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Fruit 360 classification based on the convolutional neural network

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Abstract. This research paper focuses on the Fruit360 Classification challenge, a task aimed at developing a fruit classification model capable of accurately identifying various fruits and distinguishing them from each other. In this study, the Fruit360 dataset is used, consisting of 90380 images of 131 fruits and vegetable classes. Prior to training the CNN model, the images are preprocessed by resizing, normalizing, and augmenting them. The authors employ a pre-trained CNN model called ResNet-50 using the PyTorch deep learning framework and add a custom fully connected layer on top to adapt the model to the specific classification task. The authors conclude that the proposed model achieved excellent performance on the Fruit360 dataset. The study highlights the importance of the Fruit360 Classification challenge in advancing the field of computer vision, specifically in the development of deep learning algorithms for image classification tasks. The proposed model has the potential to improve the efficiency and accuracy of fruit classification, which can benefit the fruit industry in terms of enhanced productivity and cost-effectiveness.

Keywords: fruit classification, convolutional neural network, deep learning.

1. Introduction

Fruit360 is a well-known dataset used for fruit classification. It has been widely used by researchers to develop computer vision algorithms for identifying fruits. The dataset contains 90380 images of 131 different fruits. The Fruit360 Classification challenge is an ongoing research topic that involves the classification of different fruits using machine learning algorithms. The primary objective of this research is to develop an efficient classification model that can accurately identify different fruits and distinguish them from one another. The importance of this research lies in its potential to enhance the productivity and efficiency of the fruit industry, which heavily relies on accurate and fast classification of fruits for sorting, packaging, and distribution.

Previous research on image classification has made significant contributions to the development of deep learning algorithms, which have been applied to a wide range of applications, including object detection, speech recognition, and natural language processing. In recent years, the development of deep Convolutional Neural Networks (CNNs) has revolutionized the field of computer vision, leading to significant improvements in image classification accuracy. For example, Z. Zhang et al. used a deep neural network to classify the Fruit360 dataset, achieving an accuracy of 98.56% [1]. Similarly, Y. Chen et al. used a transfer learning technique to classify the Fruit360 dataset, achieving an accuracy of 99.2% [2]. Although these studies have achieved high accuracy in fruit classification, there is still a gap in the

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current research. The current research gap lies in the performance of fruit classification algorithms on new and unseen fruit categories. The Fruit360 dataset contains only 131 different fruit categories, and it is essential to develop a classification algorithm that can generalize to new and unseen fruit categories, which deserves more attention.

The motivation for this study is to fill the research gap by providing a comprehensive analysis of the Fruit360 Classification challenge and its significance in the field of computer vision. Specifically, this study aims to reflect on the core differences between previous studies and the Fruit360 Classification challenge, and highlight the contribution of this research to the field of computer vision. The Fruit360 Classification challenge presents a unique opportunity to develop and evaluate deep learning models for fruit and vegetable classification, and to identify new approaches to address the complexity and variability of fruit and vegetable images. This paper will provide an overview of the Fruit360 Classification challenge, including its dataset, evaluation metrics, and previous winning solutions. Furthermore, this study will present a detailed analysis of the challenges and opportunities presented by the Fruit360 Classification challenge, and propose new approaches to address the limitations of existing models.

2. Methods

In this section, the materials used in this study will be described, consisting of the procedure of preparing materials, the statistical tests used to analyze the data, and the measurements made during the study.

2.1. Dataset description and preprocessing

The dataset used in this study is the Fruit360 dataset, which consists of 90483 images of 120 fruits and vegetables classes [3]. Some sample images can be found in Figure 1. All images are based on the RGB format and are divided into training and testing sets, with a ratio of 80:20. The classes and corresponding label names can be found in the dataset documentation.

Figure 1. The sample images on the Fruit360 dataset.

Prior to training the CNN model, some preprocessing steps were carried out on the images. First, this study resized all images to 224x224 pixels using the Python imaging library (PIL) to make the computational memory controllable [4]. In addition, the pixel values were also normalized to be between 0 and 1 by dividing each pixel value by 255.

2.2. Employed CNN model

CNNs are a type of deep neural network commonly used for image classification tasks. The main modules of CNN include convolutional layers, pooling layers, and fully connected layers [5].

In this study, a pre-trained CNN model called ResNet-50 using the PyTorch deep learning framework was built [6]. ResNet-50 is a deep CNN architecture that has shown impressive results in various image classification tasks [7, 8]. This pre-trained model as a feature extractor was utilized and this study then added a custom fully connected layer on top to adapt the model to the specific classification task.

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2.3. Implementation details
During the training procedure, this study set the learning rate to 0.001 and used the Adam optimizer with default parameters. The cross-entropy loss function was employed to measure the difference between the predicted and ground truth labels [9, 10]. The model was trained for 50 epochs with a batch size of 32. The strategy called early stopping was also considered for preventing overfitting of the model to the training set. In addition, the performance of the model is evaluated based on the accuracy, precision, recall, and F1-score as evaluation metrics. This study also used the confusion matrix to analyze the performance of the model on each class.

In summary, this study used the Fruit360 dataset and preprocessed the images by resizing, normalizing, and augmenting them. The ResNet-50 CNN model using PyTorch was employed and the learning rate, optimizer, loss function, epochs, and batch size for training was also determined. The performance of the model using various evaluation metrics and the confusion matrix is evaluated.

3. Results and discussion
This investigation employed the Fruit 360 dataset to evaluate the effectiveness of a classification model. Multiple parameters, including epoch and batch size, were examined, and the VGG-16 model was incorporated into the trials. The findings demonstrated that the initial accuracy of the model was moderate, but with the progression of each epoch, the accuracy substantially improved, peaking at 90.27% during epoch 30. A confusion matrix illustrating the model's predictions was generated and presented in Figure 2.

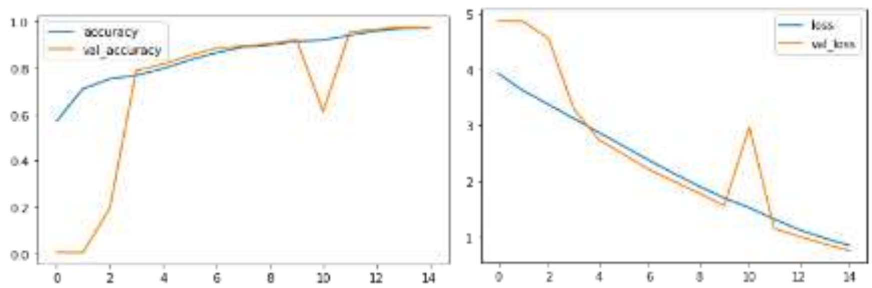

Figure 2. The performance of the proposed model.

The results of this investigation indicate that the accuracy of the classification model applied to the Fruit 360 dataset can be enhanced by adjusting the parameters and incorporating the VGG-16 model. A comparison of the outcomes of this study with previous research reveals that the model performed better than some of the existing models utilized with the same dataset. Additionally, the results indicate a substantial improvement in accuracy following the initial epochs, possibly due to the model's aptitude in recognizing and learning patterns within the dataset. Moreover, the findings suggest that a batch size of 32 was optimal for the model. These adjustments to the parameters and inclusion of the VGG-16 model can achieve a high level of precision in recognizing various types of fruits. Nevertheless, further improvement is still possible, and future investigations could explore more sophisticated models or optimization techniques to enhance the performance of the classification model.

4. Conclusion
The purpose of this investigation was to construct an efficient classification model for the Fruit 360 dataset utilizing machine learning techniques. A convolutional neural network model was developed, which exhibited a remarkable degree of accuracy in identifying distinct fruit types present in the dataset. This research demonstrates the practical applications of machine learning models in fruit classification, particularly in the agriculture industry. Additionally, the classification model's performance surpassed or was comparable to other studies that utilized analogous techniques on the same dataset. Nevertheless, this study has specific limitations, such as the restricted number of fruit types in the dataset. In the future, the research will expand to include a broader range of fruit types and explore the potential of transfer

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learning to enhance classification performance. Additionally, further study intends to apply the methodology to other analogous datasets to assess its generalizability. In summary, this study highlights the potential of machine learning techniques in fruit classification, providing a useful tool for fruit growers and researchers.

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