# Applying Machine Learning for Chili Pepper Phenotyping and Feature Extraction


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**Abstract**

Characterizing morphology in pepper is a crucial aspect of breeding and genetic studies. However, conventional phenotyping methods are not only limited in accuracy due to small sample sizes, but also constrained in the number of measurable parameters needed for comprehensive characterization. With the rapid development of computer vision and machine learning, we propose a method that leverages these technologies to automate the process of phenotyping and extracting morphological features of chili peppers, as well as building an information retrieval dataset for chili pepper varieties. We introduce a model for phenotyping and feature extraction based on longitudinal slice images of chili peppers, along with a set of image processing techniques. To address the challenge of identifying the location of chili peppers and their seeds, we utilize the YOLOv7 model. Initial test results of the YOLOv7 model showed accuracy and mAP values of 0.92 and 0.87, respectively. Next, we apply machine learning techniques to extract additional quantitative information from each chili pepper, such as the number of seeds, color, length, width, fruit area, and surface wrinkles. These features play an important role in managing, analyzing, and selecting chili varieties for breeding programs. This model would significantly enhance the efficiency of chili pepper research and breeding.

# 1 Introduction

Chili pepper, cultivated worldwide and used for thousands of years [1], is a pungent fruit from the *Solanaceae* family. Chili peppers are valued for their distinctive flavors, nutritional properties, and medicinal benefits [2]. They are an excellent source of various vitamins, including vitamins E, C, A, and B complex, and minerals such as thiamine, folate, molybdenum, manganese, potassium, calcium, and iron [3, 4]. In many regions, chili peppers play a pivotal role in local cuisines [5], imparting unique tastes and adding depth to traditional dishes [6]. Beyond culinary applications, chili peppers are also utilized in various industries, including pharmaceuticals [7], cosmetics [8], and even self-defense products, due to the presence of capsaicinoids – the compounds responsible for their characteristic pungency [9]. The chili pepper market has experienced significant growth, driven by increasing consumer preferences for diverse and authentic flavors and the recognition of the potential health benefits associated with capsaicinoids [10]. Their widespread use as condiments and functional food ingredients has increased global demand for fresh and processed chili pepper products, creating opportunities for growers, processors, and traders [11].

The great diversity of Capsicum varieties poses challenges [12]. With the wide variety of chili peppers available, each with unique distinct phenotypic characteristics in shape, size, color, spiciness, and flavor, it presents opportunities and challenges for varietal management and breeding programs [13]. Accurate and efficient characterization of these phenotypic features is pivotal for unlocking the full potential of chili pepper varieties and driving targeted breeding efforts [14]. Traditional methods of phenotyping and accurately characterizing chili pepper fruit morphology include manual inspection and measurement by trained personnel, which is labor-intensive, time-consuming, and prone to human error and subjectivity [15]. Moreover, these manual approaches often lack the precision and consistency required for comprehensive varietal analysis and comparison.

The digitization of phenotypic features [16–18] through advanced imaging techniques and computer-aided analysis offers a transformative solution to these challenges. Researchers can quantify and extract numerical features with unprecedented accuracy and objectivity by capturing high-resolution images of chili pepper fruits and leveraging machine learning algorithms [19]. This digitized approach facilitates the precise measurement of traits such as fruit dimensions, seed count, color parameters, and other relevant morphological and biochemical characteristics. The resulting numerical data enables detailed varietal profiling and supports data-driven decision-making in breeding programs. Furthermore, the digitization of phenotypic features allows for the creation of comprehensive databases, enabling efficient storage, retrieval, and analysis of varietal information [20]. This data-driven approach empowers breeders to identify desirable traits, assess genetic diversity, and make informed selections for developing new varieties tailored to specific market demands or environmental conditions [21]. By embracing the digitization of phenotypic features, the chili pepper industry can unlock new avenues for varietal management, accelerate breeding cycles, and drive the development of improved varieties that meet the evolving needs of consumers and stakeholders alike.

During the research process, three main challenges have been identified in constructing the dataset and extracting feature information of chili peppers:

The lack of standardized and diverse datasets poses a significant challenge in chili pepper de-

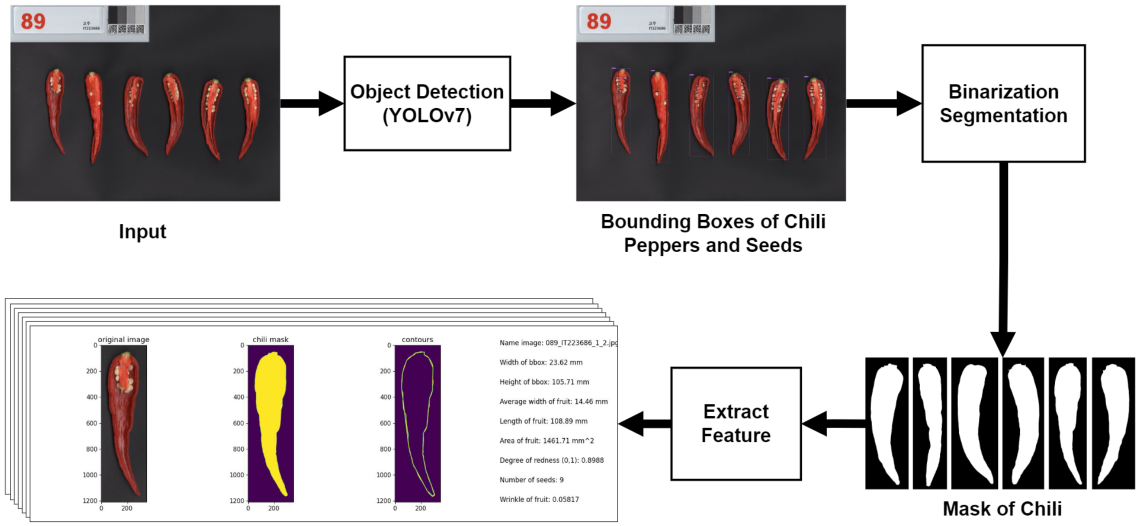


Figure 1: The proposed model is designed for phenotypic feature extraction from longitudinal slice images of chili peppers.

tection and phenotyping research using computer vision and machine learning techniques. Many existing datasets are created and annotated by individual research groups with varying protocols, leading to inconsistencies in data representation and labeling conventions.

Handling occlusion and overlapping of chili seeds. The use of cross-sectional images causes chili seeds to overlap, making it difficult for the model to identify the chili seed subjects.

Unclear subject boundaries have long been a focus in the field of image retrieval. This factor often makes subject identification in images blurry and challenging. Specifically, unclear subject boundaries can complicate object extraction and even lead to incorrect search results.

According to the reference, for the first time, we introduced a model to help determine the location of chili peppers and chili seeds and extract information about species-specific characteristics through longitudinal slice images of chili fruits. Improvements were made in the way YOLOv7 was utilized. Then, the approach using machine learning techniques in image processing was adopted and adjusted following the defined context of chili fruit. Our goal was to build an accurate chili detection framework to address the complexity of determining phenotypes and characteristics of chili peppers. This aimed to provide robust technical support for practical applications in the agricultural sector, particularly for later storing and retrieving information about each chili variety. Our research aims to facilitate the easy storage and retrieval of information about the characteristics that affect the quality of each chili variety, thereby contributing to breeding efforts and promoting the sustainable development of the agricultural industry. For the first time, we introduced a model that can help identify phenotypes and extract characteristics of chili peppers automatically through longitudinal slice images of chili peppers, as described in Figure 1.

This study's primary objective is to harness machine learning's capabilities, particularly the

YOLO (You Only Look Once) object detection model, to precisely identify phenotypes and extract morphological features of chili peppers. We aim to develop a reliable and automated system by utilizing this advanced technology. More specifically, the research employs the YOLO model to accurately identify and locate crucial elements of chili peppers, such as seeds and the fruit itself, in high-resolution imagery. This object detection capability forms the basis for subsequent extraction of morphological features. Through the analysis of identified objects, the study aims to extract and quantify significant morphological features. The parameters extracted include:

**Bounding box size:** Accurate measurement of the length and width of the fruit detection frame box.

**Fruit surface area:** Calculation of the fruit's surface area, which is relevant data for evaluating potential yield and considering processing.

**Color parameters:** Quantifying the color characteristics of the fruit, particularly the degree of redness, as an important indicator of ripeness and quality.

**Fruit size:** Precisely measuring the length and width of the fruit, enabling reliable comparison of morphological characteristics across varieties.

**Number of seeds per chili:** Accurately determining the number of seeds per chili, a trait vital for yield and genetic diversity.

**Edge wrinkles:** Measuring the wrinkled edges of the maturing fruit, a telltale sign of optimal ripeness and peak flavor, to assess the quality and consumption readiness.

By achieving these objectives, the research aims to provide a robust and scalable solution for extracting valuable numerical data from chili peppers, streamlining the varietal characterization process, and enabling data-driven decision-making in breeding programs and seed management strategies.

# 2 Materials and Methods

## 2.1 Dataset

The database we employed in this paper includes longitudinal slice images of chili peppers and meticulously labeled seeds. These chili peppers were not acquired from markets. They were instead grown and collected at the Rural Development Administration (RDA), located in Jeonju, Republic of Korea, under our direct supervision. This allowed us to maintain a high level of control over the growth conditions and the overall quality of the chili peppers. For details in figure 2

### Cultivation and Sample Selection

Chili varieties were cultivated under tightly controlled environmental conditions. Key factors, including temperature, irrigation, and fertilization, were meticulously monitored and adjusted. This stringent control was critical for maintaining sample consistency and minimizing potential environmental bias in the collected data. The experiment was conducted in a research garden comprising 77 chili varieties, each contributing unique phenotypic traits to the study. The varieties were randomly assigned to plots within a greenhouse environment and labeled with unique species codes to facilitate

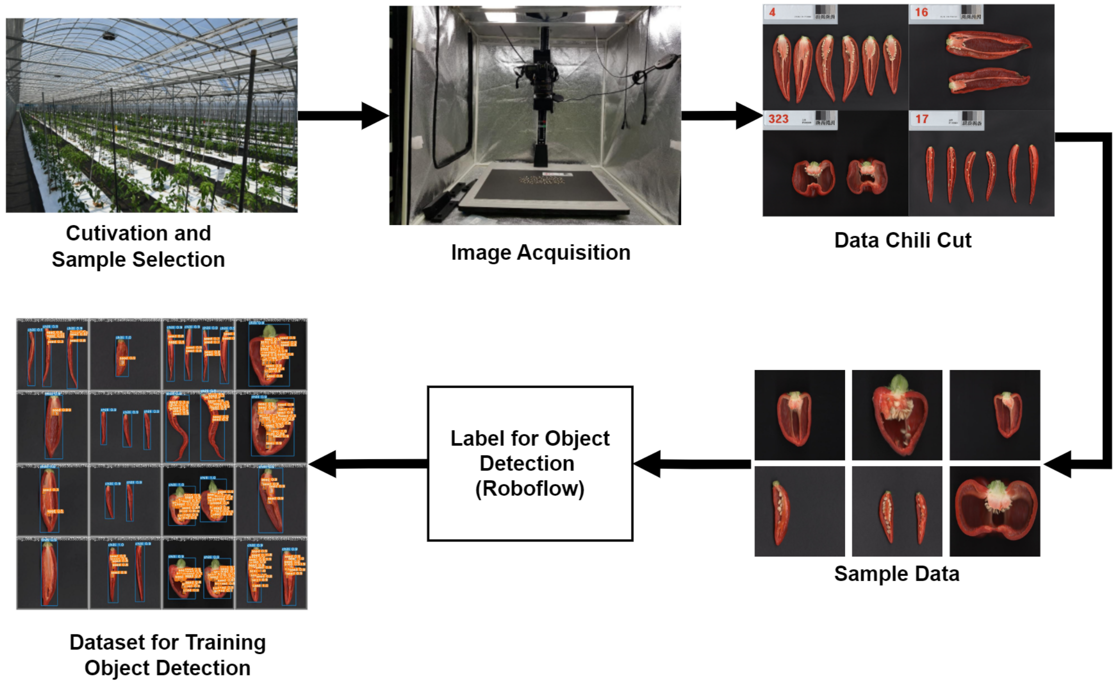


Figure 2: Pipeline for constructing the dataset

accurate identification and systematic data tracking.

The selection process of chili peppers was conducted with great care and adhered to standardized criteria. Key factors such as fruit area, weight, color, and other relevant morphological characteristics were considered to ensure uniformity. This approach enabled us to maintain a high degree of consistency in sample selection and enhanced the reliability of the collected data. For each chili variety, six trees were planted per sample plot, from which six fruit samples were collected. Sampling commenced once the plants had reached full maturity and completed fruit development, thereby ensuring that the peppers were assessed at a consistent stage in the growth cycle.

### Image Acquisition

The camera system settings were configured in accordance with the method described by Yu et al [22] to ensure consistency and reliability in image acquisition. A Canon digital camera was used to capture the images. Particular attention was paid to maintaining uniform lighting conditions, as well as consistent distances and shooting angles during image capture. These measures were implemented to minimize potential bias or variability in the image data caused by fluctuations in lighting or changes in camera positioning. All images were saved in JPG format, preserving the fine structural details of the chili peppers at a resolution of 6024 $\times$ 4024 pixels. The initial dataset comprised a total of 32 images before augmentation.

### Labeling and Dataset Construction

To standardize the input dimensions and optimize computational efficiency, we applied a cropping technique to extract 640 × 640 pixel regions from the original high-resolution images. Each cropped region was selected to ensure the presence of at least one chili pepper, thereby preserving meaningful visual information for model training. The annotation process was performed using the Roboflow platform [23], which facilitated the efficient and consistent labeling of image data. Two object classes were defined: "chili", representing the entire chili fruit, and "seed", referring to the individual seeds visible within the fruit. Bounding boxes were manually drawn around each object instance following strict annotation guidelines. We carried out the labeling process to ensure accuracy and consistency across the dataset. Manual bounding box annotations were performed for each instance of both classes, following strict annotation guidelines to ensure consistency and precision. For the "chili" class, tight bounding boxes were drawn around the full extent of the fruit, while for the "seed" class, individual bounding boxes were created for each visible seed within the chili. Annotation quality was reviewed and corrected where necessary before finalizing the dataset. The labeled dataset was exported in the YOLOv5 [24] format to ensure compatibility with widely adopted object detection frameworks and model architectures.

To enhance the diversity of the dataset and improve model generalization, various data augmentation techniques were applied, including image rotation and flipping. These augmentations synthetically expanded the training set by introducing variations in orientation and visual features, thereby increasing the model's robustness and performance on previously unseen data.

The dataset comprises over 700 annotated images of various chili pepper varieties, all captured under standardized conditions with consistent distance, lighting, and background. Each image was manually labeled with bounding boxes corresponding to individual chili peppers and seeds. To support robust model development and evaluation, the dataset was divided into training, validation, and test subsets following a 70-20-10 ratio. Specifically, 70% of the data was allocated for training, 20% for validation, and 10% for testing. The training set was used to optimize model parameters, while the validation set supported hyperparameter tuning and performance monitoring to mitigate overfitting. The test set, held out entirely from the training process, provided an unbiased assessment of the model's generalization ability on previously unseen data. This partitioning strategy ensured a reliable evaluation framework and informed the model's potential applicability in real-world scenarios.

The training, validation, and test sets were meticulously curated and organized. Image filenames and their corresponding annotation files were stored separately for each subset, ensuring clarity and ease of access. This structured dataset organization facilitated efficient data loading and preprocessing, thereby streamlining the training and evaluation processes within the method pipeline.

## 2.2 Method

In this research, we employed the YOLOv7 model to train an object detection system for identifying chili and seed objects, with the primary goal of separating them for individual processing. Subse-

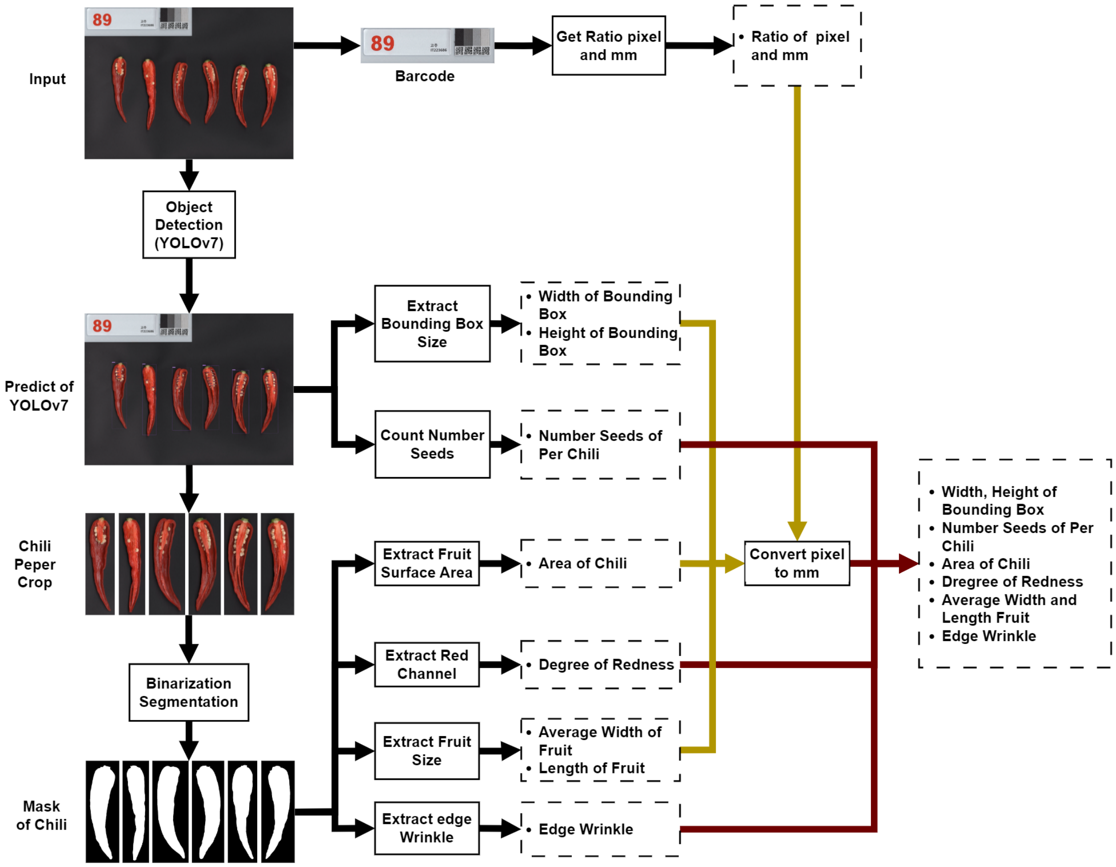


Figure 3: Pipeline of method for extracting chili features

quently, machine learning techniques were applied to extract phenotypic features from the YOLOv7 predictions (Fig. 3).

### Automated Detection of Chili Pepper and Seeds

We employed the YOLOv7 object detection model [25] to accurately identify and localize chili peppers and their seeds. As an advanced member of the YOLO (You Only Look Once) family [26], YOLOv7 offers a favorable balance between detection accuracy and computational efficiency, making it well-suited for real-time phenotypic analysis tasks. The model was initialized with pre-trained weights from the COCO dataset [27], a large-scale benchmark comprising over 330,000 images and 80 object categories. We applied transfer learning by fine-tuning the pre-trained network on our annotated chili pepper dataset to adapt the model to our specific domain. This dataset included bounding box annotations for both chili fruits and their seeds.

Through the fine-tuning process, the YOLOv7 model achieved high accuracy in detecting and localizing both classes across a variety of chili pepper types, demonstrating its effectiveness for phenotypic feature extraction in horticultural imaging applications. The predicted results from YOLOv7 are used as input for computational blocks and serve as the basis for extracting relevant object fea-

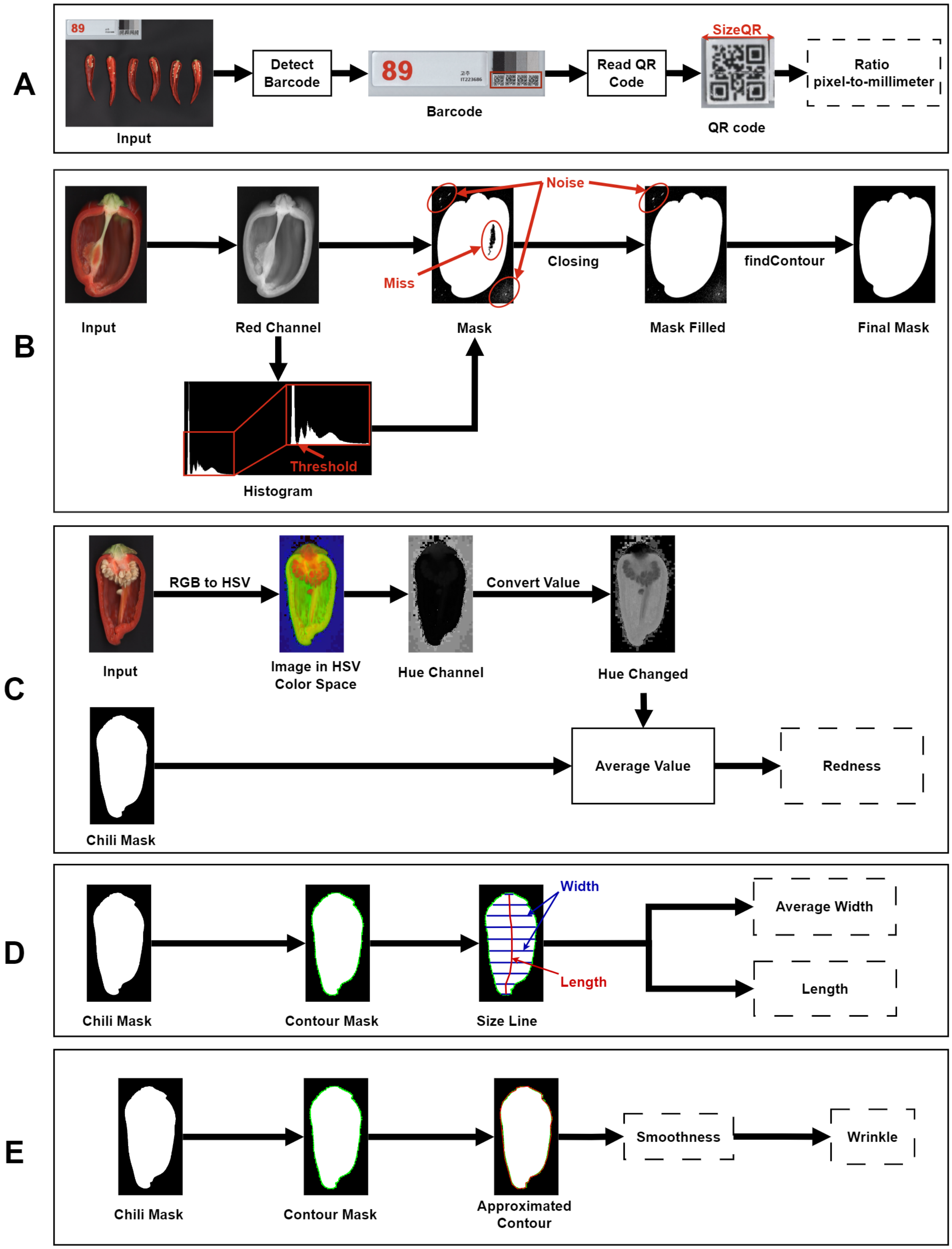


Figure 4: Workflow of the proposed image-based chili fruit phenotyping method. (A) Pixel-to-millimeter ratio calculation using the QR code. (B) Chili segmentation using the red channel, morphological closing, and contour detection. (C) Redness extraction using the hue channel in HSV color space. (D) Fruit size estimation by analyzing chili mask with dividing lines. (E) Wrinkle assessment via contour approximation and smoothness calculation.

tures.
We define [$left^c_t$, $top^c_t$, $right^c_t$, $bottom^c_t$] as the bounding box of a $t$th chili pepper and [$left^s_j$, $top^s_j$, $right^s_j$, $bottom^s_j$] as the bounding box of the $j$th seed. Using the $t$th bounding boxes, we crop the original image into the $t$th sub-image. To ensure complete inclusion, the sub-image size is expanded by 10 pixels in all directions before cropping.

$$(W_t, H_t) = (right^c_t - left^c_t + 20, bottom^c_t - top^c_t + 20) \tag{1}$$

Here, $(W_t, H_t)$ denotes the width and height of the $t$th cropped sub-image containing the chili pepper being viewed.

### Get ratio pixel and millimeter

To obtain the `ratio` between pixels and millimeters, we rely on the QR code displayed in the top-left corner of the image (Fig. 4.A). We first detect the location of the QR code, then determine its size in pixels and combine it with its actual physical size in millimeters (10 mm) to calculate the pixel-to-millimeter ratio.

$$\texttt{ratio} = \frac{10\ \text{(mm)}}{size_{QR}\ \text{(pixel)}} \tag{2}$$

Where $size_{QR}$ denotes the side length (in pixels) of a single QR code among multiple QR codes in the barcode.

### Ensure consistent orientation of the chili images

To ensure consistency in image analysis, we standardize the orientation of the $t$th chili images. This step involves aligning each chili in a predefined direction, facilitating more accurate feature extraction and sample comparison. To determine the correct orientation, we identify the region corresponding to the chili stem to assess whether the chili is positioned horizontally or vertically. If the chili is found to be in a horizontal orientation, we rotate the image 90 degrees clockwise to align it vertically.
We extract the stem region by applying a green color filter (hue channel [25, 90]) in the HSV color space ($\texttt{GreenMask}_t$). From this mask, we calculate the center point of the stem region ($CenterStem_t$). By locating this center point within the bounding box of the chili, we determine whether the chili is oriented horizontally or vertically.

$$\texttt{GreenMask}_t(x, y) = \begin{cases} 1 & \text{if } 25 \leq I_{Ht}(x, y) \leq 90 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$center_{tx} = \frac{\sum_{x=0}^{W_t} \sum_{y=0}^{H_t} x * \texttt{GreenMask}_t(x,y)}{\sum_{x=0}^{W} \sum_{y=0}^{H} \texttt{GreenMask}_t(x,y)} \tag{4}$$

$$center_{ty} = \frac{\sum_{x=0}^{W_t} \sum_{y=0}^{H_t} y * \texttt{GreenMask}_t(x,y)}{\sum_{x=0}^{W} \sum_{y=0}^{H} \texttt{GreenMask}_t(x,y)} \tag{5}$$

Here, $I_{Ht}$ denotes the hue channel of the $t$th chili image, and $I_{Ht}(x, y)$ represents the pixel value at coordinates $(x, y)$ in the Cartesian coordinate system (Oxy), $\texttt{GreenMask}_t$(x, y) indicates the pixel value at coordinates $(x, y)$, and ($center_{tx}$, $center_{ty}$) is coordinate of $CenterStem_t$.

We compare the position of the $CenterStem_t$ to the central position of the image to determine whether the chili is oriented horizontally or vertically. Since the stem is typically located at the top of the chili, the $CenterStem_t$ tends to be farther from the midpoint along the chili's length and closer to the center along its width. Therefore, if the vertical distance between $CenterStem_t$ and the image center is greater, the chili is considered to be vertical; conversely, if the horizontal distance is greater, the chili is classified as horizontal.

$$\Delta_{tx} = |W_t - 2 \times center_{tx}| \tag{6}$$

$$\Delta_{ty} = |H_t - 2 \times center_{ty}| \tag{7}$$

Where $\Delta_{tx}, \Delta_{ty}$ are twice the distance from the Center to the middle axis along the width and height of the image, respectively.
If $\Delta_{tx} > \Delta_{ty}$, the chili is horizontal and rotate the image at a right angle so that the chili stem points upwards. Otherwise, the chili is considered to be in a vertical orientation, and no rotation is applied.

### Binarization segmentation chili pepper

First, for the $t$th chili pepper image, we segment the chili pepper ($\texttt{ChiliMask}_t$) using a $\texttt{threshold}_t$. The $\texttt{threshold}_t$ is selected to ensure that the classification of the chili from the background yields the best results for most chilies in the dataset. We tested using grayscale images and each color channel of the RGB color space, and it showed that the threshold on the red channel yielded the best classification results.

$$\texttt{threshold}_t = argmax_i(histogram_t) + \gamma \tag{8}$$

$$\texttt{ChiliMask}_t\texttt{(x,y)} = \begin{cases} 0 & \text{if } I_{Rt} \leq \texttt{threshold}_t \\ 1 & \text{otherwise} \end{cases} \tag{9}$$

Here, $histogram_t$ represents the brightness frequency distribution of pixel values in the red channel of the $t$th chili image, and $\gamma$ is an iterative variable used to determine the value that optimizes the outcome. In our experiment, we empirically set $\gamma = 16$ to achieve the best result. The function $argmax_i$ identifies the value $i \in [0, 255]$ at which the frequency in the red channel histogram is the highest. $I_{Rt}$ denotes the red channel of the $t$th chili image in the RGB color space.
However, the resulting mask is not entirely accurate, as it may miss some pixels within the chili and contain noise in the background (4.B). To refine and address this drawback, we use the **Closing** method from the OpenCV library on the mask to fill in regions within the chili pepper that are not labeled as chili pepper. This helps to fill any holes or small gaps within the regions representing the chili pepper.
Next, we use the **findContours** algorithm from the OpenCV library to retain the largest contour and remove the remaining contours. This helps to eliminate any pixels not within the contour region of the chili pepper that are labeled as chili pepper. The final output of this block achieves the desired segmentation, where pixels belonging to the chili pepper are assigned a value of 1, and all other pixels are assigned a value of 0.

### Extract bounding box size

The sizes of the bounding box cover the $t$th chili pepper ($\texttt{width\_bbox}_t$, $\texttt{height\_bbox}_t$) are calculated based on the output of YOLOv7. These values are then converted to millimeters by multiplying them with the pixel-to-millimeter ratio (equa 2).

$$\texttt{width\_bbox}_t = (right_t^c - left_t^c) * \texttt{ratio} \tag{10}$$

$$\texttt{height\_bbox}_t = (bottom_t^c - top_t^c) * \texttt{ratio} \tag{11}$$

### Extract Fruit surface area

To determine the fruit surface area of the $t$th chili pepper ($\texttt{are\_pixel}_t$), we count the number of pixels in the $\texttt{ChiliMask}_t$. This pixel-based surface area is then converted to square millimeters by applying the square of the $\texttt{ratio}$.

$$\texttt{area\_pixel}_t = \sum_{y=0}^{H} \sum_{x=0}^{W} \texttt{ChiliMask}_t(x, y) * \texttt{ratio}^2 \tag{12}$$

Here, $\texttt{ChiliMask}_t$(x, y) denotes the value of $\texttt{ChiliMask}_t$ at the coordinate (x,y).

### Extract red channel

To quantify the red color intensity ($\texttt{redness}_t$) of the $t$th chili pepper, we adopt the HSV color space, specifically utilizing the hue channel to capture the chromatic information. The hue values are transformed according to Equation 13 so that higher values correspond to a deeper red coloration. The final $\texttt{redness}_t$ is computed as the average of the transformed hue values within the region defined by $\texttt{ChiliMask}_t$, as described in Equation 14. This process is visually illustrated in Figure 4C.

$$I_{Ht}(x,y) = \begin{cases} 30 - I_{Ht}(x,y) & \text{if } I_{Ht}(x,y) < 30 \\ I_{Ht}(x,y) - 150 & \text{if } I_{Ht}(x,y) > 150 \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

$$\texttt{redness}_t = \frac{\sum_{y=0}^{H_t} \sum_{x=0}^{W_t} I_{Ht}(x,y)}{30 * \texttt{area\_pixel}} \tag{14}$$

**Extract fruit size**

To calculate the actual dimensions of the $t$th chili pepper ($\texttt{length\_fruit}_t$, $\texttt{width\_fruit}_t$), we combine information from the bounding box and the $\texttt{ChiliMask}_t$. This approach captures the deviations from the $\texttt{height\_bbox}_t$ and $\texttt{width\_bbox}_t$ parameters, thereby accounting for the natural curvature and deformation along the sides of the chili pepper. Specifically, the height of the bounding box is divided into 9 equal segments using 10 horizontal separation lines (Fig. 4.D). The $\texttt{width\_fruit}_t$ is calculated as the average width of the $\texttt{ChiliMask}_t$ across these separation lines (blue segments), excluding the topmost and bottommost lines. The $\texttt{length\_fruit}_t$ is defined as the total length of the curve formed by connecting the midpoints of the valid blue segments (red segment).

$$p_i^l = \min\{x \mid \texttt{ChiliMask}_t(x, y_i) > 0\} \; x \in [0, W_t], i \in [1, 10] \tag{15}$$

$$p_i^r = \max\{x \mid \texttt{ChiliMask}_t(x, y_i) > 0\} \; x \in [0, W_t], i \in [1, 10] \tag{16}$$

$$\texttt{width\_fruit}_t = \frac{1}{8} \sum_{i=2}^{9} |p_i^r - p_i^l| \tag{17}$$

$$\texttt{length\_fruit}_t = \sum_{i=1}^{9} \sqrt{(y_i - y_{i+1})^2 + \left( \frac{p_i^l + p_i^r}{2} - \frac{p_{i+1}^l + p_{i+1}^r}{2} \right)^2} \tag{18}$$

Where $(p_i^l, y_i), (p_i^r, y_i)$ respectively represent the starting and ending coordinates of the i-th blue segment, following top to bottom.

**Count Number seeds**

To count the number of seeds in the $t$th chili pepper, we compare the center point of each seed with the boundaries of the $t$th chili bounding box. If the seed center lies within this bounding box (satisfying the condition defined in Equation 21), it is considered to belong to the chili pepper. We iterate through all detected seeds and count the number of seed centers that fall within the $t$th bounding box.

$$center^s_{jx} = \frac{left^s_j + right^s_j}{2} \tag{19}$$

$$center^s_{jy} = \frac{top^s_j + bottom^s_j}{2} \tag{20}$$

$$left^c_t \leq center^s_{jx} \leq right^c_t \quad \text{and} \quad top^c_t \leq center^s_{jy} \leq bottom^c_t \tag{21}$$

Here, $(center^s_{jx}, center^s_{jy})$ denotes the coordinates of the center point of the $j$th seed's bounding box.

**Extract edge wrinkle**

To calculate the deformation of the $t$th chili pepper wall ($\texttt{wrinkle}_t$), we analyze the shape of the chili using the **findContour** function in OpenCV to extract the contour surrounding the $t$th chili from $\texttt{ChiliMask}_t$ (denoted as $\texttt{contour}_t$). Next, we apply the **approxPolyDP** function in OpenCV to approximate the $\texttt{contour}_t$, and then compute the smoothness as the ratio between the length of the approximated $\texttt{contour}_t$ and the original $\texttt{contour}_t$. Finally, $\texttt{wrinkle}_t$ is defined as the complement of the smoothness, representing the degree of surface deformation.

$$\texttt{approximateContour}_t = \text{approxPolyDP}(\texttt{contour}_t, \epsilon) \tag{22}$$

$$\texttt{smoothness}_t = \frac{\textit{Length of } \texttt{approximateContour}_t}{\textit{Length of } \texttt{contour}_t} \tag{23}$$

$$\texttt{wrinkle}_t = 1 - \texttt{smoothness}_t \tag{24}$$

Here, $\texttt{approximateContour}_t$ denotes the approximated $\texttt{contour}_t$, $\epsilon$ represents the approximation tolerance for the $\texttt{contour}$, and $\texttt{smoothness}_t$ indicates the smoothness of the $t$th chili pepper wall.

# 3 Results

The model exhibited promising performance, providing valuable information for variety classification and quality assessment of chili peppers. The shape analysis techniques effectively quantified key morphological traits, including fruit size, surface area, and edge wrinkles, enabling reliable varietal characterization.

## 3.1 Chilies and Seeds Detection

We are training and testing for chili and seed object detection used the model YOLOv7, the output sample is represent in Figure 5. Our results demonstrate the object detection models achieved high mean Average Precision (mAP) scores, enabling accurate localization of chili peppers and their seeds within images. The image analysis methods precisely predict relevant morphological features, while the quantitative color models agree closely with actual ground-truth measurements. The performance evaluation of the YOLOv7 model for object detection is summarized in Table 1.The model achieves outstanding performance in detecting chili, with a precision of 90.5% and a perfect recall of 100%, indicating that all chili instances were correctly identified without false negatives. The mAP@50 reaches 98.5%, and mAP@50–95 is 78.9%, reflecting the model's strong ability to localize chili objects across different intersection over union (IoU) thresholds. In contrast, detection performance for seeds is relatively lower, particularly in recall (78.6%) and mAP@50–95 (45.9%), suggesting that some seed instances were missed and that precise localization under stricter evaluation criteria remains a challenge. Nevertheless, the high precision of 93.3% for seed detection shows that most predictions made were accurate. When considering both classes together, the model maintains a balanced performance, with a precision of 91.9%, recall of 89.3%, mAP@50 of 92.9%, and mAP@50–95 of 62.4%. These results indicate that YOLOv7 is effective for object detection in this context, particularly for chili, though further improvements may be needed to enhance seed detection accuracy.

Table 1: Performance Metrics of YOLOv7 for Object Detection

| **Class** | **Precision** | **Recall** | **mAP50** | **mAP50-95A** |
|---|---|---|---|---|
| Chili | 90.5% | 100% | 98.5% | 78.9% |
| Seed | 93.3% | 78.6% | 87.4% | 45.9% |
| Chili and seed | 91.9% | 89.3% | 92.9% | 62.4% |

## 3.2 Extraction Parameter and Interpretation

The results illustrated in Figure 6 demonstrate the effectiveness of the proposed image-based method for extracting key phenotypic traits of chili fruits. Each sample (A–D) presents one output from our method, including: (i) the original image with bounding boxes of chili fruits and seeds as predicted by YOLOv7, (ii) the binary chili mask, (iii) the extracted contour, and (iv) the corresponding phenotypic parameters derived from each chili sample.

The method successfully captures various phenotypic traits related to chili shape, size, and surface texture. This is evident in the variation in bounding box dimensions, fruit length, and surface area among the samples. The redness level, derived from the hue channel in the HSV color space, differs across samples and serves as an informative indicator of ripeness or pigment concentration. In addition, seed count is automatically determined based on spatial analysis, providing valuable insights into internal characteristics. Furthermore, the wrinkle index reflects the complexity and deformation of the chili wall surface, offering another layer of morphological information. Overall,

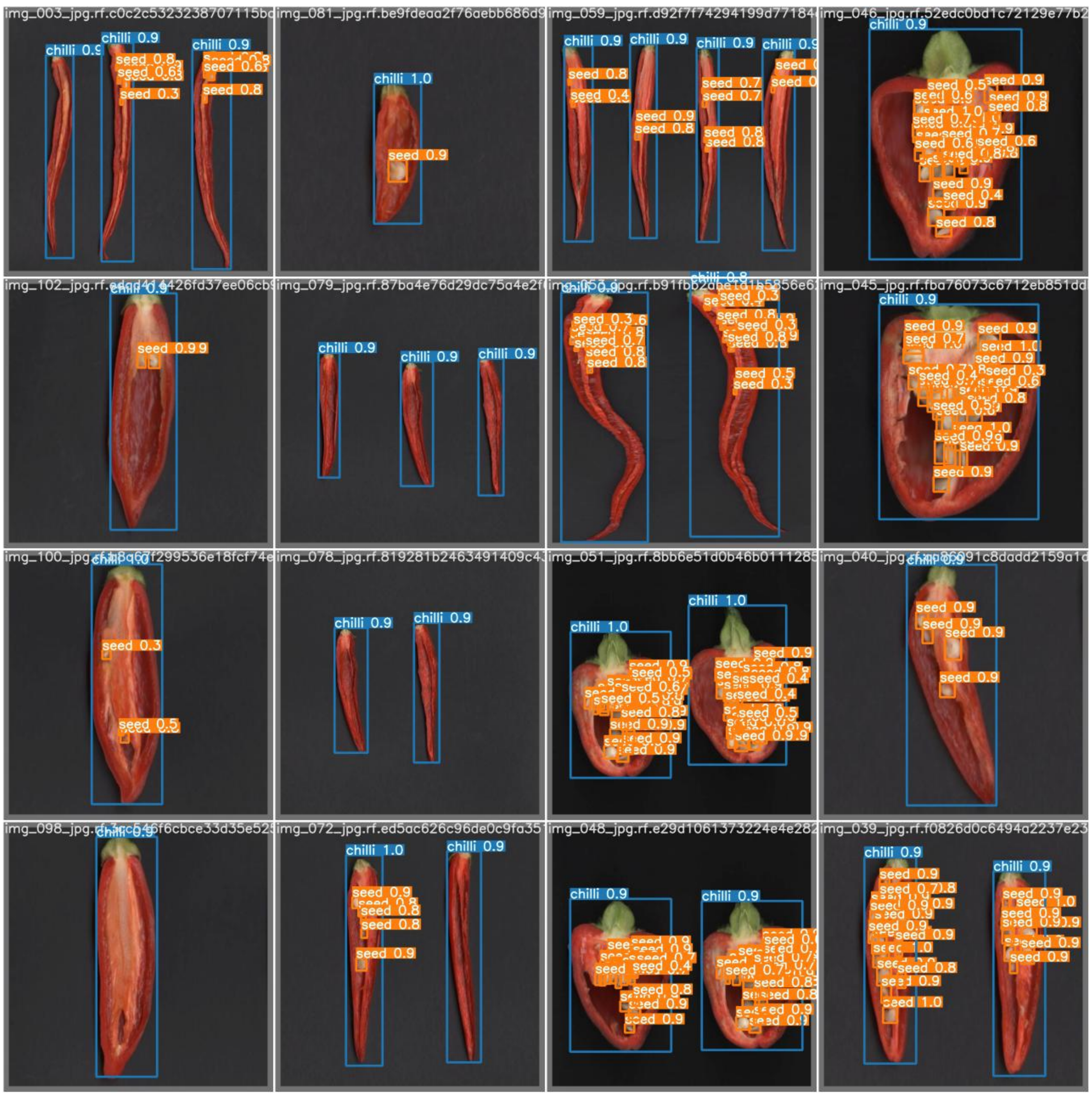


Figure 5: Output of YOLOv7 Object Detection

this image-based phenotyping approach provides a reliable and efficient method for characterizing a wide range of chili fruit traits. It holds strong potential for applications in automated grading, cultivar selection, and agricultural research.

# 4 Discussion

This study presents an integrated deep learning and image processing framework for the comprehensive phenotyping of chili peppers. The proposed approach, combining YOLOv7 for object detection with classical image processing techniques, demonstrated high precision in detecting chili fruits and seed objects. The model effectively extracted key phenotypic traits, including fruit size (length, width, area), shape, color intensity (redness), seed count, and surface texture (wrinkle). Notably, the integration of YOLOv7 with contour analysis enabled accurate segmentation even in complex scenes, supporting the reliable characterization of both external and internal fruit features. These results highlight the capability of the approach to provide an automated, non-destructive, and holistic solution for chili phenotyping.

Compared to traditional manual inspection [28], which is labor-intensive and prone to subjective bias, the proposed automated system significantly improves both efficiency and consistency. Recently, the authors in [29] proposed a method for characterizing chili peppers based on visual classification into four discrete wrinkle levels. While this approach offers a general sense of surface texture, it is time-consuming and heavily reliant on subjective human judgment, leading to potential inconsistencies and limited reproducibility. Moreover, the wrinkle degree is quantized into only four sparse categories, which fails to capture the continuous nature of surface deformation. In contrast, our study introduces a quantitative and objective metric for assessing the wrinkling degree of chili pepper contours. By analyzing the ratio between the actual contour length and its polygonal approximation, our method produces a continuous wrinkle index that accurately reflects the complexity of the fruit surface. This approach not only enables faster and more consistent analysis but also allows for precise comparisons of wrinkle levels between individual chili samples. The YOLOv7-based detection pipeline allows real-time object recognition with high scalability, overcoming limitations of manual methods in large-scale breeding and research programs. Furthermore, the combination of deep learning with advanced image processing techniques enhances the precision of phenotypic trait extraction compared to conventional computer vision approaches. The framework also complements existing automated systems by introducing additional parameters such as wrinkle index and redness level, which are rarely considered in traditional phenotyping tools. This integration demonstrates the advantages of modern object detection models like YOLOv7 in addressing the challenges of variability in fruit morphology and environmental conditions.

The ability to accurately quantify phenotypic traits of chili peppers offers substantial benefits for breeding programs, germplasm evaluation, and varietal characterization [14]. The extracted traits can support the selection of superior genotypes, contribute to germplasm conservation, and facilitate quality control in chili pepper production chains [30]. Moreover, the method can aid in climate adaptation studies by enabling precise monitoring of morphological responses to environ-

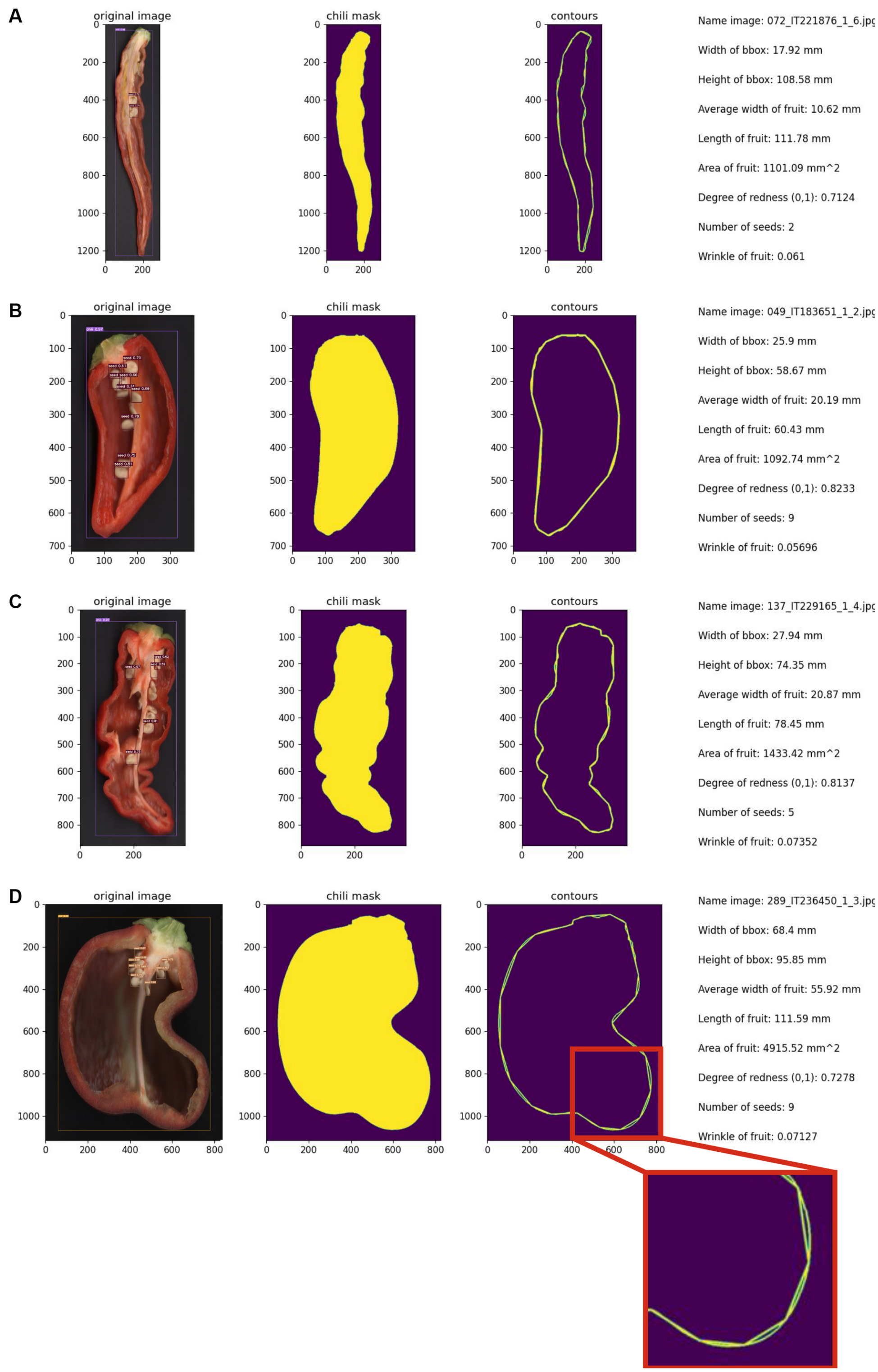


Figure 6: Visual analysis of chili fruit phenotypic traits using image segmentation and contour extraction. (A–D) Each row illustrates a sample chili fruit, showing: (1) the original image, (2) binary chili mask, and (3) extracted contour. The right side presents extracted phenotypic features, including bounding box size, average fruit width, fruit length, area, redness level, seed count, and wrinkle index.

mental stressors. The integration of such automated tools supports intellectual property protection through detailed phenotype documentation, while also promoting sustainable agricultural practices by optimizing selection and grading processes.

Despite promising results, certain limitations should be acknowledged. The dataset used may introduce biases due to limited chili varieties and controlled environmental conditions, potentially affecting model generalization. Seed detection accuracy remains a challenge, especially in cases of overlapping seeds or poor image contrast, which could impact seed count reliability. Moreover, while the system performs efficiently on standard datasets, scalability and computational efficiency may present obstacles when applied to large-scale or real-time field scenarios. Environmental variations such as lighting changes, background noise, and fruit ripeness stages can also influence the model's detection and segmentation performance.

Future work should focus on expanding the dataset to encompass a wider diversity of chili pepper varieties and varying environmental conditions, thereby enhancing model robustness. The incorporation of multimodal imaging modalities, such as infrared or multispectral imaging, could provide additional insights into internal fruit quality and stress markers. Integrating genetic and environmental data may further improve predictive models for phenotypic traits. Efforts to refine the seed detection module and capture more complex morphological features, including 3D shape analysis, are also recommended. Additionally, optimizing the computational pipeline for improved scalability and real-time deployment in large agricultural operations will be crucial for practical field applications.

# 5 Conclusion

Precise characterization of pepper morphology is paramount for both breeding programs and genetic investigations. However, conventional phenotyping approaches have often been constrained by limited sample throughput and the breadth of quantifiable parameters, thus impeding comprehensive phenotypic profiling. To address these inherent limitations, this research presents a novel model for high-throughput phenotyping and detailed characterization of chili pepper varieties, leveraging the power of machine learning and advanced image analysis. The model employs the YOLOv7 object detection algorithm, meticulously retrained on a specialized chili pepper image dataset, to achieve accurate detection and precise localization of chili peppers and their seeds within cross-sectional images. This automation significantly streamlines a process traditionally dependent on labor-intensive manual inspection. By synergistically integrating object detection with sophisticated image processing methodologies, the model facilitates the extraction of a comprehensive suite of key phenotypic traits, including length, width, area, colorimetric intensity, seed count, and the quantification of peel rigidity. The resulting phenotypic data is efficiently structured and stored in a readily accessible CSV format, enabling seamless retrieval and integration with existing genetic databases and breeding management systems. This enhanced capability to quantitatively describe and comparatively analyze chili pepper varieties based on their intricate phenotypic attributes significantly bolsters variety validation, accelerates breeding initiatives, and contributes critically to the conservation of valuable genetic resources. The findings of this research hold substantial implications for optimized germplasm management, precisely targeted breeding strategies, stringent quality control measures, enhanced climate adaptation efforts, and the robust protection of intellectual property within the agricultural sector. While acknowledging that this model represents a considerable advancement in the field, this study also identifies its current limitations and proposes pertinent avenues for future research, such as broadening dataset diversity, incorporating complementary multimodal imaging modalities, integrating relevant genetic and environmental covariates, and further optimizing scalability and computational efficiency. In conclusion, this innovative model fundamentally transforms the phenotyping and characterization workflow, providing accurate and extensive phenotypic profiles that have the potential to catalyze innovation and foster sustainable practices within the chili pepper breeding and genetics research communities.

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