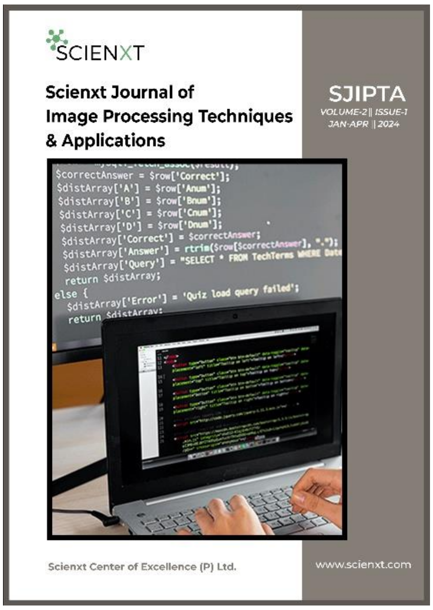

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Deep learning and image processing for weed identification in vegetable plantations

[*1]Shubhangi Bharti

[*1]UG Student, Department of Electronics and Communication Engineering, Dayananda SagarAcademy of Technology and Management, Bengaluru, Karnataka, India

**Corresponding Author: Shubhangi Bharti*
Email: shubhangibharti966@gmail.com

Abstract:

Vegetable plantations have variable plant spacing, which makes weed identification considerably more difficult than for crop weeds. There has been little work done so far on identifying weeds in vegetable plantation. Traditional methods for identifying crop weed are usually focused mainly on directly identifying weed; there is a large amount of variability in weed species. In this paper, a new method is suggested that takes a different approach, combining deep learning and image processing technology. Initially, a trained CenterNet model has been utilized for detecting vegetables and drawing bounding boxes around them. Then, the remaining green objects that do not fit within the bounding boxes are considered weeds. This way, the model concentrates on identifying only the vegetables, avoiding the need to deal with various weed species. Moreover, this approach can significantly reduce the size of training image dataset and the complexity of weed detection, thus improving weed identification performance and accuracy. For separating weeds from the background, a color index-based segmentation was conducted using image processing. The chosen color index was established and assessed using Genetic Algorithms (GAs) based on Bayesian classification error.

Keywords:

Deep learning, color indexing, image processing, genetic algorithms, and weed identification

1. Introduction:

Cultivation is an important part of global agriculture; it provides basic food for the population and contributes to economic growth. However, plant diseases still remain a persistent problem in vegetable cultivation, causing reduced yields, increased labor costs and harm to the environment. Unlike traditional crops that are evenly distributed, the unevenness of plants in the vegetable garden makes it difficult to control the plants. . However, this process is labor-intensive, time- consuming and error-prone, especially in vegetable gardens with different plant species and different growth patterns. Moreover, the presence of weeds can affect the growth and development of vegetable crops, so research and control technology are needed. Growth and development have promising solutions. Deep learning models such as convolutional neural networks (CNN) show great potential in detecting and classifying tasks, making them ideal for identifying vegetation in the field. Additionally, image processing techniques, including color-based segmentation and feature extraction, can improve the accuracy and performance of plant detection algorithms. A new method for identifying plants in the vegetable garden our method aims to overcome the problems caused by the differences between plants in the garden and the different plant species. Using the trained CenterNet model, we focus on identifying vegetation and then identify vegetation based on objects outside the vegetation region. This purpose makes it easier to identify plants and reduces the complexity of dealing with different plant species. The algorithm has been optimized to improve the removal of plants from the background. Color selection is evaluated according to Bayesian classification error, ensuring high segmentation quality and reducing computational cost. Through field experiments, we evaluate the effectiveness of our method in terms of accuracy, recall, and F1 score, and demonstrate its feasibility and effectiveness in a real farm environment. The method represents the control of weeds in cultivation and provides a powerful and effective solution for the identification and reduction of plant diseases in vegetable crops. By leveraging the power of deep learning and imaging technology, we aim to provide farmers with tools to improve crops, reduce energy costs and promote permaculture practices.

2. Background:

The approach suggested in this study for the recognition of weeds be comprised of two stages. The initial phase consists of the state-of-art CenterNet algorithm to detect bok choy in this expedition. Pictures of bok choy be collected and utilized as input data for training the neural network. The trained neural network be utilized to detect bok choy and draw bounding boxes around them, which producing bounding box coordinates and encompass class probabilities as the result. Using color information, a color index-based segmentation of the vegetation (pixels) outside the bounding boxes is carried out in the second stage, providing a visual classification of the presence of weeds in the image. Genetic Algorithms (GAs) are used to determine and assess the used color index based on the Bayesian classification error. The procedural steps of the proposed method be depicted in Fig. 1. The remaining part of this section furnishes details of each step. CenterNet model training and testing be executed in the PyTorch profound learning environment utilizing a graphical processing unit (NVIDIA GeForce RTX 2080 SUPER,

NVIDIA; Santa Clara, USA). Genetic algorithm be devised and executed utilizing the Python language with OpenCV library. Both algorithms be controlled from a computer with an Intel.

3. Literature review:

Many researchers and experts have made significant contributions to the field of weed identification in vegetable plantation and have significantly shaped its course and influenced its development. The same comprehensive survey is as shown below.

(1) The key observation from this abstract is that the rapid growth of the world's population has increased the pressure on agriculture to meet the rising demand for food. One of the significant challenges in agriculture is weed management, where excessive herbicide use can lead to environmental pollution and herbicide resistance. To address these challenges, deep learning models are being increasingly utilized in agriculture to detect and classify weeds, thus improving crop yields and reducing environmental impacts. This shift towards deep learning methods holds great potential for sustainable agriculture by minimizing herbicide use, preventing pollution, and adapting to climate change. Additionally, the abstract highlights the adoption of novel techniques to enhance the performance of deep learning models and addresses the challenges faced in adopting new technology in agriculture.

(2) The study focuses on the threat posed by mid- to late-season weeds escaping early- season management, impacting agricultural production by seeding future growing seasons. Using object detection-based convolutional neural networks on low- altitude UAV imagery, the study evaluates the detection of mid- to late-season weeds in soybean fields. Comparing Faster RCNN and Single Shot Detector (SSD) models, both exhibit similar performance in precision, recall, F1 score, and IoU, with Faster RCNN demonstrating

superior weed detection performance and inference speed compared to patch-based CNN models. The findings highlight Faster RCNN as the optimal model for rapid and accurate weed detection, offering implications for on- farm, near real-time weed management.

(3) The study addresses the global rise in herbicide use, which harms the environment, proposing precision agriculture methods to mitigate adverse effects by applying herbicides based on weed densities. However, accurate weed density estimation via deep learning requires extensive labeled agricultural data, which is labor-intensive. The paper introduces a methodology to expedite manual labeling of pixels, utilizing maximum likelihood classification for background and foreground segmentation followed by manual labeling of weed pixels. This labeled data is used to train semantic segmentation models, with ResNet-50 based SegNet demonstrating the best performance on high-resolution color images of canola fields, achieving mean intersection over union and frequency- weighted intersection over union values of 0.8288 and 0.9869, respectively.

(4) The study digitized and analyzed color slide images of weeds among various soils and residues to develop effective methods for distinguishing weeds from non-plant backgrounds. Red, green, and blue chromatic coordinates (RGB) of plants were found to differ significantly from those of background soils and residues. Several indices of chromatic coordinates were tested, including r-g, g-b, (g-b)||r-g|, and 2g-r-b, along with a modified hue. The modified hue, 2g-r-b index, and the green chromatic coordinate were identified as the most successful indices for distinguishing weeds from non-plant backgrounds, particularly under both nonshaded and shaded sunlit conditions. These findings have implications for sensor design for detecting weeds for spot spraying control, with the modified hue being computationally intensive but effective.

(5) This paper presents a method for fast pixel recording of agricultural weed prediction, addressing the concern of increasing pesticide use. Combining maximum distribution and manual registration, this method speeds up the registration process. Semantic segmentation models, including ResNet- 50-based SegNet, were trained using these data. Analysis of rape area images shows that SegNet based on ResNet-50 outperforms the relationship, achieving an average intercept association of 0.8288 and an intersection association frequency of 0.9869. This method ensures the correct use of pesticides, reducing environmental damage and increasing agricultural productivity.

4. Theoretical framework:

The deep learning and imaging principle for identifying plants in the vegetable gard en has several important features.

Deep learning modelsbecause they can lear n hierarchical representations of features from raw pixel data. Data learning: Large datasets with descriptive images are necess ary to train deep learning models to accura tely identify plants in vegetable gardens.

These documents often contain images of crops and plants and include captions indic ating the location and type of each element in the image. Image processing technolog yis used to preprocess images before puttin them into deep learning models. These tec hniques may include color normalization, r esizing, and augmentation to improve mod el robustness and generalization. Search and segmentation: Object detection algorithm (such as CenterNet) are used to detect and find objects in images. Draw a bounding b ox around the detected object to define its boundary. Additionally, segmentation tech nology can be used to separate the screen from the background, further improving the search process. Weed identification strategy focuses on initially identifying us eds using trained object detection models. After this, the produce outside the vegetable container is classified as a plant. This purpose simplifies the identification p rocess and reduces the complexity of deali ng with different plant species. Evaluation. Performance metrics such as precision, rec all, and F1 score are used to evaluate the ef fectiveness of deep learning and image pro cessing techniques in plant identification. These parameters evaluate the model's abil ity to accurately identify and classify plant s in the vegetable garden. Optimization tec hniques such as genetic algorithms (GA) can be used to tune the parameters and hyperparameters of deep learning models and image processing algorithms. These te chnologies help increase the efficiency and effectiveness of facility identification systems. Identification of weeds helps improve crop management and agricultural sustainability.

5. Research methods:

The plant identification method proposed in this study has two stages. The first step is to use the state-of-the-art CenterNet algorithm to identify the cabbage in this trip. Collect images of cabbage and use them as input to train the neural network. A trained neural network is used to identify cabbages and draw the boxes surrounding them, generating the boxes and calculating the class results. In the second stage, color index-based segmentation of plants (pixels) outside the bounding box is performed using color data to visually separate the plants in the image. A genetic algorithm (GA) is used to determine and quantify the color index using Bayesian error classification. The process structure of this method is shown in Figure 1. Training and testing of the CenterNet model was performed using a processor (NVIDIA GeForce RTX 2080 SUPER, NVIDIA; Santa Clara, USA) in the PyTorch deep learning environment. Design and implement genetic algorithms using the Python language and the OpenCV library.

Both algorithms are controlled by computers with Intel processors.

5.1 Image acquisition:

Use a digital camera to take photos of bok choy, also known as bok choy. The grocery store photographed is located in Nanjing, China, at 32°12038.17200 north latitude and 118°48051.8700 east longitude. The original size of the image is 3024×4032 pixels. Cabbage photographs were taken in many situations, including different lighting conditions, complex backgrounds, and different growth stages. In order to increase the richness of the experimental data, data augmentation techniques were used to expand 1150 images in the data set consisting of 11500 images. The images collected are detailed and pre-processed data on color, brightness, rotation and image sharpness. To manually annotate the screen (cabinet) in the input image, bounding boxes are drawn using the custom software LabelImg. Accordingly, CenterNet uses tag archives in XML format for training purposes. 80% of the data set is used for training and 20% for testing.

5.2 Training and testing:

The CenterNet model is a new tool based on metrics instead of ports. CenterNet represents objects as a point and uses heatmaps for prediction. Place. Heat maps were created using the Gaussian kernel and FCN and locations were determined according to the values. The permission field allows properties (such as size and length) to be returned directly without the need for previous anchor points.CenterNet is a standard detection level that provides faster detection by skipping the non- maximum likelihood (NMS) post- processing step. Hourglass was chosen as the backbone of the analysis for this particular extract. To train the network, each landmark is converted into a sparse map using a Gaussian kernel and focal loss (Lk). CenterNet estimates local distances to minimize errors caused by resampling from the input image to the seed of the heat map. Use Loff loss to train offsets.

5.3 Weed identification utilizing image processing:

When vegetables are placed, other green objects that fall from the connected box are marked as plants. Color index-based segmentation of outdoor scenes is learned Using binary coding genetic algorithm (GA) to identify plants in RGB color space. The goal is to remove plants from other parts of the image such as soil, straw, stones and other debris. The results of the segmentation results are then evaluated by comparing them with the widely used ExG (ExG) index [24]. They can effectively solve complex problems without depending on local conditions. Parallel research on research sites yields the best results. This string consists of long arguments and multiples; characters are the first byte in the chromosome; it is 0 for negative numbers and 1 for positive numbers. A person's fitness directly or indirectly affects his or her ability to reproduce compared to other people. GA has selected and developed a roulette selection method to select individuals with the highest potential.

6. Results and discussion:

This article presents a method to identify and classify plants in plants using deep learning and image processing tools. The image is pre-processed and scaled to fit the required input model. Training parameters such as batch size and epochs are optimized for performance. Conduct product inspections to assess correct quality, quality, quality and poor quality. Precision, recall, and F1 scores are used to measure the accuracy of the model, and the precision-recall curve provides additional information. The best starting point for the trust factor is testing. The results demonstrate the effectiveness of the model in identifying the display despite the masking challenge. Evaluation of plant segmentation performance using genetic algorithm (GA) and color index showed good results. The index outperformed traditional methods such as ExG in separating plants from the background. Use noise reduction techniques to improve segmentation accuracy. Overall, this method provides a reliable way to identify plants and segmentation in vegetable crops and has the potential to be applied in agriculture.

7. Conclusion:

This study aims to identify plants in plants using deep learning and imaging. The algorithm is explained in two steps. The CenterNet model was trained to detect the screen. Trained CenterNet has a high ratio of 95.6%, a low ratio of 95.0%, and an F1 score of 0.953. Currently, green elements remaining in the color image are considered weeds. Color indices were generated and evaluated using a genetic algorithm (GA) compatible with Bayesian classification, which cannot remove plants from the background. This way you don't have to deal with different types of plants since the purpose of the veg is to define the vegetable. Training and imaging Develop a visual method to distinguish vegetables and plants in a new and unbiased way 3) Introduce color measurements to extract plants from the background through natural conditions. While algorithms are used for robotic plants such as pesticides or any type of plants, plants can also be used for organic vegetables. Considering the high performance of this study, this device was found to be suitable for the identification of plants in cultivars and the value of application in various situations, including different illumination, complex background and different growth stages. Future work will be to identify plants in live videos. It will also present the latest results for the search engine by currently optimizing the deep learning model.

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