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Optimized YOLOv8 Model for Accurate Detection and Quantification of Mango Flowers

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ABSTRACT

Mangoes are widely cultivated and hold significant economic value worldwide. However, challenges in mango cultivation, such as inconsistent flowering patterns and manual yield estimation, hinder optimal agricultural productivity. This study addresses these issues by leveraging the You Only Look Once (YOLO) version 8 object detection technique to automatically recognize and quantify mango flowers using image processing. **This research aims** to develop an automated method for detecting and estimating mango yields based on flower density, representing the early stage of the plant growth cycle. **The methodology** involves utilizing YOLOv8 object detection and image processing techniques. A dataset of mango tree images was collected and used to train a CNN-based YOLOv8 model, incorporating image augmentation and transfer learning to improve detection accuracy under varying lighting and environmental conditions. **The results** demonstrate the model's effectiveness, achieving an average mAP score of 0.853, significantly improving accuracy and efficiency compared to traditional detection methods. **The findings** suggest that automating mango flower detection can enhance precision agriculture practices by reducing reliance on manual labor, improving yield prediction accuracy, and streamlining monitoring techniques. **In conclusion, this study** contributes to the advancement of precision agriculture through innovative approaches to flower detection and yield estimation at early growth stages. Future research directions include integrating multispectral imaging and drone-based monitoring systems to optimize model performance further and expand its applications in digital agriculture.

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1. INTRODUCTION

Fruits and vegetables provide essential nutrients for humans [1]. Flower detection and counting often face uncertainties. Multiple Hypothesis Tracking (MHT) technology is used to overcome these problems [2]. Different types of fruits are cultivated with specific challenges. Short shelf life is a constraint in global trade [3]. Apple has the most advanced cultivation techniques with the application of the latest technology [4]. Flower classification through computer vision and early flower detection ensure optimal pollination time [5]. Flower abundance management strategies increase productivity [6], while tree disease identification and flower thinning methodologies help maintain plant health [7]. Area segmentation supports flower distribution analysis 8 Y.Tian, G.Yang, while flower density detection is used in growth monitoring [8]. Flower group classification and harvest forecasting are performed to optimize production yield [9]. Flower monitoring with YOLO (You Only Look Once) version 8 and data augmentation techniques improve detection accuracy [10]. Tree monitoring system during flowering phase helps in cultivation management [11]. Advanced cultivation systems are applied to other crops. Grape flower categorization and identification are used to assess fruit quality [12], while grape variety identification supports yield classification [13]. Prediction of fruit yield through strawberry flower detection is an important tool in production planning [14]. Peach flower evaluation in Spain is used to determine yield potential [15], while flower recognition plays a role in automatic yield prediction [16]. Measurement of cucumber blooms in a greenhouse improves the effectiveness of growth monitoring [17], while a real-time pineapple flower counting system accelerates production analysis [18]. Enhancement of peach flower aroma components supports the development of superior varieties [19]. Automation of harvest maturity assessment was applied in various types of fruits. Fruit detection and counting were performed on blueberry detection [20–22, 22]. Chili identification was developed for automated harvesting [23]. Research on mango cultivation still faces certain challenges. The YOLO model finds fruits on representative sample mango trees and uses extrapolation methods to estimate the total number of fruits in a population of trees [24]. Light-YOLO is used in mango detection in the natural environment [25]. Machine vision applications are used to count the number of fruits, measure their size, and avoid branches in an automated harvesting system [26]. Apples and mangoes are both analyzed using computer vision technology for production optimization. Flower patterns in apples are studied in depth through strategies for flower abundance management, density detection, and flower cluster classification. Studies on mangoes focus more on fruit detection and automated harvesting. Studies on flower patterns and flower numbers in mangoes are still limited. Further research is needed to develop more accurate analysis systems to improve mango productivity.

Flower characteristic monitoring is an important part of agricultural systems to optimize yields [27]. Object detection and tracking are increasingly evolving with advances in image processing [28]. The YOLOv8 algorithm is designed to enable high speed and accuracy in object identification [29]. High precision in detection and efficient power consumption make YOLOv8 superior in various applications [30, 31]. The system has been used to identify apple flowers [32], strawberry flowers [14], and various other agricultural objects [33]. Research on mango fruit quality shows great potential in the application of image processing technology to improve the accuracy of harvest prediction and fruit management [34]. YOLOv8 has advantages in high precision detection and execution speed, but the application of this algorithm in mango flower detection and management is still very limited. Further studies are needed to optimize the use of this technology in supporting mango plant productivity.

Previous research has proved the importance of image processing technologies in improving the efficiency and accuracy of agricultural monitoring. Various techniques, such as Smart Agroforestry systems, have included automated leaf area measurement, species identification, and pest monitoring to improve crop management efficiency. YOLOv8 has been widely used in agricultural object identification, demonstrating excellent performance in both high-speed and high-precision detection while minimizing background noise. Compared to prior algorithms, YOLOv8 provides a lightweight and efficient solution, making it appropriate for real-time agricultural applications. Several studies have successfully used YOLO-based detection for apple and strawberry flowers, with excellent accuracy in flower categorization and early-stage production monitoring. Despite these advances, research on YOLOv8's use in mango flower recognition is still restricted, notably in recognizing and quantifying mango blooms under various environmental circumstances. Existing research focuses mostly on mango fruit detection and quality evaluation, leaving a research void in early-stage yield prediction using flower detection. This work fills a gap by using YOLOv8 for mango blossom recognition and combining picture augmentation and transfer learning approaches to improve accuracy and model resilience.

Correctly recognizing mango flowers is critical for yield calculation and agricultural optimization, allowing for early fruit production forecasting and optimal resource allocation. Traditional human counting methods are error-prone, but computer vision-based detection using YOLOv8 provides real-time, automated, and exact analysis. This research aims to create a robust mango flower recognition system utilizing YOLOv8 with picture augmentation and transfer learning, solving research gaps in early-stage yield estimation. The experimental findings demonstrate a high detection accuracy (mAP score of 0.853), greatly improving efficiency over conventional approaches. The suggested approach advances precision agriculture by enabling AI-driven yield monitoring, which benefits farmers, agritech firms, and policymakers. Societally, it improves farming efficiency, decreases reliance on human labor, and boosts food security. Future work will involve merging drone-based photography and spectrum sensors to improve detection accuracy and scalability.

2. RESEARCH METHOD

This quantitative experimental study employs deep learning and image processing methods to identify and measure mango blooms. The evaluation utilizes numerical data and statistical indicators, including mAP, Precision, and Recall, to assess the performance of the YOLOv8 model.Photos of mango blossoms were taken by hand using a phone camera. Images were taken from diverse mango groves surrounding the residential area at various times of day to guarantee dataset variety. Lighting levels were adjusted between natural daylight and darkened locations to prevent overexposure or underexposure. To prevent bright sunshine, optimal lighting was identified throughout the early morning (07:00-09:00 AM) and late afternoon (16:00-18:00 PM) hours. A total of 278 photographs were acquired, representing various lighting changes and plant conditions. The hands-on data collection technique yielded high-quality images that matched the research objectives.

Roboflow was mostly used for image labeling. Rotation, brightness modification, flipping, and scaling are examples of data augmentation procedures that increase dataset diversity. These strategies enhanced model generalisation by considering various orientations and illumination conditions. The Google Colab team created and implemented the YOLOv8 model for detection and quantification tasks. The computational configuration featured a GPU Compute Engine T4 with 12.7 GB of total system RAM and 15.0 GB of GPU RAM. The mango flower dataset may be processed and analyzed efficiently and precisely because of the high-performance hardware.

Figure 1 depicts the detection and quantification of mango blooms using the YOLOv8 approach. The detection method began with the collection of photos of mango flowers with phone cameras. These photos were fed into the YOLOv8 model, designed to recognise and quantify flowers. Individual flowers were detected by the algorithm and marked with bounding boxes. Each bounding box indicated the location of a single flower in the image, guaranteeing both a visual representation and an exact numerical count. Flower density was assessed using individual bounding boxes rather than group segmentation, allowing for more exact quantification.

A re-detection cycle was used to improve accuracy. Image reprocessing was used if the initial detection results were erroneous or needed to be verified. The first detection findings were passed back into the YOLOv8 algorithm, allowing for re-analysis with other settings or data. This repeated technique increased detection accuracy and reliability.

The detection findings, which included bounding boxes and flower counts, were combined to provide a comprehensive dataset for exact mango blossom measurements. The systematic strategy blended manual data collecting with current image processing, data augmentation, and iterative refining to improve research dependability. Figure 1 depicts the detection process and consequences.

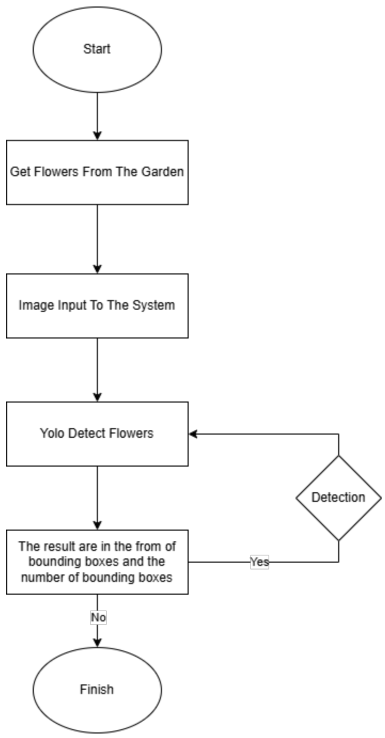

Figure 1. Model Flowchart

3. RESULT AND ANALYSIS

A crucial phase in developing a mango blossom identification model using YOLOv8 is preprocessing. The stages for dataset preparation include gathering images of mango trees and their blossoms. Images were captured from many perspectives and under diverse lighting conditions to enhance the model's accuracy. One needs to use a drone or a high-quality camera to capture images from many perspectives and distances. The subsequent crucial stage, data augmentation, is to enhance the diversity of training data, fortify the model's robustness, and recognize mango flowers in diverse situations. Commonly used data creation methodologies encompass: To increase data variety, the image may be rotated by numerous degrees to replicate different shooting angles. This technique aids in mimicking real-world variations in camera angles, making the model more adaptable to different orientations. As shown in Figure 2, rotating an image of mango flowers by 0^o, 15^o, and -15^o effectively represents various perspectives from which the flowers could be photographed in natural settings. By applying these rotations, the model can learn to recognize objects from different angles, which improves its generalization ability. Furthermore, this approach compensates for variations in camera positioning, resulting in improved adaptability in practical applications.

Figure 2. Rotating Images

To add further diversity, rotate the picture by 90 degrees, changing its orientation. This modification helps to diversify the dataset and ensures that the model can recognize objects independently of their alignment. As seen in Figure 3, rotating the picture of mango blossoms produces several orientations, imitating how the flowers may appear from various perspectives. Such adjustments are critical for enhancing the model's adaptability to various camera angles and positioning alterations. Integrating 90-degree rotations makes the dataset more robust, improving the model's generalizability to real-world situations.

Figure 3. Rotate 90 degrees

Inversion, as illustrated in Figure 4, is a technique that involves flipping an image either horizontally or vertically to create a mirrored version. This method is particularly useful in ensuring that the model can recognize mango flowers regardless of their orientation within the frame. The left and right sides are reversed by flipping the image horizontally, simulating different perspectives that may occur in real-world photography. Similarly, vertical flipping inverts the image from top to bottom, allowing the model to adapt to various positional changes. Incorporating horizontal and vertical inversion enhances the dataset's diversity, improving the model's robustness and ability to generalize across different viewing angles.

Figure 4. Flipping Images

The generalization capabilities on test data improve due to this data augmentation, which assists the model in circumventing overfitting to the training data. Dataset annotation is crucial in developing a mango blossom detecting algorithm using YOLOv8. Labelling involves annotating gathered images by delineating each mango flower with a bounding box and corresponding label. Subsequently, all the gathered photographs will be uploaded to it. Commenced purchasing each photograph, encircling the mango flower and categorising it as either "Lush" or "Not Lush". It augments the dataset's variety using data augmentation techniques, including rotation, flipping, and alterations in illumination. This annotation will generate a text file containing object coordinates, bounding boxes, and class names. The first column displays the object class name, the subsequent columns represent the x and y coordinates from the left of the box, the fourth column indicates the width, and the fifth column denotes the height of the box. The scale is positioned at coordinates 0 to 1.

Below is the YOLOv8 Architecture, which is further illustrated in Figure 5. The backbone extracts essential features from input pictures using a succession of convolutional and C2f layers that constitute the Cross Stage Partial Network with Fast Normalization. The input picture is 640×640 pixels and includes three color channels (RGB). Conv(0-1) starts with two convolutional layers that use a 3×3 kernel with a stride of 1 to extract key characteristics from a picture. Following that, C2f (2) is introduced, with n=3 and d=1, combining features from many prior layers to improve feature representation.

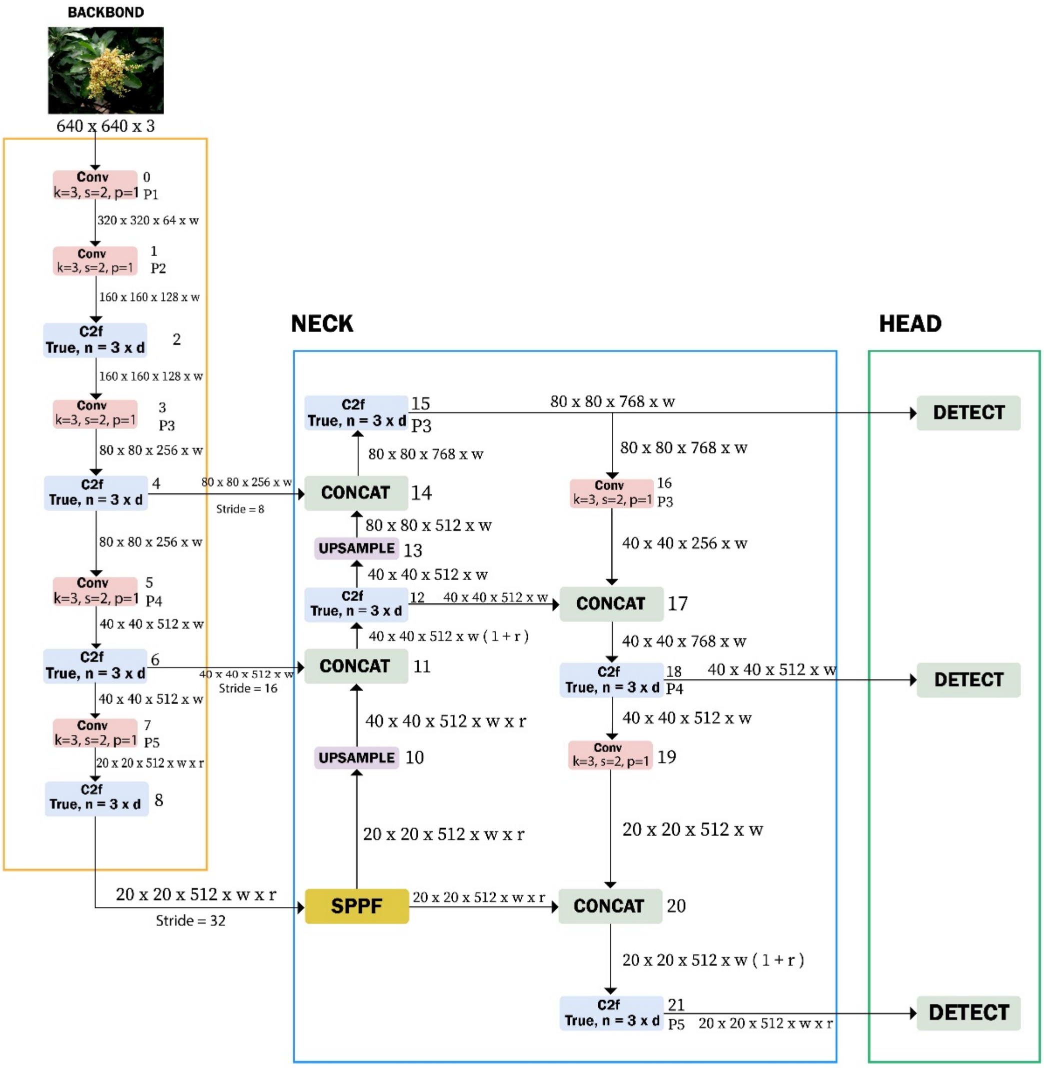

Figure 5. YOLOv8 Architecture

The procedure continues with Conv(3), a convolutional layer with a stride of 2, lowering the feature resolution to 80 × 80. C2f (4), defined by n=3 and d=1, processes the features, resulting in an 80 × 80 × 256 output dimension. Conv(5) inserts a second convolutional layer with a stride of 2, reducing the resolution to 40 × 40. C2f (6), with n=3 and d=1, refines the retrieved features, producing an output of 40 × 40 × 512. Conv(7) introduces a convolutional layer with a stride of 2, reducing the resolution further to 20 × 20. C2f (8), maintaining n=3 and d=1, produces an output dimension of 20 × 20 × 512. The Pyramid Pooling Spatial Fast (SPPF) module (9) integrates multi-scale information, resulting in a final output of 20 × 20 × 512. The SPPF mechanism enhances detection accuracy by aggregating contextual information from different receptive fields, which is particularly beneficial for identifying mango flowers with varying sizes and shapes. Small flowers and those partially occluded by leaves or overlapping with other blooms benefit from this pooling strategy, ensuring that critical features remain preserved in the final feature map. The Neck is an intermediary between the Backbone and Head, integrating features from multiple resolutions to enhance detection accuracy. C2f (10), defined by n=3 and d=1, refines features at 20 × 20 × 512. Upsample (13) increases feature dimensions to 40 × 40 × 512, preparing them for further refinement. Concat (14) combines properties from the Backbone and the Upsample output, allowing multi-resolution feature integration. This process enhances the model's ability to detect small or overlapping objects, ensuring finer object localization. Integrating Upsample and Concat techniques enables feature fusion across different scales, preserving details that might otherwise be lost when reducing resolution.

C2f (15), another layer with n=3 and d=1, analyzes these integrated features, yielding 80 × 80 × 768. Conv(16) adjusts the resolution back to 40 × 40 × 256, reducing feature dimensions while preserving critical spatial information. Concat (17) further integrates features from the Backbone and Conv output, improving feature representation for detection. C2f (18) refines these attributes with n=3 and d=1, producing 40 × 40 × 512. Upsample (19) enlarges feature dimensions to 80 × 80 × 512, followed by Concat (20), which integrates properties from the Backbone and Upsample outputs to maintain feature consistency. C2f (21) processes these attributes, yielding a 20 × 20 × 512 final output dimension. The head utilizes the processed features of the backbone and neck to identify objects. Detection occurs at three scales (80 × 80, 40 × 40, and 20 × 20), enabling the model to effectively localize flowers of different sizes. The bounding box predictions and object classification benefit from C2f layers for computational efficiency, Upsample and Concat for multi-scale feature fusion, and SPPF for contextual understanding. This structure ensures precise detection, even in dense floral clusters or images with occluded flowers. Figure 6 presents a graph of the F1 Confidence Curve for two categories: "flower-lush" (light blue) and "non-lush" (orange). The model's total F1 Score reaches a peak of approximately 0.49, represented by a prominent blue line. The confidence curve evaluates model performance at different confidence thresholds, highlighting the balance between precision and recall. Confidence threshold optimization plays a crucial role in determining detection reliability. Higher thresholds prioritize precision, reducing false positives, whereas lower thresholds enhance recall, capturing more flowers but increasing the risk of false detections. The model's optimal confidence level can be identified by analyzing points where the F1 score stabilizes, ensuring an effective trade-off between false positives and missed detections. A comparison of models trained with different data augmentation techniques would provide deeper insights into model performance across diverse conditions. Future evaluations could explore the impact of rotation, brightness adjustments, and scaling on improving detection accuracy in varying lighting environments.

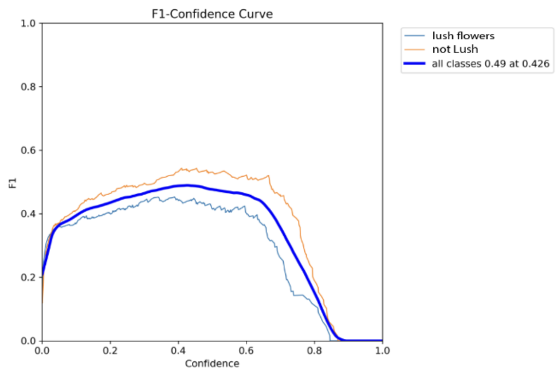

Figure 6. Confidence Curve

Figure 7 illustrates the Precision-Confidence Curve for two categories: "flowery," represented by the light blue line, and "non-lush," shown by the orange line. The curve demonstrates the correlation between Precision values and the predictive model's confidence level. The training results yielded an mAP score of 0.853, indicating the model's commendable performance in average accuracy across diverse confidence levels.

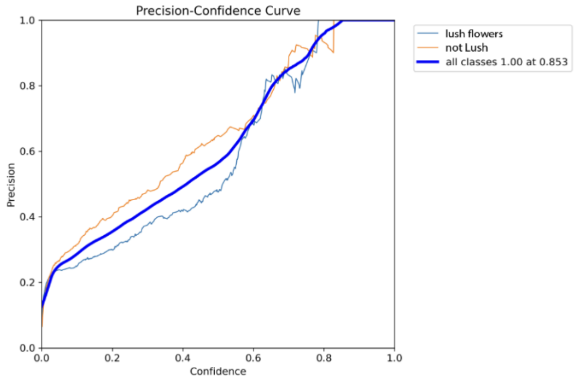

Figure 7. Precision Confidence Curve

Figure 8 presents a graph of the Precision-Confidence Curves for two categories: ”flowery,” represented by the light blue line, and ”non-lush,” shown by the orange line. These curves assist in assessing the model’s performance over a broad spectrum of trust levels. The bold blue line represents the model’s total Recall value. The highest score of around 0.72 signifies that the model exhibits commendable performance.

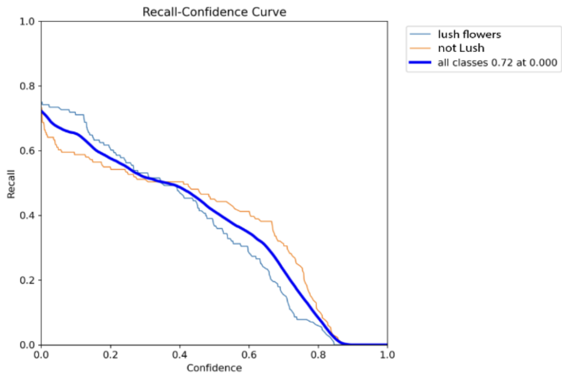

Figure 8. Recall Confidence Curve

Figure 9 illustrates the Precision-Confidence Curve for two categories: ”flower-lush,” represented by the light blue line, and ”not-bush,” shown by the orange line. This curve assesses the efficacy of the classification model, particularly in the context of unbalanced data. The dense blue line comprehensively assesses model performance across all categories. The mAP score of 0.474 indicates the model’s average efficacy across all classes.

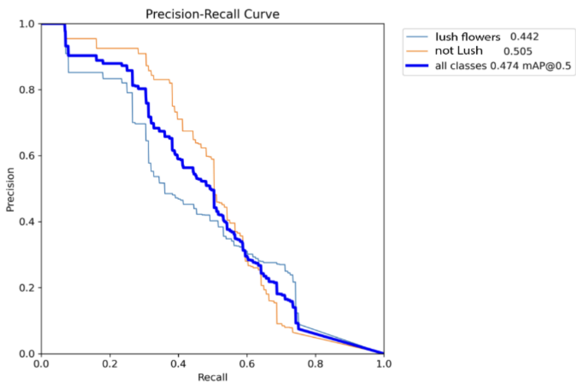

Figure 9. Precision-Recall Curve

Figure 10 presents the definitive detection results of the YOLOv8 model. Items designated as "lush-flower" with a confidence score of 0.82 are displayed within the red box. This picture illustrates the model's ability to identify and pinpoint items inside an image using previously retrieved and processed attributes. The confidence score indicates the model's proficiency in identifying and classifying items under the evaluated conditions. Although this identification was achieved in optimised lighting, the model's overall performance in diverse lighting circumstances necessitates more assessment. Augmenting the dataset with photos obtained in varied environmental circumstances is anticipated to improve detection consistency and robustness. These detections demonstrate the model's ability to properly recognise and categorise items while preserving high precision in structured environments.

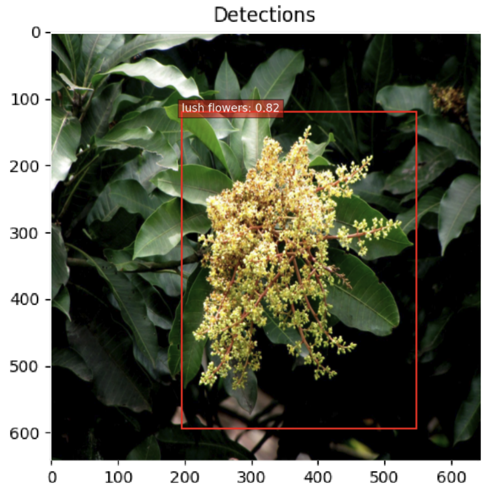

Figure 10. F1 Detection Mango Flower

4. CONCLUSION

This research presents an effective approach for identifying and quantifying mango flowers using YOLOv8, a real-time object detection algorithm. The findings indicate that YOLOv8 effectively detects and quantifies mango blossoms, offering a dependable method for yield estimation and agricultural automation. This method improves crop monitoring, land management, and production efficiency, minimizes manual labour, and facilitates real-time decision-making in mango cultivation. This research presents a quantifiable and practical approach by integrating real-time detection and re-detection cycles, thereby enhancing accuracy in dynamic environments, in contrast to previous studies that did not effectively utilise YOLOv8 across diverse field conditions. The system supports future integration with drones, spectral sensors, and web-based applications, enhancing its potential in precision agriculture. Improvements can be attained by augmenting the dataset with images from diverse locations, lighting conditions, and seasons to enhance model generalization. Advanced data augmentation methods enhance robustness, such as brightness adjustments, geometric transformations, and scaling. Integrating spectral sensors and alternative imaging technologies may enhance detection precision, while using drones and mobile devices can improve monitoring efficiency for large-scale applications. Conducting field experiments across various weather conditions and seasons is crucial for evaluating model resilience and performance in real-world scenarios. Algorithm flexibility is essential for managing diverse flower densities, occlusions, and overlapping clusters. This necessitates additional research into adaptive detection thresholds and alternative deep learning models to improve precision and computational efficiency. Involving farmers in model evaluation enhances practical relevance and usability. This study advances AI-driven digital agriculture, specifically in mango cultivation, fostering automation, efficiency, and sustainability in contemporary agricultural management.

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6. DECLARATIONS

AUTHOR CONTIBUTION

Ardi Mardiana: Managed and led analysis, designed research, and was lead programmer. Ade Bastian: Compile research reports, papers, and correspondence. Ano Tarsono: Collect image data in the field and test in the field. Dony Susandi: Primary supervisor, and responsible for conducting research reviews. Safari Yonasi: Provide conceptual contributions in developing theories or concepts that form the basis of research.

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COMPETING INTEREST

The author declares that there is no conflict of interest regarding the publication of this article.

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