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Weed Identification from Multispectral Agricultural Images

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***Abstract*— Weed control plays a critical role in agriculture, with implications for crop yields and farm incomes. The conventional processes such as manual weeding or blanket herbicide use are ineffective and environmentally unfriendly. This project involves a precision weed detection system based on multispectral imaging and machine learning. YOLO model and NDVI masks were utilized to detect and segment weeds from multispectral images. The NDVI masks made crops visible, which allowed YOLO to identify weeds with very high accuracy, attaining an average F1-score of 92%. Weed localization was also cross-validated against manual surveys with less than 5% error. This system provides a scalable, automated, and environmentally friendly solution for weed management.**

***Index Terms*— Precision Agriculture, Weed Detection, Multispectral Imaging, YOLOv5, K-means Clustering, NDVI Mask.**

I. INTRODUCTION

Weed control is an important issue in contemporary farming, greatly influencing crop yield, resource use, and farm profit. Weeds compete for essential resources like light, water, and nutrients with crops, resulting in low yields and increased vulnerability to insects and diseases. Conventional practices such as hand weeding and broadcast herbicide spraying are time-consuming, labor-intensive, and cause immense environmental harm, particularly for large-scale farms. These methods tend to be imprecise, leading to overuse of herbicides that damage the environment around them and aid in the emergence of weed species resistant to herbicides. In response to these, we suggest a technology-based solution that uses multispectral imaging and machine learning to identify weeds early and with accuracy.

Multispectral images take data across multiple spectral bands, making it possible to distinguish between weeds and crops by their distinctive spectral signatures even at early developmental stages. Our goal is to devise a technique to detect and identify weeds accurately using current technologies like image processing and deep learning. By identifying the regions with precision where weeds occur, targeted weed management becomes feasible. This technique not only reduces herbicide usage with considerable cost benefits but also enhances sustainable farming practices. Excessive or improper herbicide use is known to be harmful to the environment. It can kill beneficial insects, contaminate surrounding water bodies with runoff, and reduce soil quality. Thus, timely and precise weed detection is the key to fostering precision agriculture, where resources like herbicides are deployed judiciously and wisely. In the end, the inclusion of weed detection systems in the process of agriculture will bring about healthier crops, increased yields, and minimal environmental footprint, sustaining economic and environmental objectives.

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II. RELATED WORK

Weed identification has been a research-intensive field of study for precision agriculture, with great transition from conventional image processing to sophisticated multispectral and deep learning algorithms. Aravind et al. [1] were part of the initial researchers who introduced an automatic weed identification and intelligent herbicide sprayer robot, emphasizing the significance of automation in precision weed management. Later, Tang et al. [2] tackled the issues of changing illumination conditions through the utilization of image processing methods for site-specific spraying. Likewise, Johnson et al. [3] and Hameed et al. [4] examined traditional image processing-based weed detection systems, paving the way for further developments. Vegetation indices were also widely studied for use in crop monitoring and weed localization. Kastens et al. [5] showed that satellite-extracted NDVI was useful for crop yield modelling and decision-making at the field level. This study was further developed by Roznik et al. [6], who used high-resolution NDVI images and cropland masks to enhance accuracy in estimating yield.

Since the advancement of deep learning, attention has moved towards real-time object detection algorithms like YOLO. Rai et al. [7] offered a thorough review of deep learning implementations in precision weed control, stressing the efficacy of YOLO-based implementations. Hasan et al. [8] also supported this with evidence of high accuracy and flexibility of deep learning models in various agricultural settings. Islam et al. [9] also emphasized how multispectral images are better suited for early weed identification compared to RGB images, especially in diverse field conditions. This was corroborated by Fawakherji et al. [10], who created multispectral image mosaics to improve crop-weed segmentation. Dandekar et al. [11] were also successful in using YOLOv3 for images of agricultural fields, while Sneha et al. [12] compared YOLOv3, R-CNN, and CenterNet before concluding that YOLOv3 provided an interesting trade-off between speed and accuracy for use in weed detection applications. For limited annotated data scenarios, methods based on unsupervised learning have received attention. Agarwal et al. [13] used K- Means clustering with multispectral UAV imagery utilizing color space features in the identification of weeds. Ota et al. [14] improved on this by integrating crop row detection with clustering to identify weeds in highly infested fields. Zhang et al. [15] suggested a hybrid approach with modified GrabCut, K- Means clustering, and sparse representation classification, which was found to be effective in highly vegetated agricultural scenes.Lastly, Bhukya et al. [16] presented an end-to-end deep learning-based weed detection and removal system, summarizing the move towards more scalable and smart farming solutions.

III. METHODOLOGY

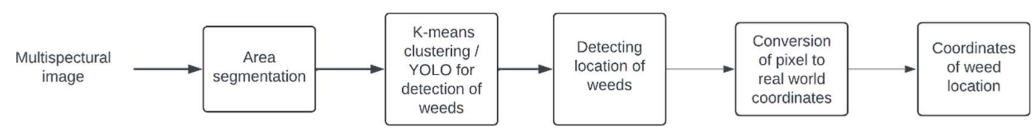

Fig.1 Proposed Architecture

The architecture depicts the end-to-end pipeline employed to detect and identify weeds in farmland using multispectral images. The procedure starts from a multispectral image, which records multiple spectral bands beneficial for detecting vegetation. The initial step is area segmentation, where a vegetation mask (usually derived from NDVI) is utilized to separate the vegetation areas from the background (like soil or non-plant regions).Once vegetation pixels are segmented, weed detection is carried out using either K-means clustering (an unsupervised method) or a YOLO-based object detection model (a supervised method), depending on the availability of training data and image characteristics.

Following detection, the next step involves determining the precise location of weeds within the image. Once the weed pixels or bounding boxes are identified, conversion of pixel coordinates to real-world coordinates is performed. This step is essential for practical field applications, enabling precise weed mapping using GPS or georeferenced data. Finally, the system outputs the coordinates of the weed locations, which can be used for site-specific herbicide application, robotic intervention, or further analysis in precision agriculture practices.

A. Data Collection and Preprocessing

Our study utilizes a multispectral image dataset of agricultural fields containing crops and weeds. The dataset includes images of sunflower and banana crop fields at various growth stages and weed infestation levels. Each image contains multiple spectral bands, including visible (RGB) and near-infrared (NIR) channels. The inclusion of NIR allows computation of the Normalized Difference Vegetation Index (NDVI), which is used to differentiate vegetation from soil and to some extent distinguish crop plants from weeds. We then apply a threshold to the NDVI image to create a mask of green vegetation. This NDVI mask is used to highlight crop regions and vegetation overall: pixels with NDVI above a chosen threshold (indicating healthy vegetation) are classified as plant (either crop or weed), while lower NDVI pixels are considered background (soil or residue). In our implementation, the threshold was selected empirically by examining the NDVI histogram such that known crop areas are included. The result is a binary mask which primarily marks all plants in the scene. This mask is later used to aid both supervised detection and unsupervised clustering. Additionally, we prepared ground-truth annotations for weeds in a subset of the images to train the supervised detection model. Using the Computer Vision Annotation Tool (CVAT), we manually labelled bounding boxes around weed instances in RGB images. These annotations, along with the corresponding images, form the training data for the YOLOv5 model described below. All annotated weeds were verified against the NDVI mask to ensure consistency (e.g., any labelled weed should correspond to a vegetative pixel region in NDVI).

B. Weed Detection with YOLOv5 and NDVI Masking

For object detection of individual weeds, we employ the YOLOv5 model, a state-of-the-art one stage detector known for its speed and accuracy in detecting small objects. We trained YOLOv5 on our annotated multispectral images (using the RGB channels for detection). To incorporate multispectral information without modifying the YOLO architecture extensively, we utilize the NDVI mask as a preprocessing step. Specifically, the NDVI mask is applied to the RGB image to filter out non-vegetation background before detection: pixels identified as non-vegetation (low NDVI) are deemphasized or set to zero in the input image. This focuses the detector on regions likely containing crops or weeds. In effect, the YOLOv8 network is guided to ignore large bare-soil areas, thereby reducing false positives and speeding up training convergence. During training, the YOLOv5 model learns to classify detected objects into two categories: crop or weed. We use a transfer learning approach, starting from YOLOv5 weights pre-trained on a large dataset and fine-tuning on our agricultural dataset. The network was trained for a fixed number of epochs with augmentation (random rotations, flips, and photometric adjustments) applied to improve robustness. The NDVI masking was applied consistently during training and inference. The model achieved a high detection performance learning the visual differences between crop plants (often arranged in rows or known spacing with possibly different spectral reflectance) and weed plants (often randomly located and sometimes different in shape or spectral signature). After training, the YOLOv5 detector is run on new multispectral field images (with NDVI masking applied) to identify weed locations. Each detection yields a bounding box around a weed cluster or individual weed and a confidence score. We record the pixel coordinates of the center of each bounding box as the detected weed positions in image space. Because YOLOv5 operates on RGB images, smaller weed patches or very early-stage weeds that present minimal contrast might sometimes be missed; however, the NDVI mask mitigates this by ensuring even subtle vegetation is present in the input. The combination of spectral filtering and deep learning provides accurate weed identification in our experiments.

C. Unsupervised Weed Segmentation with K-Means Clustering

While YOLOv8 works well on images of moderate size (e.g., drone images covering plots), for very large aerial images or when an annotated training set is limited, we integrate an unsupervised clustering method to detect weeds. K-means clustering has been applied on the spectral feature space of the image pixels to segment crops, weed, and soil regions without supervision. Prior to clustering, we utilize the NDVI- based vegetation mask to focus on vegetation pixels only. All pixels identified as vegetation (by NDVI threshold) are extracted and their color features are used for clustering, while non-vegetation pixels are immediately classified as background. We choose $k = 2$ clusters for the simplest case of separating vegetation into two classes (assuming one corresponds to crops and the other to weeds). In fields with a more complex mix of plants, k can be increased (e.g., $k = 3$ for crop, weed, and perhaps different weed species or varying crop health); however, in our scenario $k = 2$ sufficed. We perform clustering in a feature space that includes the pixel's green intensity and possibly additional indices: specifically, use the mean of the green band and the NDVI value as two key features for each pixel, since healthy crops and weeds can sometimes differ in their greenness. The K-means algorithm partitions the set of vegetative pixels into two clusters by minimizing intra-cluster variance. The clustering result is a binary segmentation of vegetation: one cluster typically represents the main crop plants and the other represents weeds (and possibly any other secondary vegetation).

Determined which cluster corresponds to weeds by leveraging prior knowledge of the field. For instance, in row-crop scenarios, crop plants occupy a smaller area in early growth than weeds or vice versa; or the spectral signature (NDVI) of crop plants might be consistently higher than weeds if crops are healthier. In our experiments, we observed that one cluster grouped higher-NDVI, larger, and regularly spaced vegetation (consistent with sown crop rows), while the other cluster captured smaller, scattered patches of vegetation (consistent with weed growth between rows). Thus, identify the latter as the weed cluster. This interpretation is further supported by the fact that usually the number of weed pixels exceeded crop pixels in infested regions, so the cluster with more pixel count or the cluster corresponding to off-row positions was labelled as weeds [5]. After clustering, we generate a weed mask image where all pixels belonging to the weed-designated cluster are marked. This mask effectively segments the weed regions without having explicitly learned from annotations. We then extract connected components from this weed mask to group contiguous weed-infested pixels. Each connected region of the mask can be treated as a distinct weed patch. For each such region, the centroid in pixel coordinates has been calculated to represent the weed patch location.

D. Coordinate Transformation and Localization

In aerial weed detection, identifying the location of weeds in real-world coordinates is essential for enabling precise and targeted agricultural interventions. While object detection models like K means yield pixel coordinates of weed locations within an image, these coordinates must be transformed into real-world distances (e.g., in meters) to facilitate field-level actions such as robotic weeding or selective herbicide application.
Initially, the weed detection system outputs the pixel coordinates (xpixel,ypixel) of each identified weed in the multispectral image. These pixel values represent positions relative to the image grid but do not convey actual spatial distances in the field.
To convert pixel coordinates to real-world coordinates (xreal,yreal), it is necessary to establish a scaling factor that quantifies the spatial resolution of the image. The scaling factors for the x and y directions are calculated as:

$$scale_x = \frac{field\ width(m)}{image\ width(pixels)} \tag{1}$$

$$scale_y = \frac{field\ height(m)}{image\ height(pixels)} \tag{2}$$

Using these factors, pixel coordinates are converted to real-world measurements using:

$$x_{real} = x_{pixel} \times scale_x \tag{3}$$

$$y_{real} = y_{pixel} \times scale_y \tag{4}$$

This transformation enables precise localization of each detected weed in the actual field, bridging the gap between image-based detection and actionable field operations.

V. DATASET

The Dataset as depicted in Fig. 2 includes high-resolution multispectral images of sunflower fields. These images capture both sunflower plants and the surrounding weeds at low altitude

Figure 2. Sunflower Crop with Weed

The Banana Dataset as depicted in Fig. 3 contains top-view multispectral images with irregular crop spacing and complex weed patterns. Unlike the Sunflower Dataset, this dataset presents a more complex field environment with varying weed densities, crop growth stages and high-altitude image.

VI. RESULTS AND DISCUSSION

The weed detection system was evaluated using multispectral images from several field scenarios. The performance of the YOLOv5-based detection was quantified using standard metrics on a test set of annotated images, while the effectiveness of the clustering approach was assessed qualitatively and by comparison to manual survey data.

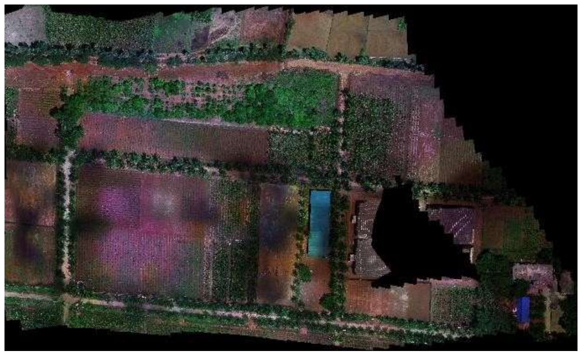

Figure: 3 Banana Crop Field Image

A. YOLOv5 Detection Performance

The YOLOv5 model, trained with NDVI mask preprocessing, achieved high accuracy in detecting weeds. On the test images (which included varying conditions of lighting, different crop types, and weed distributions), the model obtained an F1-score of 0.92 (92%), indicating a good balance between precision and recall. The precision (the fraction of detected weeds that were true weeds) was approximately 94%, and the recall (the fraction of actual weeds that were detected) was about 90%. This high precision is particularly important in precision agriculture, as false positives (incorrectly labelling crops as weed) could lead to crop damage if acted upon. The use of NDVI masking contributed significantly to this precision: in ablation tests, we found that enabling the NDVI mask reduced false detections on soil or crop residue areas by focusing the model on vegetative regions. It also helped in cases where weeds were small or partially obscured; the NDVI mask accentuates even small weeds if they have any green biomass, making them more noticeable to the detector. Qualitatively, the YOLOv5 detections aligned well with expectations. In a sample sunflower field image (captured at an early growth stage with scattered weeds), the model correctly identified even small weed clusters between the crop rows while ignoring the sunflowers themselves.

TABLE I. PERFORMANCE METRICS FOR YOLOV5 MODEL

Metrics	Value
Precision	84.26%
Recall	78.69%
F1-Score	92%

B. K-Means Clustering Results

For large-area images (for example, a Multispectral image covering an entire banana field of several hundred square meters), running YOLO on the full-resolution image is computationally expensive and not necessary if the goal is to identify general areas of heavy weed presence. Our K-means clustering approach provided an efficient alternative for such cases. Clustering has been applied to a high-resolution field. The algorithm partitioned vegetation into two clusters. Upon visual inspection, one cluster corresponded to the crop rows (banana plants in neat rows, having a distinct spectral signature and higher NDVI), and the other cluster corresponded to weed patches dispersed in the inter-row space. The weed cluster mask clearly outlined the regions of weed infestation. When comparing the clustering output to manual annotations on the field image, there was a high degree of overlap. The clustered weed regions captured most of the significant weed patches noted by experts. Some smaller weed patches that were very near to crop plants were occasionally absorbed into the "crop" cluster, a limitation of using only spectral features without spatial context. This could potentially be improved by incorporating knowledge of crop row patterns [5] or by increasing the number of clusters and then merging those corresponding to weeds. Nonetheless, the clustering approach proved effective in highlighting weed-infested zones for large-scale monitoring. One advantage observed with the clustering method is its ability to handle scenarios with no prior training data. For instance, we applied the clustering to a field image of a crop for which we had not trained the YOLO model; the unsupervised method still successfully separated vegetation into two groups, which we could interpret as crop vs. weed by context. This suggests the approach could generalize to new crop types or early detection in fields where labelled data is unavailable, albeit with some expert oversight to label which cluster is weeds.

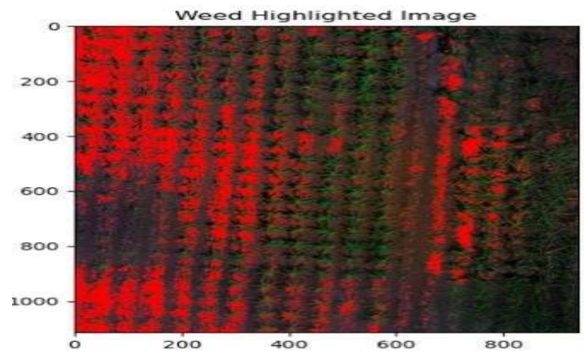

Figure 4. Weeds Detected Using K-Means Clustering

VII. Conclusion

In this work, we developed an integrated approach for early weed detection using multispectral imagery, combining a deep learning detector with spectral index masking and an unsupervised clustering method. The YOLOv5-based model, guided by NDVI vegetation masks, effectively detects weed instances at high precision and recall, achieving an F1-score of 92% on test data. This level of performance indicates the model's reliability in differentiating weeds from crops even at early growth stages. Meanwhile, the K-means clustering segmentation provides a complementary means to identify weed-infested regions in large field images without requiring annotated training data. By converting image detections to real-world coordinates, our system bridges the gap between image analysis and field application, allowing for pinpoint localization of weeds in the farm. The outcomes demonstrate that integrating multispectral information (through NDVI) and machine learning can significantly enhance weed detection capabilities. The proposed system enables precision weed management: farmers or automated equipment can target herbicide application to the specific coordinates of weeds, reducing herbicide usage and environmental impact. This promotes more sustainable farming by minimizing chemical inputs and preserving beneficial flora. The early detection aspect helps in addressing weed problems before they become severe, thereby protecting crop yields.

As a future work it is planned to extend this work by deploying the detection system on a drone platform for real-time weed scouting over large fields. This involves optimizing the YOLOv5 model for real-time inference on edge hardware and streaming geotagged detections. Additionally, incorporating other vegetation indices or hyperspectral bands could further improve the discrimination between crop and weed species. Finally, evaluating the system across different crop types and weed species in various environmental conditions will be important to ensure its generality and robustness for widespread adoption in precision agriculture.

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