Automated blueberry fruit trait phenotyping from field images by integrating a foundation segmentation model

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Background and Objectives

What is Blueberry phenotyping?
Blueberry phenotyping refers to the systematic measurement and analysis of observable characteristics or traits of blueberry plants, enhancing **breeding** programs and optimize **crop management** practices. Common phenotyping traits includes **fruits yield**, **maturity, density**, and **compactness**.

Objectives
We proposed an automated blueberry **fruit phenotyping** pipeline with multi-view imaging **robotic system**:

1) Develop **automated multi-class fruits mask annotation** pipeline
2) **Customized the AI models** for enhancing blueberry **clusters detection** and **fruits segmentation**.
3) Derive and compare blueberry fruit traits including **yield, maturity,** and **cluster compactness** across various genotypes.

Robotic System Design

Multi-view Imaging platform

- Customized ROS-based modular agricultural robot
- Mobile robot with Dual-GNSS field navigation
- Three imaging views: top, left and right view

Fig.1: Data collection with Robotic mobile platform

Robotic Blueberry Fruit Phenotyping Pipeline

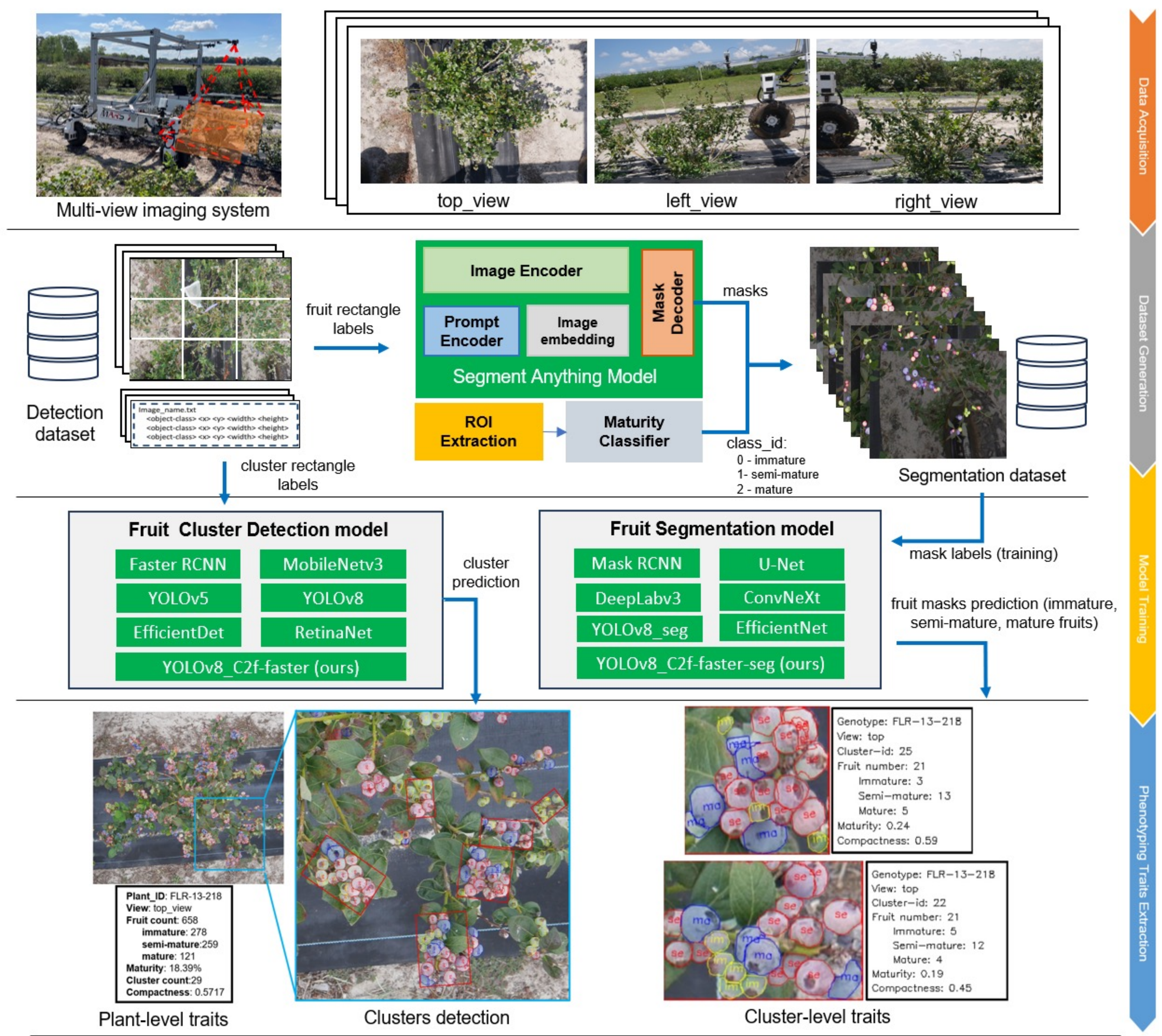

Fig.2: Overview of proposed automated fruit phenotyping pipeline

Data acquisition: multi-view imaging system with robotic mobile platform

Dataset preparation: machine-assistant labeling with pretrained maturity classifier and visual foundation model Segment Anything model (SAM)

Model training: customized AI models to enhance blueberry cluster detection and fruit segmentation (baseline: YOLOv8)

- **P2 feature:** lower feature map for enhancing small object perception
- **C2f-faster**: lightweight and faster feature extractor
- **BiFPN**: Powerful feature fusion in neck

Phenotyping traits extraction:

- **Yield estimation**: multi-view regression with number of fruit prediction
- **Maturity estimation**: ratio of mature fruits among all fruits
- **Compactness**: ratio of mask area and minimum rectangles of clusters

Result & Conclusion

Model accuracy: achieve **85.6% of mAP@0.5** and **62% of mIoU** for fruit segmentation, which is better ~5% than the baseline.

Table 1. The evaluation performance of customized models on fruit segmentation

Class	Precision	Recall	mAP@0.5	mAP@0.5-0.95	mIoU
All	83.2	76.1	85.6	63.6	62.0
Immature	87.4	71.6	85.8	60.2	59.1
Mature	82.2	83.8	88.5	69.4	67.9
semi-mature	79.8	73.1	82.5	61.2	58.9

Yield estimation: multi-view regression preforms best **23.45% of MAPE** and an **R2 value of 0.71** (Fig. 3).
Maturity estimation: multi-view and single-view prediction can achieve **~95% of accuracy** with ~5% of MAE (Fig. 4).

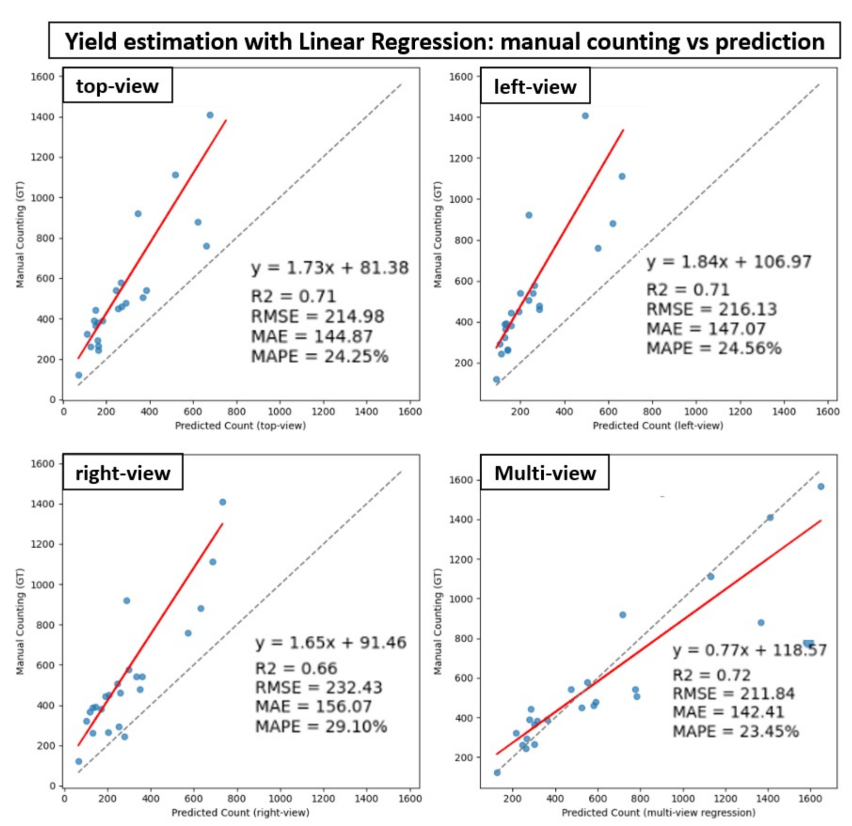

Fig.3: Linear regression comparison for yield estimation among different views

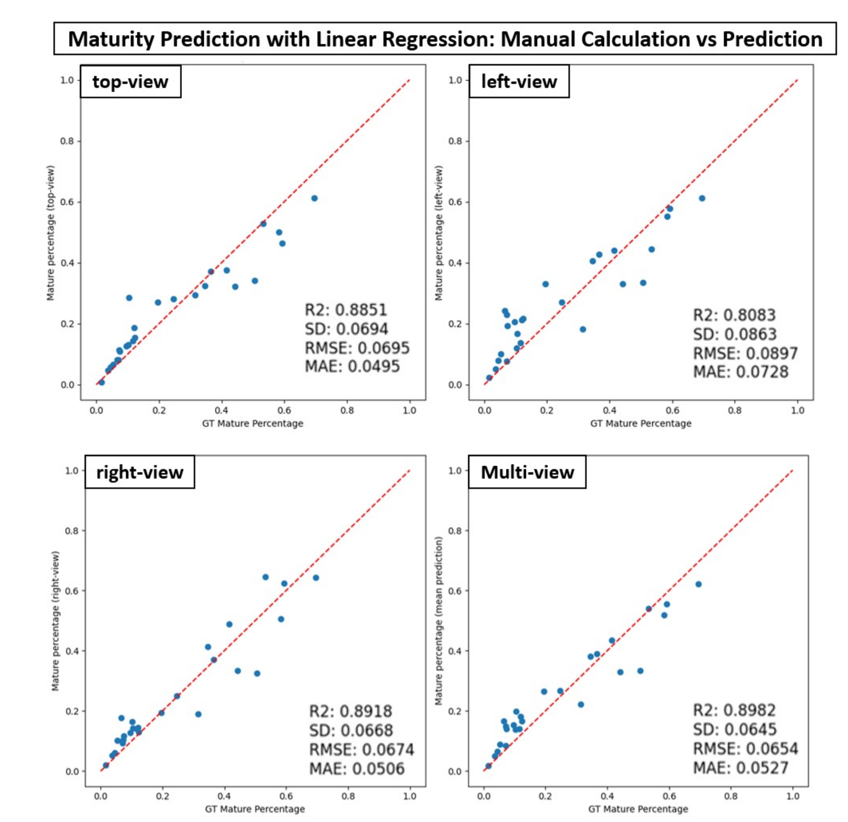

Fig.4: Linear regression comparison for maturity estimation among different views

Compactness estimation:
combining the cluster detection and fruits segmentation, extract the compactness of each cluster for breeder analysis.

$$Compactness_{cluster} = \frac{\text{Area of fruits' mask}}{\text{Area of cluster}}$$

Fig.5: Cluster compactness calculation

Reference & Acknowledgement

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