Fruit Defect Detection Using CNN Models with Real and Virtual Data

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Paula Gonzalez
Escuela Superior Politécnica del Litoral (ESPOL)

Luis Enrique Chuquimarca Jiménez
Universidad Estatal de la Península de Santa Elena

Boris X. Vintimilla
Escuela Superior Politécnica del Litoral (ESPOL)

Fruit Defect Detection Using CNN Models with Real and Virtual Data

Renzo Pacheco[1,a], Paula González[1,b], Luis E. Chuquimarca[1,2,c], Boris X. Vintimilla[1,d] and Sergio A. Velastin[3,4,e]

[1] *ESPOL Polytechnic University, ESPOL, CIDIS, Guayaquil, Ecuador*

[2] *UPSE Santa Elena Peninsula State University, UPSE, FACSISTEL, La Libertad, Ecuador*

[3] *Queen Mary University of London, London, U.K.*

[4] *University Carlos III, Madrid, Spain*

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Abstract: The present study seeks to evaluate different CNN models in order to compare their performance in recognizing a range of defects in apples and mangoes to ensure the quality of the production of these foods. Using the CNN models, InceptionV3, MobileNetV2, VGG16 and DenseNet121, which were trained with a dataset of real and synthetic images of apples and mangoes covering fruit in acceptable quality condition and with defects: rot, bruises, scabs and black spots. Training was performed with variations on the hyper-parameters and the metric is accuracy. The MobileNetV2 model achieved the highest accuracy in training and testing, obtaining 97.50% for apples and 92.50% for mangoes, making it the most suitable model for defect detection in these fruits. The InceptionV3 and DenseNet121 models presented accuracy values above 90%, while the VGG16 model obtained the poorest performance by not exceeding 80% accuracy for any of the fruits. The trained models, especially MobileNetV2, are capable of recognizing a range of defects in the fruits under study with a high degree of accuracy and are suitable for use in the development of automation applications for the quality assessment process of apples and mangoes.

1 INTRODUCTION

The food industry is subject to strict quality standards that govern all parts of the food production process. In addition, ensuring the quality of food is of the utmost importance for health. Therefore, the production of high-quality food implies that the products meet acceptable characteristics (color, odor, texture, shape, and defects) for inspectors and consumers. According to the Food and Agriculture Organization (FAO), in Latin American countries between 10% and 20% of harvested fruits and vegetables are discarded for various reasons, including non-compliance with quality standards (Munesue et al., 2015).

The early identification of defects in fruits is important to ensure the quality of these foods, to maintain their nutritional value and the satisfaction of the final consumer, and to avoid financial losses for producers. Currently, manual processes are used to inspect the quality of fruits. These techniques are slow, imprecise and give room for the appearance of defects that cause the fruit to be rejected in quality controls or by consumers. To solve this problem, machine learning techniques have been studied to assess fruit quality more quickly and accurately.

The present work seeks to perform an evaluation of CNN models for the detection of defects in apples and mangoes. The evaluation is performed using a set of real and synthetic images as input data to train and validate the models. The defects to be identified are: rot, bruises, scabs and black spots, caused by insects, diseases, climatic conditions and post-harvest handling.

This article is organized as follows: Section 2 contains a review of fruit defect identification. Section 3 describes the proposed methodology to develop the work. Section 4 presents the results of the identification of apples and mangoes with defects using existing CNN models in the state of the art. Finally, conclusions are given in Section 5.

[a] https://orcid.org/0000-0001-8162-4533
[b] https://orcid.org/0000-0003-1302-9550
[c] https://orcid.org/0000-0003-3296-4309
[d] https://orcid.org/0000-0001-8904-0209
[e] https://orcid.org/0000-0001-6775-7137

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2 LITERATURE REVIEW

This section defines the different types of defects considered in this study and their corresponding causes. In addition, current research and advances in defect detection techniques applied to apples and mangoes are outlined.

2.1 Fruit and Vegetable Defects

Within the food industry there are several quality control processes for fruits and vegetables that determine the quality of the food, based on parameters such as: color, odor, flavor, morphology and the presence of defects (Zhang et al., 2014). Each of these aspects is analyzed in detail to identify critical points in the appearance of the fruit or vegetable, and thus determine whether it is prone to deteriorate or lose its nutritional value before reaching the final consumer.

To determine what type of defect is associated with a fruit or vegetable, imperfections need to be grouped into specific categories that define a possible cause of food defects. The categories that divide these defects, depending on harvesting practices, subsequent handling and storage conditions according to (Nturambirwe and Opara, 2020):

- **Pathological Disorders.** These defects are caused by pathogenic microorganisms such as viruses, bacteria, and fungi. The presence of these pathogenic entities mainly accelerates the ripening of the fruit until it rots (Nturambirwe and Opara, 2020).
- **Mechanical Damage.** Environmental factors and post-harvest handling are the main causes of this type of damage. It manifests as variations in the external coloration of the fruit and lesions, these conditions in turn accelerate ripening and facilitate the development of infections (Nturambirwe and Opara, 2020).
- **Physiological Disorders.** These disorders manifest as changes in fruit flavor, texture and color and are caused by poor plant nutrition and unsuitable temperatures during fruit development (Nturambirwe and Opara, 2020).
- **Morphological Disorders.** These damages refer to the presence of changes in the normal appearance and shape of the fruit. This type of defects do not usually entail an alteration of the intrinsic qualities of the fruit such as its chemical composition, nutritional value, odor, color, however, they impair its aesthetics (Nturambirwe and Opara, 2020).
- **Internal Defects.** These defects are those that are not apparent to the naked eye and may be precursors of other types of disorders of physiological, morphological or mechanical damage (Nturambirwe and Opara, 2020).

2.2 Apple and Mango Defects

For the purpose of this project, defects in apples and mangoes, which can be analyzed visually and are the most common in quality control tasks for these fruits, are explored (see Figure 1). The following defects are considered:

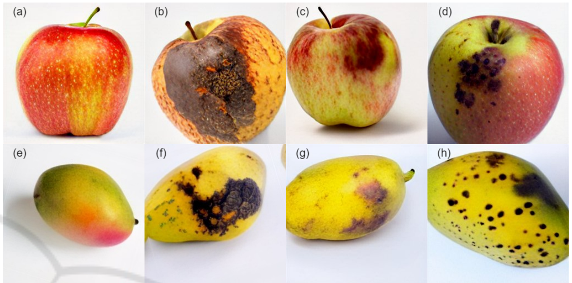

Figure 1: DALL-E mini generated synthetic images of apple and mango defects: (a) fresh apple, (b) rotten apple, (c) bruised apple, (d) scabbed apple, (e) fresh mango, (f) rotten mango, (g) bruised mango, (h) mango with black spots.

- **Rot.** This defect originates from various factors such as physical damage caused by the environment, insects and also bacterial and fungal infections according to (Enicks et al., 2020). This defect is observable to the naked eye and causes changes in the coloration and texture of the fruit skin, the skin turns brown, darkens progressively and loses firmness. When appearing at the post-harvest stage, the infections that cause this defect can continue to spread slowly even during storage under ideal conditions.
- **Bruises.** According to (Nguyen et al., 2022) bruises on fruits such as mangoes result from improper handling during handling and packing. In general damage caused by bruising does not go through the skin, but changes the coloration and texture of the affected part. This is a type of defect considered mechanical damage.
- **Scabs.** Scabbing is one of the most common conditions on apples. This type of defect is caused by fungal infections on both leaves and fruit, as indicated by (Koetter et al., 2019). Unlike a bruise, which does not affect the nutritional and chemical properties of the fruit, scab makes the fruit inedible. This defect is manifested by cracked, dry and dark colored skin in the affected area.

- **Black Spots.** According to (Crane and Gazis, 2020) black spots appear on mango as a symptom of infection by bacteria such as Xanthomonas axonopodis pv. mangiferaeindicae. The symptoms of infection include the appearance of star-shaped lesions that expand and darken over time. Even the slightest degree of infection causes the fruit to lose its quality and sales potential.

The defects selected for the study, were chosen based on the availability of data for training the CNN models with publicly available databases and the review of other studies where these defects are also subject to analysis. Rot and bruising were determined as defects to be analyzed in common for both fruits. In addition, two defects that occur more frequently in each fruit, scab in apples and black spots in mangoes, were selected.

2.3 Fruit Defect Detection Techniques

The grading and inspection of fruit quality is carried out with the purpose of providing the consumer with a product free of externally perceptible physical defects and with the assurance that the chemical properties and nutritional value of the product have not been altered. The main external characteristics evaluated to assign a quality grade to fruits and vegetables are color, texture, size, shape and the presence of defects. These indicators are key for the identification of conditions such as diseases that can contaminate entire productions as suggested by (Omar and MatJafri, 2013).

Research by (Fu et al., 2022) indicates that quality control of fruits and vegetables is commonly performed manually, with trained personnel identifying defects. However, human intervention in this process makes it susceptible to failures either by omission, ambiguous grading criteria, and the number of defects that personnel must be able to recognize. (Omar and MatJafri, 2013) argue that defects such as bruising and rot do not always manifest themselves to a degree that allows differentiation from a healthy area of fruit, which is a challenge for computational evaluation techniques that use criteria such as color, texture and size to perform the analysis.

The use of CNN models is one of the most studied methods for fruit classification and defect detection. (Wu et al., 2020) describe this type of neural networks that implement convolution layers where matrix operations are performed between the input image matrix and a smaller matrix called kernel, to extract features from the input images. These networks also employ pooling layers for the purpose of reducing the size of the output of the convolution layers. Some CNN models apply regularization processes to avoid overfitting, e.g., dropout. Finally, CNN networks perform classification by means of a fully connected layer that receives a one-dimensional or flattened vector as output from the convolution layers.

The study of (Pathak, 2021) proposes a fruit defect detection method based on CNN models. They used a proprietary model and the pre-trained models AlexNet, Le-Net-5, VGG16 and VGG19, to detect rot in apples, bananas and oranges. The results generated indicate that this method is effective in the classification of defective and non-defective fruits achieving an accuracy of 98.23% with their proposed model and 90.81% with VGG16, the model with second best performance. In that study it was found that the transfer learning methods were less effective than the proposed model, however, the training of the models was performed with only 4035 apple images for the two categories ”fresh” (1693) and ”rotten” (2342).

According to (Wu et al., 2020), CNN models can be used for the detection of fruit defects at the pre-harvest and post-harvest stages. In the case of apples, one of the subject fruits of this study, using the AlexNet model with 11 layers, an accuracy in the identification of defective fruits of 92.5% was achieved having hyperspectral images. In the study of (Fu et al., 2022), rot detection in apples was also performed with RGB images as input obtaining the lowest Mean Squared Error (MSE) and standard deviation with the AlexNet model, followed by VGG11.

For defect detection in mangoes the MobileNetV2 network model achieved an average accuracy of 73.33% in the research of (Zheng and Huang, 2021). The defects detected for the assignment of a quality grade were the presence of black spots and blemishes on the outside of the fruit. In apples, bruising can be evidenced by spots on the outside of the fruit and in the study of (Arango et al., 2021) the DenseNet121 model is the most effective with an MCC of 0.978%, performing the analysis on a dataset of RGB images and compared with AlexNet, ResNet-18, ResNet-50 and VGG19 models.

In the experiments of (Miah et al., 2021), one of the most promising results for identifying rot-related defects in both apples and mangoes was obtained, reaching an accuracy of 97.34%, these being the highest metrics achieved with the InceptionV3 model.

Table 1 details the results of the state of the art review for fruit defect detection using CNN models, recording the models, metrics and data used in these studies.

The studies presented differ in the size of their databases, the partitioning of the data for training and validation, the hyper-parameters selected, and the de-

Table 1: Comparison of CNN models performance for defect detection on apples and mangoes.

Fruit	Defect	CNN Model	Metric	Performance
Apple (Karakaya et al., 2019)	Rot	ResNet-50	Accuracy	97.00%
Apple/ Mango (Miah et al., 2021)	Rot	InceptionV3	Accuracy	97.34%
		Xception		97.16%
		VGG16		96.54%
		MobileNet		95.57%
		NASNetMobile		75.29%
Apple (Pathak, 2021)	Rot	VGG16	Accuracy	90.81%
		VGG19		76.48%
		LeNet-5		82.93%
		AlexNet		83.56%
Apple (Fu et al., 2022)	Rot	GoogleNet	MSE	4.404
		VGG11		3.934
		AlexNet		4.099
		ResNet		4.058
Apple (Arango et al., 2021)	Bruises	VGG19	MCC	0.969
		RestNet-50		0.970
		DenseNet121		0.978
Mango (Zheng and Huang, 2021)	Black spots	SqueezeNet	Accuracy	96.94%
		ResNet-50		86.67%
		Enhanced		96.67%
		MobileNetV2		73.33%
Apple (Khan et al., 2021)	Scabs	VGG16	Accuracy	87.50%

fects they cover in their input images. These studies limit the databases to less than 4000 images on average and less than 2000 images per category. On the other hand, the defects covered in the mentioned studies are limited to categorizing the input images according to the presence or not of defects, which may influence the ability of the models to detect certain types of defects with less presence in the dataset.

In the following section, the methodology used for data collection, training and evaluation of the models is detailed. The selected databases and the process of refinement and data augmentation are presented. Likewise, the generation of a synthetic image database is detailed. In addition, the architecture of the selected models and the training process with the adjusted hyper-parameters will be presented.

3 PROPOSED METHODOLOGY

The following section describes the methodology used to obtain the dataset and the training of the CNN models selected for the identification of defective fruits. On the other hand, the aspects of the process carried out to reach the necessary amount of real and synthetic images of apples and mangoes are detailed. In addition, a brief description of each model chosen for the training and subsequent evaluation is shown.

3.1 Image Acquisition Techniques

There are several image acquisition methods available depending on the characteristics and defects of the fruit to be analyzed.

To capture real images, cameras in the RGB domain are used to explore surface defects that manifest themselves in changes of color and texture of the fruit skin, as in the study by (V G and Pinto, 2021). It is also possible to use hyperspectral cameras as used in (Wu et al., 2020) where images were obtained to detect scabs, bruises, rotting and other defects in apples.

In the case of synthetic images, some techniques can be highlighted to create this type of image. The generation of synthetic datasets is not a new practice, in (Charco et al., 2021) 3000 images generated in a virtual environment with the CARLA software were used for the estimation of camera poses using the CNN ResNet-50 architecture with modifications. Also, by means of Ray Tracing it is possible to recreate objects in virtual environments using the properties of light rays.

The proposal of (Kolker et al.,) consists of modeling objects in 3D to use software to create a realistic visualization of the object after performing calculations based on the behavior of light directed at it from different angles and sources. This technique pursues this photorealism using natural laws of light propagation, reflection, and refraction, which depend on the materials.

(Plowman, 2016) indicates that other methods for generating synthetic images include modeling and rendering the objects in tools such as Blender and Unreal Engine, allowing greater control over the desired characteristics and conditions in the dataset. Since 3D modeling from scratch can be a slow and expensive process, an alternative for generating synthetic data is the capture of 3D models using LiDAR sensors and applications that use the data from these sensors to reconstruct objects in a virtual environment.

Finally, there is the possibility of using recently published tools to generate synthetic images using machine learning systems such as DALL-E and DALL-E mini models. These types of systems are capable of generating high-resolution images (in the case of DALL-E) from input text describing the desired conditions and details of objects or scenes, (Han et al., 2022).

In this research work, the dataset generation was performed by collecting real images obtained with RGB sensors and available in public databases, and additionally, synthetic images were generated using DALL-E mini from short descriptions of the fruits with the defects selected for the study.

3.2 Dataset Generation

The input dataset is composed of real and synthetic images. A total of 20,000 images make up the dataset with 10,000 for each type of image. The real images were collected from various sources online including image repositories, databases, and galleries. The synthetic images were generated using DALL-E mini. The dataset contains images of the previously selected defects as well as the fruits in a fresh state. Real and synthetic datasets of apple and mango images, with and without defects, are provided publicly at https://github.com/luischuquim/Healthy-Defective-Fruits.

The reason for generating synthetic images was to increase the volume of input images, given the low availability of public datasets with specific images of the defects selected for classification. The generation of the synthetic image dataset was performed using the DALL-E mini text-to-image model. This model is based on the BART language encoding model and the VQGAN language decoding model can generate images from short text, according to (Swords et al., 2022). Using the web application available in the HuggingFace community it was possible to obtain synthetic images for the defect categories of both fruits.

Given the variety in the quality of the datasets obtained and generated, it was necessary to refine them. The real image datasets were manually inspected to eliminate images that did not correspond to the selected defect classes and images of low quality. In addition, in certain datasets, it was necessary to edit the size of the images so that they contained only the region of interest, i.e. the fruits. Due to the lack of real image datasets for the specific defects it was necessary to apply data augmentation techniques such as randomly applying transformations, contrast changes and rotations to the images using the OpenCV and Albumentations libraries by means of Python scripts.

In the case of the synthetic dataset, refinement was performed by manual selection of the images generated by DALL-E mini due to the variety of images generated in each batch and their relevance to the given descriptive text. Finally, the size of the images was standardized to 256x256 pixels to reduce the size of the dataset for training. Although the classification performed during the experiment is binary, i.e., the images were classified according to the presence or absence of defects in the fruits, the amounts of input images were balanced for each type of defect. Table 2 shows the amount of images for each fruit and category in the dataset.

3.3 CNN Model Training

For training, the input images were organized in directories by fruit (apple and mango), each with 10,000 images and a partition of 80% for training, 10% for testing (only real images), and 10% for validation.

The models selected for this study were MobileNetV2, InceptionV3, VGG16 and DenseNet121. By means of the Keras and Tensor Flow libraries it is possible to load the models and apply modifications to them. First, the models were loaded using the weights obtained from training with the ImageNet dataset. In addition, the block of fully connected output layers was eliminated, since it was used for multiclass classification, therefore, it must be adjusted to the current binary classification problem.

For the binary classification task it is necessary to adjust the fully connected output layers of the models. For all models a dense layer with 1024 units and ReLU activation function was used, followed by a dropout layer, then another dense layer with 512 units and ReLU activation function. Finally, a layer of 2 units and softmax activation function is used to obtain the one hot encoded vector with the classification. It was decided to study the effect of the dropout layer on the performance metrics obtained by the models, so three types of tests were performed, one without using the dropout layer and the other two with dropout rate of 0.2 and 0.5, in order to mitigate overfitting.

A total of 36 training runs were conducted based

Table 2: Dataset distribution.

Fruit	Category	Dataset size			
		Real images	Synthetic images	Total per category	Total
Apple	Fresh	2500	2500	5000	10000
	Rot	1000	1000	2000	
	Bruise	750	750	1500	
	Scab	750	750	1500	
Mango	Fresh	2500	2500	5000	10000
	Rot	1000	1000	2000	
	Bruise	750	750	1500	
	Scab	750	750	1500	

on a combination of the fruit, CNN model and the following hyper-parameters: optimizer (RMSprop), learning rate (0.001), batch size (16), and epochs (10, 20, 30).

4 RESULTS

This section details the results of the CNN models evaluation based on the previously described methodology. For each fruit, a total of 36 training runs were performed with variations in the CNN models, the number of epochs and dropout rates used.

4.1 Results with the Apple Image Dataset

Table 3 shows the results obtained for the dataset of images of apples with and without defects for the four selected models and the dropout rate and epoch variations. The best results for the test accuracy for each model are highlighted.

Table 3: Comparison of CNN model accuracy with apple image dataset.

CNN Model	Accuracy
InceptionV3	93.40
MobilenetV2	97.50
Densenet121	94.50
VGG16	76.20

In the results obtained for these training runs, a trend can be found in terms of accuracy and the combination of epochs and dropout rate. The best metrics for the accuracy of the test dataset were achieved with the training of 30 epochs and dropout rate of 0.2.

Results show a trend where the accuracy improves while training with more epochs and using a low droput rate of 0.2. Also, not using dropout layers of applying a dropout rate higher than 0.5 causes the accuracy to decrease, possibly due to the loss of information in the dense layers.

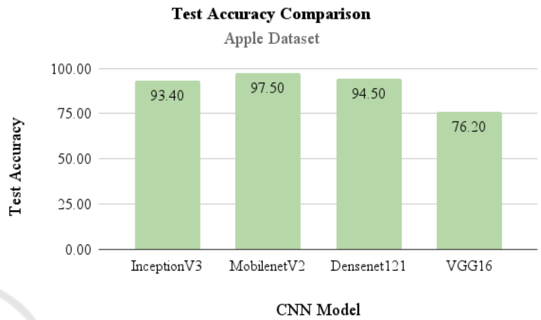

Figure 2: Defect detection accuracy for apple dataset.

As seen in Figure 2 the MobileNetV2 model recorded the highest accuracy with the test dataset at 97.50%. The InceptionV3 and DenseNet121 models presented similar percentages in this metric with 93.40% and 94.50% respectively. The VGG16 model presented the lowest accuracy with 76.20%.

Another metric considered in this analysis is the loss during each training iteration. With this metric it is possible to determine how effective is the defect detection during training, with the 30 epochs training 3 of the 4 models (all except InceptionV3) managed to reduce this metric below 0.5.

The high values for the loss metric indicate that there is a large difference between the values of the results and the expected values. In the case of the InceptionV3 and MobileNetV2 models, there is a possibility of overfitting, given the high values in the loss function while showing accuracy above 90%. This overfitting phenomenon usually occurs in dense models since the gradient step must occur throughout the neural network. Another cause of overfitting when using CNN is the lack of regularization mechanisms that allow the network to learn without memorizing, an alternative to the dropout used in the training of this study is the batch normalization according to (Goutam et al., 2020). These models are able to recognize with a high degree of efficiency the images belonging to the dataset, but present errors recognizing new images. To mitigate this problem with these models, it is possible to perform training with fewer epochs and experiment with more variations in the dropout layer.

4.2 Results with the Mango Image Dataset

For the other case study fruit, mango, the results obtained with the selected models resemble those obtained with the apple image dataset. The training runs were performed using the same hyper-parameters mentioned before. Table 4 shows the performance of the models for this dataset. The row corresponding to the best result obtained in the test accuracy for each model is highlighted.

Table 4: Comparison of CNN model accuracy with mango image dataset.

CNN Model	Accuracy
InceptionV3	91.90
MobilenetV2	92.90
Densenet121	92.50
VGG16	63.60

The best results for these training runs were found with the configuration of 30 epochs and dropout rate of 0.2 for the MobileNetV2 model, with 92.90% accuracy reached in testing. For the InceptionV3 and DenseNet121 models, the best performance in the test dataset was obtained with the 20 and 30 epoch configurations respectively, both without using dropout layer resulting in accuracy values of 91.90% and 92.50% respectively. For this dataset and fruit the VGG16 model underperformed reaching only 63.60% accuracy during testing, as shown in Figure 3.

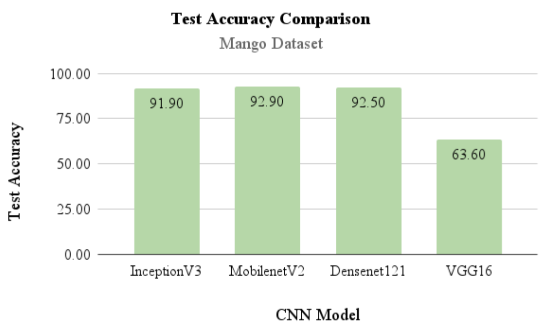

Figure 3: Defect detection accuracy for mangoes dataset.

As the number of epochs increased, the resulting accuracy remained stable and did not vary abruptly, except with the VGG16 model. The architecture of this model is quite extensive and includes hundreds of millions of parameters, it is possible that a stabilization of the obtained accuracy is achieved by training with more epochs. In the training with the mango image dataset, all models obtained values higher than 90% from early epochs, indicating a high recognition rate of the input images and the low presence of false positives and false negatives in the results.

For this training dataset, the loss function values were lower than with the apple dataset. After the 30 epochs, all models managed to reduce this metric to less than 0.50.

In the case of the InceptionV3 model, it is possible that overfitting exists given the loss values above 0.50 obtained with 20 and 30 training epochs. For this specific model, better results can be obtained by training fewer epochs or applying variations with the dropout layer.

5 CONCLUSIONS

During the dataset creation module it was possible to collect a considerable amount of images (20,000, that is: 10,000 images for apples and 10,000 images for mangoes). This dataset contains real images and synthetic images, for the case of real images public databases were used and for the case of synthetic images the text-to-image system DALL-E mini was used. The dataset that was obtained comprises images of healthy and rotten fruits, in addition to images of defects based on the presented definitions of bumps, scabs and black spots.

Since the evaluation of CNN models for defect identification is a study that has already been carried out, as an improvement we proposed the compilation of a more robust dataset, not only in quantity but also in quality. Also, the use of DALL-E mini allowed to generate images for training purposes, these images contain only the fruits with the desired defects and free of background elements and noise. These defects were represented with an equal number of images in the dataset. Therefore, the CNN models were able to identify the mangoes and apples with different types of defects.

The previously generated dataset was used to evaluate the performance of the 4 CNN models, the purpose of which was to identify whether the fruits under study in this project (apple and mango) are defective or fresh fruits. In addition, the identified defects are: rot, bruises, black spots and scabs. The 4 models chosen for this study were, MobileNetV2, InceptionV3, DenseNet121 and VGG16, with accuracies in the testing stage of: (0.975, 0.929), (0.934, 0.919), (0.945, 0.925) and (0.762, 0.6360) respectively; the values in parentheses correspond to ”apple, mango” results. As a result of the training and evaluation of the models it was possible to determine that MobileNetV2 is the CNN model that best fits the need for binary classification for defect detection in apples and mangoes.

As future work, it is proposed to implement a multiclass classifier CNN model to classify images by each defect found. In addition, we will focus on the implementation of more powerful architectures such as transformers for the detection of defects in fruits.

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