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Article

Research on the Application of Quantum Convolutional Neural Network in the Rapid Classification and Detection of Food Appearance Defects

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Abstract: In recent years, deep learning-based appearance detection technology has been widely applied in the field of appearance detection. Applying it to the field of food appearance detection is of great significance for achieving intelligent and flexible detection of food appearance defects. The quantum convolutional neural network representation layer, hidden layer neuron model, and hidden layer neuron model were designed. Through optimizing the quantum rotation angle and neural connection weights by training the error function, a food appearance defect classification system based on quantum convolutional neural network was built. The appearance of apples was used as the detection object, and image samples were collected through offline collection methods. The experimental results show that the model proposed in this paper achieved test accuracy rates of 97.16%, 91.85%, 94.23%, 97.72%, and 95.43% for five different appearance quality types of apples (good, scratches, fruit rust, insect damage, and rot), and the overall classification recognition accuracy reached 95.41%. It demonstrated excellent performance in the task of food appearance quality classification. In the process of food appearance defect detection, it solved the problems existing in manual inspection and met the intelligent requirements for defect classification in the inspection process.

Keywords: Quantum computing; Convolutional neural network; Food appearance; Defect detection; Image classification

1. Introduction

With the improvement of people's living standards, people's concepts regarding food have undergone a fundamental transformation. Their requirements for food safety are constantly increasing. Food safety issues have also received widespread attention from the entire society. Moreover, in recent years, food safety problems have occurred one after another in China, posing a huge threat to people's lives, making China now highly value the guarantee of food quality. And food quality inspection is a key link in ensuring food quality [1-2]. Driven by digital technology, machine vision technology has become the mainstream solution for food appearance defect detection [3]. By leveraging industrial cameras and image processing algorithms, the machine vision system can quickly and accurately identify the defects in food appearance, significantly improving the detection efficiency of products, reducing labor costs, and avoiding misjudgments and omissions caused by human factors [4]. The early methods applied for food appearance defect detection mainly relied on traditional image processing algorithms. With the introduction of machine learning methods, the shortcomings of traditional image processing methods in representing features under complex background conditions were supplemented. However, the generalization ability based on manually designed feature models is still limited and difficult to meet the requirements of complex backgrounds and flexible production, resulting in restricted application scope [5]. In this context, designing a fast, accurate, and non-destructive

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automated detection is of great significance for ensuring the quality and safety of the food industry.

The early methods applied to food defect detection mainly relied on traditional image processing algorithms, such as adaptive threshold segmentation algorithms, watershed algorithms, template matching algorithms, etc. [6]. For instance, Xiong et al. proposed a method based on level set mapping, using the image gray value to represent the packaging contour and defect location information, achieving the detection of biscuit packaging defects [7]. Wang et al. in the appearance inspection of bottled products, adopted the fast Hough transform to achieve the positioning of the light source boundary and established an efficient ROI (Region of Interest) extraction mechanism [8]. Tian et al. proposed an early apple defect detection method combining near-infrared (NIR) camera imaging technology with adaptive threshold segmentation algorithm, providing a new idea for the rapid and non-destructive inspection of agricultural product quality [9]. Zemmour et al. proposed a dynamic adaptive threshold algorithm specifically for fruit appearance defect detection, one of the main advantages of which is that it only requires a small amount of training images to achieve high detection performance and can perform robust detection in environments with highly variable lighting conditions [10]. Bhagat and Mehta proposed a watershed algorithm based on marker control and applied it to the image segmentation of fruit disease areas, thereby being able to calculate the infection rate of the fruit and reducing the time consumed by manual defect identification [11]. Traditional methods have three core limitations: the coverage of defect types is limited: traditional methods often require the background of the detection target to be simple and the shape to be regular, and have low accuracy and poor robustness in the identification of complex surface defects. The dependence on manual feature design is strong: various features need to be manually designed, the automation degree is limited, and a large amount of time and effort is consumed. The generalization ability of parameter tuning is insufficient: in different scenarios, the detection threshold needs to be adjusted, resulting in long debugging time, difficulty in establishing a unified standard, and poor universality.

With the development of deep learning, deep learning models based on convolutional neural network (CNN) architecture have become the mainstream method for food appearance defect detection [12]. Choi et al. classified 750 red-green-blue (RGB) images and developed a strawberry appearance defect detection model using CNN. This model can classify strawberry image samples as fresh, damaged or moldy, with accuracy, precision, specificity and sensitivity all reaching over 97% [13]. Cengel et al. used four CNN-based deep learning models to automatically identify cracks and surface damages in chicken eggs, aiming to improve the quality control level of eggs in the food industry by accurately identifying eggs with physical damages such as cracks, fractures or other surface defects [14]. Xu and Sun developed an automatic imaging analysis method to quickly, accurately and non-invasively detect cracking defects on salmon carcasses. This method improved the model classification performance by combining the adaptive threshold method, direction gradient histogram (HOG) with the CNN algorithm [15]. Medus et al. for food packaging defect detection, used hyperspectral imaging systems combined with CNN to perform real-time packaging defect control and classification for heat-sealed food trays. Once an unqualified tray is detected, it will be immediately removed from the automated production line [16].

In addition, Nithya et al. proposed a computer vision system using CNN for mango quality classification. After training and testing the system using the public mango database, the proposed method achieved an accuracy rate of 98% [17]. Naranjo et al. adopted the Faster R-CNN object detection algorithm and constructed a corresponding software system by using multiple CNN networks as the backbone architecture for the rapid detection of raspberry quality [18]. Wang et al. proposed a defect hard candy detection and classification method based on CNN, which uses the threshold method to distinguish hard candies from the background, and employs the segmentation algorithm of concave points detection and ellipse fitting to segment adhered hard candies, and finally constructed a defect hard candy classification model based on CNN [19]. Li et al. proposed a flower cauliflower surface defect detection and classification model based on CNN and transfer learning, which can classify cauliflower images into four categories: healthy, diseased, browning, and moldy, aiming to solve the problem of low efficiency in traditional manual detection of cauliflower surface defects [20]. Although these methods achieved high accuracy in food defect detection, they all detect scale-invariant defects and have not conducted sufficient research on cross-scale defects. Moreover, the detection models based on CNN architectures require the use of non-maximum suppression (NMS) to remove redundant prediction boxes, and this post-processing operation to some extent affects the detection performance of the model.

To address the limitations of traditional CNNs, such as the need for NMS to remove redundancies and the significant influence of their own parameter settings, which can easily lead to local optima, quantum computing can store more bit information, providing a new solution approach for traditional CNN problems [21]. Quantum convolutional neural networks (QCNN) have attracted widespread

attention in the field of image classification. Swati et al. first proposed the QCNN model, which uses only O(log(N)) order of variational parameters to represent the input size of N quantum bits, allowing for effective training and implementation on current quantum devices in reality, and for the classification of different quantum phases and related phase transitions [22]. Mishra and Tsai proposed a new quantum-classical convolutional neural network (QSurfNet), which consists of a QCNN module, a feature extraction module, and a surface defect recognition module, for classification of surface defect image datasets [23]. Rajesh and Naik focused on using QCNN for image recognition and target detection, and the results showed that compared with traditional computing methods, QCNN not only improved the computing speed but also achieved better performance indicators [24]. Li et al. proposed a quantum deep convolutional neural network image recognition model based on quantum parameterized circuits (QDCNN), compared with the classical model, it provides exponential acceleration for the training of the QDCNN model and has certain feasibility and effectiveness [25].

This paper aims to enhance the speed and accuracy of food appearance inspection. Taking apple appearance images as the inspection object, the layers of the quantum convolutional neural network algorithm (QCNN) were designed. The modified linear activation function ReLu was adopted as the activation function, which shortened the calculation time and improved the detection and recognition speed. The image samples were collected offline, and a total of 2104 images were obtained as test samples. The feasibility of QCNN in the apple appearance defect classification task was analyzed based on the loss curve and accuracy curve of the network model, and compared with the classical CNN method and traditional apple appearance quality classification methods to verify the classification accuracy of the proposed model on the test set data.

2. Quantum Convolutional Neural Network

2.1. Quantum Computing

2.1.1. Quantum Bit

The two ground states of a quantum bit, $|0\rangle$ and $|1\rangle$, form a set of orthogonal bases in the two-dimensional space $\mathbb{C}^2$. Unlike classical bits, their states can be in a linear superposition state of $|0\rangle$ and $|1\rangle$, as shown in Equation (1).

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle = \alpha\begin{bmatrix}11\\[0]\end{bmatrix} + \beta\begin{bmatrix}0\\11\end{bmatrix} = \begin{bmatrix}\alpha\\\beta\end{bmatrix} \tag{1}$$

Among them, the complex numbers α and β represent the quantum bit probability amplitudes. The square of a single probability amplitude represents the probability of measuring the corresponding state, and it satisfies the additivity and normalization property.

When n quantum bits form a multi-body quantum system, the 2^n-dimensional space matrix is obtained in the form of tensor product. Taking two quantum bits as an example, the result is as follows:

$$|00\rangle = \begin{pmatrix}1\\0\end{pmatrix} \otimes \begin{pmatrix}1\\0\end{pmatrix} = \begin{pmatrix}1\times\begin{pmatrix}1\\0\end{pmatrix}\\0\times\begin{pmatrix}1\\0\end{pmatrix}\end{pmatrix} = \begin{pmatrix}1\\0\\0\\0\end{pmatrix} \tag{2}$$

2.1.2. Quantum Rotating Door

Quantum gates embody the characteristics of quantum computing. They change the quantum state through unitary transformations and are the foundation for implementing quantum computing. The definition formula for a single-bit quantum rotation gate is:

$$R(\theta) = \begin{bmatrix}\cos\theta & -\sin\theta\\ \sin\theta & \cos\theta\end{bmatrix} \tag{3}$$

For the quantum state $|\psi\rangle = \begin{bmatrix}\cos\theta_0\\ \sin\theta_0\end{bmatrix}$, the action of $R(\theta)$ on $|\psi\rangle$ is equivalent to performing a phase rotation by the corresponding angle θ, and the effect is as follows:

$$R(\theta)|\psi\rangle = \begin{bmatrix} \cos(\theta_0 + \theta) \\ \sin(\theta_0 + \theta) \end{bmatrix} \tag{4}$$

2.1.3. Controlled NOT Gate

The controlled NOT gate (CNOT) implements the XOR operation and is a commonly used binary operator in quantum computing, acting on a control qubit and a target qubit. When the control bit is $|1\rangle$, it swaps the states of the target qubits $|0\rangle$ and $|1\rangle$; when the control bit is $|1\rangle$, the observed probabilities of the two states remain unchanged, so the controlled bit is considered to remain unchanged as well.

2.2. Design of Quantum Convolutional Neural Network

2.2.1. Presentation Layer Model

The quantum convolutional neural network consists of a representation layer, convolutional layers, pooling layers, fully connected layers, and an output layer. Among them, the convolutional layers, pooling layers, and fully connected layers can be represented by hidden layers. To enable the output to be correlated with the input, a quantum restricted Boltzmann network is used.

The model neurons in the representation layer achieve the operation through four parts: the input is represented by $|x_n\rangle$ quantum bit, the phase shift is realized by the Hadamard gate and the rotation gate $R(\theta_l)$, the aggregation is by the Σ operation, and the output result. In the multi-level neural network representation layer model, the output result of each level of representation layer neuron serves as the input of the next level of representation layer neuron. The next level needs to go through the four processes of input, phase shift, aggregation, and output successively, which avoids the singularity of phase shift and aggregation, allowing the neural network to fully learn and increasing the accuracy rate of identifying small components.

The logical operations of the convolutional neural network are mainly realized by the Hadamard gate and the rotation gate. The Hadamard gate mainly rotates and reflects the quantum state, that is, the initial operation on the weight matrix of the convolutional neural network is carried out, and its expression is:

$$H = \frac{1}{2}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{5}$$

Calculate the rotation of the quantum gate according to Equation (6):

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}. \tag{6}$$

In the formula:

θ —— Quantum rotation angle, rad.

When $|\tau\rangle = \begin{bmatrix} \cos\theta_0 \\ \sin\theta_0 \end{bmatrix}, \tau = 0,1$,

$$R(\theta)|\tau\rangle = \begin{bmatrix} \cos(\theta + \theta_0) \\ \sin(\theta + \theta_0) \end{bmatrix} \tag{7}$$

Then, $R(\theta)$ achieves a phase rotation of $|\tau\rangle$.

After the Hadamard gate and the rotation gate $R(\theta_l)$ are applied to $|x_l\rangle$, the result is:

$$\begin{cases} R(\theta_l)H|x_l\rangle = [\cos\theta_l \quad \sin\theta_l]^T \\ |x_l\rangle = [\cos\varphi_l \quad \sin\varphi_l] \end{cases} \tag{8}$$

In the formula:

$$\arg\left[R(\theta_l)H|x_l\rangle\right]$$

$$\arctan\left[\frac{\sin\left(\varphi_l+\frac{\pi}{4}+\theta_l\right)}{\cos\left(\varphi_l+\frac{\pi}{4}+\theta_l\right)}\right]=\varphi_l+\frac{\pi}{4}+\theta_l$$

The aggregated result is:

$$\sum_{l=1}^{n}R(\theta_l)H|x_l\rangle=\left[\sum_{l=1}^{n}\cos\theta\sum_{l=1}^{n}\sin\theta\right] \tag{9}$$

When the quantum bit is in the state $|1\rangle$, the input-output relationship of the quantum neuron is:

$$y=\sum_{l=1}^{n}\sin\theta_l' \tag{10}$$

In the formula:

$$\theta_l'=\varphi_l+\frac{\pi}{4}+\theta_l \tag{11}$$

When the quantum bit is in the $|0\rangle$ state, the input-output relationship of the quantum neuron is as follows:

$$y=\sum_{l=1}^{n}\cos\theta_l' \tag{12}$$

2.2.2. Hidden Layer Neuron Model

The design of the quantum gate model for hidden layer neurons is shown in Figure 1. In the quantum gate model of hidden layer neurons, after the phase shift gate operation on $|x_1\rangle$ and $|x'_1\rangle$, the quantum state $|0\rangle$ or $|1\rangle$ can be freely selected for computation as needed. To fully update the neural network weights, a rotation gate operation needs to be performed again, and finally, the convolution result is output.

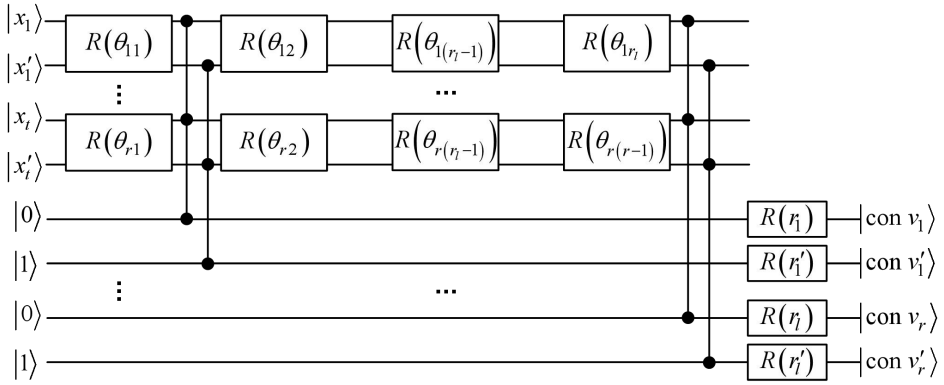


Figure 1. Quantum gate model of hidden layer neuron

2.2.3. Output Layer Neuron Model

When extracting the quantum state, the quantum state collapses to a specific state. To avoid the convolution result being damaged, the design of the output layer neuron circuit model is shown in Figure 2.

In the quantum gate model of the output layer neurons, $|x_1\rangle$ after the Hadamard gate operation can freely choose the quantum state $|0\rangle$ or $|1\rangle$ for calculation. To fully update the neural network weights, it needs to undergo the Hadamard gate operation again and finally output the classification result.

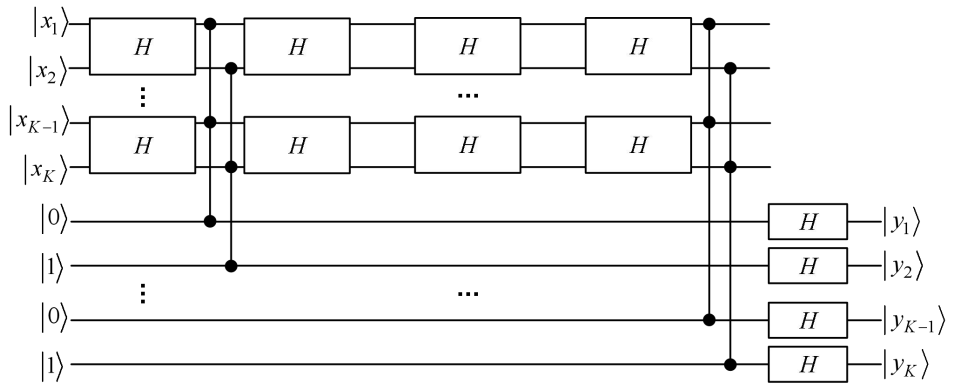


Figure 2. Output layer neuron circuit model

2.3. Parameter Optimization

2.3.1. Optimization of Activation Functions

The activation functions from the input layer to the hidden layer, and from the hidden layer to the output layer all adopt the rectified linear activation function ReLu, as shown in Equation (13):

$$u' = \min\left[\varphi_{\max}, \max\left(\varphi_{\min}, u\right)\right] \tag{13}$$

In the formula:

$\varphi_{\min} < 0, \varphi_{\max} > 1$ —— The constant value at the edge of the activation function ReLu.

u —— Input.

u' —— Output.

Compared with the traditional Sigmoid-type activation function, the modified linear activation function ReLu does not involve division and exponential operations, and thus has a faster calculation speed. At the same time, the ReLu function can completely represent negative activation values as zero, making the network sparse, and when the quantum convolutional neural network algorithm is used to train the network, it can improve its convergence speed.

2.3.2. Optimization of Rotation Angle and Connection Weights

When the neural network algorithm updates through quantum rotation gates, the angle of the rotation gate is related to the convergence rate. If the value of the rotation angle differs significantly from the expected value, then the rotation angle needs to be increased to accelerate convergence; if the value of the rotation angle is close to the expected value, then the rotation angle needs to be reduced to avoid premature convergence. Suppose the training error function is:

$$E = \frac{1}{2}\sum_{m=0}^{M}\left(\overline{y}_m - y_m\right) \tag{14}$$

In the formula:

E —— Training error value.

$\overline{y}_m$ —— Expected output at the output end of the m th neural network after normalization.

y_m —— Actual output at the output end of the m th neural network.

The test requires that the training error be less than 10^{-3}.

The rotation angles of the quantum rotation gates in the hidden layer and the output layer are θ and ψ respectively, and their update method is:

$$\begin{cases} \theta(t+1) = \theta(t) - \eta_1 \dfrac{\partial E}{\partial \theta} \\ \psi(t+1) = \psi(t) - \eta_2 \dfrac{\partial E}{\partial \psi} \end{cases} \tag{15}$$

In the formula:

t —— Number of iterations.

$\eta_1 \in (0,1), \eta_2 \in (0,1)$ —— Learning rate.

When the training error is large, the rotation angle increases at this time to accelerate convergence; otherwise, the opposite operation is performed.

The connection weights are calculated according to Equation (16):

$$\omega(t+1) = \omega(t) - \eta_3 \frac{\partial E}{\partial \omega} \tag{16}$$

In the formula: ω - connection weight.

$\eta_3 \in (0,1)$ - learning rate.

3. Food Appearance Defect Classification Based on Quantum Convolutional Neural Network

3.1. Image Acquisition

Before image collection, a field investigation was conducted at a certain fruit market to identify various fruit varieties and their defect types. Finally, apples with defects were selected and purchased. Due to the prominent defects of the apples themselves and the limitations of the experimental collection equipment, the image collection device mainly used a brand smartphone. Before the collection, to avoid the influence of environmental light and human shadows on the shooting effect, through experiments at different distances, it was concluded that the best shooting effect was achieved when the distance from the window in the laboratory was about 3 meters. Using a three-section phone stand to fix the phone at a height of 30 cm above the product being photographed (while ensuring that the phone was parallel to the desktop), the collected images could ensure a relatively high level of clarity and completeness. During the shooting process, the photographer was positioned at the front of the phone stand to avoid shadows from interfering with the shooting. Based on the defect characteristics of the purchased apples, they were classified in detail, and all apple defects were divided into the following five types: intact, insect bites, rot, fruit rust, and scratches. Images of apples with the above defect categories were taken, resulting in a total of 2104 images, which were used as test sample collections.

3.2. Feature Selection

For the defect area images obtained from the above steps, this paper conducts a feasibility analysis of their features. The data differences in terms of geometric features, color features, and texture features of the defects are statistically analyzed. The following are selected:

(1) Geometric features include area, roundness, and strip judgment (Area, Circularity, *f*).

(a) Area: The total number of pixels in the area, denoted as *F*.

(b) Roundness: The similarity between the input area and a circle is calculated, denoted as *C*. The closer the area is to a circle, the larger the value. The calculation formula is:

$$C' = \frac{F}{\left(\max^2 * \pi\right)} \tag{17}$$

$$C = \min\left(1, C'\right) \tag{18}$$

(c) Linear: Determine whether the area is in a linear shape and record it as f. Here, length1 and length2 represent the minimum length and width of the rectangular outline of the area. The calculation formula is:

$$f = length1 / length2 \tag{19}$$

(2) Color characteristics include the average gray values in the three channels (Mean, Mean1, Mean2), where *R* represents the region and p is a pixel of R. The gray value of this pixel is $g(p), F$, which represents the total number of pixels in R. The calculation formula is:

$$mean = \frac{\sum_{p \in R} g(p)}{F} \tag{20}$$

(3) The texture features mainly utilize texture feature operators. The main feature vectors within the

operator are: gray level energy (uniformity of image gray levels and fineness of texture), correlation, local uniformity, contrast, and entropy (aggregation characteristics of gray level distribution). According to statistical data, there is no difference in the data of gray level energy, correlation, and entropy among all defects. Therefore, local uniformity, contrast, and anisotropy are selected as features for research.

3.3. Classification Process for Food Appearance Defects

Based on quantum convolutional neural networks, the detection of apple appearance is carried out. The basic idea is as follows: Firstly, collect apple image samples, then extract and reduce the features of apple appearance, and then use quantum convolutional neural networks to classify and recognize the selected features, and the output result is the detection result. According to the above idea, the apple appearance detection process is designed as follows:

(1) Apple data collection and preprocessing. Use a dual-light source scanner to scan different types of apples to obtain apple sample data. Considering that there are noise data in the data and the overall data volume is small, the data needs to be processed by noise removal and data enhancement, etc.

(2) Apple appearance feature extraction. Apple appearance features include color features, texture features, and shape features. For color features, the HSV space model is used to extract the mean, skewness, and variance features of the color components, and a total of 9 color features are obtained; for texture features, the gray-level-gradient co-occurrence matrix is used to extract 15 features such as gray level, gradient, gray variance, and energy from the apple image.

(3) Apple appearance feature reduction. Considering that the selected apple appearance features are numerous, which may lead to an excessively large input data dimension for the quantum convolutional neural network, affecting the detection speed and accuracy. Therefore, for the extracted apple appearance features, PCA is used for dimension reduction processing, and finally, 3 color features of the V component in the HSV color space, 2 texture features of gray level and gradient, and 3 shape features of area, perimeter, and compactness are selected as the apple appearance features, totaling 8 features.

(4) Apple appearance detection. Based on the constructed quantum convolutional neural network, the 8 reduced apple appearance features are input into the model for learning and training, and the output result is the detection result.

4. Experimental Results and Analysis

4.1. Experimental Analysis of Quantum Convolutional Neural Network

For a standard quantum convolutional neural network with n input quantum bits, after each layer of quantum convolution and quantum pooling, the number of quantum bits is halved. Therefore, the network can have a maximum of $\lceil \log n \rceil$ layers of convolution and pooling. Due to the sharing of weights within the convolutional and pooling layers, the number of parameters in the same network layer is independent of the number of coherent quantum bits. The parameter quantity of the quantum convolutional neural network increases logarithmically with the increase in the number of quantum bits. To verify the impact of model complexity on the model's classification ability, this paper conducts a comparative experiment using different numbers of quantum convolutional layers. The comparison results are shown in Figure 3.

From the distribution of accuracy rate curves, it can be clearly seen that the model structure with one layer of quantum convolutional layer has stronger learning ability and better generalization performance compared to the model structure with two layers of quantum convolutional layers. The accuracy rate for achieving the classification task is higher, and the fewer quantum gate parameters make it more feasible.

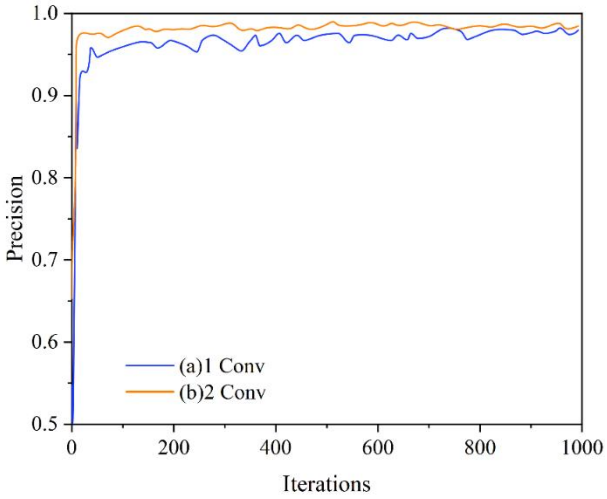


Figure 3. Classification accuracy curves w.r.t. different num-ber of convolutional layers

4.2. Experimental Setup

4.2.1. Experimental Platform

The hardware and software environments of the experimental platform in this article are respectively shown in Table 1 and Table 2.

Table 1. Hardware Environment of the Experimental Platform

Hardware Name	Model	Parameter
Processor (CPU)	Intel(R) Core(TM) i7-6800K CPU	Frequency 3. 40 GHz
Internal storage (RAM)	DDR3	16.0GB
Video card (GPU)	NVIDIA GeForce GTX 1080Ti	Video Memory: 12 GB

Table 2. Software Environment for the Experimental Platform

Name	Content
Operating system	Windows 10 64-bit Operating System
Deep Learning Framework	Pytorch
Implementation language	Python3.6

4.2.2. Evaluation Indicators

In the image classification and discrimination task, in order to evaluate the performance of the image classification system, the average classification accuracy of the overall data is generally used as the evaluation index for the experiment. For sample data $x_i, i = 1, \cdots, N$, the true value of the data's category is denoted as l_i , and the classification test result of the network model on this data set is denoted as $y_i = f(x_i)$. Then, using the binary method, the output of this data set can be represented as:

$$z_i = \begin{cases} 1, & if\ y_i = l_i \\ 0, & if\ y_i \neq l_i \end{cases} \tag{21}$$

Then, the classification accuracy of the network model can be calculated using the following formula:

$$Z = \frac{1}{N}\sum_{i=1}^{N} z_i \tag{22}$$

Here, N represents the sample size used to calculate the accuracy rate of the testing model.

4.3. Classification Detection Results and Analysis

4.3.1. Experimental Results of Quantum Convolutional Neural Network

The curve showing the loss value and accuracy rate changes of the quantum convolutional neural network after training for 30,000 times is shown in Figure 4. From the changes in network loss and accuracy rate, it can be seen that in the first nineteen epochs of training, i.e., during the 0-6,000 iterations, the convergence was relatively fast, and the accuracy rate rose the fastest. The network loss decreased from 1.35 to below 0.3, and the rate of decrease was relatively rapid. During the network iterative training from 6,000 to 15,000, the convergence speed gradually became slower, and the accuracy rate rose from 90% to 97%, with the rising speed also significantly slowing down. After the iterative training reached 15,000 times, the recognition accuracy remained basically stable and could reach above 98.7%. When the iterative training reached around 20,000 times, the recognition accuracy reached 99%. The accuracy rate and loss value gradually stabilized, and the entire network basically reached a saturated state, and no significant changes occurred in the subsequent iterative process. The changes in network loss and accuracy rate during the entire training process were relatively gentle, and the final convergence state was basically reached at the 25,000th iteration.

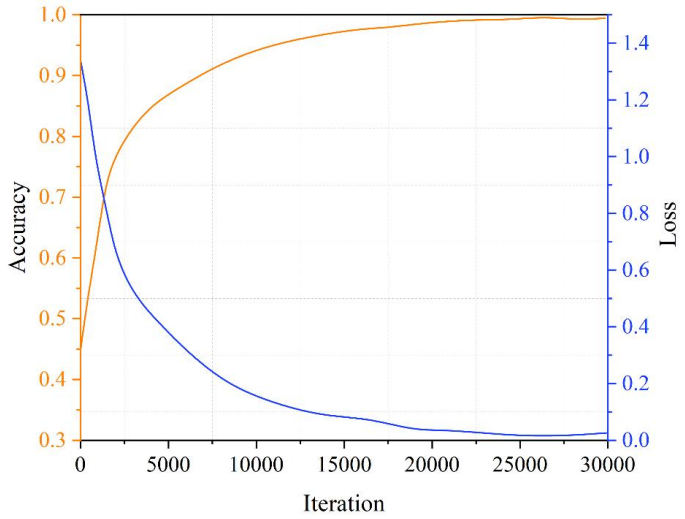


Figure 4. Curve diagram showing changes in network accuracy and loss values

The QCNN network model, which was trained iteratively for 30,000 times using the Apple Image Test Set, was subjected to classification and recognition tests. The test set samples included a total of 2,104 apple images, among which there were 410 intact apples, 410 apples with scratches, 426 apples with fruit rust, 426 apples with insect damage, and 432 rotten apples. The classification results of the QCNN network model are shown in Table 3. After statistical analysis, the numbers of classification errors for intact apples, apples with scratches, apples with fruit rust, apples with insect damage, and rotten apples in the test set samples were 12, 38, 29, 11, and 24 respectively. The classification recognition accuracy rates of the model were 97.16%, 91.85%, 94.23%, 97.72%, and 95.43% respectively, and the overall classification accuracy reached 95.41%. The QCNN network model demonstrated a high accuracy rate in the classification task of apple appearance quality, verifying the feasibility of the network structure.

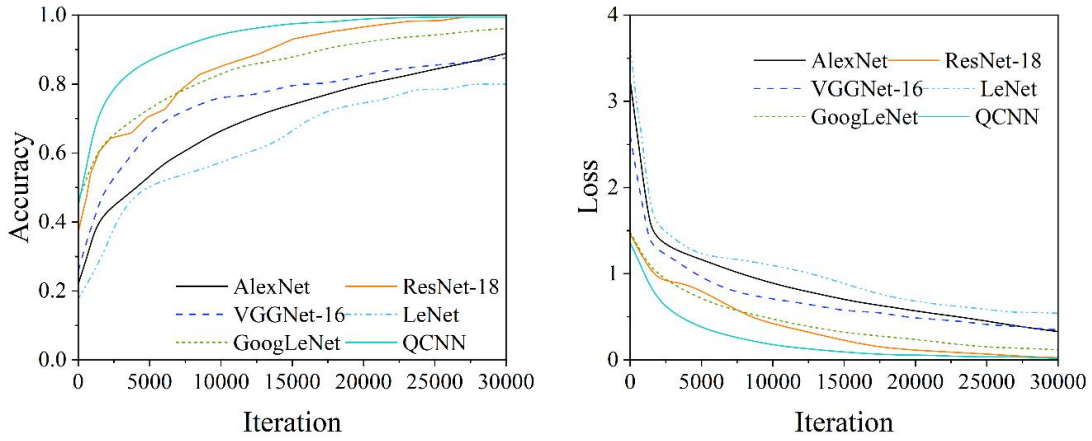
Table 3. Statistics on the classification results of the QCNN network model

Sample Category	**Number of Error Identifications**						**Precision(%)**
	Intact	**Scratch**	**Apple rust**	**Worm infection**	**Become putrid**	**Total**	
Intact	-	7	5	0	0	12	97.16
Scratch	28	-	6	0	4	38	91.85
Apple rust	12	9	-	4	4	29	94.23
Worm infection	0	0	6	-	4	11	97.72
Become putrid	2	4	10	8	-	24	95.43
Total	42	20	37	12	12	123	95.41

4.3.2. Comparison and Analysis of Classification Results of CNN Network

In order to compare the performance of different CNN networks on five different quality apple datasets, this paper trained and tested the apple dataset using the LeNet network, AlexNet network,

VGGNet-16 network, GoogLeNet network and ResNet-18 network, and compared the proposed method in this paper. Figure 5 shows the curves of classification accuracy and loss values for the LeNet, AlexNet, VGGNet-16, GoogLeNet, ResNet-18 and OF-Net networks. Based on the curve changes, it can be concluded that during the iterative training process, the classification recognition accuracy of the QCNN network model is higher than that of other classic CNN networks. In terms of time comparison, within the range of iterative training from 0 to 6000 times, the training accuracy of the QCNN network increases rapidly, and around 15000 iterations, its classification accuracy reaches 98.2%. From the change in network loss, the convergence speed of the QCNN network model is better than that of other CNN networks.



(a)Accuracy (b)Loss

Figure 5. Changes in accuracy and loss values across different network architectures

4.3.3. Comparison and Analysis of Traditional Methods for Classifying Apple Appearance Quality

The traditional methods for classifying the appearance quality of apples are mostly based on machine vision combined with traditional image processing methods, multispectral technology and SVM support vector machines. Most of these methods classify the quality of a single apple, and the recognition accuracy is relatively low. Moreover, the production process of the apple dataset in the early stage has high requirements for image acquisition conditions, otherwise it will have a significant impact on the later apple classification and recognition results. The quantum convolutional neural network (QCNN) has achieved the classification of five different quality apples, namely intact, scratched, fruit rust, insect damage and rotten apples. Compared with other methods, it has significantly improved in accuracy and efficiency, and has good practicability.

The comparison of the proposed method with the above traditional methods for classifying the appearance quality of apples is shown in Table 4. The defect recognition method based on DT-SVM extracts sample information features and tests 80 apple images through the network model obtained by iterative training, achieving a classification accuracy of 97.25%. The apple appearance defect detection system proposed by VGGNet-16 conducted experiments on 50 normal fruits and 50 defective fruits, effectively judged the surface defects of apples, and achieved a recognition accuracy of 91.04% for apple defects using histogram algorithms and perceptual hashing algorithms. The apple surface scar recognition method of AlexNet classified and recognized apples with rotten, round spots, scratches, and no scars, and processed the image data using principal component analysis (PCA) and clustering segmentation, achieving a final classification accuracy of 78.02%.

In the comparison of traditional methods for classifying the appearance quality of apples, it can be concluded that the traditional methods for classifying and identifying the appearance quality of apples are mostly for single-quality classification tasks and have not achieved the recognition of multiple apple qualities. Moreover, there is a significant difficulty in extracting the characteristics of apple samples, and the recognition accuracy is easily affected by environmental factors such as sample feature differences and image quality. In addition, some classification methods have high equipment costs and are difficult to meet the actual needs of food product quality classification. The quantum convolutional neural network can fully extract the information features of apple samples, directly use the original apple sample data for network model training, achieve the classification of five different quality apples, such as intact, scratched, fruit rust, insect damage and rotten apples, and has achieved a

higher classification accuracy, providing a new method for food product quality classification.

Table 4. Comparison of Traditional Apple Quality Identification Testing Methods

Detection Algorithm	Classification Identification Results	Precision
DT-SVM	Only defective apples	97.25%
VGGNet-16	Normal fruits and defective fruits	91.04%
LeNet	Normal fruits and defective fruits	93.79%
AlexNet	Rot, circular spots, scratches, no scars	78.02%
GoogLeNet	Good fruits and defective fruits	92.26%
The algorithm in this paper	Intact, scratched, affected by fruit rust, damaged by insects, or rotten apples	96.75%

5. Conclusion

The research proposes a food appearance defect detection method based on quantum convolutional neural network (QCNN). By selecting apple appearance detection as the research object and using the QCNN network for classification and recognition, the rapid and accurate detection of food product quality was achieved. The experimental results show that the model trained based on quantum convolutional neural network has classification accuracies of 97.16%, 91.85%, 94.23%, 97.72%, and 95.43% respectively for different quality apple test sets (including intact, scratches, fruit rust, insect damage, and rotten ones). The overall classification recognition accuracy reached 95.41%. Therefore, compared with other classification methods, the classification accuracy of the QCNN network demonstrates excellent performance, providing a new and effective means for the rapid and high-precision classification of food appearance defects.

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