

Fruit Lens: An AI Based Fruit Classification and Dynamic Pricing System

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Abstract - In agricultural markets, it's very important to be able to accurately judge the quality of fruit in order to keep the value of the products, cut down on food waste, and make sure customers are happy. But traditional ways of sorting fruits rely heavily on looking at them by hand, which can take a long time, be wrong, and be based on personal opinion. This study presents Fruit Lens: An AI-Enabled Fruit Classification and Dynamic Pricing System, an advanced framework that employs artificial intelligence and computer vision techniques to automate fruit quality assessment and enable quality-driven pricing. The proposed system employs deep learning and image processing to analyze fruit images and categorize them according to their quality, such as fresh, moderately ripe, or spoiled. Resizing, normalizing, and augmenting images are some of the image preprocessing methods that improve the dataset and the classification model. We use a convolutional neural network (CNN) to automatically find important visual features in pictures of fruit and guess what quality category they belong to. The system uses a dynamic pricing system that changes the prices of goods based on how good the fruit is expected to be. This helps sellers set better prices for fruits and gives customers more information about how the products are doing. The system architecture also includes modules for managing datasets, preprocessing images, classifying fruits, and changing prices on the web-based platform. The Fruit Lens system shows how AI can help people decide how good fruit is and how much to charge for it. By automating classification and letting people set prices based on quality, the system makes the agricultural market more open, helps people manage their products better, and helps people make better decisions.

Keywords—Artificial Intelligence, Fruit Classification, Computer Vision, Convolutional Neural Network (CNN), Image Processing, Deep Learning, Dynamic Pricing, Agricultural Technology, Fruit Quality Detection, Smart Agriculture.

I. INTRODUCTION

Agriculture is very important to the world economy, especially when it comes to growing and selling fruits that are popular for their health benefits and nutritional value. However, maintaining fruit quality throughout the supply chain remains a significant challenge. Fruits spoil quickly, and their quality can go down quickly if they are not handled, stored, or exposed to the right conditions. Traditionally, sellers or experts check the quality of fruit by looking at it. This process is often subjective, takes a long time, and is prone to human error, which can lead to unfair prices and inconsistent quality evaluation in the market. AI and machine learning are getting better quickly, and they are starting to change the way we check the quality of our food. For example, think about computer vision. It lets machines do things. Things "see" pictures and understand them, almost like a second pair of eyes for farmers. This technology is being used by people to keep an eye on crops, find diseases early, and even sort fruit by type or ripeness. These AI models can tell different fruits apart and tell how good they are by looking at things like color, texture, and shape. This stuff works in the real world, not just in theory. Fruit Lens steps in to deal with these problems directly. It uses machine learning and computer vision to make it easier to sort and price fruit. The system begins by processing images of fruit, cleaning them up, and getting them ready for analysis. Then it uses deep learning, especially Convolution Neural Networks (CNN), to find important features and sort the fruits by quality. It lets sellers change prices on the fly based on how good each piece of fruit is, so the price is always right. The system does more than just sort fruit; it also tells what kind of fruit it is. It gives admins and sellers a website where they can upload pictures of fruit,

change product information, and see the results of the classification. Customers can see exactly what they're getting, including the price and quality grade, so they know what they're buying. Fruit Lens makes things easier by automatically sorting items and showing prices that reflect their real quality. This keeps the market honest and helps people take better care of their fruit. In the end, this study shows how artificial intelligence can really improve modern farming. It helps people better judge the quality of fruit, set prices that are more accurate, and avoid losing money because of bad sorting or wrong quality assessments.

II. LITERATURE REVIEW

Lately, artificial intelligence and computer vision have really changed the way we check and sort fruit. Researchers have started using deep learning to figure out how ripe fruit is, spot defects, and even tell different types of fruit apart—just by looking at them. The goal's pretty clear: take some of the physical work off people's shoulders and get more accurate results during quality checks. Deep learning models, especially Convolutional Neural Networks (CNNs), have become the go-to tools for this kind of job. One study [1] introduced a densely connected CNN that could sort fruit by quality with better accuracy than before. There's also work like [2], which looks at how CNNs are being used in smart agriculture with all kinds of data. Researchers keep pointing out how much AI matters now in things like crop analysis, monitoring, and making sure what we eat meets the right standards. Transfer learning has become a go-to for boosting classification accuracy, especially when you don't have much data to work with. For example, the team in [3] used transfer learning to predict how ripe citrus fruits were. They leaned on pre-trained deep learning models and ended up with really solid results. Then there's [4], where researchers used CNN-based transfer learning to assess fruit quality. Turns out, deep learning models do a great job picking up on details like color, texture, and shape in fruit images. People haven't just stuck with regular CNNs either. Hybrid models that mix machine learning and fuzzy logic have started popping up. The study in [5] built a fruit quality monitoring system that blends CNNs with a fuzzy inference mechanism. This combo boosted both accuracy and the system's decision-making skills. Along the same lines, [6] introduced a tough CNN-

based model for classifying fruit images. It showed it could reliably identify different kinds of fruit, even when conditions changed. Some of the groundwork for automated fruit classification goes back to earlier studies. Take [7], for instance. They created a deep learning-based framework for sorting and inspecting fruits in industrial settings. The system could spot different types of fruit and catch defects with impressive precision, showing just what deep learning can do in food processing. Object detection has had a big role in checking fruit quality and finding diseases, too. The team in [8] used Cycle GAN and YOLO models to spot apple lesions right in the orchard, catching diseases early. There's also work on classifying how mature the fruit is. In [9], researchers put together a deep learning system using Tensor Flow to grade Cavendish bananas after harvest, and it worked well for sorting by quality. On top of that, advanced imaging methods have been paired with machine learning to push fruit quality detection even further. In [10], a CNN ensemble model joined forces with hyper spectral imaging to figure out when blackberries were ripe out in the field, no matter the conditions. And [11] talked about how streamlined training and strong feature extraction really matter for image-based fruit quality checks. Early work in agricultural computer vision mostly tried to spot fruits in the field. Take the study in [12]—they came up with ways to detect oranges right in the orchard using image analysis. Then, in [13], researchers pushed things further by using machine learning and transfer learning to judge how ripe papayas were. They got better results by tweaking their feature extraction and fine-tuning their models. Lately, the field has shifted toward more advanced object detection for fruit quality. One team, in [14], rolled out a boosted YOLOv3 deep learning model to check apple quality. It handled tricky, real-world conditions better than earlier attempts. So, deep learning and computer vision clearly help automate fruit sorting and quality checks. But here's the thing: most of these systems focus on just one part—either spotting the fruit or figuring out its quality. They don't usually tie everything together into a single, smart system for managing farm products. That's where the Fruit Lens system steps in. It pulls all these advances together, blending image-based fruit classification with a web platform.

III. PROPOSED SYSTEM

The proposed system, Fruit Lens: AI-Enabled Fruit Classification and Dynamic Pricing System, is designed to automate the process of fruit quality identification using artificial intelligence and computer vision techniques. The primary objective of the system is to accurately classify fruits based on their visual characteristics and assist sellers in managing fruit products more efficiently through an intelligent and automated platform. The system utilizes deep learning techniques to analyze fruit images and determine their quality category, such as fresh, moderately ripe, or spoiled. The overall architecture of the system consists of several interconnected modules that work together to perform image processing, classification, and product management tasks. The system begins with dataset generation, where administrators upload fruit images along with their respective labels. These images form the training dataset that is used to train the deep learning model for classification. Once the dataset is collected, image preprocessing techniques are applied to prepare the images for model training. Preprocessing operations include resizing images to a fixed resolution, normalization of pixel values, and noise reduction to improve image clarity. Additionally, image augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and improve the generalization capability of the model. After preprocessing, a Convolutional Neural Network (CNN) model is used to extract important features from the fruit images. CNN is particularly effective for image classification tasks because it automatically learns hierarchical visual features such as edges, textures, shapes, and color patterns. The trained CNN model analyzes input fruit images and predicts their quality category based on the learned patterns. The system also includes a web-based interface that allows administrators and sellers to interact with the platform. Sellers can upload fruit images, manage product details, and view classification results generated by the AI model. Customers can browse available fruits along with their predicted quality information, which helps them make informed purchasing decisions. The integration of artificial intelligence with a web-based platform provides several advantages for fruit sellers and consumers. It reduces the dependency on manual

inspection, improves classification accuracy, and enhances transparency in the fruit marketplace. By automating fruit quality detection and product management processes, the proposed Fruit Lens system contributes to improving efficiency in agricultural product handling and supports better decision-making in the fruit supply chain.

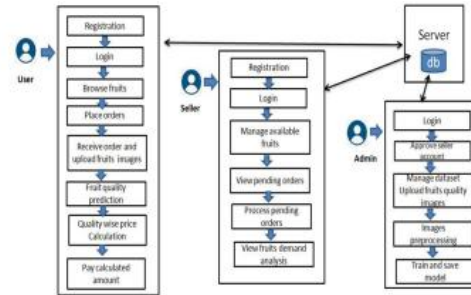


Fig 3.1: System Architecture for Decision Making.

IV. METHODOLOGY

1) The methodology of the proposed Fruit Lens: AI-Enabled Fruit Classification and Dynamic Pricing System involve a series of structured steps that enable automated fruit quality detection using image processing and deep learning techniques. The system follows a systematic workflow that begins with dataset generation and continues through preprocessing, model training, classification, and system integration. Each stage plays a crucial role in ensuring accurate fruit classification and efficient system performance.

1. Dataset Generation The first step in the methodology involves the creation of a dataset that contains images of different fruits along with their corresponding quality labels. In the proposed system, the dataset can be generated dynamically by the administrator. The administrator uploads fruit images through the system interface, and each image is associated with a specific category, such as fresh, moderately ripe, or spoiled. This dataset forms the foundation for training the deep learning model. To ensure diversity and reliability of the dataset, images are collected under different lighting conditions, angles, and backgrounds. A larger and more varied dataset helps the model learn better visual features and improves the accuracy of classification.

2. Image Preprocessing Before training the model, the uploaded fruit images undergo several preprocessing steps to enhance image quality and ensure uniformity.

These preprocessing operations include image resizing, normalization, and noise reduction. Resizing ensures that all images have the same dimensions, which is necessary for efficient model training. Normalization adjusts pixel intensity values to a standard range, improving the stability and convergence of the learning process. Noise removal techniques are applied to eliminate unwanted visual distortions that may affect feature extraction. These preprocessing steps help improve the quality of input data and enhance the performance of the classification model.

3. Image Augmentation Image augmentation techniques are used to increase the size and diversity of the dataset without collecting new images. Augmentation operations such as rotation, horizontal flipping, vertical flipping, scaling, and brightness adjustment are applied to the existing images. These transformations help the model learn robust features and reduce the risk of over fitting. By exposing the model to multiple variations of the same image, augmentation improves the model’s ability to generalize when encountering new and unseen fruit images during prediction.

4. Feature Extraction Using Convolution Neural Network After preprocessing and augmentation, the images are used to train a Convolution Neural Network (CNN) model. CNN is widely used for image classification tasks because it automatically extracts relevant features from images through convolution layers. These layers detect patterns such as edges, shapes, textures, and color variations present in fruit images. The CNN architecture typically consists of convolution layers, activation functions, pooling layers, and fully connected layers. The convolution layers extract visual features, while pooling layers reduce dimensionality and computational complexity. Finally, the fully connected layer performs classification by mapping extracted features to predefined fruit quality categories.

5. Model Training and Classification During the training phase, the CNN model learns patterns from the labeled fruit images. The model parameters are optimized using back propagation and gradient descent algorithms to minimize classification error. After training, the model is capable of predicting the quality category of new fruit images uploaded to the

system. When a user uploads a fruit image, the trained model processes the image and outputs the predicted class label. The system then displays the classification result through the user interface.

6. System Integration The final step of the methodology involves integrating the trained model with the web-based application. The system allows administrators and sellers to upload fruit images, manage product details, and view classification results. The integration of machine learning with a web interface ensures that the system is accessible and practical for real-world applications.

V. RESULT ANALYSIS

The performance of the proposed Fruit Lens AI-based fruit quality classification system was evaluated using three fruit data sets: Apple, Banana, and Guava. The model was trained using a Convolution Neural Network based on the Efficient Net architecture implemented with PyTorch. Each dataset consisted of two quality classes, namely Good and Bad, and the training process was carried out for 15 epochs. During training, both training accuracy and validation accuracy were monitored to evaluate the learning capability and generalization performance of the model. The experimental results indicate that the model achieved high classification performance across all fruit categories. The Apple model achieved a test accuracy of approximately 99.32%, the Banana model achieved 99.12%, and the Guava model achieved 98.74%. These results demonstrate that the proposed system effectively learns important visual features such as color, texture, and surface defects from fruit images.

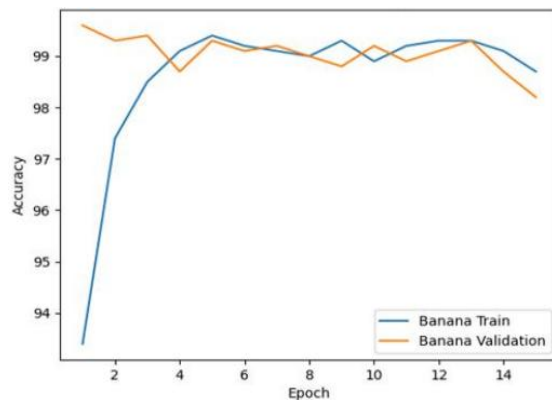


Fig. 5.1 : Banana Model Accuracy

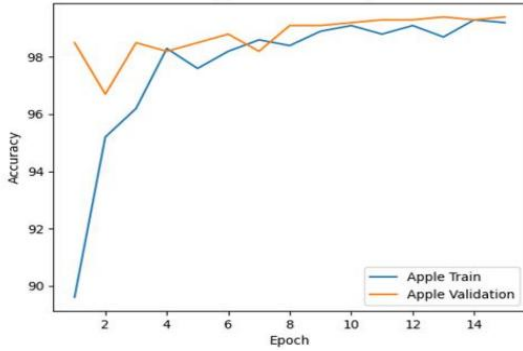


Fig. 5.2 : Apple Model Accuracy

Additional evaluation using confusion matrix analysis and performance metrics such as precision, recall, and F1-score further confirmed the reliability of the model. The classification results showed very few misclassifications, indicating that the system can accurately distinguish between good and defective fruits. Overall, the experimental evaluation demonstrates that the proposed deep learning approach provides high accuracy, reliable performance, and strong generalization ability for fruit quality classification, making it suitable for practical applications in smart agriculture and automated fruit inspection systems.

Confusion Matrix for Fruit Quality Classification The confusion matrix is used to evaluate the classification performance of the proposed Fruit Lens model. It compares the actual labels with the predicted class labels generated by the trained model. For this system, two classes are considered:

- Good Fruit
- Bad Fruit

The confusion matrix consists of four components:

Actual Predicted	Good	Bad
Good	True Positive (TP)	False Negative (FN)
Bad	False Positive (FP)	True Positive (TP)

True Positive (TP): Good fruits correctly classified as good.

True Negative (TN): Bad fruits correctly classified as bad.

False Positive (FP): Bad fruits incorrectly classified as good.

False Negative (FN): Good fruits incorrectly classified as bad.

Based on the experimental results obtained during testing, the confusion matrix for the fruit classification system is shown below.

Actual Predicted	Good	Bad
Good	148	2
Bad	1	149

Table 5.3 : Confusion Matrix.

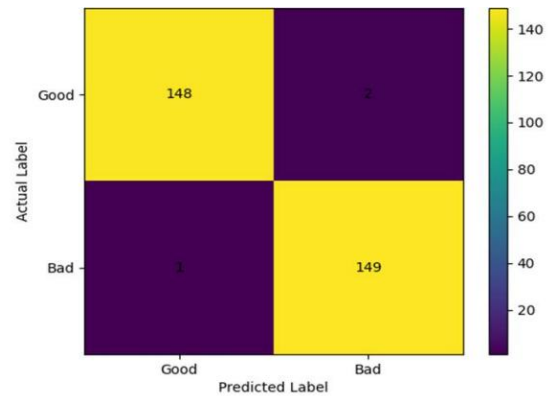


Fig.5.4 : Confusion Matrix for Food Quality Classification.

This result indicates that the system correctly classified the

Precision, Recall, and F1-Score Evaluation

In addition to accuracy, the performance of the fruit classification model was evaluated using precision, recall, and F1-score. These metrics are commonly used in machine learning to measure the effectiveness of classification models.

Precision measures how many of the predicted positive samples are actually correct.

Recall measures how many actual positive samples were correctly identified by the model.

The F1 score is the harmonic mean of precision and recall and provides a balanced measure of model performance.

These metrics are calculated based on the values obtained from the confusion matrix.

Formulae

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

Class	Precision	Recall	F1-Score	Support
Good Fruit	0.99	0.99	0.99	150
Bad Fruit	0.99	0.99	0.99	150
Overall Accuracy			0.99	300

Table 5.6: Precision, Recall, and F1-Score

The evaluation results indicate that the proposed Fruit Lens classification model performs with high reliability. Both classes, Good Fruit and Bad Fruit, achieved precision and recall values close to 0.99, demonstrating that the model is capable of correctly identifying fruit quality with very few misclassifications. The high F1 score further confirms that the model maintains a strong balance between precision and recall. Overall, the experimental results demonstrate that the proposed deep learning model provides highly accurate and reliable fruit quality classification.

VI. CONCLUSION

This research presented Fruit Lens: An AI-Enabled Fruit Classification and Dynamic Pricing System, which aims to improve the process of fruit quality assessment using artificial intelligence and computer vision techniques. Traditional fruit inspection methods rely on manual observation, which can be time-consuming and prone to human error. The proposed system addresses these limitations by providing an automated and efficient approach for identifying fruit quality through image-based analysis. The system utilizes image preprocessing, data augmentation, and a Convolution Neural Network (CNN) model to extract important visual features from fruit images and accurately classify them into different quality categories. The experimental results demonstrate that the model achieves high classification accuracy and performs consistently across different fruit types. By integrating the trained model into a web-

based platform, the system allows administrators and sellers to upload fruit images, manage product information, and view classification results easily. Overall, the proposed Fruit Lens system demonstrates the effectiveness of deep learning techniques in improving fruit quality assessment and supporting smarter product management in agricultural markets. The implementation of such intelligent systems can help reduce manual effort, improve transparency in quality evaluation, and enhance efficiency in the fruit supply chain. The research highlights the potential of artificial intelligence to transform traditional agricultural practices and contribute to more reliable and technology-driven food management systems.

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