are now used, manpower is still indispensable. In the traditional cigarette manufacturing, product quality inspection cannot be fully detected by machine vision because the middle and bottom of the cigarette are obscured. The quality inspection needs to be completed by employees. Whether the employees carry out quality inspection according to the specification on time, whether the employees have violations or wrong operations and whether the employees keeps good working state become the management focus of product quality control. At the moment, the employee behavior is traced back, analyzed and evaluated through replaying and watching video surveillance after quality accidents are feedback from the market. The manual checking method has the disadvantages of low efficiency, poor accuracy, time-consuming and high cost.

Deep learning has set off a new climax of artificial intelligence. In recent years, with the improvement of deep learning (Deep learning, 2015) methods and the breakthrough of large databases, neural network models have extra-ordinary performance of high precision, good generalization and strong robustness in more and more complex tasks. They have been widely used in various fields of social life, such as speech recognition (Graves et al., 2013), automatic driving (Chen et al., 2015), image classification (Krizhevsky et al., 2015) and etc. In 2012, the AlexNet network won the championship in the image classification competition and enabled the rapid development of convolutional neural networks. Much research is carried out to improve the performance to apply convolutional neural networks to solve industrial problems.

The novel contribution of this paper is to propose a method for quality control in cigarette manufacturing based on employee portrait. Firstly, the employee behaviour is recognized based on Convolutional Neural Network (CNN) and analysed. The employee behaviour data is obtained. Secondly, behaviour evaluation index system is proposed. The employee behaviour score is calculated. The employee portrait is described by employee behaviour data and score. Finally, Warning is issued in real time when abnormal behaviour and violations or wrong operations are found.

The contributions of this paper are summarized as follows. In Section 2, we propose a method for quality control in cigarette manufacturing. The construction of employee portrait is presented. CNN is introduced to identify employee behaviour. The behaviour evaluation index system is proposed to calculate employee score. In Section 3, we conducted simulation and performance evaluation of CNN and carry out application implementation in Qujing Cigarette Factory. The accuracy, generalization and robustness of CNN are verified by comparing with linear classification, Bayes classification and nearest neighbor. The application effectiveness in Qujing Cigarette Factory are presented. Finally, we conclude our work in Section 4.

2 QUALITY CONTROL SYSTEM

The study is based on industial internet paltform in cigarette manufacturing and is the follow-up research work of reference (Qiying et al., 2020). The schematic diagram of the quality control system based on employee portrait is shown in Figure 1. It mainly consists of behaviour recognition system and evaluation system and early warning system.

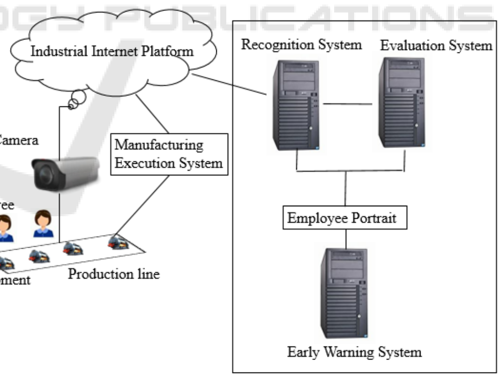

Figure 1: Schematic diagram of the quality control system based on employee portrait.

The working video of the employees are shot by the camera and uploaded to the industrial internet platform. After the video streams are converted into images, the behaviour recognition system performs face recognition and behaviour comparison. The time on duty and quality inspection frequency is calculated. The working trajectory is described through heat map by echarts. The evaluation system retrieves the data interface of MES system, read the excipient replacement frequency, cigarette rejection rate and the equipment operating parameters and calculated employee behaviour score based on the evaluation index system. The early warning system issues warnings to the employees and the managers when abnormal behaviour is found, quality inspection is not carried out within the specified time, and the behaviour score is below the threshold.

2.1 Employee Behaviour Recognition

2.1.1 CNN

The employee behaviour is identified based on convolutional neural networks (CNN). The original model is VGG16 and its principle is shown in Figure2.

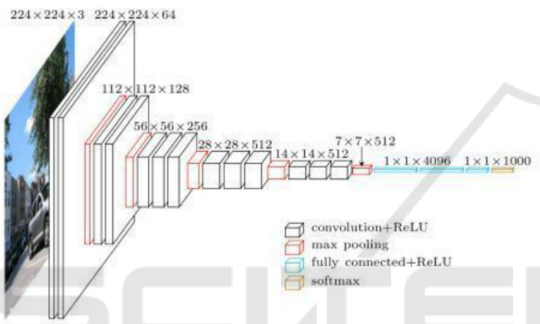

Figure 2: The principle of VGG16.

The forward propagation process includes padding, convolution, activation function, pooling, full connection and softmax classification.

Padding operations are adopted in order to overcome the drawback that pixels in corners or edges of the image are weakened when convolving. P-layer data are filled around the original image data. In addition to retaining more valid information, padding also keeps the height and width constant before and after convolution.

The convolution layer mainly uses the convolution operation to extract features from the input image (Zhenzhen et al., 2018). The *i*-th convolution calculation C_i^k of the *k*-th convolution layer is expressed as follows:

$$C_i^k = \mathrm{conv}(\mathrm{A}, \mathrm{K}_i^k, valid_i^k) + b_i^k \, (i = 1, 2, ..\mathrm{F}_k) \quad (1)$$

Where A is the input of CNN and a matrix, F_k is the number of the convolution kernels of the *k*-th convolution layer, $valid_i^k$ is and b_i^k are respectively the valid value and the bias term of the *i*-th convolution calculation of the *k*-th current convolution layer.

The activation function is to introduce nonlinear elements (Guozhu et al., 2021; Zhipeng, 2018) in the neural network. Compared with function Sigmoid and tanh, function ReLU has faster convergence and simpler expression. The result e_i^k of C_i^k being activated with the function ReLU is expressed as follows:

$$e_i^k = \mathrm{ReLU}(C_i^k) \quad (2)$$

The function of the pooling layer is to reduce the size of the network, improve the computing speed, and improve the robustness of the extracted features.

The pooling layer downsamples the feature map output by the convolution layer (Liu, 2021), reduces the size of the feature map and further extracts important features in the feature map, which greatly reduces the subsequent operation. The maxi-pooling is adopted in the paper. The pooling calculation result P_p of the current pooling layer is expressed as follows:

$$P_\mathrm{p} = \beta \cdot \mathrm{down}(\mathrm{B}) + b_\mathrm{p} \quad (3)$$

Where B is the output of the last function ReLU, b_p and β are respectively the bias term and amplification value of the current pooling layer.

The result e_p of P_p being activated with the function ReLU is expressed as follows:

$$e_\mathrm{p} = \mathrm{ReLU}(P_\mathrm{p}) \quad (4)$$

The fully connected layer converts the two-dimensional feature image output by the convolution into a one-dimensional vector and achieves end-to-end learning (Yang, 2021; Zhichao et al., 2019). The output *z* of the fully connected layer is as follows:

$$z = w \cdot v + b_d \quad (5)$$

where w,v and b_d are respectively is the weight vector, the input and the bias term of the *d*-th fully connected layer.

The softmax function at the output layer can compress a *K*-dimensional vector v containing any real number into another *K*-dimensional real vector $\sigma(v)$, so that each element is between (0,1) and the sum of all elements is 1. The *j*-th element $\sigma(v)_j$ is calculated as follows:

$$\sigma(v)_j = \frac{e^{v_j}}{\sum_{k=1}^{K} e^{v_k}} (\mathrm{j} = 0,1,2 \ldots K) \quad (6)$$

The purpose of backward propagation is to bring the training samples into the model, so that the loss function is minimized. The cross entropy is used as the loss function in the model. The cross entropy $J(p, \sigma(v))$ of ovector $\sigma(v)$ is calculated as follows:

$$J(p, \sigma(v)) = -\sum_i p_i \log(\sigma(v)_i) \quad (7)$$

where p is the label vector of the category to which the image belongs.

The error δ_j^l of the *j*-th neuron of the *l*-th layer is calculated as follows:

$$\delta_j^l = \nabla_a J \odot \sigma^{'}(z_j^l) \quad (8)$$

Where $\nabla_a J$ is a vector whose elements are the partial derivatives of loss function with respect to the output of j-th Neuron of the l-th layer, z_j^l is a small change and $\odot$ is the Hadamard product.

The current layer error δ_j^l can be expressed by the next layer error δ_j^{l+1}as follows.

$$\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma^{'}(z^l) \quad (9)$$

When the change rate of the loss function with respect to any bias in the network and the change rate of the loss function with respect to any one of the weights respectively satisfy formula (10) and (11) , the model training ends.

$$\frac{\partial J}{\partial b_j^l} = \delta_j^l \quad (10)$$

$$\frac{\partial J}{\partial \mathrm{w}_{jk}^l} = a_k^{l-1} \delta_j^l \quad (11)$$

2.1.2 Employee Behaviour Data

The employee behaviour data is obtained from behaviour recognition system and MES system.

The behaviour recognition system obtains employee behaviour data by performing face recognition and behaviour comparison, as shown in Figure 3. The face recognition is based on DeepID2 (Sun et al., 2014). After face recognition, employee information is obtained and the time on duty is accumulated by the timer. The working trajectory and staying time of the employee is expressed by heat map. The behaviour recognition is based on CNN. The time interval at which employees perform quality inspection is analysed and the times performing quality inspection is calculated.

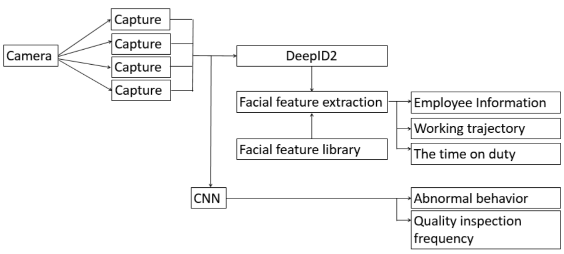

Figure 3: Acquisition of employee behaviour data by behaviour Recognition System.

The times for excipient replacement can be read from manufacturing execution system (MES). The employee behaviour data is shown in Table I.

Table 1: The employee behaviour data.

Employee Name	The times Appearing in area A	The times Appearing in area B	The times Appearing in area C	The times executing quality inspection	The times executing excipient replacement	The minutes on duty(min)
A	40	20	25	50	13	205
B	9	16	45	49	13	214
C	32	13	28	46	13	209
D	48	26	13	63	13	216

2.2 Employee Behaviour Evaluation

The employee behaviour will affect the equipment operating parameters. In the employee behaviour evaluation, the equipment operating parameters are considered and are read from MES. The operating parameters of the equipment is shown in Table II.

Table 2: The operating parameters of the equipment.

Equipment Number	Equipment Efficiency	Rejection rate	Downtime (min)	Yield(the number of cigarettes)	Abnormal quality
A	85%	2.3%	60	288563	86 cigarettes are rejected at 9:30
B	93%	1.86%	26	301325	None
C	96.5%	1.35%	13	338963	None
D	91.2%	1.73%	42	298923	None

Employee behaviour data and the operating parameters of the equipment are assigned different weights, and the behaviour score is finally calculated according to the behaviour evaluation index system.

In order to make the weight realistic, all the people in Qujing Cigarette Factory are selected to evaluate the importance of employee behaviour data and equipment operating parameters. The evaluation results are divided into 5 levels and they are respectively “unimportant”, “somewhat important”, “important”, “very important” and “extremely important”. The “unimportant” result is assigned the value of 1. And so on, the other results are assigned the value of 2, 3, 4 and 5. Only the indexes with proportion of importance and above (%) more than 60% are only selected to calculate the weight. The evaluation results of the importance of each behaviour are shown in Table III.

Table 3: The evaluation results of the importance of each index.

Index	Proportion of importance evaluation results(%)					Proportion of importance and above(%)
	unimportant	a bit	important	very	extremely	
On duty	0	10	30	20	40	90
Quality inspection frequency	0	20	10	30	40	80
Excipient replacement frequency	0	20	40	30	10	80
Rejection rate	0	10	30	40	20	90
Heat map	0	20	30	40	10	80
Equipment efficiency	0	10	30	50	10	90
Equipment downtime	0	45	10	35	10	55
yield	0	50	30	10	10	50

The weight W_j of the j-th index is calculated by the formula (12).

$$W_j = \frac{\sum_{k=1}^{3} P_{jk} * assign_k}{\sum_{i=1}^{6}\sum_{k=1}^{3} P_{ik} * assign_k} \quad (12)$$

Where P_{jk} is the k-th importance evaluation result starting from "important" of j-th index and $assign_k$ is the proportion of k-th assigned value to the sum of assigned value from "important".

For example, the weight W_1 of "on duty" is calculated as the following.

W_1 = (30*0.25+20*0.33+40*0.42)/{(30*0.25+20*0.33+40*0.42)+(10*0.25+30*0.33+40*0.42)+(40*0.25+30*0.33+10*0.42)+(30*0.25+40*0.33+20*0.42)+(30*0.25+40*0.33+10*0.42)+(30*0.25+50*0.33+10*0.42)} = 30.9/(30.9+29.2+24.1+29.1+24.9+28.2) = 30.9/166.4=0.186

Similarly, the weight W_2 of "Quality inspection frequency" is 0.175. The weight W_3 of "Excipient replacement frequency" is 0.145. The weight W_4 of "Rejection rate" is 0.174. The weight W_5 of "Heat map" is 0.149. The weight W_6 of "Equipment efficiency" is 0.169. The weights for each index are as shown in Table IV.

Table 4: The weights for each index.

Index	weight	Proportion of importance evaluation results(%)					Proportion of importance and above(%)
		unimportant	a bit	important	very	extremely	
On duty	0.186	0	10	30	20	40	90
Quality inspection frequency	0.175	0	20	10	30	40	80
Excipient replacement frequency	0.145	0	20	40	30	10	80
Rejection rate	0.174	0	10	30	40	20	90
Heat map	0.149	0	20	30	40	10	80
Equipment efficiency	0.169	0	10	30	50	10	90

The behaviour score S is calculated with data within 240 minutes according to formula (13).

$$S = \sum_{i=1}^{6} \text{value}_i \text{weight}_i \quad (13)$$

where value_i is the value of the index in Table I and Table II, weight_i is corresponding weight in Table IV.

2.3 Employee Portrait

As shown in Figure 4, the employee portrait is described by employee behaviour data and employee behaviour score.

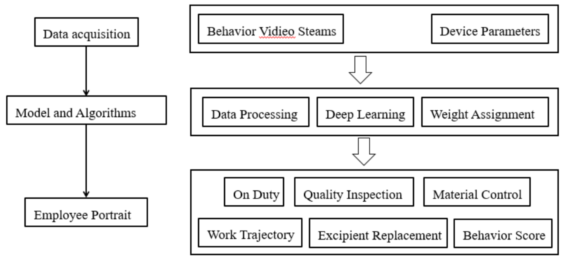

Figure 4: Employee Portrait.

3 RESULTS

3.1 Performance Analysis of CNN

In order to verify the accuracy of employee portrait model, we compared the accuracy of CNN with the accuracy of three other algorithms, which are respectively linear classification, Bayes classification and nearest neighbor. In order to verify the generalization, different sample sizes are adopted. The accuracies for different algorithms at different sample sizes are shown in Table V.

Table 5: The accuracies for different algorithms at different sample sizes.

Accuracy / Sample size / Algorithm	10000	15000	20000	25000	30000
Linear classification	51.7%	54.3%	52.4%	55.9%	35.2%
Bayes classification	62.3%	66.6%	68.9%	64.4%	64.4%
Nearest neighbor	68.8%	64.2%	65.4%	65.5%	62.2%
CNN proposed	94.4%	95.5%	97.8%	97.7%	98.1%

From Table V, the accuracies of CNN in the paper are all higher than that of the other three models at different sample sizes. Although the accuracies of Bayes classification and nearest neighbour is higher than linear classification, they still don't meet the requirements. In addition, the accuracy of CNN in the paper will not be affected by the sample size and the spatial dimension of sample features. The CNN in the paper has good generalization.

Gaussian noise, impulse noise, gamma noise, exponential noise and uniform noise are added to the sampled data with the sample size of 30000. The accuracy comparison results are shown in the Table VI.

Table 6: The accuracies for different algorithms under different kinds of noise.

Accuracy Noise / Algorithm	Gaussian	Impulse	Gamma	Exponential	Uniform
Linear classification	53.4%	57.2%	54.4%	57.9%	55.2%
Bayes classification	52.6%	56.8%	58.3%	54.4%	54.8%
Nearest neighbor	58.8%	54.7%	52.4%	56.9%	55.2%
CNN proposed	98.4%	98.3%	99.8%	98.1%	98.0%

From Table VI, the accuracies for the other three algorithms are very low under different kinds of noise. The CNN in the paper is insensitive to any kind of noise and the accuracy can reach at least 98%. The model has good robustness.

3.2 Application Implementation

The quality control system has been implemented in the roll-up and packaging workshop of Qujing cigarette factory, as shown in Figure 5.

Figure 5: The roll-up and packaging workshop of Qujing cigarette factory.

The employee behaviour is acquired in real production environment. The acquisition parameters are shown in Table VII.

Table 7: The acquisition parameters for employee behaviour in real production environment.

Machine Model	cigarette machine protos70
Camera Position	cigarette aisles
Frequency	2s
Image specification	640*480px
Image format	JPEG
Duration	7*24h
content	employee behaviour
Size	30000

Both the violations or wrong operations and quality inspection are acquired, as shown in Figure 6.

Figure 6： Violations or wrong operations and quality inspection acquired.

In order to make CNN have good generalization performance and have high accuracy in the real production environment, the image is enhanced before training by a series of random transformations, such as pulling up, panning, cutting, zooming in, zooming out, flipping, rotating, pixel filling. The original image is shown in Figure 7 and the transformed image is shown in Figure 8.

Figure 7: Original image.

Figure 8: Transformed image.

As shown in Figure 9 and Figure 10, the behaviour of quality inspection and playing telephone are recognized.

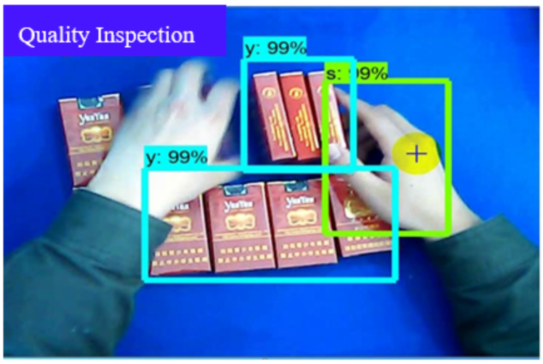

Figure 9: The recognition result of quality inspection behaviour.

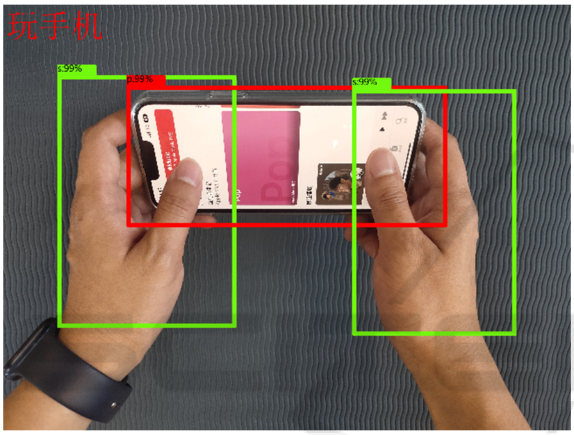

Figure 10: The recognition result of playing telephone behaviour.

When the forbidden behaviour is found, such as playing telephone, closing the eyes, long absence from work, warning is sent to the employee and manager. It is required that quality inspection is performed at least once every 20 minutes. When the quality inspection behaviour is not recognized within 20 minutes, warning is also sent to the employee and manager.

The employee portrait is shown in Figure 11.

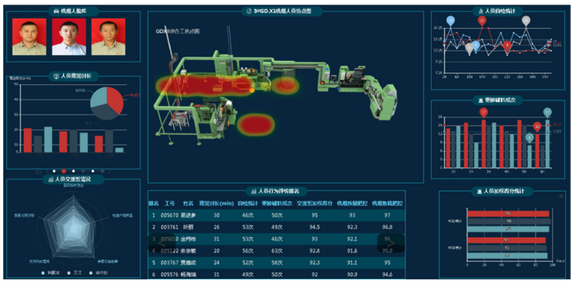

Figure 11: Employee Portrait.

The equipment efficiency is required to be at least 88% to complete the specified production tasks. In order to get the corresponding threshold of employee behaviour score for equipment efficiency value of 88%, the behaviour scores of all employees and the corresponding equipment efficiencies are analysed statistically for 3 months. The behaviour scores of one employee and the corresponding equipment efficiencies for 3 months is shown in Figure 12. It is found that the average behaviour score is 86 when the equipment efficiency reaches 88%. When the behaviour score is lower than the threshold of 86, warning is sent to the employee and manager. It helps the manager make decisions for personnel adjustments.

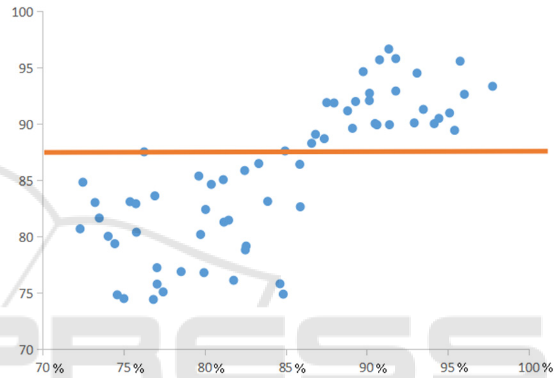

Figure 12: The behaviour scores of one employee and the corresponding equipment efficiencies for 3 months.

3.3 Application Effectiveness

As shown in Figure13-Figure15, the application in Qujing cigarette factory has achieved remarkable results in improving quality and efficiency and reducing quality defect rate. Compared to 2020, the Overall Equipment Effectiveness (OEE) and capacity utilization rate are respectively increased by 4.87% and 0.6%, and the quality defect rate of cigarette sampled was reduced by 0.75%.

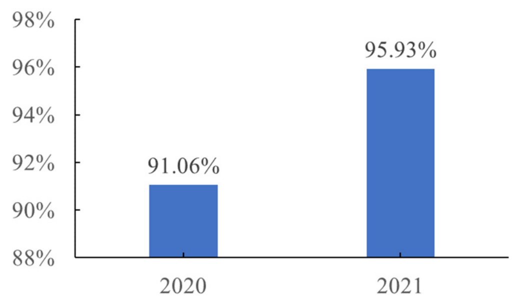

Figure 13: OEE.

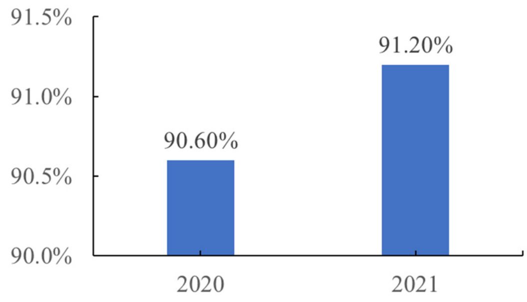

Figure 14: Capacity utilization rate.

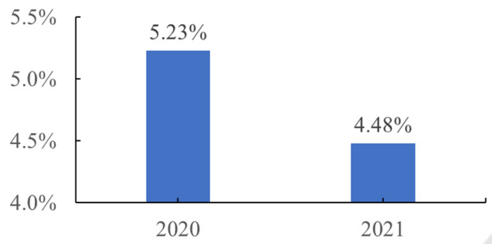

Figure 15: Quality defect rate of cigarette sampled.

The *OEE* is calculated by formula (14).

$$OEE = \eta \times \sigma \times \chi \tag{14}$$

Where η is equipment efficiency, σ is equipment utilization rate and χ is the rate of qualified products. η, σ and χ are respectively calculated by formula (15)-(17).

$$\eta = \frac{actual\ yield}{theoretical\ yield} \tag{15}$$

$$\sigma = \frac{actual\ production\ time}{planned\ production\ time} \tag{16}$$

$$\chi = \frac{actual\ yield}{actual\ yield + yield\ of\ unqualified\ products} \tag{17}$$

The capacity utilization rate ς is calculated by formula (18).

$$\varsigma = \frac{actual\ capacity}{theoretical\ capacity} \tag{18}$$

The quality defect rate of products sampled τ is calculated by formula (19).

$$\tau = \frac{the\ unqualified\ products\ sampled}{actual\ yield} \tag{19}$$

4 CONCLUSIONS

In this paper, we propose a method for quality control in cigarette manufacturing based on employee portrait. The abnormal behaviour and violations or wrong operations can be recognized and warning can be issued in time. The managers can know the working state and take actions for personnel deployment and training based on behaviour score. The method improves OEE and capacity utilization rate and reduces the quality defect rate of cigarette sampled. In the future, we will further optimize CNN by changing the number of convolution layers, the number of convolutional kernels, and the activation function to improve the recognition rate. Also behaviour recognition system will be deployed on the production line based on edge computing and the end-edge-cloud collaborative computing will be realized.

ACKNOWLEDGEMENTS

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