Weed detection in agricultural fields using machine vision

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Abstract: Weeds have the potential to cause significant damage to agricultural fields, so the development of weed detection and automatic weed control in these areas is very important. Weed detection based on RGB images allows more efficient management of crop fields, reducing production costs and increasing yields. Conventional weed control methods can often be time-consuming and costly. It can also cause environmental damage through overuse of chemicals. Automated weed detection and control technologies enable precision agriculture, where weeds are accurately identified and targeted, minimizing chemical use and environmental impact. Overall, weed detection and automated weed control represent a significant step forward in agriculture, helping farmers to reduce production costs, increase crop safety, and develop more sustainable agricultural practices. Thanks to technological advances, we can expect more efficient and environmentally friendly solutions for weed control in the future. Developing weed detection and automated control technologies is crucial for enhancing agricultural efficiency. Employing RGB images for weed identification not only lowers production costs but also mitigates environmental damage caused by excessive chemical use. This study explores automated weed detection systems, emphasizing their role in precision agriculture, which ensures minimal chemical use while maximizing crop safety and sustainability.

1 Introduction

Weeds pose a significant threat to agricultural productivity, necessitating the advancement of weed detection and control technologies. This study uses machine vision, specifically RGB and drone imagery, to detect weeds efficiently, supporting sustainable agricultural practices.

Traditional weed control methods, both mechanical and chemical, have notable drawbacks, including potential harm to crops and environmental impacts. Recent innovations in precision agriculture, such as weeding robots and spraying drones, leverage computer vision and deep learning to enhance the accuracy of weed detection and classification, offering a more sustainable approach.

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The specific task is using machine vision technology in agriculture to detect nearby weeds and in cropfield environments to detect weeds using drone vision. For this, Python is used as the programming language and the open Computer Vision (CV) module within it.

The first task was to detect weeds in drone footage taken from a field at 50 meters. Delineated the edges of the field, determined the positions of the weeds, and highlighted them in a dataset. In this process, extracted features such as color features and three types of texture features. Used this dataset to perform classification at the end. It's important to note that the field contained no crops, only weeds, and focused on two weed categories. However, the technology shows promise for expanding the weed classification to include multiple weed classes and potentially even crop classes.

The second part of the task deals with the detection of emerging weeds. The main objective is to detect green plant parts using simple RGB camera images. Once detected, we can highlight the individual plants into a weed dataset. If we can do this, these small images will contain, in a good case, only one plant, which can be used in a deep learning system to classify which plant is in a given image. The advantage of using drones is that during critical phases of the growing season, plant changes can be detected very quickly, and data can be collected with an average resolution of 2-5 cm/pixel size [1]. This is the point where we can predict weed pressure, weed amounts, and weeds type, and based on that, we can do precision weed control.

Problems are caused by weeds on the cropland. Mechanical weed destruction was employed, but that typically has the potential to harm the crop as well. The other method, chemical weed destruction, is associated with a significant environmental impact. In the last years, precision agriculture made a lot of innovations, making small weeding robots, and have spraying drones too.

All of the above mention new robots use CV and Deep Learning (DL) to detect and classify weeds and crops before the robots.

In the agriculture field, the reachable dataset is important. We can make images as we did in this case. But to make faster progress, we need other images and mainly labeled dataset to make tests and make it possible to teach our artificial networks. On the internet, there are lots of databases about dogs and cats, as well as human faces. However, we can only find some usable datasets about crops, plants, leaves, fruits, vegetables, and weeds. Hasan et al. made a dataset about five weed types with 1200 images for each [2].

Dandekar et al. worked on on-site weed management CV system and used a public weed database on Kaggle [3]. This is a labeled dataset but contains only 1300 images altogether. Even more, it is an augmented dataset. The original number of images was only 546.

Bigger weed datasets exist but are usually made in artificial environments. Ramirez-Paredes and Hernandez-Belmonte analyzed malting barley using image processing techniques primarily focused on shape recognition [4]. Initially, Hu moments were considered for application, but ultimately, alternative central moments were utilized. Additionally, color features and Local Binary Patterns (LBP) were integrated into the analysis. Classification was conducted employing a linear Support Vector Machine (SVM). Despite capturing images against a clean background, a recurring challenge was encountered when barley grains occasionally touched each other. Achieving satisfactory results necessitated using up to 25,000 training images, a task feasible for seeds but challenging for weeds.

Bhunia et al. undertook a study on image classification, employing feature extraction techniques based on color and texture [5]. Opting for the HSV (Hue, Saturation, Value) color space for color representation, Bhunia derived texture parameters from the Gray Level Co-occurrence Matrix (GLCM), supplemented by LBP. Various distance calculation methods were utilized to classify the extracted vectors. The system's performance was evaluated using five publicly available image databases.

Hamuda et al. applied HSV color space transformations to detect cauliflower plants [6]. This process involved erosion and dilation procedures on the images, followed by contour identification, center determination, and bounding rectangle detection for the cauliflower. Remarkably, this approach achieved a 99% accuracy rate in detecting cauliflower, even in images with minimal weed interference. The experiment was conducted under various weather conditions, including sunny, partially cloudy, and completely cloudy scenarios.

Detecting weeds is not easy at the moment. The main problem is the overlapping weeds and crops. Zhang et al. took the image and made a lot of tiles of it and using SVM to determine the tiles class [7]. They make three different sizes of tiles from each image, and after classification put together these tiles and use a comparative selection to define the border between weeds and lettuce.

The other problem is that sometimes the weeds and the crops look very similar. Therefore, Bakhshipour and Jafari took the sugar beet and 4 similar weed types [8]. They used the image binary mask, and got furier features and shape features. After they used SVM and Artificial Neural Network (ANN) to make classification. The SVM was slightly better with 95% accuracy.

Nowadays, researchers try to use Neural Networks to identify weeds. Usually, it is slow and can't be applicable in real-time. Zhu et al. used the YOLO algorithm with a lightweight attention module to detect crops and weeds in real time [9]. The real-time part was alright still the detection of maize rate was 92.45% and the weeds recognition rate was 88.94%.

In this work, the weeds were extracted from images, and color and texture information was extracted from them. The main objective is to understand how these features can be used as classifier methods, and what improvements can be made by combining them.

2 Methodology

This research utilizes Unmanned Aerial Vehicles (UAV) equipped with RGB cameras to capture field images at a resolution that allows for subsequent analysis. The process involves identifying and classifying weeds using computer vision techniques such as noise reduction, thresholding, and color space transformations.Technical basics of UAV, and the image metadata that was taken, can be seen in (Table 1)

Machine vision uses many technological methods, which I will demonstrate by processing images. The pictures were taken with a UAV in a cropland. The UAV, the camera, and the position main parameter are indicated in Table 1.

Table 1. The UAV and image metadata.

UAV type	DJI Mavic
Camera producer:	Hasselblad
Camera type:	L1D-20c
Exposition time:	1/240s
Time:	2022.05.06. 10:45
GPS latitude:	47.3155228499
GPS latitude:	17.3555173999
Altitude:	50 meter
Image resolution:	5472 x 3648

2.1 RGB image

Figure 1 presents an RGB image, which can be captured directly using a camera or extracted from video footage, contingent upon the available technology. The image was made in 50 meters high by UAV.

In most cases, the images are available as RGB images. The RGB image is built up from:

- R - Red
- G - Green
- B - Blue

Each pixel shows how much red, green, and blue components can be used to produce that particular color. In the RGB color space, for example, the shades of grey have the same number of R, G, and B components. Specifically, white contains the maximum R, G, and B components. If we want to highlight the green color of plants, then unfortunately, the RGB image is unsuitable because the sunny part of a green and the same green behind a shadow in RGB representation is very different, even if the human eye sees the region as similar green. Therefore, computer vision often uses other color spaces.

Fig. 1. RGB image of cropland.

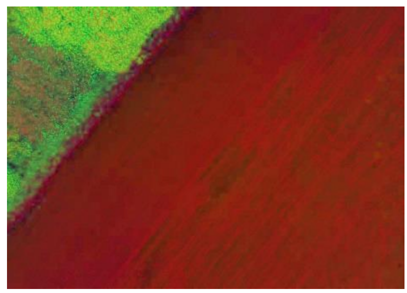

Fig. 2. HSV color space transformation.

2.2 HSV Image

In our case, the useful color space is the HSV color space:

- H – Hue (hue)
- S – Saturation
- V – Value (value or brightness)

The HSV model is most commonly represented as a cylinder. The hue, i.e. what color is regardless of the effect of light or shade, is defined from 0 to 360 degrees along the circle.

Saturation is a percentage value between 0 and 100. It shows how much grey a given pixel contains.

The value or brightness is also a percentage value, where 0 is completely black, and 100% is completely white.

It is easier to extract colors from images converted to HSV color space because the HSV color space is spectrally represented by the colors of the objects and not by the effects of illumination, shadows, or other colors. The original RGB image is converted to HSV image range in Figure 2, then normalized the values to the RGB range 0 to 255 and – not very professionally – plotted as if it were an RGB image. This makes the image look strange colors. Although not professional, it does give us some useful information.

2.3 Noise reduction

Camera images contain a lot of pixelated noise, which is perfectly normal, but this noise can drive many algorithms in the wrong direction. Therefore, in almost all cases (whether CV or ANN processing), the first step is to remove these noises.

Ahmad *et al.* made classification experiments with two types of weed [10]. They measured the noise in a variance based from no noize to 0.05 sigma noize in 6 steps. The classification result was 98.4% without noise filtering, and was 98.29% with noise mean filtering. As visible, it is almost the same. But even a small noise like 0.01 sigma made the classification result 91.32% without noise filtering, and with noise reduction, the result was 96.23%. So, here the noise filtering made about a 5% difference. With a big 0.05 sigma noise, the result was 87.61% without filtering, and 92.85% with filtering. With filtering, even here, it was about 5% the difference.

There are many methods available for this; typically, some form of filtering is used to remove noise from the image. Blur, Median, and Gaussian are typically used. An unfortunate side effect of this is that the image becomes slightly blurred.

2.4 Thresholding

The next method is cropping or thresholding, which means the image is converted into a 2-state binary image. Considering one part as the background and the other part that matters to me. In Figure 3, we want to highlight the green-colored plants for further processing and consider the remaining part as background. Therefore, in the HSV image, set the H value to highlight the range between 120-180 degrees, which indicates the green level. This process creates a mask that shows the green regions.

Fig. 3. Green color mask applied to HSV image.

2.5 Making a mask

Masks often need to be produced in machine vision projects. Such a mask is the 'color' mask above. But can also create a mask based on the histogram or even the texture of the image. For example, green plants have quite a distinctive texture compared to the rest of the image.

2.6 Erosion and dilation

There are two opposing operations in the binary image set. One is erosion, which means that the edges of the white areas are reduced by a few pixels. It's like erosion. On masks, if a small white noise appears, we can remove it with this operation. Of course, then the object you are interested in will be smaller too. The operation is often repeated several times in succession for the desired effect.

The counterpart to this operation is dilation, where we add parts to the white areas as go. This seems to increase the noise, but if there are black holes inside a white object or notches around the edges, this is the operation we need to remove or fill them.

The two operations are usually performed in sequence because this removes the white noise, removes the black holes in the objects we want, and doesn't change the size of our object because as much as one operation cuts off, the other builds back. The result is shown in Figure 4.

Fig. 4. The result after some erosion and dilation.

2.7 Using Binary Masks

After dilating and eroding, we get the mask. Using this mask can separate the forest, which is not interesting to us or our Region of Interest (ROI).

Using the binary mask and the original image we can cut out the forest (Figure 5). If in the field there are dense weed spots, this step can cut out those parts too.

After inverting the binary mask and using the original image, cut out the field and the weeds in it (Figure 6). We can't see too many weeds in the image at the moment. But when zooming it out, we will see the weeds in it.

Fig. 5. The forest part.

Fig. 6. The field part with the weeds on it.

After enlarging, it can find our real targets (Figure 7). At this point, start again the process steps. So, make a green mask again, but at this time, don't use any dilate or erode steps. So, the green mask now contains the weeds only.

Fig. 7. Weeds on the field after enlarging it.

2.8 Edge detection

The next step is to find the weed's contour or edges. Use the Laplacian filter or even the Canny edge detector algorithm.

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2.9 Weeds positions - ROI

Now have the weeds, so a box could be drawn around it (Figure 8). From now the background is not inportant.

Important concept the ROI. This means that there are regions of interest in a given image. In our example, not interested in the background and the soil. Now only interested in weeds, where these areas will be the 'ROI-s'.

In the next chapter let see these CV techniques on a closer image, where the weeds have more details.

Fig. 8. The green boxes around the weeds.

3 Results

Initial tests conducted using images from UAVs demonstrate the potential of this technology in identifying and categorizing various weed species. However, challenges remain in improving image resolution and classification accuracy, particularly at greater altitudes.

The methods described in the previous chapter were applied to pictures taken from the experimental site (Figure 9). These pictures, captured two years ago, were processed using Python with the CV module.

One of the tasks is to detect the weeds that are emerging. It is important to determine the type of weeds and their density. This information can help choose the right control method. This can be a chemical solution or, increasingly, precision weed control. Precision techniques can even selectively kill weeds that threaten or compete with the main crop.

The photo above shows the weeds sprouting. The picture was taken with a mobile phone. As you can see, it is a simple RGB image. First, we applied HVS transformation on the image and then filtered out the green component.

Fig. 9. Original RGB image with weeds.

Figure 10 shows the green plant parts. The algorithm has also made parts visible that were not visible to us or that we had not noticed first. It is important to notice, that we are not talking about a dense weedy surface. The above algorithm would not work there in that case. That would require a different approach. However, in that case, it is also true that a precision weed control method would no longer be appropriate, but some kind of total weed control method.

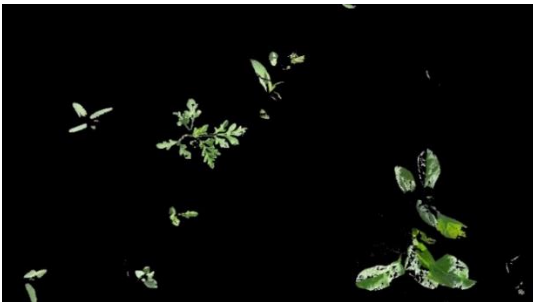

Fig. 10. Green weeds with a black background.

Another thing to note is that a given weed will break down into several segments during processing. These should not be considered as separate, because that, would cause a gross statistical error. On the other hand, we want to identify and further analyse weeds by species and possibly by stage of development.

Therefore, reshape the image. Create a greyscale. Then, we start to enlarge the plant parts, i.e. dilate the image. In this way, make the closed parts merge and close the smaller holes. After this step, the images can be eroded so that the unnecessary clumps can be broken up and the noise can be reduced. After another dilation and 2-3 iterations, the binary image is obtained.

The regions in the resulting image are counted and visualised using a pseudo-coloring method (Figure 11).

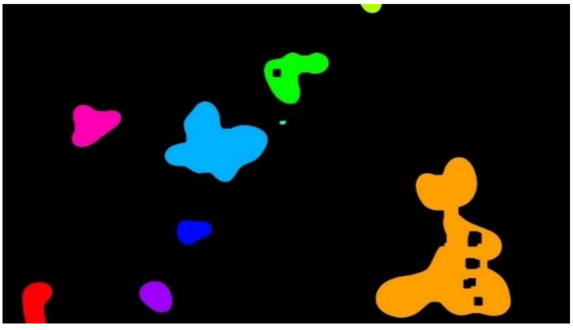

Fig. 11. Regions highlighted, numbered, and colored.

This image can be used to scroll through the colors to determine the minimum and maximum coordinates of the object. In other words, it is possible to put a frame on it. In our case, store these coordinates in an array. This array contains the areas of interest to us, such as the ROIs. What is outside these areas is not interest to us. What is inside these are our weeds or crops themselves. Cut these regions out of the picture and put them in a dataset. From the given image, the algorithm has highlighted the gallery in Figure 12.

Fig. 12. Weed dataset gained from the image.

For one thing, if the camera is positioning the images with precision, we can use the ROI data to know site-specifically where weeds are located. With precision hoes, electricity, heat, and lasers, can now kill weeds without chemicals. If thinking about chemical treatment, we can spray the right chemical on the weed leaves with precision. In this way, the amount of spray applied can be significantly reduced.

On the other hand, concrete statistics on weed infection can be produced in a given area. What percentage of the soil is covered by weeds? Exactly where they cover it.

In the case of a time series study: how fast weeds are growing, or how effective weed control was.

The images highlighted in the gallery can be further analyzed using additional image processing methods, or they can be fed into neural networks to classify the weeds in each image. In this way, we can classify them by weed species and weed stage of development. With this information, we can now decide on the precision weed control method or chemical, if have different types of sprays.

3.1 Weed classification

We have compiled a weed dataset from cropland images, consisting of 670 labeled images. This dataset (Figure 13) is a valuable resource for training and testing various machine-learning models aimed at weed detection and classification tasks.

Fig. 13. Sample images from the weed dataset.

From a height of 50 meters, weed detection becomes challenging as the images tend to be blurred, and the weeds appear too small for accurate identification. To address this issue, flights was conducted at around 20 meters altitude for better image clarity. These challenges provide a try about the potential of this dataset.

Manually annotated the images was used as the label. Of the 670 images, 308 were labelled as belonging to the star-shaped weed class, while the remaining 362 were classified under other weed classes.

3.2 Extract colour feature vectors

In the next step, we extract feature vectors from the dataset. These feature vectors were derived using a combination of color-based features and two texture-based features. This approach enables us to capture comprehensive information from the images, facilitating more effective weed detection and classification algorithms.

For the color-based features, we employed color histograms. Initially, we utilized the original RGB images, which comprise three bands: Red, Green, and Blue. Additionally, transformed the images to the HSV color space, where the three bands represent Hue, Saturation, and Value. From these six channels, constructed histograms with 32 elements each for the R, G, B, H, S, and V bands, resulting in a total of 192 parameters. These histograms provide valuable insights into the distribution of colors within the images, aiding in weed detection and classification tasks.

3.3 Extract texture feature vectors

In addition to the color-based features, we also utilized Histogram of Oriented Gradients (HOG) features [11]. These features offer a detailed representation of the gradient information present in the images, capturing texture and shape characteristics essential for weed detection. With 3780 parameters, the HOG features provide a comprehensive descriptor of the image content, enhancing the accuracy and robustness of our weed classification algorithms.

Furthermore, GLCM features were incorporated into our analysis. These parameters were used to classify plants and weeds [12]. With 72 parameters, these features provide insights into the spatial relationships of pixel intensities within the images. GLCM features offer valuable information about texture patterns, aiding in the differentiating of weeds from background elements. By leveraging both GLCM and other feature types, enhances the discriminative power of our classification models, ultimately improving weed detection accuracy.

3.4 Support Vector Machine Classification

We allocated 75% of the dataset for training an SVM [13], while the remaining 25% of images were reserved for testing the system. This division ensured that our SVM model was trained on a substantial portion of the data while still maintaining a separate set of images for evaluating its performance and generalization capabilities.

When training and testing the SVM, observed different accuracies for each feature type can be seen in Table 2. Specifically, the histogram-based features achieved an accuracy of 71.43%, HOG features at 76.78%, and GLCM features at 54.1%. This indicates varying degrees of effectiveness in capturing relevant information for weed detection within the dataset.

The highest accuracy of 77.98% was achieved when utilized a combination of histogram, HOG, and GLCM features together. This result underscores the effectiveness of integrating multiple feature types for weed detection, as it allows for a more comprehensive representation of the image content, ultimately leading to improved classification performance.

Table 2. Features, size, and result.

Name	Vector size	Accuracy
Histogram	192	71.43%
HOG	3780	76.78%
GLCM	72	54.17%

```
Accuracy: 77.97619047619048%
confusion_matrix
[[78 12]
 [25 53]]
```

We generated a confusion matrix to evaluate the classification performance. It revealed 131 true classifications (78 true positives and 53 true negatives) and 37 false classifications (12 false positives and 25 false negatives). This analysis provides a detailed breakdown of the model's accuracy and errors, aiding in further refinement and optimization of the weed detection system.

As evident from our results, even with a limited dataset, able to extract features from the images to achieve some level of classification. However, to improve our approach, need to focus on enhancing the quality of the images by capturing better data. This entails creating improved datasets with higher resolution and more diverse samples.

Additionally, should explore the incorporation of additional features beyond those currently utilized, such as deep learning-based features, LBP features [14] or spatial features, to further enhance the accuracy and robustness of our classification models. By continuously refining our datasets and feature extraction methods, can strive towards achieving more accurate and reliable weed detection systems.

The study successfully demonstrated the capability of machine vision, utilizing RGB images captured by drones, to detect weeds in crop fields. This was achieved even at an altitude of 50 meters, although the images lacked sufficient detail for precise classification. At 50 meters, the resolution of images was a significant limitation, resulting in images that were too blurry for detailed analysis. This limitation affected the ability to classify weeds accurately, as noted by the difficulty a plant expert would have in identifying the weeds from these images. Despite the initial success in detecting weeds, the classification of the weed species and stages of development was hampered by the low image resolution. The current technology does not provide enough detail to make fine distinctions among different types of weeds.

These results underline the potential of UAV-based machine vision in agriculture while also highlighting the technological advancements needed to overcome the current limitations in image resolution and classification efficacy.

4 Conclusions

Integrating machine vision in weed detection represents a promising advancement in agricultural technology. Future work will aim to refine image-capturing techniques and explore the efficacy of machine-learning models in improving the specificity and accuracy of weed detection.

To illustrate the usefulness of machine vision, we created a program in Python programming language to detect early weeds and to find and extract weeds from a drone image of a field into a database.

The weed detection program searched for green plants in an RGB image, and cut them out, and placed them in a dataset. From there, a classifier SVM can now identify the weed species, stage of development, number of individuals, density, and exact location of specific weeds. This is now suitable for precision weed control.

From the above, 1) The close image has more details that can be used to identify a weed; 2) Possible to teach a CNN to make the classification; 3) Extract texture and shape features and use an SVM or KNN vector classification algorithm.

The other images were made with UAV 50 meters high, which managed to detect the weeds. They even managed to get the weed images from the image, but didn't have enough details to classify it well enough. Even a plant doctor can't classify most of the image because it has small resolution, and looks very blurry. To address the issue of insufficient resolution and blurry images from UAV photography at 50 meters height, which complicates weed classification, consider the following strategies:

- Lower flight altitude: decrease the flight altitude to enhance image resolution;
- Image enhancement techniques: apply advanced imagining techniques such as deblurring or super-resolution;
- Better camera/sensor;
- Use of multi or hyperspectral cameras: beyond RGB, employing and winning additional data that might help differentiate weeds from other crops based on spectral signatures.

Our next plan is to use the UAV 30 meters high and also 20 meters high. It means, that our weeds will be bigger in the image, and there will be more details on it. It means we can make better classifications on it.

To fly closer has cost. It means we must make more images. To make more images must fly more time, so the pilot must be longer on the same field. On the other hand more images means need bigger memory capacity, more processing time, and more storage capacity. So need to find the balance. What is that high where still can make good enough weed classification?

Our other plan is to make our computer vision and classification processes more robust. It means more pictures should be taken in different weather conditions like sunny, cloudy, semi-cloudy, or even lightly rainy. It is also important to take images in the morning or evening when the rough ground and even the weeds have long shadows.

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