Title:

Automatic Fruits Freshness Classification Using CNN andTransfer Learning.

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Main points to notice:

- struggle to accurately classify the fruits freshness in scenarios

Our target:

- Increase accuracy
- Use more dataset
- cloud-based framework

Summary:

1. Introduction

Computer vision-based approaches are thought to be the most intelligent and cost-effective solutions for automatic object detection and recognition of various objects, such as fruits. Multi-fruit categorization can be utilized in self-service fruit purchasing in supermarkets and can assist the breeding of various fruit species.

Studies on object classification use various approaches, such as Support Vector Machines (SVMs), linear discriminant analysis, or k-nearest neighbors (k-NN), to improve accuracy or speed. Fruit freshness is a major factor in determining the quality of fruits.

Figure 1. Top-row: Fresh fruits and Bottom-row: rotten fruits.

Several machine learning-based methods for fruit freshness classification have appeared in the literature. This study proposes a novel and automatic fruit freshness classification method using fine tuning and transfer learning of the AlexNet.

We develop an automatic fruits classification method based on transfer learning that accurately classifies whether the fruits are fresh or rotten. Our developed method obtains over 99% fruit freshness classification accuracy and is much lower computational complexity.

This manuscript reviews the recently developed fruits freshness classification methods, describes our developed method, and lists simulation results and comparisons.

2. Related Work

Researchers use deep learning to classify fruits and vegetables and improve the backbone of the YOLOv4 model using the Mish activation function. They later evaluate and extensively test the specially designed CNN model to detect several fruit freshness level.

Researchers used texture features, k-NN, Linear Discriminant, SVM, Google Net, ResNet18, ResNet50, ResNet101, VGG16, VGG19, and NasNetMobile to classify rotten and good apples. The ResNet18 model achieved the highest validation accuracy. In [9], the authors apply machine learning to classify the maturity status of papaya fruit by using LBP, HOG, Gray Level co-occurrence Matrix (GLCM), SVM, K-Nearest neighbor (KNN), and Naive Bayes methods. The K-Nearest neighbor (KNN) with the HOG features results high accuracy with much less training rate.

A system for classifying fruits and vegetables in supermarkets is implemented, which combines backdrop removal with a split-and-merge strategy and employs color, shape, and texture as key identifying characteristics. Authors published a method for identifying fruit flaws in retail, which uses color as a feature and produces color histograms. The Fisher-LDA is employed to decrease features size and to reduce noise, and then the SVM is employed to find the orange problematic zones.

In [15], CNN is used to detect various fruits, in [16], a deep learning-based technique is used for the freshness classification of Hog Palm fruit, in [17], a VGG16-based method is used to extract various robust fruits features, and in [18], SVM achieved highest 99% classification accuracy.

The recent methods that handle fruit freshness detection and classification problems include machine learning algorithms, deep learning models, and a few researchers' own datasets. Our work is latest addition in this domain and aims to achieve high fruit freshness classification of different fruits.

3.1. Data Collection

To develop our fruits freshness classification method, we acquire different fruits images data from Kaggle. This dataset contains images in separate files such as fresh apples, fresh bananas, fresh, oranges, and rotten apples, bananas, and oranges.

3.2. Pre-Processing

Data pre-processing is conducted before data manipulation to fit the data for Convolutional Neural Network (CNN) and various filters are employed therein.

Image augmentation is conducted by flipping all images to x-axis and randomly rotating images.

The converted dataset is labelled according to each class they belong to, and the string labels are changed into numeric format.

3.3. Data Manipulation

We split the pre-processed datasets into three parts: validation, train set, and test set. Out of these 100 images, 85 images contain plane background, and 15 images contain complex background.

3.4. AlexNet Architecture

AlexNet is an eight layers weighted model in which the first five are convolutional layers, while the remaining three are fully connected layers. The activation function is chosen such that the gradient function converges quickly and also at the infinity of the activation function is not 0.

The ReLU function is used in the first five convolutional layers, and the output is passed to three fully connected layers. The final output layer applies the Softmax activation function.

3.5. Transfer Learning of the CNN

The CNNs are networks that use constitutional filters to find neurons outputs that are linked to specific local input areas. They correctly extract features from the input image.

Transfer learning is a technique in which we use pre-trained network as a starting point to solve specified classification problems.

3.6. SoftMax Classifier

Softmax is a multinomial logistic regression classifier that is widely used in diverse fields including deep learning for various objects classification.

We select Softmax loss function for fruits classification and show that it has good performance and converges quickly.

The LossSo f tmax function maximizes the possibility of data and ignores the information from the prevailing incorrect labels. The AlexNet model is used to process the gathered data and is fine tuned in which epochs, batch sizes, and learning rate are set.

The softmax classifier is used to predict the final status of the fruit instantly. The steps shown in Algorithm 1 are simple and easy for readers to follow.

Our developed algorithm was executed on an Intel® NY USA Core I-i53550 machine with a CPU@3.30 GHz and a NVIDIA GTX1080 graphics card. The parameters and experimental setup are listed in Table 1, along with the learning rate, validation frequency, epochs, and batch size.

4.2. Datasets Description

We choose three publicly available datasets to simulate and validate our developed fruits freshness classification method. These datasets contain 12,000 diverse images of fresh and rotten categories of fruits and vegetables.

This data set contains 13,346 images of fresh and rotten fruits. The fresh fruits category contains at least 1400 images, while the rotten categories contain over 2200 images.

Dataset 3 contains total of 3200 images in a duration of two weeks in March 2022. It has been organized into 16 major classes, and the augmented images result in a total of 12,335 images.

Table 2. Statistics in Dataset 2.

A confusion matrix is a popular parameter that assesses the effectiveness of any classification model. We use the confusion matrix to compute several classification performance matrix.

Accuracy is a well-known parameter and is widely used in classification and recognition related tasks. It can be calculated as True Positives + True Negitives + False Positives + False Negatives.

4.4. Fruits Classification Analysis

For Dataset 1, Figure 6 shows that our developed method achieves 100% classification accuracy for the fresh categories of apple, banana, and mango, and 99% accuracy for the fresh categories of orange and strawberry.

Figure 6. Confusion matrix for Dataset 1.

For the rotten categories of banana, strawberry, apple, mango, and orange, our developed method yields 100% accuracy, while for the fresh categories of bell pepper, carrot, cucumber, potato, and tomato, our method yields 98% accuracy.

Figure 7 shows that our developed method obtains 99.2%, 100%, and 99.7% accuracy for the classification of fresh apple, banana, and orange, respectively. Similarly, for the rotten categories, our proposed algorithm obtains 99.8%, 100%, and 99.7% accuracy.

Figure 7. Confusion matrix for Dataset-2.

Figure 8 reports our experiments on Dataset 3, which contains several classes. We obtained 100% classification accuracy for fresh categories of apple, banana, guava, jujube, orange, pomegranate, and strawberry, and 96% classification accuracy for fresh categories of grape.

4.5. Comparison

We compare our developed method with three recently reported fruit freshness classification methods on same datasets. The mean accuracy is shown in Table 3.

The YOLO based method [5], the ResNet-50 based method [24], and the detailed classification results by implementing several architectures [20], all reported encouraging classification accuracy. Our developed method achieves a mean accuracy of 99.1% on all three fruits datasets.

4.6. Discussion

Our method performs well on all three datasets and achieves at least 98% classification accuracy. It is believed that for Dataset 2, our proposed method has almost solved the fruit freshness classification problem by achieving the 99.8% accuracy. We used the AlexNet architecture to achieve high accuracy and outperform several recently published works in the fruits freshness classification problem. The AlexNet architecture is computationally efficient and does not require high performance workstation.

4.7. Limitations

Our method uses the AlexNet architecture and was pre-trained on ImageNet dataset, but the method might struggle to accurately classify the fruits freshness in scenarios such as fruits placed inside plastic bags, sliced, or unpicked from farm.

4.8. Computational Complexity

In Figure 9, we show the computational complexity of our developed method. It takes almost 67 h to train on three different databases and requires almost 8.8 ms to yield the final classification result on average.

5. Conclusions

This paper proposed a fully automated fruit freshness classification method using a deep convolutional neural networks model. The model achieved an average accuracy of 99% on three publicly available fruits datasets.

We aim to increase the variety of fruits, develop a user-friendly mobile application, and generalize the evaluation of our developed method on more classes such as extra vegetable species.