Southern Region Small Fruit Consortium Proposal Final Report

Title: **Enabling high-throughput yield prediction for efficient blueberry production**

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Objectives:

The overall goal of this study is to **develop a smartphone app to accurately predict blueberry yield and maturity before harvest (Fig. 1)**. We will use image-based analysis combined with deep learning and big data to provide an ***accurate***, ***inexpensive***, and ***convenient*** way for predicting blueberry yield and maturity in the field setting. Specifically, we aim to:

Objective I: develop 2D image-based deep learning models to accurately estimate per-plant yield and maturity for various blueberry cultivars under various production systems.
Objective II: develop a smartphone app to allow convenient yield and maturity monitoring before harvest.

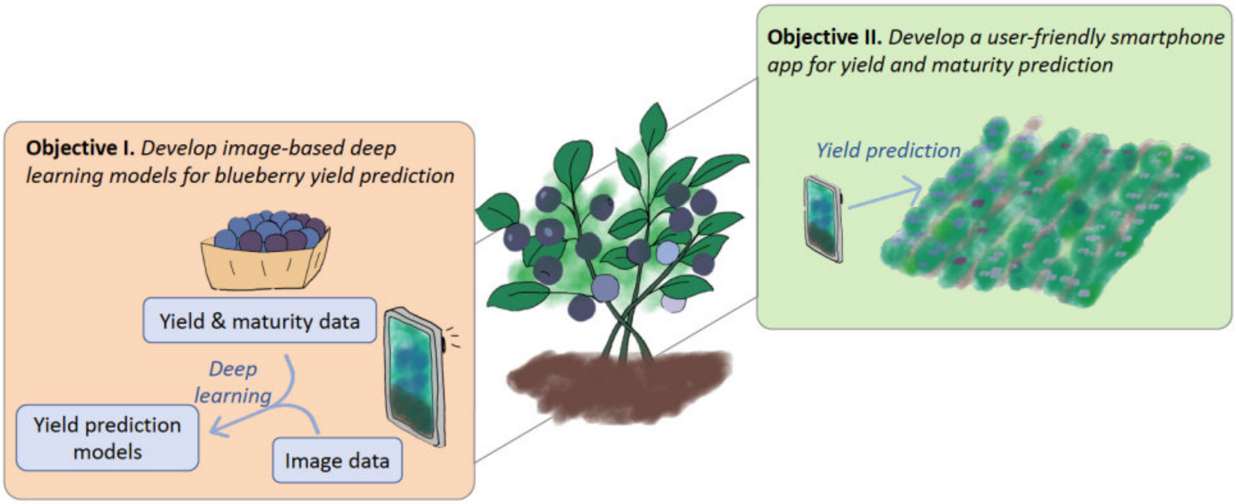

Figure 1. Overview of objectives and outcomes

Justification and Description:

The health benefits and improved qualities of cultivated blueberries has led to a surge of the global blueberry industry. Since 1970, the global blueberry production has constantly been increasing at an average annual rate of 6.1% (FAOSTAT, accessed on 2021-04-22). United States, the No. 1 blueberry producer in the world, produced a total value of $908,677,000 blueberries in 2019 (USDA NASS, accessed on 2021-04-23). The United States blueberry market is projected continue to grow with a 2.1% compound annual growth rate between 2020 and 2025 driven by the anticipated increase in consumer demands [the United States Blueberry Market – Growth, Trends, and Forecasts (2020-2025)]. To meet the demands of an expanding market, it is crucial to develop strategies to improve the efficiency of blueberry production further.

Yield data is critical for blueberry growers to optimize production and marketing strategies. Traditionally, blueberry yield can only be obtained after harvest. Estimating blueberry yield before harvest, either based on a visual assessment or manual sampling, remains largely inaccurate. If yield and maturity can be accurately predicted before harvest, growers will be better informed about harvest time, labor needs, and optimal marketing strategies (Swain et al. 2010). To facilitate more effective decision-making, maximize profitability while minimizing risks, we propose ***an efficient and user-friendly strategy to predict blueberry yield and maturity based on image***. A major deliverable of this study will be a smartphone app to allow growers to monitor single-plant yield and maturity in near real-time by taking pictures of a blueberry plant in the field.

Image-based plant analysis, especially when assisted with deep learning, is a promising tool for blueberry yield and maturity estimation. Deep learning is a computational method that trains computers to learn as the human brain through examples. By feeding computers with a large volume of data, deep learning can successfully extract meaningful information from digital images for applications such as self-driving car, facial recognition, and yield prediction (Voulodimos et al. 2017). The distinct color and shape of mature berries make blueberry yield and maturity great traits for image-based plant analysis. Previous studies, although limited, have shown promising results. Ni et al. (2020) used Mask R-CNN, a deep learning-based object instance segmentation technique, to measure blueberry number, maturity, and compactness based on images of single southern highbush blueberry bunches (Ni et al. 2021; Ni et al. 2020). The detected berry number had a high accuracy compared to manually counted berry number ($R^2 = 0.886$). Meanwhile, the estimated maturity level was also highly correlated with ground truth ($R^2 = 0.908$) (Ni et al. 2021). Previous research demonstrated the excellent performance of deep learning on detecting berries and measuring maturity on single clusters. ***To translate research findings into more profitable and efficient blueberry production, this study will develop a smartphone app to enable <u>accurate, inexpensive</u>*, **and** *<u>convenient yield prediction for blueberries</u> in the field setting.***

Approach
<u>*Objective I*</u>: develop 2D image-based deep learning models to accurately estimate per-plant yield and maturity for various blueberry cultivars under various production systems.

Models for single-plant berry detection and yield prediction were trained with images of single blueberry plants and manually collected yield and maturity data. To increase the robustness of the model, a wide range of genotypes were phenotyped, including filed-grown southern highbush cultivars 'Kirra', 'Farthing', 'Arana', 'Vario' (3-4 years old, 10 plants in total), field-grown southern highbush selections (6 years old, 8 genotypes, 24 plants), field-grown rabbiteye cultivars 'Premier', 'Alapaha', 'Powderblue' (9 years old, 26 plants), and container-grown southern highbush selections (4 years old, 5 genotypes, 12 plants in total). An average of 3-4 plants per genotype were phenotyped during the peak of the 2022 harvesting season (4/15/2022-06/21/2022 for field data and 3/3/2022-4/28/2022 for greenhouse data). For field data, two images per plant were collected, one from each side of the row. A 12-megapixel RGB camera on a Google Pixel 5a smartphone were used for image acquisition (**Fig. 1**). Four ArUco markers mounted onto two 48-inch rods were placed on the left- and right-side of the plant to mark the vertical boundaries of the plant. Berries from the two sides were harvested separately for the measurement of yield and average berry weight. Average berry weight was calculated by measuring the weight of 30-50 berries per side. Maturity level of a plant was calculated as the percentage of fully ripe berries over the total number of berries, based on manually annotated images of each plant.

Field images were manually annotated with the open-source image annotation software COCO Annotator to create a custom blueberry dataset for deep learning research (**Fig. 1**). Pretrained Mask R-CNN models based on He et al. (2017) and our 2022 data in Detectron2 (Facebook AI Research) were used to detect individual berries and estimate their maturity levels. Statistical models (e.g., multiple linear regression) and machine learning models (e.g., support vector machine, random forest, artificial neural network, etc.) are being evaluated to predict the ground truth yield based on estimated berry count, average berry weight, plant age, genotype, and visually estimated canopy density to better account for occlusion effect.

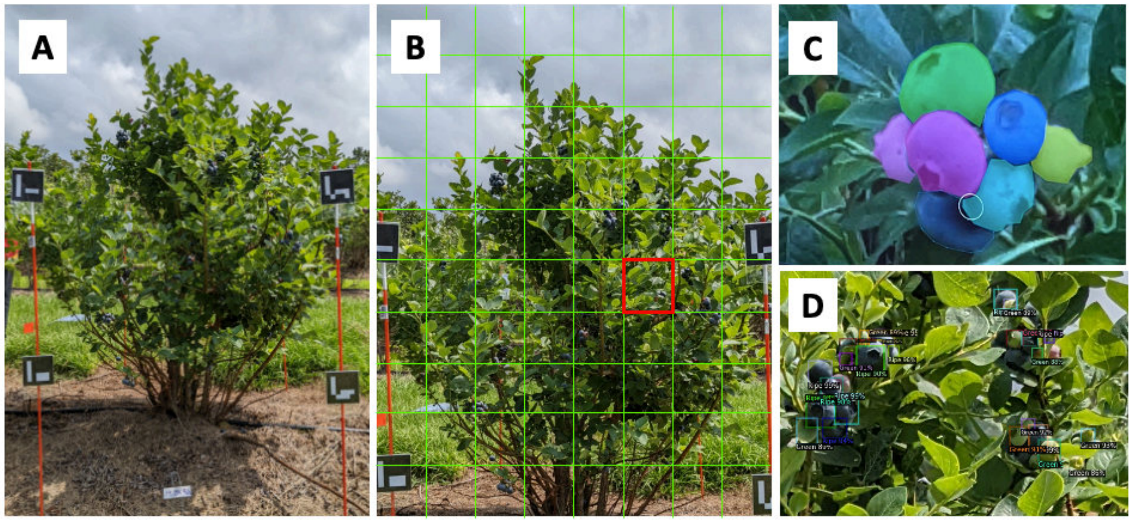

Figure 1. Steps of image data collection. (A) Raw image data collection: Images of a blueberry plant taken with a Google Pixel 5a smartphone on two sides of the row. Four ArUco markers were used to determine the vertical boundaries of the plant. **(B) Image preprocessing:** the full-size images (2024×4032) were split into smaller images (224×224) to match the input size of the deep learning model. **(C) Manual annotation:** ripe and unripe berries were manually annotated with COCO Annotator. **(D) Prediction:** raw images were processed with the prediction model to detect ripe and unripe berries.

Objective II: develop a smartphone app to allow convenient yield and maturity monitoring before harvest.
A smartphone app will be developed for blueberry yield prediction in the field setting. TensorFlow Lite, the open-source real-time object detection android app from Google, will be modified towards blueberry yield prediction application. The generic object detection model will be replaced by a blueberry detection and yield prediction model developed from this study. The smartphone app will be developed in 2024 with a user-friendly interface. User-friendliness and robustness will continue to be tested and improved.

Results
In 2022, we have made progress towards data collection, analysis, and software development. Specifically,

- **60** southern highbush and rabbiteye blueberry plants, including **15** cultivars and selections, were phenotyped on both commercial and research farms for yield and average berry weight at different maturity stages.
- **120** field image data were collected. Manual annotation is in progress.
- **3120** 360-degree-image data were collected in greenhouse on **12** container-grown southern highbush plants of five genotypes. Phenotypic data on greenhouse-grown plants were collected four times throughout the harvest season.
- **All** the greenhouse data and field data have been annotated.
- **Preliminary** prediction models were trained and tested for berry detection and yield prediction on a portion of the dataset.

- **Framework** of the smartphone app has been built and tested on a Google Pixel 5a smartphone. Further development on the user interface and berry detection-based yield prediction will be continued as we optimize the yield prediction model.

Our preliminary data have shown promising results. The current prediction model can:
- **Accurately detect an average of 91%** of the ripe berries captured in an image taken in the field with a Google Pixel 5a smartphone (**Fig. 2a**).
- **Accurately predict yield in the greenhouse**, based on 360-degree-view image data of a container-grown plant, with an R^2 of 0.90 between predicted and measured yield (**Fig. 2b**).
- **Moderately predict yield in the field**, with an R^2 of 0.59 between predicted and measured yield (**Fig. 2c**).

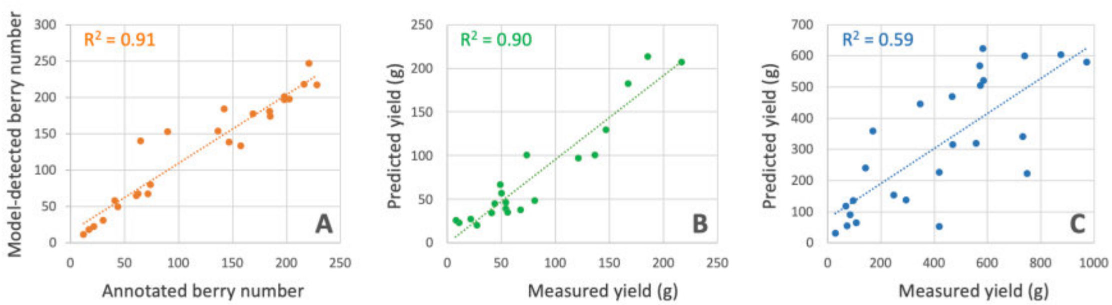

Figure 2. Preliminary results on image-based berry detection and yield prediction. (A) Model detected berry number as compared to annotated berry number captured in the image (R^2 = 0.91). **(B)** Predicted single plant yield (g) based on 360-degree-view images as compared to the measured yield of container-grown blueberries in the greenhouse (R^2 = 0.90). **(C)** Predicted per-plant yield (g) vs. measured per-plant yield (g) of field-grown blueberry plants (R^2 = 0.59). Yield was estimated as model-detected berry number × measured average berry weight (g).

Conclusion

We expect the accuracy for both berry detection and yield prediction to continue to increase as we complete data analysis in 2022 while collecting more data in 2023. Once the prediction model is fully developed (expected by the end of 2022), it will be implemented in a smartphone app for near-real-time, in-field berry detection and yield prediction. Preliminary results already proved the high accuracy of berry detection through machine learning models. On the other hand, in-field yield prediction is still challenged by occlusion: many berries are blocked by leaves, stems, or other berries, and therefore not captured in the image. In addition, it takes more yield and image data on a broader range of genotypes to estimate occlusion ration to further improve the accuracy of yield prediction. Therefore, we will continue this study for multiple years to collect more image and yield data to further improve the accuracy of image-based yield prediction.

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