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CNN-ENABLED DETECTION SYSTEM FOR AGRICULTURAL ANOMALY ANTICIPATION

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A B S T R A C T

Artificial intelligence is a rapidly developing field today. One of its different applications is object acknowledgment, utilizing PC vision. The advancements in Deep Learning (DL) techniques have made it possible to quickly identify, localize, and recognize articles from images or recordings. A growing number of farming and agricultural applications are utilizing deep learning techniques. Automatic weed recognition and grading can assist with weed control and thereby contribute to higher yields. Weed identification in crops through symbolic means is inherently problematic due to the presence of comparable varieties ('green-on-green') between the two weeds and harvests, as well as the similarity in their developmental morphologies and surfaces. The mix of these two advances prompts the justification for this undertaking. In this proposed model, the essential point is to perceive the weeds in crops by using YOLOv3 with PyTorch and OpenCV. The presentation of the subsequent framework is contrasted, and comparable ventures are found during the analysis. A technique is created to gather information for weed recognition, along with a pipeline to deal with the pictures. The information will be utilized to prepare cutting-edge object identification models like YOLO. To find an ideal model for the continuous discovery of weeds, the model will foster an information assortment procedure that will be utilized in a CNN and profound learning base model to anticipate yields and weeds uniquely in contrast to symbolism. This work centres around weed recognition using picture-handling strategies

1. INTRODUCTION

Horticulture is the beginning of human food in this world. Weed is something undesirable in horticulture. Obtrusive weeds are one of the primary issues that each rancher experiences while developing yields. To expand the yield, ideal evacuation of weeds is important as the weeds kill or ruin the development of harvests by taking water, supplements, and daylight. Ranchers use herbicides to dispose of the weeds or physically eliminate them. Be that as it may, the utilization of herbicides increases the expense of

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creation and opens people to perilous synthetic substances, as certain pesticides might stay with crops and may bring on some issues for people. Besides, herbicides can be variable to climate conditions for stretched periods and may cause pollution in soil and water, unfavorably influencing non-target creatures, and influencing the soundness of individuals. The recognizable proof and request of weeds are of most critical particular and pragmatic importance in the provincial business. In past days weed acknowledgment and ejection were done by using a couple of men, particularly for that objective. Profound learning (DL) is a significant part of ML (S. Kumar, Balyan, & Chawla, 2017). For picture characterization, object discovery, and acknowledgment, DL calculations enjoy numerous upper hands over customary ML draws near. Separating and choosing to segregate highlights with ML strategies is troublesome because yields and weeds can be compared. This issue can be tended to productively by utilizing DL approaches given major areas of strength for their learning capacities. Indeed, a weed is a botanical species that is considered undesirable.

Figure. 1 Weed having narrow leaves (ICAR- Indian Institute of Maize Research (ICAR-IIMR), 2024).

There is no organic classification for weeds, as a yield that is considered a weed in one context may not be considered so in another. It suggests any plant that develops or propagates forcefully or is found past its regular environment. The term is also used to describe organisms outside of the kingdom Plantae that can dwell in a diverse setting and reproduce rapidly. These have embryos that can last for many years in the agricultural ecosystem. They rival the expected plants for provisions like direct daylight, natural manures, water, and (less significantly) space for development. Inaccuracy cultivating, weed scientific classification is a significant issue. Weed categorization is crucial for understanding and suppressing weed species. There are two sorts of weeds in light of the recurrence of the edges present in them (Figure1 and Figure 2).

2. RELATED WORK

The author of (Panqueba & Medina, 2016)introduced an application for computer vision called "A computer vision program to recognize hazardous weed in primary stage harvests". This program aims to identify undesirable weeds in crops grown on a single field, thereby enhancing horticultural outcomes. Following the establishment of the form, image processing was managed by neural organizations. This study examines and foresees the incorporation of image protection, arrangement, and ANN. To improve the infrastructure, herbicides were utilized. In the particular case of this application, design delivery was critical due to the considerable challenge posed by determining focal points and fabricating the veil while utilizing comparable levels of light power. In (Shinde & Shukla, 2014) authors "Computer vision can detect weeds in fields. Computer vision incorporates a distinctive image processing paradigm. Weeds in farmlands were diagnosed using traits such as scale, morphology, wavelength absorbance, and texture. They exhibited weed detection utilizing Dimension attributes in this article. Upon picture assembling, the Excessive Green calculation was created to avoid soil as well as other unwanted parts from the picture. To wipe out the commotion from photos, picture augmentation techniques are applied. The labeling approach was utilized to retrieve each component in the image. Subsequently, size-based metrics including longest chord, longest periphery, and longest perpendicular pentatonic scale were calculated for each label. Additionally, weed, and crop segmentation was performed at a reasonable threshold level. In (D. A. Kumar & Prema, 2016) author proposed "A Revolutionary Methodology for Weed Segmentation Employing Curvelet Transform and Tamura Texture include (CTTTF) with RVM Classification" A weed is a flora category that develops among fundamental homestead items. These weeds also deplete soil water, leading to decreased water for productive agro products; as a corollary, these weeds would be spotted and knocked out early. This article discusses an effective weed categorization process that involves curvelet makeover and patch-level Tamura texture morphological operations. For crop and weed segmentation and weed division, the implication vector machine segmentation algorithm was proposed. The discoveries are tantamount to utilizing a random forest classifier and a support vector machine strategy. In terms of accuracy, precision, and delicacy, the suggested methodology excels all other transforms. In (Paikekari, Ghule, Meshram, & Raskar, 2016) the author portrays "Weed recognizable proof utilizing picture handling" and shows how they can use picture examination to identify and isolate weed-impacted zones from rural plants. The motive for adopting such a strategy is to locate and reuse weed-infested zones for subsequent sowing. This particular area can be examined for additional weed control systems, which will add to expanded yield. By employing techniques such as edge recognition and color segmentation, they reduced the amount of herbicide required for application by scattering it exclusively in areas containing weeds. In (Pandey, Jain, Sayeed, & Shashikala, 2016) the author proposed "Weed acknowledgment in a harvest column utilizing computer vision strategies was a huge and basic activity that could very well impact crop yield. This article showed two unique strategies: crop line ID in photos from ranch regions with significant weed challenges and further weed and harvest differentiation. To begin, picture handling for crop line acknowledgment principally comprises of three cycles: picture sifting, visual division utilizing Otsu's system, and yield column acknowledgment.

Figure. 2 Weed having Wide Leaves (ICAR- Indian Institute of Maize Research (ICAR-IIMR), 2024).

Second, the box plotting methodology is used to further define the weeds and harvests. Due to environmental situations, the proposed methodology was impervious to illumination. In (Aware & Joshi, 2016) the author proposed "Harvest and weed examination surface and shape and aspect perspectives, as well as modernized herbicide dosing," they contrived a picture handling calculation for produce analysis and weed control. Crop recognizable proof framework in light of five morphological qualities. Energy, instability, idleness, geographic repetitiveness, and difference are the five boundaries. Additionally, characteristics based on morphological size are utilized for pest and harvest location. All data have been analyzed, and the majority of decisions have been made for crop and weed detection. Segmentation refers to the process of isolating units from an image by using an image processing method. The units to be sprinkled are governed using strategic planning. Additionally, a Cartesian robot grabber is now being invented to identify weed concentrations on real-world landscapes by computing coordinates in order to precisely dispense herbicides. In (Desai, 2015) the author proposed "Image Processing for Weed Removal" Weed recognition and taxonomy are vital technical and economic challenges in the farming industry. Weeds are detached from photos and investigated utilizing morphology, tone, and size properties. These qualities have been utilized to recognize identical weeds and yield assortments. They portrayed a few different arrangement calculations like SVM, NN, and DA, and techniques including Otsu's and 2GR-B, which are intended to observe among weeds and harvests. He assessed every feature of these techniques and methodologies. His core goal in this study is to examine the methodologies for detecting weeds in fields using image processing.

3. METHODOLOGY

Companies have recently switched from theorizing to delivering solutions to current and business dilemmas. Many consumers are curious about neuronal networks from a range of perspectives. Engineers utilize them to develop an effective framework that promotes societal issues. For instance, neural networks can be used to regulate contemporary processes. Numerous dispersions are linked with the concept of brain organization. Frequently, tens or even thousands of worldwide conferences, seminars, congresses, and courses begin in earnest all throughout the planet. Above all, while Deep Learning (investigations of multiple layers NN) is a review categorization without someone else, it seems to have the same target as conventional Machine Learning:"growing toward a certain concealed framework from core instructive pieces (most or all of the time)".

3.1 Adam

Adam is an adaptive learning rate optimization technique devised exclusively for deep neural network training(Le et al., 2011). The approach can be conceptualized as a fusion of stochastic gradient descent with momentum and RMSprop. Adam optimizer dramatically reduces training time in deep learning frameworks (Bohra & Bhatnagar, 2021).

3.2 Batch Normalization

Batch normalizing lessens the level of variance in hidden layers value alters (co-variance shift). This is accomplished by standardizing the subset of dataset values supplied into the neural network. This process has the potential to shorten training time while accelerating the amount at which neural networks evolve.

3.3 OpenCV

OpenCV (Open-Source Computer Vision Library) is a computing tool library geared primarily at real-time computer vision(Culjak, Abram, Pribanic, Dzapo, & Cifrek, 2012). OpenCV is a real-time optimized Computer Vision library, and also tools and hardware. OpenCV is a gigantic outside structure for computer vision, AI, and picture handling, and it consistently plays a critical piece of progressive activity, which is imperative in the present frameworks. It can analyze photographs and recordings to discern products, individuals, and even human penmanship.

3.4 Convolutional Neural Networks

CNN is a sophisticated and high-potential alternative to the conventional artificial neural network model(O'Shea & Nash, 2015). It is developed to accommodate increasing layers of difficulty, preprocessing, and gathering evidence. It is influenced by the arrangement of neurons in the cerebral system of an organism's brain. CNNs are among the most efficient and versatile models for specialized image and non-image data. The CNN is constructed in four phases once the input data is loaded into the convolutional model:

Convolution: The process uses the input data to create feature maps, which are subsequently produced by an algorithm.

Max-Pooling: It aids CNN in recognizing a picture based on alterations.

Flattening: The resulting data is then compressed for evaluation by a CNN at this phase.

Full Connection: It is generally portrayed as a hidden layer that generates a model's loss function.

3.5 PyTorch

PyTorch is an open-source AI system that spotlights the Torch library, essentially created by Facebook's AI Research unit for applications, for example, PC vision and regular language handling (FAIR). It is open-source programming accessible under the Modified BSD permit(Stevens, Antiga, & Viehmann, 2020). No matter what the way that the Python point of interaction is more experienced and the main role of advancement, PyTorch likewise has a C++ interface. PyTorch accompanies two undeniable level highlights:

Tensor calculation (like NumPy) with impressive speed increase given by graphics processor units (GPU). Deep neural networks are based on an autonomous distinguishing algorithm based on type.

3.6 You Only Look Once (YOLOv3)

Convolutional neural networks, or CNNs, like YOLO, are capable of real-time object detection at a faster and more precise pace than other types of networks(Redmon & Farhadi, 2018). Each of its two completely linked layers and twenty-four convolutional layers are identified by their respective utilities. When it comes to testing, YOLO examines the complete picture, letting the world around it guide its assumptions. Zones are scored according to how closely they resemble predefined groupings; high-scoring zones are noted as particular identifications of the class that they most closely resemble. The YOLOv3 algorithm divides an image into grids, with each grid cell predicting the presence of a predefined number of border boxes, or anchor boxes, that include objects that score highly in predefined groupings. The accuracy of the prognosis is indicated by the confidence score assigned to each boundary box. The most common geometries and sizes are found by combining the ground truth box proportions from the raw dataset to produce the boundary boxes.

3.7 VGG16

VGG16 is a CNN (convolutional brain organization) system(Dey, Khalil, Kumar, & Bayoumi, 2021). The most particular trait of VGG16 is that rather than countless hyper-boundaries, they accentuated keeping up with the 3x3 channel of convolution layer in step 1 and also use familiar cushioning with max-pool layer of 2x2 in step 2. This example of convolution and max pool layers is preserved all through the format. Finally, it highlights two FC (totally associated layers) and a SoftMax for yield. The 16 in VGG16 refers to the weighted layers within it. This organization is somewhat gigantic, with around 138 million (assessed) boundaries. (Figure 3).

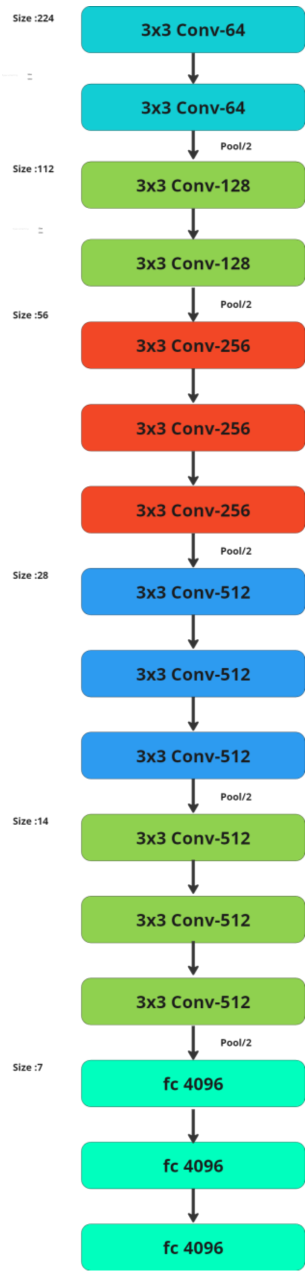

Figure 3. VGG16 Layers

4. DATA COLLECTION AND RESIZING

For this work, an open-source dataset is used (Utsav Panarav, 2022). This dataset contains 1300 labeled photographs of sesame crops and various types of weeds.

Each image is 512 x 512 pixels in size. The image labels are in YOLO format. In all 589 photographs of weeds and crops were taken. The dataset is cleaned after collecting the photographs. After cleaning 546 pictures were left out. For image processing, the photo size is kept at 4000X3000 pixels, which is quite huge, and the model would take a long time to train, so the model converted all photos to 512X512X3 size. However, 546 images are not enough for training, so it used a data augmentation approach to turn 546 images into 1300 images. A brief comparison of different datasets is shown in (Table 1)

Table 1. Comparison of different datasets.

Reference Datasets	Purpose	Plant	Image Size	Feature
Perennial ryegrass and weed (Yu, Schumann, Cao, Sharpe, & Boyd, 2019)	Weed detection and control	Dandelion ground ivy, spotted spurge, and ryegrass	920×1080 33,086	Weed Images:17,600 Other images:15,486 (Perennial Ryegrass).
(Santos Ferreira, Freitas, da Silva, Pistori, & Folhes, 2019)	Weed detection by using ConvNets	Soil, soybean, broadleaf and grass weeds	4000×3000 15,336 ,	The images analyzed in this study exhibit a ratio of 3:7:3:1 for soil, soybeans, grass, and broadleaf weeds, respectively.
Plant seedlings dataset (Giselsson, Jørgensen, Jensen, Dyrmann, & Midtiby, 2017)	Identifying plant species and weeding in the early growth stage	12 weed and crop species of Danish arable land	5184×3456 407	Accessible data has been made available, comprising complete images along with automatically segmented plants, as well as individual plants without segmentation.
Crop and Weed (Olsen et al., 2019)	Instance segmentation for fine detection	Maize, bean, and weeds	1200×2048 2489	The dataset includes Maize and common bean crops, along with cultivated and natural weeds characterized by their respective species.
Crop-Deep (Zheng et al., 2019)	Crop classification and testing	30 common vegetables and fruits	1000×1000 31,147	The dataset has 1100+ annotated samples per category, including vegetables, fruits, and various growth stages, with some categories exhibiting high similarity.
Food crops and weed (Sudars, Jasko, Namatevs, Ozola, & Badaukis, 2020)	Crop and weed identification	6 food crops and 8 weed species 9	720×1280 1118	The dataset includes 14 food crops and weeds captured at various growth stages in controlled and field conditions. It provides manually annotated images for accurate analysis and classification. This dataset is valuable for developing algorithms and models in crop and weed identification, monitoring, and management.
Crop-Weed(Utsav Panarav, 2022) (This work)	Crop and weed classification	Seaseme Crops and Weeds	512 X 512 1300	Basic sesame crops and weeds data set

5. IMPLEMENTATION

A conventional weed recognition system is composed of four critical steps: picture capturing, image pre-processing, feature extraction, and weed identification and categorization. The hereunder is the methodology that was designed to produce this application and accomplish all the key targets (Figure 4).

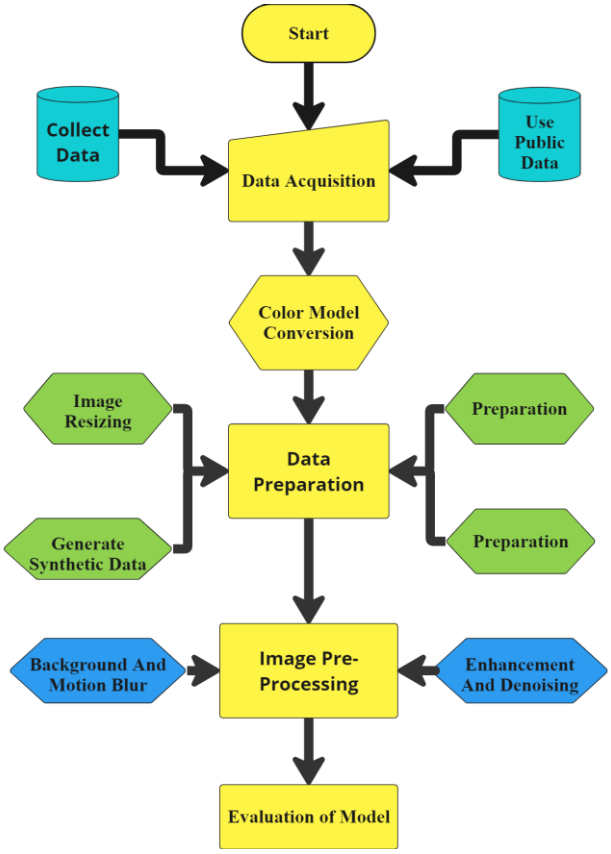

Figure 4. Flowchart of the Model.

Image Acquisition

Weed pictures were procured in RGB design from an online dataset or a yield field utilizing a top-quality camera. Each subsequent picture is kept in a satisfactory scale and JPEG design.

Conversion into Data frames

This model read data from an image, matched it to its corresponding text file, and created a data frame containing the width, height, x-center, and y-center values to make it more readable and get more data for training the model.

Conversion into Pascal VOC

Labeled datasets are required for computer vision challenges. Object detection concerns, in particular, need the enclosure of things within a frame. Because Pascal VOC data is used for object identification and categorization, the model reformatted the dataset to this format to make the Open CV methodology quicker to deploy. It allows us to quickly tweak datasets while utilizing a uniform representation format. Width, height, class, x min, x max, y min, and y max are all included in the Pascal VOC dataset.

Data Pre-processing

The model produced background photographs from the dataset to use as negative samples if any were found. Furthermore, data was partitioned into training and test data, comprising subparts: weed, crop, and background.

Data Fine Tuning

The dataset has been further partitioned into training, validation, and testing. Kera's layers were used to generate the model architecture. The model was trained, and its accuracy was determined.

Feature Extraction

Following pre-handling, boundaries for weed identification are obtained. The most common method of characterizing a collection of highlights for the optimal exchange of information for division and perception is followed by a specific feat extraction. Various types of highlights are surface elements such as entropy, energy, contrast, and so on. Size, shape, and variety-based highlights are used to extract features. This model removed the highlights from the named pictures as well as the negative examples, for example, background pictures.

Performing Detection

The model defined a function for feature importance calculation and used it for the detection algorithm to predict the category.

6. RESULTS

This part discusses the results of some experiments designed to validate the proposed weed detection algorithms. Here the model compared the findings of several models with past results from other models (Table 2). Heatmap and confusion matrix are shown in (Figure 6) and (Table 3).Model detection (Figure5), model prediction (Figure7) and Image classification (Figure8) were achieved as shown in the mentioned figures.

Table 2. Comparison of performance.

Work Done By	Database	Methodology	Accuracy/ Precision
(Chavan & Nandedkar, 2018)	Plant seedlings dataset (Giselsson et al., 2017)	AgroAVNET (A hybrid model of AlexNet and VGGNET)	Accuracy: 98.23
(Trong, Hyun, Young, & Bao, 2021)		Yielding multi-fold training (YMufT) strategy and DNN; Min-class-max-bound procedure (MCMB); Resnet	Accuracy: 97.18
(Xu et al., 2021)		Convolutional neural network separable depthwise.	Accuracy: 99.63
(Olsen et al., 2019)	Deepweed (Giselsson et al., 2017)	Classification of dataset include Inception-v3 and ResNet-50 For comparison baseline performance was established using CNN models	Accuracy: 95.1(Inception-v3),Accuracy: 95.7(ResNet- 50)
(Santos Ferreira et al., 2019)		Unsupervised Deep Learning of representation and Image Clusters (JULE) and Deep Clustering for Unsupervised Learning of Visual Features (Deep Cluster)	Precision: 95
(Hu, Coleman, Zeng, Wang, & Walsh, 2020)		Uses Learn-ing Mechanism using Graph based tech-nique Graph Weeds Net (GWN)	Accuracy: 98.1
(Naresh & Nagendraswamy, 2016)	Flavia (Wu et al., 2007)	MLBP(Mod-ified Local binary pat-terns)	Accuracy: 97.55
(Mahajan, Raina, Gao, & Pandit, 2021)		Adaptive boosting included support vector m1a2chine	Precision:95.85
(Yang, 2021)		MTD (multi-scale triangle descriptor) and LBP-HF	Accuracy: 99.1
Proposed Implementation ion	Seasame+ Weeds(Utsav Panarav, 2022)	Architecture Opencv+Pytorch. Utilization of pascal transformation for Labeling.	Accuracy :97.00

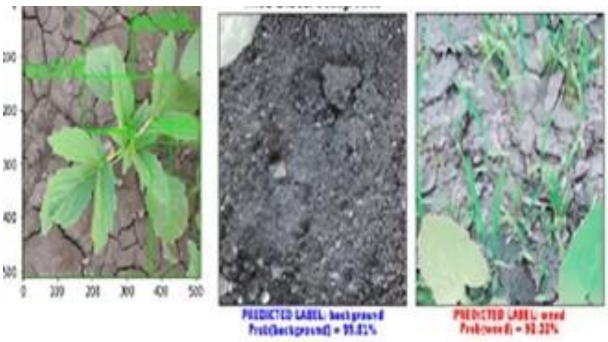

Figure 5. Model detecting image category.

Table 3. Confusion Matrix Showing Performance of Model.

	Precision	Recall	F1-Score	Support
0	0.98	0.99	0.99	10769
1	0.97	0.93	0.95	3147
2	0.94	0.94	0.94	2331
Accuracy			0.97	16247
Macro Avg.	0.96	0.95	0.96	16247
Weighted Avg.	0.97	0.97	0.97	16247

7. CONCLUSION AND FUTURE SCOP

This work presents a comprehensive examination of weed detection in crop fields through the utilization of advanced image processing methods. The primary objective is to develop an efficient and accurate system for identifying and managing weeds, ultimately enhancing agricultural productivity. The methodology involves several crucial steps, including image segmentation, feature extraction, and clustering techniques, which collectively contribute to the accurate analysis of crop photos.

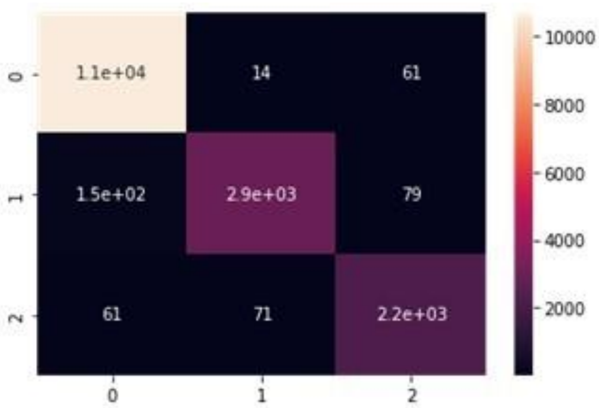

Figure 6. Heatmap and confusion matrix for the model.

By employing image segmentation, the system can separate the crop regions from the background and isolate weed-infested areas. Subsequently, feature extraction techniques are applied to extract relevant characteristics from the segmented images, such as color, texture, and shape attributes. These extracted features play a vital role in distinguishing weeds from the surrounding crops. Finally, clustering algorithms are employed to group similar weed instances, allowing for precise identification and subsequent control measures.

However, the performance of the weed detection model can be influenced by several factors, including the resolution of the methodology and the constraints associated with image acquisition. Higher-resolution images generally yield better results due to the increased level of detail captured. Furthermore, the availability of high-quality and properly labeled training datasets significantly contributes to the accuracy and generalization capability of the model. To expand the applicability of this research, future endeavors can explore the integration of the weed detection system with mobile phones and drones.

This integration would facilitate real-time recognition with high accuracy, accelerating the weed identification and clearance process.

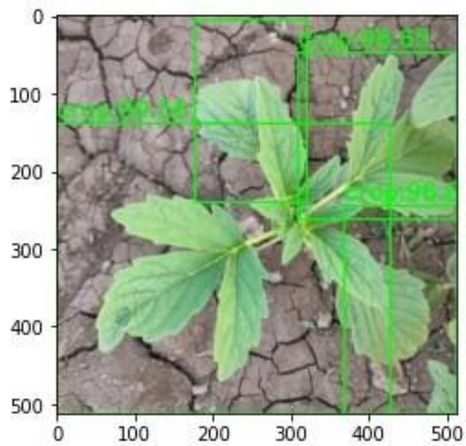

Figure 7. Model Prediction on object

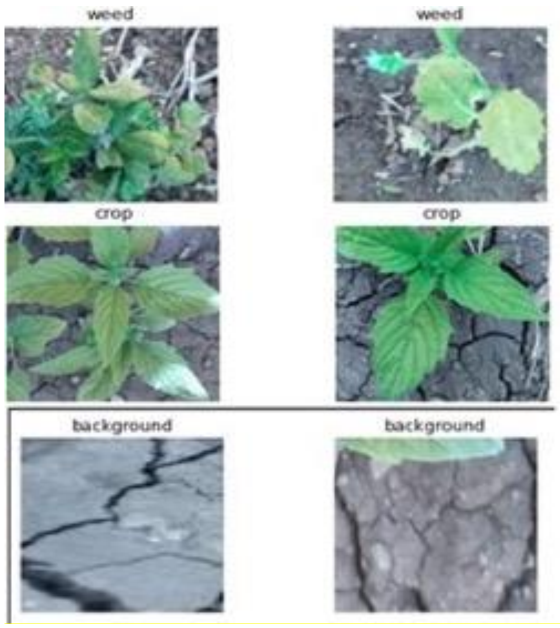

Figure 8. Image Classification into categories

By leveraging the ubiquity of mobile phones and the maneuverability of drones, farmers and agricultural professionals can easily capture images of their fields, which can then be processed by the weed detection system to provide instant feedback and guidance on weed management strategies.

Moreover, this research holds the potential for broader utilization by incorporating pest detection capabilities, transforming the model into a multi-purpose tool for increasing agricultural yields. By integrating weed and pest detection, farmers can effectively identify and address both weed and pest issues simultaneously, reducing the overall impact on crop growth and optimizing resource allocation.

Looking ahead, it is essential to develop highly accurate prediction methodologies that leverage large and diverse datasets encompassing a broad range of crop and weed species. By training the model on extensive datasets, it can generalize well across different weed-crop scenarios, offering robust weed detection capabilities in various agricultural settings. Additionally, the creation of large, generalized datasets specific to weed-crop contexts will contribute to the development of customized machine-learning models tailored to address the challenges unique to weed management.

Addressing class imbalance complications is another crucial aspect of future research. As weed occurrences are often outnumbered by non-weed instances, class imbalance can pose challenges to the model's performance. Balancing the representation of different classes through techniques like oversampling or under-sampling can help mitigate this issue and improve the overall accuracy of the weed detection system.

Furthermore, accurately determining the growth stage of weeds is an essential factor in effective weed management. Weed control strategies often vary depending on the developmental stage of the weed. Therefore, developing algorithms that can accurately identify and classify weeds based on their growth stage will enable more targeted and efficient weed management practices.

To ensure the commercial viability and real-world applicability of the weed detection system, extensive field trials and validation studies are necessary. Rigorous testing across diverse geographical locations, crop types, and weed species will validate the performance and robustness of the model. These trials will provide insights into the system's efficacy under real-world conditions and guide further improvements and optimizations.

In conclusion, this work represents a significant step forward in weed detection and management in agricultural fields. By employing advanced image processing techniques and machine learning algorithms, it offers a promising approach to identifying and controlling weeds, ultimately enhancing agricultural productivity. Through further research and development, incorporating mobile and drone integration, addressing class imbalance complications, accurately determining weed growth stages, and conducting comprehensive field trials, this system can be refined and optimized for commercial deployment, empowering farmers with a valuable tool for efficient weed management and increased crop yields.

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