STUDY OF DEEP LEARNING METHODS FOR REMOTE SENSING OF TURF WEEDS USING VISIBLE SPECTRUM IMAGERY

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Introduction

- Weed management in turfgrass is a serious issue in United States.
- Precision herbicide spraying applications to control weeds in turfgrass cut the excessive use of herbicides thereby reducing herbicide wastage, costs, and human labor.
- Integration of remote sensing, deep learning, and Unmanned Ground Vehicle(UGV) can be an important tool for real-time weed detection to perform selective herbicide application in turfgrass.
- In this research, we attempt a Proof of Concept(POC) implementation to investigate the feasibility of the use of deep learning in weed detection in turfgrass.

Objectives

- Developing a digital library of turfgrass weeds St Augustine, Crabgrass, Zoysia Matrella, Centipede Grass, Bermuda Grass, Common Lespedeza, White Clover, and Virginia Buttonweed representative of all weather conditions, from greenhouse and turfgrass field.
- Develop, implement and test high-performing and efficient Convolutional Neural Network (CNN) Architecture for real-time detection of the weeds in turfgrass.

Materials and Methods

Data Collection: 500 RGB images of weeds grown in the greenhouse in October 2021 and weeds present in turfgrass field in June 2022 were collected using DSLR D3400 18-55 mm lens at the resolution of 6000*4000.

Fig 1. Image acquisition from Greenhouse and Turfgrass field

- Patches of 640*640 pixels were extracted from original images to feed into object detection models as shown in figure 2.

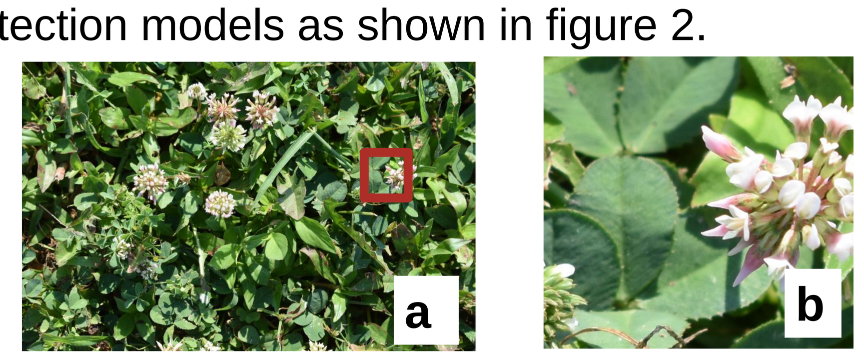

Fig 2. a) Original image of dimension 6000*4000, b) 640*640 pixels extracted from the original image. Red box in 2a refers to the 640*640 patch.

- Similarly as above 224*224 pixels were extracted from original images to feed into image classification models.
- Total 7053 and 6466 images were prepared for building object detection and image classification models respectively as shown in Table 1.

Table 1. Training and Testing dataset distribution of images extracted from original images.

Task	Training	Testing
Object Detection	6127	926
Image Classification	5555	911

- Two transfer learning image classification ResNet-50 and VGG-19 were trained shown in Figure 3. Training setup is shown in table 2.
- Two versions of You Look Only Once(YOLO) v5 and v6 were trained as objected detection algorithms with epochs 30 and 100 respectively on NVIDIA GeForce RTX 2080 in PyTorch with 1 GPU shown in Figure 4.

Materials and Methods Cont.

Table 2: Training setup of image classification models

Frameworks	Tensorflow
Optimizer	Adam
Loss Function	Sparse Categorical Entropy
Epochs	10
Hyperparameter Tuning	Bayesian Optimization
Batch Size	32

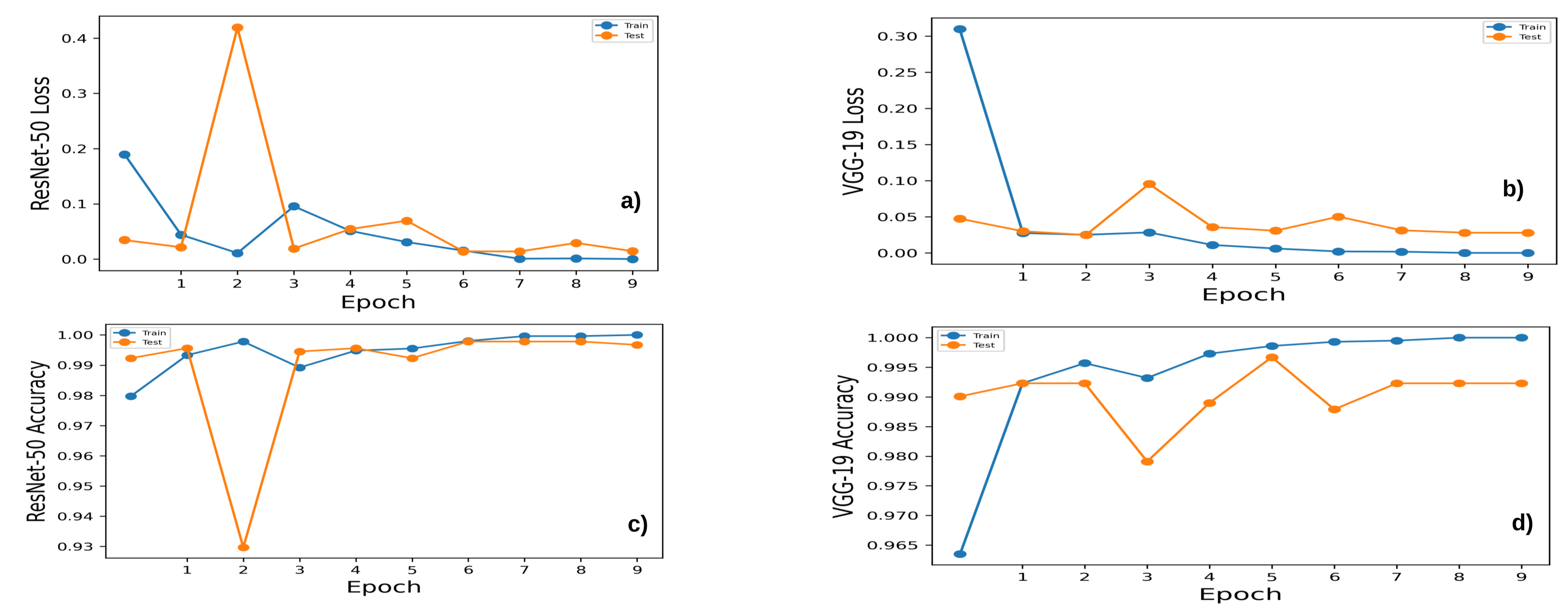

Fig 3. a) and b) represent training and testing loss, c) and d) training and testing accuracy curves for ResNet-50 and VGG-19 respectively.

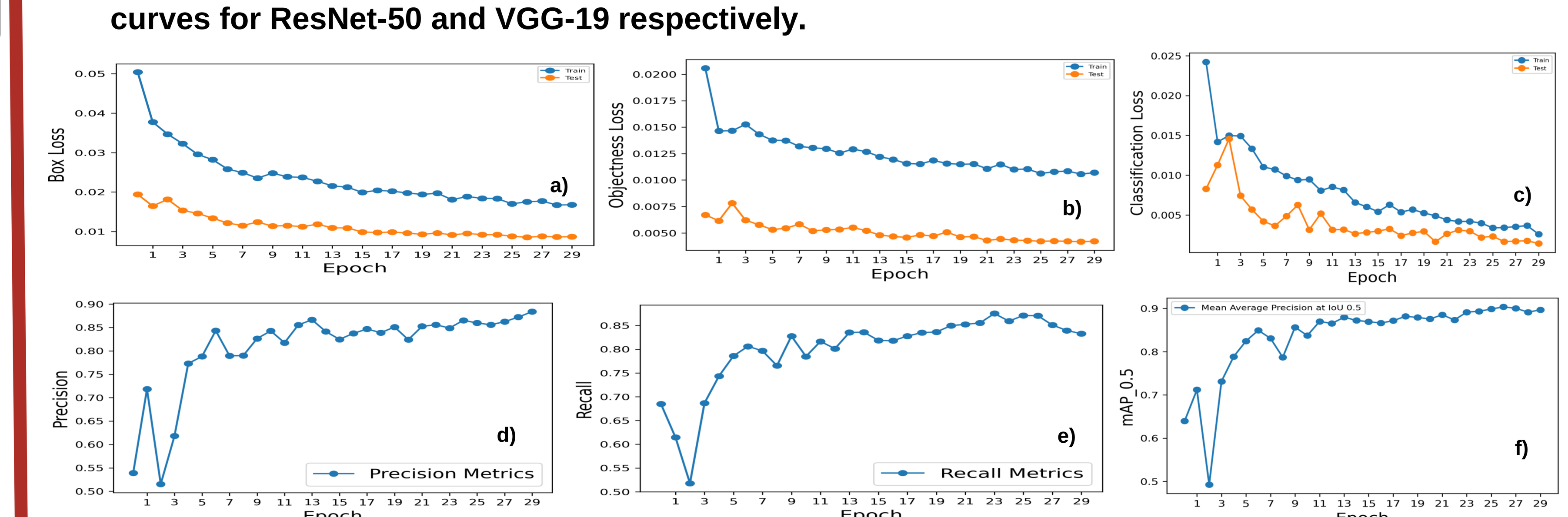

Fig 4. a), b) and c) represent the bounding box regression loss, objectness loss and classification loss YOLOv5m model, d) and e) Precision and Recall respectively, f) represent mean average precision at IoU threshold 0.5.

Results

- Value of hyper-parameters chosen after tuning with Bayesian optimization for both classification models:

1. **Learning rate**: 0.004229, Optimum learning rate at which weights are updated.
2. **beta_1**: 0.9, beta_1 of Adam is the initial decay rate used when estimating first moment of gradient.

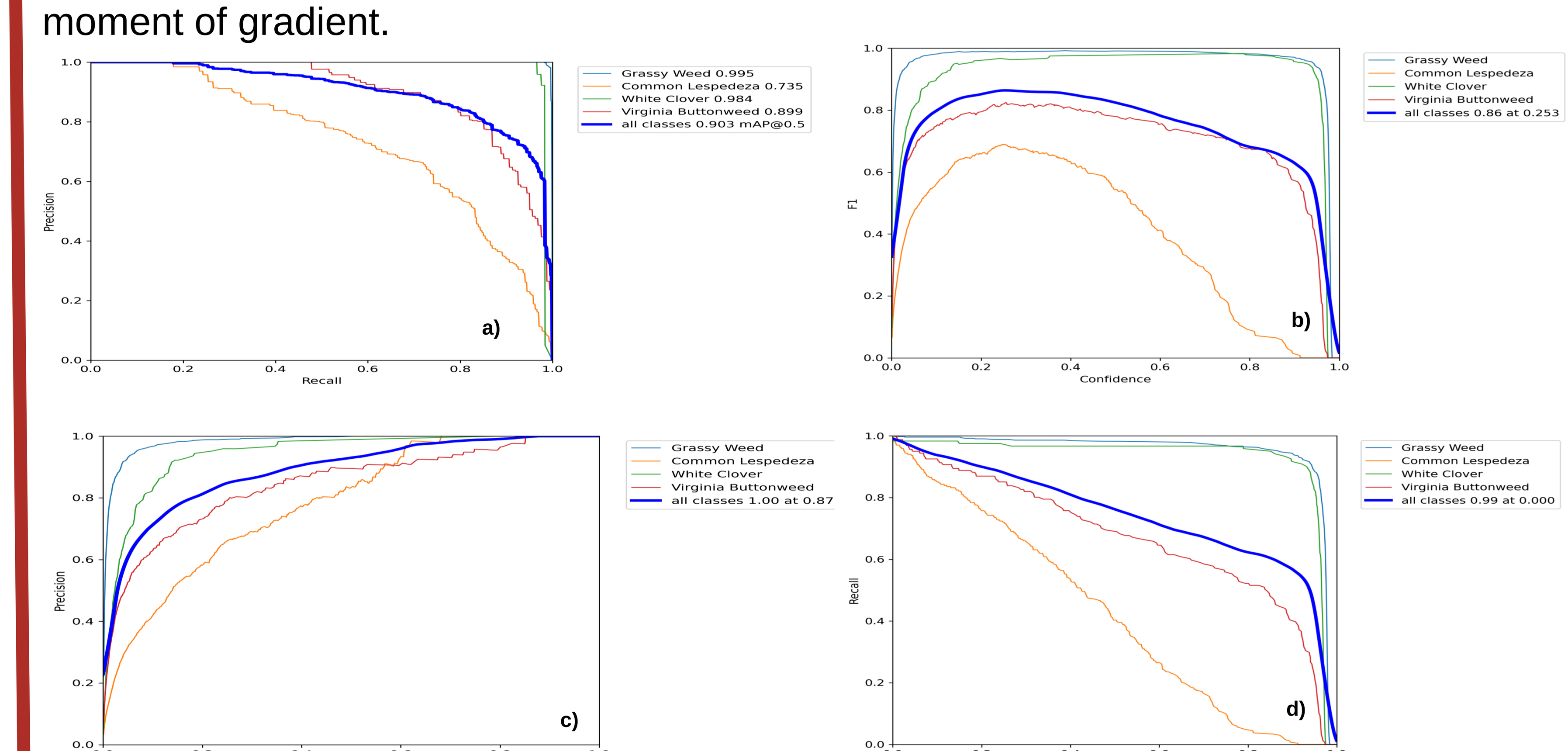

Fig 5. a) Represents tradeoff between different thresholds of precision and recall, b) F1 curve helps in designing balance between precision and recall, c) and d) shows how precision and recall change with change in confidence values.

Results Cont.

Table 3. Testing accuracy of ResNet-50 and VGG-19 models.

Model	Testing Accuracy
ResNet-50	99.67%
VGG-19	99.45%

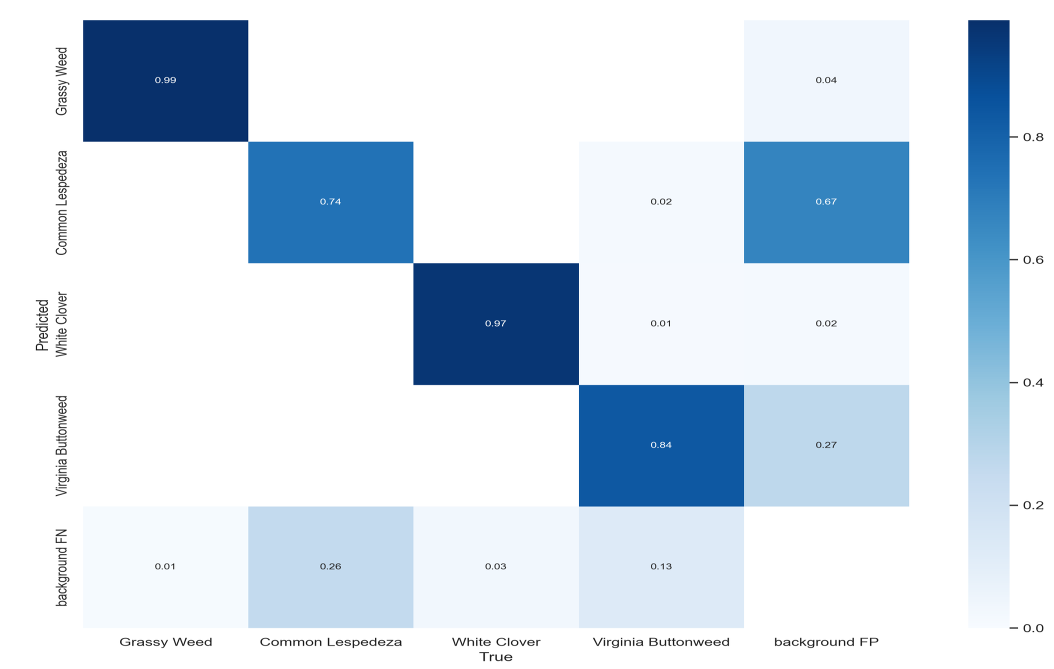

Fig 6. Confusion matrix of YOLOv5m on test data

- YOLOv6 achieves 0.91 mAP and YOLOv5 achieves 0.90mAP at IoU threshold 0.5.
- At 0.25 confidence, Grassy weed and White clover can be detected most of the time. Virginia Buttonweed also performs well. Model is mainly getting confused between Common lespedeza and background.
- In figure 7 model is robust in detecting weeds irrespective of weather conditions, and locations especially if the frame contains a uniform distribution of weeds.

Fig 7. Green rectangle represents to correctly detected weeds and red rectangle represents incorrectly detected weeds.

Discussion & Conclusion

Table 4. Comparison of inference speed of YOLOv6 and YOLOv5 tested on NVIDIA GeForce RTX 2080.

Operation	YOLOv6s	YOLOv5m
Pre-process	0.25 ms	2.0 ms
Non-maximum Suppression (NMS) per Image	1.26 ms	8.8 ms
Average Inference Time	6.75 ms	99.5 ms

- Though classification models ResNet-50 and VGG-19 achieve 99% test accuracy and outperform YOLOv5 and YOLOv6 which archives mAP 0.90, but tradeoff between speed and accuracy in real-time detection of weeds for effective spot spray our research shows that YOLO should be the preferred model to be deployed.
- If we compare inference speed of YOLOv5 and YOLOv6, YOLOv6 is faster and YOLOv5 is 15 times slower than YOLOv6.
- YOLOv6's faster inference in real-time with a high mean average precision of 0.90 implies that the proposed research has the potential to revolutionize turf weed management in the climate change decade, leading to improved sustainability in weed management, reduced environmental impacts, and enhanced economic viability of farming operations.