Freshness Identification of Iberico Pork Based on Improved Residual Network and Transfer Learning

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***Abstract*—In order to improve the accuracy of pork freshness identification, a method for pork freshness identification based on improved residual network and transfer learning was proposed. First of all, the pork freshness was classified into fresh, secondary fresh grade I, secondary fresh grade II, secondary fresh grade III, deteriorated grade I, deteriorated grade II and deteriorated grade III, a total of 7 grades, according to the aerobic plate count, coliform bacteria and pH value of pork combined with national pork food standards. The Resenet-50 model was trained with the AAUSet data set to have the ability to extract image features. Then, the Resenet-50 model was improved using model transferring and model fine-tuning in the following ways: first, replace the full connection and classification layers of the Resenet-50 model with a 3-layer adaptive network; next initialize the improved Resenet-50 model weights using the network parameters trained on the AAUSet; then use LReLU as the activation function of the adaptive network; finally, transfer the knowledge gained by the improved Resnet50 model on AAUSet to the task of Iberico pork freshness identification. The images of Iberico pork were preprocessed with rotation, alignment and scale-zooming, and then images of the 7 freshness grades were selected, a total of 23 427 images forming the sample set. Then, 80% of the samples were randomly selected from the sample set to be used as the training set, and the remaining 20% for the test set. The test results showed that transfer learning could significantly improve the convergence speed and classification performance of the model, and data augmentation could increase the diversity of data, avoiding over-fitting phenomena. The accuracy of classification in transfer learning and data augmentation could reach as high as 94.5%. Moreover, the test process was simple, high real-time and non-destructive, making the test method a more efficient method for classifying pork freshness.**

Key words Transfer learning, Pork freshness, Image identification, Residual network

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I. INTRODUCTION

During the storage process of pork, the enzymatic actions as well as the contamination of microorganisms or the disease before slaughtering pig can result in changes like autolysis and decomposition of pork, resulting in a decrease in the freshness of pork. The decomposition of pork components is bound to have its nutritional value reduced. Moreover, both the microorganism involved in the deterioration as well as its toxins and the toxic decomposition products after deterioration can cause human poisoning and diseases.

The deterioration of pork is a gradual process with complex changes, and it is also affected by many factors. Therefore, how to accurately and quickly assess the quality and safety of meat is related to the health and vital interests of consumers.

The evaluation indicators of pork quality are color, texture, pH, tenderness and freshness. Among them, freshness is an important and complex indicator parameter for evaluating meat quality and safety, which contains various microbial, physicochemical and biochemical features. The main components of pork, such as protein, fat and carbohydrates, can be decomposed by enzymes and bacteria, producing odor. The protein in pork can be gradually decomposed into hydrogen, sulfide, ammonia and ethyl mercaptan, producing small toxic molecules like histamine, tyramine, putrescine and tryptamine. Fats are broken down into aldehyde compounds and aldehyde acids. Carbohydrates can be decomposed into alcohols, ketones, aldehydes, hydrocarbons and carboxylic acidic gas. These substances, together with other basic nitrogen compounds, can affect the color, texture and shape characteristics of pork during storage [1-3].

Physicochemical analysis of TVB-N and microbial populations are conventional analytical methods for freshness. These methods are non-destructive, inefficient, and/or time consuming. Near-infrared (NIR) spectroscopy, combined with computer vision (CV), has been used to assess pork freshness due to its speed, simplicity, and ability to measure food properties, and good achievements have been made [4-5]. The combination of hyperspectral imaging(HSI) technology and traditional imaging technology has also been applied in food quality testing. Huang et al. (2013) used HSI technology to predict the total viable count (TVC) in pork meat, achieving good results [6-7]. Chen et al. (2013) evaluated the freshness of salted pork in jelly (SPIJ) using HIS, which showed good testing results [8-9]. Multispectral imaging technology (MSI), like HIS, is a new type of detection technology that combines traditional imaging and spectroscopy to obtain spatial and spectral information from the testing object [10-15]. Non-destructive testing of pork freshness has also achieved high precision. Panagou et al. evaluated the microbiological quality of beef filets during aerobic storage by combining the MSI system with a linear algorithm [16], and the results showed that the MSI system had a good classification effect on the deterioration of three types of beef slices. The combination of MSI with linear partial least squares regression (PLSR) has been proved to be a good way for the rapid and non-destructive determination of aerobic plate count (APC) in cooked pork sausages [17].

Due to the high cost and high equipment cost, near-infrared, hyperspectral and multi-spectral imaging inspection systems have become just laboratory test facilities. Therefore, in order to meet the needs of consumers, it is particularly important to investigate low-cost pork freshness detection methods.

With the rapid development of deep learning and computer vision technology, it is possible to develop a low-cost pork freshness identification system based on deep learning and computer vision. Transfer learning can help solve the problem of small sample classification, and it has been widely recognized and studied. It extracts the features of small samples by using the model trained on massive data sets, and then the extracted features are used for the fine tuning of full connected neural networks, thereby reducing the difficulties in using deep networks to solve problems [18-20]. Pan et al. [21], Cheriyadat [22], Yang et al. [23] made detailed explanation to the history, classification, and challenges of transfer learning. Based on transfer learning, Lin et al. [24] and Schmidhuber [25] first proceeded pre-training to CNN through large samples, then replaced the full connected layers with extreme learning machine (ELM), and finally trained the CNN model using small samples, which improved the classification accuracy and shortened the training time.

As a strain of Huai pig, Iberico is a local fine variety grown in the Huaibei Plain. Its pork quality is superior to that of other varieties. The quick identification of Iberico pork freshness is helpful to protect the health of consumers.

Aiming at the freshness classification of small samples of Iberico pork, the freshness images of various types of pork accumulated by the Key Laboratory of Disease Control and Prevention of Anhui Agricultural University for many years were used as the data set (AAUSet), and the images were marked according to the grades. The residual network ResNet-50 was used for the identification training on AAUSet, so as to construct the parameter model of the residual network ResNet-50. Then, the trained ResNet-50 model was transferred to the Iberico pork image data set (IPIDS) based on transfer learning and model fine tuning. Consequently, the identification and classification of Iberico pork freshness grades were completed with few image samples of Iberico image samples.

This paper was mainly arranged as follows: Chapter 1 introduced related work, Chapter 2 introduced test data, Chapter 3 introduced test methods, Chapter 4 introduced test results and analysis and finally came the conclusion.

II. TEST DATA

A. Iberico pork sample preparation

The grading of Iberico pork freshness was mainly based on the aerobic plate count, coliform bacteria and pH value. The counting of coliform bacteria was based on the standard GBT 4789.32-2002 for the Rapid Detection of Coliform Bacteria in Food of China. The aerobic plate count of microorganisms was determined according to the standard

GB 47892-2010 for Food Microbiological Examination: Aerobic Plate Count of China. The pH value was method based on standard GB5009.237-2016 for Food pH Determination of China. Therefore, the design of the Iberico pork image samples was followed the idea of shooting and saving the photos of the muscle and fat tissue in the hind leg of Iberico pig which was slaughtered normally without freezing processing as the images of fresh pork samples. The fresh pork samples were divided into 3 portions of A, B, C. Portion A consisted of 14 slices of meat, and every 2 slices were placed into a sealed bag, a total of 7 small portions. Portion B was made up of 12 slices of meat, and every 2 slices were placed into a sealed bag, a total of 6 small portions. Portion C was composed of 10 slices of meat, and every 2 slices were placed into a sealed bag, a total of 5 small portions.

The samples of portions A, B, and C were placed and stored under -20 ℃. After freezing for 1 d at -20 ℃, the samples labeled with A were taken out and stored under 4 ℃ for 1 d, and then the first small portion of samples of A was marked for aerobic plate count, coliform bacteria and pH detection.

Next, the meat samples of portion B were taken out after storing at -20 ℃ for 2 d, and then stored at 4 ℃. And then the second small portion of portion A and the first small portion of portion were taken and marked separately for aerobic plate count, coliform bacteria and pH detection.

Finally, all samples in portion C were taken out after storing at -20 ℃ for 3 d, and then stored at 4 ℃ for 1 d. And then, the third small portion of portion A, the second small portion of portion B and the first small portion of portion C were taken and marked for aerobic plate count, coliform bacteria and pH detection.

Thereafter, one small portion was taken from portions A, B, C respectively every day for the statics of microorganism total amount and pH detection, and it took 7 d for all samples to be tested.

B. Freshness classification standard

According to national regulations, at the dilution extent of 1/10 000, the fresh meat was the pork with aerobic plate count of 2.46-16.2 CFU/mL and coliform bacteria of 3.48-5.97 CFU/mL at the detected pH of 5.6-6.2. The secondary fresh meat was that with aerobic plate count of 16.8-370.43 CFU/mL and coliform bacteria of 9.24-93 CFU at detected pH of 6.2-6.7 under the dilution extent of 1/10 000. The deteriorated meat was the pork with aerobic plate count of 410-3 070 CFU/mL and the coliform bacteria of 240-1100 CFU/mL at detected pH over 6.7 under the dilution extent of 1/10 000.

According to the national standards, the secondary fresh meat was further classified into 3 grades. Secondary fresh meat grade I was the meat with the aerobic plate count of 16.2-28.4 CFU/mL, coliform bacteria of 5.97-9.2 CFU/mL and pH of 6.1-6.3. Secondary fresh meat grade II was the meat with the aerobic plate count of 28.4-142 CFU/mL, coliform bacterial of 9.2-28 CFU/mL and pH of 6.2-6.5. Secondary fresh meat grade III was the meat with the aerobic plate count of 142- 370 CFU/mL, coliform bacteria of 28-93 CFU/mL and pH of 6.4-6.7.

The deteriorated meat was also classified into 3 grades. The deteriorated meat grade I was the pork with the aerobic plate count of 370-1 040 CFU/mL, coliform bacteria of 93-240 CFU/mL and pH of 6.7-6.8. Deteriorated meat grade II was the pork with the aerobic plate count of 1 040-1 420 CFU/mL, coliform bacteria of 240-290 CFU/mL and pH of 6.8-7.0. Deteriorated meat grade III was the pork with the aerobic plate count of 1 420-3 070 CFU/mL,coliform bacterial of 290-1100 CFU/mL and pH value of greater than 7.0.

C. Sample image acquisition and augmentation

Each time before testing the aerobic plate count, coliform bacteria and pH of Iberico pork samples, the images of the detected samples were taken. The images should be taken under single background with proper bright light, and the camera was slightly backlit. The image was 1920*1080. The folders of photos were named according to the date when the images were taken. Single images were named and saved using numbers, and saved in JPG or PNG format. After completing the microorganism counting, the images of pork samples in portions A, B, C were marked separately according to the aerobic plate count, coliform bacteria and pH by referring to the classification standards in Section 2.2, thereby classifying the images into the corresponding 7 grades. Finally, all images of the 7 grades were named according to the grades and saved in the folder of samples. The images of the 7 grades of samples were shown in Fig. 1.

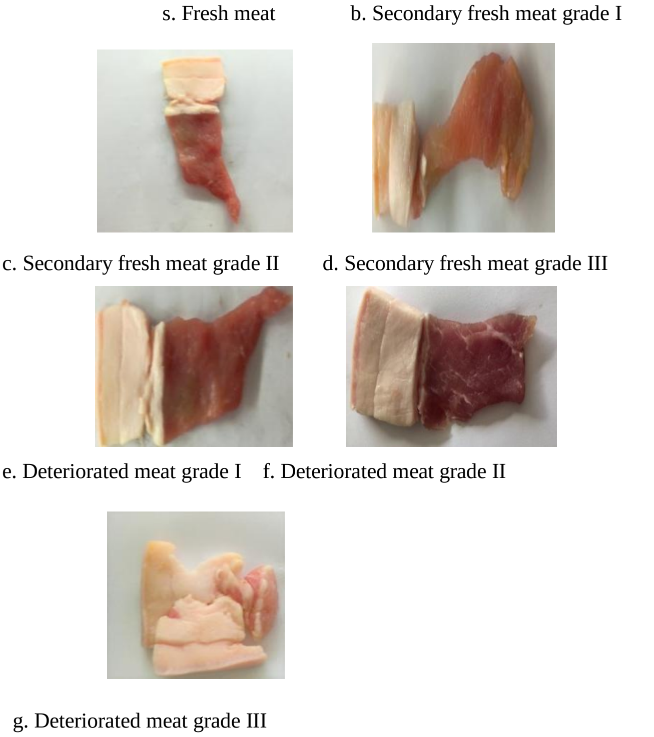


Fig.1 Pork samples

The sample images were taken using a high-definition camera, and the captured sample images were cropped to 224*224. Next, the images of the targets were cut out by using the minimum bounding rectangle of the edge, so as to shrink the images. As shown in Fig. 2, each saved image was about 11 KB. Then, augmentation was conducted to the images marked with fresh, secondary fresh grade I, secondary fresh grade II, secondary fresh grade III, deteriorated grade I, deteriorated grade II and deteriorated grade III through affine transformation, perspective transformation and image rotation.

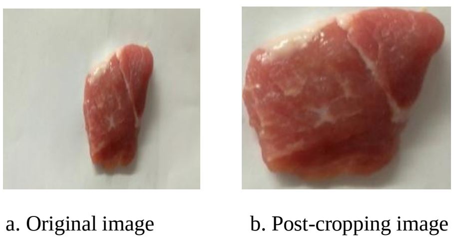


Fig. 2 Sample cropping

III. TEST METHOD

A. Deep residual neural network

Proposed by He et al. in 2015, the Deep Residual Neural Network (ResNet) overcome the gradient dispersion problem in the training process by introducing the residual module [26], so that the neural network can still achieve good training results even there are hundreds of layers, which enhances the feature learning ability and improve the classification performance of the model. The residual module is shown as Fig. 3.

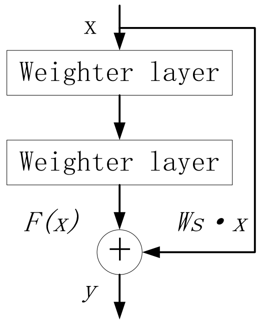


Fig. 3 Residual module

As shown in Fig. 3, inputting x can merge with F(x) through skipping-layer input, where it is the input of the next residual module. The process can be summarized as:

$$y = F(x, \{W_i\}) + W_s \cdot x \qquad (1)$$

Where, *x*, *y* represent the input and output of the unit, respectively; Wi is the weight of the ith layer of the neural network; *F* is a function of *x* and { W_i }, indicating the mapping that the residual unit needs to learn. When the input and output dimensions of the residual connection are the same, W_s becomes 1; when the dimensions are different, it can be converted into the same through matrix W_s. If the residual y-x=0, then y=x is an identity mapping with no additional parameters and computational complexity; if it is not equal to 0 but infinitely close to 0, then the residual network needs to learn the difference between the input and output. The learning objectives get simplified in this way. During the training process, the deep layer error can be propagated to the shallow layer through the shortcut, which reduces the gradient dispersion caused by the excessive number of layers. In this paper, the Resnet-50 deep residual network was used as the feature extractor of the images to learn the abstract features of the images.

B. Transfer learning

In the supervised learning mode, the training of the residual network model is based on big data. There should be enough label images to achieve automatic image classification,. However, the number of Iberico pork freshness images was far from enough to the requirements for deep network models.

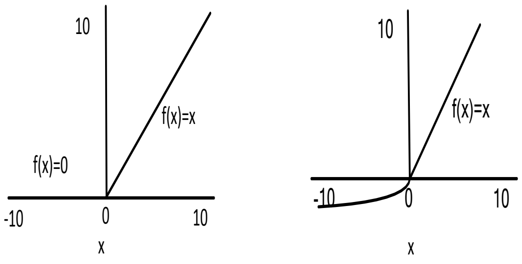
Transfer learning maps the source dataset image and the target dataset image into a high-dimensional subspace, in which the distribution difference between the source dataset image and the target dataset image is reduced, thereby achieving the approximate distribution of the source image data and the target image data. Therefore, in this paper, the transfer learning method based on middle-level expression was adopted, which combined the transfer learning with the deep learning. AAUSet was used for the pre-training of ResNet-50 network, and then the trained network parameters were used as the initial parameters for the network model. Next, the ResNet-50 network was improved, and the images of 7 grades of Iberico pork were used for the fine-tuning of the improved ResNet-50, so as to realize the automatic classification of the freshness images of Iberico pork.

C. Improvement of ResNet-50 model

In order to speed up the classification of Iberico freshness images and improve the generalization ability of ResNet-50 model, the Resenet-50 model was trained with AAUSet, to make it have the ability to extract image features. Then, the Resenet-50 model was improved based on the ideas of model transfer and model fine tuning. First, replace the full connection layers and classification layers of the Resenet-50 model with a 3-layer adaptive network; next, initialize the improved Resenet-50 model weights using the network parameters trained on the AAUSet; finally, use LReLU as the activation function of the adaptive network. The nonlinear mapping function in Resenet-50 was a rectified linear unit (ReLU), and the expression was equation (2), and the schematic diagram was shown in Fig. 4 (a). When the input value $x \le 0$, the output of ReLU was 0, indicating that the unit was in an inactive state, and the corresponding weight needed no update, thereby resulting in waste of neurons. The expression of the leaky-rectified linear hidden unit (LReLU) was expressed by equation (3), where, α=0.01, and the diagram was shown in Fig. 4 (b). When the input value $x<0$, the output value was negative, indicating that the neurons were still active, avoiding the problem of necrosis of the original neurons. The application of LReLU can reduce the number of neurons in the adaptive network or allow dropout to exist in a large proportion without affecting the classification performance of the model.

$$f(x) = \begin{cases} 0 & x < 0 \\ x & x \ge 0 \end{cases} \tag{2}$$

$$f(x) = \begin{cases} x & x < 0 \\ \alpha(e^{x} - 1) & x \ge 0 \end{cases} \tag{3}$$



(a)Relufunction (b) LRelu

Fig. 4 Activating function

The improved Resene-50 model was shown in Fig. 5. As shown in Fig. 5, L1, L2, L3, and L4 were respectively the 4 residual blocks in the ResNet-50 model. There were 1 000 neurons in the B1 layer of the adaptive network; there were 256 in the B2 layer, and Dropout=0.8; there were 7 neurons in B3 layer, and the activation function of each layer of neurons adopted LReLU, which realized the nonlinear mapping of features.

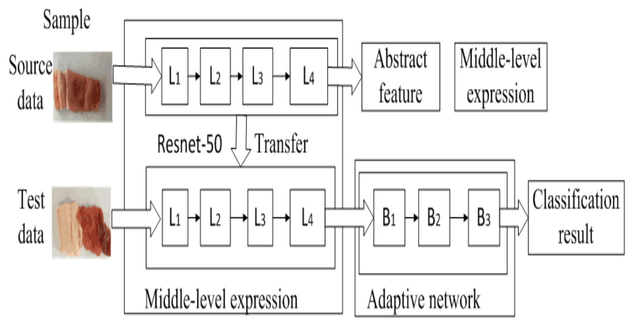


Fig. 5 Migration learning based on middle-level expression

IV. TEST RESULTS AND ANALYSIS

The main configuration of the test software and hardware environment was as follows: CPU was Intel Core i7-6700k, motherboard was ASUS Z170, graphics card was GeForce GTX1080, hard disk was Samsung SSD 950 PRO256GB+ Seagate ST2000 2.0TB, memory was Kingston DDR464GB, operating system was Windows 10 Enterprise Edition, and Caffe system was the Windows 10 version. The training process parameters were shown in Table 1.

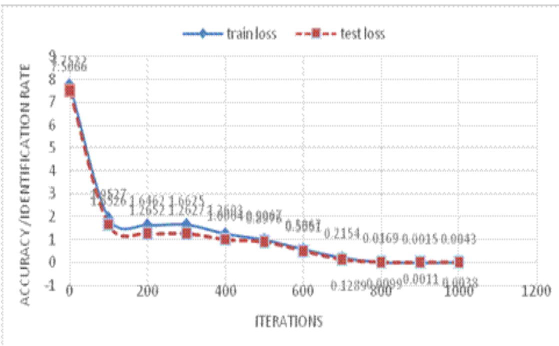
TABLE1 MODEL TRAINING HYPER-PARAMETERS

Parameter name	Parameter value
Momentum	0.9
Epoch	1 200
Optimizer	SGD
Learning rate	$1*10^{-3}$
Attenuation coefficient	$1*10^{-5}$
Batch	20

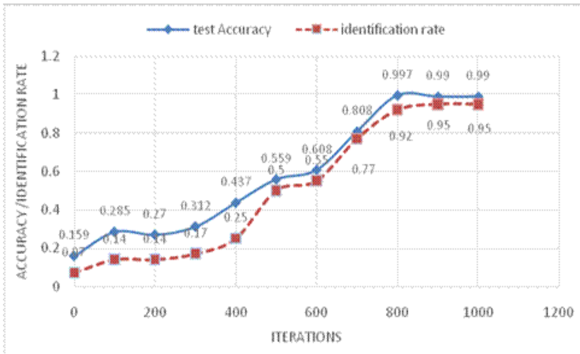
A total of 23 427 freshness images of Iberico pork were used in the test, and the number of initial images and augmented images were as shown in Table 2. The training set and the test set were randomly assigned in the ratio of 4:1, and the training and verification sets were assigned in the ratio of 9:1. The cross entropy cost function was used to supervise the training of the improved Resenet-50 network. The cross entropy was mainly used to measure the difference between the real sample distribution and the predicted sample distribution. In the model loss and the model accuracy curve during the training process were shown in Fig. 6. In the model training loss curve in Fig. 6 (a), the abscissa was the training epochs (the traversal of all samples in the training set once is called epochs), and the ordinate was the model loss. As shown in Fig. 6(a), after about 800 iterations of epochs, the model losses on the training set and the verification set were all stabilized near zero. In the changing curve for classification accuracy in the training process in Fig. 6(b), the abscissa was epochs, and the ordinate was the model classification accuracy. As shown in Fig. 6(b), after about 800 epoches, the classification accuracy of the training set and the test set was stable at 99.7% and 92%, respectively, and the accuracy of the verification set was up to 98.7%. Therefore, the transfer model proposed in this paper showed good performance in meat image classification.

TABLE 2 NUMBER OF INITIAL IMAGES AND AUGMENTED IMAGES

Category	Number of initial images	Number of initial and augmented images	Number of images for verification
Fresh meat sample	1 239	3 679	368
Secondary fresh grade I	2 418	7 254	725
Secondary fresh grade II	670	2 010	201
Secondary fresh grade III	604	1 810	181
Deteriorated grade I	257	771	77
Deteriorated grade II	1 832	5 495	550
Deteriorated grade III	803	2 408	240



a. training loss curve



b. the changing curve for classification accuracy

Fig. 6 Model loss and classification accuracy curve

In this paper, the confusion matrix was used to quantitatively evaluate the degree of confusion between categories. The rows and columns of the matrix represented the real and prediction conditions, respectively. Any element xij in the matrix represented the proportion of the number of pictures of the ith category predicted as the jth category in the total number of images in such category. The diagonal element value indicated the classification accuracy of different Iberico pork freshness, and the other positions were the corresponding error rates. The confusion matrix was shown in Table 3, where, xx is fresh meat, cx1 is secondary meat grade I, cx2 is secondary fresh meat grade II, cx3 is secondary fresh meat grade III, fb1 is deteriorated meat grade I, fb2 is deteriorated meat grade II, and fb3 is deteriorated meat grade III.

As shown in Table 4, the classification effect of fresh pork was the best, and the accuracy rate was up to 99%, while the accuracy rates of secondary fresh grade III and deteriorated grade I were the poorest of 91%. Overall, the average classification accuracy was 94.5%. therefore, the improved deep residual neural network based on transfer learning achieved good classification effects on the data set of Iberico pork freshness.

In addition, comparison was made between the original ResNet-50 model and the transfer learning model proposed in this paper. As shown in Table 5, ResNet-50 (AAUSet) was obtained only by training with AAUSet data set, ResNet-50 (IPIDS) was obtained only by training with IPIDS, while ResNet-50 (transfer) was the fine-tuning model after training with AAUSet, which was then transferred to IPIDS data base. Proposed (ReLU) and Proposed (LReLU) were improved ResNet-50 network models, and the activation functions in their adaptive networks were ReLU and LReLU, respectively. The classification accuracy of the models in the table was obtained in the test set of this paper, and Flop was the floating-point computation of the model.

As shown in Table 5, the classification accuracy was the poorest of Resnet-50 (IPIDS). According to Fig. 6 and Table 4, using only AAUSet data set to train the model could result in serious over-fitting phenomenon. The proposed method in this paper, which pre-trained the model using AAUSet and then transferred to IPIDS data base for fine tuning, was superior than the one using AAUSet or IPIDS for training. In addition, the improvement of the model reduced the computation, shortened the training time of the model, and improved the model classification performance compared with the original model. The effect of using ReLU or LReLU on the efficiency of the model in the adaptive network was not significant, and the classification accuracy of the model was slightly improved.

TABLE 3 CONFUSION MATRIX

class	xx	cx1	Cx2	Cx3	Fb1	Fb2	Fb3
xx	0.99	0．01	0	0	0	0	0
cx1	0	0.98	0	0	0.02	0	0
Cx2	0.07	0	0.92	0.08	0	0	0
Cx3	0	0	0.09	0.91	0	0	0
Fb1	0	0	0	0.04	0.91	0.05	0
Fb2	0	0	0	0	004	0.94	0.02
Fb3	0	0	0	0	0.02	0.01	0.97

TABLE 4 MODEL PERFORMANCE COMPARISON

Model name	FLOPs	Number of layers	Training time //h	Classification time//h	Classification accuracy//%
Resnet-50 (AAUSet)	3.8×10^9	50	43	0.0574	85.77
Resnet-50 (IPIDS)	3.8×10^9	50	23．6	0.051	68.93
Resnet-50 (Transfer)	3.8×10^9	50	41.85	0.051	94.57
Proposed (ReLU)	2.28×10^9	52	41.7	0.048 2	94.78
Proposed (LReLU)	2.28×10^9	52	41.25	0.047 9	95.22

V. CONCLUSION

In this paper, the AAUSet source data is used to create the image data set containing 7 grades of pork freshness. In view of the fact that IPIDS data is insufficient, and it is unable to train deep neural net work, the transfer learning model based on middle-layer expression is designed, which replaces the full connection layers and classification layers with a 3-layer adaptive network. Moreover, the model is conducted with fine tuning by using the image data of the 7 grades of Iberico pork, realizing the accurate classification of the 7 grades of pork freshness. The results show that the proposed method in this paper is suitable for the classification of pork images, and the classification accuracy is 94.5%. therefore, the classification of Iberico pork freshness can be achieved based on residual network and transfer learning, which provides a new idea for the healthy and safe classification of meat.

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