A digital weed counting system for the weed control performance evaluation

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Abstract: The weed counting method is one of the keys to indicate the performance of the weed control process. This article presents a digital weed counting system to use instead of a conventional manual counting system called "Göttinger Zähl- und Schätzrahmen" or "Göttinger Rahmen" due to the limitation of human counting on big-scale field experiment areas. The proposed method demonstrated on the maize field consists of two main parts, a virtual weed counting frame and a weed counting core, respectively. The system was implemented as a mobile application for the smartphone (Android) with server-based processing. The pre-processed image on the mobile phone will be sent to the weed counting core based on the pre-trained convolution neural network model (CNN or deep learning) on the server. Finally, the number of detected weeds will be sent back to the mobile phone to show the results. In the first implementation, 100 frames on a 1-hectare field area were evaluated. The absolute weed counting errors were categorized into three groups, A-Group (0-10 weeds error) achieves 73 %, B-Group (11-20 weeds error) achieves 17 %, and C-Group (21-30 weeds error) achieves 10 %, respectively. For overall performance, the system achieves the R^2 = 0.97 from the correlation and 12.8 % counting error. These results show the digital version of "Göttinger Rahmen" has the potential to become a practical tool for weed control evaluations.

Keywords: Göttinger Rahmen, weed counting, mobile application, field experiment, image processing, data labeling, deep learning

1 Introduction

Weed control is one crucial agricultural process to increase the yield of products. Various weed control methods are evolving all the time. On the research project "Agro-Nordwest", several weed control methods such as mechanical field robots, a tractor-implemented and the chemical weed control are being tested. In a scientific view, weed density is one of the keys to evaluating the performance of each weed control and crop protection method. The reference method is the manual counting based on human observation to get the number of weed in one-square meter with the weed counting frame called "Göttinger Rahmen" [Kl11]. However, with the limitation of human workers, weather conditions, and the time required, this method will leave workers exhausted in the big scale area, and counting results may not result in the same number between two persons. Therefore, the digital weed counting frame is a promising solution for increasing the capacity to do the weed counting job faster than human counting.

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Due to the evolution of the data storage and computation performance of the graphic processing units (GPUs) it is possible to achieve the capacity to analyze big data with artificial intelligence analysis (AI) in various fields. In precision farming, the farmers can use big data analysis to make the decision for the crop protection process to increase their productivity [Va17]. For example, several reviews use the image processing technique and the convolution neural networks (CNNs or deep learning) method to locate the weed location for the precision spraying [Wu21; Ha21]. Furthermore, the extracted features from the supervised datasets can also classify weed species without manual feature selection [We20].

With the advantages of CNN, this work presents the weed counting method as a server-based mobile application called the "ExSnap" system to use instead of manual counting for the weed control performance evaluation in the field experiments.

2 Material and Methods

This section describes the ExSnap system implementation. Figure 1 shows the design concept. The system consists of two main parts; the first part is the virtual weed counting frame in the ExSnap mobile application, which is installed on the cellphone (Android system). This part will take the snapshot by the size of a 1-square meter, and the image will be sent to the second part via the file transfer protocol. The second part is an ExSnap core processing server installed on the PC based on MATLAB and a deep network designer to detect and count the weed and send the result back to the first part.

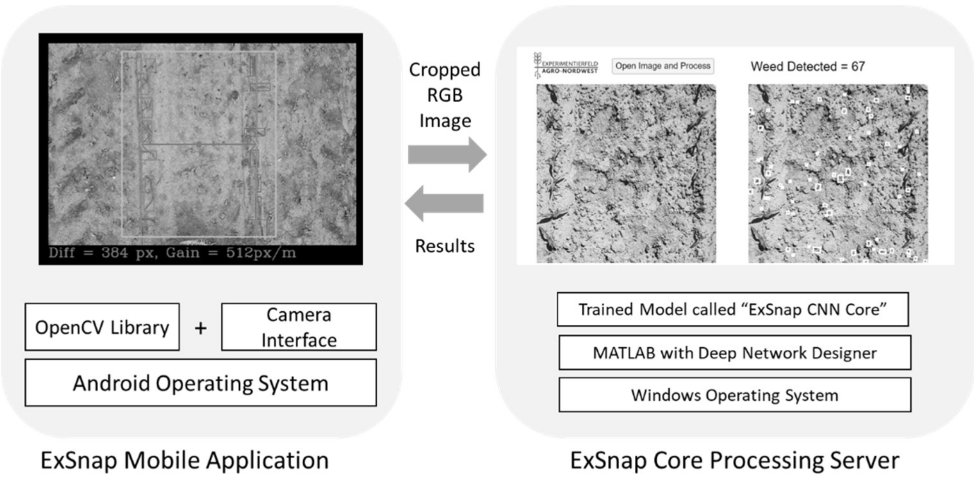

Fig. 1. ExSnap system diagram

2.1 Virtual weed counting frame ("Digital Göttinger Rahmen")

Figure 2 shows the virtual weed counting frame estimation. The 1-square meter weed counting frame can be calculated from the ratio of the distance between two maize rows on the field (R_d) in centimeters and the distance in pixel measured from the camera (V_d). Let the size of the weed counting frame be $G_f = 100$ cm, the distance $R_d = 75$ cm in the experiment. The virtual weed counting frame size (V_f) can be calculated from the Eq. 1,

$$V_f = \frac{G_f}{R_d} V_d = \frac{100}{75} V_d \quad (1).$$

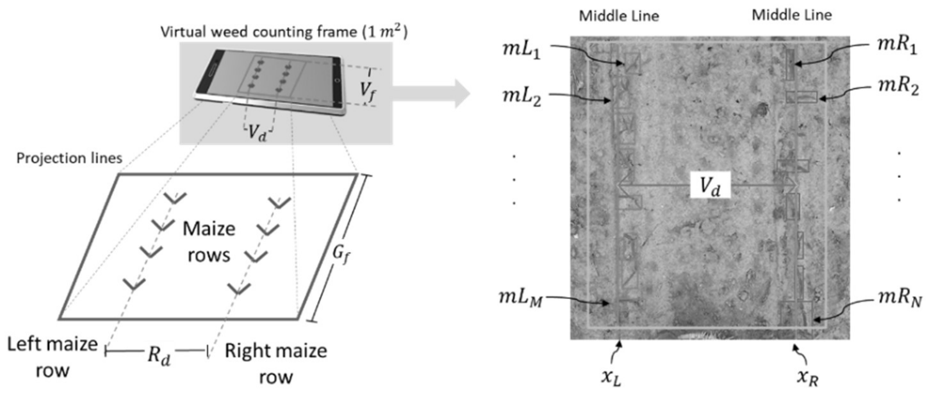

Fig. 2: A virtual weed counting frame estimation

To estimate V_d, two maize rows' detection is needed. This process uses the color blob detection technique to get the hue value of the leaves that is between 60° to 150° (green color). Then create the binary mask image from green pixels with the erosion and dilation morphology and locate the maize plants in the frame. By observation, the size of the section should be more than 300 px^2 per plant. Let mL_i and mR_j is the x-position of each maize plant, x_L and x_R is the x-position of left and right maize row, the V_d can be calculated from their absolute different value via Eq. 2,

$$V_d = |x_L - x_R| = \left| \frac{\sum_{i=1}^{M} mL_i}{M} - \frac{\sum_{i=1}^{N} mR_i}{N} \right| \quad (2).$$

Where M and N is the number of maize plants on the left and right sides, respectively. When the V_f is obtained, the virtual weed counting frame can be placed on the middle frame of a snapshot for real-time processing instead of the one-square-meter weed counting frame. In addition, the virtual weed counting frame can also serve as the guiding grid lines profile for each device to reduce the real-time computation time.

2.2 Weed counting core

This work uses the deep network designer on MATLAB R2020b (MathWorks, USA) with a modified AlexNet model (71 layers, 78 connections, and four outputs) in the training process. Based on the color blob detection technique, all unknown objects will be masked by the green pixels between 60° to 150° of hue value. By assumption, the unknown objects must be divided into two main classes, e.g. weed and maize plants. However, some detection mistakes are difficult to control in real-world conditions. For example, there are occasions when detecting only part of the leaves and some of the soil area. These classes were also taken into the network. Table 1 shows 5,254 images in total from four classes, e.g. weed, a maize plant, plant leaves, and soil area, as shown in Figure 3. All samples were split into 48 % for the training samples, 12 % for the validation samples in the training process, and 40 % for testing the trained network.

	Weed	**Maize Plant**	**Plant Leaves**	**Soil Area**	**Total**
Training	1,198	299	229	796	2,522
Validation	300	75	57	199	630
Testing	998	249	191	664	2,102
Total	**2,496**	**623**	**477**	**1,659**	**5,254**

Tab. 1: Number of samples of a training data set

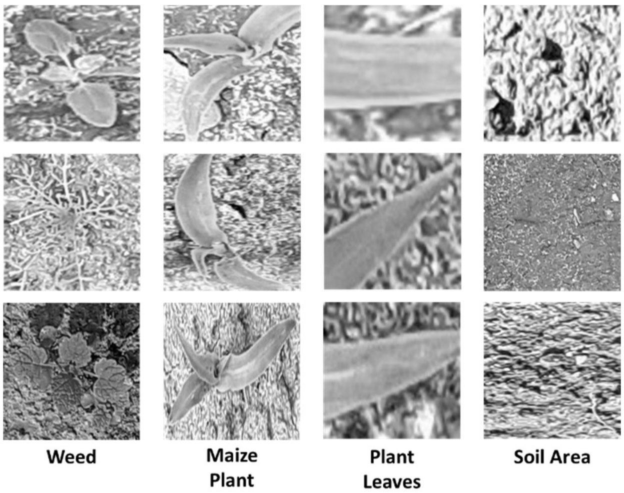

Fig. 3: Four groups of training set samples

In the training process, all images were resized to 224 × 224 pixels, 2,522 images were trained with 30 epochs, 570 iterations. As a result, the validation accuracy achieves 94.45 %, and the confusion matrix with 2,102 testing sets reaches 91.2 % overall performance, as shown in Figure 4. These show the possibility of using the trained model as a weed counting core in the system.

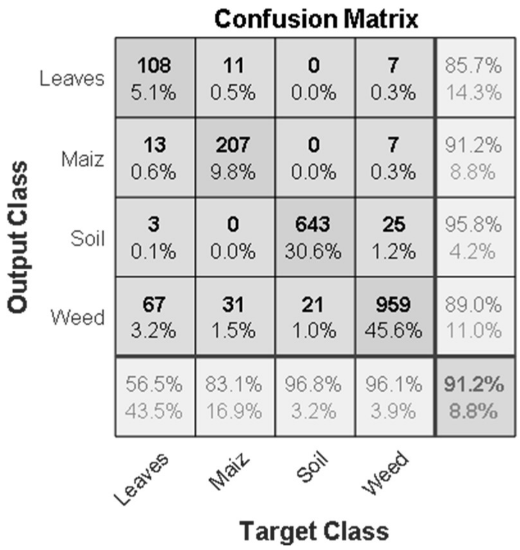

Fig. 4: An ExSnap CNN Core Overall Performance

3 Results and Discussion

This section shows the weed counting results of the first experimental setup, which was demonstrated in a maize field area, Hof Langsenkamp (Belm, Germany), with a 1-hectare experiment area. The number of detected weeds from the ExSnap system will be counted and used for documentation purposes. Compared with the manual counting method, the 100 weed counting frames with the weed density between 0-220 weeds were evaluated with R^2 = 0.97. From 4,432 weed samples from manual counting, the ExSnap system achieves 3,865 weed samples. The counting error of 12.8 % is a result of the weed detection process. For example, the weeds that were close together were counted into one weed. The weed counting results are categorized into three groups: A-Group, B-Group, and C-Group, for weed counting errors between 0-10 weeds, 11-20 weeds, and 21-30 weeds. From 100 weed counting frames, Table 2 shows the number of weed counting frames for each group. The system gave the best results in the A-Group, which achieves 73 frames from 100 frames with an average computation time between 4 to 11 seconds/frame, while the manual counting achieves 1-5 mins/frame.

A-Group (%)	B-Group (%)	C-Group (%)	Total (%)
73	17	10	100

Tab. 2: Percent of weed counting frames for each group

4 Conclusions

The first setup of a digital weed counting system for the weed control performance evaluation was implemented into a mobile phone called the "ExSnap" system. The system consists of two parts, a virtual weed counting frame estimation based on the image processing technique and the weed counting core based on the deep learning method. The proposed method achieves weed detection results on the snapshot image with the weed counting number. The ExSnap system has been applied in maize field plots, with a correlation R^2 = 0.97 and 12.8 % overall weed counting error. The results illustrate that the ExSnap system has the potential to be used in the field experiment.

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