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Article *in* Procedia Computer Science · March 2022

DOI: 10.1016/j.procs.2022.01.200

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 200 (2022) 13–20

Procedia Computer Science

www.elsevier.com/locate/procedia

3rd International Conference on Industry 4.0 and Smart Manufacturing

Machine Learning-Based Digital Twin for Monitoring Fruit Quality Evolution

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Abstract

A technological gap to monitor fruit quality evolution in the food supply chain is causing a huge waste of fruits. A digital twin is a promising tool to minimize fruit waste by monitoring and predicting the status of fresh produce throughout its life. In post-harvest engineering, the digital twin could be defined as a virtual representation of real produce. The objective of this work is to present a new approach to create a machine learning-based digital twin of banana fruit to monitor its quality changes throughout storage. The thermal camera has been used as a data acquisition tool due to its capability to detect the surface and physiological changes of fruits throughout the storage. In this study, after constructing the dataset of thermal data belonging to four classes, the training of the model has been performed using intelligent technologies from SAP. The solution has applied a deep convolutional neural network to monitor the fruit status based on the thermal information, and the training process has shown higher accuracy. Thus, 99% of prediction accuracy has been achieved which is proved to be a promising technique for the development of fruit digital twins. The application of thermal imaging techniques can be used as a data source to create a machine learning-based digital twin of fruit that can minimize waste in the food supply chain.

Keywords: digital twin; thermal images; machine learning; image classification; food waste

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10.1016/j.procs.2022.01.200

1. Introduction

Food waste is a big problem for environmental, economic, and food security reasons. Around the globe, the volume of food waste is estimated to be 1.6 billion tonnes of which 81% of this amount is in acceptable conditions for human consumption [1]. Fresh fruit and vegetables have been identified as the main contributor to the number of wasted foods. Research showed that while fruits and vegetables comprised a whopping 85% of food waste by mass, they only contributed to 46% of the wasted carbon footprint [2]. For instance, only in Italy, 34% of the total wasted weight at the retailer level is from fruit and vegetables. Apple, lettuce, pear, banana, pepper, grape, sweet, and tomatoes are fruits and vegetables in “hotspot categories”, contributing to most of the waste [3]. As a part of this category, banana is among commonly wasted fruits where the effects during handling and storage have a severe impact on the appearance quality of the fruit through causing brown to black discoloration of the skin called a bruise.

So far, retailers do not have good visibility to monitor the real-time status of fruits in the stock and find themselves wasting huge volumes of food. Digital twin (DT) technology is believed to be a promising tool to monitor the status of fresh fruit. The report indicates the use of mechanistic models to develop the DT of fresh produces that simulates the thermal behavior of fresh produce throughout the cold chain using measured temperature data [4]. However, identifying an appropriate data acquisition system for fruits is still challenging. To overcome this challenge, controlling the level of bruise using infrared thermal cameras is noteworthy. A bruise is a damage to fruit tissue that causes physical changes of texture or chemical changes of color, smell, and taste resulting in spoilage. The extent of bruising is partly dependent on physiological and biochemical properties, and environmental conditions such as temperature, humidity, and several other postharvest treatments [5], and the risk is high in matured fruits. Storage duration can also increase the sensitivity of fruit to bruising or tissue damage [6–8]. Thermal imaging is an emerging, non-contact technique suitable for the fruit and food industry and is commonly used for fruit safety and quality assessment [7, 9–12]. It can monitor a product without sample extraction that can cause permanent damage. The infrared thermal imaging detects temperature differences between bruised tissues and sound tissues caused by the difference in thermal diffusion coefficients [13]. The utilization of this technology allows detecting the heat given off by an object in the form of infrared radiation. This radiation generates electrical signals and provides images (heat map). Fruit with bruises has a lower reflection since damaged cells beneath the skin become filled with water. Hence, infrared radiation penetrates the skin and reaches this water accumulation where it will be more strongly absorbed compared to undamaged fruit flesh [14]. This leads to contrast in thermal images where the bruises appear darker than undamaged parts from the same fruit. More interestingly, the detection of thermal images works well in all brightness levels to distinguish the targets easily from the background depending on the radiation difference. This technique is very efficient to detect bruises before they become visible to the naked eye [14]. Through this principle, thermal images that are captured in specific ranges made it possible to distinguish between areas with defects in the tissue and the sound ones [15].

Recently, there are several reports on the application of IoT technologies in smart farming and post-harvest. However, many of these inventions are not described under DT applications. The details on present trends of DT in postharvest supply chains have been reported [16]. There are also pieces of evidence to suggest that machine learning and deep learning techniques can be applied using images from crops and other agricultural products. For instance, reports by [17, 18] have indicated the potential use of optical sensors in the inspection of vegetables, fruits, and crops with machine learning approaches. Similarly, generic algorithm approaches have been applied using neural networks to identify different tissues of cherry [18]. The application of neural network classifiers has been found very effective to grade banana fruit [19]. This work has indicated the potential implementation of the result in sorting banana fruit in the production factories. The study by [20] has also proposed the use of neural networks in the determination of ripeness of the banana using RGB color components of banana captured on daily basis until its full rotting. Reports have proven that the application of machine learning has shown superior results in agricultural applications including image classification (leaf picking) by robotic systems [21] and in fruit detection, segmentation, and counting [22, 23]. More specifically, deep learning has been found effective in image classification [24] and therefore, the technique has become more candidate in the internal defect detection of fruits.

DT is a virtual representation of merely anything: it can be either an object, product, or asset [25, 26]. It establishes the link between a physical entity and its virtual counterpart [27, 28] enabling simulation, analysis, and control. It is a dynamic software simulation model of a thing or system that relies on a sensor or other data to understand its state, respond to changes, and improve operations. In post-harvest, DT can be defined as a virtual representation of fresh horticultural produce that contains essential components and material properties connected to the real-world product and processes by sensor data, which is preferably continuously updated in real-time throughout the product's life-cycle [16]. It realistically represents a fruit mirroring its behavior, thus enabling to monitor fruit status based on the level of product defect.

Creating a DT of food products is still at a conceptual level. Siemens [29], one of the leading companies in the application of DT, has proposed the development of DT of food products containing all information about ingredients, receipts, production processes, status, and location to ensure food security, sustainability, and to minimize risks related to environmental pollutions. Similarly, a report by [30] has proposed a solution to monitor and detect the physical damage of fruits during the supply chain process where 20% of product damage is occurring. In this context, an IoT platform service was designed to generate predictive insights that can support the decision-making processes of agricultural producers and exporters by reducing waste. The system uses fruit-shaped devices (DTs) that mimic the physical characteristics of real fruit. This device travels along with the fruits during transportation and captures all the information's through sensors. The information is processed by the IoT cloud platform to detect failures in the process and forecast future product damages. Recently, advances in applications of DT in the post-harvest sector have been reported by [4, 16, 29]. This report has indicated potential uses of DT in many areas including cold chain operations, product, and process design, food traceability, supply chain logistics, and food safety.

This paper seeks to propose a methodology for creating a DT of fruit using a thermal camera as a data source. The proposed solution has been aimed to help retailers and other stakeholders involving in the fruit supply network by enhancing the visibility of their stock. It has also described the use of a deep convolutional neural network (CNN) in the creation of machine learning-based DT. The manuscript is organized as follows. Section 2 illustrates the proposed solution architecture. Section 3 describes the research approach whereas section 4 presents the evaluation of the model. Section 5 provides concluding remarks in the article.

2. Conceptual Framework

A DT is one of the promising solutions to prevent wastes along the food supply chain. A DT of a certain product can be defined as a virtual replica of its real-world counterpart with all basic elements including product properties and geometric information including shape, size, and structural components of produce. It should also be able to simulate accurately and realistically all relevant changes throughout the product's life cycle. Moreover, it should be connected to the real-world product using sensors that can continuously update information in real-time (Fig.1).

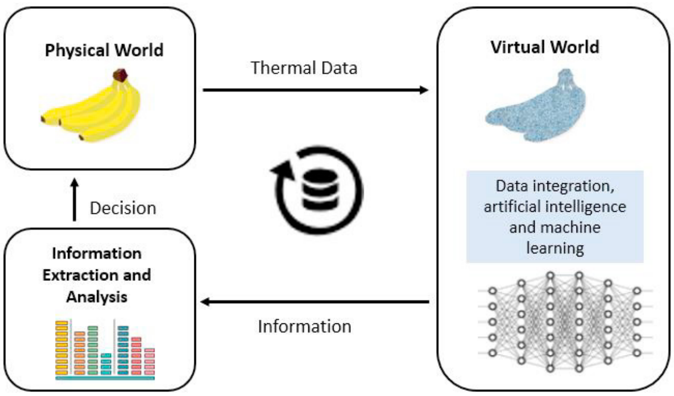

Fig. 1. Digital twin of fruit produce

In the proposed framework, the sensor data that feeds the DT will be stored and processed by the platform, as shown in Figure 2. The implementation process follows different steps including the integration of smart components into new or existing products, connecting the products or services to a cloud-based location with streaming, Big Data, and analytics capabilities to capture sensor data, constantly analyzing the data, and final utilization of digital insights to transform the food retail business.

The DT solution will have mainly two layers: the first layer is the IoT edge that can connect the thermal camera with IoT cloud services. Thermal cameras can be connected using a WiFi gateway and an MQTT message broker will be required if cameras are more than one. The second layer of the proposed solution is IoT cloud service that can offer business services and other capabilities to address different use cases like supply chain, product, and service management. This architecture can use SAP Edge Services Cloud Edition to connect the IoT sources to Cloud Services, and SAP Document Services to store the picture from the network of thermal cameras. SAP Intelligent service is used for image classification and prediction of the quality of every single fruit during storage. Similarly, SAP Asset Intelligent Network collects the forecast data and monitors the digital replica of the fruit, and notifies the end-users. FooDT client - Retailer Front-End is a custom responsive Web Application proposed for the end-user to provide an easy representation of the SAP Asset Intelligent Network notification for the end-user to support their decision-making process. Based on this information, the end-user can take action to save the product from loss.

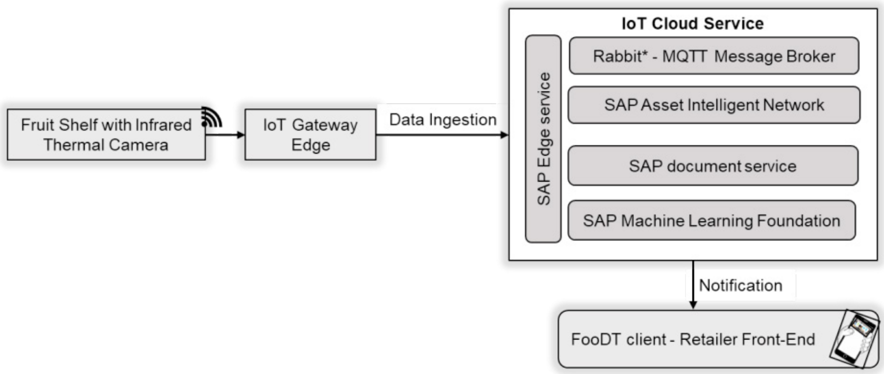

Fig. 2. The architecture of the proposed solution

The category of fruit status was proposed based on the daily experience and the trends followed by the retailers (Fig. 3). Accordingly, the label *'fresh'* is given for fruits that can fully satisfy the interest of customers, and fruits that are predicted as *'good'* are still with good market value and force the retailers to provide some discounts. Similarly, fruit under the class of *'bad'* is the status with a high degree of wastage, but it can still be donated to charity organizations or any user to save a life. After all, if proper follow-up is not applied, the fruit will be exposed to the risk of wastage which in this case is labeled as *'rotten'*.

This solution will have a significant impact on the optimization of logistics infrastructures such as warehouses and food distribution centers improving visibility. During inventory operations, the DT can be constantly updated with data collected from food products using this technology. Its implementation will largely be managed from the cloud to make quick decisions in real-time (near real-time). With the implementation of this solution, retailers will have a clearer picture of the contents of their inventories, with more visibility towards food products that are becoming eligible for redistribution before the waste happens. Besides, this solution can solve problems related to storage spaces by unused items.

3. Research Approach

To create a DT of banana fruit a thermal imaging technique was used as a data acquisition tool to evaluate product quality based on temperature changes. The mages captured by the thermal camera have been used as an input dataset for CNN training. These images provide underlying physiological information on the status of fruit using machine learning which can offer an effective prediction. More specifically, deep learning has been used for classification purposes. Image classification using thermal images is based on the patterns of the image captured by infrared thermal cameras. In this training, a supervised type of machine learning technique has been applied. This type of machine learning is mainly based on training inputs and desired outputs (called "labels"). This technique is becoming more effective and its application in image processing and classification has increased tremendously.

3.1 Collection of datasets

The dataset was created by the images captured using FLIR One thermal camera. The images were collected during different phases of storage time. Before starting the training process, the dataset of fruit images was categorized into four grades identified as *fresh, good, bad,* and *rotten* (Fig. 3)

Fig. 3. Four classes of the dataset used during training of the model

The predictive model has been trained in the SAP intelligent service [31]. TensorFlow, a powerful deep neural network architecture has been used as part of the Intelligent technologies offered by SAP. It is a popular framework for machine learning open-sourced by Google. The framework includes deep neural networks and advanced predictive modeling capabilities.

For the retaining purpose, the training dataset contains 3968 images while the validation and test dataset were created using 496 images under each category containing four labels. The training dataset consists of 80% of the data from the original training set, while the remaining 20% of records were being allocated to the validation and test dataset.

3.2 Deployment of the model

The training algorithm was evaluated in two stages including training and inference. The learning stage is used to describe the data and built a trained model. In the learning process, the image needs to be transformed into a vector representation. This representation is used by the learning algorithm in which the algorithm chooses a model and efficiently searches for the model's parameters.

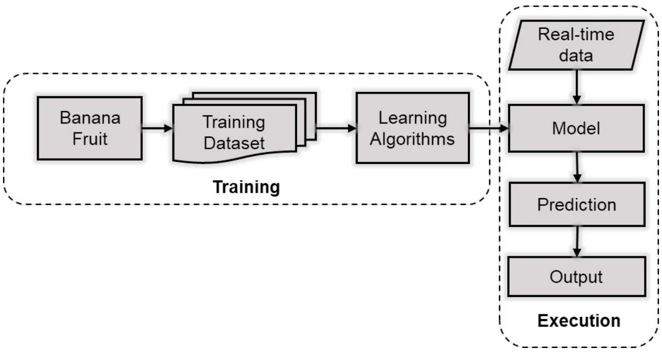

Fig. 4. Model training and execution process

The inference stage uses the trained model to make predictions about new data. The process uses feature vectors as a representation of real-world data that can be used by training and inference components. It is the process used to test the model performance on new data to observe the performance providing the final predictive power of the model. The inference stage uses the model to make intelligent remarks about new data. This is equivalent to applying the model in real-life cases. In the scenario of DT, the process will use real-time data captured by the thermal camera.

Once it is trained, the concept of DT can be implemented by injecting real-time data into the trained neural network (Fig. 4). Therefore, the prediction will be executed based on the historical data stored in the SAP Document cloud storage and the end-users will receive the notification about the status of the product.

4. Model Evaluation

Convolutional neural networks are a special kind of multi-layer neural network (Fig. 5). It is a well-known feed-forward network that can extract topologic details from an image. They can train with the back-propagation algorithm to recognize patterns from images. In feature extraction, all neurons in a feature share the same weights (but not the biases). Weight is responsible for the steepness of the activation function. It increases the steepness of the activation function and determines the speed of triggering for the function while bias is a constant which helps the model in a way that it can fit best for the given data. Based on this concept, all neurons detect the same feature at different positions in the input image.

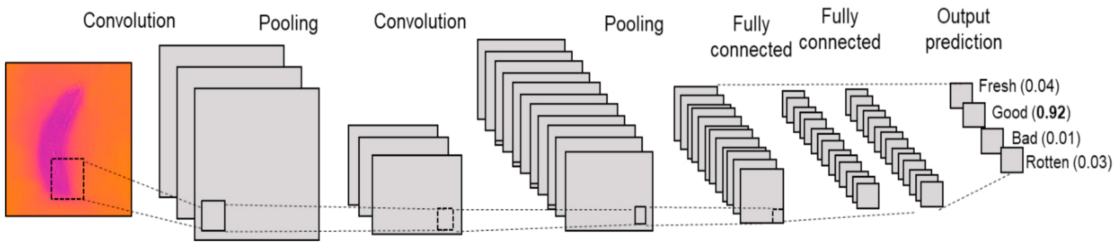

Fig. 5. Principle of Convolutional Neural Networks

In CNNs, the convolutional layer is considered as the core building block of the neural network aimed to extract the features. The layer consists of a set of learnable filters (kernels) that are used to recognize patterns from the image. Convolution works by sliding the filter over the input image and takes the dot product between the filter and chunks of the input image. The pooling (subsampling) layer reduces the size of the feature maps by using some functions to summarize sub-regions and each grid will create value. This layer controls overfitting, and it works by sliding a window across the input and feeding the content of the window. Therefore, the main purpose of pooling is to reduce the number of parameters in the network and to make learned features more robust by making them more invariant to scale and orientation changes.

The fully connected layer is fully connected with the output of the previous layer. It takes all neurons in the previous layer and connects them to every single neuron it has. Adding a fully connected layer is also a way of learning non-linear combinations of these features.

Model Performance

The model performance was mainly evaluated through accuracy and loss. The training accuracy shows the percentage of the data used in the current dataset that were labeled with the correct class and the validation accuracy shows the precision of randomly selected images from a different class. While the loss indicates how well the model is performing with the training and validation dataset. It's calculated using the summation of the errors made for each example in training or validation sets. The loss function calculates the difference between the predicted values and actual values of the training data while accuracy compares the classified image to another data source that is ground truth data. Learning rate is another key component that can affect the convergence of neural networks during training.

It has a significant influence on epochs. A small learning rate causes the training process to take several epochs to converge and vice versa. In this training, an optimized learning rate has been used.

After the training, the model is found to have a summary with batch size, learning rate, the total number of training epochs (the number of passes of the entire training dataset), best accuracy, final test accuracy, predict top classes, and the starting and lasting time of training as described in Table 1. The model is trained over 150 epochs; however, no improvement was found after epoch_21.

Table 1. Training summary

Properties	**Value**
Training batch size	64
Learning rate	0.001
Total training epoch	150
Epoch with the best accuracy	6
Best validation accuracy	0.99
Predicted top classes	4
Final test accuracy	0.99

The main objective of the training is to make the loss as small as possible. Thus, the end of training shows promising results with an average training accuracy of 99% and validation accuracy of 99% which indicates the decent performance of the image classifier. At the end of the training, cross-entropy loss and validation-cross entropy losses have significantly decreased to be 0.005 and 0.08, respectively. This was followed by model testing with various new images which has shown a positive result. After the completion of the training phase, the model has successfully predicted the status of the fruit.

The performance of the model is promising to create machine learning-based DT of fruits. This is a step forward to help stakeholders involving in the fruit supply chain. Because monitoring of the fruit status manually by operators is expensive, tedious, laborious, and inherently unreliable due to its subjective nature. Therefore, the application of machine learning-based DT in this area can be considered as a new approach in the food supply chain to reduce operation time, cost, and improve the decision-making process.

5. Conclusion and Future Works

This work has used SAP intelligent technologies to test a methodology for machine learning-based DT of banana fruit. This approach has been used to test the capability of thermal imaging techniques in capturing real-time data from fruit that will enable retailers to monitor the status of the product before the loss occurs. This approach has been tested with banana fruit; however, it can be also easily implemented using other fruits. In this paper, a promising result has been achieved to minimize fruit waste along the food supply chain. This work is expected to contribute new value for retailers and enhance collaborations amongst stakeholders in the fruit supply chain network.

The thermal imaging technique is found to be a promising data acquisition system to capture defects of fruits during the development of fruit DT. Analysis of temperature distribution on the product can serve as an indicator to evaluate the defects on the product. In the study, the environmental temperature was not fully controlled. Although detection of thermal images works well in all brightness levels to distinguish the targets easily from the background depending on the radiation difference, there is still a challenge to maintain its accuracy. The accuracy is highly dependent on environmental and weather conditions thus it may not be possible to implement in areas with no temperature control.

Further developments will be required to validate this methodology with other fruits. In addition, the research will need to integrate the required components with SAP Intelligence Service. Besides, future work will focus on developing a supply chain DT to analyze the food supply chain behavior based on different scenarios.

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