Towards a digital peanut profile board: A deep learning approach

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Abstract. *Artificial intelligence, particularly deep learning, offers promising avenues for revolutionizing object detection and counting in digital agriculture. Peanut farmers face challenges in precisely determining optimal maturity for digging, traditionally relying on the Peanut Maturity Index (PMI) through a manual, subjective, and labor-intensive classification process. To expedite this and reduce subjectivity, we explored deep learning algorithms to develop a digital peanut profile board. Our study utilized data from a 54.76-hectare commercial irrigated peanut field in Eufaula, Alabama, during the 2022 growing season. Weekly peanut biomass samples were collected from 20 locations at five time points (97, 118, 125, 132, and 139 Days After Sowing or DAS), and manual maturity assessments were performed using the hull-scrape method and profile board, resulting in 100 images with around 20,000 objects. We combined brown and black pods into one class and employed the algorithm for object detection and counting, using RoboFlow for data labeling and dataset creation. Model training was conducted in Google Colab using transfer learning, partitioning the dataset into 70% training, 10% testing, and 20% validation. The model, trained for 50 epochs, achieved an mAP50 of 0.97 and an mAP50-95 of 0.726. These results demonstrate the successful application of deep learning in detecting and counting peanut pods across different color classes, substantiating the feasibility of a digital peanut profile board. Our research highlights the transformative potential of deep learning in digital agriculture, offering greater precision, reduced subjectivity, and improved decision-making for peanut farmers. This innovation marks a significant step forward in agricultural technology.*

Keywords.
web application, peanut maturity, YOLOv9, artificial intelligence.

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Introduction

Determining when peanuts have reached maturity is challenging due to their growth underground and their indeterminate growth patterns (Sanders et al., 1980). The Hull–Scrape method is widely used by researchers and growers (Williams and Drexler 1981). However, it is laborious and highly subjective, requiring extensive sampling due to peanut variability in the field (Ashapure et al., 2019). This method involves classifying maturity levels based on mesocarp color from field samples, in recent years, researchers have been developing alternative solutions to modernize this method, making it more efficient and reducing human error (Souza et al., 2023).

Recent advancements in deep learning, particularly the development of sophisticated neural networks, have enabled modern approaches to predicting the peanut maturity index by integrating satellite and unmanned aircraft images (Souza et al., 2023). Methods include using high-resolution satellite images and non-linear models (Santos et al., 2021), high-resolution satellite images and multitarget regression (Oliveira et al., 2024), and UAV data to develop neural network models for both irrigated and rainfed fields (Santos et al., 2021). To enable the development of large-scale models for peanut farmers, it is necessary to increase the number of maturity samples collected from fields. This will help create robust models capable of predicting maturity across various varieties and growing conditions. To achieve this goal, we propose accelerating color classification and reducing the subjectivity of the PMI classification by developing a digital peanut profile board. This solution could facilitate the development of large-scale models and provide farmers with a new method for generating the PMI using images and mobile devices.

The continuous advancements in visual sensor technology, computational capabilities, and data-driven machine learning methodologies have catalyzed a burgeoning interest in digital agricultural technologies, particularly in the development of automated and intelligent systems (Zhao et al., 2024). The adoption of deep learning-based computer vision applications, such as object recognition techniques, has surged in agriculture. This growth is largely attributed to the decreasing costs of hardware (e.g., cameras, storage, and computational systems) and the enhanced computational power available in recent years (Liu et al., 2023; Tian et al., 2023). Object detection plays a crucial role in digital agriculture, enhancing precision farming by minimizing labor and costs, optimizing resource use, and ultimately boosting agricultural productivity and yield (Badgujar et al., 2024). The selection of an algorithm for agricultural tasks often prioritizes high speed (near real-time), accuracy, and compact model size, making the one-stage detector You Only Look Once (YOLO, Redmon et al., 2016) increasingly popular for its real-time capabilities, good accuracy, and suitability for resource-constrained devices. We posit that YOLO presents a feasible approach for detecting peanut maturity, offering a practical and efficient alternative to manual peanut maturity classification. While various techniques exist to estimate peanut maturity, a notable research gap remains: no one-stage detector has been developed that can effectively predict peanut maturity using mobile phone images. Based on this rationale, the objective of this research was to train, validate, and test a one-stage object detector, and to deploy the model on a web application capable of detecting and identifying peanuts, as well as classifying them to generate the Peanut Maturity Index (PMI).

Material and Methods

Sites description

We used data from three commercial peanut fields in Alabama from the 2022 and 2023 seasons. Images of the peanut profile board were collected throughout the season, from the beginning of maturation to one day before harvest (Table 1).

Table 1. Sampling date and study areas information.

Field	Sampling date	Variety	Number of photos
1	08/19/22,08/24/22, 09/09/22,09/16/22,09/25/22	Georgia-O6G	118
2	09/18/23,08/24/23,09/04/23	Georgia-O6G	59
3	09/28/23, 09/12/23,08/25/23	Georgia-O6G	53

Dataset

The dataset was split into training, validation, and test sets. The images were taken using mobile phones with the aid of artificial light. Photos were captured above the peanut profile board after the manual classification of the pods (Figure 1).

Fig 1. Photo of a peanut profile board after classification. Pods sorted by color class according to maturity level, with mature pods categorized in the black class.

Pods are classified on six classes (white, yellow 1, yellow 2, orange, brown and black class). After the classification it is possible to calculate the peanut maturity index (equation 1).

$$PMI = \frac{N\_bbp}{T\_p}$$

Where, PMI is the peanut maturity index considering brown to black classes, N_bbp is the number of pods in the brown and black classes and T_p is the total number of pods among the six classes.

We aim to develop a model capable of generalizing the PMI based on the image of the profile board. The board has six classes, but changing the PMI formula, we can transform these six classes into two. To calculate the PMI, we combined the six classes into one class called “wo,” which includes pods from white, yellow 1, yellow 2, and orange, and another class called “bb,” which includes pods from brown and black. Based on this, we can represent the classification of the model to calculate the PMI as follows:

$$PMI = \frac{N\_bb}{N\_bb + N\_wo}$$

Where, PMI is the peanut maturity index considering brown to black classes, N_bb is the number of pods in the brown and black classes and N_wop is the total number of pods among the white, yellow 1, yellow 2, orange, brown and black classes.

After acquiring the images, each pod in each image was annotated using the Roboflow labeling web platform (Dwyer et al., 2024). A total of 232 images were collected and the dataset was split into training (70%), validation (20%), and test (10%) sets. The training data was augmented by rotating the images 90 degrees clockwise, counterclockwise, and upside down, as well as by applying up to 1px blur and adding noise to up to 0.5% of pixels. This procedure increased the dataset to 483 images for training, 47 images for validation, and 24 images for testing the algorithm.

YOLOv9

Object detection techniques are often categorized into one-stage and two-stage methods. Notable examples of one-stage methods include YOLO (You Only Look Once) (Terven et al., 2023) and SSD (Single Shot MultiBox Detector) (Liu et al., 2016). These techniques predict bounding boxes and class labels simultaneously in a single pass through the neural network, which enhances their inference speed by eliminating the region proposal step (Vo et al., 2024). YOLOv9 represents a significant leap forward in real-time object detection technology (Wang et al., 2024). Released in February 2024, this version of YOLO incorporates innovative techniques like the Generalized Efficient Layer Aggregation Network (GELAN).

Generalized Efficient Layer Aggregation Network – GELAN: GELAN is an innovative architectural enhancement that integrates concepts from CSPNet (Cross Stage Partial Network) and ELAN (Efficient Layer Aggregation Network). This lightweight network architecture is constructed around gradient path planning, which enables efficient aggregation of information across layers. By focusing on a lightweight design, rapid inference, and accuracy, GELAN effectively addresses the information bottleneck problem. This results in increased efficiency and accuracy for real-time object detection (Vo et al., 2024). The structure of GELAN within YOLOv9 is illustrated in Fig. 2. We used the algorithm YOLOv9 with GELAN enchancement to further support real time application of the model.

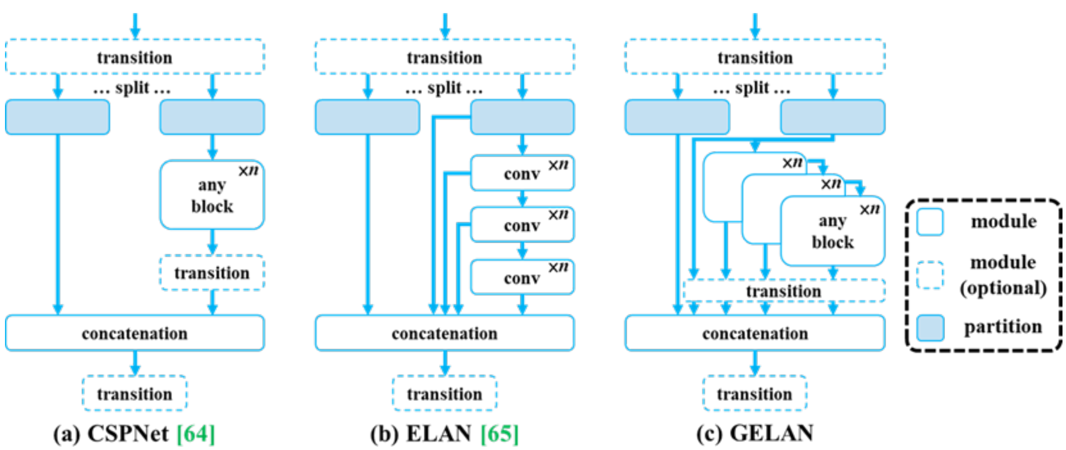


Fig 2. The architecture of GELAN within YOLOv9 (Wang et al., 2024).

Implamentation

The entire framework was developed using the Ultralytics library, with the YOLO model implemented on a Python platform. The system was operated on a GoogleColab environment, with the free computational resources available. The input resolution was 640 x 640 pixels after resizing and batch size was set to four. Data augmentation techniques included rotating images by 90° in different directions (clockwise, counter-clockwise, upside down), applying up to 1px blur, and adding noise to up to 0.5% of pixels. These augmentations aimed to enhance model robustness by simulating various real-world conditions. The model was trained for 50 epochs.

Performance evaluation

The evaluation utilized standard metrics from MS COCO (Lin et al., 2014). Performance of the YOLOv9 model was assessed using mAP@0.50 and mAP@0.95, along with parameters count and GFLOPs, impacting inference speed directly. Precision-recall curves were employed to assess each data acquisition setting, where precision (Eq. (1)), recall (Eq. (2)), and mAP (Eq. (3)) at IoU of 0.50 (mAP@0.50) were computed.

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$mAP = \frac{1}{k}\sum_{i=1}^{N} APi$$

where *P* is precision, *TP* is true positive, *FP* is false positive, *R* is recall, *FN* is false negative, *AP* is average precision, *mAP* is mean average precision.

Results

The train loss curve, showed a steady decrease from 1.09 to 0.87 by the end of 50 epochs, indicating the model's improvement in minimizing prediction errors. Precision and recall metrics, shown in Figure 1, improved from 0.82368 to 0.95914 and from 0.83312 to 0.95576, respectively, highlighting the model's growing capability to accurately detect and classify peanut pods. Additionally, the model's performance was evaluated using Mean Average Precision (mAP) at two different thresholds: mAP50 and mAP50-95. After 50 epochs, the model achieved an mAP50 of 0.97033 and an mAP50-95 of 0.72491, as depicted in Figure 3, indicating high precision and consistency in detecting objects across various levels of peanut maturity. These results demonstrate that the YOLOv9 model, enhanced with the Generalized Efficient Layer Aggregation Network (GELAN), effectively learns and improves its performance over time, validating its robustness and potential for accurate peanut maturity classification.

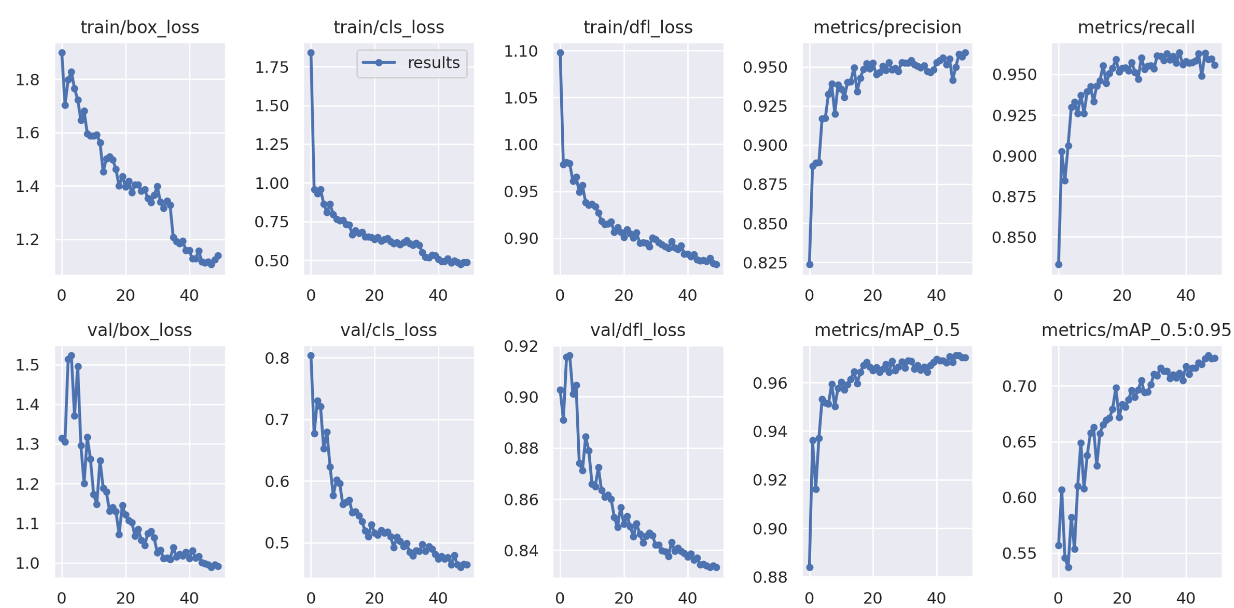


Fig 3. Training and validation metrics of YOLOv9-Gelan-C.

The model underwent rigorous training, and its performance metrics were recorded. The evaluation focused on key metrics such as precision, recall, and mean average precision (mAP) for both 50% and 50-95% thresholds. Table 2 provides a comprehensive overview of these metrics across different classes of the validation dataset. The model achieved a high precision of 0.954 and recall of 0.966 across all classes (ALL). This indicates that the model is highly accurate in correctly identifying peanut pods while maintaining a low rate of false negatives. For the brown and black (BB) class, which is critical for assessing peanut maturity, the model achieved even higher precision (0.967) and a slightly lower recall (0.958). The mAP50 of 0.974 and mAP50-95 of 0.695 underscore the model's excellent performance in detecting mature peanut pods, crucial for determining the optimal harvesting time. The white, yellow, and orange (WO) class also showed robust performance, with a precision of 0.941 and a recall of 0.973. The mAP50 of 0.966 and mAP50-95 of 0.757 indicate that the model effectively distinguishes less mature pods, contributing to a comprehensive maturity assessment. The overall mean average precision (mAP50) of 0.97 and mAP50-95 of 0.726 across all classes demonstrate the model's high accuracy and reliability. These metrics reflect the model's ability to maintain consistent performance across different levels of peanut maturity.

Table 2. Performance metrics for validation dataset during the training of the algorithm,

Class	Images	Instances	Precision	Recall	MAP50	MAP50-95
ALL	47	8194	0.954	0.966	0.97	0.726
BB	47	4913	0.967	0.958	0.974	0.695
WO	47	3281	0.941	0.973	0.966	0.757

The confusion matrix demonstrates the performance of the YOLOv9 model in classifying peanut maturity indices. The model achieves high accuracy with 97% of 'bb' (brown black) and 98% of 'wo' (white to orange) peanuts correctly classified. However, there is a notable confusion, with 55% of 'bb' misclassified and 45% of 'wo' misclassified as background, indicating the need for further refinement (Figure 4).

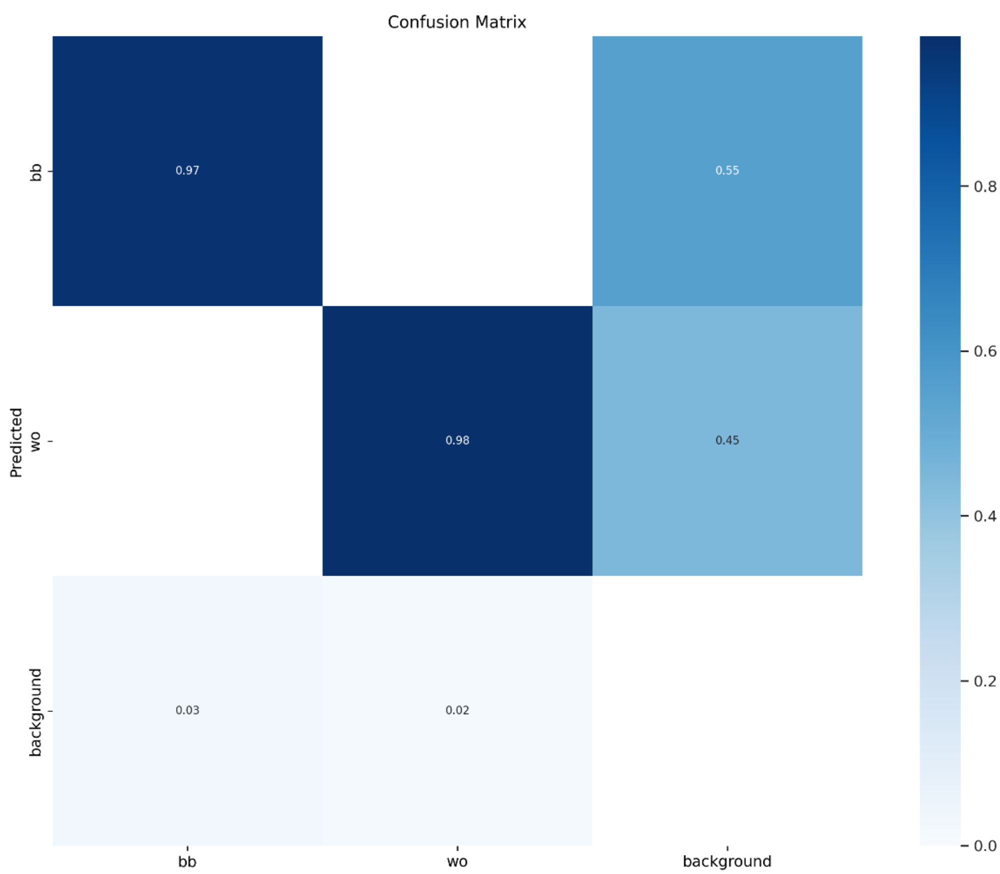


Fig 4. Confusion Matrix of YOLOv9 Model for Peanut Maturity Classification.

Performance analysis of the YOLOv9 model was done by comparing the predicted Peanut Maturity Index (PMI) with the observed PMI for the test dataset (Figure 5). The graph offers a visual representation of the model's accuracy and the correlation between the predicted and actual maturity indices. The model demonstrates a strong correlation between the predicted PMI and the observed PMI, indicated by an R^2 value of 0.9962. This high R^2 value signifies that the model's predictions closely align with the actual maturity index, reflecting its reliability in practical applications. The linear trend observed in the scatter plot of Figure 5 indicates a consistent relationship between the predicted and observed PMI. This linearity reinforces the model's ability to maintain accuracy across different levels of peanut maturity. The uniform distribution of data points along the line of equality (where predicted PMI equals observed PMI) illustrates that the model performs effectively across the entire range of peanut maturity levels. This consistency is essential for ensuring reliable maturity assessments throughout the growing season.

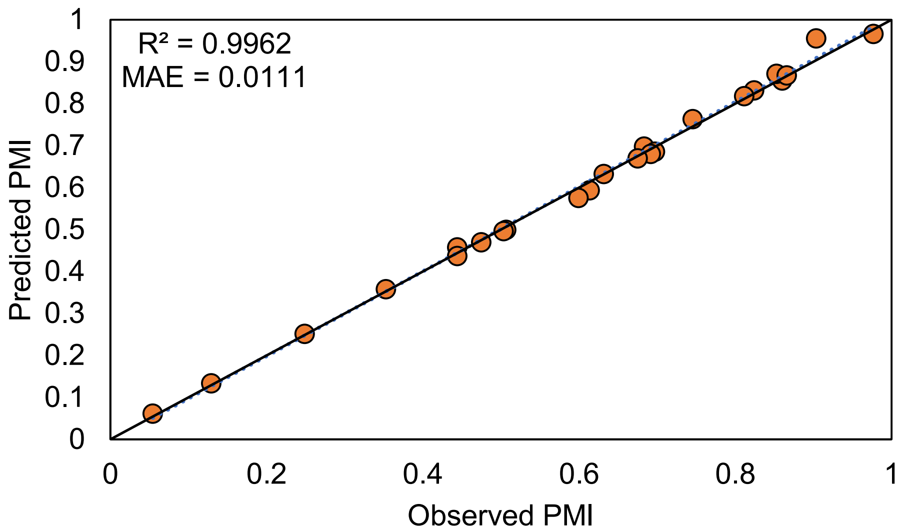


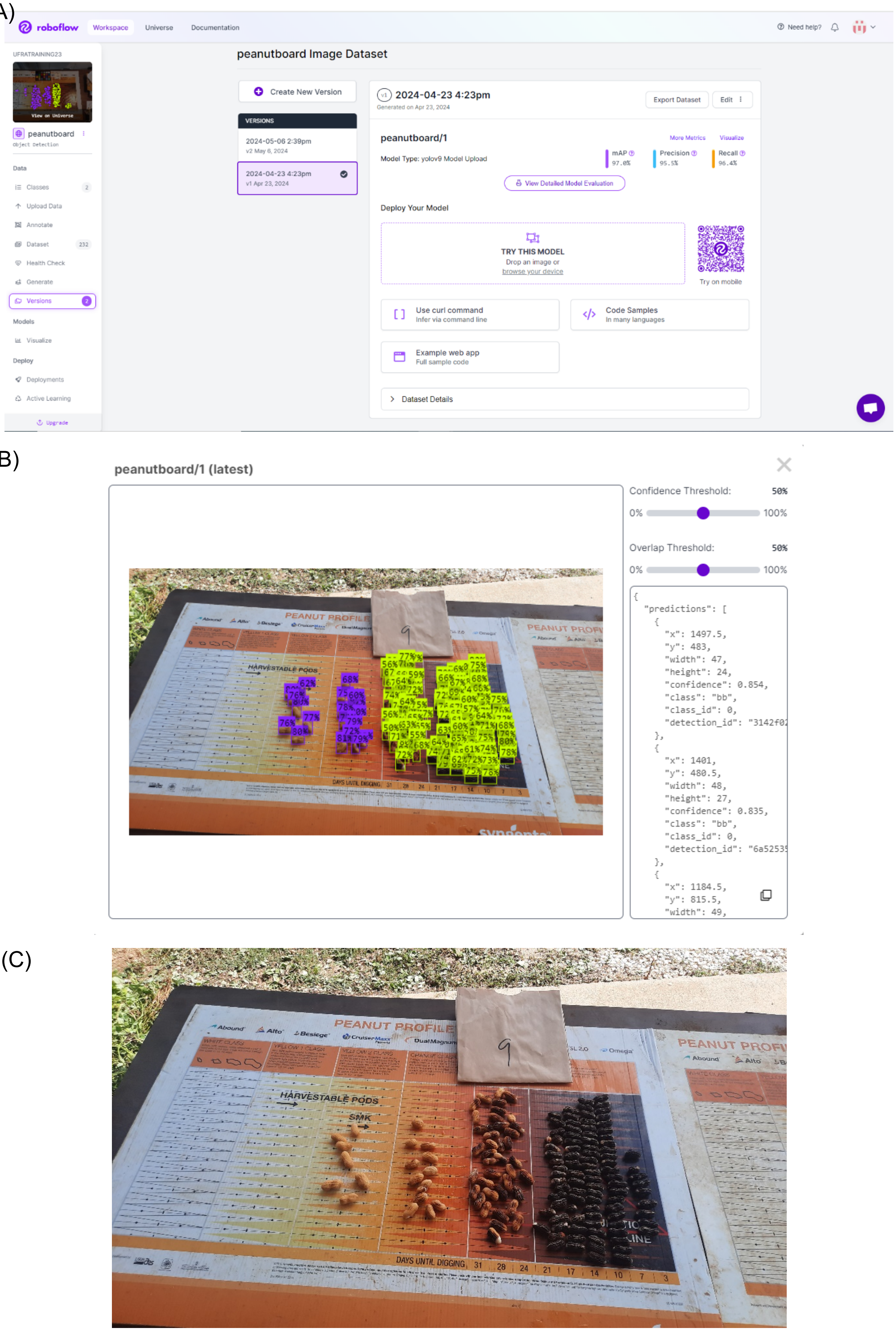
Fig 5. Performance analysis of test dataset comparing the predicted PMI based on YOLOv9 detection and observed PMI. Observation: MAE (mean absolute error) is expressed in percentage.

In this study, we deployed the YOLOv9 object detection model on a web platform designed for real-time analysis of peanut maturity classification. Figure 6 (A) illustrates the integration of our model with the platform, showcasing its capability to accurately detect and classify peanut pods based on color. The second image visualizes the results of our YOLOv9 model, depicting bounding boxes overlaid on the peanut profile board, indicating successful localization and classification of peanut pods. Subsequently, the third image displays a peanut profile board segmented by color categories, demonstrating the initial input for our model. The deployed platform generates a dictionary with all the predications. This integration underscores the effectiveness of YOLOv9 in automating the classification process, enhancing efficiency and accuracy in detecting and classifying the pods.

(A)

(B)

(C)



{
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    {
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Fig 3. Integration of YOLOv9 object detection model with peanut pod classification: web platform deployment (A), Bounding Box Visualization (B) and original photo (C)

Conclusion

Our findings demonstrated a promising alternative to predict multiple Peanut Maturity Indices (PMI) at a field scale using the YOLOv9 model enhanced with the Generalized Efficient Layer Aggregation Network (GELAN). This approach significantly reduces the subjectivity associated with traditional methods of determining peanut maturity. The high precision and recall metrics across different maturity classes highlight the model's robustness in accurately classifying peanut pods, providing a reliable tool for farmers and researchers. Another promising outcome is the strong correlation between the predicted and observed PMI values, with an R^2 value of 0.9962 and a mean absolute error (MAE) of 0.0111%. Future research should focus on expanding the applicability of the YOLOv9 model enhanced with the Generalized Efficient Layer Aggregation Network (GELAN) across diverse peanut varieties and varying field conditions to ensure its robustness and generalizability. Additionally, integrating this model with real-time monitoring systems and mobile applications could provide farmers with instant feedback, facilitating timely decision-making in peanut cultivation.

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