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Vegetable and fruit freshness detection based on deep features and principal component analysis

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ABSTRACT

Vegetable and fruit freshness detecting can ensure that consumers get vegetables and fruits with good taste and rich nutrition, improve the health level of diet, and ensure that the agricultural and food industries provide high-quality products to meet consumer needs and increase sales and market share. At present, the freshness detection of vegetables and fruits mainly relies on manual observation and judgment, which has the problems of subjectivity and low accuracy, and it is difficult to meet the needs of large-scale, high-efficiency, and rapid detection. Although some studies have shown that large-scale detection of vegetable and fruit freshness can be carried out based on artificially extracted features, there is still the problem of poor adaptability of artificially extracted features, which leads to low efficiency of freshness detection. To solve this problem, this paper proposes a novel method for detecting the freshness of vegetables and fruits more objectively, accurately and efficiently using deep features extracted by pre-trained deep learning models of different architectures. First, resized images of vegetables and fruits are fed into a pre-trained deep learning model for deep feature extraction. Then, the deep features are fused and the fused deep features are dimensionally reduced to a representative low-dimensional feature space by principal component analysis. Finally, vegetable and fruit freshness are detected by three machine learning methods. The experimental results show that combining the deep features extracted by the three architecture pre-trained deep learning models GoogLeNet, DenseNet-201 and ResNeXt-101 combined with PCA dimensionality reduction processing has achieved the highest accuracy rate of 96.98% for vegetable and fruit freshness detection. This research concluded that the proposed method is promising to improve the efficiency of freshness detection of vegetables and fruits.

1. Introduction

Vegetables and fruits are an essential part of people's daily diet, providing a variety of vitamins, minerals, cellulose and other nutrients needed by the body (Broekmans, et al., 2000; Hervert-Hernandez et al., 2011; Jones et al., 2010; Liu, 2013; Zhao et al., 2022). Fresh vegetables and fruits are also rich in natural plant compounds, such as flavonoids and carotenoids, which have antioxidant and anti-inflammatory effects and can help reduce the risk of chronic diseases (Lester, 2006; Rickman et al., 2007; Slavin and Lloyd, 2012; Zheng et al., 2017). Keeping vegetables and fruits fresh is essential to reaping the full nutritional value provided (Barrett and Lloyd, 2012; Kader, 2008). However, in the process of picking, storage and transportation, due to the lack of nutritional compensation, water evaporation, quality reduction, metabolic disorders and other phenomena will occur, resulting in changes in appearance, weight, taste, smell, etc., and the freshness will gradually decrease (Wang et al., 2018; You et al., 2022; Zhu et al., 2022). The freshness of vegetables and fruits has become the focus of people's attention when purchasing, so as to avoid purchasing low-quality products that lose their nutritional value (Gunden and Thomas, 2012; L. S. Li et al., 2017; Rahman et al., 2021). In this regard, it is necessary to research and develop technologies and methods that can quickly and accurately detect the freshness of vegetables and fruits, so as to improve product quality and market competitiveness.

At present, the freshness detection of vegetables and fruits mainly relies on human visual judgment, which has problems such as subjective factors, low grading accuracy, and slow speed, which brings difficulties to the export of vegetables and fruits, and also brings hidden dangers to the health of consumers (Arce-Lopera et al., 2013). In order to solve these problems, an automated technology with the characteristics of

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non-destructive, fast, accurate and safe is needed to meet the large-scale detection of freshness of vegetables and fruits (Chen et al., 2023; Gopal et al., 2016; Y. Li et al., 2022; Ying et al., 2015). With the rapid development of the information age, the application of automatic detection technology for vegetable and fruit freshness will continue to be promoted, which will not only protect the interests of consumers, increase the economic value of vegetables and fruits, but also enhance the competitiveness of vegetables and fruits in the international export market (Ren, et al., 2020). Therefore, the development of automatic detection technology for vegetable and fruit freshness will have a profound impact on the agriculture and food industry and become an important development direction in the future.

Existing researches shows that most of the current methods for automatic detection of vegetable and fruit freshness are based on feature engineering, that is, feature extraction is performed on images of vegetables and fruits of different freshness, and then machine learning methods are used to detect the freshness of vegetables and fruits according to the extracted features (Altaheri et al., 2019; Guo et al., 2022; X. Y. Huang et al., 2019; Koyama et al., 2021; Sarkar et al., 2022; Zhang et al., 2019). However, feature engineering methods are usually based on static feature extraction, and the freshness of vegetables and fruits may be affected by many dynamic factors, such as temperature, humidity, and storage time. These factors may be ignored during feature extraction, resulting in the model being insensitive to changes in the freshness of vegetables and fruits (Nturambirwe and Opara, 2020). In practice, designing and selecting appropriate features can be a complex and time-consuming process. Especially when a large number of features or multi-modal data are involved, feature engineering may require more effort to ensure that the extracted features can effectively represent freshness of vegetables and fruits (Makino and Amino, 2020). To overcome these shortcomings, some scholars consider using deep learning techniques to implement freshness detection of vegetables and fruits, so that the model can automatically learn features from the data, thus alleviating the dependence on manual feature engineering (Gao, et al., 2022). Furthermore, deep learning models can also better handle complex data, while being able to adapt to dynamic changes and handle non-linear relationships. However, deep learning methods for freshness detection of vegetables and fruits often require a large amount of labeled data to train an accurate model, which greatly increases the workload of data set collection (Kazi and Panda, 2022). In this regard, few scholars have proposed using pre-trained deep learning models to detect the freshness of vegetables and fruits to reduce reliance on large amounts of labeled data and thereby improve data efficiency.

The novelty of this research are as follows.

- The pre-trained deep learning models is used to extract deep features, which overcomes the problems of large time cost and poor adaptability of manual feature extraction.
- Evaluate the performance of deep features extracted by pre-trained deep learning models of different architectures on vegetable and fruit freshness detection.
- Evaluated the freshness detection performance of vegetables and fruits in different feature space dimensions.

The rest of this paper is structured as follows. Section 2 is the literature survey. Section 3 presents the materials and methods. Section 4 presents the experimental results. Section 5 is the analysis and discussion. Section 6 presents the conclusions.

2. Literature survey

Koyama et al. (Koyama, et al., 2021) extracted the mean, minimum and standard deviation of each component of color in spinach leaves as color features. Local features are extracted using bag-of-words of key points from oriented FAST and rotated BRIE. Feature combinations selected from spinach images are fed into a support vector machine (SVM) to recognize the freshness of spinach samples. Sarkar et al. (Sarkar, et al., 2022) analyzed ten major color variation features of two sets of oyster mushrooms in terms of histograms of each layer, and also analyzed five minor features of each layer, such as mean, standard deviation, entropy, kurtosis, and skewness, and four other grayscale feature, contrast, correlation, energy and homogeneity. They employed a principal component analysis (PCA) threshold classifier to study different features of mushroom images and classified them into fresh and deteriorated classes and achieved a classification accuracy of 93.3%. Mukherjee et al. (2021) used hue and entropy features to identify gradient changes occur to the amla samples. Their model considers both color features and texture features to design a freshness detection scheme, and uses separate models for research, achieving freshness detection with 97.5% accuracy. Their experimental results also showed that hue histograms have higher accuracy than texture features in fruit quality assessment. Sarkar et al., 2022a,b,c) proposed a simple three-category freshness detection algorithm based on supervised learning for freshness prediction of Amla samples. The study used an artificial neural network model to study six major features from the red-green-blue and hue-saturation-vital component colorspaces and ten other minor features. In their study, using the hue histogram of the image, the classification accuracy was higher than 96.5%, and all major features were able to produce more than 83% efficiency in freshness class determination, whereas, minor features could achieve a highest classification accuracy of about 77%. Sarkar et al., 2022a,b,c) used a Canny edge detection scheme to detect the peripheral surface of the sample and analyze these edges to identify unevenness in surface smoothness. Support vector machine (SVM) and artificial neural network were further applied to establish two accurate classifier models, which can detect deteriorated samples with a peak accuracy of more than 95%. Combined machine learning and terahertz sensing for real-time noninvasive assessment of fruit quality by Ren et al. (Ren, et al., 2020). In their method, time-domain, frequency-domain, and time-frequency-domain multi-domain features are extracted and fed into three machine learning classifiers to accurately assess the moisture content of apple and mango slices. Although the above researches have realized the detection of freshness of vegetables and fruits, manual feature extraction has the disadvantages of a lot of attempts and huge time-consuming.

In order to overcome the shortcomings of manual feature extraction, some scholars have applied deep learning to the freshness detection of vegetables and fruits (Fahad, et al., 2022; Mukhiddinov et al., 2022). Fahad et al. (Fahad, et al., 2022) used two deep learning models, VGG16 and YOLO, to identify and classify fruits and vegetables. In research (Mukhiddinov, et al., 2022), the authors proposed a deep learning system for multiclass fruit and vegetable classification based on the improved YOLOv4 model. Their proposed system first identifies the type of object in an image and then classifies it into one of two categories: fresh or rotten. The experimental results show that compared with the previous YOLO series, the proposed method can obtain higher average precision than the original YOLOv4 and YOLOv3. Although the above studies have shown the application potential of deep learning in the field of vegetable and fruit freshness detection, the amount of data required to train the deep learning model is large and time-consuming, which also limits the deep learning of vegetable and fruit freshness detection. application in real-world scenarios. In response to this problem, few scholars use pre-trained deep learning models to detect the freshness of vegetables and fruits (Ni et al., 2020). Abayomi-Alli et al. (Abayomi-Alli, et al., 2023) used five deep learning models (ShuffleNet, SqueezeNet, EfficientNet, ResNet18 and MobileNet-V2) to detect the freshness of fruits on a self-made data set. This study did not directly use the pre-trained deep learning model, but re-trained it on the data set to detect the freshness of the fruit, which inevitably increased the time cost. In addition, this study did not evaluate the impact of the combination of multiple models on the detection of fruit freshness. Therefore, inspired by the few training parameters and short training time of pre-trained deep learning models, this study proposes a novel freshness detection method for vegetables and fruits.

Based on the above analysis, this paper proposes a novel method for detecting the freshness of vegetables and fruits more efficiently using deep features extracted from pre-trained deep learning models of different architectures. In the proposed method, images of fresh and rotten vegetables and fruits are fed into a pre-trained deep learning models to extract deep features of vegetables and fruits, the deep features extracted from pre-trained deep learning models of different architectures are fused to better reflect the freshness of vegetables and fruits, the dimensionality of fusion features is reduced by the PCA, the freshness of vegetables and fruits is detected by three effective machine learning methods, the performance of the proposed method is evaluated by four evaluation metrics.

3. Materials and methods

Fig. 1 shows the general process of the method proposed in this study for the freshness detection of vegetables and fruits. This process mainly includes the image size of fresh and rotten vegetables and fruits are reset to the input dimensions of the pretrained deep learning models, the deep features of vegetables and fruits are extracted by the pre-trained deep learning models, the extracted deep features are fused, the PCA is used to reduce the dimension of the deep features, three machine learning methods are used to detect the freshness of vegetables and fruits, and finally four indicators are used to evaluate the performance of the proposed method.

3.1. The dataset

The dataset used in this study is from research (Mukhiddinov, et al., 2022) and is available at the following URL https://www.kaggle.com/datasets/muhriddinmuxiddinov/fruits-and-vegetables-dataset. This dataset includes images of the five most popular vegetables (tomatoes, cucumbers, carrots, potatoes, and bell peppers) and five fruits (bananas, oranges, mangoes, apples, and strawberries), where each vegetable and fruit is divided into two categories: fresh and rotten, with a total of 20 categories. The dataset contains 12,000 images, approximately 600 images per category (Fruits (5997 images for 10 classes), Vegetables (6003 images for 10 classes)). The dataset gathered from different online sources such as Google Images, Bing Images, Kaggle, Fruit360, and Sriram R.K., which provided samples of the pure-fresh category and a single item with a white background, respectively. Fig. 2 shows samples of vegetables and fruits in the two categories of fresh and rotten in the dataset. More details about the dataset used in this study can be found in the study (Mukhiddinov, et al., 2022).

3.2. Reconstruct image size

The images in the dataset are obtained from different online sources, and the sizes of these images are diverse and cannot meet the input requirements of the pre-trained model. Therefore, before inputting the images of vegetables and fruits in the dataset into the pre-trained model to extract deep features, their sizes need to be reconstructed to meet the input size requirements of the pre-trained model. For example, the input size of GoogLeNet is a picture of 224 × 224 pixels, so this study will read all the pictures of vegetables and fruits in the dataset and reconstruct their size to 224 × 224 pixels in order to use the GoogLeNet pre-trained model to extract the depth features of the pictures of vegetables and fruits. For other pre-trained deep learning models in this study, the same method was used to reconstruct the size of the images of vegetables and fruits in the dataset.

3.3. Pre-trained deep learning models

According to the performance of features extracted by six pre-trained deep learning models, VGG19, VGG16, Alexnet, GoogLeNet, DenseNet-201 and ResNet-101, on the freshness detection of vegetables and fruits, this research selected three pre-trained deep learning methods: GoogLeNet, DenseNet-201 and ResNet-101 to automatically extract the freshness features of vegetables and fruits (G. Huang et al., 2017; Xie et al., 2017; Szegedy et al., 2015). These three pre-trained deep learning models are briefly introduced as follows.

3.3.1. GoogLeNet

GoogLeNet was proposed by the Google team in 2014 and won the Classification Task champion in the ImageNet competition that year. While focusing on deepening the network structure, GoogLeNet introduces a new basic structure (Inception module) to increase the width of the network (Szegedy, et al., 2015). The introduced Inception combines feature information of different scales to obtain better feature representation. GoogLeNet has a total of 22 layers and no fully connected layer. The GoogLeNet input layer accepts images of 224 × 224 pixels. This study extracts the features of the fully connected layer named " loss3-classifier " in the GoogLeNet pre-trained deep learning model, with a dimension of 1 × 1000.

3.3.2. ResNeXt-101

ResNeXt is a simple, highly modular network structure for image classification. The main reason why ResNeXt was proposed is that the traditional way to improve the accuracy of the model is to deepen or widen the network, but as the number of hyperparameters increases, the difficulty of network design and computational overhead will also increase. Based on this, the ResNeXt structure, which can improve the accuracy without increasing the complexity of the parameters and reduce the number of hyperparameters, is proposed (Xie, et al., 2017). The ResNeXt network adopts the idea of VGG stacking and the idea of split-transform-merge of Inception at the same time, and the scalability is relatively strong. The idea of split-transform-merge is to first assign the input to multiple channels, then transform each channel, and finally

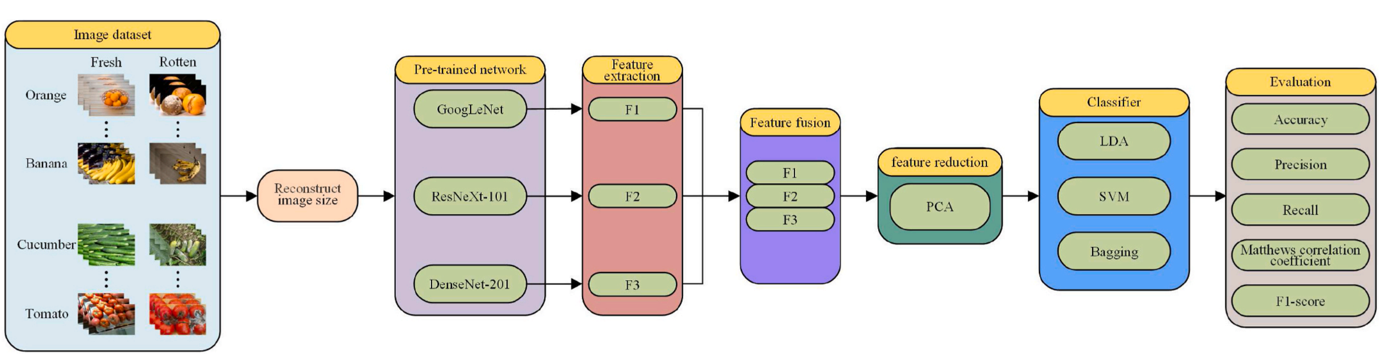

Fig. 1. The schematic diagram of the proposed method in this research.

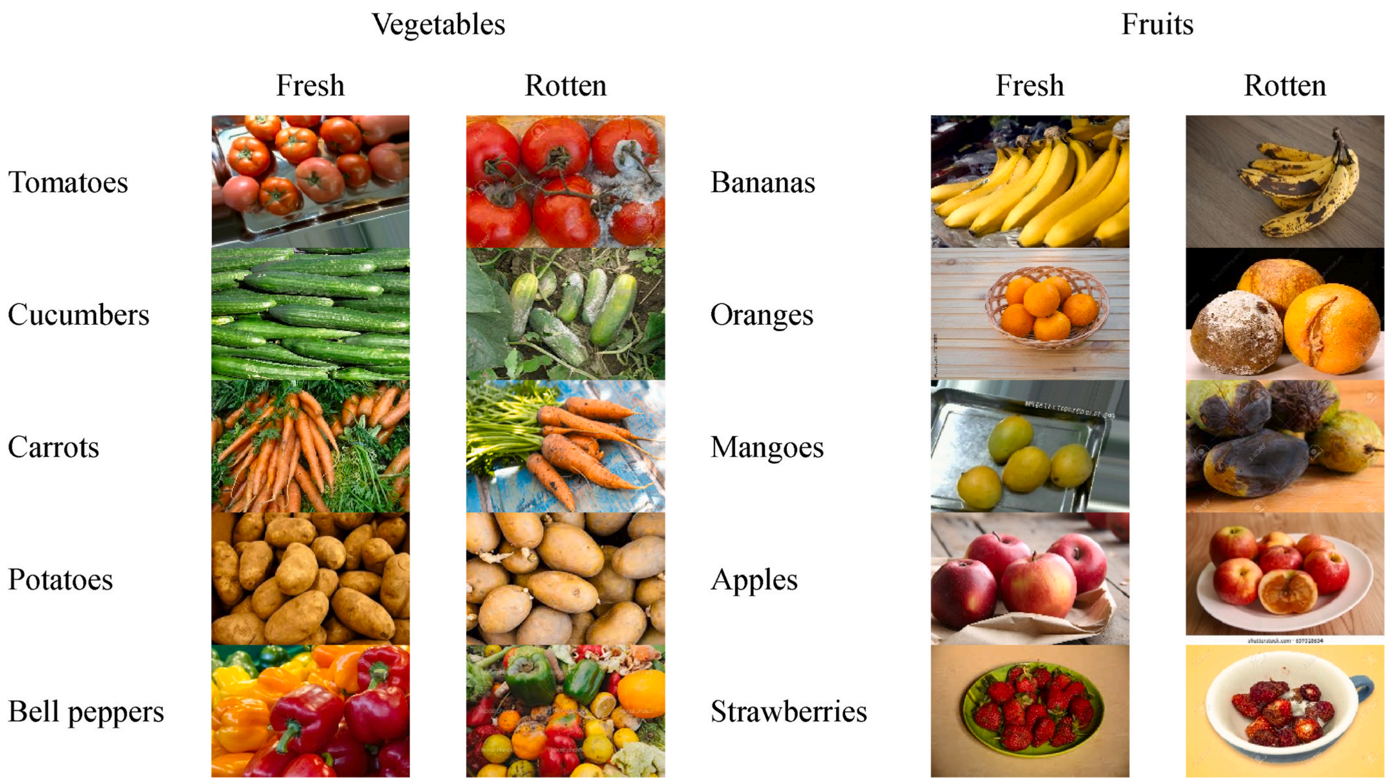

Fig. 2. Samples of vegetables and fruits in the dataset.

fuse the results of all branches. ResNeXt-101 is a variant of ResNeXt based on the number of layers, and its input layer can accept pictures of 224 × 224 pixels. This study extracts the features of the fully connected layer named “fc1000” in the ResNeXt-101 pre-trained deep learning model, with a dimension of 1 × 1000.

3.3.3. DenseNet-201

DenseNet is a densely connected network, that is, all layers are connected to each other, specifically, each layer accepts all previous layers as its additional input (G. Huang et al., 2017). Another major feature of DenseNet is to achieve feature reuse through the connection of features on the channel. These features make DenseNet’s parameter volume and computational cost less and better. DenseNet starts with features, and through the extreme use of features, it can achieve better results and reduce parameters. DenseNet-201 is a variant of DenseNet based on the number of layers, and its input layer can accept pictures of 224 × 224 pixels. This study extracts the features of the fully connected layer named “fc1000” in the DenseNet-201 pre-trained deep learning model, with a dimension of 1 × 1000.

3.4. Feature reduction

Feature reduction refers to combining the original feature space into a new feature space through feature vector conversion to achieve feature dimensionality reduction (Fadilah et al., 2012). While changing the original feature space, the new feature space retains the information in the original feature as much as possible. PCA is an effective dimensionality reduction algorithm and has been applied in the field of agricultural product quality inspection (Fadilah, et al., 2012; Mu et al., 2022). Based on this, this study applies PCA to reduce the feature dimensionality of features automatically extracted from vegetables and fruits. The basic idea of the PCA algorithm is to convert the original correlated vectors into a set of uncorrelated new vectors, namely principal components, through orthogonal transformation (Abdi and Williams, 2010). Select a few new vectors that can reflect the characteristics of the original data to the greatest extent to replace the original data, and then achieve the purpose of feature dimensionality reduction. The steps of the PCA algorithm are as follows:

Construct sample matrix X. The X is a matrix of $N \times P$, the jth feature of the ith sample in sample matrix X is represented as x_{ij}, $i = 1, 2, \cdots, N$, $j = 1, 2, \cdots, P$, N is the number of samples, and P is the number of features.

The sample matrix X is normalized

$$Z_{ij} = \frac{x_{ij} - \overline{x_j}}{s_j} \tag{1}$$

$$S_j = \frac{1}{N-1} \sum_{i=1}^{N} \left(x_{ij} - \overline{x_j}\right) \tag{2}$$

Where, S_j represents the standard deviation, and $\overline{x_j}$ represents the mean.

Calculate the covariance matrix R, let $|R - \lambda E| = 0$ solve the eigenvalue λ_1, λ_2, $\cdots$, $\lambda_P(\lambda_1 \geq \lambda_2 \geq \cdots, \geq \lambda_P)$, and eigenvector $a_k = (\beta_{1k}, \beta_{2k}, \cdots, \beta_{Pk})$, $k = 1, 2, \cdots, P$. Then the expression of the kth principal component is

$$F_k = \left[\sum\nolimits_{i=1}^{P} \beta_{ik}\left(x_{1i} - \overline{x_j}\right), \sum\nolimits_{i=1}^{P} \beta_{ik}\left(x_{2i} - \overline{x_j}\right), \cdots, \sum\nolimits_{i=1}^{P} \beta_{ik}\left(x_{Ni} - \overline{x_j}\right)\right]^T \tag{3}$$

3.5. Classifier

In this study, three popular machine learning techniques namely linear discriminant analysis (LDA), SVM and bagging are used for freshness detection of vegetables and fruits. The details of these three types of machine learning are as follows:

The main idea of the LDA classifier is that the intra-class variance is the smallest and the inter-class variance is the largest after projection, that is, the high-dimensional data samples are projected to the low-dimensional classification space, and the standard is to separate the data of different categories as much as possible, and the projection points of the same category of data are as close as possible (Coomans et al., 1979; El Orche, Bouatia and Mbarki, 2020; Jia et al., 2019). The LDA basic model can achieve better results in linearly separable scenes, but it is not suitable for linearly inseparable situations. It is necessary to introduce the kernel function technique to the LDA classifier for non-linear extension. Therefore, in order to effectively detect the freshness of vegetables and fruits, the LDA classifier in this study introduces a quadratic polynomial kernel function for nonlinear expansion.

The process of SVM classifier to classify data can be understood as solving the hyperplane with the largest interval, and the interval space between the hyperplane and the closest points on both sides is the largest (Di Rosa, Leone, Cheli and Chiofalo, 2017; Pardo and Sberveglieri, 2005; Sliwinska et al., 2014). Although the SVM classifier is efficient and practical in many scenarios, in practical applications, many data sets are not linearly separable. At this time, a new concept needs to be introduced: the kernel function, which can map the samples from the original space to a higher-dimensional feature space, so that the samples are linearly separable in the new space. In the SVM classifier, the choice of kernel function is the variable that affects the SVM classifier the most. The most commonly used kernel functions are linear kernel, polynomial kernel, Gaussian kernel, etc. In this study, the cubic polynomial is selected as the kernel function of the SVM classifier.

The bagging classifier is a parallel algorithm, and its core idea is: on the original data set, through the sampling method with replacement, reselect T new data sets to train T classifiers respectively (Qiao, et al., 2022; Tripoliti et al., 2013; Voss et al., 2019). The bagging classifier samples each time to train the model, which has strong generalization ability and is effective in reducing the variance of the model. For the vegetable and fruit freshness detection problem in this study, the decision tree is selected as the weak learner of the Bagging classifier, and the output method uses the voting method, that is, the category or one of the categories that get the most votes is the final model output.

3.6. Performance evaluation

In this study, accuracy (Acc), precision (Pre), recall (Rec), matthews correlation coefficient (MCC) and F1-score (F1) were used to evaluate the performance of the proposed method for vegetable and fruit freshness detection (Duong et al., 2020). The values of these four detection indicators are calculated based on the ten-fold cross-validation of the proposed method (Rehman, et al., 2022).

$$\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$\text{Pre} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Rec} = \frac{TP}{TP + FN} \tag{6}$$

$$\text{MCC} = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}} \tag{7}$$

$$\text{F1} = \frac{2 * \text{Pre} * \text{Rec}}{\text{Pre} + \text{Rec}} \tag{8}$$

Where, *TP*, *FP*, *TN* and *FN* correspond to true positive, false positive, true negative, and false negative, respectively.

4. Result

In this study, three pre-trained deep learning models (GoogLeNet, DenseNet-201 and ResNeXt-101) were used to extract deep features of vegetable and fruit freshness. For the GoogLeNet deep learning model, the 1000-dimensional deep features of the loss3_classifier layer are extracted. For the DenseNet-201 deep learning model, the 1000-dimensional deep features of the fc1000 layer are extracted. For the ResNeXt-101 deep learning model, the 1000-dimensional deep features of the fc1000 layer are extracted. Since the deep features extracted by different pre-trained deep learning models have different abilities to reflect the freshness of vegetables and fruits, this study analyzed the performance of the freshness detection of vegetables and fruits in the following seven cases.

Case A. Deep features are extracted by GoogLeNet deep learning model.

Case B. Deep features are extracted by DenseNet-201 deep learning model.

Case C. Deep features are extracted by ResNeXt-101 deep learning model.

Case D. Combination of deep features extracted by GoogLeNet and DenseNet-201 deep learning model.

Case E. Combination of deep features extracted by GoogLeNet and ResNeXt-101 deep learning model.

Case F. Combination of deep features extracted by DenseNet-201 and ResNeXt-101 deep learning model.

Case G. Combination of deep features extracted by GoogLeNet, DenseNet-201 and ResNeXt-101 deep learning model.

4.1. Analysis of feature dimension for vegetable and fruit freshness detection

The high-dimensional deep features extracted by the pre-trained deep learning model contain redundant components, so this study applied PCA to reduce the high-dimensional deep feature space to a low-dimensional feature space that can effectively represent the freshness of vegetables and fruits. In order to ensure better accuracy of vegetable and fruit freshness detection while selecting a lower-dimensional feature space as much as possible, the accuracy of different dimensional low-dimensional feature spaces for vegetable and fruit freshness detection was evaluated in this study. Fig. 3 shows the accuracy of the freshness detection of vegetables and fruits in different dimensional feature spaces in seven cases. Since the information contained in the lower-dimensional feature space is not enough to detect the freshness of vegetables and fruits, the minimum dimension of the low-dimensional feature space in this study is set to 5. It can be seen from Fig. 3 , in the seven cases, when the feature space dimension is less than 10, the accuracy of the three classifiers for detecting the freshness of vegetables and fruits is low, but at this time, with the increase of the feature space dimension, the accuracy of the three classifiers for detecting the freshness of vegetables and fruits increases rapidly. When the feature space dimension increases to around 30, with the increase of the feature space dimension, the accuracy rate of the three classifiers for vegetable and fruit freshness detection increases slowly. When the dimension of the feature space increases to around 50, the accuracy of the three classifiers for vegetable and fruit freshness detection hardly changes with the increase of the dimension of the feature space. Maybe the dimension of feature space higher than 60 will achieve higher accuracy of vegetable and fruit freshness detection, but considering the calculation cost and the accuracy of vegetable and fruit freshness detection, this study reduced the high-dimensional deep feature space of seven cases to a 50-dimensional low-dimensional feature space.

4.2. Analysis of Case A ~ Case G for vegetable and fruit freshness detection

Fig. 4 shows the accuracy of vegetable and fruit freshness detection achieved by three classifiers when the feature dimension is 50 in seven cases. As shown in Fig. 4, according to the number of deep learning

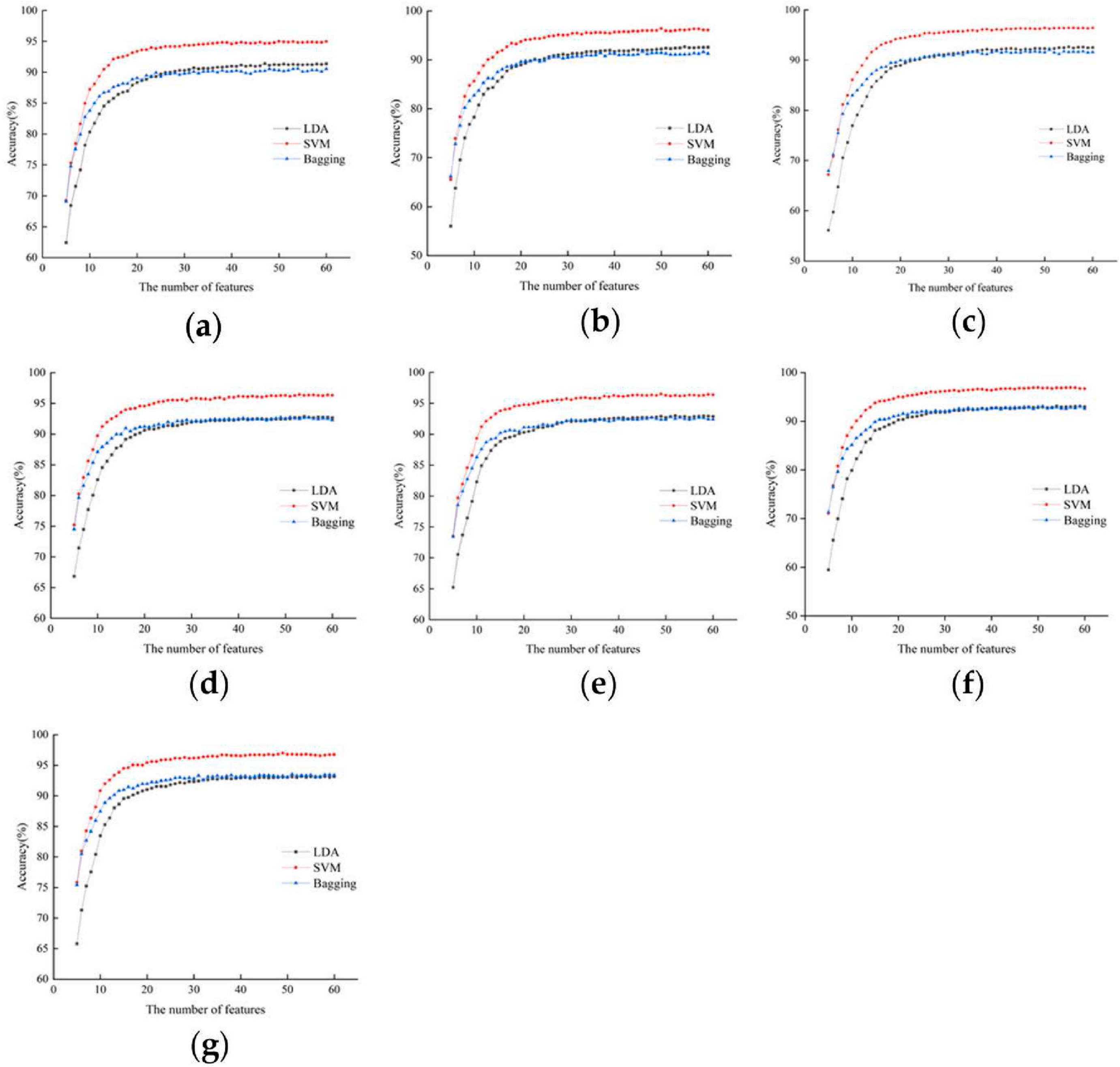

Fig. 3. The accuracy of the freshness detection of vegetables and fruits in different dimensional feature spaces in seven cases. (a)~(g) are Case A ~ Case G in turn t.

models used to extract deep features, Case G (feature set extracted by three pre-trained deep learning models) achieves the highest detection accuracy, Case D , Case E and Case F (feature set extracted by two pre-trained deep learning models) has the second highest detection accuracy, and Case C (feature set extracted by one pre-trained deep learning models) has the lowest detection accuracy. For all seven cases, the SVM classifier achieves the highest freshness detection accuracy. For Case G, the Bagging classifier achieves the second highest freshness detection accuracy, and the LDA classifier has the lowest freshness detection accuracy. For the other six cases, the accuracy of the freshness detection of the LDA classifier is placed in the second position, and the accuracy of the freshness detection of the Bagging classifier is the lowest. The comprehensive comparison results show that Case G has the highest accuracy of vegetable and fruit freshness detection, and Case A has the lowest accuracy of vegetable and fruit freshness detection For Case G, LDA classifier, SVM classifier and Bagging classifier achieved 93.19%, 96.98% and 93.54% freshness detection accuracy for vegetables and fruits, respectively. For Case A, LDA classifier, SVM classifier and Bagging classifier have 91.40%, 94.99% and 90.58% detection accuracy of freshness of vegetables and fruits respectively.

4.3. Analysis of vegetable and fruit freshness detection performance

In this study, accuracy, precision, recall, matthews correlation coefficient and F1-score were used to further evaluate the performance of the proposed method for vegetable and fruit freshness detection. Table 1 shows the performance of the SVM classifier for detecting the freshness of vegetables and fruits for Case G. As shown in Table 1, the proposed method achieves a higher detection accuracy, recall, matthews correlation coefficient and F1-score of 99.95%, 99.36%, 99.49% and 1.00 for

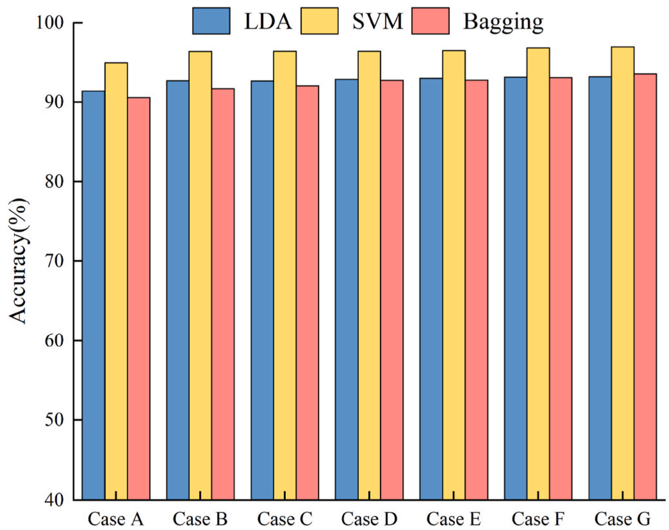

Fig. 4. Accuracy of freshness detection of vegetables and fruits under seven cases.

Table 1
Freshness detection performance of Case G.

	Acc	Pre	Rec	MCC	F1
Fresh Apple	99.82%	98.68%	97.71%	98.10%	0.98
Fresh Banana	99.95%	99.68%	99.36%	99.49%	1.00
Fresh Mango	99.88%	98.68%	99.01%	98.78%	0.99
Fresh Orange	99.83%	98.68%	98.03%	98.27%	0.98
Fresh Strawberry	99.95%	100.00%	99.00%	99.48%	1.00
Rotten Apple	99.43%	93.19%	95.41%	93.99%	0.94
Rotten Banana	99.92%	99.65%	98.78%	99.18%	0.99
Rotten Mango	99.73%	97.95%	96.63%	97.15%	0.97
Rotten Orange	99.74%	97.62%	97.12%	97.24%	0.97
Rotten Strawberry	99.90%	99.16%	98.83%	98.94%	0.99
Fresh Bell pepper	99.74%	97.54%	97.38%	97.33%	0.97
Fresh Carrot	99.58%	96.41%	95.48%	95.72%	0.96
Fresh Cucumber	99.82%	97.88%	98.52%	98.10%	0.98
Fresh Potato	99.52%	95.57%	95.11%	95.09%	0.95
Fresh Tomato	99.82%	97.86%	98.67%	98.17%	0.98
Rotten Bell pepper	99.10%	89.01%	93.23%	90.63%	0.91
Rotten Carrot	99.39%	93.63%	93.79%	93.39%	0.94
Rotten Cucumber	99.63%	97.57%	94.94%	96.06%	0.96
Rotten Potato	99.14%	90.44%	92.14%	90.83%	0.91
Rotten Tomato	99.66%	99.66%	96.31%	96.37%	0.98

fresh banana, and a higher detection accuracy, precision, matthews correlation coefficient and F1-score of 99.95% , 100.00%, 99.48% and 1.00 for fresh strawberries. In contrast, the proposed method has low detection accuracy, precision, matthews correlation coefficient and F1-score for rotten bell pepper, which are 99.10%, 89.01%, 90.63% and 0.91, respectively, and low detection recall, matthews correlation coefficient and F1-score for rotten potato, which are 92.14%, 90.83% and 0.91, respectively. In terms of freshness detection performance for all categories of vegetables and fruits, only rotten bell peppers were detected with less than 90% accuracy. The comprehensive comparison results show that the proposed method has advantages in the detection of fresh banana and fresh strawberries, the worst performance in the detection of rotten bell pepper, and the second worst in the detection of rotten potato.

5. Discussion

This study proposes a novel method for the detection of freshness of vegetables and fruits. The proposed method uses the pre-trained deep learning model to extract deep features, effectively avoiding the poor adaptability and time-consuming problems caused by manual feature extraction. Since the high-dimensional deep features extracted by the pre-trained deep learning model contain a large number of redundant components, this study uses PCA to reduce the high-dimensional deep features to a low-dimensional feature space that can effectively represent the freshness of vegetables and fruits. In addition, in order to fully extract the features of the freshness of vegetables and fruits, this study further evaluates the ability of the features extracted by different pre-trained deep learning models in the detection of freshness of vegetables and fruits.

As shown in Fig. 5, in order to further evaluate the impact of the use of PCA dimensionality reduction on the freshness detection of vegetables and fruits, the accuracy of the freshness detection of vegetables and fruits in the feature space with a dimension of 50 and all feature spaces was calculated based on case G. It can be seen from Fig. 5 that the use of PCA feature dimensionality reduction improves the accuracy of the LDA classifier and Bagging classifier in detecting the freshness of vegetables and fruits. This can be explained by the fact that the feature space with a dimension of 50 not only effectively removes redundant information in all feature spaces, but also retains important features for freshness detection of vegetables and fruits. It is worth noting that compared with the entire feature space, the use of PCA feature dimensionality reduction slightly reduces the accuracy of the SVM classifier for vegetable and fruit freshness detection. This may be because the use of PCA feature dimensionality reduction causes the feature space with a dimension of 50 to lose a tiny part of the information that represents the freshness of vegetables and fruits. Therefore, PCA dimensionality reduction can ensure a high accuracy of freshness detection of vegetables and fruits while greatly reducing the feature dimension.

As shown in Fig. 3, for all cases, the accuracy of vegetable and fruit freshness detection is low at low feature dimensions, which is caused by the loss of most of the information representing the freshness of vegetables and fruits while PCA removes redundant components. As the dimension of the feature space increases, the information contained in the feature space that characterizes the freshness of vegetables and fruits also increases, thereby improving the accuracy of freshness detection of vegetables and fruits. When the feature space is increased to 50 dimensions, the accuracy of vegetable and fruit freshness detection has not been improved by continuing to increase the dimension of the feature space, which can be explained by the limited information carried by the added features that can characterize the freshness of vegetables and fruits.

In order to further verify that the 50-dimensional low-dimensional feature space can effectively represent the freshness of vegetables and

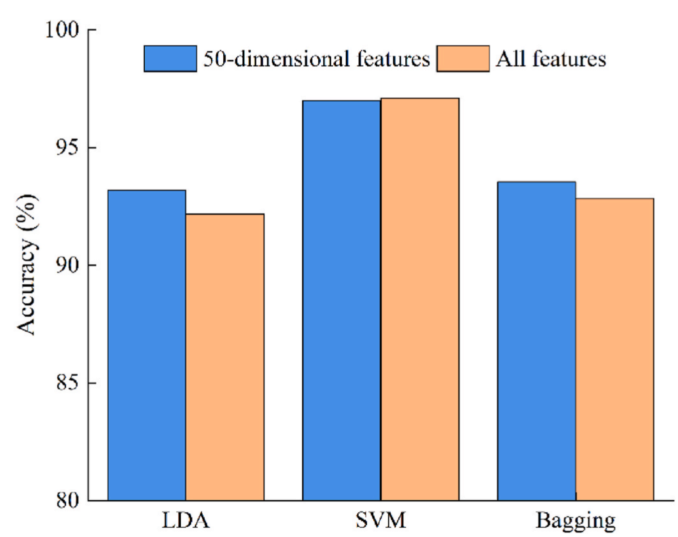

Fig. 5. The impact of PCA dimensionality reduction on the accuracy of freshness detection of vegetables and fruits.

fruits, this study conducted a statistical analysis on the feature of the 50-dimensional low-dimensional feature space. Since the features of the 50-dimensional low-dimensional feature space do not satisfy the normal distribution, this study selected the Kruskal-Wallis test for statistical analysis. The p value is less than 0.05, indicating that the features are statistically different. The results of statistical analysis of the features of the 50-dimensional low-dimensional feature space show that the p-values of all features are less than 0.05, indicating that there are statistical differences in the 50-dimensional low-dimensional feature space, which further confirms that t the 50-dimensional low-dimensional feature space has a significant ability to detect the freshness of vegetables and fruits. In addition, the feature correlation matrix of the 50-dimensional low-dimensional feature space was calculated and a heat map was drawn based on the values of the feature correlation matrix. As shown in Fig. 6, when the correlation coefficient between two different features is close to 0, it means that there is almost no linear relationship between them. This may indicate that these features are independent for describing the freshness of vegetables and fruits. Therefore, the heat map of the feature correlation matrix once again verified that the features of the 50-dimensional low-dimensional feature space provide different information and have advantages in the model detection of the freshness of vegetables and fruits. As we expected, the 50-dimensional low-dimensional feature space not only retains most of the information for vegetable and fruit freshness detection but also reduces the dimensionality of the feature space.

In this study, the accuracy of freshness detection of vegetables and fruits was evaluated for seven cases. It can be observed that in all cases, Case G has the highest detection accuracy of freshness of vegetables and fruits. This can be explained by the fact that the feature set in Case G is composed of deep features extracted by three pre-trained deep learning models, compared with the feature set extracted by one pre-trained deep learning model or two deep learning pre-trained models, the feature sets extracted by the three pre-trained deep learning models contain richer freshness information of vegetables and fruits. As shown in Fig. 4, the accuracy of vegetable and fruit freshness detection for Case A is the lowest. This may be due to the inconsistent feature distribution between the data set in the pre-training stage of the GoogLeNet deep learning model and the freshness detection task of vegetables and fruits, resulting in poor performance on the freshness detection task of vegetables and fruits. It can also be seen from Fig. 4 that as the number of pre-trained deep learning models for extracting deep features increases, the accuracy of vegetable and fruit freshness detection also improves. As we expected, the increase in the number of pre-trained deep learning models for extracting deep features helps to extract features that characterize the freshness of vegetables and fruits.

As can be seen from Table 1, the model proposed in this study has the best detection performance for fresh bananas. This may be due to the smaller differences in shape and color of fresh bananas in the data set, making it easier to extract important features that characterize fresh bananas. In addition, the model proposed in this study also has advantages in the detection of fresh strawberries, which can be explained by the model's better ability to capture the differences in texture of fresh strawberries compared to other vegetables and fruits in the dataset. However, this method performed poorly in the detection of rotten bell peppers and rotten potatoes. This may be due to the fact that the color and type of rotten peppers are more variable in the dataset and the model cannot easily capture the important information that characterizes rotten peppers, the color of rotten potatoes confuses the color characteristics of the potato itself and the color characteristics of the rotten parts, thus reducing the detection performance of the model rotten bell peppers and rotten potatoes.

This study also analyzes the generalization ability of the model to further highlight the advantages of the model proposed in this study in the detection of freshness of vegetables and fruits. In this study, 100 images (20 categories, 2000 images in total) were randomly selected from the images contained in each fresh and rotten vegetables and fruits for processing to simulate the impact of different lighting and background conditions on image acquisition. These images are processed by adding different lighting and background effects to the original image. Specifically, values are randomly selected within the interval of plus or minus 0.6, and combined with the original image to obtain images of vegetables and fruits with different lighting and background effects to simulate the effects of other conditions such as light and darkness. This study trained the proposed model on the remaining datasets, and then tested the trained model on a test set composed of images based on different lighting and background conditions, achieving a vegetable and fruit freshness detection accuracy of 95.36%. The experimental results show that the model proposed in this study has strong generalization ability, further highlighting the advantages of the model proposed in this study in detecting the freshness of vegetables and fruits.

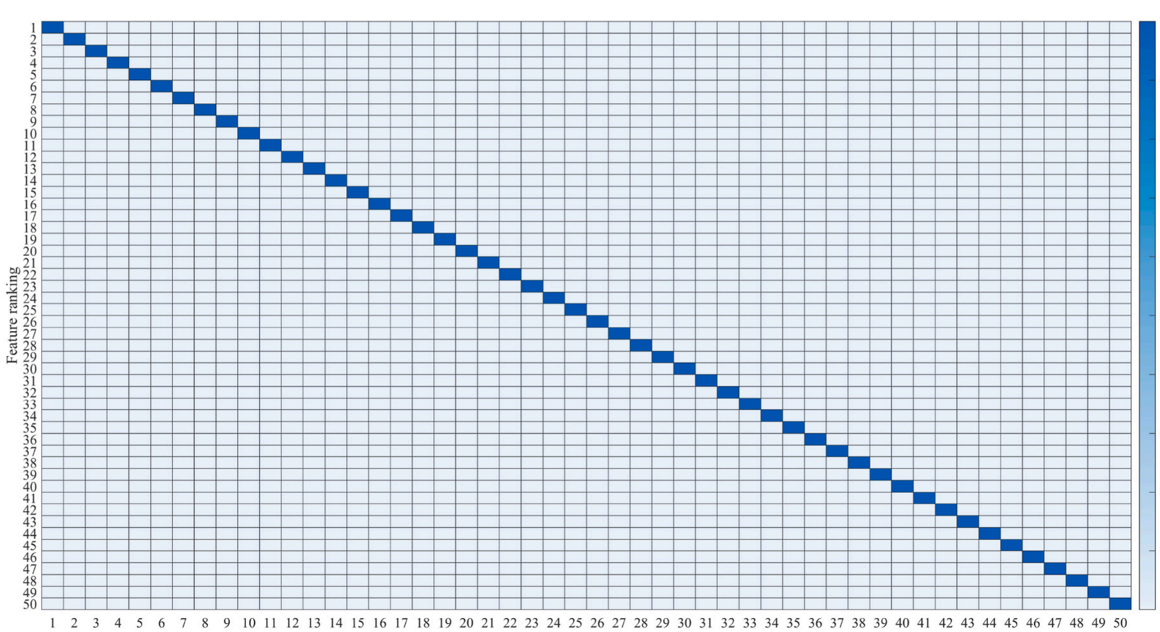

Fig. 6. Heat map of the feature correlation matrix of the 50-dimensional low-dimensional feature space.

The application of the method of this research to existing agriculture will have a significant impact on the vegetable and fruit production and processing industries. These industries mainly use fresh vegetables and fruits as raw materials for preparing various food products. In the agricultural production process, cameras installed near the production line can be used to detect the freshness of vegetables and fruits, and then perform corresponding processing based on the detection results. A camera system can be used in farm fields or agricultural production lines, where the camera provides image input every time a batch of vegetables or fruits passes through the production line. Using a model like the one proposed in this study, it is possible to automatically determine the freshness of vegetables and fruits through input image data from cameras, and improve the efficiency of agricultural production lines. For the fruit and vegetable retail industry, manual separation of vegetables and fruits according to their freshness is an important and time-consuming step. Based on a model like the one proposed in this study, automatic sorting and grading of vegetables and fruits can be achieved, thereby reducing the time and labor costs required in the entire process, which helps ensure the consistency and freshness of the final product. The application of this technology can not only optimize the efficiency of agricultural production lines, but also improve the quality of vegetable and fruit products, bringing significant benefits to the agricultural and retail industries. Considering that the agricultural production industry and the fruit and vegetable retail industry usually have a certain equipment base, they can support the deployment of camera systems. The cameras can be easily integrated into existing production lines equipment, ensuring real-time data collection and processing. In addition, cloud computing and edge computing technologies can ensure real-time processing of data and provide reliable storage solutions. As society's focus on food quality and traceability increases, the agricultural and retail industries will be significantly more receptive to new technologies. This automated vegetable and fruit freshness detection technology is expected to attract attention within the agricultural and retail industries and be recognized by manufacturers and retailers. Taking these factors into consideration, large-scale deployment of vegetable and fruit freshness detection technology is feasible in the agricultural and retail industries and will bring significant benefits to improve product quality, reduce costs, and reduce waste.

6. Conclusion

This paper proposes a novel method for more efficient vegetable and fruit freshness detection tasks using deep features extracted from pre-trained deep learning models of different architectures. In the proposed method, the image sizes of fresh and rotten vegetables and fruits are reset, the deep features representing the freshness of vegetables and fruits are extracted by deep learning models with different architectures, the deep features are fused, the high-dimensional deep feature space is reduced to a low-dimensional feature space by PCA, and the freshness of vegetables and fruits is detected by machine learning methods. The experimental results show that the combination of deep features extracted from three pre-trained deep learning models GoogLeNet, DenseNet-201 and ResNeXt-101 combined with PCA dimensionality reduction processing achieves the highest accuracy rate of 96.98% for vegetable and fruit freshness detection. The results show that the method proposed in this study is suitable for the freshness detection of vegetables and fruits. Although the performance of the proposed method is promising, further research is needed to hopefully be used as a front-line tool in the future. Although the performance of the proposed method is promising, further research is needed to hopefully be used as a front-line tool in the future.

CRediT authorship contribution statement

Yue Yuan: Methodology, Validation, Formal analysis, Investigation, Writing – original draft. **Xianlong Chen:** Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no conflict of interest in this work.

Data availability

Data will be made available on request.

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