Automated Weed Recognition in Sesame Crop Fields Using Deep Learning

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***Abstract*—Agriculture is one of the origins of human nourishment in this world. Nowadays due to growing population we need the greater productive capability of the agriculture to meet the demands. So, to increase the crop yield, we started using herbicides. By doing so we got success in increasing the productivity but we have forgotten the damage done to the environment. So, the idea is to reduce the usage of herbicides by spraying them only in the areas where weed is present. The goal is to detect weeds in agricultural fields. A deep learning system is used in this project to identify weeds that are growing between crops. The primary characteristics of photos taken in agriculture are analyzed using the DL approach, CNN. This dataset is used to recognize weeds and crops to distinguish between weed and crop, a CNN uses rectified linear units (RELU) on a fully connected surface. Crop identification is done using features from a deep learning network.**

***Index Terms* - Agriculture productivity, Crop yield enhancement, weed detection technology, Convolutional Neural Network (CNN) in farming, Rectified Linear Unit (ReLU), Agricultural image analysis, Deep learning-based weed control.**

I. INTRODUCTION

Crops and weeds fight for resources including sunshine, water, nutrients, and space. They can drastically lower crop yields, degrade harvest quality, and raise the need for herbicides if they are not controlled. Effective weed detection systems help in: reducing manual labor, minimizing the usage of herbicides, thus decreasing environmental pollution, enhancing crop health and yield by addressing weed issues promptly, allowing for targeted weeding, reducing overall costs. The resemblance between weeds and crops is one of the main obstacles to weed detection. Weeds often mimic the appearance of crops, making manual detection difficult. Accurate identification is further complicated by elements including complex crop canopies, environmental unpredictability, and the presence of many weed species. Traditional techniques, including mechanical weeding or the use of broad-spectrum herbicides, are imprecise and may damage crops and the environment. As a result, there is now more interest in cutting-edge, technologically driven methods.

1.1OBJECTIVE

This project's main goal is to use deep learning techniques to create an accurate and efficient system for weed detection in agricultural fields. Conventional methods of weed control, including manual identification and the application of broad-spectrum herbicides, are often labor-intensive and lack precision, leading to excessive chemical use and potential environmental damage. Deep learning, particularly through the use of CNNs, provides an advanced method for analyzing complex visual data, facilitating the accurate distinction between weeds and crops. By making sure that weeds are properly controlled, the objective is to reduce the need for chemical pesticides, lower the labor expenses related to hand weeding, and eventually increase crop yields. These systems are appropriate for a variety of agricultural situations because they can process large volumes of picture data and adjust to different crop environments. The ultimate goal is to create an intelligent system that can detect weeds on its own without constant human supervision. By fulfilling these objectives, the system is anticipated to promote more sustainable and profitable farming practices.

1.2 PREVUE

This research explores the use of deep learning in agriculture, with a particular emphasis on the crucial problem of weed control. A deep learning-based model that can recognize weeds from Kaggle photos was designed, developed, and tested as part of the study. After reviewing current weed detection techniques, the project develops a deep learning strategy specifically suited to the difficulties of agricultural weed detection. The study then goes on to explain how a sizable and varied dataset of agricultural photos was gathered and curated. The deep learning 2 model, which is intended to detect weeds in real time with great accuracy, is then trained using these photos. The report also contains a thorough assessment of the model's functionality.

1.3 SCOPE OF WORK

The scope of this work encompasses the development and validation of a deep learning-based weed detection system. The first phase involves the collection and pre-processing of a large dataset of images from various agricultural settings. This dataset taken from Kaggle includes images of sesame crop and various weed species captured under a range of conditions, such as different growth stages, lighting conditions, and weather scenarios. To train a reliable model that performs well in a variety of settings, the dataset's diversity is essential. The research then concentrates on creating and deploying a convolutional neural network (CNN) in conjunction with a support vector machine (SVM) that is especially suited for weed detection. This involves selecting a appropriate architecture, tuning hyperparameters, and employing data augmentation techniques to improve model performance. The model will be trained and validated using the collected dataset, with an emphasis on achieving high accuracy and low false positive rates. Lastly, the scope includes performance evaluation of the system. The model can be tested using a different set of photos that are fresh to the model and weren't used for training. The outcomes of these experiments will provide suggestions for further research, like improving the model, growing the dataset, or adding more features, such as improved weed recognition.

II. LITERATURE REVIEW

A survey of the literature on weed detection systems provides a comprehensive knowledge of the state of the field's research, covering the several deep learning models and techniques that have been used for weed identification. Finding the advantages and disadvantages of various strategies is made easier by this. It helps us select the best deep learning approaches for our project by evaluating the effectiveness and suitability of various approaches applied in related research. It provides useful tips and methods for putting deep learning models into practice, such as model topologies, evaluation procedures, and pre-processing approaches that have worked well in earlier studies.

A study titled "UAV-based weed detection in Chinese cabbage using deep learning" [1] was published. A Convolutional Neural Network (CNN) was used in this study to identify weeds. After pre-processing the acquired photos using the Simple Linear Iterative Clustering Super Pixel algorithm, the images were divided into three categories: weeds, soil, and crops. Then, using the segmented images, the CNN-based classifier was constructed. The performance of CNN was assessed using the Random Forest (RF) approach. Advantages and disadvantages: With average accuracy of 92.41%, precision of 75.45%, specificity of 93.88%, and sensitivity of 80.29%, the CNN outperformed the RF-based classifier.

"A study on the effectiveness of deep learning algorithms for identifying crop and weed species against various image backgrounds" [2] A Convolutional Neural Network (CNN), Visual Group Geometry (VGG16), and Residual Network (ResNet50) deep learning architecture were used to build the weed classification models in this study. 97% accuracy in training and validation. Model performances seem to be affected when evaluated with photos that have a different object backdrop than the ones used in model construction

"Detecting weeds in canola fields with a deep convolutional neural network and maximum likelihood classification" [3] Initially, maximum likelihood classification was used to separate the foreground and background. Weed pixels were manually tagged in the second step. When SegNet and UNet were compared for performance, SegNet performed better than UNet. Nevertheless, an examination of soil qualities to look into the connection between densities and soil attributes was not part of the study.

"A Precision Agriculture Weed Detection Model Powered by Deep Learning and Computer Vision" [4] The model employs two primary procedures: an optimum extreme learning machine (ELM) for classifying weeds and a multiscale Faster RCNN for object recognition. The Farmland Fertility Optimization (FFO) technique is used to optimize the parameters of the ELM model. The model increases productivity, decreases the use of herbicides, and successfully detects weeds among crops. Accuracy rises and loss falls as the number of epochs grows. It's possible that the FFO algorithm used for parameter optimization needs to be carefully adjusted or is sensitive to particular circumstances. Furthermore, the caliber and representativeness of the training dataset have a significant impact on the model's performance.

"Faster RCNN model for weed detection: An improved anchor box method" In order to effectively detect and locate crops, a thorough dataset was used to train the pretrained Faster RCNN ResNet model using deep learning techniques [5]. With a high prediction accuracy, the deep learning-developed algorithm effectively finds and distinguishes pea plants from weeds; the model can identify the crop with up to 100% accuracy. Variants of weeds or crops not included in the training data may be difficult for the algorithm to recognize and distinguish.

"Evaluation of convolutional neural networks for weed detection in turf based on herbicide susceptibility" [6] This study sought to ascertain whether it would be possible to identify and differentiate between weed species growing in bermudagrass turf or weeds that are herbicide-susceptible using image classification convolutional neural networks, such as DenseNet, EfficientNet, and ResNet. Benefits: The 240 × 216-pixel sub-images were discovered and discriminated by DenseNet, EfficientNet-v2, and ResNet with an exceptional detection speed (≥77.94 fps). Cons: All three neural networks performed poorly when it came to recognizing and distinguishing between crabgrass and tropical signal grass growing in bermudagrass turf. Neural networks are more likely to mistakenly categorize crabgrass as tropical signal grass or vice versa.

According to the publication "Weed detection based on the optimized segmentation line of crop and weed" [7], weed detection is carried out using the most effective crop and weed segmentation line. Using the G and R components of the RGB color space directly was one way to categorize weeds. Using the spectral data inside the green band, where hue was determined to be wavelength and saturation to be reflectance, was an additional technique. An H-S optimized model could be used to avoid the lighting effect. All of them simply used the spectrum information of visible light, which would reduce production costs and increase the viability of applications in fields. These techniques might not be able to accurately detect weeds since they are limited to using the spectrum information from visible light. Adding more spectral bands or features might enhance functionality.

A controller area network (CAN) for a weed-detection and spray-control system integrates two optical weed sensors with spray control and a global positioning system (GPS) to accomplish real-time weed recognition, spot spraying, and weed-infestation mapping, according to the paper "A real-time, embedded, weed-detection system for use in wheat fields" [8]. The system was evaluated in a variety of wheat fields with varying circumstances, often achieving over 70% classification accuracy. The sensor functioned better when taught with multiple weed species, according to test results. The sensor identified three weed species with accuracies ranging from 60% to 78% after being trained with a single weed species. When training with all three species, the accuracy rose to 78–91%. The effectiveness of the models was significantly affected by the position of.

III. MATH

Accuracy = $\frac{TN+TP}{TN+FP+TP+FN}$

Precision = $\frac{TP}{TP+FP}$

Recall = $\frac{TP}{TP+FN}$

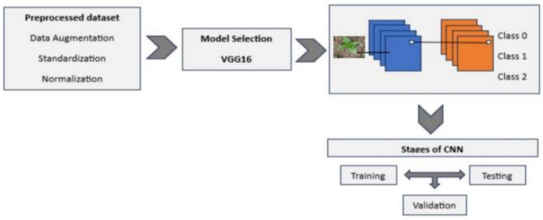
F1 Score = 2 * $\frac{Precision * Recall}{Precision + Recall}$

IV. METHODOLOGY

In this project, we're using a well-structured approach to create a weed detection system with deep learning. We begin by compiling a varied collection of photos from Kaggle that depict weeds and sesame crops under a range of circumstances, including weather, growth phases, and lighting. After collecting the data, we carefully prepare it by resizing, normalizing, and augmenting the images with techniques like flipping and rotating to make the dataset more robust. For the model, Our Convolutional Neural Network (CNN) is built to interact with a Support Vector Machine (SVM) classifier. The CNN extracts features from the image, and the SVM classifies these features to determine if they are weeds or crops.

We train the model on this processed data, fine-tuning the model's parameters and applying methods to prevent overfitting, so it performs accurately and efficiently. Once trained, we validate the model with part of the dataset, making further adjustments if needed. Lastly, we evaluate its accuracy, precision, recall, and F1-score using entirely new photos to determine how effectively it can differentiate between crops and weeds. If there are any mistakes, we examine the incorrect classifications to see what went wrong, which aids in further model improvement. This methodical technique guarantees that our technology is dependable, flexible, and prepared to assist more environmentally friendly weed control in agriculture.

V. MODEL AND ARCHITECTURE



BLOCK DIAGRAM

INPUT MODULE

The Input Module collects images of sesame crops and weeds. The images are gather from various agricultural environments and stored in a Kaggle dataset. The module ensures that the input data, consisting of crop and weed images, is formatted correctly for further processing.

Image Format: Images are standardized to 224x224 pixels to match the input size required by the VGG16 model.

Data Augmentation: Various augmentation techniques such as rotation, scaling, and flipping are applied to enhance the model's resilience and the dataset's diversity.

PREPROCESSING MODULE

The pre-processing module gets the raw picture data ready for model training and feature extraction.

Resizing: All images are resized to 224x224 pixels to be compatible with the VGG16 model.

Normalization: To improve model performance, pixel values are normalized between 0 and 1.

Label Encoding: Images are labelled as either 'crop' or 'weed' and binary encoded for classification purposes.

Data Augmentation: Techniques like random rotation and flipping are used to avoid overfitting and enhance the dataset.

WEED DETECTION MODULE (RCNN WITH VGG16)

For accurate weed and crop categorization, the Weed Detection Module employs a Region-based Convolutional Neural Network (RCNN) with a VGG16 backbone for feature extraction.

VGG16 Backbone: A feature extractor is employed with the VGG16 network. In order to differentiate between crops and weeds, its 16 layers—13 convolutional and 3 fully connected—are skilled at gathering high-level picture characteristics.

The Region Proposal Network (RPN) eliminates the need for a thorough search throughout the full image by identifying areas where a crop or weed is more likely to be found.

Region-based Feature Extraction: The proposed regions are pooled, and the features extracted by VGG16 are used for classification.

Classification Layer: The model uses these features to classify each region as either 'crop' or 'weed.' VGG16's strong feature extraction capabilities make this process more accurate.

Bounding Box Prediction: The RCNN also predicts bounding boxes around the detected objects, localizing the crops and weeds in the image.

REPORT GENERATION MODULE

Based on the outcomes of the weed detection procedure, the Report Generation Module produces an extensive output.

Bounding boxes are created around the objects that were recognized, indicating the presence of crops and weeds in the image.

Actionable Insights: Based on the detection results, the system suggests applying herbicides or manually pulling weeds.

Performance Metrics: To evaluate the model's performance, the report provides metrics for accuracy, precision, recall, F1-score, and intersection over union (IOU).

This version emphasizes the application of VGG16 within the RCNN framework, demonstrating how its potent feature extraction capabilities improve weed detection.

VI. TEST CASES AND FINAL RESULTS

TEST CASES

Test Scenario: Testing the model accuracy on test dataset.

Step	Step Details	Expected Results	Actual Results	Pass / Fail
1	Load the trained	Model should load	Model loaded	Pass

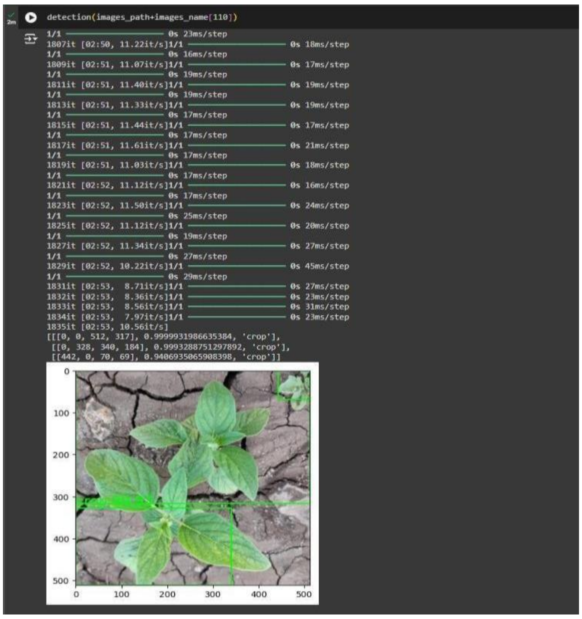
	CNN model	successfully.	successfully	
2	Feed the test dataset to the model.	Model should predict weed detection accurately.	Model predicted accurately.	Pass
3	Compare	Accuracy should meet or exceed threshold.	Accuracy was 96%.	Pass

Test Scenario: Testing the model handling the non-weed images.

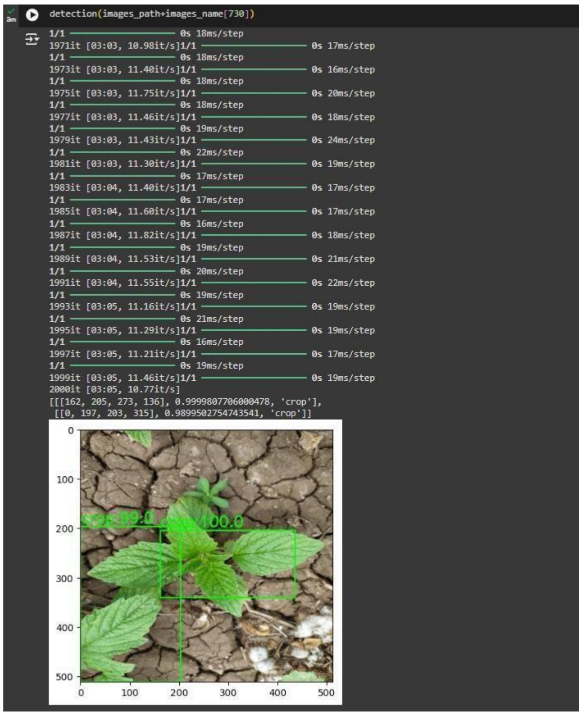
Step	Step Details	Expected Results	Actual Results	Pass/ Fail
1	Load the trained CNN model.	Model should be loaded successfully.	Model loaded successfully.	Pass
2	Feed non-weed images to the model.	Model should correctly identify non-weed images.	Model identified non-weed images correctly.	Pass
3	Verify no false positives	No false positives should be detected.	No false positives detected	Pass

FINAL RESULT

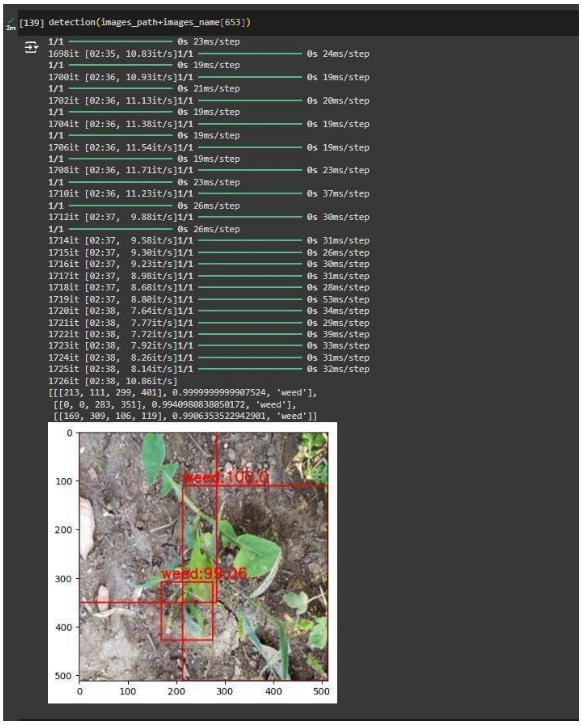
The results of applying CNN for feature extraction and SVM for classification to weed identification in sesame crops demonstrate a significant increase in efficiency and accuracy. The program demonstrated efficacy in identifying sesame crops and weeds, achieving a 96% accuracy rate. An effective convolutional neural network, the VGG16 architecture, assisted in identifying pertinent characteristics in the image data. This model captured intricate patterns and traits that set weeds apart from sesame plants by utilizing the capabilities of deep learning CNN. The SVM classification device, known for its advanced size object processing, is effectively classified in the correct category of extracted functions. There are few misclassifications of weed as a crop and crop as a weed which lead to an accuracy of 96% only.



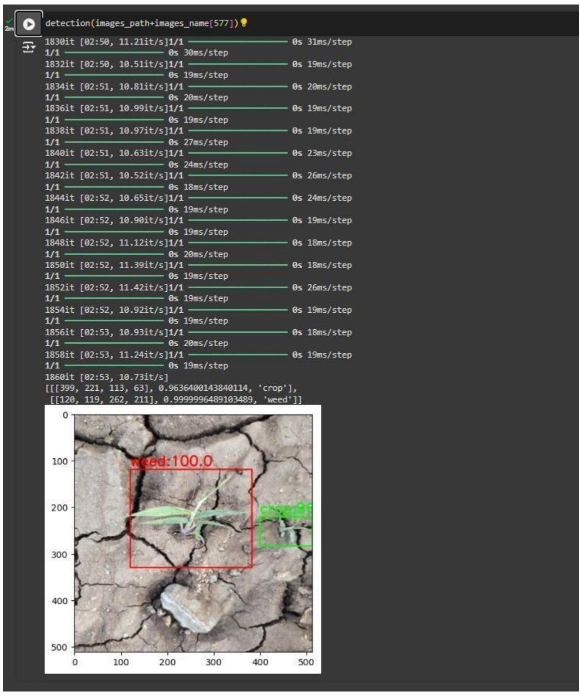
Detection of sesame crop



Detecting crop as crop



Detecting weed as weed



Misclassification of weed as crop towards right in image

VII. CONCLUSION

In summary, weed detection using deep learning algorithms is a significant advancement in precision agriculture, offering an automated, precise, and effective solution to one of the most challenging issues in farming. These systems use convolutional neural networks (CNNs) and advanced imaging technologies to distinguish between weeds and crops in real time. This lessens the need for chemical pesticides and enables precise weed control. In addition to saving farmers money on labor and running costs, this promotes environmentally responsible practices. Deep learning-based weed detection systems are becoming a more crucial tool in contemporary farming to protect the environment and boost agricultural output while preserving production.

Looking forward, the prospects for weed detection through deep learning methodologies are extensive and encouraging. As technological advancements continue, we anticipate enhancements in model precision, allowing for the identification of a wider range of weed types and crop types and improved functionality in more intricate environments. The incorporation of multispectral and hyperspectral imaging, in conjunction with Internet of Things (IoT) devices, will significantly bolster the system's capacity to assess crop health, identify pests, and manage soil conditions effectively. Furthermore, progress in robotics and autonomous vehicles will facilitate the development of fully automated weed management systems capable of operating continuously and independently in agricultural fields.

Deep learning's application in agriculture might go beyond weed identification as well. This technology could be repurposed to monitor other vital elements of crop health, including disease identification, nutrient deficiencies, and pest outbreaks. With continued research and innovation, these systems could evolve into essential components of a fully autonomous agricultural ecosystem, propelling the next wave of precision farming and addressing the increasing global demand for sustainable food production.

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