Computer Vision for Pollinator Ecology

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Background

- Pollinator ecology requires monitoring of flowers and recording the number and kind of insect or animal which visit them
- Traditional methods for monitoring visitors require many hours of tedious review or live monitoring
  - ➢ Resource-intensive, often leading to backlogs & delays
- **Computer Vision (CV):** A field of study solving visual problems & streamlining workloads through deep learning algorithms
- **Object detectors:** CV networks that can detect and localize specific entities within a larger image.
  - ➢ Lower-cost, less time-consuming than traditional methods.
- **Application:** Deployment in the field for real-time monitoring or review of old datasets

Figure 1: Applications for CV. Data from 2021 was fed to an object detector to identify pollinators within the images. CV networks may also run on smart cameras in the field.

Materials & Methods

Dataset

- 10,000 images from the iNaturalist Research-grade Database
- Eight taxa commonly found on flowers represented as classes:
  - Bees, Lepidoptera (Butterflies and moths), flies, Wasps, Beetles, Bugs (Hemiptera), Ants, Spiders
- Consistent & accurate manual annotation of images to provide good training data
- Variable situations, hundreds of species represented for model fitness
- Examples per class weighted according to frequency observation and importance as pollinators

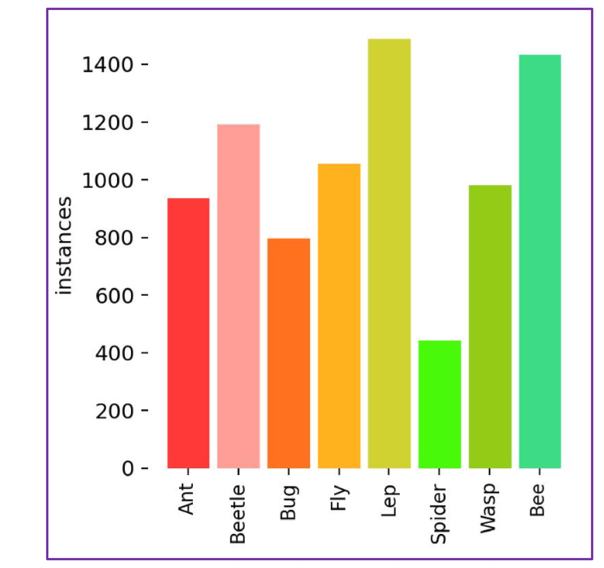


Figure 2: Number of examples per class

Model

- YOLOv5 architecture: Convoluted neural network for object detection
  - **YOLOv5s**: smaller, easier to fit in the field, less accurate
  - **YOLOv5m**: larger, more accurate

Training

- Images input at 448x448 pixels in size
- Batch size 32, 350 epochs training time
- Several models of YOLOv5m & YOLOv5s tested with different hyperparameters
  - ➢ **Learning Rate Optimizers:** AdamW & SGD
  - ➢ **Weighted image selection:** Class frequency taken into account
  - ➢ **Early stopping:** Model training stopped after 15 more epochs if no improvement demonstrated
  - ➢ **Single-Class Training:** Multiple classes merged into one category used for training

Results

- **Single-class training**
  - Significantly better performance
  - Best model: 91.3% precision, loss 0.023
  - Highly accurate
- **Multiple-class training**
  - Accuracy for each class increases with number of examples
  - Best model: 75.5% precision, loss 0.029

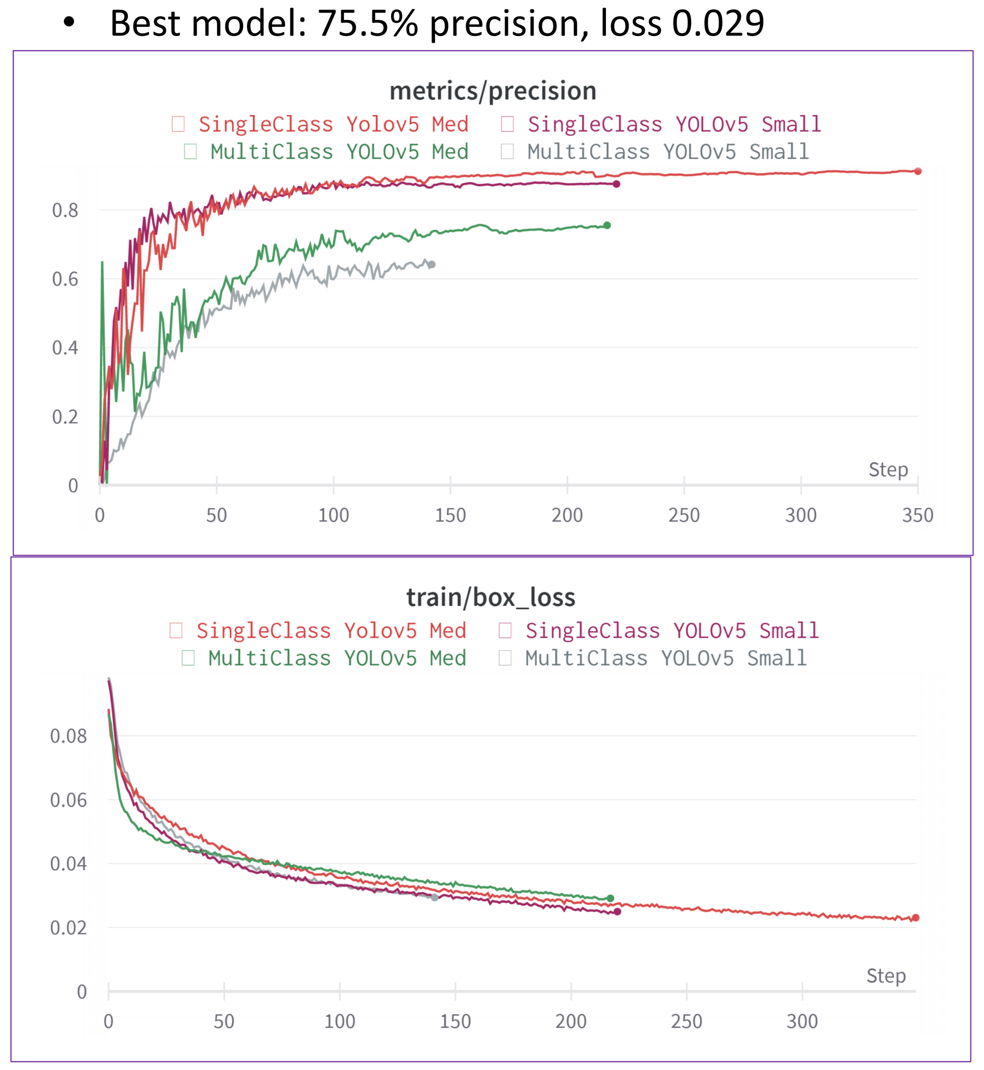
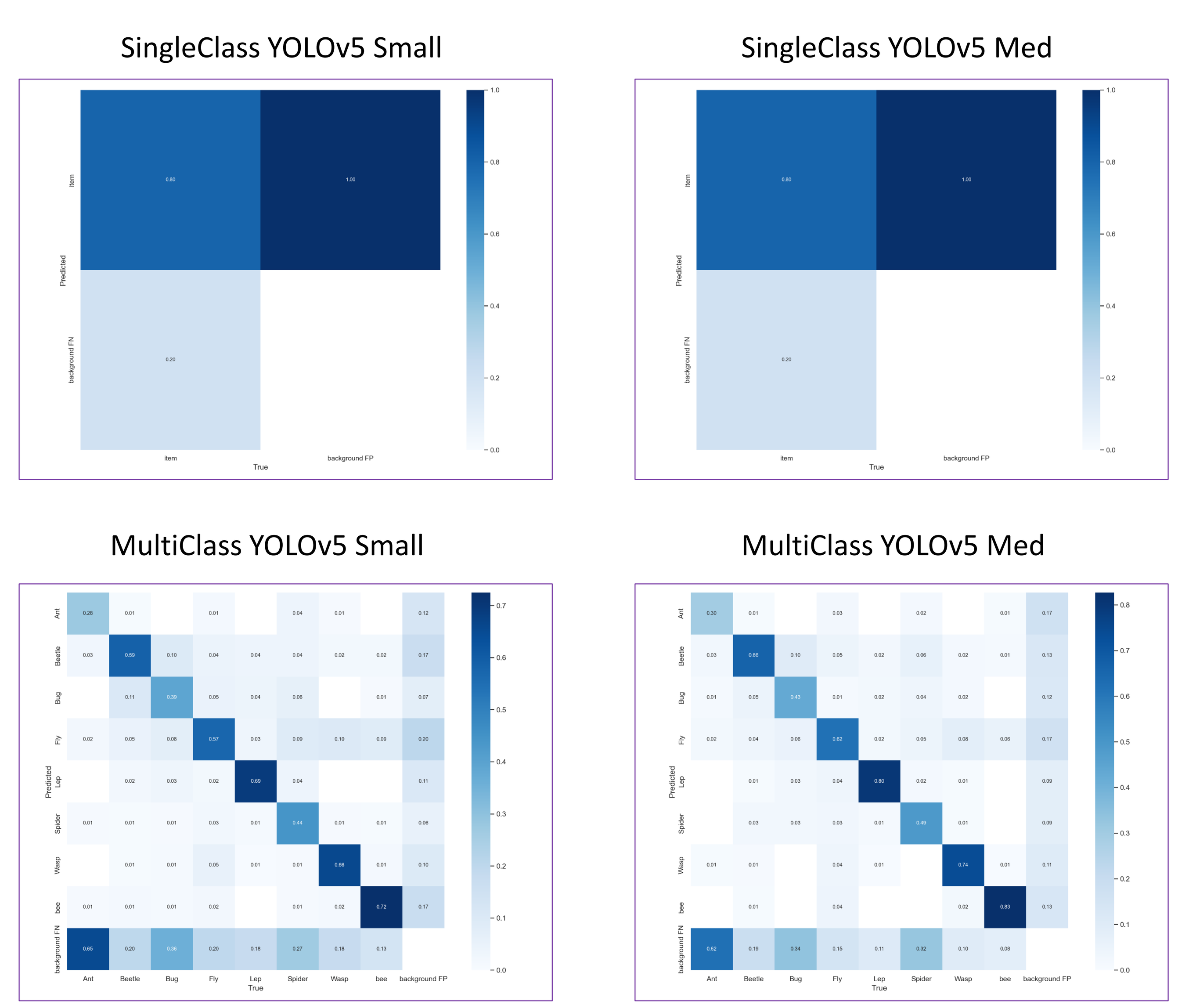


Figure 3: Precision and loss among the best YOLOv5m & YOLOv5s models. Precision measures the number of correct predictions in a sample and loss measures the number of errors.

Hyperparameter impact

- Early stopping important for minimizing loss
- YOLOv5m models not statistically different in performance from YOLOv5s
- No difference between learning rate optimizers
- No training improvement from weighted image selection

Confusion Matrices



Conclusions

- Application of YOLOv5 object detectors is useful for pollinator ecology
  - high precision means majority of visits detected
- No difference was found between the larger and smaller models in terms of performance
  - Similar precision and loss results between small and medium model sizes across all trials
- Single-class detectors were able to perform significantly better than multi-class detectors.
  - More work needed to improve multi-class detection to single-class standards

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