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Convolutional Neural Network as a Tool for Predicting Fruit Quality and Freshness Based on Images

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Abstract. The lack of technology that can monitor changes in fruit quality in the supply chain can result in a large amount of fruit being wasted. Digital imagery can be used to reduce fruit wastage in monitoring and predicting fruit quality throughout its life. In post-harvest engineering, digital images can be used as virtual representations of real products. This research will present a new approach to monitor the quality changes of banana fruit with machine learning-based imagery, using a thermal camera to acquire data with its ability to detect surface area and physiological changes of banana fruit. In this research, model training has been performed using intelligent technology from SAP after the thermal data dataset has been built. By using thermal information to monitor the status of the fruit, this solution utilizes a deep artificial neural network. The training process has shown that it is more accurate. Therefore, the thermal imaging technique has been used as a data source to create a machine learning-based digital twin of the fruit that can reduce waste in the food supply chain. Thus, 99% prediction accuracy has been achieved.

Keywords: d*igital imagery, machine learning, CNN*

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1. Introduction

So far, fruit suppliers do not have good visibility to monitor the quality of fruit in real time in large stocks and end up only being killed if they find that the fruit stock is reduced / damaged. Convolutional Neural Network (CNN) technology with Machine Learning is believed to be a tool for monitoring the quality of fresh fruit, a mechanistic model that uses fruit images to simulate the behavior and thermal changes of products using measured temperature data [4]. However, the challenge is to identify the right data acquisition system. For this reason, controlling the degree of bruising with infrared thermal cameras must be considered. Bruising is an indication of damage to the fruit tissue that causes physical and textural changes (chemical changes such as color, odor and taste) that can cause spoilage of the fruit. Physiological and chemical properties, environmental conditions, temperature, humidity and producer treatment affect the degree of bruising of the fruit [1].

Thermal camera imagery is the best technique without touching the fruit that can monitor fruit products without sample extraction that can damage the original fruit [2]. This thermal technology can monitor the temperature difference in fruit bruise tissue caused by thermal diffusion coefficients, within the infrared radiation of the thermal camera. The resulting electrical signal will generate a heat map of the fruit image. The color of the bruise on the fruit has a low reflection because the damaged cells below are filled with water, so it can be penetrated by infrared radiation and absorbed a lot compared to the flesh of the fruit, so it looks more contrast [5]. This technique works better in all brightness levels of bruises that distinguish tissues easily depending on the radiation, before being viewed directly with the eyes. By doing so, the thermal image of the fruit image can distinguish the defective or healthy tissue under the fruit skin. [6].

Recently, there have been several reports on the application of IoT technologies in smart agriculture and post-harvesting[7]. However, many of these findings are not described in terms of digital imagery applications. Details on the current trend of digital imagery in the post-harvest supply chain have been reported. There is also evidence to suggest that machine learning and deep learning techniques can be applied using images of crops and other agricultural products[8]. For example, reports have indicated the potential use of optical sensors in the inspection of vegetables, fruits, and crops with machine learning approaches[9]. Similarly, a generalized algorithmic approach has been applied using neural networks to identify different cherry tissues. The application of neural network classifiers has proven to be very effective for grading banana fruit. This research has shown the potential application of the results in sorting banana fruits in production factories. Studies have also proposed the use of artificial neural networks in the determination of banana ripeness using the RGB color components of bananas taken daily until the banana decays completely[10]. Reports have proven that the application of machine learning has shown superior results in agricultural applications including image classification (leaf picking) by robotic systems and in fruit detection, segmentation, and counting[11].

More specifically, deep learning has been shown to be effective in image classification and therefore, this technique has become more of a candidate in fruit internal defect detection. A digital image is a virtual representation of anything: it can be an object, product, or asset. Digital images establish a relationship between a physical entity and its virtual counterpart that enables simulation, analysis, and control[12]. This research produces a technique to see the quality of banana fruit images in real time with a thermal camera as a data source [13]. This solution is to help farmers or those interested in supplying fruit to improve visibility of fruit stocks. This research also describes the implementation of Convolutional Neural Network (CNN) in the use of machine learning-based images [14].

2. Methods

This research proposes the application of digital imagery to prevent waste in the food supply chain. A digital image is a virtual replica of a product that includes all basic elements such as properties, shape, size, and structural components, and can simulate changes throughout the product's life cycle. The product will be connected to the real world through sensors that update information in real-time.

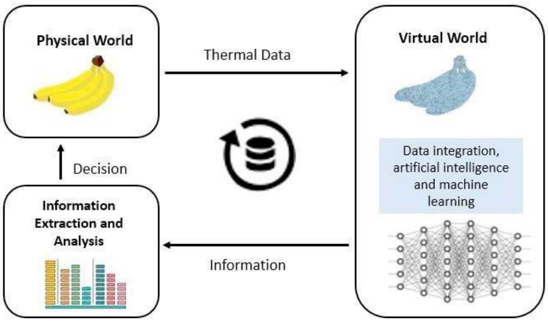

Figure 1. Digital Twin Of Fruit Produce

Sensor data will be stored and processed by a cloud-based platform. Implementation includes integration of smart components, connecting products to the cloud, and continuous data analysis to transform the food retail business. The solution consists of two main layers: IoT edge that connects thermal cameras with IoT cloud services, and IoT cloud services that handle supply chain management and services. SAP Edge Services, SAP Document Services, and SAP Intelligent are used for image classification and fruit quality prediction during storage.

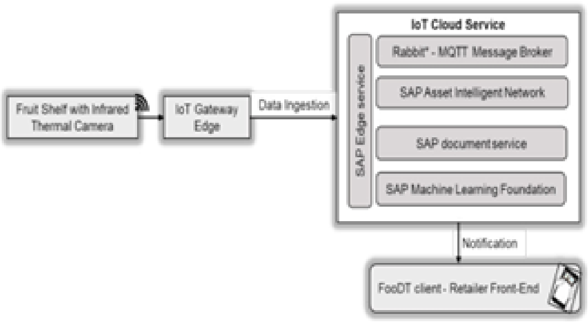

Figure 2. Solution Architecture

Fruit status categories ('fresh', 'good', 'bad', 'rotten') are proposed based on daily experience and retailer trends. This solution is expected to improve the visibility and optimization of logistics infrastructure, enable quick real-time decision-making, and address storage issues with unused items. This research utilizes a banana fruit imaging method with a thermal camera used as a CNN training input dataset so that it can acquire data as a material for evaluating fruit quality by looking at temperature changes [15]. The image provides physiological characteristics as a basis for fruit quality using machine learning that will provide effective prediction of fruit status.

3. Results and Discussion

The data from the images are captured with a FLIR One thermal camera and collected during different storage phases. The images will be classified into 4 classes namely fresh, good, bad and rotten [16]. The predictive model has been trained using SAP intelligent services. In this process, TensorFlow, a powerful and popular artificial neural network architecture from Google, is used as part of SAP's intelligent technology[17]. TensorFlow is well-known in machine learning for its capabilities in deep neural networks and advanced predictive modeling[18]. For storage purposes, the training dataset contains 3,968 images, while the validation and testing datasets each contain 496 images in each category with four labels. The training dataset consists of 80% data from the original training set, while the remaining 20% is allocated to the validation and testing datasets[19].

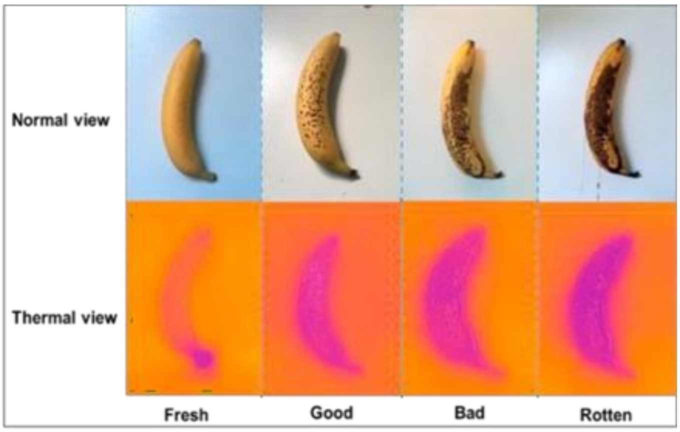

Figure 3. Classes of data modeling

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3.1 Model Deployment and Evaluation

The training algorithm is evaluated through two stages: learning and inference. The learning stage is used to describe the data and build the trained model. In this stage, images are transformed into a vector representation, which is then used by the learning algorithm to select an appropriate model and find model parameters efficiently [20].

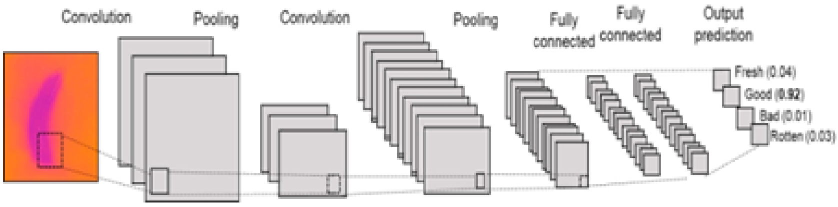

Figure 4. Model training process

The inference stage uses the trained model to make predictions about new data. This process utilizes feature vectors as a representation of real-world data that can be used by the training and inference components. This stage tests the performance of the model on new data to evaluate the final predictive ability of the model. Inference allows the model to make intelligent decisions about new data, similar to the application of the model in real-life situations. In the context of digital imagery, this process uses real-time data captured by a thermal camera. Once the training is complete, the digital image concept can be implemented by feeding real-time data into the trained neural network (Figure 4). Predictions are then made based on historical data stored in the SAP Document cloud storage, and end users will receive notifications regarding product status.

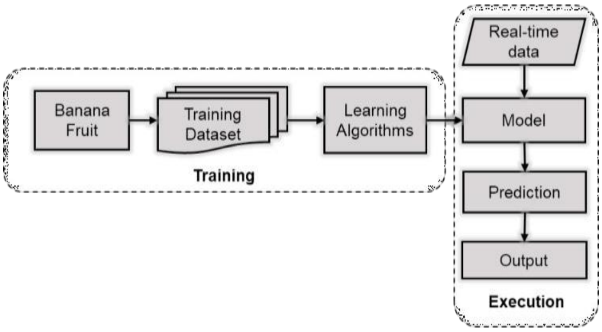

Figure 4. CNN Principle

Convolutional artificial neural networks are a special type of multi-layer neural network (Fig. 5). It is a feed-forward network that is well known for its ability to extract topological details from an image. It can be trained using back propagation algorithms to recognize patterns in images. In the feature extraction process, all neurons in a feature have the same weight (no bias). These weights control the steepness of the activation function and the triggering speed of the function, while the bias is a constant that helps the model adjust to the given data. Based on this concept, all neurons detect the same feature at various positions in the input image.

3.2 Model performance

The performance of the model is evaluated mainly based on accuracy and loss. Training accuracy measures the percentage of correctly labeled data in the training set, while validation accuracy indicates the accuracy of randomly selected images from different classes. Loss assesses the performance of the model by calculating the number of errors that occur for each example in the training or validation set. The loss function measures the difference between the predicted and actual values, while the accuracy compares the classification results with the ground truth data. In addition, the learning rate is an important factor that affects the convergence of the neural network during training.

The learning rate affects the training process significantly. A low learning rate can slow down the convergence of the model, requiring more epochs to achieve stable results, while a high learning rate can speed up the process. In this training, the optimized learning rate is used. After training, the model was summarized with information such as batch size, learning rate, total number of epochs (number of iterations through the entire dataset), best accuracy, end-of-test accuracy, top class prediction, and training start and end times, as listed in Table 1. The model was trained for more than 150 epochs, but there was no significant performance improvement after the 21st epoch. The main objective of this training is to minimize the loss. The final training results show excellent performance, with training and validation accuracy reaching 99% respectively, signifying the effectiveness of the image classifier. At the end of training, the cross- entropy loss and validation-cross entropy loss decreased significantly to 0.005 and 0.08. Testing the model with new images also showed positive results, and the model successfully predicted the fruit status.

Table 1. Training summary

Properties	Values
Training group size	64
Learning level	0.001
Total training time	150
Epoch with best accuracy	6
Best validation accuracy	0.99
Top class prediction	4
Final test accuracy	0.99

The performance of this model is promising for machine learning-based fruit quality identification. This is a significant advancement to support stakeholders in the fruit supply chain. Given that manual monitoring of fruit status is expensive, tedious, laborious, and unreliable due to its subjective nature, the application of machine learning-based quality identification offers an innovative approach to reduce operation time, cost, and improve the decision-making process in the fruit supply chain. Thermal imaging techniques are proven to be an effective data acquisition system for detecting defects in fruits through temperature distribution analysis. However, environmental temperatures that are not fully controlled can affect detection accuracy, especially in areas without adequate temperature control. Therefore, further development is required to validate this methodology with other fruits and integrate the components with SAP Intelligence Service. Future research will focus on developing fruit imagery in the supply chain to analyze the behavior of the food supply chain in various scenarios.

4. Conclusions

This research utilizes SAP intelligent technology to test a machine learning-based banana fruit imagery methodology. This approach evaluates the ability of thermal imaging techniques to capture real-time data from fruit, allowing retailers to monitor product status before losses occur. Although tested with bananas, the methodology can be easily applied to other fruits. The results showed a training and validation accuracy of 99% signifying the effectiveness of the image classifier and great potential in reducing fruit wastage along the food supply chain and is expected to provide added value to retailers as well as improve collaboration among stakeholders in the fruit supply chain network.

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