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WEED DETECTION ON CARROTS USING CONVOLUTIONAL NEURAL NETWORK AND INTERNET OF THING BASED SMARTPHONE

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Abstract. *This study proposes a method based on Convolutional Neural Network (CNN) for automated detection of weed in color image format. The image is captured and transmitted to the Internet of Thing (IoT) server following an HTTP request made through the internet which is made available using the GSM based modem connection. The IoT Server save the image inside server drive and the results are displayed on the smartphone (Vision app). The results show that carrot and weed detection can be monitored accurately. The results of the study are expected to provide assistance to farmers in supporting smart farming technology in Indonesia.*

Keywords: weed detection, convolutional neural network, Internet of Thing, smartphone

WYKRYWANIE CHWASTÓW NA MARCHWI PRZY UŻYCIU KONWOLUCYJNEJ SIECI NEURONOWEJ I INTERNETU RZECZY OPARTEGO NA SMARTFONIE

Streszczenie. *W niniejszym opracowaniu zaproponowano opartą na konwolucyjnej sieci neuronowej (CNN) metodę automatycznego wykrywania chwastów w formacie kolorowego obrazu. Obraz jest przechwytywany i przesyłany do serwera Internetu rzeczy (IoT) po żądaniu HTTP wykonanym przez Internet, który jest udostępniany za pośrednictwem połączenia modemowego GSM. Serwer IoT zapisuje obraz na dysku serwera, a wyniki są wyświetlane na smartfonie (aplikacja Vision). Wyniki pokazują, że wykrywanie marchwi i chwastów może być precyzyjnie kontrolowane. Oczekuje się, że badania pomogą rolnikom we wspieraniu technologii inteligentnego rolnictwa w Indonezji*

Słowa kluczowe: wykrywanie chwastów, konwolucyjna sieć neuronowa, Internet rzeczy, smartfon

Introduction

Weeds are plants that interfere with cultivated plants. It competes against the cultivated plants in terms of uptake of nutrients, water, sunlight and growing space. Beside removing nutrients and moisture, weeds also harbour insects and disease. Knowing a weed’s life cycle characteristics when you first discover its identity is crucial since they have a significant impact on the choice and effectiveness of a particular control method.

Weed are often categorized into broadleaf, sedges, and grasses weeds based on gross morphological features [8, 16, 18, 20, 24]. Because they stand out like a sore thumb, broadleaf weed identification is rather straightforward. These weeds can quickly transform a beautiful yard into a graveyard because their leaves don’t resemble grass at all, despite the fact that some of their flowers are attractive (Fig. 1).

Fig. 1. Broadleaf weeds

Sedges are grass-like plants classified as one of the most harmful weeds in the world. They infect lawns and gardens all over the world. A sedge species that is invasive has even spread to Antarctica! With that kind of an introduction, it shouldn’t come as a surprise that sedges are an issue in Florida (Fig. 2).

Grassy weeds are true grasses or monocots. One leaf develops from a grass seed after it has germinated. It grows closed, rigid nodes (joints) and hollow, spherical stems. The parallel-veined, much longer than it is wide leaf blades alternate on either side of the stem (Fig. 3).

On the other hand, if the life cycle of the weeds are to be considered, then, they would be classified as annual, biennial, and perennial. Any scale, including huge territories like states and small areas like lawns and backyards, can use this classification system. This way of classifying the weeds may be complicated by a number of factors, such as the fact that many species share characteristics with other classes. The existence of some plants that may have more than one type of growth cycle and might, thus, fit into numerous groups is another problem with categorising weeds. The aim of classifying weeds base on their life cycle is to make identification, research, and control easier. Identification is the first step in an efficient weed management approach.

Fig. 2. Sedges weeds

Fig. 3. Grassy weeds

Annual and perennial weeds have different population ecologies [31]. The intrinsic rate of increase, r, and the carrying capacity, K, are the two variables in the logistic equation for population growth. Annual weeds are typically "pioneer" plants that colonise open areas and expand through the distribution of seeds. A significant percentage of a plant's biomass is devoted to reproduction, and individual plants may not live very long. They are known as "r-selected species" because their population number frequently falls significantly below the carrying capacity and is controlled by how the environment physically affects r [2, 9, 13, 19, 32, 42].

According to several studies, weeds release allelopathy compounds and host pests and pathogens that is capable of endangering cultivated plants [3, 28]. Allelopathy, an environment friendly, economical, and effective weed management process occurs when a plant species generates chemicals that harm another plant species either directly or indirectly through the microbial decomposition of left overs [22, 35]. A study by Liebman and Dyck [25] show that using allelopathic plants as part of an intercropping system or as part of a crop rotation could provide a non-herbicide weed control strategy. Over time, several literatures have discussed the application of allelopathy in rotations (see [6, 11, 14, 17, 23, 26, 37, 41, 46]). However, many have investigated how to manage allelopathic cover crops for weed control [10].

Carrots are one type of vegetable that is widely cultivated. Carrots is beneficial for health, being a source of vitamin A, vitamin B and vitamin C [12, 36]. Weeds that are allowed to grow in carrot fields tend to reduce carrot production. To increase carrot production, it is necessary to control the weeds that grow in the carrot plantations. Computer vision is the latest technology in identifying weeds which is very effective and low cost.

Several studies related to weed detection using vision can be found in [4, 5, 7, 21, 27, 33, 39, 40, 43–45]. Utilising machine vision to detect between-row weeds in real time suggested in [27], methods for detecting weeds using Bayesian and fuzzy k-Means models proposed in [40]. For developing a computer vision technique for weed identification employ the support vector machines [39]. Weed detection in orange groves based on neural networks presented in [43]. Weeds was mapped that are a nuisance in agricultural fields using UAVs and individual plant detection [33], Airborne imagery and neural networks to study weed identification in rice fields was employed in [5]. A computer vision system based on geometry to detect weeds in corn fields was applied in [21]. The efficacy of artificial neural networks and support vector machines for weed detection was examined in [4].

Similar type of studies was conducted for image processing and ground-based machine vision techniques [38]. Deep Learning models for object detection with patch-based classification for weed detection using UAV imagery in different seasons was evaluated in [44]. A farming robot that uses image processing to apply herbicides and detect weeds was developed [7]. In light of these studies, further investigation is deemed necessary as an effort to address food insecurity and provide low-cost system tools.

The CNN methods have been applied in detecting weeds. Using two separate CNNs to analyse RGB and near infrared (NIR) photos to identify crops and weeds quickly and accurately was proposed in [34]. They obtained an average network precision of 98.7%. The CNN were used to develop a vision-based classification system to distinguish valuable crops from weeds. They aimed to destroy sugar beets, a significant crop in Northern Europe [29]. At the same time, was presented image-based weed detection from winter wheat fields with heavy leaf occlusion. Their outcome from the trained model in term of precision and recall yielded 86.6% and 46.3% respectively [15].

Moreover, unsupervised learning for feature clustering using K-means prior to the training module as a replacement to the initialization weights for conventional CNN parameters that are random was proposed. The defined method achieved a better accuracy in weed identification which is 92.89% [38]. In [47] showed that employing DCNN for weed detection in perennial ryegrass is feasible. They discovered that, mostly as a result of the low accuracy values, GoogleNet is not a DCNN that is successful at detecting these weed species. Furthermore, they suggested utilising deep convolutional neural networks and maximum likelihood classification to identify weeds in canola fields. Their research was based on ResNet-50 and VGG16 models' UNET and SegNet meta-architectures. Asad & Bais [1] discovered that SegNet significantly outperformed UNET. However, the above research has weaknesses in presenting data online. Meanwhile, online data presentation is indispensable in modern technology.

In this work, a weed detection system in carrots using CNN has been proposed. Using GSM Module and the internet, the processed image is sent to an IoT server in response to an HTTP request. The IoT Server save the sent image inside server drive and the results are displayed on the smartphone (Vision app). The main contribution and novelty of this paper is the weed detection in carrots using CNN and the weed detection results are displayed in real time using the IoT.

The paper is organized as follows: Section 1 presents the architectures of vision technology utilizing IoT. Section 2 discusses the methodology of the semantic segmentation technique for precise weed mapping. Chapter 3 then provides results and a discussion on the performance of UNET for weed detection in carrot plants. Lastly, the final section offers some conclusions.

1. Architecture

The entire project is constructed using a smartphone with camera, a GSM modem, and an IoT server. The smartphone with camera is the main system responsible for capturing, converting and processing of image as shown in Fig. 4.

Fig. 4. Camera smartphone for weed detection

On daily basis, the camera snaps the image of the field one row after the other. For each row, immediately after an image is captured, it is processed using CNN method. Smartphone-based image processing scheme can be illustrated as in Fig. 5.

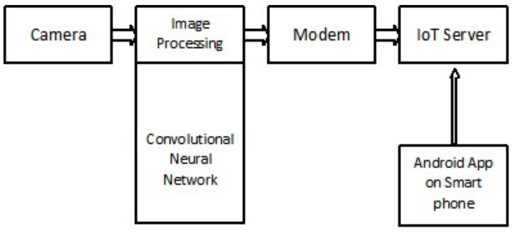

Fig. 5. Image processing scheme based Android App on Smartphone

At certain period, the converted image is transmitted to IoT server following an internet-based HTTP request which is made possible using a modem from GSM Module. The IoT Server can be any Virtual Private Server running an Operating System (OS) with some image processing resources and applications. Once the image is received, the IoT Server store it within the drive by giving a unique name (based on time), with a specific image file format.

2. Methodology

This study employed semantic segmentation technique for accurately mapping of weeds. One of the major problems in agriculture images for semantic segmentation is that of manual pixel labelling. To address this issue, we propose a two-step method for the purpose of manual data labelling. Computer procedure of the proposed method can be shown as in Fig. 6.

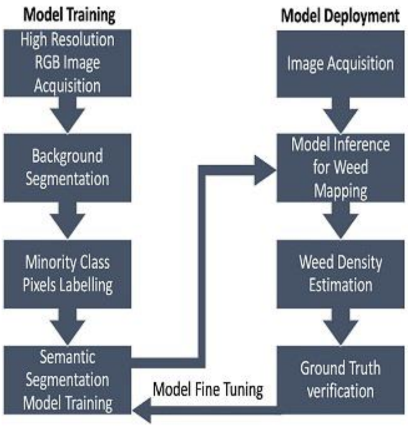

Fig. 6. Flowchart for proposed weed detection

2.1. Data description

In this work, we have selected a high resolution RGB image of a carrot plant with some weeds surrounding the plant. The carrot image was obtained using an iPhone 11 camera in the Bojonggambir area, Tasikmalaya, Indonesia. The image augmentation method employed in this study involves adding effects to the image, such as changes in light and contrast, image blurring caused by vibration, and changes in the equipment's crop line alignment. The dataset was improved using the following methods: flipping the dataset horizontally and vertically, rotation, changing the color, shearing, scaling, cropping, blurring, and zero padding.

2.2. Two-step manual labelling

Based on the method in ref [1], we have proposed a two-step manual labelling procedure for the weed detection method' data preprocessing stage. The first step in this study is to separate the carrot plants from the background weed and soil plants. After that, the minority class pixels on the background segmented image are labelled using the labelling tool.

2.3. Semantic segmentation

For weed mapping and detection, we employ semantic segmentation. Encoding blocks and decoding blocks are the two primary building blocks of deep learning based semantic segmentation. While the decoding blocks up samples sample feature space to picture dimensions, the encoding block down samples features from images. In this study, we have used UNET with fully convolutional network.

3. Results and discussion

UNET is commonly considered as a fully convolutional network (FCN).

However, UNET is different from SegNet in that its entire feature map in UNET is transferred from the encoder block to the decoder block that results in reduce memory requirement. We can have a concatenation operation between encoder and decoder blocks by introducing a skip connection. The rationale behind concatenating skip connections is to allow a combination of local information extracted from the encoding block and global spatial information. Other than that, UNET is also known to work fine with small datasets which makes it more suitable for this project. The entire UNET architecture is depicted by Fig. 7.

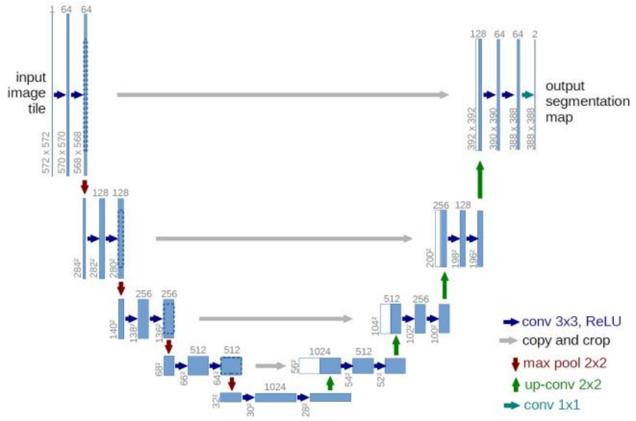

Fig. 7. UNET meta-architecture

The first stage is to differentiate the color between the carrot and weed plants. Carrot plants are marked in green while weed plants are marked in red. The second stage is optimization of training speed. At this stage the image size is changed to 128×128. In the third stage is the segmentation of carrots. This section is divided into several sections including model preparation, model structure in charts, data preparation, storing data in memory, training, and implementation. In the fourth stage is weed segmentation. This section has several sections including model preparation, model structure, memory data storage, data inspection, training, and implementation. The results show that our algorithm can detect weeds accurately as shown in table 1.

In Fig. 8, weeds are shown in red while carrot plants are shown in green. The segmentation results show that weeds can be detected accurately by the CNN method. In addition, the image processing results from the camera are sent to a smartphone using the vision app display. The results of online data processing can be seen in Fig. 9.

Table 1 shows the overall accuracy for all classifiers applied to the carrot's dataset. According to these results, the U-Net model demonstrates superior classification performance at 75.3%, outperforming SegNet (61.65), FCN-32s (68.75), FCN-16s (72.95), U-Net (75.35), and DepLabV+ (71.85) in distinguishing between weeds and crops.

Table 1. Overall accuracy for the classifiers

Methodology	Over all accuracy
SegNet	61.65
FCN-32s	68.75
FCN-16s	72.95
DeepLab	71.85
U-Net	75.35

U-Net has a symmetrical architecture with an encoder-decoder structure that facilitates precise localization and classification. The encoder captures context by down-sampling, while the decoder reconstructs the image by up-sampling, enabling detailed segmentation. The skip connections in U-Net directly link the encoder layers to the corresponding decoder layers. This allows the model to retain spatial information that is typically lost during the down-sampling process, resulting in better performance, especially for tasks requiring precise boundary delineation.

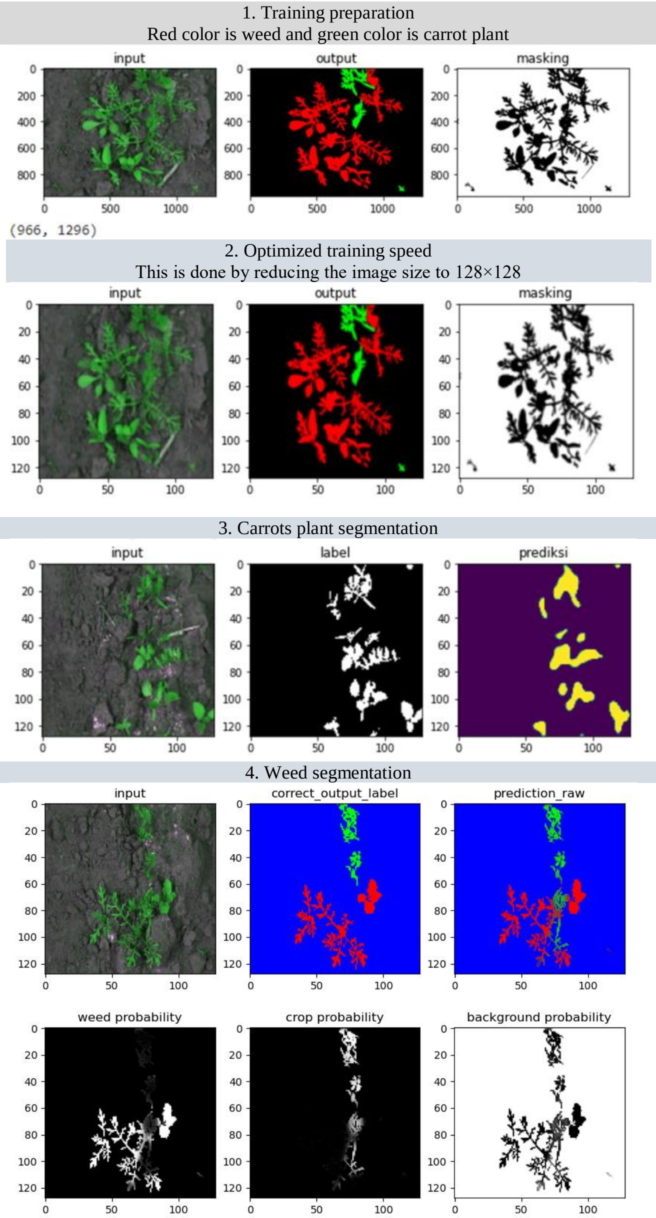

Fig. 8. Results of weed detection

Fig. 9. Results of image processing by smartphone

4. Conclusion

In this report, we have examined a weed detection system utilizing smartphone-based image processing. The type of plant used in this study is a carrot plant. The research stages were training, optimization of training speed, segmentation of carrots and segmentation of weeds. Our finding is the U-Net model demonstrates superior classification performance at 75.35, outperforming SegNet (61.65), FCN-32s (68.75), FCN-16s (72.95), U-Net (75.35), and DepLabV+ (71.85) in distinguishing between weeds and crops. The results show that carrot and weed detection can be monitored accurately.

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