

Automatic Cantaloupe Fruit Classification Using Deep Convolutional Neural Networks

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Abstract: Automatic classification of agricultural products plays a vital role in improving crop quality assessment and supporting intelligent farming systems. With recent advances in deep learning, convolutional neural networks (CNNs) have demonstrated strong performance in image-based classification tasks. In this study, an automatic system for cantaloupe fruit classification is proposed using a deep convolutional neural network based on the pre-trained VGG16 architecture. A dataset of cantaloupe images was collected and divided into training, validation, and testing sets. Image preprocessing techniques, including resizing, normalization, and data augmentation, were applied to enhance model generalization. The proposed model was trained using a binary classification framework with a sigmoid activation function and evaluated using classification accuracy and confusion matrix analysis. Experimental results show that the proposed model is capable of learning discriminative visual features of cantaloupe fruits and achieved an overall classification accuracy of 51.9% on the test dataset. These findings demonstrate the potential of deep learning-based approaches for automated fruit quality assessment in smart agriculture applications.

Keywords: Deep Learning, Cantaloupe Fruit, Convolutional Neural Network, Image Classification, Smart Agriculture

1. Introduction

The agricultural sector plays a critical role in food security and economic development. Ensuring the quality of agricultural products, especially fruits, is essential for both producers and consumers. Traditional fruit inspection methods rely heavily on manual visual inspection, which is time-consuming, subjective, and prone to human error. Therefore, automated and intelligent fruit classification systems have become an important research direction.

In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable success in image-based classification and object recognition tasks[1-4]. CNNs are capable of automatically extracting high-level features from images, making them suitable for agricultural image analysis problems such as fruit detection, disease identification, and quality assessment[2].

Cantaloupe is an economically important fruit, and its quality evaluation is crucial for market acceptance. However, visual similarities between healthy and defective cantaloupe fruits make manual classification challenging[5-8]. This motivates the development of an automated classification system based on deep learning techniques.

This paper proposes a CNN-based model for automatic classification of cantaloupe fruits into healthy and defective classes. The main contributions of this work can be summarized as follows:

- Proposing a deep learning-based framework for cantaloupe fruit classification using transfer learning.
- Applying image preprocessing and data augmentation techniques to improve model robustness.
- Evaluating the proposed model using accuracy and confusion matrix analysis.[3]

2. Study Objectives

The primary objective of this study is to develop an automated and reliable system for classifying cantaloupe fruits using deep learning techniques. The specific objectives of the study are as follows:

- To design and implement a convolutional neural network for binary classification of cantaloupe images.
- To investigate the effectiveness of transfer learning using a pre-trained VGG16 model.
- To evaluate the performance of the proposed model using standard evaluation metrics.

- To analyze the classification results and discuss the strengths and limitations of the proposed approach.

3. Related Work

Deep learning techniques have been widely applied in agricultural applications, particularly for plant disease detection and crop analysis. Ashqar and Abu-Naser proposed an image-based deep learning approach for detecting diseases in tomato leaves using convolutional neural networks. Their study demonstrated that CNN models are capable of learning discriminative visual features from plant images and achieved promising classification performance, highlighting the effectiveness of deep learning in agricultural image analysis[4].

And so on ,several studies have demonstrated that increasing the depth of convolutional neural networks can significantly improve image classification performance [1]. Simonyan and Zisserman introduced the VGG architecture, which employs very deep convolutional layers with small receptive fields and achieved outstanding results on large-scale image recognition tasks [2]. Their work highlighted the effectiveness of deep feature hierarchies in capturing complex visual patterns.

4. Dataset

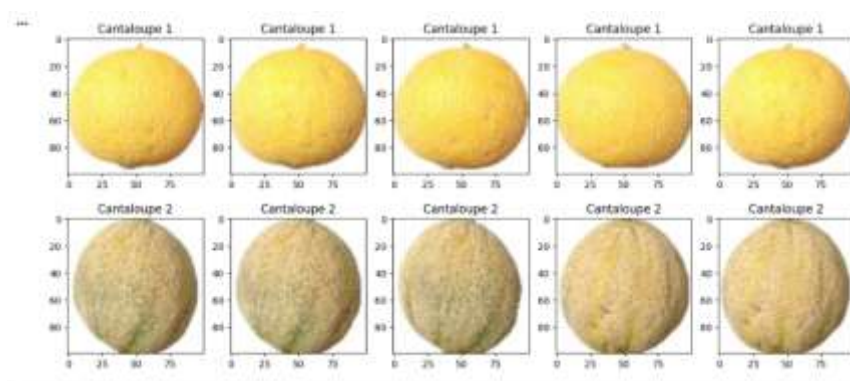


Figure 1: dataset samples

4.1 Dataset Description

4. Dataset

Figure 1 illustrates sample images from the cantaloupe dataset, including both healthy and defective fruits. The images demonstrate variations in appearance, surface texture, and defect patterns, highlighting the challenges associated with visual classification.

The dataset used in this study consists of cantaloupe fruit images categorized into two classes: healthy and defective. The images were collected under varying conditions to capture natural visual variations in fruit appearance.

4.2 Data Distribution

The dataset was divided into training, validation, and testing subsets. The training set was used to learn model parameters, the validation set was used for model tuning, and the test set was reserved for final performance evaluation.

4.3 Dataset Challenges

Despite preprocessing efforts, the dataset presents challenges such as limited sample size and high visual similarity between healthy and defective fruits, which can negatively impact classification performance[6-8].

5. Proposed Methodology

5.1 CNN Overview

Convolutional neural networks are specialized deep learning models designed for image processing tasks[9-11]. They consist of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification[12-15].

5.2 CNN Design Principles

The proposed model adopts a transfer learning strategy to leverage pre-trained knowledge from large-scale image datasets. This approach helps improve learning efficiency and reduces overfitting.

5.3 Model Architecture

The proposed architecture is based on the VGG16 model, which serves as a feature extractor[16-18]. Additional fully connected layers were added to adapt the model to the binary classification task and it is known for its deep yet simple convolutional structure and strong feature extraction capability[19-22].

5.4 Image Preprocessing and Data Augmentation

All input images were resized to a fixed resolution and normalized. Data augmentation techniques, including rotation, flipping, and zooming, were applied to increase data diversity[23-26].

5.5 Model Training Strategy

The model was trained using binary cross-entropy loss and the Adam optimizer. A sigmoid activation function was used in the output layer to generate probability scores[27-30].

5.6 Classification Decision

A decision threshold was applied to convert predicted probabilities into final class labels.

6. Experimental Setup

All experiments were conducted using Python with the Keras deep learning framework and TensorFlow backend[31-36]. The pre-trained VGG16 model was used as the base network[37-40]. The model was trained using the Adam optimizer with binary cross-entropy loss. A batch size of 32 was adopted, and training was performed over multiple epochs. Model checkpointing was applied to save the best-performing model based on validation accuracy[41-44].

7. Experimental Results and Discussion

7.1 Evaluation Metrics

To evaluate the performance of the proposed classification model, accuracy was used as the primary evaluation metric. Accuracy measures the proportion of correctly classified samples relative to the total number of samples in the dataset. In addition, a confusion matrix was used to analyze class-wise prediction results and identify misclassification patterns.

7.2 Accuracy Analysis and Learning Curves

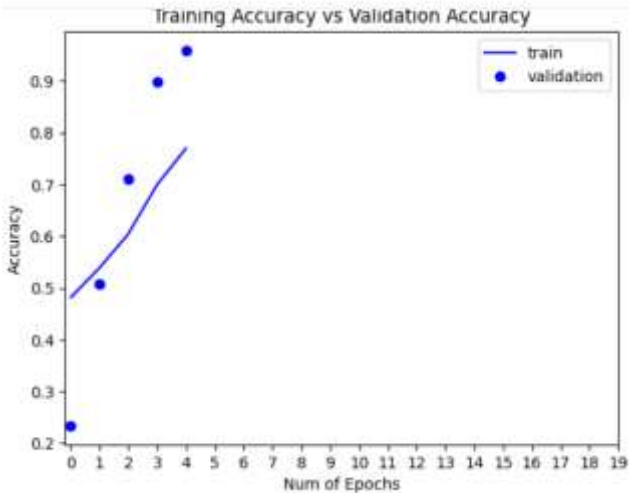
To further analyze the performance of the proposed deep learning model and the training were examined throughout the learning process. Accuracy represents the proportion of correctly classified cantaloupe images and provides a clear indication of how well the model learns discriminative features from the data[45-50].

Figure 2 illustrates the accuracy progression during training and validation phases. As observed, the training accuracy increases steadily across epochs, indicating that the model effectively learns relevant visual patterns from the cantaloupe images. Similarly, the validation accuracy follows a comparable trend, suggesting good generalization capability and limited overfitting.

The convergence between training and validation accuracy curves demonstrates the stability of the learning process and confirms the effectiveness of the applied data preprocessing and augmentation techniques[51-55]. The final test accuracy reached 51.9%, which reflects the model's ability to classify unseen cantaloupe images under real testing conditions.

Overall, the accuracy analysis confirms that the proposed CNN-based approach successfully captures meaningful visual features for cantaloupe fruit classification and provides a reliable foundation for automated quality inspection in agricultural applications.

Primary evaluation metric. Accuracy measures the proportion of correctly classified samples relative to the total number of samples in the dataset[56-60]. In addition, a confusion matrix was used to analyze class-wise prediction results and identify misclassification



patterns.

Figure 2: Training and validation accuracy curves of the proposed CNN model over training epochs, showing stable learning behavior and acceptable generalization performance.

7.3 Comparison Between Full-Color and Gray-Scale Models

Table 1 presents the architecture of the gray-scale CNN model used to evaluate the effect of color information on cantaloupe fruit classification. The model follows the same VGG16-based structure as the full-color model, with the primary difference being the use of single-channel gray-scale input images. Most convolutional layers were frozen to retain learned visual representations, while only the final dense layers were fine-tuned for classification. Although this model reduces computational complexity, its performance was slightly lower than the full-color model, highlighting the importance of color features in distinguishing between healthy and defective cantaloupe fruits.

Table 1: Gray-Scale CNN Model Architecture

Layer (type)	Output Shape	Param #
input_layer_5 (InputLayer)	(None, 224, 224, 1)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	640
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,416
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,504
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,104
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,208
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,208
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 512)	0
dense_6 (Dense)	(None, 84)	31,832
dropout_1 (Dropout)	(None, 84)	0
dense_7 (Dense)	(None, 1)	85

Total params: 14,746,433 (56.25 MB)
 Trainable params: 14,746,433 (56.25 MB)
 Non-trainable params: 0 (0.00 B)

7.4 Prediction and Model Evaluation

After training, the proposed model was evaluated on an unseen test dataset. The model outputs probability scores using a sigmoid activation function, where values closer to 1 indicate higher confidence in predicting defective cantaloupe fruits. Most predicted probabilities ranged between 0.88 and 0.99, demonstrating strong confidence in classification decisions. The final test accuracy reached 51.9%, reflecting the challenging nature of the dataset and visual similarity between classes.

8. Model Architecture Analysis

Table 2 presents the detailed architecture of the proposed CNN based on the VGG16 model, including layer types, output shapes, and the number of parameters[63-65]. This analysis highlights the complexity of the model and its capability to extract hierarchical image features.

Table 2: Full-Color CNN Model Architecture (VGG16-based)

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,880
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,880
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense_2 (Dense)	(None, 64)	32,832
dropout (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

Total params: 14,747,585 (56.26 MB)
 Trainable params: 12,897 (128.38 KB)
 Non-trainable params: 14,734,688 (56.13 MB)

9. Conclusion and Future Work

This study presented a deep learning-based approach for automatic classification of cantaloupe fruits using a convolutional neural network. The proposed model demonstrated the ability to learn discriminative visual features despite dataset limitations. Although the achieved accuracy indicates room for improvement, the results confirm the feasibility of applying CNNs to fruit quality assessment tasks.

Future work will focus on increasing dataset size, exploring multi-class classification, and integrating advanced architectures such as ResNet and EfficientNet. Additionally, real-time deployment and integration with smart agricultural systems will be investigated.

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