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IMPROVED SMALL AGRICULTURAL PLANT SEGMENTATION USING POST-TRAINING ADAPTIVE NEURAL NETWORK

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Precision agriculture enables an automated and data-driven way of improving agricultural crop yields. Soil nutrition, spraying pesticides against pests and diseases can be applied at a large scale. However, defeating weeds poses a significant challenge. High weed localization precision is required as herbicides kill both weeds and crops, cutting or laser removal also should be performed with care. Robotic devices have been proposed to remove weeds, all relying on neural-network-based weed localization. Robots typically perform on-device processing, without Internet connection. Typically, weed removal should be performed at early stages of growth, so the plants occupy a small part of the image, which makes the segmentation task difficult. Existing weed segmentation approaches have insufficient ratio of quality to computation complexity for edge deployment. In the meantime, it is estimated that weeds are accountable for 31.5% yield loss. To solve the problem of on-device weed segmentation, we propose PAN+PTA semantic segmentation neural network, computational complexity of the network can be adjusted after training in a range from 13,08 to 18,12 GFlops. Consequently, the network can be adapted to a wide range of devices without additional training or costly redeployment. We achieve this by 1) integrating the Post-Train Adaptive (PTA) network as encoder in Pyramid Attention Network (PAN); 2) introducing width multipliers to configure initial capacity of the PTA network. To train and evaluate the neural network we use WE3DS dataset, which contains annotations of 7 crops and 10 weeds. The lightest configuration of PAN+PTA achieves higher Dice Score compared to PAN with MobileNetV2 encoder, while reducing the number of computations by a factor of 1.9. Additionally, the trained network in heavy configuration with width multiplier of 1.5 has Dice Score of 0.5112 and computational complexity can be adjusted in range of 32.34%, which is a substantial improvement over existing U-Net+PTA network (Dice Score: 0.4348, range: 3.66%), while reducing inference GFlops by 80%.

Keywords: weed image segmentation, weed removal, precision agriculture, on-device segmentation, edge computing, dynamic neural network, crop field health monitoring.

Introduction

Ensuring high and sustainable yields requires constant intervention in the plant growing process. Precision agriculture enables automated and data-driven adjustment of plant treatment strategy. Approaches include monitoring weather and soil conditions, detecting pests and diseases via smartphones and drones [1], and locating weeds [2; 3]. Using the collected and analyzed data, machines can be used to apply fertilizers to the soil or to water plants, spray pesticides to remove pests, diseases, and weeds. Pesticides targeted against pests or diseases have small impact on plant growth if applied correctly. However, removing weeds requires much higher precision, for instance, herbicides can be sprayed [4], but if splayed on agricultural crops, they will also die. Other approaches include robotic devices that remove the weed using a laser or by cutting the plant [5; 6]. All these approaches are highly dependent on precision of weed localization. The task is formulated either as detection or segmentation, with the latter providing more information where plant leaves/stem are located. Subpar weed segmentation quality leads to weeds not being fully removed and increases cultivated crop damage. Typically, removal should be performed when both crops and weeds are small and take small part of an image, making the segmentation problem difficult. In the meantime, weeds are estimated to cause 31.5% reduction in plant production [7]. Furthermore, weed segmentation should be performed on-device and in real-time as Internet connection is often slow or completely unavailable in the fields. Therefore, proposing new weed segmentation approaches, that offer better quality, while still being mobile friendly is an important research direction.

Recently, Post-Train Adaptive (PTA) [8] dynamic neural network has been proposed. The network has variable number of computations, which can be controlled after the training procedure is complete, without retraining. The configuration can be applied based on hardware capabilities of the inference device or input image complexity.

To improve weed segmentation quality, in this work we propose to integrate the PTA neural network as an encoder inside the PAN [9] segmentation network. Additionally, we introduce width multipliers to the PTA network as a way to configure initial network computational capacity.

To summarize, our main contributions are as follows:

1. We significantly improve weed segmentation quality by integrating the PTA network into PAN segmentation neural network and introducing width multipliers to control the initial computational capacity.
2. We substantially improve the range between post-train configurations. Thus, ensuring that a single trained neural network can target devices with different computational capabilities.

Related Works

Several existing robot-based weed removal systems have been proposed in the literature. In [4] autonomous spraying robot has been presented. On the back the robot has a row 12 nozzles, spanning approximately 0.66m. Each nozzle is actuated independently. YOLO10s detection neural network is used to detect weeds, then nozzle located above the weed sprays the herbicide against the weed. The authors of [5] note high damage and low effectiveness of chemical and mechanical approach to weed removal. To resolve the problem, the authors propose a laser-based removal using a small wheeled robot. The robot uses YOLOv4-tiny neural network for weed detection and then removes the weed using a laser located on a robot arm. The authors deploy the robot in the outdoor cotton field, and report 72.35% weed removal rate. Inference runs on Nvidia Jetson Xavier AGX mobile platform. The authors note the need to expand weed detection capabilities to more diverse environmental conditions. [10] propose a similar approach for weed detection in corn field, based on YOLOX detection neural network. The robot has a continuous track instead of wheels, uses laser to remove weeds as well. In [6] the authors develop CNN-based neural network architecture for sugar beet and weed segmentation. Inference is performed in real time on a Bosch Bonirob large agricultural robot, which then physically removes weeds.

Several open datasets have been developed that contain annotated weed and crop images. The authors of WE3DS [2] propose an RGB-D weed segmentation dataset, which contains RGB images and corresponding depth maps. The authors have used dual camera setup to estimate depth. The dataset includes soil, 7 crop species, and 10 weed species. As has been shown, including depth to the segmentation model offers significant gains in Intersection over Union metric. However, to extract depth information either dual camera setup should be used, or separate monocular depth estimation neural network. Both approaches increase cost of the weed segmentation hardware (second camera or more capable hardware are required correspondingly). The authors of [3] propose CropAndWeed dataset with 74 plant species (16 crops, 58 weeds) along with soil and vegetation classes (instances that cannot be unambiguously identified). The authors provide several groupings of the collected data. For instance, Fine24 that groups crops and weeds into 24 superclasses, CropsOrWeed2 (all crops class vs. all weeds class), CropsOrWeed9 (8 crop classes vs. generic weed class), and several others.

Purpose

Despite recent advancements in crop and weed recognition, the field needs further development. Many of the works frame the problem as detection, which is typically computationally simpler than image segmentation, and select smaller neural networks to perform real-time on-device inference [4; 5]. However, detecting the weed might be insufficient precise for stem removal, especially in cases when crop and plant leaves are interleaved. Also, the number of crops and weeds detected remains limited. Besides, existing models have a fixed number of computations, requiring retraining when targeting devices with different computational capabilities to ensure the best quality.

Therefore, the purpose of this work is to develop an effective on-device segmentation neural network, specifically for precision agriculture tasks such as weed removal. The goal is to create a system that can distinguish between crops and weeds (even at early growth stages) without Internet connectivity or costly redeployment. The developed network should be able to switch between light and heavy configurations based on hardware capabilities or accuracy requirements without retraining. Thus, adjusting quality/performance ratio on demand using a single neural network.

Materials and Methods

Post-Train Adaptive [8] neural network is one of dynamic neural networks [11; 12]. It can be on-the fly reconfigured to use light (L), heavy (H), or both (B) computational branches. Thus, adjusting its computational capabilities. Overall, 3 configurable blocks are included in the network. Notable configurations are LLL (the lightest), HHH (equivalent in the number of parameters and computations to the MobileNetV2 [13]), and BBB (the heaviest configuration). In addition to configurability, previous research shows [8; 14] that the network outperforms baseline MobileNetV2 neural network.

In [14] the PTA network has been applied to image segmentation problem as a backbone inside of U-Net [15] neural network. The authors show that PTA network has improved image segmentation Dice score of the baseline MobileNetV2 model. However, the relative difference between BBB and LLL configurations remains small at 3.66%.

To improve the range in flops between the heaviest and the lightest configurations, we propose to use PAN [9] segmentation neural network with PTA backbone as an alternative to the U-Net. We also introduce width multipliers for the PTA following [13], which increases the width of the blocks, while the number of blocks remains the same. This leads to increase in encoder feature map sizes, resulting in higher computational capability of the network. With width multiplier equal to 1.0 network is equivalent to the original PTA network. Considered network configurations are summarized in Table 1. Complexity is shown in GFlops and computed for RGB image of size 768×768 as an input. We use the following formula to compute range between LLL and BBB configurations:

$$\text{Range} = \frac{GFlops_{BBB} - GFlops_{LLL}}{(GFlops_{BBB} + GFlops_{LLL})/2} \cdot 100\%. \quad (1)$$

PAN is a lightweight semantic segmentation neural network, which combines Feature Pyramid Attention (FPA) and Global Attention Upsample (GAU) module. The FPA offers better semantic features by using multi-scale context with attention, while GAU uses global semantic information as attention to gate low-level features; thus, improving localization.

Table 1

Considered width multipliers of the PTA network, and their corresponding computational complexity range

Width Multiplier	Encoder Feature Map Sizes	U-Net			PAN		
		LLL (GFlops)	BBB (GFlops)	Range (%)	LLL (GFlops)	BBB (GFlops)	Range (%)
0.75	3, 16, 24, 24, 72, 1280	30.40	31.08	2.20	4.46	5.77	25.64
1.00	3, 16, 24, 32, 96, 1280	31.47	32.65	3.66	6.20	8.49	31.15
1.50	3, 24, 40, 48, 144, 1920	39.76	42.34	6.28	13.08	18.12	32.34
2.00	3, 32, 48, 64, 192, 2560	48.68	53.21	8.89	21.77	30.65	33.88

As can been seen from Table 1, using PAN increases range of GFlops between the lightest (LLL) and heaviest (BBB) configuration from 3.66% to 31.15% using 1.0 width multiplier. Also, by selecting initial computation budget using width multiplier of 2.0 the range can be further increased up to 33.88%.

To train the models we use Dice Loss, which has been shown as effective loss for image segmentation training [16]:

$$\text{Dice Loss} = 1 - \frac{2\sum_{i=1}^{C} p_i g_i + \varepsilon}{\sum_{i=1}^{C} p_i^2 + \sum_{i=1}^{C} g_i^2 + \varepsilon}, \quad (2)$$

where p_i is predicted probability distribution, g_i is the ground true. C is the number of classes, ϵ is a small constant.

PTA neural networks additionally employ PTA sampling training strategy to ensure that all configurations are trained following [8].

To evaluate the model, we use Dice Score with macro averaging. Per class dice score is defined as follows:

$$\text{Dice Score}_i = \frac{2TP_i + \varepsilon}{2TP_i + FP_i + FN_i + \varepsilon}, \quad (3)$$

where TP_i, FP_i, FN_i are True Positives, False Positives, False Negatives correspondingly, i is a class index, ε is a small constant. Dice Score$_i$ for all classes from 1 to C are then averaged to form global Dice Score:

$$\text{Dice Score} = \frac{1}{C}\sum_{i=1}^{C} \text{Dice Score}_i. \quad (4)$$

Experiments

All models are trained using the Stochastic Gradient Descent optimizer with a maximum learning rate of 0.07, trained for 20 epochs. Batch size is 6. The best model is selected on validation set, results are reported on the test set. For experiments we select open WE3DS dataset, which contains annotations of 7 crops and 10 weeds. We do not use depth maps to train the model as we target monocular weed segmentation in resource constrained environments. WE3DS train subset has been split into actual train and validation with 0.8/0.2 proportion. We use test set as defined by the authors. As the dataset includes not only grown crops and weeds, but also tiny seedlings, therefore we use relatively high image resolution of 768×768 pixels.

Results and Discussion

Dice Score of the proposed PAN+PTA semantic segmentation neural network is shown in Fig. 1. PAN+MobileNetV2 baseline is shown with a horizontal red line. Note, that PAN+PTA with width multiplier of 1.0 and HHH configuration is equivalent to the PAN+MobileNetV2 in terms of both the number of computations and parameters. However, the PTA network uses PTA sampling training strategy and can be switched to any other configuration with the same width multiplier. As can be seen, all PTA-based configurations with width up to 1.5 are substantially better than MobileNetV2 baseline. Also, the quality of the network scales with the growth of width multiplier. One exception is width multiplier 2.0, where the network starts to overfit the training dataset.

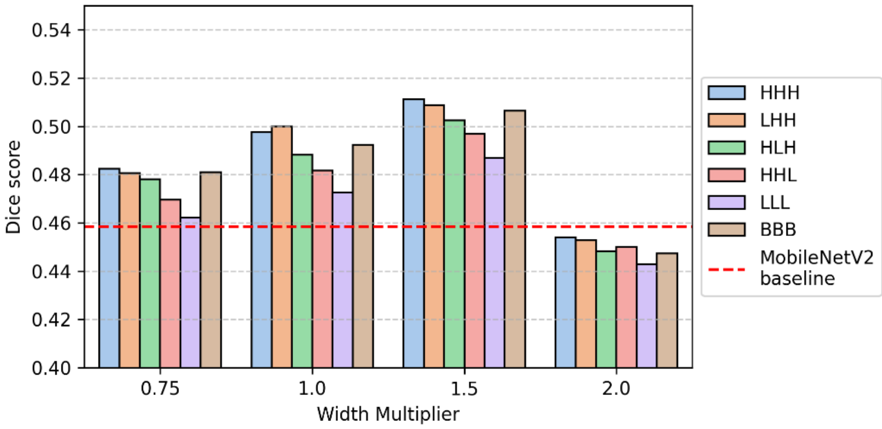

Fig. 1. PAN neural network with PTA backbone with different width scaling factors against the MobileNetV2 baseline

The best result is achieved by the HHH configuration and width multiplier 1.5 (Dice Score 0.5112) against the MobileNetV2 encoder (Dice Score 0.4584). Even PTA network with the lightest configuration LLL, width multiplier 0.75 (Dice Score 0.4622) outperforms PAN with MobileNetV2 baseline, while reducing the number of computations by a factor of 1.9. Summary of the PAN+PTA network quality is shown in Table 2.

Table 2
PAN+PTA network configuration and their Dice Score on the WE3DS dataset

Width Multiplier	Dice Score		
	PTA-LLL	PTA-HHH	PTA-BBB
0.75	0.4622	0.4824	0.4809
1.00	0.4727	0.4975	0.4924
1.50	0.4869	0.5112	0.5065
2.00	0.4429	0.4541	0.4474

In Fig. 2 we show a representative sample of detections using WE3DS dataset. As demonstrated, the dataset contains top-down images, where most of the image is taken by the soil class. Hence, we have highly imbalanced segmentation task. In Fig. 2a several instances of Broad Bean (agricultural crop) are shown with input image [2] at the top, at the bottom segmentation by the proposed PAN+PTA model (width multiplier: 1.5, PTA configuration: HHH) is shown highlighted in green. Plant instances have been correctly classified and segmented. In Fig. 2b Rye Brome (weed) is shown. As can be seen, weed growth is barely visible on the top image. However, it is still correctly segmented by the model (highlighted in orange color).

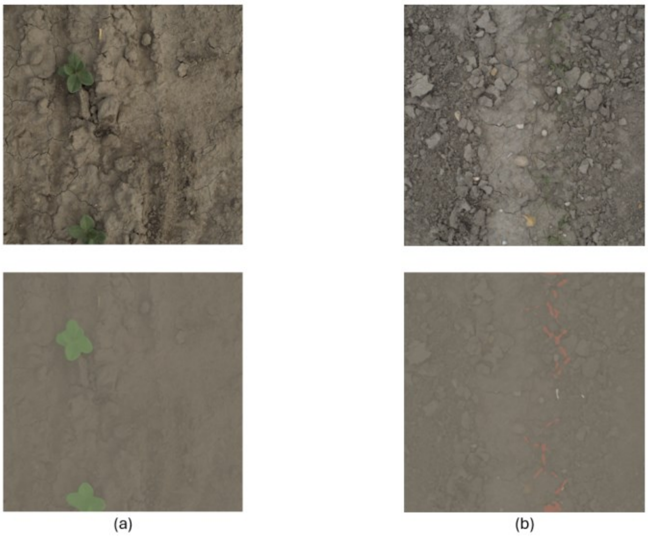

Fig. 2. Sample image segmentations: (a) Broad Bean (crop); (b) Rye Brome (weed)

Finally, for comparison we perform training of the original U-Net+PTA network with different width multipliers on the WE3DS dataset. The results are shown in Fig. 3.

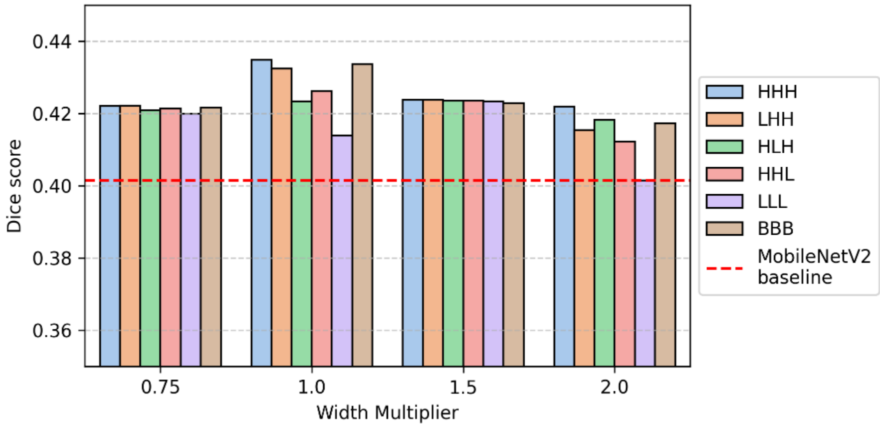

Fig. 3. U-Net neural network with PTA backbone with different width scaling factors against the MobileNetV2 baseline

In this case Dice Score improvement does not correlate with the increase of the width multiplier. Besides, PTA with 0.75x and 1.5x multipliers does not have any difference in quality between light and heavy configurations, which defeats the purpose of dynamic configuration selection after training. Overall, the network performs much worse (the best Dice Score is 0.4348) than the proposed PAN+PTA (the best Dice Score is 0.5112), confirming the benefits of the new approach.

Conclusions

A novel PAN+PTA mobile-friendly neural network has been proposed in this work as an effective approach for crop and weed segmentation even at early growth stages, when the plants are small. It is capable of distinguishing between 7 crop species and 10 weeds. The best result is achieved by the HHH configuration and width multiplier 1.5 with Dice Score of 0.5112, which is an improvement over the MobileNetV2 encoder with Dice Score 0.4584. Additionally, PTA network with the lightest configuration LLL, width multiplier 0.75 outperforms PAN with MobileNetV2 encoder, while reducing the number of computations by a factor of 1.9.

Besides, PAN+PTA network extends the computational complexity range of the segmentation neural network from 3.66% (the original U-Net+PTA, width multiplier 1.0) to 32.34% (PAN+PTA, width multiplier 1.5) between LLL and BBB configurations. The final network can switch between 6 configurations adapting to different hardware capabilities without retraining, ensuring balance between quality and inference speed.

Future research direction includes extension of the developed neural network to a wider range of crops and weeds, providing a comprehensive solution to plant health monitoring (including diseases and pests), and deployment of the development neural network to a hardware platform.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization, I.U. and K.K.; methodology, I.U.; software, K.K.; validation, I.U. and K.K.; formal analysis, I.U.; investigation, I.U.; resources, K.K.; data curation, K.K.; writing – original draft preparation, K.K.; writing – review and editing, I.U.; visualization, K.K.; supervision, I.U.; project administration, I.U.; funding acquisition, K.K. All authors have read and agreed to the published version of the manuscript.

DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

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ПОКРАЩЕНА СЕГМЕНТАЦІЯ МАЛИХ СІЛЬСЬКОГОСПОДАРСЬКИХ РОСЛИН НА ОСНОВІ ЗМІНЮВАНОЇ ПІСЛЯ НАВЧАННЯ НЕЙРОННОЇ МЕРЕЖІ

Точне землеробство дозволяє автоматизовано та на основі даних підвищувати врожайність сільськогосподарських культур. Підживлення ґрунту, обприскування пестицидами проти шкідників і хвороб можна застосовувати у великих масштабах. Однак боротьба з бур'янами є більш проблемною. Потрібна висока точність локалізації бур'янів, оскільки гербіциди вбивають як бур'яни, так і сільськогосподарські культури, зрізання або лазерне видалення також слід виконувати з обережністю. Для видалення бур'янів запропоновано роботизовані пристрої, які використовують нейронні мережі для локалізації бур'янів. Роботи зазвичай виконують обробку на пристрої, без підключення до Інтернету. Як правило, видалення бур'янів має проводитись на початкових етапах зростання, відповідно рослини займають незначну частину зображення, що робить задачу сегментації складною. Існуючі підходи сегментації бур'янів мають недостатнє співвідношення якості та обчислювальної складності для крайових обчислень. Водночас, за оцінками, бур'яни є причиною зниження зборів врожаю на 31,5%. Для вирішення проблеми сегментації бур'янів безпосередньо на пристрої в цій роботі запропоновано нейронну мережу семантичної семегментації PAN+PTA, обчислювальну складність якої може бути відрегульовано після навчання в діапазоні від 13,08 до 18,12 гігафлопс. Таким чином, мережа може ефективно адаптуватися до пристроїв з різними обчислювальними можливостями без повторного навчання, що економить витрати на навчання та розгортання. Ми досягаємо цього шляхом 1) інтеграції мережі Post-Train Adaptive (PTA) як кодувальника в Pyramid Attention Network (PAN); 2) введення множників ширини для конфігурації початкової ємності мережі PTA. Для навчання та оцінки нейронної мережі використано набір даних WE3DS, який містить анотації 7 культур і 10 бур'янів. Найлегша конфігурація PAN+PTA досягає вищого Dice Score порівняно з PAN з кодувальником MobileNetV2, одночасно зменшуючи кількість обчислень у 1,9 рази. Крім того, навчена мережа в важкій конфігурації з множником ширини 1,5 має показник Dice Score 0,5112, а обчислювальна складність може бути відрегульована в межах 32,34%, що є суттєвим поліпшенням порівняно з існуючою мережею U-Net+PTA (Dice Score: 0,4348, діапазон: 3,66%), при цьому зменшуючи гігафлопси, необхідні для виведення, на 80%.

Ключові слова: сегментація зображень бур'янів, видалення бур'янів, точне землеробство, сегментація на пристрої, кордонні обчислення, динамічна нейронна мережа, моніторинг стану посівів.