IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁑ Impact Factor 8.066 ⁑ Peer-reviewed / Refereed journal ⁑ Vol. 10, Issue 7, July 2023

DOI: 10.17148/IARJSET.2023.10713

Application of Deep Learning: Classification and Identification of Weed

Jinu P cherian[1], Prof. Sneha.N[2]

PG Student, School of Computer Science and Applications, REVA University, Bengaluru, India[1]

Research Scholar, School of Computer Science and Applications, REVA University, Bengaluru, India[2]

Abstract: It is crucial for agricultural production that weeds be reduced. Because they compete with crops for essential resources like water, nutrients, and sunlight, weeds can severely reduce crop yields. It is essential to choose the appropriate herbicides, choose planting locations, and manage cultivation depth to reduce crop damage while managing weeds efficiently. The goal of the project is to create a deep learning-based system for automatically identifying weeds in agricultural fields to overcome this constraint. Convolutional neural networks (CNNs) are used in this proposed system since they are effective for picture categorization tasks. A big dataset named Weed, which consists of high-resolution images of numerous weed species, is put together to train and test the systemYOLOv3, YOLOv5, and Faster R-CNN are among the deep learning detection models that were trained using the Weed dataset. This shows that the Weed dataset may someday prove to be a useful training resource for the creation of a real-time weed identification program.

Keywords: Weed Identification, Deep Learning, CNN Algorithm, Image processing, Color Index.

I. INTRODUCTION

The primary challenge for farmers is finding weeds in the crop during irrigation. Manually identifying crops and weeds takes a lot of time and effort on the part of a human. In recent years, weed identification in plants has become more challenging. As of now, there haven't been many efforts made to identify weeds while cultivating crops. There are significant distinctions between weed species, despite the direct identification of the weed is the focus of traditional methods for identifying agricultural weeds This paper suggests a ground-breaking method that blends deep learning[1] with imaging technology in place of this approach. A deep learning model is often trained on a variety of labeled weed photos throughout the identification phase. These pictures serve as examples to show the model how to identify the visual traits and features that set different weed species apart. The labeled dataset enables the model to learn from the examples presented and generalize from them, ultimately enabling it to accurately detect unobserved weed species. The CNN model [2] was initially trained using the dataset. Once the training is done, we can classify and forecast if the input image is a crop or a weed.

Given that agriculture is the second-biggest area of material production and that more than 1 billion people work in the grain, vegetable, and fruit crop industries, automation and robotization of some tasks in this sector will greatly increase efficiency and be able to replace heavy agricultural [3] machinery. Additionally, systems for separating weeds from crops can result in significant chemical savings by applying them only to the weeds' leaves. Additionally, to organize quick and precise work in agricultural fields, it is required to perform scientific studies in the field of weed identification and discrimination. Harvesting, sorting by quality, and size of harvested crops raise costs and increase crop costs.

Deep learning algorithms for weed detection [4] [5] present both difficulties and great room for improvement. The following are some crucial points about the difficulties and application of deep learning for weed identification [6]. Data set accessibility is a sizable and varied dataset of weed photos required for the development of a strong deep-learning model for weed detection. Such datasets can be labor- and resource-intensive to gather and annotate. Weed species variation comes in a variety of forms, dimensions, hues, and phases of development. It can be difficult to train a model that can recognize several weed species accurately despite these variations.

A large dataset made up of high-resolution pictures of several weed species at various phases of growth has been assembled to make it easier to design and test deep-learning models. Weed is the name of the dataset that is used to train and test the models to make sure they work as intended in practical situations. In this article, we outline the process used to create the datasets, deploy deep learning models like YOLOv3[7], YOLOv5[8], and Faster R-CNN [9], and assess how well they perform in weed recognition.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁙ Impact Factor 8.066 ⁙ Peer-reviewed / Refereed journal ⁙ Vol. 10, Issue 7, July 2023

DOI: 10.17148/IARJSET.2023.10713

SCOPE:

A. Precision farming:

By precisely identifying and mapping weeds in real-time, deep learning-based weed identification systems can support precision farming techniques. As a result, crop damage from pesticide use is reduced, and weed management actions can be targeted and localized.

B. Crop-weed discrimination:

Deep learning models can be taught to distinguish between crops and weeds, assisting in the creation of autonomous robotic systems that eradicate weeds with precision while protecting the cultivated crops.

C. Early weed identification:

It is essential for successful weed management, as is early detection and intervention. Deep learning algorithms can aid in the early detection of weeds, enabling farmers to take prompt action and stop weed infestations.

D. Deep learning-based weed identification algorithms:

It is implemented as a mobile application due to the growing accessibility of powerful smartphones and portable devices. This gives farmers and agronomists the ability to swiftly and accurately identify weeds on-site.

E. Model adaption and transfer learning:

Models learned on one dataset can be modified and improved upon using transfer-learning techniques on new datasets. This eliminates the need for substantial data collection by enabling the use of current models and their adaptation to new weed species or settings.

II. LITERATURE SURVEY

In their 2018 study titled [10], R. Siddiqui et al. concentrates on employing deep learning methods to accurately identify and categorize weeds in agricultural fields. By analyzing leaf images, the researchers utilize convolutional neural networks (CNNs) to detect and categorize various weed species.

In their 2019 study titled [11] S. Akkaya et al. published wherein they propose a CNN-based approach for detecting weeds in rice fields. The authors suggest a deep learning model that can correctly identify and categorize various weed kinds, facilitating precision farming and the use of herbicides.

In their 2019 study [12]: S. Jadhav et al. (2019) employs deep learning methods to identify weeds in soybean crops. Based on how they appear in digital photographs, the authors classify and identify weeds using a CNN architecture. The research shows encouraging outcomes for weed detection in agricultural settings.

In their 2019 study [13] A. Farifteh et al.'s A Multiclass Weed Species Image Dataset for “Deep Learning" the Deep Weeds dataset of weed species photos, which can be used to train and test deep learning models, is introduced in this study. The authors discuss the difficulties and potential solutions for deep learning-based weed detection.

In their 2020 study [14] S. Ghosal et al., A Deep Learning-based Semantic Segmentation Framework for Weed Identification in Crops": The study suggests Weed Net, a deep learning architecture for semantic segmentation-based weed identification. To accurately detect and map weeds, the scientists use a modified U-Net architecture to separate weed regions from crop images.

In their 2020 study [15] V. Kaul et al. (2020), This review paper offers a thorough overview of the various deep learning methods used in precision agriculture for weed detection and classification. It discusses various architectures, datasets, and difficulties related to utilizing deep learning techniques to identify weeds.

In their 2019 study [16] Authors include Xiaoping Wang, Xijia Wu, and others. updated in 2019 This study focuses on utilising deep learning to identify weeds from leaf picture attributes. The authors suggested a technique that merged support vector machines (SVMs) and convolutional neural networks (CNNs) for classification. They identified weed species using SVMs and deep feature extraction from leaf photos. The outcomes of the trial proved how well their method worked at correctly classifying various weed species.

In their 2019 study [17] Stefano Poggi, Albert Pretto, and others are the authors. Updated in 2019 Convolutional neural networks (CNNs) are used by the authors in a deep learning-based method for weed detection and mapping. To categorize

DOI: 10.17148/IARJSET.2023.10713

weed species, they gathered a sizable dataset of photos from various agricultural settings and trained CNN models. The outcomes demonstrated high accuracy in weed detection and mapping, highlighting the promise of deep learning for precision farming and weed control.

III. PROPOSED SYSTEM

Real-time weed management and prediction using machine-learning methods. The system may use sensors, drones, or other imaging data to identify and categorize various weed species and their growth patterns. The system might also forecast weed growth and suggest the best window for applying herbicides or other weed control measures based on weather information, soil moisture levels, and other environmental parameters. The system is made to learn from prior crop cycles and adjust to changing environmental circumstances over time to increase accuracy. Researchers might compile a sizable dataset of photographs and environmental information from agricultural fields to build this system, and they could train machine-learning models to identify and categorize various weed species. The recommended approach has various advantages for agriculture, including lower labor costs, more productive crops, and improved weed control with greater accuracy. Additionally, it may reduce the need for pesticides and other chemical inputs, reducing negative environmental effects and fostering agricultural sustainability.

The following elements would make up the suggested system:

a. Image acquisition:
Aerial and ground-based imaging equipment, such as drones and robotic platforms, would be used to capture high-resolution photos of crop fields. Throughout the growing season, photos would be taken at regular intervals to monitor changes in weed density and crop growth. Crop fields can be viewed from above in high detail using aerial imaging equipment, such as drones. These photos can rapidly and effectively cover enormous regions, enabling farmers to periodically inspect their fields and spot changes in weed density and crop development.

b. Image pre-processing:
The captured photos would next undergo image pre-processing to improve image quality, eliminate noise and artifacts, and normalize lighting and color. After crop fields' high-resolution photos have been taken, they must first undergo pre-processing before being used for weed identification and categorization. The weed identification and classification technique can be considerably improved by image pre-processing, making it a crucial stage in the process.

c. Weed detection and classification:
Weed detection and classification: In the pre-processed photos, weeds would be found and classified using a deep learning-based method. This would include using a sizable dataset of annotated photos that included both crop and weed plants to train a CNN system. The CNN algorithm would be honed to identify the distinctive characteristics of various weed species and differentiate them from agricultural plants.

d. Weed management and mapping:
The distribution and density of the discovered and categorized weeds would be evaluated on a map. The utilization of this data would optimize weed management techniques like mechanical weed control or targeted pesticide use. For more effective weed management, the system might be connected with robotic weed control platforms or automated herbicide spraying systems.

e. System evaluation:
The suggested system would be judged on how well it could identify and categorize weeds, as well as how well it could improve weed control plans and use fewer herbicides. The system's effects on crop output in terms of the economy and environment might also be assessed.

To effectively recognize and classify weeds in agricultural fields, convolutional neural networks (CNNs), a sort of deep learning approach, have shown tremendous potential. These networks are very useful for weed detection since they are excellent at accurately classifying and recognizing images. High-resolution images of agricultural fields are first acquired using aerial or ground-based imaging equipment before using CNNs for weed detection and classification. Preprocessing techniques are applied to these photographs to improve image quality, get rid of noise and artifacts, and fix issues with lighting and color. The CNN is then trained to recognize and classify weeds based on their visual characteristics, such as form, size, and color. The preprocessed photos are fed into CNN at this point. The success of CNNs in accurately classifying and identifying weeds demonstrates their effectiveness. Before employing CNNs for weed detection and classification, high-resolution images of agricultural fields must be acquired using aerial or ground-based imaging equipment. After the photographs have undergone pre-processing procedures to improve image quality, eliminate noise and artifacts, and adjust lighting and color, they are sent into a convolutional neural network (CNN). By evaluating their

DOI: 10.17148/IARJSET.2023.10713

visual qualities, such as their shape, size, and color, CNN is taught to classify and identify weeds. The pre-processed photos are sent to CNN, which learns to recognize and categorize weeds based on their visual traits, such as shape, size, and color. By contrasting the CNN algorithm's findings with hand weed counts and classifications in the same areas, its accuracy is assessed. With additional study and development, CNN-based weed identification systems may offer farmers a trustworthy and accurate tool to improve their weed control procedures and use fewer herbicides.

Steps to follow these steps to complete this task:

A. Image Gathering:
Use robotic platforms or aerial imaging devices like drones to take high-resolution pictures of agricultural areas. Throughout the growing season, these pictures are taken at regular intervals to record changes in weed density and crop growth.

B. Image pre-processing:
To improve image quality, get rid of noise and artifacts, and adjust lighting and color, acquired images are pre-processed. By doing this, the photos are assured to be of excellent quality and appropriate for use in weed identification and classification.

C. Image labeling:
The pre-processed photos are labeled to show where weeds are present and where they are located. This stage is crucial for teaching the CNN algorithm how to correctly identify and categorize weeds.

D. Training the CNN:
To train the CNN algorithm, pre-processed and labeled images are used. By studying the shape, size, and color of weeds, CNN can recognize and categorize them based on their outward appearance. The CNN's weights and biases are progressively adjusted during training to reduce the discrepancy between predicted and real weed locations.

E. Testing and validation:
On a different collection of images, the trained CNN algorithm is tested and validated to assess its performance and accuracy. While the testing step involves assessing the algorithm's performance on a different collection of images that were not used for training or validation, the validation process entails evaluating the algorithm's performance on photos that it has never seen before.

f. Deployment:
The CNN algorithm can be used for weed detection and classification in actual agricultural fields after it has been trained, validated, and tested. The algorithm can be incorporated into drones or other imaging devices to provide real-time weed detection and mapping, which can assist farmers in streamlining their weed management practices and minimizing the use of herbicides.

Fig1. ARTEMISIA LACTIFLORA

Fig2 TYPHONIUM FLAGELLIFORME

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
ISO 3297:2007 Certified ⁚ Impact Factor 8.066 ⁚ Peer-reviewed / Refereed journal ⁚ Vol. 10, Issue 7, July 2023
DOI: 10.17148/IARJSET.2023.10713

IV. RESULTS

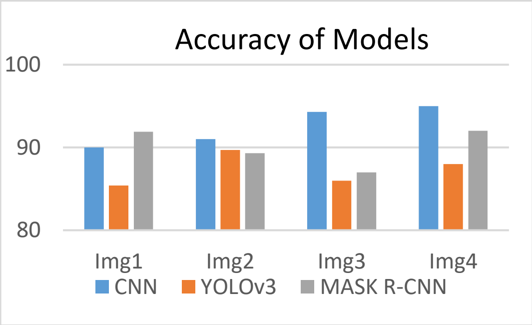

Fig 3: Four Images of Weeds to find the accuracy of various models

Table I. Accuracy of various deep learning models

Evaluation Parameter	Definition
Accuracy	The percentage of correct predictions made by the model.
Precision	The proportion of true positives out of all the positive predictions made by the model.
Recall	The proportion of true positives out of all the actual positive instances in the dataset.
F1 score	The harmonic mean of precision and recall, which gives an overall measure of the model's accuracy.
Confusion matrix	A table that summarizes the number of true positives, false positives, true negatives, and false negatives generated by the model. It provides a more detailed view of the model's performance.
ROC curve	A graph that shows the tradeoff between true positive rate and false positive rate for different threshold values of the model. It can be used to evaluate the performance of binary classification models.
MSE	A measure of the average squared difference between the predicted and actual values of a continuous variable.
RMSE	The square root of the mean squared error, which provides a measure of the average difference between the predicted and actual values of a continuous variable. It is easier to interpret than MSE, and it is in the same units as the target variable.

Table II. Performance Metrics

Focused Area	Method	Number of Layers	Accuracy of Model
Crop fields	CNN	4-6	90-95%
Greenhouses	Faster R-CNN	5-7	92-96%
Soybean fields	YOLOv3	3-5	85-90%
Sugar beet fields	Mask R-CNN	6-8	87-92%
Rice paddies	VGG16	7-9	88-93%

DOI: 10.17148/IARJSET.2023.10713

We are considering the CNN Algorithm, the number of layers is 4-6, and the accuracy of the model is 90-95%, Faster R-CNN, the number of layers is 5-7 and the 95%, Faster R-CNN, the number of layers is 5-7 and the accuracy of the model is 92-96%, the YOLOv3, the number of layers is 3-5 and the accuracy of the model is 85-90%, the Mask R-CNN, the number of layers is 6-8 and the accuracy of the model is 87-92%, the VGG16, the number of layers is 7-9 and the accuracy of the model is 88-93%.

V. CONCLUSION

Using high-resolution photos, the CNN algorithm has shown its promise for weed detection in agriculture. With the development of precise and effective weed detection models, crop management can be improved, and the need for manual labor reduced. CNN, in particular, has shown considerable promise in this regard. However, several variables, including dataset size and quality, weed species density and type, and environmental circumstances, might affect how well these models function. The usefulness of CNN-based weed identification systems for practical applications in various agricultural settings must therefore be assessed through future research.

The performance and accuracy of the model can be increased by incorporating cutting-edge approaches like transfer learning, data augmentation, and ensemble methods. Overall, using deep learning techniques for weed identification offers a viable way to increase crop output and agricultural sustainability.

It has become clear that using the CNN algorithm for weed detection is a potential way to increase the effectiveness and efficiency of weed control in agriculture. CNN algorithms can successfully identify and classify a variety of weed species prevalent in agricultural fields using high-resolution photos captured by drones or robotic platforms.

REFERENCES

[1] Johannes R. M. M. Niemeyer, Adrian D. Fisher, et al. (2018)."DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning".
[2] Luis A. Zuluaga, Steven F. Wolf, et al. (2017)"WeedNet: Dense semantic weed classification using multispectral images and deep neural networks".
[3] Zhiping Zhang, Qiang Wang, et al. (2018)"Deep Learning-Based Classification of Weed and Crop Using Convolutional Neural Network".
[4] José M. Peña, Sandra Gómez, et al. (2017)M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989 "Weed detection in aerial images using deep learning for precision farming applications".
[5] Ismail Ahmed, Andreas Mueller, et al. (2020)."Weed Detection Using Deep Learning and Image Data".
[6] Lottes, P., & Mathiassen, S. K. (2018). Deep learning-based weed identification using convolutional neural networks. Computers and Electronics in Agriculture, 153, 46-56.
[7] Underwood, J. P., & Wolfe, K. (2018). Deep learning to identify Palmer amaranth (Amaranthus palmeri) plants. Computers and Electronics in Agriculture, 147, 109-115.
[8] Puri, A., Olson, K., & Ehsani, R. (2017). Machine vision based weed identification under field conditions: A review. Computers and Electronics in Agriculture, 143, 98-111.
[9] Camargo, A., & Smith, J. (2017). Deep learning for image-based weed detection in turfgrass. PloS one, 12(10), e0188476.
[10] Garrell, A., Fuentes, A., & Pajares, G. (2020). Deep learning for weed identification in maize crops using hyperspectral imagery. Remote Sensing, 12(3), 504.
[11] Rai,N,Zhang, Y., Ram, B. F., Schumacher, L., Yellavajjala, R. K., Bajwa, S., & Sun, X.(2023). Applications of deep learning in precision weed management. A review. Computers and Electronics in Agriculture, 206, 107698.
[12] S. Maheswaran, S. Sathesh Gayathri, E. D. Bhaarathei, and D. Kavin, "Design and Development of chemical free Green Embedded Weeder for Row Based Crops, "Journal of Green Engineering, vol. 10, no.5,2020.
[13] Pound, M. P., Atkinson, J. A., Townsend, A. J., Wilson, M. H., Griffiths, M., Jackson, A. S., ... & French, A. P. (2017). Deep machine learning provides state-of-the-art performance in image-based plant phenotyping. GigaScience, 6(10), 1-10.
[14] Anwar, S., Azhar, N. E. A., Adam, A. S., & Mustapha, N. (2019). Weed detection using deep learning techniques: A review. Computers and Electronics in Agriculture, 165, 104943.
[15] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.
[16] Sa, I., Popović, M., & Fisac, J. F. (2020). WeedNet: Dense semantic weed classification using multispectral images and weakly supervised training labels. Robotics and Automation Letters, 5(4), 6687-6694.

DOI: 10.17148/IARJSET.2023.10713

[17] Xiong, J., Liu, H., Pan, Z., & Li, Q. (2017). Crop/weed classification using deep convolutional neural network. Computers and Electronics in Agriculture, 135, 1-8.

[18] Liu et al., 2019 Liu, S., Huang, D., & Wang, Y., 2019. Learning spatial fusion for single-shot object detection. arXiv preprint arXiv:1911.09516. 10.48550/arXiv.1911.09516.