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Artículos científicos

Clasificación de frutos del durazno en maduros, no maduros y dañados hacia la cosecha automatizada

Classification of Peach Fruits in Ripe, Unripe and Damaged Towards Automated Harvest

Classificação de frutos de pêssego em maduros, imaturos e danificados para colheita automatizada

Ma. Dolores Arévalo Zenteno
Universidad Autónoma del Estado de México, Centro Universitario UAEM Texcoco, México
mdarevaloz@uaemex.mx
https://orcid.org/0000-0002-4615-6890

José Sergio Ruiz Castilla
Universidad Autónoma del Estado de México, Centro Universitario UAEM Texcoco, México
jsruizc@uaemex.mx
https://orcid.org/0000-0001-7821-4912

Joel Ayala de la Vega
Universidad Autónoma del Estado de México, Centro Universitario UAEM Texcoco, México
jayalad408@uaemex.mx
https://orcid.org/0000-0003-3279-4143

Resumen

A partir de la tecnología de visión artificial, específicamente de redes neuronales convolucionales, se propuso una solución para realizar el reconocimiento de frutos de durazno maduros, así como la identificación de frutos dañados. La finalidad es obtener frutos con el nivel de calidad adecuado para su comercialización. Para lograr este propósito, se obtuvieron imágenes de duraznos en un ambiente no controlado. Se recortaron las imágenes digitales hasta obtener el área de interés. Se configuraron tres conjuntos de datos: el primero, de duraznos maduros e inmaduros; el segundo, también de duraznos maduros e inmaduros pero con enfoque en un área textural, y el tercero, de duraznos sanos y dañados. Se aplicó una red neuronal convolucional, que fue programada en el lenguaje Python, las librerías de Keras y TensorFlow. Durante las pruebas se obtuvo una precisión de 95.31 % a la hora de elegir entre maduros y no maduros. Mientras que al clasificar los duraznos sanos y dañados se obtuvo 92.18 % de precisión. Por último, al clasificar las tres categorías (dañados, inmaduros y maduros), se obtuvo 83.33 % de precisión. Los resultados anteriores indican que con inteligencia artificial embebida en un dispositivo físico se puede hacer la clasificación del fruto del durazno.

Palabras clave: durazno, red neuronal convolucional, visión artificial.

Abstract

Using computer vision technology, specifically convolutional neural networks, a solution was proposed to perform the recognition of ripe peach fruits, as well as the identification of damaged fruits. The purpose is to obtain fruits with the appropriate level of quality for their commercialization. To achieve this purpose, images of peaches were obtained in an uncontrolled environment. Digital images were cropped until the area of interest was obtained. Three data sets were configured: the first, for ripe and unripe peaches; the second, also of ripe and unripe peaches but only focused on a textural area, and the third, of healthy and damaged peaches. A convolutional neural network was applied, which was programmed in the Python language, the Keras and TensorFlow libraries. During the tests, a precision of 95.31 % was obtained when choosing between mature and immature. While when classifying healthy and damaged peaches, 92.18 % accuracy was obtained. Finally, when classifying the three categories (damaged, immature and mature), 83.33 % precision was obtained. The previous results indicate that with artificial intelligence embedded in a physical device, the classification of the peach fruit can be done.

Keywords: peach, convolutional neural network, computer vision.

Resumo

Utilizando tecnologia de visão artificial, especificamente redes neurais convolucionais, foi proposta uma solução para realizar o reconhecimento de frutos de pêssego maduros, bem como a identificação de frutos danificados. O objetivo é obter frutas com o nível de qualidade adequado para sua comercialização. Para tanto, imagens de pêssegos foram obtidas em ambiente não controlado. As imagens digitais foram recortadas até que a área de interesse fosse obtida. Três conjuntos de dados foram configurados: o primeiro, para pêssegos maduros e verdes; a segunda, também de pêssegos maduros e verdes, mas com foco em uma área textural, e a terceira, de pêssegos saudáveis e danificados. Foi aplicada uma rede neural convolucional, que foi programada na linguagem Python, nas bibliotecas Keras e TensorFlow. Durante os testes, obteve-se uma precisão de 95,31% na escolha entre maduro e imaturo. Ao classificar pêssegos saudáveis e danificados, obteve-se 92,18% de acerto. Por fim, ao classificar as três categorias (danificado, imaturo e maduro), obteve-se 83,33% de precisão. Os resultados anteriores indicam que com inteligência artificial embutida em um dispositivo físico, a classificação do pêssego pode ser feita.

Palavras-chave: pêssego, rede neural convolucional, visão computacional.

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Introduction

Peach fruit

The peach fruit is a highly consumed fruit. In addition to having a sweet taste and a delicate aroma, it is characterized by being yellow, red, pink or a combination of these, having a size of 4 cm to 8 cm in diameter, having a marked longitudinal groove and a mesocarp very meaty. Precisely for these characteristics, it is widely cultivated for its commercialization and used in various ways in the culinary art. The peach, also known as peach, is consumed as fresh fruit, although it can also be processed to obtain other agro-industrial products. To achieve a quality peach harvest, and with it a profit margin for the producers, they must organize and schedule the production seasons in each region, as well as plan the distribution of the fruit in the consumption centers in a regulated manner to avoid that the supply is greater than the demand. Finally, we must not forget the use of new varieties that, in addition to having the ideal quality characteristics, allow to extend the ripening and harvest periods (Baíza, 2004).

Regardless of the region, the fruit should be harvested when the color of the pulp changes from green to light yellow. With this, it is achieved that the fruit has greater weight and an optimal flavor and, therefore, greater profit for the producer. On the contrary, if it is harvested when it is ripe, it hurts easier and rots quickly.

Related jobs

Alipasandi, Ghaffari and Zohrabi (2013) They introduced color characteristic extraction techniques to classify three varieties of peach fruit into ripe and immature. The authors concluded that these have a more significant effect than the shape characteristics in terms of classification. Other works have focused on developing identification systems through the leaves of trees and plants (Cervantes et al., 2017; Kadir, Nugroho, Susanto and Insap, 2011). For example, Hati and Sajeevan (2013) used image processing techniques to extract geometric characteristics of the leaves: aspect ratio, width ratio, vertex angle, vertex ratio, base angle, moment ratio, and circularity. . Developing an application with java led to a recognition accuracy of 92%. The contribution of this work was, precisely, the extraction of characteristics. Subsequently, Amlekar, Manza, Yannawar and Gaikwad (2014) discovered that biometric patterns such as the venation pattern make classification tasks easier. Two models were used to evaluate its precision: the so-called nearest neighbor and the backpropagation neural network. The results indicated greater precision in the neural network.

Convolutional neural networks

Research with convolutional neural networks (CNN) has advanced in recent years. Some of the efforts related to CCN have been geared towards testing modifications to the architecture. Along these lines, Simonyan and Zisserman (2015) presented six different network configurations by changing the depth of the convolutional layers, inserting non-linearity, forcing a regularization and decreasing the number of parameters in the layer stack. And they looked at the effect of CNN depth on large-scale image recognition settings. This was a comprehensive evaluation of deep networks using a 3×3 convolution filter architecture. In the end, they were able to demonstrate that significant improvement can be achieved over prior art configurations by increasing depth to up to 19 layers. and requiring fewer times to match.

For his part, Morris (2018) designed a CNN to discriminate the boundaries of the leaves. Furthermore, using these boundary predictions, he proposed a method to generate closed boundary leaf segmentations. While Sharpe (2019) analyzed the behavior of three CNNs: DetectNet, VGGNet and GoogLeNet to detect Geranium carolinianum weeds in strawberry crops. The goal was to help strawberry growers apply herbicide only to weeds. The photos were taken with a digital camera. GoogLeNet and VGGNet were not very successful during image validation. CNN training with cropped images increased the detection of Geranium carolinianum during validation for VGGNet (77%) and GoogLeNet (62%). DetectNet, trained on Geranium carolinianum leaves, achieved the highest precision (94%) for plant detection during validation, making it the most viable CNN test for image-based remote detection of Geranium carolinianum in competition with the Strawberry. Sharpe (2019) suggests, for future research, to identify the optimal approach for in situ detection and to integrate the detection technology with a precision sprayer. In sum, the use of DetectNet as the decision system for a digital camera-based machine vision subsystem seems a viable option for precision control of Geranium carolinianum in Florida strawberry production.

The works of Ma et al. (2018), Heyan, Qinglin and Yuankai (2018) and Krizhevsky, Sutskever and Hinton (2012) are other examples of the ability of CNNs in great depth to extract discriminatory features exclusively from images of plants.

Materials and method

Digital Imaging Data Set

The images were taken with a 24.2 megapixel Nikon d3500 professional camera with the AF-P DX Nikkor 18mm-55mm and AF-P DX Nikkor 70mm-300mm lenses. After shooting, the images were cropped until leaving only the area of interest: on the one hand, whole peaches; on the other, considering only the texture. Finally, image sets were made with ripe and unripe peaches, healthy and damaged. The groups of images can be seen in figure 1.

Figura 1. El conjunto de datos de imágenes digitales de frutos: *a)* maduros e inmaduros, *b)* maduros e inmaduros (textura) y *c)* sanos y dañados

Fuente: Elaboración propia

The image sets of ripe, immature, healthy, and damaged peaches for the three scenarios are detailed in Table 1.

Tabla 1. Cantidad de imágenes para cada conjunto de datos de imágenes digitales.

Durazno completo	Duraznos maduros e inmaduros	Área de textura	Cantidad	Durazno completo	Cantidad
Maduros entrenamiento	160	Maduros entrenamiento	200	Sanos entrenamiento	320
Maduros validación	40	Maduros validación	40	Sanos entrenamiento	160
Inmaduros entrenamiento	128	Inmaduros entrenamiento	100	Dañados entrenamiento	80
Inmaduros validación	32	Inmaduros Validación	20	Dañados validación	40
Total	360	Total	360	Total	600

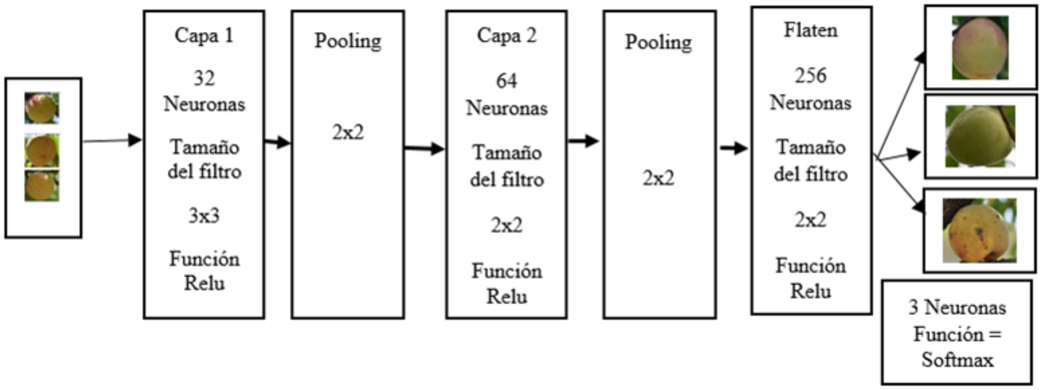
Fuente: Elaboración propia

The digital image data sets have been classified considering that cutting the peach involves detecting the ripe fruit and cutting. However, when the fruit is damaged, it should be cut but separated from the healthy, ripe fruit. Unripe fruits should not be cut until they reach maturity.

Model

The CNN used has three layers with 2 × 2 and 3 × 3 filters. The first two layers include pooling action. CNN has as input the images of the data sets. In the output, the classification data is obtained in two or three categories. Details can be seen in figure 2.

Figura 2 Arquitectura de la CNN usada para el entrenamiento



Fuente: Elaboración propia

Layer one has 32 3 × 3 neurons and the Relu function is applied. Next, layer two has 64 2 × 2 neurons and the Relu function. Third, the Flaten layer includes 256 neurons, a 2 × 2 filter, and the Relu function. Finally, the Dropout layer has three neurons and the Softmax function, which means that the category is classified with the highest similarity value found during recognition.

It should be noted that, with 560 images and 25 epochs, another classification of peaches was made: ripe, immature and damaged. After training, 60 images were tested.

Results

A test with 64 images was applied for each case. True positives, true negatives, false positives and false negatives were obtained, which allowed obtaining other indicators related to precision, sensitivity and specificity, see Table 2.

Tabla 2. Resultados obtenidos durante las pruebas con 64 imágenes

	Matriz de confusión			Precisión	Sensibilidad	Especificidad
Duraznos maduros e inmaduros		Positivos	Negativos	95.31	93.93	96.77
	Positivos	31	1			
	Negativos	2	30			
Duraznos maduros e inmaduros (textura)	Positivos	25	7	84.37	89.28	80.55
	Negativos	3	29			
Duraznos sanos y dañados	Positivos	31	1	92.18	88.57	96.55
	Negativos	4	28			

Fuente: Elaboración propia

In the results, a precision of 95.31% is observed when classifying ripe and immature peaches, that is, only 1 out of 20 peaches is classified badly. On the other hand, with the images in which only the texture was considered, a lower value was obtained, 84.37%; this means that 3 out of 20 peaches are misclassified. Finally, 92.18% was obtained when classifying healthy and damaged peaches: at least 2 out of 20 peaches would be classified badly.

From the classification of three categories, the confusion matrix presented in Table 3 was obtained.

Tabla 3. Matriz de confusión de la clasificación de duraznos dañados, inmaduros y maduros.

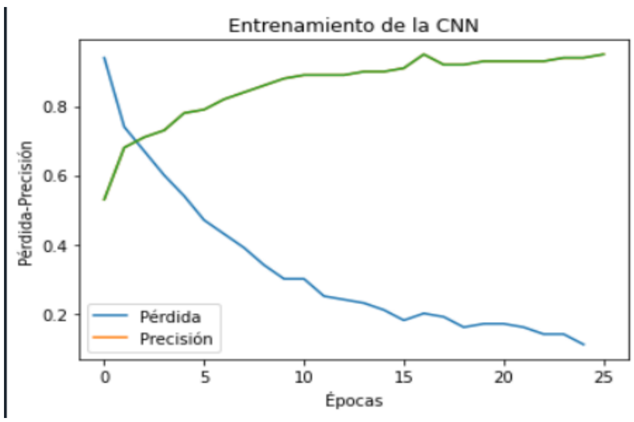
Duraznos	Dañados	Inmaduros	Maduros
Dañados	19	0	1
Inmaduros	4	14	2
Maduros	3	0	17

Fuente: Elaboración propia

During the training, in the classification of the three categories, a precision of 95.54% was obtained. While during the tests with 60 images, the accuracy of 83.33% was obtained, by dividing the true positives of the three categories by the total of units to be classified. This classification is key since the algorithm must identify the type of peach once the image is obtained.

The behavior of loss and precision during the 25 epoch training can be seen in figure 3.

Figura 3 Comportamiento de la pérdida de la precisión



Fuente: Elaboración propia

You can see a loss with a trend of 0.0, while a precision with a trend of 100%.

Discussion

CNNs have various areas of application. However, regardless of the area, the robustness of the data set is essential: it must be the result of a systematic taking of images in optimal conditions of the characteristics that are to be considered as classifying features. Also, the CNN model complements the correct identification of particular interests in the images. As the training of a CNN must serve for real cases, then the data set must have balancing characteristics, that is, the same number of images for the different groups to be used. Similarly, the number of images for validation should be sufficient to avoid overfitting or standardization of CNN images.

Here an accuracy of 95.31% was obtained when classifying ripe and unripe peaches. However, when three classes were involved, namely mature, immature and damaged, an accuracy of 92.8% was obtained. That is, despite the fact that the third group had their physical characteristics very explicit within the images, it was a factor for the precision to decrease considerably. Thus, more research should be carried out, application of specialized networks so that the classification of more than two groups has better results.

Conclusions

After analyzing the results, it can be concluded that the precision suggests that the classification developed here can be implemented in a machine that could harvest peaches in an automated way.

It is also important to note that images that only show the texture of the peach detract from the results, so it is best to use the full image of the peach.

Classifying the three categories showed acceptable results, with an efficiency of 83.33%, which implies that it hits four and fails one out of every five classifications.

When working with CNN it is convenient to do it with a large amount of data (data set of photos) and thus improve precision. The more photographs, the more likely it is to increase reliability.

Future lines of research

This work can be of great support for new research related to the classification of fruits at harvest time, or for the classification and application of prices. It is important to note that CNNs perform better with a greater number of uncontrolled images. Images can be sourced from businesses, farmers, and more.

Once the classification of peach fruit between ripe and unripe, as well as healthy and damaged peaches, has been taken care of, future research will focus on algorithms to classify by size, since peach fruits can have different dimensions, and among that variety the market can require certain minimum sizes. Thus, the fruits that are smaller in size than that accepted by the market can be discriminated. The other line of research will be the classification of the fruit by shape. It is known that the market can reject fruits that are deformed, despite complying with the required maturity and size, among other factors, so that it is possible to discriminate fruits that do not have the roundness that the quality standard demands. useful for producers. Finally, as a third line of research, it will be to try to generalize the method and model so that it is able to work with other fruits. The set of algorithms could be incorporated into a fruit sorting machine just by adjusting the sorting parameters. The application of CNN is infinite.

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Rol de Contribución	Autor (es)
Conceptualización	Sergio Ruíz
Metodología	Dolores Arévalo, Sergio Ruíz
Software	Dolores Arévalo, Sergio Ruíz
Validación	Dolores Arévalo, Sergio Ruíz
Análisis Formal	Dolores Arévalo, Sergio Ruíz
Investigación	Dolores Arévalo
Recursos	Dolores Arévalo
Curación de datos	Dolores Arévalo
Escritura - Preparación del borrador original	Dolores Arévalo
Escritura - Revisión y edición	Dolores Arévalo, Sergio Ruíz, Joel Ayala
Visualización	Dolores Arévalo, Sergio Ruíz, Joel Ayala
Supervisión	Sergio Ruíz, Joel Ayala
Administración de Proyectos	Sergio Ruíz, Joel Ayala
Adquisición de fondos	Dolores Arévalo