BME/ECE 6885 Computer Vision
Final Report
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Strawberry Ripeness Classification using YOLOv8

Abstract:

This project aims to classify the developmental growth stages of strawberry fruit, specifying its ripeness and location using the You Only Look Once version 8 (YOLOv8) deep learning model. The primary focus is on enhancing accuracy in identifying strawberry ripeness, contributing to efficient agricultural practices and crop management.

Problem Statement:

Accurate classification of strawberry ripeness is crucial for predicting yield, efficient field management, and optimizing crop production. Traditional methods are often time-consuming and costly. This project addresses the need for a rapid and precise automatic classification system for strawberry maturity.

Background:

Strawberry cultivation plays a crucial role in agricultural economics, particularly in Florida, USA, where it ranks third in crop production value. Efficient strawberry maturity classification is vital for optimizing harvest management, reducing waste, and maximizing economic benefits. Traditional methods based on physical appearance or chemical substance content analysis are time-consuming and costly. As a result, there is a growing interest in leveraging advanced technologies, such as deep learning and image processing, to enhance the accuracy and efficiency of strawberry ripeness classification.

Previous Work:

Paper [1]: A fine recognition method of strawberry ripeness combining Mask R-CNN and region segmentation.

The paper introduces a comprehensive approach to strawberry ripeness recognition by combining deep learning and image processing techniques. The proposed method incorporates self-calibrated convolutions into the Mask R-CNN backbone network, enhancing the model's performance in detecting and segmenting strawberries. The three-stage process involves detection, segmentation, and classification, with a focus on color feature extraction. Experimental results demonstrate a significant improvement in model performance, achieving a final average precision (AP) of 0.937. The incorporation of self-calibrated convolutions is identified as a key factor in enhancing the model's robustness, particularly in complex field environments. The method outperforms common feature extraction methods and established models like AlexNet and ResNet18.

Paper [2]: Strawberry Maturity Classification from UAV and Near-Ground Imaging Using Deep Learning.

This study addresses the challenge of efficient strawberry maturity classification for precise yield prediction and field management. Leveraging the You Only Look Once (YOLOv3) deep learning method, the research compares two imaging methods: aerial and near-ground imaging. The study reveals the effectiveness of YOLOv3 in classifying three and seven strawberry maturity stages in UAV and near-ground digital camera images, respectively. Aerial imaging provides a quick method for large-scale data collection, achieving a high Average Precision (AP) of 0.93 for fully matured fruit. On the other hand, near-ground imaging offers detailed information on seven maturity stages, including a class for wasted strawberries (ROF) with an AP of 0.80. The study suggests the applicability of either imaging method for fruit maturity and yield prediction based on specific needs.

Project Goal:

Building on the insights from these previous works, the goal of this project is to contribute to the field of strawberry ripeness classification by implementing the YOLOv8 model. The project aims to address limitations identified in previous approaches, such as the lack of diverse datasets to perform under different weather conditions, enhance robustness in ripeness classification that can perform well under different physical conditions, and explore the practical implications of the model in real-time scenarios such as robotics and UAVs.

Methods:

- Algorithm: YOLOv8 is employed for its proficiency in small object detection.
- Image Processing: Data augmentation techniques were used to increase the dataset size and also to create a more robust model to perform under various physical conditions.

  The augmentation techniques used were:
  - Saturation: Between -30% and +30%
  - Brightness: Between -20% and +20%
  - Exposure: Between -11% and +11%
  - Blur: Up to 5.5px
  - Noise: Up to 5% of pixels
- Image Classification: Labeled the developmental stages into 5 categories:
  - Flower (1)
  - Small green (2)
  - Turning white (3)
  - Turning red (4)
  - Ripe red (5).

Data:

Obtained from Mendeley, consisting of 247 images of strawberry plants on a farm.

Folder structure: train, valid, test, with subfolders images, and labels.

Data augmentation creates a total of 567 images including

- 480 training images
- 75 validation images
- 12 test images.

Results:

Classification Accuracy: Achieved mAP of 82.1% at a 50% confidence level.

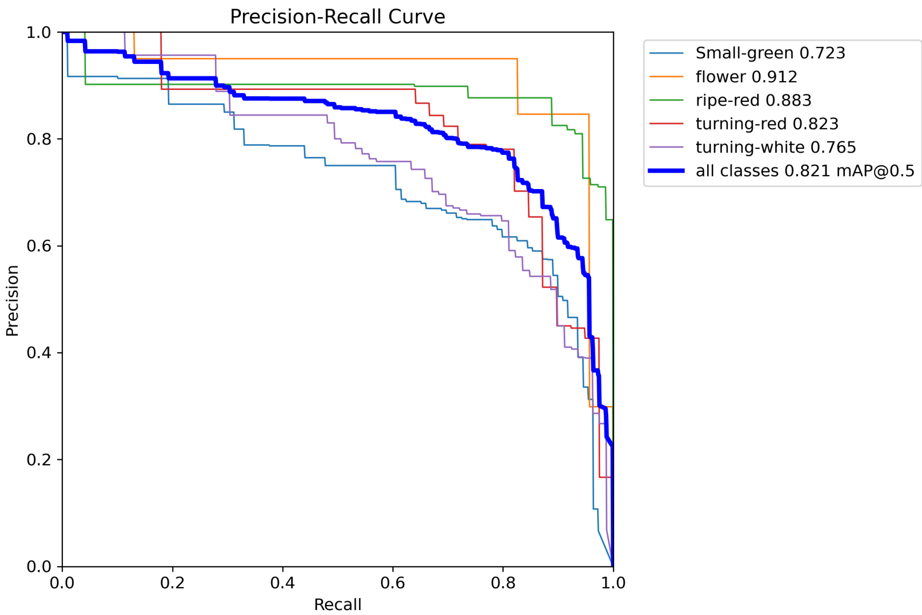


Figure 1. *Precision-Recall Curve*

Conclusion:

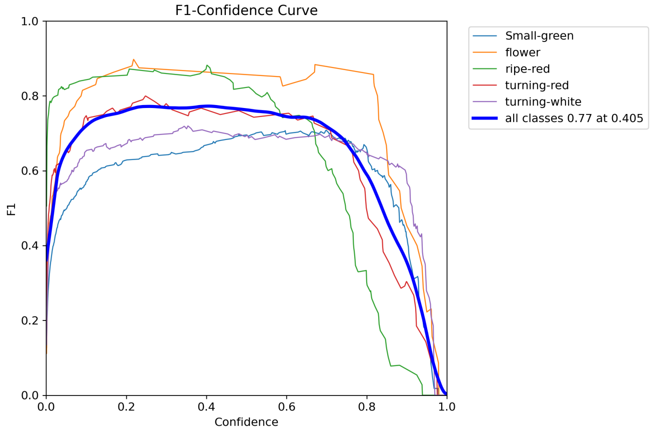
In conclusion, this project successfully tackled the critical issue of accurately classifying the developmental growth stages and ripeness of strawberry fruit through the implementation of the YOLOv8 model. Drawing inspiration from and building upon the advancements highlighted in two prominent research papers, the project utilized data augmentation techniques to enrich the dataset and enhance the model's robustness. The outcomes demonstrated commendable success, achieving a mean average precision (mAP) of 82.1% at a 50% confidence level. The classification into five distinct ripeness categories showcases the model's proficiency in small object detection, addressing a significant gap in traditional methodologies. While acknowledging achievements, the project also identifies avenues for improvement, such as the need for a more diverse dataset and potential fine-tuning of hyperparameters. These findings contribute to the evolving landscape of strawberry ripeness classification, underscoring the significance of advanced deep learning techniques in optimizing agricultural practices. The project's implications extend beyond its immediate objectives, offering valuable insights for real-time applications in robotics and UAVs, thereby paving the way for future advancements in precision agriculture.

References:

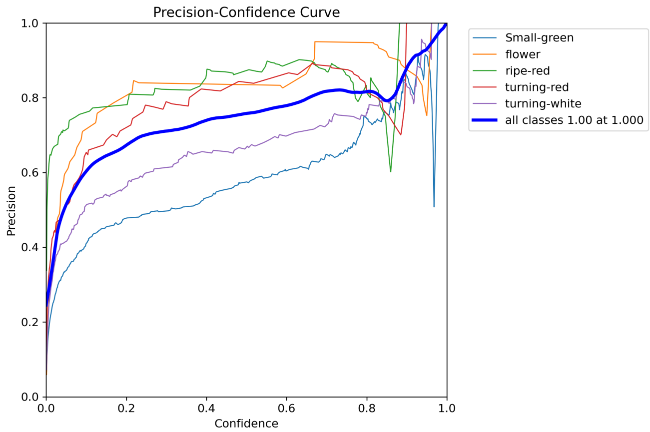
[1]: https://doi.org/10.3389/fpls.2023.1211830

[2]: https://doi.org/10.1016/j.atech.2021.100001

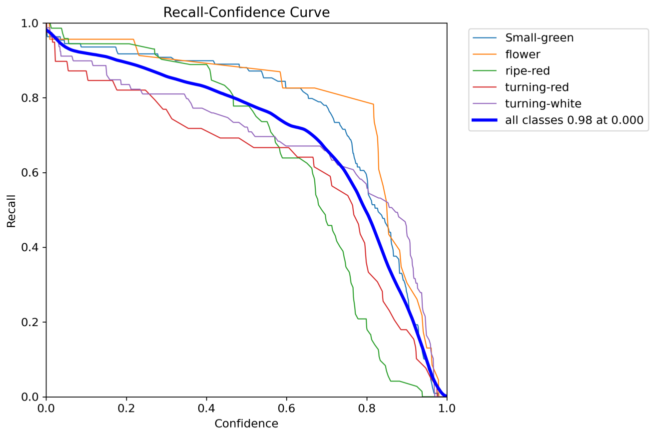
Appendix:



(a)



(b)



(c)

Figure 2. *Validation Results (a) F1-Confidence Curve (b) Precision-Confidence Curve (c) Recall-Confidence Curve*

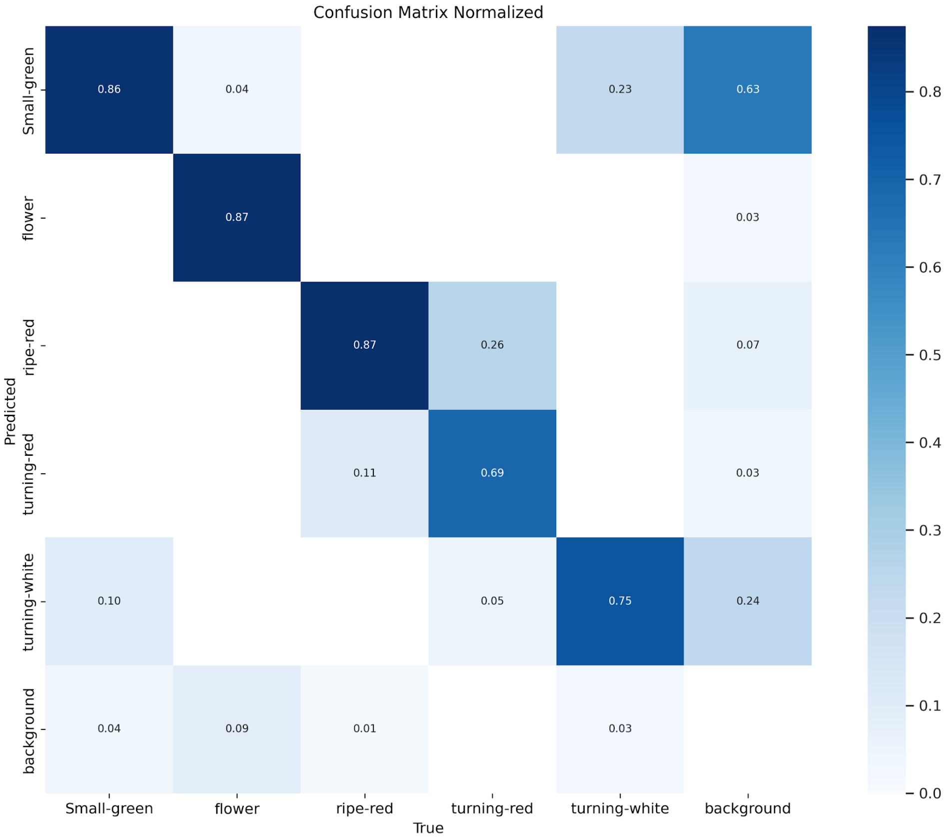


Figure 3. *Validation Results: Confusion Matrix Normalized*

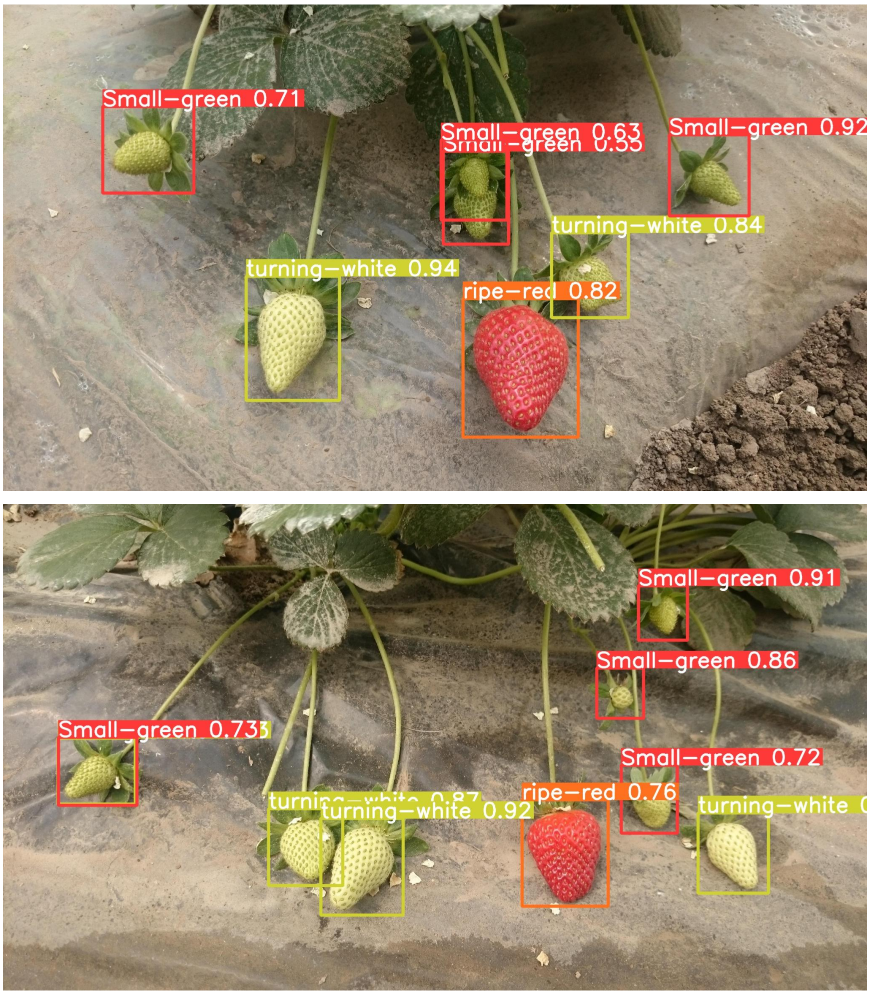


Figure 4. *Test Results*