Apple Classification Based on HOG, KNN and SVM

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Abstract: In the rapid development of deep learning, traditional machine learning in the field of classification has the advantages of simplicity, ease of understanding, and strong interpretability. Apples, as an important global agricultural product, bring a lot of economic value and have health benefits for human beings. However, they are time-consuming and labour-intensive to sort manually. Therefore, realizing the intelligence of classification process is helpful to improve economic efficiency. For the apple dataset with high similarity, this research adopts two models, k-nearest neighbor (KNN) and support vector machine (SVM), and combines four models with two features, Histogram of Oriented Gradients (HOG) feature extraction and original features, to compare and research the models suitable for apple classification. It is found that HOG features do not perform well on apple images of similar shape and size, but both SVM and KNN using raw features show good performance on both training and test sets. The proposed method is simple to implement, has high accuracy and is suitable for further extension of application to other fruit domains.

1 INTRODUCTION

Apple, as one of the most important agricultural products all over the world, brings a lot of economic benefits. Selection and sorting after harvesting are an important part of the commercialization process. Sorting apples manually is time-consuming and labor-intensive for different varieties of apples. Some different kinds of apples are very close to each other in terms of shape, color and size. The shortcoming of detection will finally result in loss of efficiency. Automate and de-manipulate the apple classification process by extracting features of different apples can effectively increase the speed, save money and time costs. Trying to research a model with high accuracy in apple classification task requires a combination of both feature extraction method and classifiers. Finding the best of data features and classifier is of great importance.

Currently, many apple classification methods have been proposed. In Bhargava and Bansal's work in 2021, they segmented the apple images by the grab-cut method and fuzzy c-means clustering, extracted multiple features, and used principal component analysis (PCA) to select them. The classification was done by applying KNN, LR, SRC, and SVM classifiers. The cross-validation technique with distinct values of k was used to validate the performance of the system. The method obtained more than 95% accuracy on the SVM model when k equals to 10 (Bhargava and Bansal 2021). A. K. Bhatt and D. Pant together trained a back-propagation neural network to classify apples, using surface apple quality parameters as the independent variables and apple quality as the dependent variable (Bhatt and Pant 2015). The experimental results obtained are in good agreement with the true values and have shorter computation time and higher accuracy (Bhatt and Pant 2015). Misigo. R investigate the applicability and performance of Naive Bayes algorithm in classification of apple fruit varieties and compare the performance of Park Bayes technique with principal components, fuzzy logic, MLP neural performance (Misigo 2016). These methods either use relatively expensive instruments, such as X-ray scanners, near-infrared spectrometers, and industrial cameras, or are complex to operate, require the design of specialized hardware modules, and have cumbersome procedures that are not applicable to the promotion of their use in the market.

Using a combination of HOG feature extraction method and machine learning models has been widely researched by scholars before. Xin Guo et al. addressed the problem of poor recognition ability of traditional algorithms for small fruit targets in natural environments by classifying apples with improved

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HOG and SVM with the Focus plus CSP cascade module added for deep feature extraction (Guo et al 2022). The combination of HOG and KNN is also widely used. FAIA Putra et al. proposed a vision-based vehicle detection system with HOG feature detection and KNN classifier (Putra et al 2020). Hivi et al. applied PCA downscaled HOG feature and use SVM, KNN and Multilayer Perceptron Neural Network (MLPNN) three different classifiers to recognize face expression (Dino and Abdulrazzaq 2019).

According to Liu's work in 2019, he concluded through experiments that machine learning has the advantage of simplicity and efficiency in image classification and recognition compared to neural networks in classifying small samples of data. Based on his work and related research by other scholars, this research further explores the performance of traditional machine learning on apple classification.

2 METHODS

This research consists of three main parts. The first part is to preprocess the fruit dataset by selecting all the apple image classes to form the apple dataset. The second part is to extract HOG features and original features for each image for subsequent comparison. The last part is to classify the images based on the features using two classification tools KNN and SVM.

2.1 Data Visualization

The research is based on the Fruits-360 dataset. Up to now, there are 61934 images of 90 kinds of fruits with hundreds of shooting angles in the set, each image is formatted as 100100 pixels. The advantage of this dataset is that its images have the object without the noisy background, which may avoid reduction of the classification accuracy when changing the background environment of the images.

The research selected all the apple varieties to form the apple dataset, and all the apple classes in it are shown in Fig. 1.

After selecting, the apple dataset has a total of 8538 images, of which 6404 are training images and 2134 are test images. The ratio of training set to test set is 3:1, The number of training and test sets for each apple species is shown in Fig. 2

As shown in Fig. 2, some apple classes are duplicated. For example, Apple Red 1 and Apple Red 2 should be in the same class. By merging all identical classes, the final dataset is shown in Fig. 3.

2.2 HOG Feature Extraction

The HOG feature detection algorithm, an image descriptor that addresses human target detection, was first proposed at CVPR-2005 by French researcher Dalal et al. The feature extraction method is widely used in computer vision and image processing, mainly for detecting and recognizing objects in an image by extracting the feature descriptors of the image. HOG is aiming to describe an image with a locally oriented gradient histogram that represent occurrences of specific gradient direction in local parts of the image. The steps of the extraction algorithm for realizing HOG features are in Fig. 4.

2.3 Machine Learning Classifiers

Apple classification task is viewed as a part of Supervised learning. Due to multiple apple labels, some models like KNN, SVM and NB are the three most used methods for multiple classification (Binkhonain and Zhao 2019). In this research, the KNN and SVM models are used to classify apple classes with features extracted and not extracted with HOG respectively.

Figure 1: All the apple classes (Photo credit: Original).

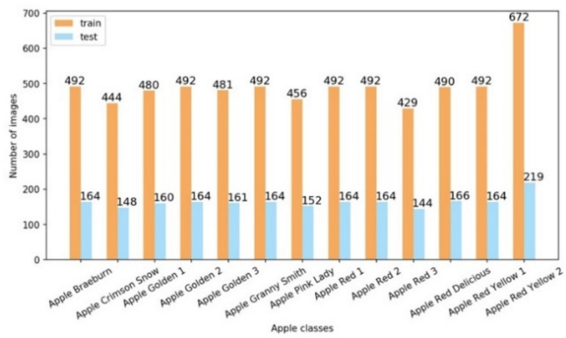


Figure 2: Selected apple dataset (Photo credit: Original).

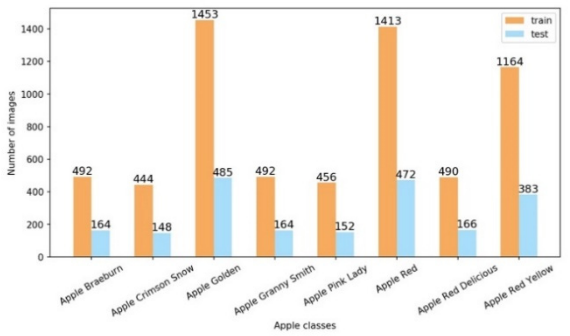


Figure 3: Classes of apples after merging (Photo credit: Original).

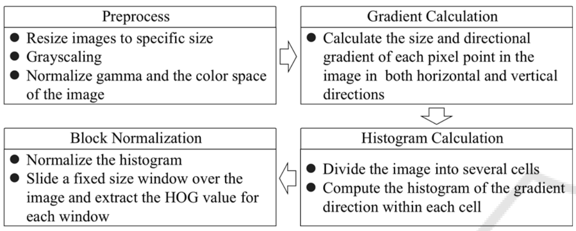


Figure 4: HOG feature extraction process (Photo credit: Original).

2.3.1 K-Nearest Neighbor

The work uses KNN to classify different kind of apples. Unlike other complex deep learning models, KNN is an easy understanding and not time-consuming algorithm. For classification problems, the main idea of the KNN algorithm is to decide the class of a sample point based on the class of the k nearest neighbors around that sample point. For the HOG feature vector of the test image, calculate the distance between it and the HOG feature vector of each sample in the training set. This can be done using different distance metrics, commonly the Euclidean distance, seen in the Eq. (1), where d is the Euclidean distance, x stands for test image, y stand for training image, and n is the total number of neighbors.

$$d = \sqrt{\sum_{k=1}^{n}(x_i - y_i)^2} \qquad (1)$$

The value of k determines how many neighbors a test point decides its own category based on the condition of using the Euclidean distance. Generally, different values of k will lead to greatly distinct results. Smaller values of k result in higher model complexity that is prone to overfitting. Predictions of test points are very sensitive to neighboring instance points. Larger values of k will make the model too generalized to accurately predict the testing data points, which is known as underfitting. To find the best k value, the common method is to use K-fold cross validation. The basic idea is dividing the dataset into k groups with same size, keeping one-fold for testing and other k-1 folds for training. The process needs k times and each time different fold are used for validation.

2.3.2 Support Vector Machine

SVM is a popular machine method due to its high learning qualities and well results. Built by Vapink's study in 2013, the model seeks the optimal balance between learning capacity and complexity based on small and medium-sized dataset, which gives it a strong ability to generalize. The main idea is to discover a hyperplane to correctly classify data points from different categories (Çakir et al 2023)**Erro! A origem da referência não foi encontrada.**. In high-dimensional space, the optimal function expression of a hyperplane is in Eq. (2), where w is the weighted vector, x is the input feature vector, b is the distance between the data point and the hyperplane.

$$w^T x + b = 0 \qquad (2)$$

The w and b need to fulfil the following inequalities, seen in Eq. (3):

$$\begin{cases} w{x_i}^T + b \geq +1 \;\; if\; y_i = 1 \\ w{x_i}^T + b \leq -1 \;\; if\; y_i = -1 \end{cases} \qquad (3)$$

Then, the distance from any point (x1, x2) in space to the target hyperplane can be expressed according to Eq. (4):

$$r = \frac{|w^T x + b|}{||w||} \qquad (4)$$

If the function interval r is made equal to 1, then there is Eq. (5):

$$\widetilde{N} = \frac{1}{||w||} \qquad (5)$$

Therefore, the formula for taking the interval maximization is shown in Eq. (6):

$$f = max \frac{1}{||w||} \qquad (6)$$

2.4 Evaluation Criteria

To assess the performance of the model, four evaluation metrics are used in this research: Accuracy, Recall, Precision and F1-score. The assessment metrics are determined by the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values, as shown in Table 1.

Table 1: Confusion Matrix of classification.

Predicted	Actual	
	positive	***negative***
positive	TP	FP
negative	FN	TN

Since this research is a multi-category problem, Macro Average rule is used for calculating Recall, Precision and F1-score. By using the confusion matrix, they are calculated separately for each category and then averaged (Zheng 2022).

2.4.1 Accuracy

The proportion of correctly categorized samples to total samples. It is calculated by multiplying the accuracy of each category by the proportion of that category in the total sample and then summing. The formular is given in Eq. (7):

$$Accuracy = \frac{\sum(TP_i)}{\sum(TP_i+FP_i+FN_i)} \tag{7}$$

2.4.2 Recall

The proportion of correct predictions that are positive to all that are actually positive, as shown in Eq. (8):

$$Recall = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{TP_i}{TP_i+FN_i}\right) \tag{8}$$

2.4.3 Precision

The proportion of all predictions that are correctly predicted to be positive, as shown in Eq. (9):

$$Precision = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{TP_i}{TP_i+FP_i}\right) \tag{9}$$

2.4.4 F1-Score

As defined in Eq. (10), the F1 score can be thought of as a kind of reconciled average of model precision and recall, which has a maximum value of 1 and a minimum value of 0.

$$F1 = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{2TP_i}{2TP_i+FP_i+FN_i}\right) \tag{10}$$

3 RESULT AND DISCUSSION

3.1 HOG Feature Extraction Result

In accordance with the HOG feature extraction process in Fig. 4, HOG features are extracted from all the images, and Fig. 5 is an example of a comparison image before and after extraction.

3.2 Predict Result

In this research of KNN classification model, the range of k values is set from 1 to 20, and the score of each k value with raw features and HOG features are shown in Fig. 6. The two figures illustrate that the model runs best when k equals to 1 for both raw features and HOG features. Considering both model accuracy and overfitting, the k value of 3 is chosen to build the KNN model.

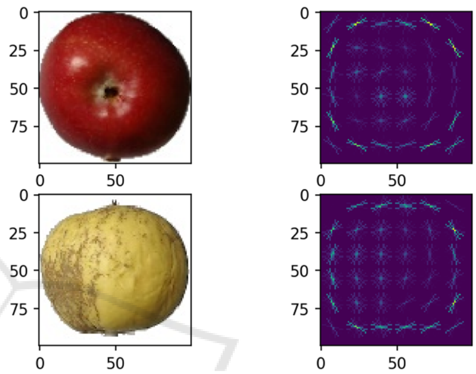
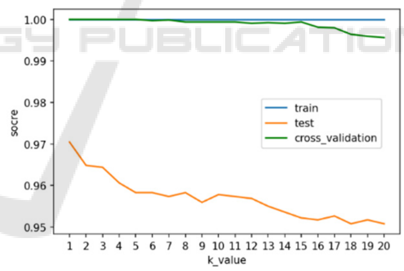
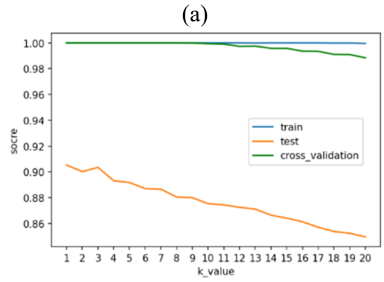


Figure 5: The comparisions of images before and after HOG feature extraction (Photo credit: Original).



(a)



(b)

Figure 6: The score of KNN for different k. (a) KNN with raw features (b) KNN with HOG features (Photo credit: Original).

3.3 Evaluation

In order to evaluate the performance of each classification model, the research compares the predicted results with the actual results of the testing set. The confusion matrix is shown as Fig. 7, showing that KNN and SVM both perform well on predicting the test set when trained with raw features compared to using HOG features. It can be seen that for all model, Apple Red Delicious are correctly classified, Apple Braeburn has the worst classification result with relatively high probability of being classified as Apple Red and Apple Red Yellow. According to Fig. 7, Apple Braeburn is the biggest challenge for these models with the lowest F1-score, precision and recall ， even for the least misclassified SVM model with raw features. The evaluation scores of each model are shown in Fig. 8. This clearly shows that SVM with raw features performs best on the apple classification task with the highest Precision, Recall, F1-score and Accuracy, KNN with raw features second. Both KNN and SVM with HOG features don't perform that well.

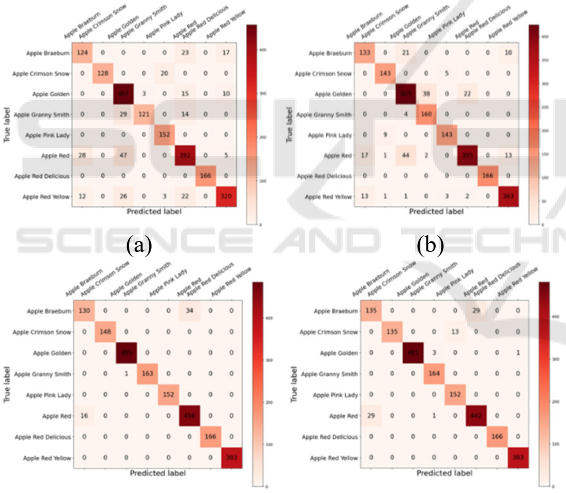


Figure 7: The confusion matrix of model. (a) SVM with HOG features, (b) SVM with raw features, (c) KNN with HOG features, (d) KNN with raw features. (Photo credit: Original).

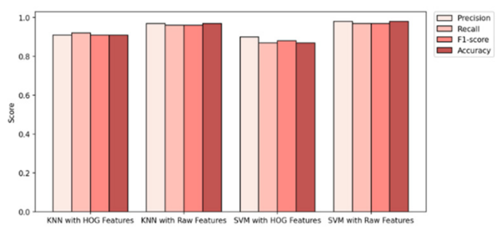


Figure 8: Evaluation score of each model (Photo credit: Original).

In this research, a total of four models are constructed by combining HOG features and original features, KNN and SVM. Each model is trained in a short period of time and achieved more than 90% accuracy. It can be seen from the result that the value of k has a significant effect on the predict outcome. According to the cross-validation result of each k and the effect of overfitting, k equals to 3 is chosen to train the KNN.

Since apples are similar in shape and size between some of the different species, the model using HOG features is not as well as the model that uses the raw features directly. SVM with raw features performs best on the apple classification task, which exceeds 97 per cent in all evaluation indicators.

This research uses separate KNN and SVM, in future investigation, further improvement in classification accuracy can be attempted by using a hybrid of KNN and SVM. The model was proposed by Zhang et al., which has reasonable computational complexity in training and exceptional results in practice (Zhang et al 2006)**Erro! A origem da referência não foi encontrada.**. Due to the high similarity of apple images and poor performance of HOG features, another idea to improve the model is using wavelet transform to extract image texture features. It is based on research by Jiang et al. specifically for the problem of recognizing and classifying high similarity images in a specific domain (Jiang et al 2018).0

It should be noted that this research is based on a small sample dataset, with many images of an apple species coming from a rotational shot of a single apple. Not enough training samples may lead to overfitting of the model. In addition, the classification of apple species in this research is not so rigorous, and there may be cases where different classes are treated as the same class or the same class is treated as different classes.

4 CONCLUSION

In current research, SVM with raw features achieved best results in both training and testing process. Surprisingly, the KNN model also has a good performance on this task. Through the research, this study found that HOG features work less well on high similarity datasets like Apple image set than using raw features. This is probably because the individual apple types are similar in shape and size, differing mainly in color. This finding could help other researchers to avoid the use of HOG when classifying images with a high degree of similarity in shape and size. Furthermore, the success of SVM with raw features in apple classification provides value for the application of traditional machine learning in agriculture.

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