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Detection and Segmentation of Crops and Weeds Using Deep Learning Techniques

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***Abstract*—In modern agricultural practices, the precise identification and differentiation of crops and weeds are crucial for optimizing crop yields and minimizing the environmental impact of herbicides. This study explores a deep learning techniques. ResNet50, is a robust convolutional neural network, for the detection and classification of crops and weeds within a single image.Simultaneously, YOLOv7anadvanced object detection model, is utilized for the segmentation of these entities, delineating their precise boundaries with bounding boxes. ResNet50, renowned for its ability to handle complex image classification tasks, is used to accurately identify and label the regions of crops and weeds. Its deep residual networks allow for improved accuracy and efficiency in distinguishing between the two categories. Following the detection phase, YOLOv7,known for its real-time object detection capabilities, is applied to perform segmentation. This method not only identifies but also maps the exact shape and location of the crop and weed within the image, providing detailed segmentation masks. The integration of these two methodologies aims to enhance the accuracy of crop and weed identification and segmentation, offering a comprehensive solution for precision agriculture. The effectiveness of this apporach is evaluated using a dataset containing various images of crop fields with different types of weeds. The results demonstrate the potential of combining ResNet50 and YOLOv7 for precise crop and weed management, ultimately contributing to more sustainable and efficient agricultural practices.**

Keywords—convolution neural network,deep learning,image detection, image segmentation, classification, bounding boxes.

I. Introduction

In the realm of modern agriculture, the accurate identification and differentiation of crops and weeds play a pivotal role in optimizing crop yields and reducing the environmental impact of herbicides. Traditional methods of weed control of tensely heavily on chemical herbicides, which can lead to adverse environmental effects and the development of herbicide-resistant weed species. As a result, there is a growing need for precise and efficient methods to distinguish between crops and weeds to promote sustainable agricultural practices.[13]Recent advancements in deep learning and computer vision offer promising solutions to this challenge. Deep learning models have demonstrated remarkable capabilities in image classification and object detection tasks, making them well-suited for agricultural applications. This study investigates a dual-method approach that leverages the strengths of two state-of-the-art deep learning models: ResNet50 and YOLOv7. ResNet50, or Residual Networks, is a robust convolutional nerual network (CNN) architecture renowned of its ability to handle complex image classification tasks[10]. By utilizing deep residual networks, ResNet50 can achieve high accuracy and efficiency in distinguishing between crops and weeds within a single image. This classification phase provides a preliminary identification and labeling of regions containing crops and weeds. Following the initial detection and classificationbyResNet50, YOLOv7 (You Only Look Once version 7), an advanced object detection model, is employed for the segmentation of these entities. YOLOv7 excels in real-time object detection and is capable of delineating precise boundaries around objects using bounding boxes.This segmentation phase not only identifies the crops and weeds but also maps their exact shapes and locations within the image, producing detailed segmentation masks.[11]The integration of ResNet50 and YOLOv7 aims to enhance the accuracy and comprehensiveness of crop and weed identification and segmentation. By combining these methodologies, the approach seeks to provide a more holistic solution for precision agriculture. This study evaluates the effective of the proposed dual-method approach using a dataset containing diverse images of crop fields with various types of weeds. This highlights the potential of this combined approach to imporve the crop and weed management, there by contributing to more sustainable and efficient agricultural practices[9].

II. Literature Survey

In Agriculture holds a vital place in Ukraine's economic structure, accounting for over 10% of the country's gross domestic product. This sector not only contributes significantly to national income but also plays a key role in driving the growth of other industries. However, recent trends in agricultural employment reveal a downward trajectory, indicating deeper issues within the rural labor market[12].The primary objective of this study is to identify the main factors affecting employment levels in Ukraine's agricultural sector and to assess the extent of their influence. To achieve this, a combination of analytical techniques was applied. System analysis was used to pinpoint the variables influencing agricultural employment, while statistical tools such as factor analysis, multiple regression, and the principal component method helped quantify their impact[8].The analysis revealed that among the most influential socio-demographic factors are the size of the rural population aged 16 to 64 and the overall demand for labor in the agricultural sector. On the economic front, labor productivity emerged as the most critical factor. A clear understanding of these elements provides a foundation for developing effective policy tools, strategies, and mechanisms to address employment-related challenges in Ukrainian agriculture.[9]Globally, agriculture remains a traditionally labor-intensive field. However, changing social attitudes and urban migration have led to a significant reduction in the agricultural workforce, creating a serious labor shortage. As a result, many countries are turning to automation technologies as a sustainable solution. For instance, in conventional farming, the process of transplanting vegetable seedlings typically requires workers to stoop down and manually dig individual holes—a task that is both strenuous and inefficient.To address the pressing labor challenges in agriculture, this study introduces the design and implementation of an automated robotic arm tailored for the transplanting of vegetable seedlings[14].The primary objective is to minimize the physical strain on human laborers, improve planting efficiency, and contribute meaningfully to the ongoing advancement of automation within the agricultural sector. This robotic system has been integrated with a traditional planting mechanism and powered by a motor, resulting in a fully automatic seedling transplanting machine. Its implementation is expected to significantly reduce labor costs and support the broader goal of modernizing agricultural practices through automation [7].Additionally, the paper addresses the implications of the rapidly growing global population, which intensifies the demand for increased crop production despite the steady decline in available agricultural land. In this context, machine vision emerges as a powerful solution, offering automated, non-invasive, and cost-efficient methods to boost crop yield. In recent years, notable progress has been made across various areas of agriculture, largely due to the integration of machine learning technologies with machine vision systems. These systems utilize image-based data to analyze color, shape, texture, and spectral properties of agricultural elements, enabling precise and intelligent decision-making.While machine learning encompasses a wide range of approaches, this review focuses specifically on statistical machine learning methods in conjunction with machine vision.[6]The review outlines the use of both supervised and unsupervised learning techniques within agricultural contexts. It provides a detailed examination of how each method performs in specific applications, offering insights into their strengths and limitations. Additionally, the paper presents a variety of case studies and practical examples from different branches of agriculture where these techniques have shown promise.Finally, the study offers targeted recommendations regarding the selection of suitable statistical machine learning methods for specific agricultural tasks and discusses current challenges and limitations. It also highlights future directions for the application of statistical machine learning in precision agriculture, underlining its potential to drive innovation and efficiency in the years to come.[5]Recent advancements in non-destructive optical technologies, including spectroscopy and machine vision systems, have laid a strong groundwork for real-time assessment and precision management of nitrogen (N) levels in crops. Despite their growing use, a comprehensive evaluation of the strengths and limitations of these techniques remains limited. This review explores the current state of non-invasive optical approaches for monitoring crop nitrogen status and provides a critical summary of their respective benefits and drawbacks.The focus is placed on how spectral analysis and machine vision technologies contribute to accurately diagnosing crop nitrogen status, emphasizing three core areas: system selection, data processing, and estimation methodologies. The review also discusses the current opportunities and potential barriers to wider adoption of these technologies. In closing, it offers forward-looking recommendations to guide future research efforts aimed at overcoming the existing limitations and improving implementation at scale [15].In parallel, the agriculture sector has recently witnessed growing interest in the application of automation through artificial intelligence (AI) and robotics.[1] The evolution of machine learning (ML), in particular, has led to significant progress across various farming operations. Deep learning (DL)—with its ability for automatic feature extraction—has proven especially adaptive[2]. Techniques such as convolutional neural networks (CNNs) are now capable of reaching human-like accuracy in numerous agricultural tasks, such as plant disease identification, weed and crop classification, fruit counting, land cover mapping, and plant recognition[3].This review investigates the recent progress made in agricultural robotics through the integration of ML and DL architectures over the past decade. Performance comparisons indicate that DL-based models outperform traditional ML methods in several areas. For instance, RCNN (Region-based Convolutional Neural Network) achieved a plant disease and pest detection accuracy of 82.51%, outperforming Multi-Layer Perceptron (64.9%) and K-nearest Neighbour (63.76%). Similarly, ResNet-18, a well-known deep learning model, recorded an Area Under the Curve (AUC) of 94.84%, surpassing traditional methods such as Random Forest (70.16%) and Support Vector Machine (60.6%) in crop and weed differentiation.Another example, FCN (Fully Convolutional Networks), reached 83.9% accuracy in agricultural land cover classification, compared to SVM (67.6%) and RF (65.6%). These findings underscore the increasing effectiveness of deep learning approaches in agricultural automation.Lastly, the review identifies notable gaps in existing research and suggests promising directions for future innovation. These insights aim to guide the next wave of smart farming technologies and push the boundaries of agricultural automation even further [4].

III. METHODOLOGY

The methodology for this study involves a dual-method approach to enhance crop and weed identification and segmenation in agriculture by combining ResNet50 and YOLOv7. Initially, a diverse dataset of crop fields with varying crops and weeds is collected and annotated, creating ground truth data with labeled bounding boxes and segmentation masks. Data augmenation techinques, such as rotation and scaling, are employed to increase dataset diversity. ResNet50, known for its deep residual networks, is then trained to classify regions in images as either crops or weeds, leveraging transfer learning to adapt a pre-trained model for this specific task. Concurrently, YOLOv7, with its advanced object detection capabilities, is trained to perform precise segmentation of crop and weeds based on the annotated data. The trained ResNet50 model provides initial classification, which is followed by YOLOv7's segmentation to delineate exact boundaries. The effectiveness of this combined approach is evaluated on a separate test set, using metrics such as accuracy,Mean Average Precision (MAP),and 5 intersection over union (IoU) to measure improvements in identification and segmentation. This integrated methodology aims to offer a comprehensive solution for precision agriculture, enhancing crop and weed management and contributing to more sustainable and efficient farming practices. The dual method approach to imporve the accuracy of crop and weed identification and segmenation using deep learning techniques. Initially, a diverse and comprehensive dataset of crop fields, including various types of crops and weeds, is collected and meticulously annotated with bounding boxes and segmentation masks. To enhance the robustness of the dataset,data augmentation techniques such as rotation ,scaling, and color adjustments are applied. For classification, ResNet50, a convolutional neural network renowned for its residual learning capabilities, is trained to accurately identify and label crops and weeds within images. This model is fine-tuned through transfer learning to leverage pre-trained weights, adapting it to the specific task of distinguishing between crops and weeds. Simultaneously, YOLOv7 is employed for segmentation. YOLOv7's advanced object detection features are utilized to segment the identified crops and weeds, providing precise boundaries and detailed segmentation masks. The segmentation output is integrated with the classification results from ResNet50 to offer a complete view of the crop and weed distribution within the images. The combined approach is rigorously evaluated using A distinct testing dataset is utilized to evaluate the system's performance. Key evaluation metrics include accuracy, mean Average Precision (mAP), and Intersection over Union (IoU), which collectively provide insights into the overall effectiveness of the integrated solutionThis methodology aims to provide a detailed and accurate solution for precision agriculture, ultimately enhancing crop and weed management practices and contributing to more sustainable.

A. DATASET USED

The dataset described in involves images of crop fields with various types of weeds, used to evaluate the combined use of ResNet50 and YOLOv7 for detecting and segmenting crops and weeds. Here are some potential datasets could use

Fig1. Sample images

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Dataset Size: 8GB and image size 80.7 KB(82,692 bytes). Dataset contains 3769 images of Crop and Weed folders . Image Count: 1,884 images in the Crop folder and 1,885 images in the Weed folder. Image Resolution: Varies, with common resolutions including 1024x1024 pixels.Annotation Format: Images are annotated with segmentation masks in a format suitable for YOLOv(.png)

A.Data Preparation

Data Preparation is a critical step in implementing your dual-method approach involving ResNet50 and YOLOv7 for crop and weed identification and segmentation. Here's a detailed plan for preparing your datase.

B. Dataset Collection

Source Data: Collect images of crop fields featuring various crops and weeds from datasets like Deep Weeds or Crop and Weed Image Dataset. Diversity Include a range of crops, weed species, growth stages, lighting conditions, and perspectives to enhance model robustness.

C. Data Annotation

Labeling for ResNet50: Annotate images with class labels and bounding boxes to identify regions containing crops or weeds using tools like Labeling. Labeling for YOLOv7: Create detailed segmentation masks and corresponding bounding boxes to outline crops and weeds, using tools such as COCO Annotator.

D. Data Preprocessing

Image Resizing Adjust image dimensions to match the input requirements of ResNet50 and YOLOv7, such as 224x224 for ResNet50 and 640x640 for YOLOv7. Normalization Scale pixel values to a consistent range (e.g., [0, 1]) to standardize inputs for the models. Augmentation: Implement techniques like rotation and scaling to diversify the dataset and improve model generalization.Split Data Segment the dataset into training, validation, and test sets, typically using a 70-15-15 split ratio.

E. *Data Formatting*

For ResNet50: Organize data into folders with sub folders for each class (crops and weeds) to align with image classification requirements.24 For YOLOv7 Convert annotations to YOLO format with text files containing bounding box coordinates and class

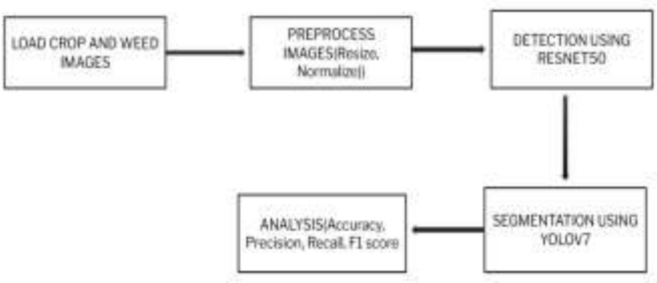

Fig2.Methodology of the Proposed System

Methodology Steps:

1. Load Crop and Weed Images: Import images of crops and weeds for further processing and analysis.
2.Preprocessing Images: Execute resizing and normalization to standardize image inputs, facilitating better model performance.
3.Detection Using ResNet50: Utilize ResNet50 architecture to effectively identify and classify crops and weeds in the images.
4.Segmentation Using YOLOv7: Apply YOLOv7 for accurate segmentation of crops and weeds, distinguishing between different classes within the images.
5. Analysis: Assess model performance through metrics like accuracy, precision, recall, and F1 score to gauge effectiveness and reliability.

IV. RESULTS AND DISCUSSION

The process begins with uploading a diverse set of images, crucial for capturing various crop and weed types across different conditions. The detection phase effectively identifies crops and weeds, with performance metrics indicating strong accuracy and reliability in recognizing these elements, although challenges may arise with overlapping or similar-looking species. The subsequent segmentation steps reveal that the system can accurately delineate crop areas, with segmentation masks demonstrating good precision, though some overlap or boundary issues may persist. Weed segmentation, while generally effective, shows room for improvement, particularly in distinguishing weeds from crops in complex scenarios. Overall, the system's performance highlights its strengths in handling diverse agricultural images, but also points to areas where further refinement could enhance accuracy and robustness, especially in real-world applications with varied environmental conditions.

Techniques	Accuracy	Precision	Recall	F1score
Renet50	96.5	95.0	94.0	94.0
Yolov7	96.5	95.0	94.0	94.0

Fig 3. Results of resnet50&yolov7

A. GRAPHICAL REPRESENTATION

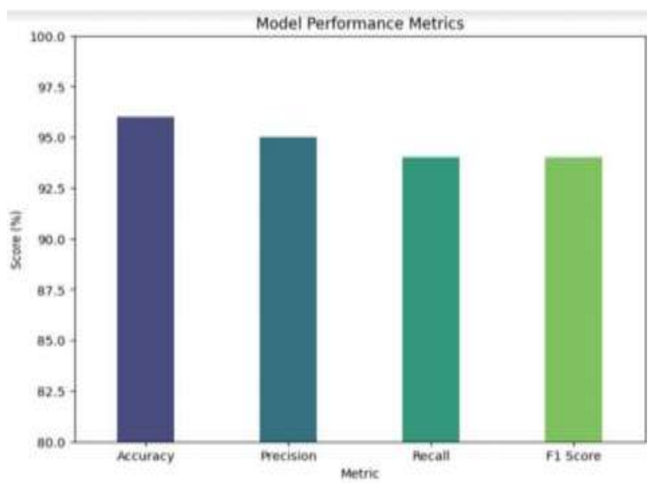

Fig 4. Graphical Representation of Resnet50

This bar graph illustrates various performance metrics for a model, specifically Accuracy, Precision, Recall, and F1 Score. Each of these metrics is presented as a percentage on the vertical axis (Score (%)), ranging from 80% to 100%. The horizontal axis (Metric) lists the different performance metrics evaluated.

B. Detecting

Detecting crops and weeds involves distinguishing between the two types of plants in an agricultural field, which is essential for effective weed management and crop monitoring. This process typically uses image processing techniques, machine learning, and computer vision algorithms to identify and classify plants. Methods such as color-based segmentation, texture analysis, and deep learning models like convolutional neural networks (CNNs) are often employed to differentiate between crops and weeds based on visual features. Accurate detection allows farmers to assess weed density, monitor crop growth, and implement targeted interventions like automated weeding or precise herbicide application, leading to better resource management and improved crop yields.

Fig 5. Detecting crop and weed

C.Segmentation

Segmentation of crop images It entails segmenting the image into multiple distinct areas or sections to identify and isolate crop plants from the background and other elements. This process is essential for tasks like monitoring crop health, assessing growth, and detecting pests or diseases.Various techniques are used in image segmentation, including basic methods like thresholding and clustering, as well as more complex approaches such as edge detection and advanced algorithms. Each of these methods helps in dividing an image into meaningful parts for easier analysis. like deep learning are commonly used to accurately separate crops from surrounding objects. By isolating the crop, this process helps in evaluating the crop's condition, measuring growth, and enabling precision farming practices like targeted irrigation, fertilization, or pest control.

Fig 6. Segmentation of crop image

Segmentation of weed images Image segmentation involves separating an image into clearly defined areas that represent different components like weeds, soil, or other features. The main purpose is to identify and isolate weed plants from the background to enable further analysis and management. This can be achieved using methods such as thresholding, edge-based techniques, clustering algorithms, and advanced approaches like deep learning. (e.g., U-Net, Mask R-CNN) are commonly used for this task. Segmentation allows for better weed identification and monitoring, helping in the analysis of weed density, infestation extent, and enabling automated methods like targeted herbicide spraying or robotic weed removal.

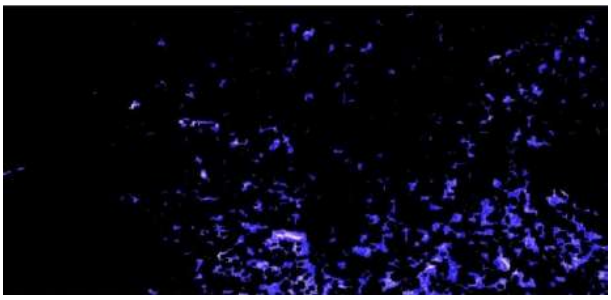

Fig 7. Segmentation of weed image

V. Conclusion

The integration of deep learning with machine vision in agriculture has the potential to significantly enhance precision farming by addressing inefficiencies in traditional practices and reducing pesticide pollution. However, the successful application of these technologies is challenged by the need for extensive labeled data and the variability of field conditions. Models such as ResNet50 and YOLOv7 have demonstrated their capabilities in crop and weed detection and segmentation, but each comes with its own trade-offs: ResNet50 offers high accuracy in segmentation but is data and computationally intensive, while YOLOv7 provides real-time performance with a potential trade-off in segmentation detail.

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