COUNTING OF WEED NUMBERS IN FARMS BY DEEP LEARNING-STRONGSORT

Mustafa Güzel[1], Bülent Turan[2], Bahadır Şin[3], Alper Baştürk[4]

[1]Faculty of Agriculture, Tokat Gaziosmanpaşa University, 60250 Tokat, Türkiye

[2]Faculty of Engineering and Natural Science, Tokat Gaziosmanpaşa University, 60250 Tokat, Türkiye

[3]Faculty of Agriculture, Sakarya University of Applied Science, 54050 Sakarya, Türkiye

[4]Faculty of Engineering, Erciyes University, 38039 Kayseri, Türkiye

ABSTRACT

The knowledge of weed numbers is very helpful for many studies due to minimizing weed harm on the crops as well as knowing the weed species and classes. In this study, we used a deep learning architecture that was capable of detecting some weeds to count the weed numbers instead of classical manual weed counting methods. The pre-trained deep learning weight belongs to YOLOv5 which is used in this study, can detect 5 different phenological terms (cotyledon leaves period, 3-5 leaves period, pre-flowering period, flowering period, and fruit and seed setting period) of some harmful weeds (sherlock mustard-*Sinapis arvensis* L., creeping thistle-*Cirsium arvense* L. Scop, and forking larkspur-*Consolida regalis* Gray) in wheat production and other crops with 98% highest accuracy. StrongSORT with the OSNet tool is used as the multi-object tracker. The weeds successfully counted from any image resources (image, video, webcam, etc.) while avoiding recounting the same object by computer vision. It plays an important role in the studies aimed to understand weeds population spread, resistance gaining to herbicides by weeds, the economical threshold of weeds, etc. It also provides these parameters cheaper and faster than classical methods.

Keywords: Weeds counting, deep learning, StrongSORT

INTRODUCTION

Image processing and deep learning are used in many fields today. One of these usage areas is precision agriculture. Different image processing and deep learning methods/models can be used for different applications in precision agriculture. For example, detection of pests and diseases in cultivated plants [1, 2, 3, 4], detection of weeds [5, 6, 7, 8, 9], counting weeds and determining their ratio to cultivated plants [10, 11], many fields of study such as crop yield estimation [12, 13, 14, 15] can be given.

Weed detection has an important place in precision agriculture. If weeds can be detected instantly by machine vision, systems that work in real time and spray can be developed. Among these systems, it can consist of a drone and necessary equipment that can perform detection and spraying, or it can be built on other mechanical systems that can travel in agricultural land. In addition, these systems can detect the presence of weeds growing in the cultivated plant and use less herbicide at the time of spraying. Thanks to such applications, the amount of drugs used and therefore the cost can be reduced significantly. This is an important result, because spraying is an important factor that increases product costs. In addition, during the use of pesticides in conventional spraying methods, the entire land is exposed to these active substances. As a result, crop plants are also exposed to pesticides. This causes residue on the product, phytotoxic effects and even deterioration in the amount of product. It has been determined by various studies that there are complete product losses as a result of faulty applications.

In addition, knowing the type and phenological period of weeds in the field is extremely important in terms of determining the time and form of spraying. Today, as a result of herbicide applications made in inappropriate periods and forms, the problem of herbicide resistance in weeds arises and is becoming increasingly common. It is also very important to be able to detect the presence of weeds in the field in real time. When literature research is conducted on the subject, it is observed that various studies have been carried out, but the scarcity of these numbers draws attention.

Additionally, while weed detection is performed in real time, each video frame is reprocessed and from it is obtained independently of each other. Therefore, it is of absolute importance to be able to identify the same weed detected from different video frames. If this process cannot be performed, the same weed will be sprayed again and again each time it is detected in different video frames while spraying.

Determining the weed density in the field is of great importance to deciding on spraying and to determining the estimated damage level of the weeds in the field. Under normal conditions, weeds in the field are determined by classical methods. Whereas, this determination can be made thanks to the video footage taken. However, the most important point to be considered here is the possibility of counting the same weed many times. If this happens, it will lead to incorrect results and as a result, it will cause incorrect applications and calculations.

For this reason, it is necessary to follow up together with the detection of weeds. In this study, we focused on the tracking of weeds detected with a deep learning network. Thus, multiple object tracking will be performed for the weed types determined in the study.

RELATED STUDIES

In the literature, there are studies on the detection of weeds in cultivated plants. However, there were no studies on tracking the detected weeds in consecutive frames. In real-time applications, object tracking must be performed in order for the decision-making systems to work stably. Multiple object tracking has both academic and commercial potential today [16]. For this reason, it is used in many areas such as automatic driving, smart monitoring, and behaviour recognition [17]. There are many studies on object tracking in the literature [18, 19, 20]. These studies mostly propose methods for stable tracking of objects. Also, there are studies that develop trackers for the use of researchers [21, 22, 23]. Researchers whose aim is to use the tracker rather than to develop it, prefer the tracker they have determined in accordance with their own purposes and carry out their applications. The aim of this study is not to develop a tracker. It is the tracking of the objects (specific weeds) detected by the trained network in video frames and the processing of the obtained data.Therefore, in the study, the StrongSORT tracker, which was determined as the most suitable for the purpose of the study, was preferred among the tracker with different characteristics.

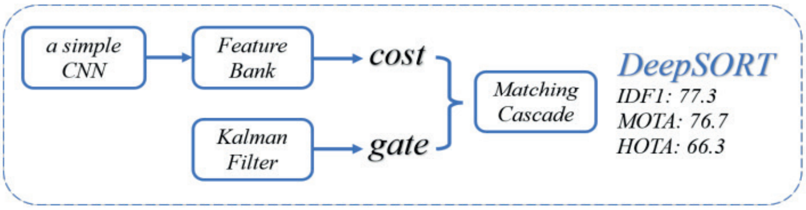
MATERIAL AND METHOD

In this study, with significant economic damage and toxic effects in the wheat production areas of the Tokat region; wild mustard (Sinapis arvensis L.), villagemigrant (Cirsium arvense) and field hazelnut (Consolida regalis) plants were determined by deep learning method and followed by StrongSORT application and counted. In the detection of weeds; YOLOv5s pre-trained neural network was used, which was trained with the presence of related plants and had a detection ability of 98%.

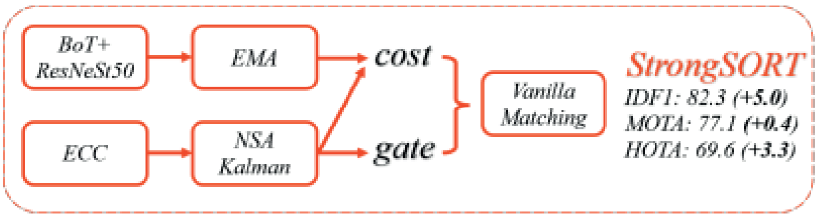
StrongSORT

It is a detection-tracking algorithm made available by the developers of the StronSORT application as open source on the internet and continues to be updated with new updates to minimize the problems faced by users. Multi-Object Tracking systems (MOT-Multi Object Tracking), currently in use, have difficulties in classifying detected objects because they use detect-track and detected-related tracking paradigms. Although the advantages of such approaches against each other are compared, the success and superiority of the locator-following paradigm has been demonstrated in the StrongSORT algorithm [23].

StrongSORT is the development of the DeepSORT algorithm, which was created before and is frequently used. Figure 1 shows the test results of DeepSORT and StrongSORT algorithms with the same data sets. At its best, this algorithm offers 2 simple trained neural network weights for users to work on the objects they want to detect themselves. The second important feature of the algorithm is; It is to minimize the related tracking leaks by offering a Gaussian-Smoothing Filter (GSF) for objects that are missed during tracking even though they are detected [23].



(a)



(b)

Figure 1. DeepSORT (a) and StrongSORT (b) algorithm performances on IDF1, MOTA, HOTA datasets

$$e_i^t = \alpha e_i^{t-1} + (1-\alpha) f_i^t \quad (1)$$

EXPERIMENTAL RESULTS

The open source codes and requirements given by the developers of the StrongSORT algorithm are loaded. Although the Python programming language is run with the Linux operating system, it is integrated as "Anaconda" for Windows operating system users. After downloading the relevant algorithms from open source, commands are written as in Figure 2.

Figure 2. Python commands

According to Figure 2;

- "python" is the programming language to be used,
- "track_v5.py" is the tracking algorithm adapted for the YOLOv5 version,
- "9.mp4" is the image source (photo, video, webcam, etc.) to be detected and tracked,
- Neural network model trained with a previously prepared data set to be used to detect "best.pt" objects,
- After the "save-txt" detection and tracking process, the information about the detected objects is recorded in .TXT format so that they can be analyzed later,
- "count" calculates how many of the related objects are in total,
- "img-size" refers to the resolution at which the relevant image source should be evaluated.

After running the codes in Anaconda (Python for Windows), the system creates a text document with the extension ".TXT" in the "Runs" folder, as a result of trying the number of frames or instant detections of the image source to be detected. A sample text content obtained from the detection and follow-up studies is shown in Figure 3.

*9.txt - Notepad

File Edit View

```
2821 7 578 701 1883 185 256 -1 -1 -1 -1
2821 7 599 1563 1569 181 198 -1 -1 -1 -1
2821 7 601 889 1829 177 210 -1 -1 -1 -1
2821 7 608 952 2067 102 92 -1 -1 -1 -1
2821 7 609 2675 1612 181 249 -1 -1 -1 -1
2821 7 613 3234 1652 145 181 -1 -1 -1 -1
2821 7 629 3622 2077 178 82 -1 -1 -1 -1
2821 7 630 1615 1199 222 261 -1 -1 -1 -1
2821 7 632 1839 1359 204 148 -1 -1 -1 -1
2821 7 633 2686 1082 96 140 -1 -1 -1 -1
2821 7 640 2931 1160 172 133 -1 -1 -1 -1
2821 7 645 2214 1885 174 150 -1 -1 -1 -1
2821 7 649 3370 1426 109 177 -1 -1 -1 -1
2821 7 650 1131 1016 228 253 -1 -1 -1 -1
2821 7 655 1915 856 227 189 -1 -1 -1 -1
2821 7 656 3383 1175 214 186 -1 -1 -1 -1
2821 7 665 1008 1782 124 123 -1 -1 -1 -1
2821 7 666 2407 809 195 176 -1 -1 -1 -1
2821 7 669 1693 594 175 150 -1 -1 -1 -1
2821 7 670 369 520 286 246 -1 -1 -1 -1
2821 7 671 2625 1294 119 222 -1 -1 -1 -1
2821 7 674 2126 486 184 252 -1 -1 -1 -1
2821 7 676 3547 765 106 181 -1 -1 -1 -1
2821 7 679 2847 625 153 144 -1 -1 -1 -1
2821 7 683 1867 364 202 169 -1 -1 -1 -1
2821 7 687 2757 1287 110 192 -1 -1 -1 -1
2821 7 689 602 684 155 148 -1 -1 -1 -1
2821 7 691 771 185 166 202 -1 -1 -1 -1
2821 7 694 475 218 144 117 -1 -1 -1 -1
2821 7 695 7 451 109 125 -1 -1 -1 -1
2821 7 698 1021 2 166 192 -1 -1 -1 -1
2821 7 699 1378 1 172 206 -1 -1 -1 -1
2821 7 700 2029 0 213 178 -1 -1 -1 -1
```

Figure 3. Text document (TXT) showing the information of detected objects

According to the information given in Figure 3;

- The 1st column (2821) contains the total number of frames the image source contains and the number of frames in which the object was detected,
- The 2nd column (7) shows which class the detected object belongs to,
- The 3rd column (700) is the total number of all objects detected in all frames of the image source without applying any classification filters,
- 4,5,6,7. column (2029 0 213 178) indicates between which coordinates (X1Y1, X2Y2) the detected object is in the image.

After detecting, tracking and counting, the system presents the images with the same name as the image source, created under the folder named “Runs”, to the user, and creates visuals in which the objects are labelled in order to review them in real-time. Sample images of weeds that were detected, followed and counted are given in Figure 4 and Figure 5.

Figure 4. Detection and enumeration of field hazelnut (Consolida regalis Gray) plant

Figure 5. Detection and tracking of wild mustard (Sinapis arvensis L.) and village nomad (Cirsium arvense L. Scope) plants

CONCLUSION

The StrongSORT algorithm used in this study was combined with the detection capability of a previously trained artificial neural network. At the end of the study, it was ensured that the numbers of the presences of 3 different weeds, which were determined by the pre-trained net, belonging to 5 important phenological periods, were also known clearly. With this ability brought to computer vision;

- By knowing the pre- and post-application customs in a known area, the success of weed control applications can be interpreted,
- It will be possible to determine the resistance properties of weeds, especially against chemical applications used in traditional agriculture,
- Knowing the net number of weeds per unit area will shed light on new studies such as determining the economic damage thresholds, making more precise planning in the selection of the control method and estimating the damage before harvest.

ACKNOWLEDGMENT

This work was supported by the project numbered 120O888 within the scope of TÜBİTAK 3501 Career Development Program.

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