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Adaptive Weed Classification in Agriclture: Dynamic Green Prior for improved Plant Localization and Accuracy.

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Abstract

Adaptive techniques for weed classification in agricultural environments are necessary because they must take into account differences between crop appearance and variables related to the environment. This paper proposes a plant localization method based on dynamic green prior that is specially designed for weed classification applications. Unlike static methods, the system dynamically modifies the green detection parameters in response to seasonal variations, lighting conditions and real-time environmental cues. Using comprehensive testing on real-world agricultural datasets, the effectiveness of the dynamic method has been exhibited in precisely localizing plants and classifying weeds. The accuracy rate of the model trained using the preprocessed image is 99.27%. There is a significant improvement of 2% with the inclusion of pre-processing.

Keywords: Weed Classification, Plant localization, Dynamic Green Prior, green detection parameter, seasonal variations, Image preprocessing.

I. Introduction

Weed Image pre-processing is a critical first step in the area of precision agriculture, where precise weed detection and treatment are necessary for boosting crop production and lowering resource consumption. The advancements in computer vision technology have enabled automated weed identification systems, although their effectiveness depends on image preprocessing.

Preparing weed images is challenging because of the large variety of image properties produced by variations in temperature, light and plant type. This introduction provides an overview of the importance of weed image pre-processing and the need for innovative solutions to address the challenges associated with weed identification in agricultural contexts.

Weed detection is crucial for precision farming approaches because it makes weed control strategies more focused and efficient. The labour-intensive and time-consuming nature of conventional methods, including manual inspection, is the motivation behind the adoption of automated systems powered by computer vision. In agricultural images, image preprocessing is necessary to minimize noise, strengthen features and streamline input data so that the images are prepared for further work.

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In this regard, the challenges brought on by variations in illumination, various soil types and a large range of weed species should be addressed by the development of novel pre-processing approaches for weed images. Expert techniques to increase the accuracy and reliability of weed identification systems are being explored, including color segmentation, adaptive feature enhancement and image filtering.

Green prior plant localization is a comprehensive strategy for environmental conservation and monitoring that makes use of state-of-the-art technology to protect biodiversity and encourage long-term relationships between human civilizations and the natural world. The major advantages of the proposed dynamic method is as follows:

- The approach makes use of predictive modeling techniques, and iteratively improves the green color prior, making it robust and flexible in a range of agricultural situations.
- It proposes the use of a local variance preprocessing method for data enhancement.
- The importance of adaptive techniques in weed classification is highlighted by our research, which also presents an achievable way forward for sustainable agricultural practices by enabling focused weed management interventions while minimizing the need for herbicides.
- A major development in weed classification techniques, dynamic green prior-based plant localization offers improved reliability and precision in weed detection across a range of environmental situations.

The remainder of the paper is organized as follows: Section II briefly elaborates on the recent research in weed classification. The pros and cons of each method are discussed and pave the way to the proposed work. Section III elaborates on the proposed pre-processing method for weed classification. Section IV analyzes the proposed pre-processing with the ablation study. Section V concludes the work and gives a brief explanation of the future work.

II. Review of Literature

This section explores significant current studies that apply image analysis to detect weeds. Many image processing methods are presented in recent research that has been published in the literature. For weed detection, multiple research investigations used the image processing strategy.

Wei et al. have provided advances in weed detection using ground-based machine vision and image processing techniques [1]. They have focused on different machine vision and image processing techniques used for ground-based weed detection. The authors have applied preprocessing methods such as color space transformation, normalization and size reduction and got an enhanced image. The threshold value is applied for vegetation segmentation.

According to Tejedai, the primary stage of image processing involved the identification of green vegetation to effectively remove soil content from the image, thereby reducing superfluous information [2]. Subsequently, the attention has been directed toward the segmentation of vegetation

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and the removal of undesirable data utilizing medium and morphological filters. Lastly, an object labeling process has been executed within the image to facilitate weed identification by applying a threshold linked to the detection area. The source image is converted to grayscale intensity where hue and saturation information is eliminated while retaining the luminance. To reduce noise, a median filter is used and the image is segmented. Then morphological operations are used to fill image regions and holes.

Images are used as sets in morphological analysis to represent image shapes; these sets of images can be binary or grayscale images [3]. There are two inputs required by the morphological process: structural elements and grayscale images. Morphology operators work by converting one set into another to identify the original set's unique structure. Next, the converted set has unique structure information and distinct structuring components. Therefore, some attributes of the organizing components are correlated.

The amount and the locations of weeds have been a problem in weed management that experts have faced for several decades [4]. Three methods (SVM, YOLOV3, RCNN) have been presented for weed estimation based on deep-learning image processing in lettuce crops. These methods were complemented with a Normalized Difference Vegetation Index (NDVI) as a background subtractor for removing non-photosynthetic objects.

Over-dosing of spray chemicals is costly and poses a serious threat to the environment, whereas, under-dosing results in inefficient crop protection and thereby low crop yields [5]. Weed/crop detection and classification were performed through the Random Forest classifier. In image pre-processing, the image data recorded by a camera mostly consists of errors related to geometry and brightness values of the pixels which are corrected by using appropriate mathematical techniques. The undesired and noisy regions are removed and morphological features are applied to remove illumination and motion blurring effects from the images. Image enhancement techniques are used for improving the visual appearance of images or for converting them to a form, which is better suited for human or machine interpretation. In image enhancement, the pixel brightness values are modified to improve its quality.

The intensity values from more than one channel must be used to obtain color indices suitable for vegetation segmentation across varying illumination levels. In this approach, a grayscale image is created by combining two or more color channels. Finally, a threshold is used to create a binary image with vegetation and background pixels separated into two classes. Among several color indices that have been used for this purpose, the Excess Green Index (ExG) is still found to be popular in recent weed detection. A detailed review of weed spraying [6] is discussed (Liu, B. et al., 2020). An in-depth analysis of the Faster Region-based Convolutional Neural Network (RCNN) with ResNet-101(Saleem, M.H., Potgieter, J. and Arif, K.M., 2022) is designed in [7].

The development and introduction of current Harvest Weed Seed Control (HWSC) and its efficacy in Australian grain production systems are described [8]. The use of HWSC has likely

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contributed to lower annual grass population densities and thus mitigated the impacts of herbicide resistance as well as slowing the further evolution of resistance. In addition, low weed densities enable the introduction of site-specific weed control technologies and the opportunity to target specific in-crop weeds with non-selective alternative weed control techniques. With an awareness of the evolutionary potential of weed species to adapt to all forms of weed control, there is an understanding that HWSC treatments need to be judiciously used in grain cropping systems to ensure their ongoing efficacy.

The first large, public, multiclass image dataset of weed species from the Australian rangelands is created, allowing for the development of robust classification methods to make robotic weed control viable. To develop an efficient crop weeds classification system, a dissimilarity-based method [9] has been designed to select few but representative samples and consider data diversity.

A novel graph-based deep learning architecture, namely Graph Weeds Net (GWN), [10] 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.

An imbalanced dataset is a significant challenge when training a Deep Neural Network (DNN) model for deep learning problems, such as weed classification. An imbalanced dataset may result in a model that behaves robustly on major classes and is overly sensitive to minor classes. In [11], a Yielding Multi-fold Training (YMufT) strategy is designed to train a DNN model on an imbalanced dataset. Deep and shallow learning classifiers are used to identify weeds from crops using the Deepweed and Grass broadleaf dataset [12].

III. Materials and Method

The materials and techniques utilized in the suggested weed image processing approach are presented in this section. The architecture of the weed classification with the proposed pre-processing method is displayed in Figure 1.

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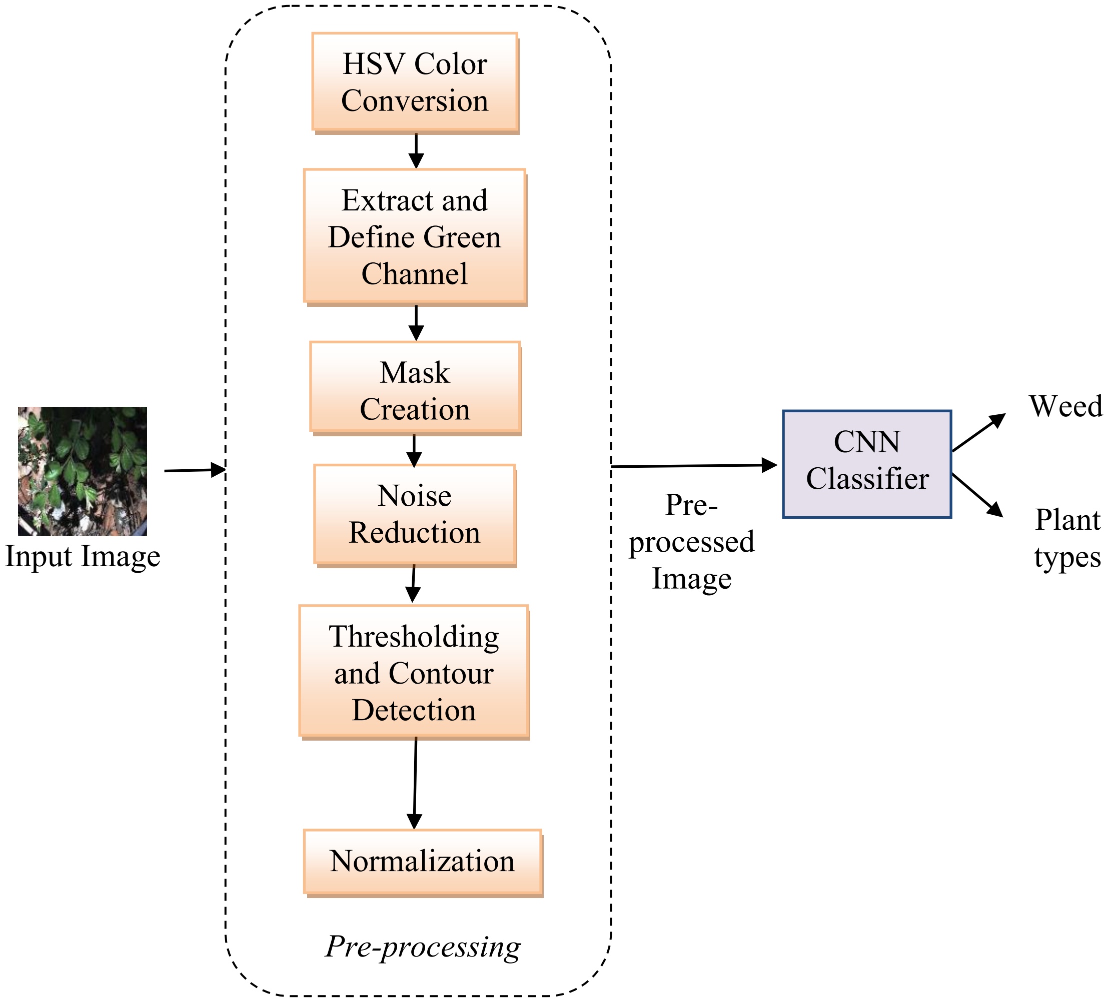

Fig. 1 System Architecture of the Proposed Weed Classification System

The proposed pre-processing algorithm is given in the Algorithm 1. The original input image $I(x, y)$ is in RGB format, where x and y denote the pixel coordinates. The input image is converted into the HSV color space. Then the green channel is extracted from the HSV image $I_{HSV}(x, y)$. The Green Color Prior in HSV is defined in Algorithm 2.

Algorithm 1: Dynamic Green Prior Based Plant Localization

Input: RGB image $I(x, y)$

Output: Preprocessed image $P(x, y)$

Steps:

1. Convert Image to HSV Color Space $I_{HSV}(x, y) = HSV(I_{RGB}(x, y))$.
2. Extract Green Channel using

$$G(x, y) = I_{HSV}(x, y)G$$

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3. Define Green Color Prior in HSV using Algorithm 2.
4. Create Mask $M(x, y)$ for Green Parts.
5. Reduce Noise with Gaussian Blur.
6. Create Binary Mask $M_{contour}$ using threshold $T(x, y)$.
7. Find Contours in Binary Mask.
8. Localize Plant Region $E(x, y)$ using

$$I(x, y) \odot M_{contour}(x, y)$$

9. Normalize Pixel Values and pre-processed image $P(x, y)$ is created.
10. Return pre-processed Image.

Dynamically Estimation of the lower and upper bounds for the green color prior based on statistical properties of the green channel. The mean (μ) and standard deviation (σ) of the green channel are calculated. Lower and upper thresholds are determined based on statistical properties, with an option to adjust sensitivity and robustness using a constant k.

Algorithm 2: Dynamic Green Prior

Input: HSV image $I_{HSV} = (x, y)$, Green channel G(x,y)

Output: Lower and upper bounds for green color lower_green, upper_green

Steps:

1. Compute the mean and standard deviation of the green channel

$$\mu = mean(G(x, y))$$

$$\sigma = std(G(x, y))$$

2. Determine lower and upper thresholds based on statistical properties:

$$lower\_green = [\mu - k \cdot \sigma, 30, 30]$$

$$upper\_green = [\mu + k \cdot \sigma, 255, 255]$$

3. Adjust k (a constant) based on desired sensitivity and robustness.

To dynamically define the lower and upper bounds for the green color prior in the HSV color space, Algorithm 2 is invoked. This algorithm utilizes statistical properties of the green channel within the input image to adaptively determine the optimal prior for isolating green regions, such as plants

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Then a mask is created for Green Parts using

$$M(x,y) = \begin{cases} 255 & if\ lower\_green \leq G(x,y) \leq upper\_green \\ 0 & otherwise \end{cases} \quad (1)$$

The above equation generates a binary mask M(x,y) where pixel values are set to 255 if they fall within the defined green color prior, and 0 otherwise. Then noise is reduced with Gaussian Blur and smoothens irregularities, thereby enhancing the quality of subsequent processing steps.

Thresholding is done to create a binary mask T(x,y), distinguishing between foreground (plant) and background regions.

$$T(x,y) = \begin{cases} 255 & if\ B(x,y) > T_{threshold} \\ 0 & otherwise \end{cases} \quad (2)$$

Contours are identified in binary masks representing boundaries of regions of interest. The plant regions are located by creating an empty mask $M_{contour}$ with the same size as $I(x,y)$. Contours are drawn on the empty mask to outline the plant region. Finally, the plant regions are identified by performing an element-wise multiplication between the input image $I(x,y)$ and the cntour mask contour $M_{contour}$ *(x, y)*.

$$E(x, y) = I(x, y) \odot M_{contour}(x, y) \quad (3)$$

where $\odot$ denotes element-wise multiplication

Now, the pixels are normalized to the range [0, 1] by dividing by 255.0, facilitating consistent input for subsequent processing or analysis using

$$P(x,y) = \frac{E(x,y)}{255.0} \quad (4)$$

where $P(x,y)$ is the resulting preprocessed image for further analysis or classification.

IV. Experimental Results and Analysis

The proposed method is experimented on the DeepWeed dataset [14]. It consists of 17,509 images: 8 target weed species and various off-target plant life native to Australia. The target weed species include Chinee apple, Lantana, Parkinsonia, Parthenium, Prickly acacia, Rubber vine, Siam weed and Snakeweed. For each target 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.

The dataset was collected from several locations to balance any scene bias. Positive and negative cases were evenly collected at each location. The dataset contains the Negatives class with 9106 images of other elements captured like soil and vegetation. All images are in JPEG format and resolution of 256 × 256 pixels. Table 1 shows the distribution of weed species in the DeepWeeds dataset. Figure 2 shows some sample images from the DeepWeeds dataset.

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Table 1 Distribution of Weed Species in DeepWeeds Dataset

Class	Species	No. of Samples	Percentage
0	**Chinese Apple**	1125	6.43
1	**Lantana**	1064	6.08
2	**Parkinsonia**	1031	5.89
3	**Parthenium**	1022	5.84
4	**Prickly acacia**	1062	6.07
5	**Rubber Vine**	1009	5.76
6	**Siam Weed**	1074	6.13
7	**Snake Weed**	1016	5.80
8	**Negatives**	9106	52.01

Fig. 2 Sample Images from DeepWeeds Dataset

Experiments are conducted and the results are evaluated using accuracy, precision, recall and F1 Score. Accuracy measures the proportion of total labels that the model correctly predicted.

$$Accuracy = \frac{CorrectlyPredictedLabels}{TotalLabels} \quad (5)$$

Precision focuses on ensuring we get all positive predictions correct. It measures what fraction of the positive predictions were positive.

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$$Precision = \frac{TruePositives}{TruePos+FalsePos} \tag{6}$$

Recall, also known as Sensitivity, measures how well a model can remember the positive labels in the dataset. It measures what fraction of the positive labels in our dataset the model predicts as positive.

$$Recall = \frac{TruePos}{TruePos+FalseNeg} \tag{7}$$

F1-Score is the harmonic mean of Precision and Recall. It penalizes models that have a significant imbalance between either metric.

$$F_1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{8}$$

The results obtained for all the classes are provided in the Table 2.

Table 2 Performance of the proposed Method for all classes

Label	Accuracy	Precision	Recall	F1-score
0	99.54	99.63	98.9	98.9
1	99.68	99.5	98.4	99.17
2	98.98	99	99.37	99.4
3	99.64	99.62	99.1	99.05
4	99.67	99.47	98.48	99.4
5	99.35	98.68	98.27	98.06
6	98.69	99.47	99.47	98.34
7	99.12	99.36	98.8	98.75
8	98.79	98.37	99.18	99.46

In the above table, it is observed that all the values are above 98%. It is inferred that the accuracy, precision, recall and F1-score are above 99% for Class 3 (Parthenium) only. For Class 5 (Rubber Vine), the precision, recall and F1 values are in the range of 98%. The average accuracy and precision are compared with recent methods in Table 3.

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Table 3 Comparison of Results with Other Methods

Method	Accuracy (%)	Precision (%)
DBAL (2022) [9]	99.18	-
Guldenring et al. (2021) [14]	94.9	-
Pen and Wang (2021) [15]	96.9	-
Hasan et al. (2023) [16]	98.49	98.49
Kavitha et al. (2024) [12]	99.2	99
Proposed Method	99.31	99.31

To estimate the efficiency of the proposed method, the pre-processing is skipped and experimented. The results and the improvement ratio are displayed in Table 4.

Table 4 Performance Improvement of Proposed Pre-processing Method

	Without Pre-processing	With pre-processing	% of Improvement
Accuracy	97.49	99.27	1.83
Precision	96.38	99.23	2.96
Recall	96.36	98.89	2.62
F1- Score	96.78	98.95	2.24

In Table 4, it is noted that all the performance measures are improved by approximately 2%. Figure 3 shows the graph representing all the performance with and without the pre-processing method.

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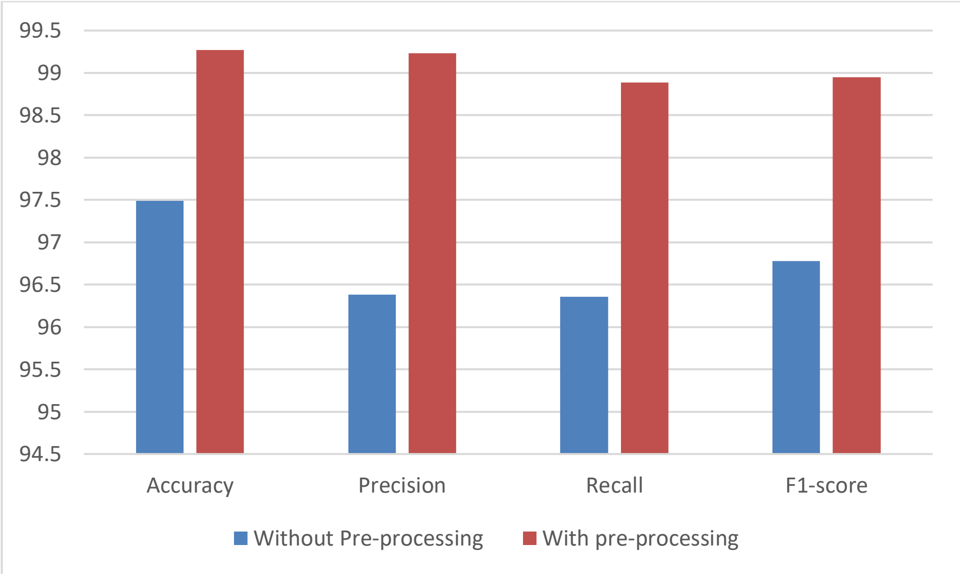

Fig. 3 Comparison of proposed method with and without pre-processing

V. Conclusion

This algorithm preprocesses RGB images for weed classification by isolating the plant region using the green channel. It first converts the image to HSV color space to facilitate better color segmentation. Then, it dynamically estimates the prior green color based on the statistical properties of the green channel, ensuring adaptability to variations in lighting conditions and plant appearance. This dynamic process calculates the mean and standard deviation of the green channel, allowing the algorithm to adjust the lower and upper bounds accordingly, enhancing sensitivity and robustness in green color detection. Subsequently, a binary mask is created to extract green regions. Gaussian blur is applied to reduce noise, followed by adaptive thresholding to create a binary mask. Contours are detected in the binary mask to localize the plant region, which is then normalized. This comprehensive preprocessing pipeline enables the deep learning model to focus on relevant features for accurate weed classification, improving its performance across diverse environmental conditions. In the future, the pre-processed image can be given as input to other pre-trained network models. The proposed pre-processing method can be tested in other weed datasets also.

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