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A novel method for vegetable and fruit classification based on using diffusion maps and machine learning

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ABSTRACT

Vegetable and fruit classification can help all links of agricultural product circulation to better carry out inventory management, logistics planning and supply chain coordination, and improve the efficiency and response speed of the supply chain. However, the current classification of vegetables and fruits mainly relies on manual classification, which inevitably introduces the influence of human subjective factors, resulting in errors and misjudgments in the classification of vegetables and fruits. In response to this serious problem, this research proposes an efficient and reproducible novel model to classify multiple vegetables and fruits using handcrafted features. In the proposed model, preprocessing operations such as Gaussian filtering, grayscale and binarization are performed on the pictures of vegetables and fruits to improve the quality of the pictures; statistical texture features representing vegetable and fruit categories, wavelet transform features and shape features are extracted from the preprocessed images; the feature dimension reduction method of diffusion maps is used to reduce the redundant information of the combined features composed of statistical texture features, wavelet transform features and shape features; five effective machine learning methods were used to classify the types of vegetables and fruits. In this research, the proposed method was rigorously verified experimentally and the results show that the SVM classifier achieves 96.25% classification accuracy of vegetables and fruits, which proves that the proposed method is helpful to improve the quality and management level of vegetables and fruits, and provide strong support for agricultural production and supply chain.

1. Introduction

Vegetables and fruits are important crops in agriculture (Wang et al., 2022). For planting, picking, packaging and sales, it is necessary to accurately classify and sort different types of vegetables and fruits (Bhargava and Bansal, 2021). By sorting vegetables and fruits, farmers can better manage and organize their crops, optimize resource use, and increase production efficiency and yields. At the same time, the classification of vegetables and fruits also helps farmers to carry out different treatments and nutritional management of different varieties of vegetables and fruits, so as to improve production efficiency, optimize resource utilization, reduce waste, and provide high-quality products to consumers (Sivaranjani et al., 2022). Vegetables and fruits are important raw materials in the food industry, and the classification of vegetables and fruits is crucial for food processing, quality control and supply chain management. In the process of food processing, different varieties of vegetables and fruits may need to be handled and processed in different ways, so accurate classification can improve the quality and taste of products (Mukhiddinov et al., 2022). In addition, for food supply chain management and product traceability, the classification of vegetables and fruits can help trace the source and production process of products, ensure that products meet quality standards and food safety requirements, thereby improving food safety and consumer trust (Hassoun et al., 2023; Amin et al., 2022).

The automatic classification of vegetables and fruits can greatly improve the efficiency of classification (Huynh et al., 2022). Traditionally, the classification of vegetables and fruits is often done manually, which is time-consuming and error-prone (Pu et al., 2015). Using automatic classification technology, such as image recognition and machine learning algorithms, can quickly and accurately classify vegetables and fruits, saving human resources and time costs (Mukhiddinov et al., 2022). The automatic classification of vegetables and fruits can eliminate the influence of human factors on the classification results, and can achieve higher consistency and accuracy (Fahad et al., 2022). Manual classification may be affected by factors such as subjective judgments, differences in experience, and fatigue, while automatic

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classification is based on algorithms and models, which can be classified more objectively and reduce errors and inconsistencies. Whether on a farm or in a market, the volume of vegetables and fruit to be processed can be enormous (Hameed et al., 2021). Utilizing the automatic classification technology of vegetables and fruits, a large number of images or data can be quickly processed to improve production efficiency and market operation efficiency (Sivaranjani et al., 2022; Kheiralipour and Pormah, 2017). By continuously training and adjusting the algorithm model, the automatic classification system of vegetables and fruits can be adapted to new varieties of vegetables and fruits, and even to different classification standards and needs, which enables the system to respond to changing agricultural and market environments (Feldmann et al., 2020). Combining technologies such as image recognition, machine learning and artificial intelligence, the automatic classification algorithm and system of vegetables and fruits can be continuously improved, and the accuracy and efficiency of classification can be improved, which also provides opportunities for the development of agricultural intelligence, agricultural product quality inspection, supply chain management and other fields (Zhang et al., 2018; Steinbrener et al., 2019; Kazi and Panda, 2022).

Existing research shows that sensors for automatic classification of vegetables and fruits mainly include spectrometers (Saad et al., 2022), tactile sensors (Guilherme et al., 2020), odor sensors (Jia et al., 2019), and image sensors (Iqbal et al., 2016; Rehman et al., 2022). A spectrometer is an instrument used to measure the spectral properties of objects, which can be used for automatic classification of vegetables and fruits (Saad et al., 2022; Weng et al., 2020). Different kinds of vegetables and fruits have different absorption, reflection or emission characteristics in the spectrum, and spectrometers can capture and analyze these spectral features to classify different kinds of vegetables and fruits (Ghooshkhaneh et al., 2023). However, using a spectrometer requires certain environmental conditions, such as a stable light source and an interference-free background. If the environmental conditions do not meet the requirements, the spectral data of vegetables and fruits captured by the spectrometer will be affected, thereby affecting the accuracy and stability of vegetable and fruit classification. In addition, the spectral scanning and data processing of the spectrometer will take a certain amount of time, which cannot meet the real-time needs of vegetable and fruit classification, especially when performing large-scale classification tasks, this may become impractical. The tactile sensor classifies the types of vegetables and fruits by measuring their firmness characteristics, surface texture characteristics and shape characteristics, etc (Zhang et al., 2021a). However, it is precisely because the tactile sensor mainly perceives the shape, hardness, texture and other attributes of vegetables and fruits, which makes it insensitive to other attributes such as color and taste. Therefore, tactile sensors cannot provide comprehensive feature information in the classification of vegetables and fruits (Guilherme et al., 2020). Tactile sensors can perceive some physical properties of objects, but there may be certain limitations for complex vegetable and fruit classification tasks, for example, there are many kinds of vegetables and fruits, and the difference between attributes such as shape and firmness may be small, and it may be difficult for tactile sensors to accurately distinguish different kinds of vegetables and fruits. Studies have shown that although odor sensors can be used to classify vegetables and fruits in some cases, their application scenarios are subject to some limitations and challenges (Jia et al., 2019). Vegetable and fruit odors are often complex mixtures of several chemical components. Odor sensors need to distinguish different odor components and accurately associate them with specific vegetable and fruit species, which is challenging for odor sensors in vegetable and fruit classification applications (Kang et al., 2021). Odor sensors can only perceive specific odor components or are only sensitive to specific concentrations of odors, which results in some subtle odor differences not being captured by the sensor, thereby affecting the classification accuracy of vegetables and fruits (Guilherme et al., 2020). The response of the odor sensor is affected by environmental factors, such as temperature, humidity, etc., which lead to changes in the response of the odor sensor, which in turn affects the classification of vegetable and fruit odors. In addition, odor sensors are susceptible to interference from other odors in the external environment, such as air pollution from the surrounding environment, odors, or other sources of odors. Compared with the above-mentioned sensors for vegetable and fruit classification, the automatic classification technology of vegetables and fruits based on image processing has the advantages of rich feature information, high resolution, large-scale data processing and visualization (Bhargava and Bansal, 2021). Image sensors can capture multi-dimensional features of vegetables and fruits, including color, texture, shape, size, etc., which are very important in the distinction and classification of vegetables and fruits (Ghazal et al., 2021). In contrast, spectrometers mainly focus on the spectral characteristics of objects, tactile sensors mainly focus on the tactile characteristics of objects, and odor sensors mainly focus on the odor characteristics of objects. Therefore, the image sensor can provide more comprehensive and diverse feature information, which helps to classify vegetables and fruits more accurately. In addition, image sensors often have high resolution and can capture detailed image data, making it easier to differentiate between vegetables and fruits with subtle differences (Steinbrener et al., 2019). With the advancement of image sensor technology, it has become easier to obtain large-scale image data, which provides abundant training data for automatic classification using machine learning algorithms. Large-scale image datasets can help classifiers learn more accurate feature representations and classification patterns, improving classification accuracy and robustness (Mukhiddinov et al., 2022). Compared with tactile sensors and odor sensors, image sensors are non-contact and can acquire image data without direct contact with vegetables and fruits, which makes image sensors more convenient and practical and avoids the possibility of causing damage or contamination to objects. In addition, image sensors can perform fast image capture and processing under real-time requirements, which is suitable for efficient automatic classification systems (Yag and Altan, 2022). Since the data generated by the image sensor is visualized, people can visually observe and verify the classification results of vegetables and fruits, which can correct the classification errors of vegetables and fruits in time (Ghazal et al., 2021). Based on the above analysis, image processing has obvious advantages in automatic classification of vegetables and fruits. Furthermore, Behera et al. (Behera et al., 2020a; Ratha et al., 2023a) reviewed high-quality papers related to fruit recognition in the past 20 years, deeply discussed many technical issues related to fruit recognition, such as image preprocessing, segmentation, feature extraction and classification, and proposed a commonly accepted framework for fruit recognition based on image processing technology. In addition, they also summarized almost all papers on citrus diseases and fruit classification between 2010 and 2021, analyzed in detail the technological development of citrus diseases and fruit grading, covering aspects such as image processing, machine learning and deep learning, and proposed a framework for automatic prediction and grading of citrus diseases based on a combination of deep learning and machine learning based on image processing technology (Palei et al., 2023). This series of research once again highlights that automatic fruit and vegetable classification systems based on image processing have aroused great interest among researchers in this field.

Existing studies have shown that the classification accuracy of vegetables and fruits based on image processing largely depends on the quality of extracted features (Ghazal et al., 2021). Some scholars have adopted various methods to classify vegetables and fruits (Bhargava and Bansal, 2021). Bhargava et al. (Bhargava et al., 2022) extracted features such as statistics, color, texture, geometry, Laws' texture energy, the histogram of gradients, and discrete wavelet transform (DWT) from preprocessed vegetable and fruit images, and selected essential features from the feature vector through principal component analysis (PCA) and input them into the logistic regression (LR), sparse representation based classifier (SRC), artificial neural networks (ANN) and support vector machine (SVM) classifier to classify the health and defects of vegetables and fruits. Rajasekar et al. (Rajasekar and Sharmila, 2019) blended three basic features for characterizing objects: color, shape, and texture fed into k-nearest neighbors (KNN), linear discriminant analysis (LDA), naive bayes (NB), error-corrected output classifiers, and decision tree (DT) classifiers to identify fruits. Huynh et al. (Huynh et al., 2022) proposed a two-stage model for classifying fruit using camera images. In the first stage, Densnet121 is used to obtain features from the fruit dataset. In the second stage, the most important features are selected from the fruit images using the Adaptive Particle-Grey Wolf Optimization feature subset selection method. The selected subset features are fed to KNN, SVM, DT, random forest (RF) and multi-layer perceptron (MLP) classifiers to classify the fruit. Ghazal et al. (Ghazal et al., 2021) evaluated the performance of different combinations of handcrafted visual features for fruit classification. Their results show that the fruit classification method combining Hue, Color-SIFT, DWT and Haralick features outperforms other hand-crafted visual features. Patel et al. (Patel and Chaudhari, 2020) evaluated the performance of different classifiers based on color, zone, area, centroid, size, equvidiameter, perimeter and roundness features extracted from fruit images. The evaluation results show that compared with other classifiers, the multi-class SVM classifier achieves the highest accuracy rate of 91.67%. Kang et al. (Kang and Gwak, 2022) combined the bottleneck features of two multi-task deep convolutional neural networks (ResNet-50 and ResNet-101) with different architectures to classify different types of vegetables and fruits. Their experimental results show that the proposed transfer learning-based ensemble model outperforms other transfer learning-based models. Behera et al. (Behera et al., 2020b) extracted deep features from the fully connected layer of the deep learning model and input them into the SVM classifier to classify fruits and vegetables. Experimental results show that the method of using deep learning features combined with the SVM classifier has better fruit classification results than the method of using transfer learning. Ratha et al. (Ratha et al., 2023b) evaluated the performance of three feature extraction methods, namely deep learning method, DWT method and hybrid method (deep learning method combined with DWT method), for classifying papaya maturity stages. Their experimental results show that the hybrid method can extract more comprehensive feature information and achieve the best classification performance of papaya maturity stages. Iqbal et al. (Iqbal et al., 2016) proposed a method for classifying selected citrus fruits such as oranges, limes, and lemons based on color analysis of single-view fruit images. The analysis also showed that the color information found from the hue mean and hue median can be used for fruit classification based on ripeness. Siswantoro et al. (Siswantoro et al., 2020) proposed a method for classification of Indonesian fruits using MPEG-7 color and texture descriptors. In their method, descriptors are extracted directly from images without preprocessing and segmentation steps; PCA was used to reduce the dimensionality of the descriptors; Four simple classifiers were used to classify fruit images. The proposed method is verified on a dataset of Indonesian fruit images containing 15 categories. The verification results show that a simple classifier ensemble using LDA achieves the best accuracy rate, and k-nearest neighbors as the base classifier trained using CSD, SCD, and a combination of CLD and EHD classifier.

The aim of this research is to design an efficient and reproducible model to classify various types of vegetables and fruits using handcrafted features. In the proposed method, preprocessing methods such as Gaussian filtering, image grayscale and morphological processing are performed on the vegetable and fruit images to improve the quality and characteristics of the image; extract statistical texture features, DWT features and shape features to effectively characterize the categories of vegetables and fruits; diffusion maps (DM) feature dimensionality reduction method to reduce the redundancy between different features; five popular machine learning methods to classify vegetables and fruits. After rigorous experiments and analysis of various types of features, we propose a novel vegetable and fruit classification method that combines statistical texture features, DWT features and shape features with high classification accuracy.

The innovations of this research are as follows:

- This research proposes a novel, efficient, and reproducible method for vegetable and fruit classification based on handcrafted features
- The classification performance of different feature combinations for vegetables and fruits was evaluated to find the correct combination of hand-crafted features that would provide better accuracy.
- The classification performance of different classifiers on vegetables and fruits is compared extensively to find the best classifier for fruit classification using handcrafted features.

The rest of the paper is organized as follows: Section 2 describes materials and methods. Section 3 gives results. Section 4 presents discussion. Section 5 conclusions.

2. Materials and methods

Fig. 1 shows the structure block diagram of the method proposed in this research, which mainly includes database acquisition, vegetable and fruit image preprocessing, feature extraction, feature dimensionality reduction, vegetable and fruit classification and performance evaluation. Each part of the proposed method will be given in detail below.

2.1. Dataset acquisition

The dataset selected for this study can be obtained for free at the following URL: https://www.kaggle.com/datasets/sshikamaru/fruit-recognition?resource=download. The dataset has a total of 33 categories of vegetables and fruits, and contains a total of 22495 images. The images are of size 100 × 100. Many images in the dataset are rotated from the original images to aid in training. In the current study, 18 types of vegetables and fruits commonly found in the current market were selected for the purpose of classification. Table 1 gives the details of vegetable and fruit classes and some example images in the dataset.

2.2. Preprocessing

Preprocessing vegetable and fruit images is the key to optimizing image data, extracting relevant features, and improving the accuracy and efficiency of classification algorithms (Lv et al., 2022). In this research, initially, a smooth Gaussian filter with a standard deviation of 0.2 was used to reduce the influence of noise, blur and other visual disturbances in the image, making the image clearer and easier for subsequent processing. Then, the image is converted to a grayscale image, and thresholding is used to convert the grayscale image into a binary image. Closed operation morphological processing combined with erosion and dilation operations to eliminate small noise, fill gaps, connect fractures, enhance features, smooth edges, and further improve image quality and features.

2.3. Feature extraction

Feature extraction is to extract representative information from raw data for machine learning and pattern recognition tasks (Wang et al., 2021). The purpose of feature extraction is to transform data into a more discriminative and interpretable representation for subsequent classification tasks. Through feature extraction, the dimensionality of the data can be reduced, the representation ability of the data can be improved, the computational complexity of the algorithm can be reduced, and the accuracy and generalization ability of the model can be increased (Hasan et al., 2020). Selecting an appropriate feature extraction method and an appropriate feature representation is crucial to the success of a machine learning task (Wan et al., 2018). According to the literature review (Ghazal et al., 2021), the most commonly used features for vegetable and fruit classification (statistical texture features, DWT

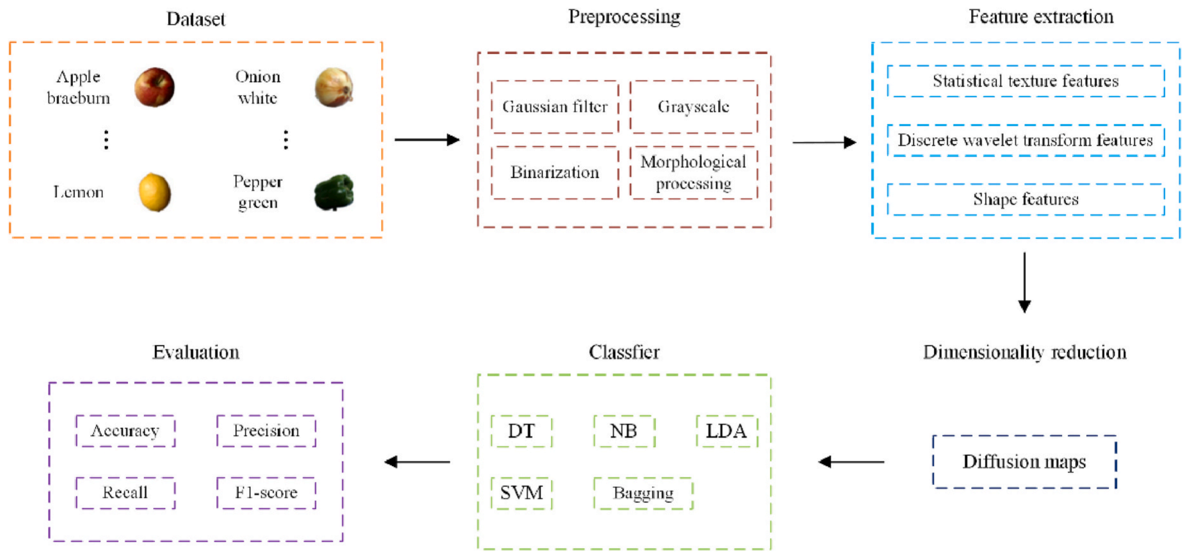

Fig. 1. The structure block diagram of the method proposed.

Table 1
Classes of vegetables and fruits with sample images.

Sr#	Category	Sample image	Sr#	Category	Sample image
1	Apple braeburn		10	Corn	
2	Blueberry		11	Banana	
3	Lemon		12	Mango	
4	Orange		13	Pear	
5	Raspberry		14	Apple granny smith	
6	Tomato		15	Pepper red	
7	Onion white		16	Pomegranate	
8	Pepper green		17	Cantaloupe	
9	Cucumber ripe		18	Avocado	

features and shape features) are extracted from the pictures for classification tasks, the details are as follows:

2.3.1. *Statistical texture features*

Statistical texture features describe texture features by calculating the statistical properties of local regions of the image (Itsarawisut and Kanjanawanishkul, 2019; Dhiman et al., 2022; Sinanoglou et al., 2023; Ropelewska et al., 2022; Backes and Khojastehnazhand, 2024). In this research, the grey-level co-occurrence matrix of each image is calculated, and then thirteen Haralick statistical features such as energy, contrast, correlation, variance, homogeneity, sum average, sum variance, sum entropy, entropy, difference entropy, information measure of correlation I, information measure of correlation II, maximal correlation coefficient are extracted. Further details of the statistical properties of Haralick can be found in (Haralick et al., 1973; Lofstedt et al., 2019; Rocha et al., 2010).

2.3.2. *Discrete wavelet transform features*

The discrete wavelet transform (DWT) feature is that the image is converted to the frequency domain by Single-level discrete 2-D wavelet transform, and the approximation coefficients, horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients are extracted (Ghazal et al., 2021; Yag and Altan, 2022; Mallat, 1989). Since the size of the preprocessed image is 100×100, the size of the approximation coefficients, horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients obtained after processing by Single-level discrete 2-D wavelet transform is 50×50. Then, the column vectors of the four features are respectively averaged to obtain a feature vector of size 1×50, and combined into a feature vector set of size 1×100. Apply PCA to the feature vector set to reduce the dimension, conduct various experiments, select the dimension of the DWT feature vector set with the best accuracy, and finally get a DWT feature vector set with a dimension of 30.

2.3.3. *Shape features*

Histogram of oriented gradients (HOG) is a commonly used shape feature extraction method, especially suitable for image recognition tasks (Dalal and Triggs, 2005; Jahanbakhshi et al., 2020; Zhang et al., 2014). HOG features are mainly used to describe the local shape and edge direction in the image. In this research, 4356 HOG features are extracted for each image of size 100×100. In order to reduce the size of the HOG feature vector dimension, PCA is used to compare the accuracy of vegetable and fruit classification under different HOG feature dimensions and select the dimension of the feature vector according to the best classification result obtained, and finally select the dimension of the HOG feature vector to be 6.

2.4. Feature dimensionality reduction

In this research, the DM dimensionality reduction method is used to reduce the dimensionality of the new feature vectors formed by the combination of the three features, in order to expect the combined features to better represent the categories of vegetables and fruits (Damelin et al., 2015; Trstanova et al., 2020). The DM is a nonlinear dimensionality reduction method used to map data into low-dimensional spaces for tasks such as visualization and classification. Based on the idea of graph theory and manifold learning, DM captures the inherent structure of data by establishing a similarity matrix and diffusion process between data points. The dimensionality reduction process of DM is to construct a similarity matrix based on the distance or similarity between data points; based on the similarity matrix, a weight matrix is constructed to describe the relationship between data points; the weight matrix is normalized to ensure the stationarity of the diffusion process; the normalized weight matrix is used in the diffusion process to transfer the information of each data point from its neighbors to other data points; perform eigenvalue decomposition on the diffusion matrix to obtain eigenvectors and eigenvalues; select the eigenvectors with larger eigenvalues to map the data into a low-dimensional space. The advantage of DM is that it can preserve the local structure and nonlinear relationship of the data and can discover the potential manifold structure in the data and map it to a low-dimensional space, thereby revealing the intrinsic characteristics and interrelationships of the data (Banisch et al., 2020).

2.5. Classification

In this research, five popular machine learning methods are used to classify vegetables and fruits, the details are as follows:

2.5.1. Decision trees (DT)

The DT classifier is a classification model based on the DT algorithm. The DT classifier splits the data by selecting the best features and gradually builds a tree for classification prediction (Huynh et al., 2022). According to the value of the feature, the sample is assigned to different sub-nodes step by step, until the leaf node is reached and the category of the sample is determined. The DT classifiers are interpretable, understandable and implementable, and are suitable for classification problems dealing with discrete and continuous features.

2.5.2. Naive bayes (NB)

The NB classifier is a probability-based classification algorithm suitable for processing large-scale data and high-dimensional features (Zhang et al., 2021a; Silva et al., 2022). The NB classifier assumes that each feature of the sample is independent of each other, and performs classification prediction by calculating the probability and conditional probability of each category (Ropelewska, 2020). The advantages of NB classifiers include simple calculation and fast speed, especially suitable for processing large-scale data sets. The NB classifiers work well for datasets with high-dimensional features and are robust to missing data.

2.5.3. Linear discriminant analysis (LDA)

The LDA classifier projects samples into a low-dimensional space and builds a classification model by calculating the category mean, scatter matrix, and projection direction (Dong et al., 2022; Zhu et al., 2020). It takes into account the differences between categories and has a better classification effect on high-dimensional data. The goal of the LDA classifier is to find a projection direction that can maximize the separation of samples of different classes. Through dimensionality reduction and projection, LDA enables efficient classification in low-dimensional spaces.

2.5.4. Support vector machine (SVM)

The basic principle of the SVM classifier is to find an optimal hyperplane to separate samples of different categories (Rehman et al., 2022; Zhang et al., 2021b). This hyperplane corresponds to a linear decision boundary in a high-dimensional feature space that maximizes the separation of samples from different classes. Facing the problem of linear inseparability, the kernel function technology is introduced into the SVM classifier to map the data into a high-dimensional feature space, thereby transforming the nonlinear problem into a linearly separable problem. The SVM classifiers can effectively deal with linear and nonlinear problems in high-dimensional feature space, with better generalization ability and less memory consumption.

2.5.5. Bagging

The principle of the Bagging classifier is to randomly select a part of samples from the original training data set with replacement to generate multiple different training subsets. For each training subset, train a base classifier using the same classification algorithm or a different classification algorithm (Huynh et al., 2022). For the samples to be classified, predictions are made on all base classifiers, and weighted voting is used for integrated prediction. By integrating the prediction results of multiple base classifiers, the Bagging classifier can reduce the variance of the model and improve the accuracy of classification.

Since each base classifier is trained independently on different training subsets, the bagging classifier can reduce the risk of overfitting and has better generalization ability.

2.6. Performance evaluation

Performance evaluation is used to evaluate the performance of the proposed model. By comparing the prediction results of the proposed model with the truth labels, a quantitative indicator of the performance of the proposed model can be obtained. The results in this research were all obtained by ten-fold cross-validation (Gupta et al., 2018). In this research, four quantitative indicators (accuracy, precision, recall and F1-score) were used to evaluate the performance of the proposed model, more details can be found in (Zhang et al., 2020; Hu et al., 2021).

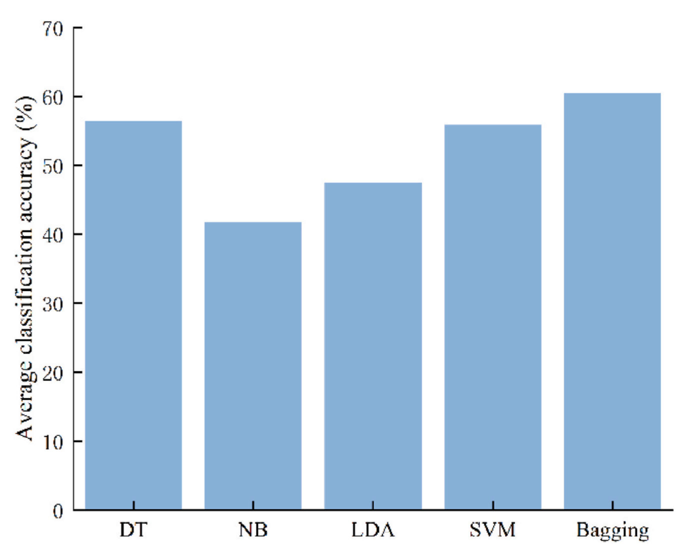

Fig. 2. Vegetable and fruit classification accuracy based on statistical texture features.

3. Result

3.1. *Results of statistical texture features classification for vegetables and fruits*

Fig. 2 shows the classification accuracy of vegetables and fruits obtained by five classifiers based on statistical texture features. As shown in Fig. 2, the classification accuracy of vegetables and fruits of the five classifiers in descending order is Bagging > DT > SVM > LDA > NB. The best vegetable and fruit classification accuracy achieved by the bagging classifier is 60.34%. The NB classifier achieved the lowest vegetable and fruit classification accuracy of 41.77%.

3.2. *Results of discrete wavelet transform features classification for vegetables and fruits*

Fig. 3 shows the classification accuracy of vegetables and fruits achieved by five classifiers based on DWT features. As shown in Fig. 3, the SVM classifier achieves the highest classification accuracy of 79.36% for vegetables and fruits. The second is the LDA classifier, which achieves a vegetable and fruit classification accuracy of 69.59%. Next, the Bagging classifier achieved 68.41% classification accuracy for vegetables and fruits. Placed in the fourth position is the DT classifier which achieves 59.79% classification accuracy for vegetables and fruits. The NB classifier achieved the lowest vegetable and fruit classification accuracy of 54.32%.

3.3. *Results of shape features classification for vegetables and fruits*

Fig. 4 shows the classification accuracy of vegetables and fruits based on five classifiers based on shape features. As shown in Fig. 4, the classification accuracy of vegetables and fruits achieved by SVM, Bagging and LDA classifiers are all higher than 80%, which are 94.16%, 89.13% and 85.38%, respectively. The DT classifier achieves 76.19% classification accuracy for vegetables and fruits. The NB classifier achieved the lowest vegetable and fruit classification accuracy of 69.93%.

3.4. *Results of combined features classification for vegetables and fruits*

This research combines different types of features to achieve better vegetable and fruit classification accuracy. Although the combination of different types of features can make up for the inability of a single feature to fully represent the types of vegetables and fruits, it cannot avoid the information redundancy between different feature combinations. Therefore, in this research, the DM dimensionality reduction technique is used to deal with the redundant information existing in different types of feature combinations. Figs. 5–8 shows the classification accuracy of vegetables and fruits in different feature space dimensions obtained through DM dimensionality reduction for four different feature combinations. Considering that the low-dimensional feature space contains less information representing the types of vegetables and fruits, it is difficult to achieve high classification accuracy, so this study set the minimum low-dimensional space obtained by DM dimensionality reduction to 5. For four different feature combinations, as the dimension of the feature space increases, the classification accuracy of vegetables and fruits also increases. When the feature space contains enough classification information of vegetables and fruits, the classification accuracy reaches the best and then there are slightly lowered. For these four different feature combinations, the SVM classifier achieves the highest vegetable and fruit classification accuracy, and the NB classifier has the worst vegetable and fruit classification accuracy. Comparing the classification performance of these four different

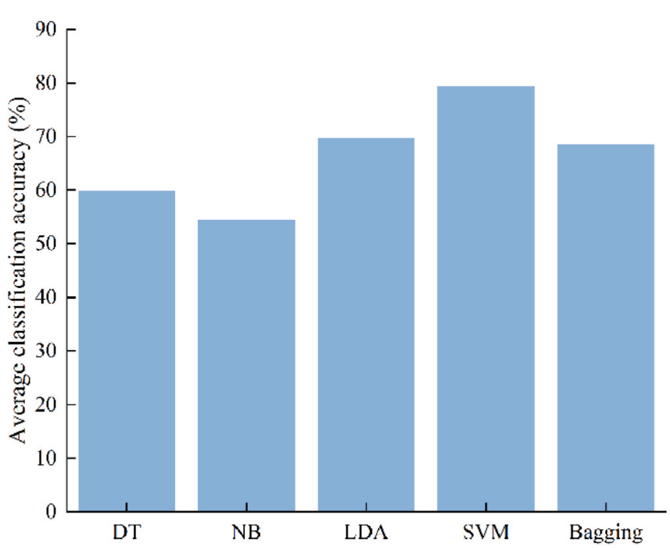

Fig. 3. Vegetable and fruit classification accuracy based on DWT features.

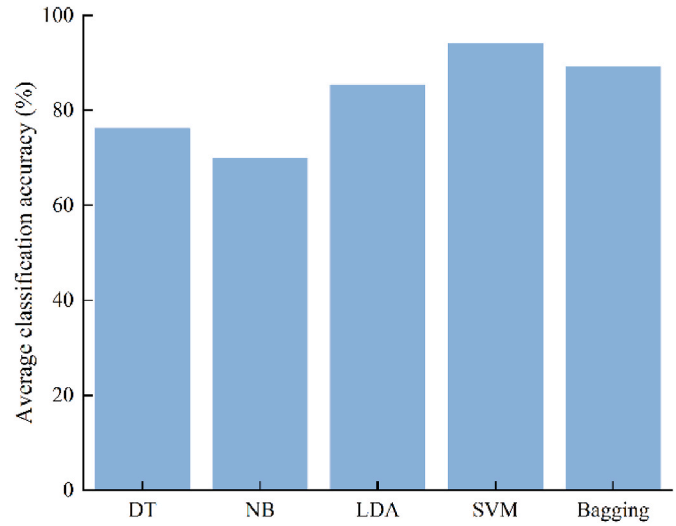

Fig. 4. Vegetable and fruit classification accuracy based on shape features.

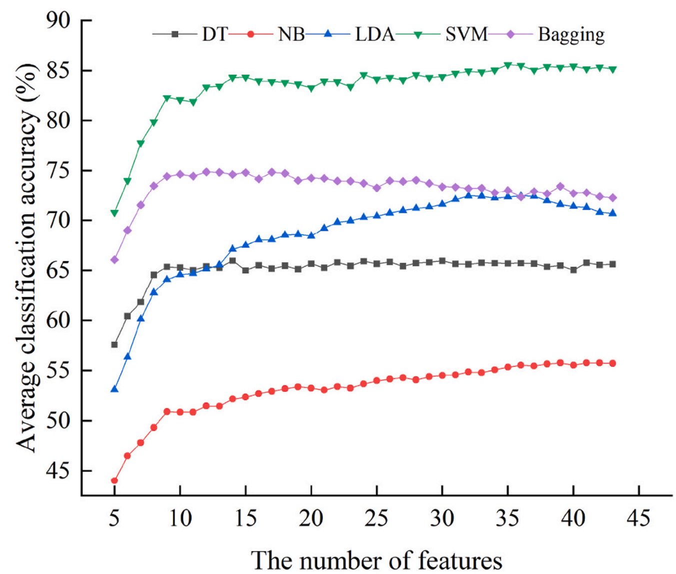

Fig. 5. For the combined features composed of statistical texture features and DWT features, the classification accuracy of vegetables and fruits with different feature numbers.

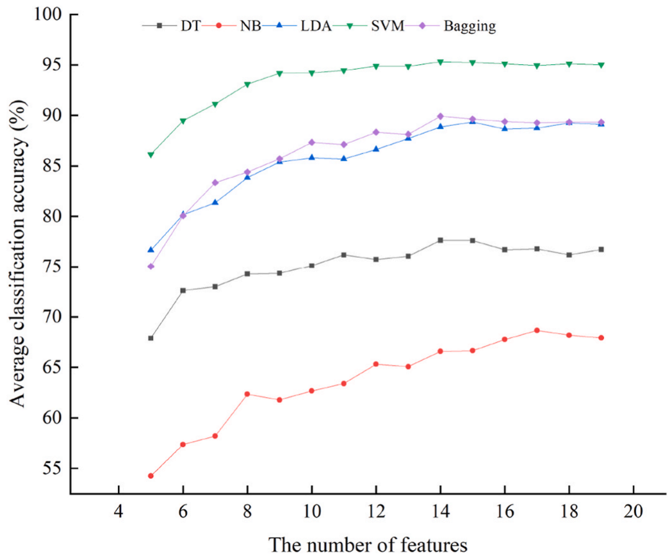

Fig. 6. For the combined features composed of statistical texture features and shape features, the classification accuracy of vegetables and fruits with different feature numbers.

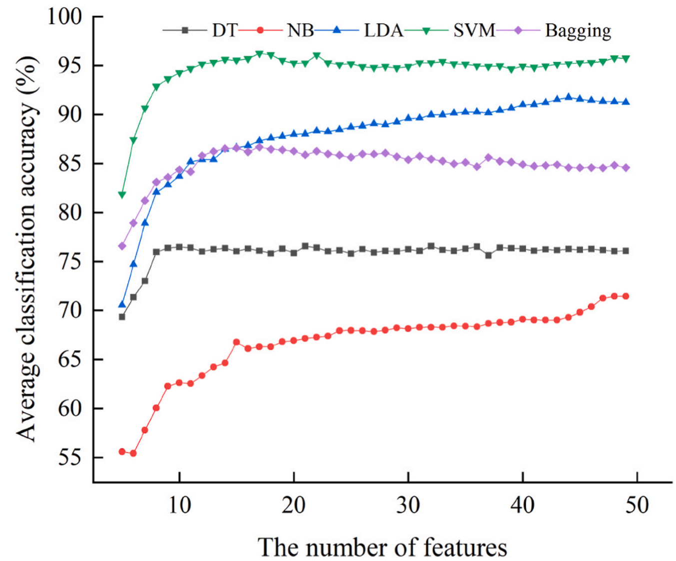

Fig. 8. For the combined features composed of statistical texture features, shape features and DWT features, the classification accuracy of vegetables and fruits with different feature numbers.

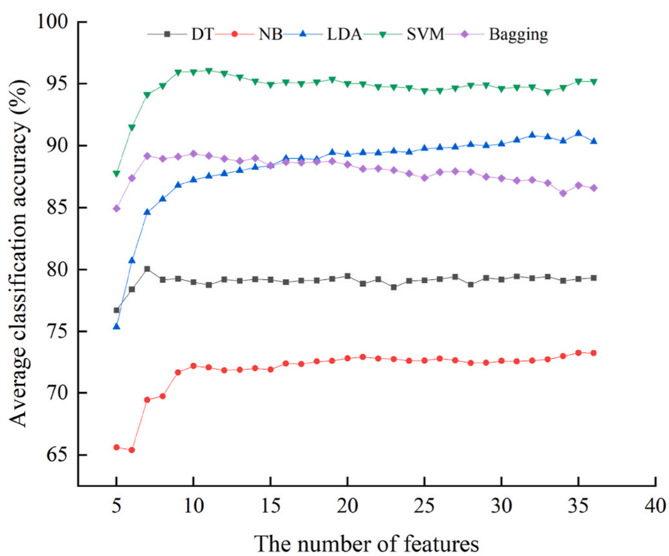

Fig. 7. For the combined features composed of shape features and DWT features, the classification accuracy of vegetables and fruits with different feature numbers.

Table 2
Performance evaluation of the proposed method.

Category	Accuracy	Precision	Recall	F1-score
Apple braeburn	98.39%	80.32%	92.89%	0.86
Blueberry	99.73%	98.66%	95.89%	0.97
Lemon	99.09%	94.36%	88.41%	0.91
Orange	99.25%	94.97%	90.61%	0.93
Raspberry	99.65%	94.73%	98.98%	0.97
Tomato	99.56%	96.41%	98.24%	0.97
Onion white	99.16%	90.56%	92.01%	0.91
Pepper green	99.05%	96.85%	83.11%	0.89
Cucumber ripe	99.96%	99.49%	99.49%	0.99
Corn	99.85%	100.00%	96.89%	0.98
Banana	99.98%	100.00%	99.59%	1.00
Mango	99.19%	94.07%	90.61%	0.92
Pear	99.76%	97.87%	98.99%	0.98
Apple granny smith	99.31%	91.98%	95.53%	0.94
Pepper red	98.95%	91.79%	93.99%	0.93
Pomegranate	99.89%	98.98%	98.98%	0.99
Cantaloupe	100.00%	100.00%	100.00%	1.00
Avocado	99.89%	98.83%	98.83%	0.99

feature combinations on vegetables and fruits, the combination of statistical texture features, DWT features and shape features performed best, followed by the combination of shape features and DWT features, the combination of texture features and shape features is placed in the third position, and the lowest vegetable and fruit classification performance is achieved by the combination of statistical texture features and DWT features.

3.5. Classification performance analysis

It can be seen from Figs. 5–8 that the combined features composed of statistical texture features, shape features and DWT features have the best classification accuracy of vegetables and fruits and the highest classification accuracy rate of 96.25% is achieved by the SVM classifier when the feature space dimension is 13. Therefore, the classification performance of the proposed method in this research is studied by taking the best vegetable and fruit classification cases as examples.

The accuracy, Precision, Recall and F1-score of the proposed method for each vegetable and fruit are shown in Table 2. It can be seen from Table 2 that the proposed method has the best classification performance for cantaloupe, and the accuracy, precision, recall and F1-score are 100.00%, 100.00%, 100.00% and 1, respectively. It has the lowest accuracy, precision and F1-score for apple braeburn, which are 98.39%, 80.32% and 0.86 respectively. pepper green has the lowest recall of 83.11%. Combining the classification performance of various types of vegetables and fruits, the proposed method has better classification performance for cantaloupe, banana and cucumber ripe, and poor classification performance for apple braeburn, pepper green and onion white.

4. Discussion

This research evaluates the classification performance of single feature sets and multi-feature combinations for vegetables and fruits. It can be seen from Figs. 2–4 that the shape feature has the best classification accuracy for vegetables and fruits which may be due to the advantages of HOG shape features in scale invariance, illumination invariance, local object description and interpretability compared with texture features and DWT features, which leads to the highest classification accuracy of vegetables and fruits. Among the three features in this study, the statistical texture feature has the worst classification accuracy for vegetables and fruits, which may be affected by the light intensity of the pictures in the data set, the low image quality or the inconspicuous texture structure, which leads to the inability of statistical texture features to achieve high classification accuracy (Weng et al., 2020). Figs. 5–8 shows the classification accuracy of combined features for vegetables and fruits. Compared with a single feature, the combined feature has significantly improved the classification accuracy of vegetables and fruits, which can be explained by the combined feature making up for the lack of single feature in representing the category information of vegetables and fruits (Amin et al., 2022; Ghazal et al., 2021; Rocha et al., 2010). Although the combined features composed of more categories of features may achieve higher classification accuracy of vegetables and fruits, but the combination of different features will inevitably bring some information redundancy (Rajasekar and Sharmila, 2019; Itsarawisut and Kanjanawanishkul, 2019; Backes and Khojastehnazhand, 2024; Zhang et al., 2014). In this regard, this research applies DM feature dimensionality reduction technology to reduce redundant information of combined features. It can be seen from Figs. 5–8 that when the dimensionality of the combined features is low, the information contained in the feature space is not enough to represent the types of vegetables and fruits, resulting in low accuracy. As the dimension of combined features increases, the information representing vegetables and fruits contained in combined features also increases, and the classification accuracy also increases. However, the dimension of combined features continues to increase, and combined features will bring redundant information representing vegetables and fruits, which in turn will affect the classification accuracy of vegetables and fruits (Bhargava et al., 2022).

In order to further verify that the features obtained by using the DM feature dimensionality reduction technology in this research can effectively remove redundant information in the combined features, the Kruskal Wallis Test was used to analyze the differences between the features after dimensionality reduction in representing vegetables and fruits (P-value<0.05 was considered statistically different) (Van Pelt et al., 2018; Kaur et al., 2022). In this research, taking the combined features of statistical texture features, shape features and DWT features as an example, the features obtained by DM feature dimensionality reduction technology are used for statistical analysis in IBM SPSS Statistics 25. As shown in Table 3, the features processed by the DM feature dimensionality reduction technology have statistical differences between the types of vegetables and fruits, which fully explains that the feature after dimensionality reduction effectively removes redundant information between combined features while ensuring the classification accuracy of vegetables and fruits.

Inevitably, this study still has shortcomings. First, the pictures of vegetables and fruits in this study have good lighting conditions, and our future work will test the method proposed in this study in a dataset that includes factors such as shadows and color bias. Second, damage to vegetables and fruits will inevitably occur during fruit storage and transportation. In the future, we will also conduct research on defect detection of vegetables and fruits. Finally, the real-time performance of automatic classification of vegetables and fruits is also a formidable challenge. In the future, we will design a fast and accurate automatic classification system for vegetables and fruits for use in actual automated harvesting and sorting scenarios.

5. Conclusions

This research proposes an efficient and reproducible novel model to classify multiple vegetables and fruits using handcrafted features. In the proposed model, images of vegetables and fruits are preprocessed to improve image quality; statistical texture features, wavelet transform features and shape features are extracted from preprocessed images to form combined features; DM feature dimensionality reduction method is used to reduce the redundancy of combined features; five machine learning methods are used to classify vegetables and fruits. Experimental results show that the SVM classifier achieves an accuracy rate of 96.25% for vegetable and fruit classification, which means that the method proposed in this study has significant application potential in the fields of food processing and inventory management.

Table 3
Kruskal Wallis Test of features obtained by DM dimensionality reduction.

Feature	P-value	Feature	P-value
F1	0.00	F8	0.00
F2	0.00	F9	0.00
F3	0.00	F10	0.00
F4	0.00	F11	0.00
F5	0.00	F12	0.00
F6	0.00	F13	0.00
F7	0.00		

CRediT authorship contribution statement

Wenbo Wang: Conceptualization, Methodology, Software, Visualization, Resources, Writing – original draft, Writing – review & editing. **Aimin Zhu:** Conceptualization, Methodology, Software, Visualization, Resources, Writing – original draft, Writing – review & editing. **Hongjiang Wei:** Writing – review & editing. **Lijuan Yu:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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