# Papaya Seed Adulteration Detection in Black Pepper

Priyanshu Shukla[1], Naveen Kamalla[1], and Jugal Alan[1]

Indian Institute of Technology, Ropar, Punjab, India
{2024csm1016, 2024csm1009, 2024aim1004}@iitrpr.ac.in

**Abstract.** Adulteration of food is a major concern in the spice industry. Among various types, adulteration of black pepper with papaya seeds is a deceptive and harmful practice. This study proposes a deep learning-based object detection model using the YOLOv8s architecture to detect such adulteration. A data set consisting of RGB images was created, covering pure black pepper, pure papaya seeds, and adulterated mixtures. YOLOv8s was trained and evaluated, achieving high seed detection accuracy and low mean relative adulteration error demonstrating its effectiveness for real-time spice purity assessment.

**Keywords:** Object Detection · Computer Vision · YOLOv8s · Food Adulteration · Machine Learning.

## 1 Introduction

Food adulteration remains a critical issue globally, particularly in the spice industry, where visual similarities between adulterants and genuine products make detection difficult [1]. Adulteration not only deceives consumers but also poses significant health risks, compromises nutritional value, and reduces consumer trust in food safety. Among the various forms of spice adulteration, one of the most deceptive is the mixing of dried papaya seeds with black pepper. Due to their close resemblance in size, shape, and color, distinguishing between the two using the naked eye becomes nearly impossible, especially in large-scale handling or packaging processes.

Traditional techniques for adulteration detection, such as chemical analysis or microscopic examination, are often time-consuming, destructive, and unsuitable for real-time applications. With the advent of artificial intelligence and computer vision, deep learning has shown immense potential for developing automated, fast, and non-destructive quality assessment systems [2]. In particular, object detection models based on convolutional neural networks (CNNs) have demonstrated high accuracy in identifying and localizing multiple objects in complex scenes [3].

This study leverages the capabilities of YOLOv8, a recent lightweight and high performance object detection architecture developed by Ultralytics [5], to tackle the problem of spice adulteration. A custom dataset was created comprising RGB images of pure black pepper, pure papaya seeds, and adulterated mixtures in various proportions and arrangements. The YOLOv8s model was trained to detect and classify individual seeds, allowing both qualitative and quantitative analysis of adulteration in real-time scenarios.

The goal of this work is to provide a practical and scalable solution for the spice industry that can be implemented for the detection of adulteration in real time during sorting, packaging or quality control. The proposed model demonstrates strong detection performance and offers a foundation for building more robust food authenticity systems using computer vision and deep learning.

## 2 Dataset

### 2.1 Data Collection

A custom image dataset was developed to train and evaluate the object detection model for identifying adulteration in black pepper with papaya seeds. The dataset comprises high-resolution RGB images captured under natural and controlled lighting conditions using a digital camera. To ensure diversity and robustness, images were collected across different lighting angles, and seed arrangements. The seeds were kept on an A4 white paper. The pure black pepper and papaya seeds images were collected in natural lights but for the adulterated dataset we used the setup shown in figure 1.

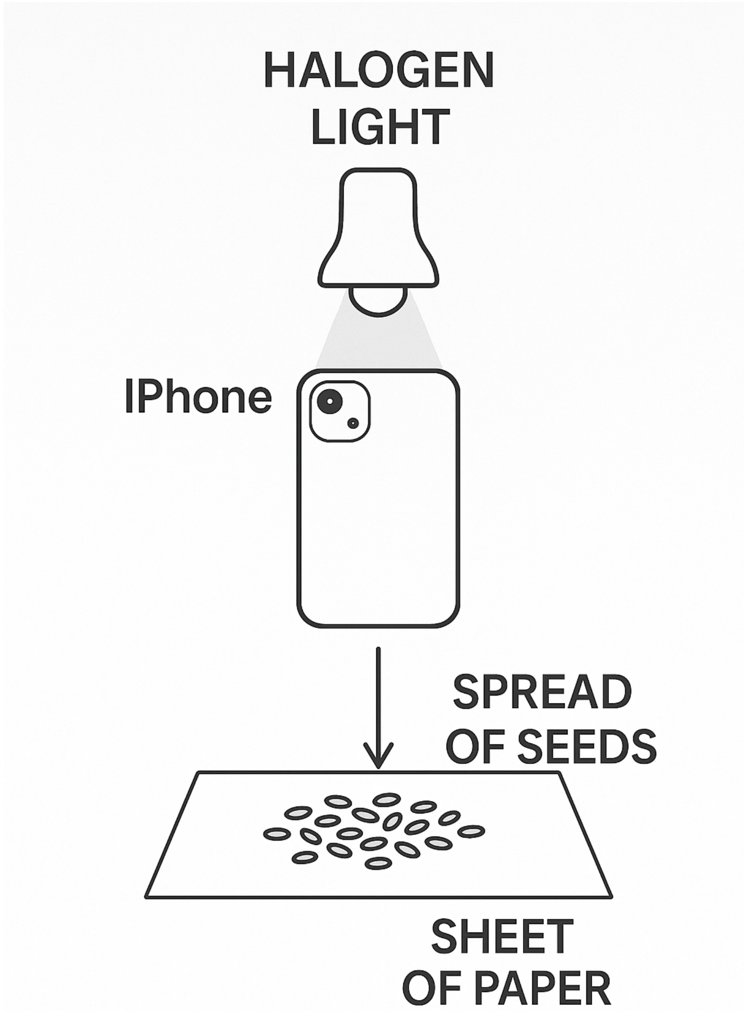



Fig. 1: Experimental setup used for collecting data on black pepper adulteration with papaya seeds. The setup includes a controlled lighting environment where images of adulterated samples are captured using iphone 16 camera (48MP Fusion: 26 mm, f/1.6 aperture, sensor-shift optical image stabilisation, 100% Focus Pixels, support for super-high-resolution photos (24MP and 48MP)) to create a dataset for object detection.

Fig. 2: Pure Black pepper shot

Fig. 3: Pure Papaya shot

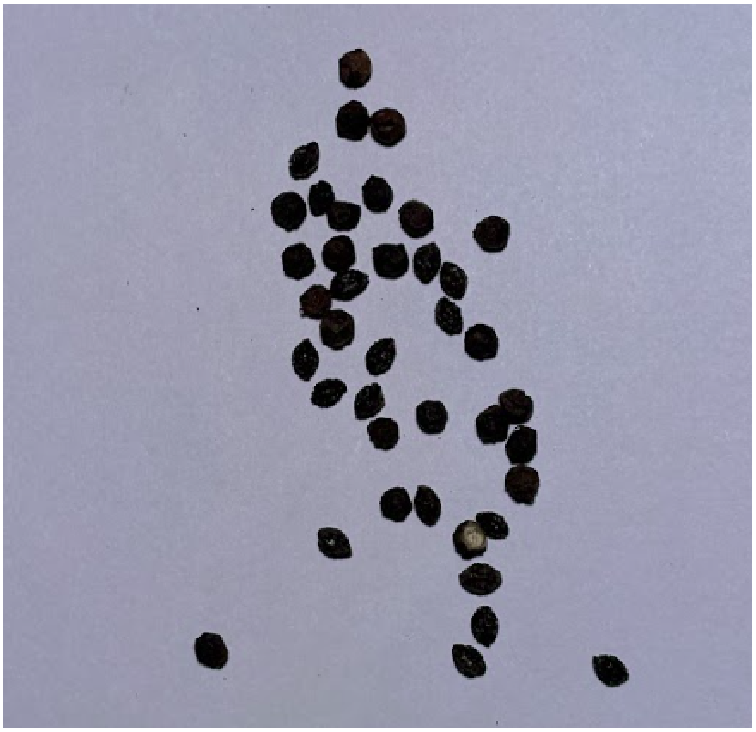


Fig. 4: Adulterated shot

The dataset includes three primary categories:

- Pure Black Pepper: Images containing only single black pepper seeds.
- Pure Papaya Seeds: Images containing only single dried papaya seeds.
- Adulterated Samples: Images of mixed samples with varying proportions of black pepper and papaya seeds as shown in table 1 with 10 spreads of each category (cell), simulating real-world adulteration scenarios.

Table 1: Sample Distribution for Different Proportions of Papaya Seeds(PS) in Adulterated Black Pepper(BP)

| **Sample Size** | **10% Papaya Seeds** | **20% Papaya Seeds** | **40% Papaya Seeds** | **50% Papaya Seeds** | **60% Papaya Seeds** | **80% Papaya Seeds** |
|---|---|---|---|---|---|---|
| 10 | 9 BP, 1 PS | 8 BP, 2 PS | 6 BP, 4 PS | 5 BP, 5 PS | 4 BP, 6 PS | 2 BP, 8 PS |
| 20 | 18 BP, 2 PS | 16 BP, 4 PS | 12 BP, 8 PS | 10 BP, 10 PS | 8 BP, 12 PS | 4 BP, 16 PS |
| 40 | 36 BP, 4 PS | 32 BP, 8 PS | 24 BP, 16 PS | 20 BP, 20 PS | 16 BP, 24 PS | 8 BP, 32 PS |
| 60 | 54 BP, 6 PS | 48 BP, 12 PS | 36 BP, 24 PS | 30 BP, 30 PS | 24 BP, 36 PS | 12 BP, 48 PS |
| 80 | 72 BP, 8 PS | 64 BP, 16 PS | 48 BP, 32 PS | 40 BP, 40 PS | 32 BP, 48 PS | 16 BP, 64 PS |

The final dataset consists of:

- Total images: 1277
- 552 images of pure black pepper
- 425 images of pure papaya seeds
- 300 images of adulterated samples

### 2.2 Data Preparation

To facilitate model training and evaluation, 30 images of sample size 80 were manually annotated using the Label Studio tool [4]. The annotations were saved in YOLO format, specifying the class label along with normalized bounding box coordinates (center x, center y, width, height). Two classes were defined:

0: Papaya Seed
1: Black Pepper

The dataset was organized following the YOLOv8 directory structure, with separate folders for images/train, images/val, images/test and corresponding labels/train, labels/val, labels/test. This ensured compatibility with the Ultralytics training pipeline.

# 3 Model

The detection of adulterants in black pepper was approached using a deep learning-based object detection model, YOLOv8s. YOLO (You Only Look Once) is a family of real-time object detection systems, with YOLOv8 being the latest iteration developed by Ultralytics. The 's' in YOLOv8s stands for the 'small' variant, optimized for lower computational costs while maintaining a good balance between speed and accuracy.

## 3.1 Model Architecture

YOLOv8s features a convolutional neural network backbone designed for real-time detection. Key components of the YOLOv8s architecture include:

- **Backbone:** CSPDarknet-based backbone with feature extraction layers that downsample the input image while learning robust representations.
- **Neck:** A feature pyramid network (FPN) structure that merges features from different scales to improve object localization across varied object sizes.
- **Head:** A detection head that predicts bounding boxes and class probabilities directly from multiple scales, using anchor-free methods for simplified training and improved precision.

## 3.2 Training Configuration

The model was trained using the Ultralytics YOLOv8 pipeline on a dataset prepared as described in the previous section. Key training parameters include:

- **Input size:** $640 \times 640$ pixels
- **Batch size:** 16
- **Epochs:** 100
- **Optimizer:** SGD with momentum
- **Learning rate:** 0.01
- **Loss function:** Combination of objectness loss, classification loss, and box regression loss (CIoU Loss)
- **Data augmentation:** Mosaic, flipping, rotation, and brightness adjustment enabled via Ultralytics built-in augmentation

## 3.3 Training Infrastructure

Training was performed on Google Colab using a Tesla T4 GPU with 16GB VRAM. The model was trained on the manually annotated dataset, consisting of 30 labeled images of sample size 80 with both adulterated and non-adulterated samples. The dataset was split into training, validation, and test sets in the 70:20:10 ratio.

## 3.4 Model Evaluation Metrics

The performance of the model was evaluated using the following standard object detection metrics:

- **Precision:** Measures the proportion of correctly identified instances out of all predicted instances.
- **Recall:** Measures the proportion of correctly identified instances out of all actual instances.
- **mAP@0.5:** Mean Average Precision at IoU threshold of 0.5 – a key metric for object detection accuracy.
- **F1 Score:** Harmonic mean of precision and recall, used for balanced assessment.

### 3.5 Model Advantages

YOLOv8s was selected for its fast inference capabilities and high accuracy with limited computational overhead. It is particularly suitable for deployment in real-time systems, including embedded devices used in quality control or industrial inspection setups.

## 4 Results

### 4.1 Model Learning Curve

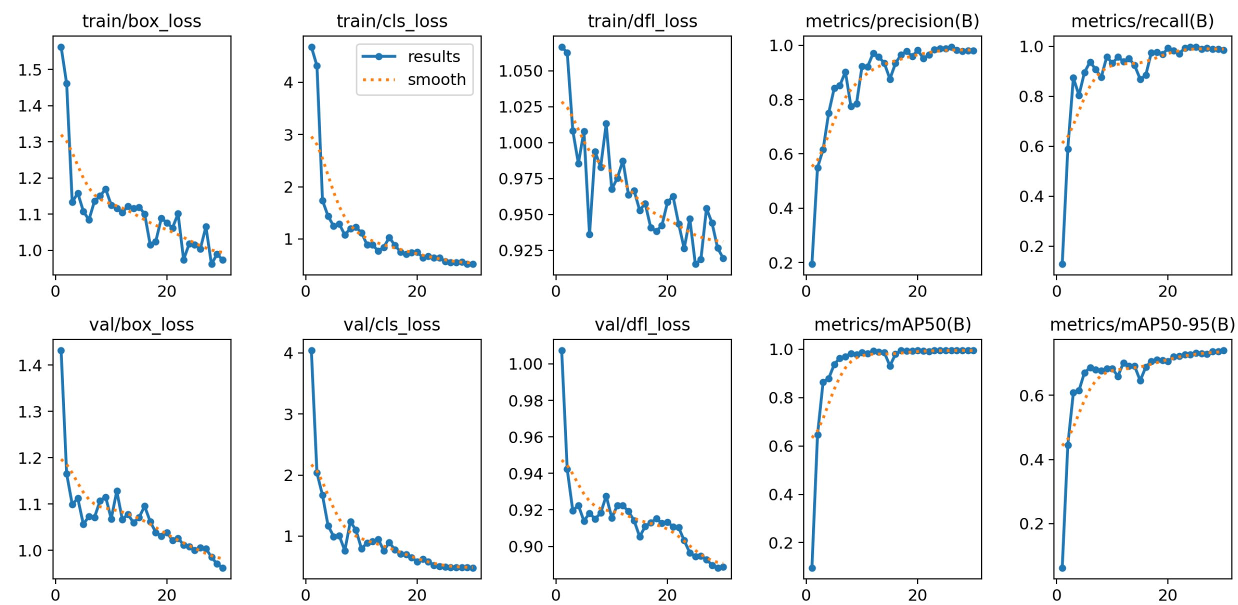



Fig. 5: Yolov8s model learning Curve

### 4.2 Evaluation Metrics

To assess the performance of the seed adulteration detection system, the following metrics were computed over a total of 300 samples:

1. **Mean Relative Adulteration Error (MRAE %)**
   This metric quantifies the average deviation of predicted adulteration from the actual adulteration levels, normalized by the actual values:

$$\text{MRAE (\%)} = \left| \frac{\text{Predicted} - \text{Actual}}{\text{Actual}} \right| \times 100$$

   **Result:** MRAE = **12.27%**
2. **Mean Seed Detection Accuracy (MSDA %)**
   This metric captures how accurately the system detects individual seeds, comparing the correctly identified seed instances against the total ground truth seeds:

$$\text{MSDA (\%)} = \frac{\text{Correctly Detected Seeds}}{\text{Total Seeds}} \times 100$$

   Separate scores can be evaluated for:

- Papaya Seed Detection Accuracy
- Pepper Seed Detection Accuracy

**Result:** MSDA = **88.99%**

3. **Normalized Root Mean Square Error (NRMSE)**
NRMSE is a normalized measure of the differences between predicted and actual adulteration values:

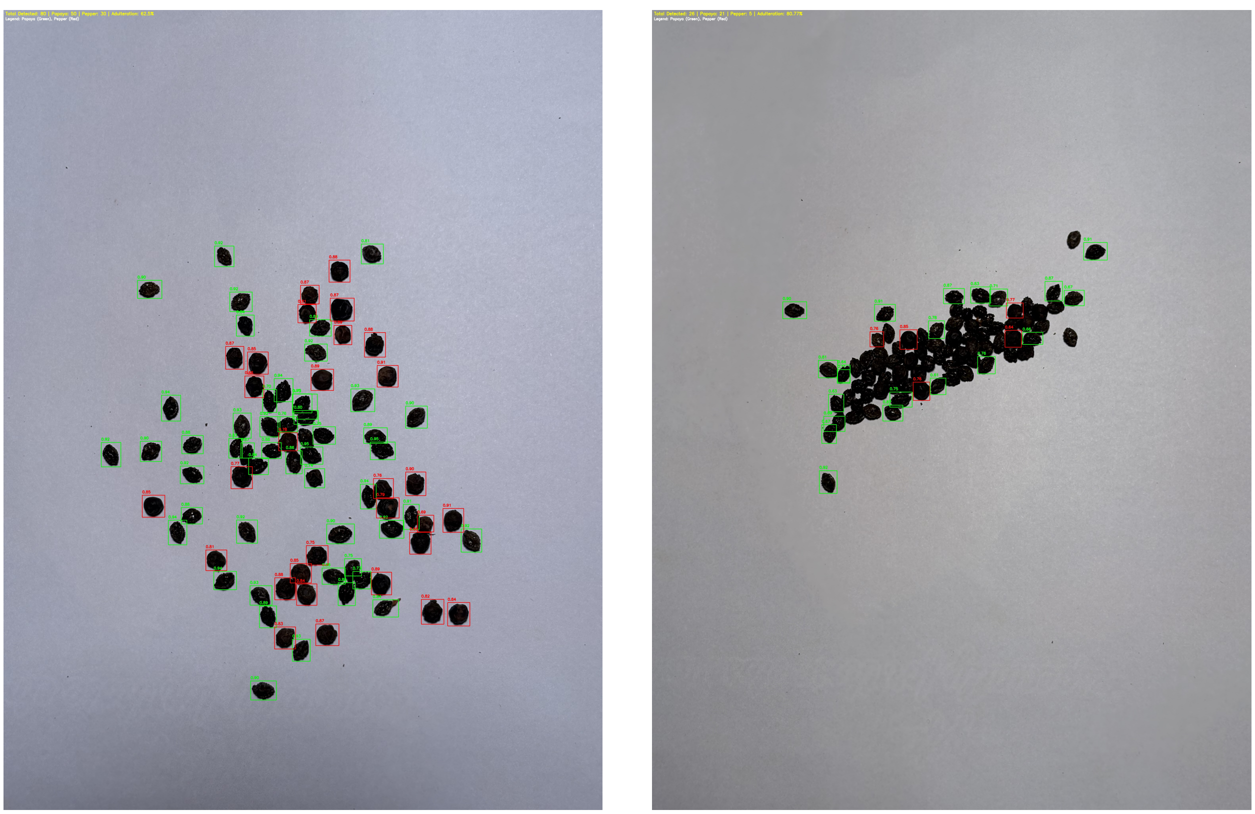
$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{\max(y) - \min(y)}$$

where:

- $\hat{y}_i$ is the predicted adulteration
- $y_i$ is the actual adulteration
- $n = 300$

**Result:** $\text{NRMSE}_{\text{adul}} = \mathbf{0.0813}$

### 4.3 Adulteration Detection and Seeds Locality



(a) Sparse sample (b) Dense sample

Fig. 6: Model outputs on adulterated samples: (a) sparse distribution, (b) dense distribution.

### 4.4 Model Output Graphs

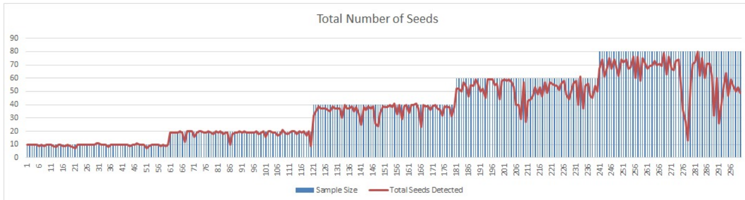



Fig. 7: Total Number of Seeds - Actual vs Predicted

**Observations on Fig 7:**

– x-axis indicate the sample size.
– The model predictions closely follow the actual counts in many regions, showing effective detection.
– There are regions (e.g., around sample indices 225–235) where a sharp dip or deviation is noticeable, indicating possible false negatives or under detection.
– Overall, the model seems to adapt well as the sample size increases, but performance fluctuations highlight areas for potential improvement in consistency or robustness against noise.

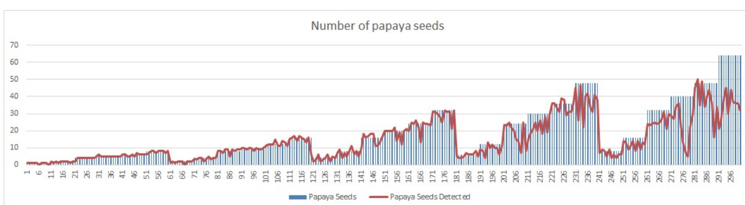



Fig. 8: Total Number of Papaya Seeds - Actual vs Predicted

**Observations on Fig 8:**

– The number of papaya seeds varies significantly between samples, some samples containing no seeds and others having up to 60.
– The model predictions closely follow the actual seed counts in many regions, showing strong performance in identifying papaya seeds.
– In certain sample ranges, such as 175–185 and 245–255, noticeable gaps or under-detections are observed, indicating potential weaknesses in sensitivity or sample complexity.
– The model generally captures the upward trend in seed count across samples and aligns well with actual values, suggesting reasonable robustness, though with room for tuning.

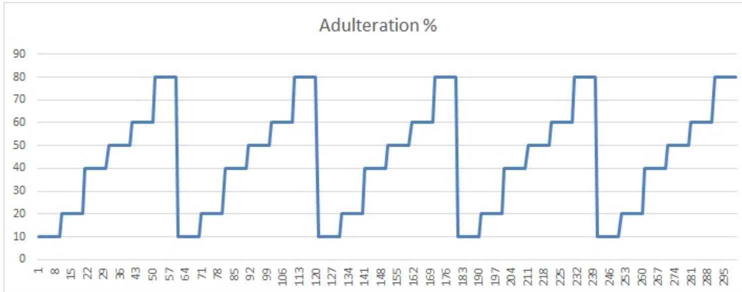



Fig. 9: Actual Adulterated Percentage

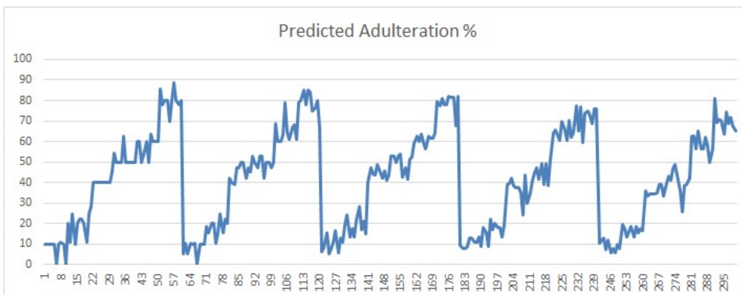



Fig. 10: Predicted Adulterated Percentage

**Observations on Fig 9 and 10:**

- The x-axis represents the adulteration percentage.
- The actual adulteration percentage graph (Fig 9) displays a clear stepped pattern, incrementing in stages from low to high adulteration, then resetting. This suggests a systematic variation in test samples.
- The predicted adulteration graph (Fig. 10) largely mirrors this pattern, indicating that the model is able to follow the adulteration trend effectively.
- Minor discrepancies are observed in some regions (for example, near sample indices 60–70 and 180–190), where the model either overestimates or underestimates the percentage.
- The model shows good responsiveness to sudden changes (resets), although occasional noise introduces fluctuations that could be smoothed out with further tuning.

## 5 Conclusion

This work demonstrates the feasibility of using YOLOv8s to detect papaya seed adulteration in black pepper. The model achieved good seed scores for our model evaluation metrics, enabling accurate and real-time adulteration detection. Future improvements may include larger datasets, hyperspectral imaging, and deployment on embedded AI systems.

## 6 Future Work

In the future, our aim is to explore the use of hyperspectral imaging to detect subtle differences between papaya seeds and black pepper. Unlike RGB or thermal imaging, hyperspectral sensors capture reflectance across hundreds of narrow wavelength bands, allowing for precise material differentiation.

To collect ground truth for hyperspectral analysis:

- The seeds will be placed under consistent lighting and captured using a hyperspectral camera.
- Spectral signatures for pure black pepper and papaya seeds will be cataloged.
- A classification model (e.g., SVM or CNN) will be trained using pixel-level spectra.
- Ground truth masks will be generated manually and with clustering (e.g., k-means) to assist labeling.

This approach will help improve detection in cases where papaya seeds are highly similar in texture and shape to black pepper, but differ in their chemical composition.

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