Weed Detection using Semi-Supervised Learning

1 Introduction

Weed detection plays a critical role in agricultural automation, helping optimize crop yields while minimizing herbicide usage. Traditional supervised learning methods require large labeled datasets, which are expensive and time-consuming to obtain. In this report, we explore a semi-supervised learning (SSL) approach for weed detection, where a small amount of labeled data is augmented with a larger pool of unlabeled data. The YOLOv8 model was employed to predict weed locations in images, with a training pipeline that combined both labeled and pseudo-labeled data.

2 Methodology

2.1 Dataset and Preprocessing

The dataset used for this weed detection task consists of labeled and unlabeled images. Labeled data contains both the images and their corresponding annotations in YOLO format, which includes the bounding box coordinates (i.e., x_{center}, y_{center}, width, height) along with the class labels (weed or crop). The labeled data consists of 200 images, and a larger set of unlabeled images is used for the semi-supervised learning process.

The dataset is preprocessed by reading image files and annotations, and organizing them into a pandas dataframe.

2.2 Model Architecture

For weed detection, we utilized the YOLOv8 (You Only Look Once) model, a state-of-the-art object detection framework. YOLOv8 is known for its speed and accuracy in real-time object detection tasks. Initially, we fine-tuned a pretrained YOLOv8 model on the labeled dataset of 200 images, where the model learned to predict bounding boxes and labels for weeds and crops.

2.3 Semi-Supervised Learning Approach

Once the model was fine-tuned on the labeled data, it was used to generate predictions on a larger pool of unlabeled images. These predictions, referred to as pseudo-labels, were added to the training set. By using the model's predictions as pseudo-labels, we effectively increased the size of the labeled dataset, improving the model's overall performance.

2.4 Training Methodology

The training process included the following steps:

1. **Fine-tuning on Labeled Data:** The YOLOv8 model was fine-tuned on the 200 labeled images.

2. **Model Prediction on Unlabeled Data:** After fine-tuning, the model was used to predict bounding boxes and labels for the larger pool of unlabeled images. Predictions with confidence scores above 0.8 were retained as reliable pseudo-labels.

3. **Retraining with Pseudo-Labels:** The model was retrained on the combined dataset of labeled and pseudo-labeled data, which further improved its performance.

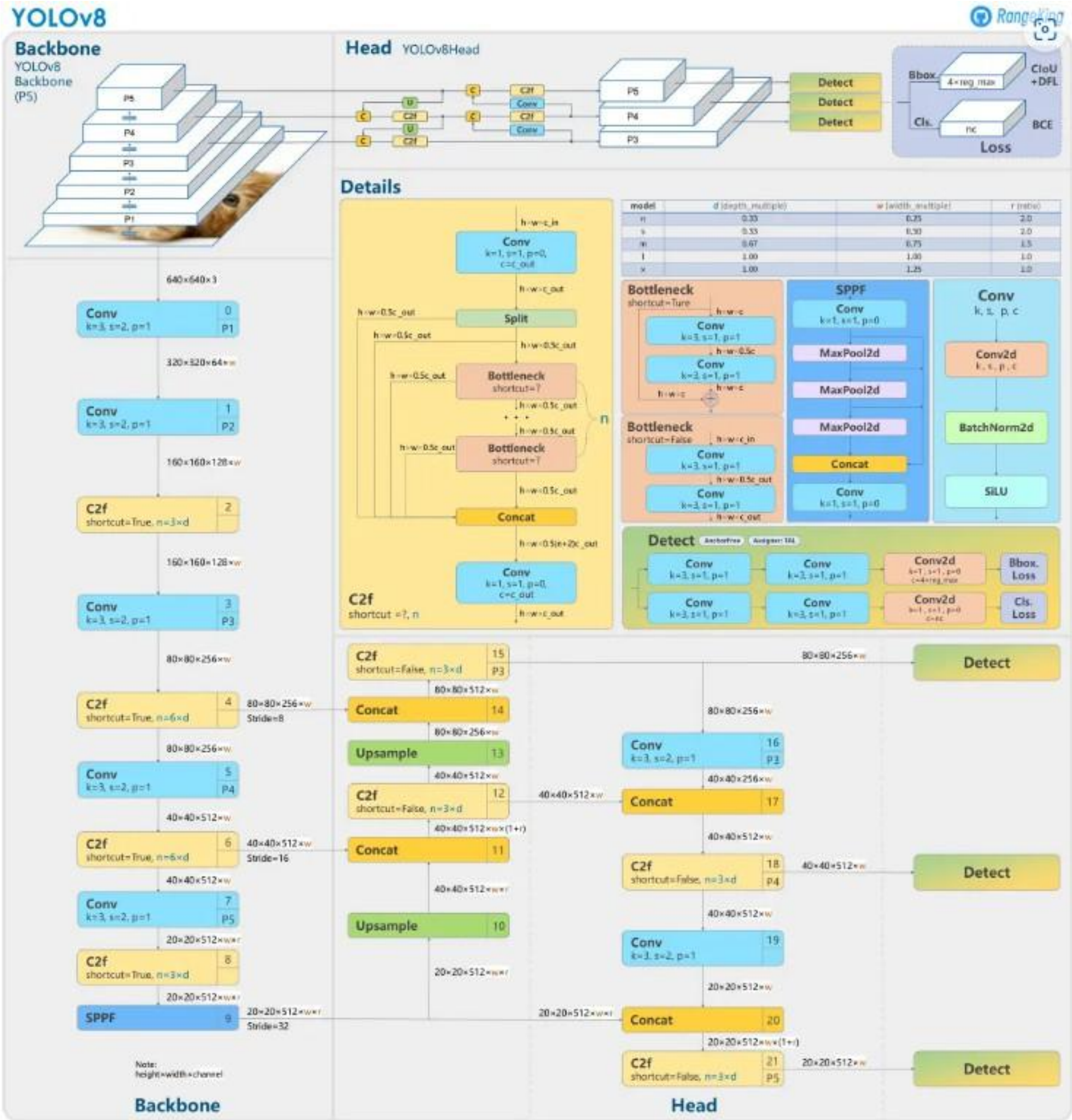
4. **Evaluation:** The model's performance was evaluated on a separate test set using standard metrics such as mean average precision (mAP) and F1-score.

3 Results

The model showed significant improvement after incorporating pseudo-labeled data. Initially, the combined performance score was 0.17 before using the unlabeled data. After generating pseudo-labels for the unlabeled data and retraining the model, the performance score increased to 0.85. This improvement underscores the effectiveness of the semi-supervised learning approach, where the model leverages its own predictions to expand the training set, thereby improving generalization and detection accuracy.

4 Conclusion

In this report, we demonstrated how semi-supervised learning can be applied to weed detection using the YOLOv8 object detection model. By fine-tuning the model on a small labeled dataset and augmenting it with pseudo-labels from unlabeled data, we were able to significantly improve performance. This approach offers an efficient solution for scenarios with limited labeled data and holds great potential for scaling as more unlabeled data becomes available.



YOLOv8 Architecture, visualisation made by GitHub user RangeKing