Weed Classification using Deep and Shallow Learning Classifiers with Texture Feature Extraction

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Abstract

Weeds are one of the most significant elements affecting agricultural production. The waste and pollution in farm caused by spraying chemical herbicide are becoming increasingly evident. If the weeds are identified from crops, there will be tremendous improvement in the agricultural production level, thereby achieving precise spraying only for weeds. This paper gives its contribution in weed identification in two publicly available datasets. The weeds are segmented and its texture features are extracted. The obtained texture features are classified using deep learning and shallow learning classifiers. The experiments substantially proved that the proposed method with shallow learning classifier achieves approximately 4% higher than deep learning classifiers. It also achieves 0.02% higher accuracy than recent methods on the compared datasets.

Keywords: weed, texture, deep learning, classifier, segmentation

I. Introduction

Currently, many smart agriculture tasks, such as plant disease detection, crop yield prediction, leaf disease detection, species identification, soil detection, weed detection are automated using computer vision technology [1–3]. Controlling weeds is a crucial part of raising agricultural output. Many studies have suggested accurate variable spraying techniques to avoid the waste and pesticide residue issues that the conventional full-coverage spraying strategy causes [4]. To obtain real-time accurate detection and identification of crops and weeds is a crucial problem that needs to be solved in order to achieve exact variable spraying. Traditional image processing and deep learning are the main techniques for weed detection in fields utilizing computer vision technologies.

The extraction of image features such as color, texture, and shape, and combination with conventional machine learning techniques, such as random forest or Support Vector Machine (SVM) algorithm, are required when weed detection is carried out using conventional image-processing technology [5]. These techniques rely heavily on the quality of feature extraction, pre-processing techniques, and the ability to manually design features. Deep learning algorithms can extract multi-scale and multidimensional spatial semantic feature information of weeds through Convolutional Neural Networks (CNNs) due to their enhanced data expression capabilities for images, avoiding the drawbacks of conventional extraction methods. This is possible due to improvements in computing power and an increase in data volume. As a result, researchers are paying more and more attention.

Weeds are unwanted plants that emerge on agricultural grounds on their own [6]. If not effectively handled, these plants' competition with crops for water, nutrients, and sunlight could have a negative effect on crop yield and quality, driving up production costs and lowering the economic value of cultivated lands [6–8]. Crop production loss and weed competition are closely connected [7]. In general, the application of herbicides is required to preserve the quality of agricultural products. However, improper use of herbicides can result in decreased productivity, environmental contamination, and a variety of adverse consequences on the biotic and abiotic environment, which pose a threat to human health [9–11].

Many European nations began limiting the use of pesticides in agriculture to address these problems [7]. Several studies are being done to find a chemical reduction and precise administration of herbicides based on the weed coverage in order to address these difficulties. The majority of these techniques are developed in recent years and are based on Deep CNN, which are producing excellent results in weed detection and classification [6, 11].

From image analysis point of view, weeds are pixels that have different textures from the cultivated crops. Hence, in this paper, the texture features are analysed from each individual segment or region. It is further classified to identify weeds.

The main contributions of this work include:

- Identifies individual regions from the image.
- Extracts texture features of each region.
- Classifies the features using deep and shallow learning classifiers.

The remaining of the paper is organized as follows: Section 2 briefly discusses some works related to weed identification. Section 3 elaborates the proposed method with all its steps. Section 4 demonstrates the proposed method with some experimental results. Section 5 concludes and discusses the proposed method with some future scope.

II. Related Works

In 2021, Güldenring et al. considered numerous non-annotated agricultural images, which are easy to obtain and used them to pre-train deep neural networks [12]. Only a limited number of annotated images are taken to fine-tune those networks in a supervised training manner for relevant downstream tasks, such as plant classification or segmentation.

With recent advancements in High Level Synthesis (HLS) techniques, new methods for accelerating deep networks using Field Programmable Gate Arrays (FPGAs) are emerging. FPGA-based DNNs present substantial advantages in energy efficiency over conventional CPU- and GPU accelerated networks. In [13], GPU- and FPGA-accelerated deterministically binarized DNNs are used for weed species classification for robotic weed control.

In [14], a weed detection pipeline is presented which consists of the evaluation of various neural networks, image resizers, and weight optimization techniques. Although a significant improvement in the mean Average Precision (mAP) was attained, the Chinee apple weed did not reach a high average precision. Hence, an in-depth analysis of the Faster Region-based Convolutional Neural Network (RCNN) with ResNet-101 is designed in [15].

The first large, public, multiclass image dataset of weed species from the Australian rangelands is created [16], allowing for the development of robust classification methods to make robotic weed control viable. To develop efficient crop weeds classification system, a Dissimilarity-Based Active Learning (DBAL) method [17] has been designed to select few representative samples and consider data diversity.

A novel graph-based deep learning architecture, namely Graph Weeds Net (GWN), [18] has been developed to recognize multiple types of weeds from conventional RGB images collected from complex rangelands. GWN collects regional patterns in line with set image scopes and formulates multi-scale graph representations for weed classification. Additionally, GWN provides suggestions for key regions, creating opportunities for further within-image actions for robotic in-field systems.

In [19], a fine-tuning strategy has been used to train models to get better performance in classification tasks. Then neural network pruning techniques are used to reduce neural network size and computational cost and subsequently retrain models by knowledge distillation to minimize pruned model performance loss. Next, trained models are converted to an available ONNX format, thus simplifying the process from theory to practice. And finally, they deploy and inference models in a high-performance deep learning inference platform.

In [20], a classification approach of Zea mays L., narrow-leaf weeds and broadleaf weeds from multi-plant images has been presented. Moreover, a large image dataset were generated. Images were captured in natural field conditions, in different locations and growing stages of the plants.

An imbalanced dataset is a significant challenge when training a Deep Neural Network (DNN) model for deep learning problems. An imbalanced dataset may result in a model that behaves robustly on major classes and is overly sensitive to minor classes. In [21], a Yielding Multi-fold Training (YMufT) strategy is designed to train a DNN model on an imbalanced dataset.

A novel weed identification system [22] has been developed that relies on a combination of fine-tuning pre-trained convolutional networks (Xception, Inception-Resnet, VGNets, Mobilenet and Densenet) with the traditional machine learning classifiers (SVM, XGBoost and Logistic Regression) trained with the previously deep extracted features. The aim of this approach was to avoid overfitting and to obtain a robust and consistent performance.

Another method [23] combined deep learning and image processing technology. Firstly, a trained CenterNet model was used to detect vegetables and draw bounding boxes around them. Afterwards, the remaining green objects falling out of bounding boxes were considered as weeds. In this way, the model focuses on identifying only the vegetables and thus avoids handling various weed species. Furthermore, this strategy can largely reduce the size of training image dataset as well as the complexity of weed detection, thereby enhancing the weed identification performance and accuracy.

In [24], the existing problem in integrating deep learning techniques is solved in order to identify the weed plants across the vegetable plantation using CNN and advanced deep learning techniques like feature selection algorithms such as gabor filter. Initially a trained model was used over the data sets in order to draw the overlay by boundary boxes across the vegetable and weed leaves. The remaining space which was falling out of the overlay boundary boxes will be considered as weed through advanced detection techniques.

III. Proposed Methodology

The proposed method is described in Fig. 1. It consists of three important steps: ROI extraction, feature extraction and classification. Weed identification is the task of identifying the odd man out from the picture. In technical terms, it is a process of identifying different textures from the common texture. For this process, the image is segmented according to the texture or crops using ROI extraction. Then the texture features are extracted from each segment. Finally, the features are classified using classifier.

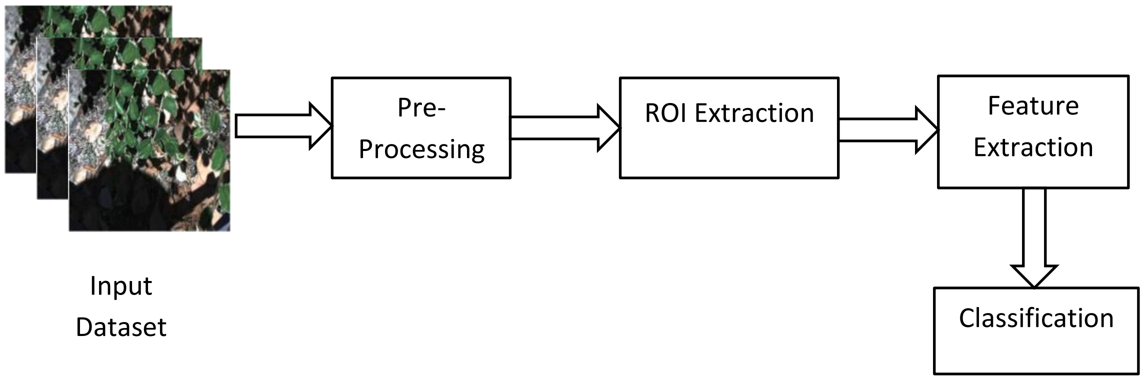

Fig. 1 Proposed System Architecture

Pre-Processing:

Let I be the input image with RGB color space. The HSV color space is the best color space for separating soil and green crop [25]. Hence the image is converted from RGB to HSV color space. Then the soil background is removed from the crop using thresholding function. For the HSV image I_{hsv}, the thresholding function is defined as

$$I_{Bin} = \begin{cases} 255 & [H_l\ S_l\ V_l] - I_{hsv} \leq 0 \ and \ I_{hsv} - [H_h\ S_h\ V_h] \leq 0 \\ 0 & Otherwise \end{cases} \quad (1)$$

Where I_{Bin} is the thresholded binary image, $[H_l\ S_l\ V_l]$ and $[H_h\ S_h\ V_h]$ are the lower and higher values for hue, saturation and value channels respectively. After this process, the input image is converted into a binary image.

ROI Extraction:

For ROI extraction, Connected Component Analysis (CCA) is used [26]. The input to the algorithm is the binary image and the output is the segmented region. The CCA algorithm follows the below algorithm.

Algorithm 1: Connected Component Analysis

Input: Binary Image

Output: ROI

Steps:

1. The first component is initialized with the first white pixel.
2. Scan pixel by pixel looking for adjacent pixels.
3. Add these pixels to this component, when no more connected pixels are found.
4. If there are more pixels, a new component is created.
5. Repeat until all pixels are assigned to one region.
6. All pixels assigned to a component are marked with the same unique label.
7. Extract the objects by using their labels.

Feature Extraction:

The rotation-invariant uniform local binary pattern ($LBP_{P,R}^{riu2}$) operator, presented in Ojala et al. [27], is implemented for extracting texture features of the plants. In addition, the main characteristics of this operator are its monotonic gray-scale transformation, illumination and rotation invariance [28]. For the center pixel (x_c, y_c) of a 3 x 3 circular neighbourhood of center R, the $LBP_{P,R}^{riu2}$ is given as

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), & \text{if } U(LBP_{P_t R}) \leq 2 \\ P+1, & \text{otherwise} \end{cases} \quad (2)$$

where

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|,$$

g_c and g_p represents the gray value of the center and its eight neighbourhood pixels,

p is the number of pixels and

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Classification

In order to capture the spatial and temporal features of the input data, CNN networks use the convolution operation in each layer. Convolution is carried out between the input data, which are N-dimensional arrays, and the filters. CNN considerably lowers the number of learnable parameters than Artificial Neural Networks, enabling them to add more layers. Deep CNN is the term typically used to describe networks with more than three layers.

In this study, the VGG16 and Xception CNN models are assessed for weed classification in natural field settings because they performed so well on tasks involving plant classification. Another justification for using the VGG16 network is that it has excellent accuracy performance even when trained on a dataset with few images.

In addition to deep learning classifiers, the most well-known shallow classifier named SVM is also used in this work. SVM is a supervised machine learning algorithm that solves binary classification problem.

IV. Experimental Results

The proposed method is experimented on DeepWeeds [29, 30] and Grass-Broadleaf datasets. The DeepWeeds datasets consists of 17,509 images of 8 weed species (Chinee apple, Lantana, Parkinsonia, Parthenium, Prickly acacia, Rubber vine, Siam weed and Snake weed). For each weed species (positive class), around 1,000 images were obtained; off-target flora and backgrounds not containing the weeds of interest are collected as a single negative class, which includes around 8,000 images. All images are in JPEG format and resolution of 256 × 256 pixels. This large dataset is public and can be downloaded at https://github.com/AlexOlsen/DeepWeeds. Figure 2 shows some sample images from DeepWeeds dataset.

Fig. 2 Sample Images from DeepWeeds Dataset

The Grass-Broadleaf dataset consists of 4 classes. Figure 3 shows some examples of the dataset. It belongs to the Kaggle competition, which can be found at the following site (https://www.kaggle.com/fpeccia/weed-detection-insoybean-crops). There are 15,336 images in the Grass-Broadleaf dataset. This dataset was constructed to perform weed detection and discriminate weeds between grass and broadleaf of soil and soybean [31]. All the images are in 4000 x 3000 resolutions. Both datasets are described in Table 1.

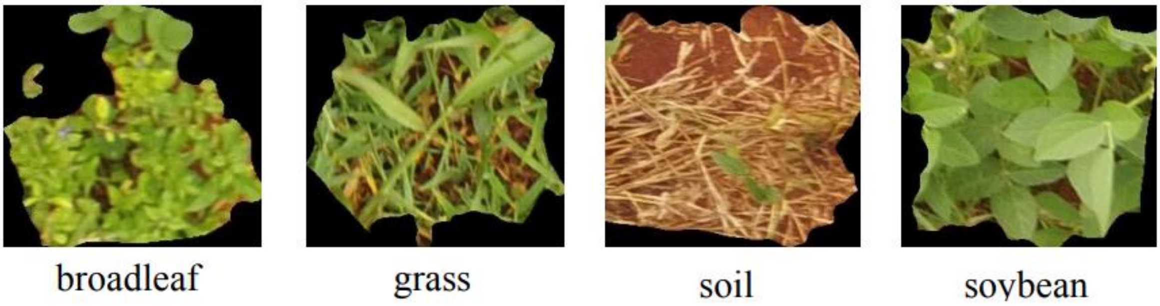

Fig. 3 Sample Images from Grass-BroadLeaf Dataset

Table 1 Details of DeepWeeds and Grass-BroadLeaf Datasets

Dataset	**Index of Class**	**Class Name**	**Number of Images**
DeepWeeds	0	Broadleaf	1191
	1	Grass	3520
	2	Soil	3249
	3	Soybean	7376
Grass-BroadLeaf	0	**Chinese Apple**	1125
	1	**Lantana**	1064
	2	**Parkinsonia**	1031
	3	**Parthenium**	1022
	4	**Prickly acacia**	1062
	5	**Rubber Vine**	1009
	6	**Siam Weed**	1074
	7	**Snake Weed**	1016
	8	**Negatives**	9106

Any classification methods are evaluated using some standard metrics such as accuracy, precision and recall. In this research, the performance of the proposed method is measured using accuracy, precision, recall, specificity and F-Measure. Table 2 displays the performance metrics used in evaluating the proposed method.

Table 2 Performance Metrics

Metrics	**Formula**
Accuracy	$acc = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \times 100$
Precision	$P = \frac{T_p}{T_p + F_p}$
Recall	$R = \frac{T_p}{T_p + F_n}$
F1- Score	$F_1 = 2 * \frac{P * R}{P + R}$

T_p – True Positive, T_n- True Negative, F_p- False Positive, F_n- False Negative

The proposed method is tested on deep learning and shallow learning classifiers. The results are displayed in Table 3 which are tested on both datasets.

Table 3 Results Obtained by the Proposed Method

Dataset	**Metrics**	**VGG16**	**Xception Network**	**SVM**
DeepWeeds	**Accuracy (%)**	97.44	98.6	99.2
	Precision (%)	96.24	97.26	99
	Recall (%)	95.7	96.36	98.6
	F1 Score (%)	95.26	95.2	99.4
Grass-BroadLeaf	**Accuracy (%)**	97.15	97.5	99.52
	Precision (%)	89.12	98.67	96.25
	Recall (%)	90.54	92.36	94.7
	F1 Score (%)	91.25	92.79	95.6

From the above table, it is inferred that the SVM classifier works better for Weed classification. When deep learning classifiers are compared, Xception network has better results than VGG16 network. The improvement ratio is calculated for SVM classifier over deep learning classifiers and is shown in Table 4.

Table 4 Performance Improvement of Deep Learning Classifier over Shallow Learning Classifier

Dataset	Metrics	VGGNet	Xception Network
DeepWeeds	Accuracy	1.81%	0.61%
	Precision	2.87%	1.79%
	Recall	3.03%	2.32%
	F1 Score	4.35%	4.41%
Grass-BroadLeaf	Accuracy	2.44%	2.07%
	Precision	8.00%	-2.45%
	Recall	4.59%	2.53%
	F1 Score	4.77%	3.03%

We reached 4.41% increment of F1 score in DeepWeeds dataset. In Grass-Broadleaf dataset, we reached maximum increment of 8% in precision obtained by VGGNet. But there is a decrement of 2.45% precision obtained by Xception network. The proposed method is compared with recent methods and the comparison is shown in Table 5 and 6. For the comparison, the results obtained by SVM classifier are used.

Table 5 Comparison of Proposed Method with Other Methods on DeepWeeds DATaset

Method	Accuracy (%)	Precision (%)
DBAL (2022) [17]	99.18	-
DeepCluster (2018) [32]	70	64.3
Güldenring et al. (2021) [12]	94.9	-
Faster RCNN (2022) [15]	-	-
GWN (2020) [18]	98.1	98.2
Pen and Wang (2021) [19]	96.9	-
Olsen et al. (2019) [29]	95.7	-
Proposed Method	99.2	99

Table 6 Comparison of Proposed Methods on Grass Broad-leaf dataset

Method	Accuracy (%)	Precision (%)
DBAL [17]	99.5	-
DeepCluster [32]	92	88.4
Proposed Method	99.52	96.25

From Table 5 and 6, it is observed that the accuracy obtained by the proposed method is greater than DBAL method by 0.02% on both datasets. Figure 4 shows accuracy comparison in bar charts on DeepWeeds dataset.

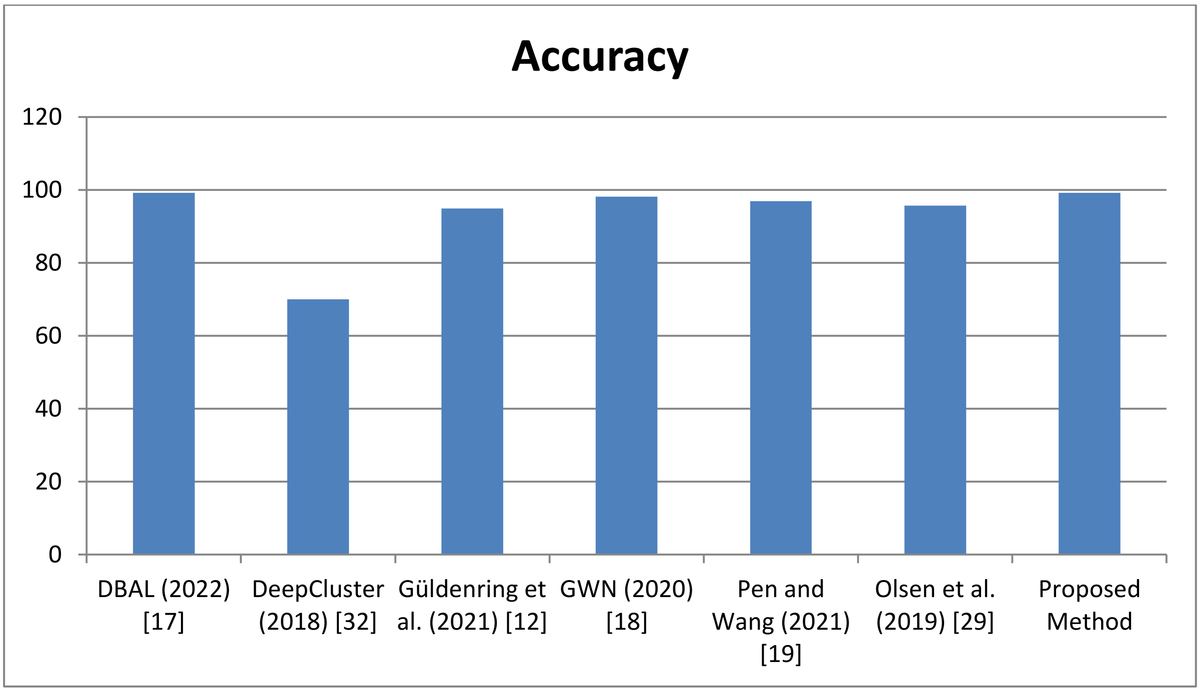

Fig. 4 Bar Chart Comparison of Proposed Method with Other Methods on DeepWeeds Dataset

V. Conclusion

Weed identification is one of the challenging tasks for farmers. Computer Aided Design is a techniques that automates many human tasks. This paper automates one such task of human by identifying weeds from the crop. The crops and weeds are extracted by Connected Component Analysis. From the segmented crops, the weeds are identified by texture extraction. Finally, the texture features are classified using deep and shallow learning classifiers. The proposed method is tested on two standard datasets. SVM, the shallow learning classifier, works better than deep learning classifiers. It achieves 3% improvement over deep learning classifiers approximately. The proposed method is also compared with other recent methods and proved 0.02% increase in accuracy. In future, different texture extraction methods can be used with different datasets.

Compliance with ethical standards

Conflict of interest: This work entitled "Weed Classification using Deep and Shallow Learning Classifiers with Texture Feature Extraction" is not submitted anywhere else. There is no conflict of interest from authors.

Data Availability:

The datasets used in this research are publicly available from the following websites:

DeepWeeds: https://github.com/AlexOlsen/DeepWeeds

Grass-Broadleaf: https://www.kaggle.com/fpeccia/weed-detection-insoybean-crops

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