INTERNSHIP PROJECT REPORT

On

WEED DETECTION USING AI

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BONAFIED CERTIFICATE

This is to certify that this project report entitled **“WEED DETECTION USING AI”** submitted to National Institute of Technology, Warangal and National Institute of Technology, Srinagar, is a bonafide record of work done by **“”** under my supervision from **“20 May 2023”** to **“20 Jun 2024”**

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Date: 19 June 2024

DECLARATION

This is to declare that this report has been written by us. No part of the report is plagiarized from other sources. All information included from other sources have been duly acknowledged. We aver that if any part of the report is found to be plagiarized, we are shall take full responsibility for it.

ACKNOWLEDGEMENT

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ABSTRACT

Weeds impact agriculture by competing with crops for resources. This project develops an AI-based system to detect weeds and recommend pesticides using CNNs like YOLOv5 and Faster R-CNN. A large, labeled image dataset improves model performance. The system suggests appropriate pesticides using a rule-based or machine learning model. A user-friendly application provides immediate analysis and recommendations from field images. This tool enhances weed management, reduces herbicide use, and supports sustainable farming.

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INTRODUCTION

1.1 Background to the study

Weed detection is vital in modern agriculture to manage unwanted plants competing with crops. Traditionally, it involved manual scouting and chemical herbicides, which are labor-intensive and environmentally harmful.

Technological Advancements

Recent innovations have transformed weed detection:

1. Remote Sensing: Uses satellite imagery, drones, and aircraft for large-scale field monitoring, differentiating crops and weeds via spectral signatures.

2. Machine Learning and AI: Algorithms like CNNs identify weeds from images by analyzing shape, color, and texture.

3. Robotics: Autonomous robots detect and remove weeds using sensors and cameras, applying mechanical tools or precision spraying.

4. IoT and Smart Farming: Integrates various sensors for real-time data analysis, optimizing weed management and herbicide application.

Benefits

- Efficiency: Reduces time and labor for weed control.

- Precision: Enhances accuracy in weed identification, minimizing crop damage and herbicide use.

- Sustainability: Less reliance on herbicides supports environmental health.

Challenges

- Cost: High initial investment can be a barrier for small-scale farmers.

- Complexity: Requires technical expertise to implement and maintain.

- Adaptability: Needs to work with different crops, weed species, and conditions.

Future Directions

Future research aims to improve AI models, develop cost-effective solutions for smallholders, and integrate multi-source data for better weed management.

1.2 Problem statement:

Develop cost-effective, accurate, and sustainable weed detection technologies for modern agriculture, focusing on remote sensing, machine learning, robotics, and IoT, while ensuring accessibility for small-scale farmers.

1.3 Aim of the study:

To develop an AI-based system for accurately detecting weeds andrecommending appropriate pesticides to optimize crop yield.

1.4 Objectives of the study

- Develop a reliable weed detection model using deep learning techniques.
- Create a comprehensive image dataset for training and validating the model.
- Implement robust preprocessing techniques to enhance data quality.
- Integrate a pesticide recommendation system based on weed detectionresults.
- Develop a user-friendly interface for farmers to use the system.

2.LITERATURE SURVEY

Wang A., Zhang W., Wei X.A, the authors summarize different problemsand provided solutions to weed classification using IP and DL techniques. Four basic steps of classification, such as pre-processing, imagesegmentation, feature extraction (biological morphology, spectral feature, visual texture, spatial context), and classification (convolutional machine learning), have been discussed in detail. Some challenges like leaf overlapping, light variation, and stages of plant growth and their solutions were discussed. Semi-supervised learning techniques have been proposed by the authors to improve the current performance of the aforementioned techniques.

Li N., Zhang X., Zhang C., Ge L., He Y., Wu X, the challenges faced by vision-based plant and weed detection and their solutions have been discussed. Two main challenges of weed detection are the light problems, i.e., the algorithm may work differently due to the presence of light, and discrimination between crop and weed, i.e., sometimes both may look similar. Shading or artificial lighting can be used to control the variation of natural light, or image processing techniques like segmentation of background (and then converting the image into Grayscale) can be used to tackle this problem. For the second problem, different types of IP-based classification techniques were discussed, which were based on shape, texture, height, and DL. The authors discussed the comparison of traditionalclassification and DL methods. They also highlight the application of online cloud databases as an important future direction to further improve the recognition or detection of weeds and crops.

Perhaps the paper most related to our work is, the authors review DL approaches to weed detection based on four steps: data acquisition, dataset preparation, weed detection, and localization and classification of weeds in crops. They develop a taxonomy for DL applications specifying the weed andcrop type, the DL architecture applied, and the IP technique. In data acquisition, they detail how data or images have been collected, for example, using digital cameras, public datasets, camera moving vehicles, etc. They discuss and classify 19 public datasets according to several standard parameters, such as modality, dataset size, etc. In the data preparation phase, after acquiring images using different sources, images are prepared for training and testing, which includes different techniques, for instance, image processing, image labelling, image augmentation, etc. Weed detectionis classified as a plant-based classification or a weed mapping approach. In the former, every plant needs to be localized in an image before detection, and in the latter, the density of the presence of weed in an image is used to detect that weed. In the last step, the authors discuss different algorithms, such as CNN, YOLO, FCN, GCN, and hybrid models, along with learningmethods, such as supervised, unsupervised, and semi-supervised.

3.METHODOLOGY

3.1 Project Description:

- **Weed Detection Using YOLOv5**

Overview

The objective of this project is to develop an efficient and accurate weed detection system using YOLOv5 (You Only Look Once version 5), a state-of-the-art object detection algorithm. This system aims to assist in precision agriculture by identifying and localizing weeds in crop fields, thereby enabling targeted weed management practices that can improve crop yields and reduce the usage of herbicides.

Objectives

1. Develop a Dataset: Collect and annotate a diverse dataset of images containing various types of weeds and crops.
2. Model Training: Train a YOLOv5 model on the annotated dataset to detect and classify weeds.
3. Model Evaluation: Evaluate the performance of the trained model using standard metrics such as precision, recall, and mAP (mean Average Precision).
4. Deployment: Deploy the trained model in a real-time weed detection system that can be used in agricultural fields.
5. Performance Optimization: Optimize the system for speed and accuracy to ensure real-time processing capabilities.

Scope

The scope of this project includes:

- Data collection and annotation.
- Model training and hyperparameter tuning.
- Development of a deployment pipeline.
- Field testing and validation.
- User interface design for ease of use by farmers and agricultural technicians.

Methodology

1. Data Collection and Annotation:
   - Collect images from various sources, including public datasets and field photography.
   - Annotate the images using labeling tools to create bounding boxes around weeds and crops.

2. Model Training:
   - Preprocess the dataset to match the input requirements of YOLOv5.
   - Train the YOLOv5 model using annotated images.
   - Fine-tune the model by adjusting hyperparameters to improve detection accuracy.

3. Model Evaluation:
   - Split the dataset into training and validation sets.
   - Evaluate the model using the validation set.
   - Calculate performance metrics such as precision, recall, F1-score, and mAP.

4. Deployment:
   - Develop a real-time detection system using the trained YOLOv5 model.
   - Create a user interface to display detection results and statistics.

5. Performance Optimization:

- Optimize the model for faster inference without sacrificing accuracy.
- Implement techniques like model pruning and quantization if necessary.

Tools and Technologies

- YOLOv5: For object detection.
- Python: Primary programming language.
- PyTorch: For deep learning model development.
- OpenCV: For image processing.
- LabelImg: For data annotation.
- Flask: For developing the deployment pipeline.
- Docker: For containerizing the application.

Expected Outcomes

- A robust and accurate weed detection system capable of real-time processing.
- A significant reduction in herbicide usage due to targeted weed management.
- Improved crop yields through efficient weed control.
- A user-friendly interface for monitoring and managing weed detection.

By leveraging the capabilities of YOLOv5, this project aims to create an effective weed detection system that contributes to sustainable and efficient agricultural practices.

3.2. Steps of Implementation:

1.Data collection:

- **Gathering Crop and Weed Datasets**:

To train a YOLOv5 model for weed detection, you'll need a comprehensive dataset containing images of both crops and weeds. Here's a structured approach to gathering this data:

- **Field Data Collection**:
  - **Capturing Images**: Use drones, smartphones, or cameras mounted on agricultural machinery to capture images of crop fields. Ensure the images are taken under various lighting conditions and from different angles to enhance model robustness.
  - **Seasonal Variations**: Collect images throughout different seasons to include weeds and crops at various growth stages
  -
- **Public Datasets**:
  - Utilize existing public datasets from agricultural research institutions and open-source platforms. Examples include:
    - **PlantVillage**: Contains images of various crops and diseases, which can also include weed images.
    - **WeedID Dataset**: Specifically focused on different types of weeds

2. Creating Labels for the Data

1. **Annotation Tools**:
   - Use annotation tools like LabelImg, RectLabel, or VGG Image Annotator (VIA) to manually label the images. YOLOv5 requires labels in a specific format where each image has a corresponding text file containing class labels and bounding box coordinates.
2. **Labeling Guidelines**:

- **Class Labels**: Define clear class labels such as crop and weed. If distinguishing between different types of crops and weeds, create more specific class labels (e.g., corn, soybean, dandelion, thistle).
- **Bounding Boxes**: Draw bounding boxes around each instance of crops and weeds in the images. Ensure accurate and consistent labeling to enhance model performance.

3. **Automation and Semi-Automation**:
   - Use pre-trained models to assist in labeling. For instance, a pre-trained YOLOv5 model can be used to generate initial bounding boxes, which can then be refined manually.
   - Consider tools like Roboflow or Supervisely for efficient data annotation and management.

3. Data Augmentation

To improve the model's generalization capabilities, apply data augmentation techniques such as:

- **Flipping**: Horizontally and vertically flip images.
- **Rotation**: Rotate images by various angles.
- **Scaling**: Adjust the scale of the images.
- **Color Jittering**: Alter brightness, contrast, and saturation.
- **Cropping**: Randomly crop portions of images.

4. Data Splitting:

Divide the annotated dataset into training, validation, and test sets. A common split is 70% for training, 20% for validation, and 10% for testing. Ensure the split maintains a representative distribution of all classes.

5. Preparing the Dataset for YOLOv5

YOLOv5 expects data in a specific directory structure:

YOLOv5, a state-of-the-art object detection model, requires a specific directory structure and label format for training. This section provides a detailed guide on organizing your dataset and preparing the labels.

Images: Place the images in the respective train, val, and test folders.

Labels: Each image should have a corresponding label file in the same folder hierarchy

Label files should follow the YOLO format:

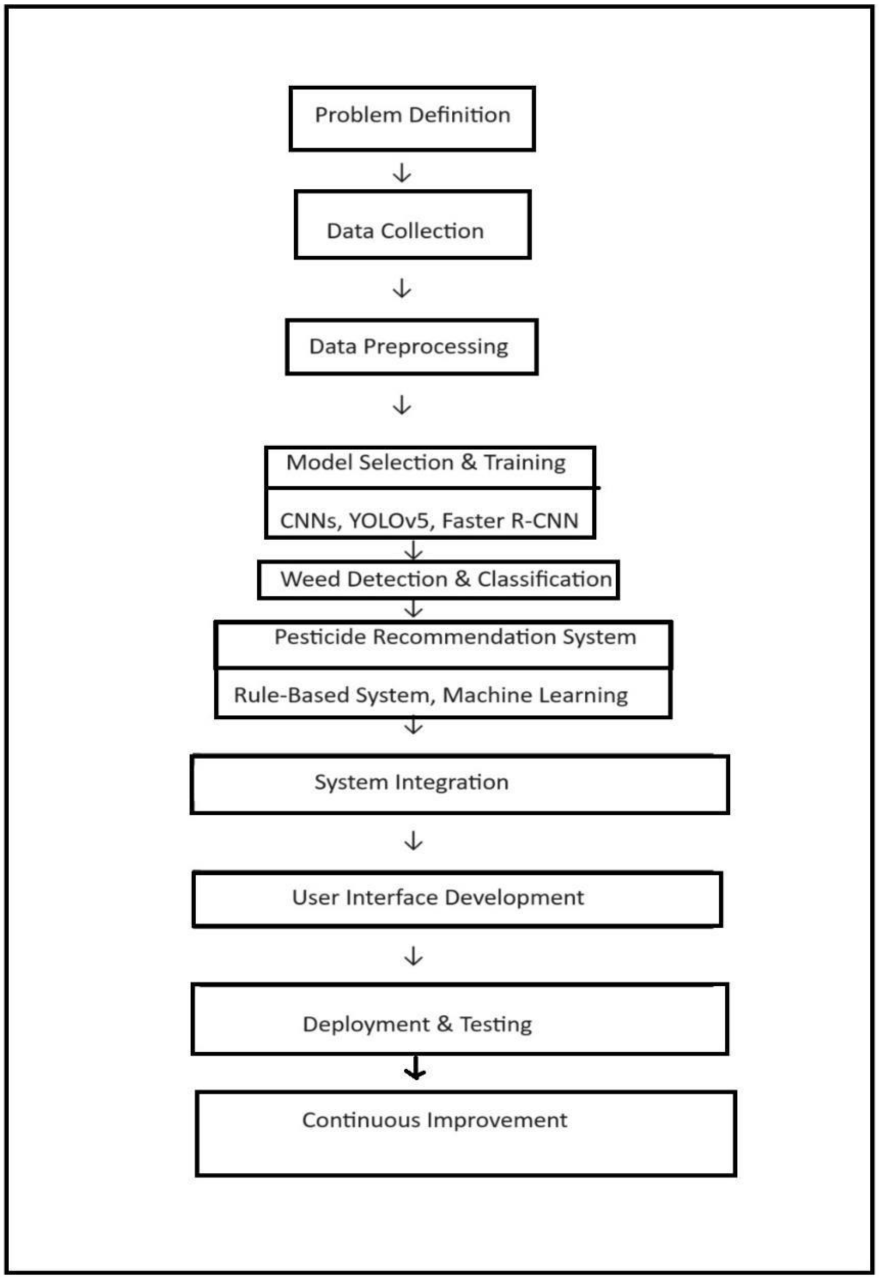
<class_id> <x_center> <y_center> <width> <height>

where the coordinates are normalized between 0 and 1.

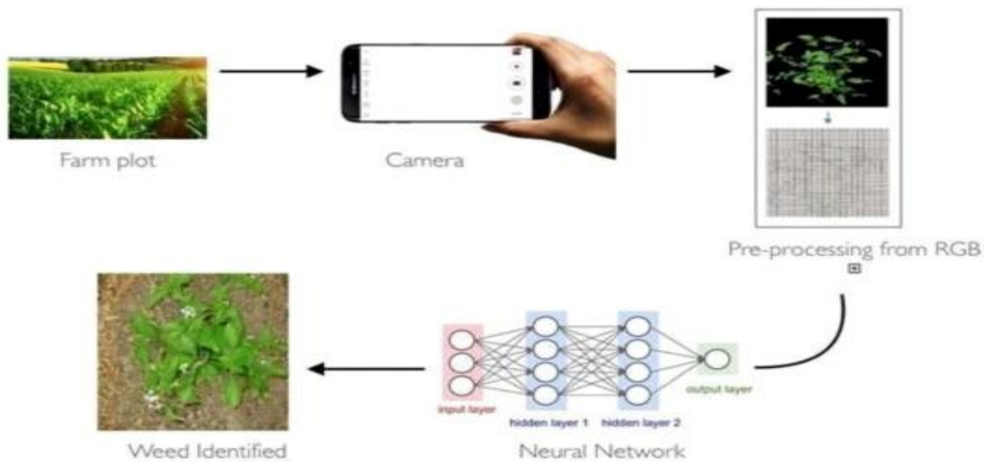
6. Conclusion:

Effective weed detection using YOLOv5 requires a well-prepared dataset with diverse and accurately labeled images. By following the steps outlined above, we can collect and annotate a high-quality dataset, apply necessary augmentations, and structure the data appropriately for training the YOLOv5 model. This will ultimately contribute to better weed management practices and more efficient agricultural operations.

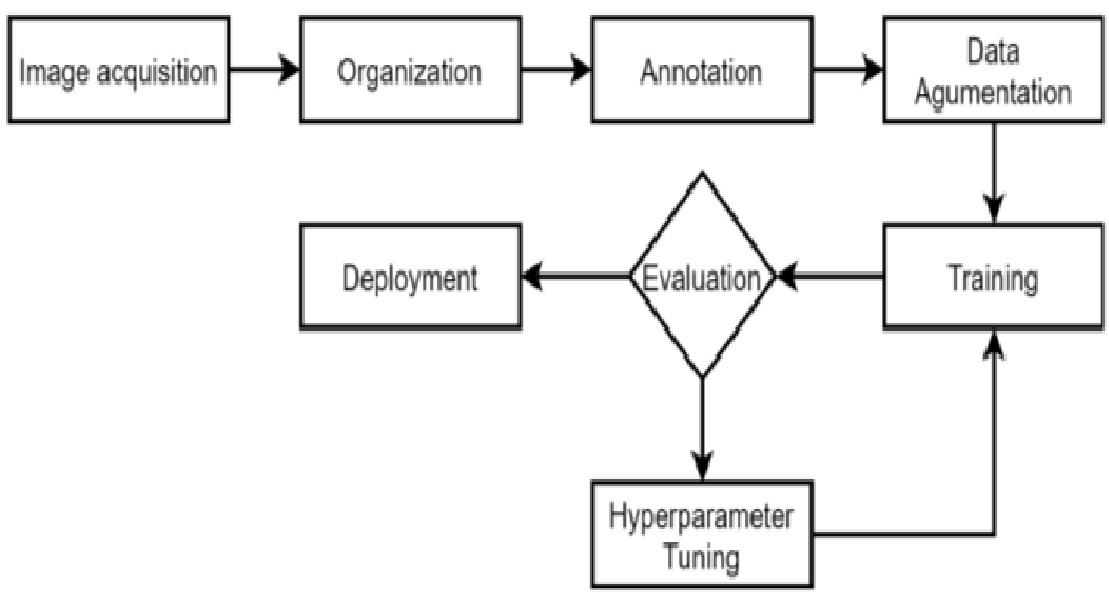
3.3. Flow chart:



3.4. Work flow:



3.5. Block Diagram



4.RESULT AND DISCUSSION

4.1. Experimental Setup

1. Data Collection

- Objective: To gather a comprehensive dataset of images containing crops and weeds under various conditions.

- Equipment:

  - High-resolution RGB cameras

  - Multispectral and hyperspectral cameras (optional for advanced detection)

  - Drones for aerial imagery

  - GPS devices for geotagging images

- Procedure:

  1. Capture images from different angles, heights, and times of day to account for variability in lighting and growth stages.

  2. Collect images in diverse weather conditions and across different seasons.

  3. Ensure images cover various types of crops and common weed species.

  4. Manually annotate the images, labeling regions of interest (crops and weeds).

2. Data Preprocessing

- Objective: To enhance image quality and prepare data for model training.

- Tools: Python libraries (OpenCV, PIL, scikit-image)

- Procedure:

  1. Image Enhancement: Adjust brightness, contrast, and remove noise.

  2. Normalization: Standardize image sizes and pixel values.

  3. Data Augmentation: Apply transformations such as rotation, flipping, and cropping to increase dataset diversity.

3. Feature Extraction and Model Development

- Objective: To develop and train an AI model for weed detection.
- Tools: TensorFlow, Keras, PyTorch
- Procedure:

1. Model Selection: Choose appropriate models (e.g., CNNs, YOLO, Faster R-CNN).

2. Feature Extraction: Use convolutional layers to automatically learn features from the images.

3. Model Training: Split the dataset into training, validation, and test sets. Train the model on the training set while tuning hyperparameters.

4. Loss Function and Optimization: Use appropriate loss functions (e.g., cross-entropy loss) and optimizers (e.g., Adam, SGD) to improve model performance.

4. Localization and Segmentation

- Objective: To accurately localize and segment weeds within images.
- Tools: Deep learning libraries with segmentation models (e.g., U-Net, Mask R-CNN)
- Procedure:

1. Region Proposal: Implement algorithms to propose potential weed regions within images.

2. Segmentation: Use pixel-wise segmentation models to delineate weed boundaries.

3. Validation: Evaluate segmentation accuracy using metrics like Intersection over Union (IoU).

5. Model Evaluation and Optimization

- Objective: To assess and enhance the model's performance.
- Tools: Evaluation metrics (accuracy, precision, recall, F1 score), visualization tools
- Procedure:

1. Performance Metrics: Calculate accuracy, precision, recall, F1 score, and IoU.

2. Model Tuning: Adjust hyperparameters, use techniques like cross-validation, and implement model regularization.

3. Error Analysis: Analyze misclassified instances to understand model weaknesses and make necessary improvements.

6. Real-Time Implementation

- Objective: To deploy the trained model for real-time weed detection.
- Equipment: Drones, autonomous robots, embedded systems (e.g., NVIDIA Jetson)
- Procedure:

1. Integration: Embed the trained AI model into hardware systems.
2. Real-Time Processing: Optimize the model for real-time inference (e.g., reducing latency, increasing frame rates).
3. Field Testing: Conduct field trials to assess the system's real-world performance and make adjustments as needed.

7. Documentation and Reporting

- Objective: To document the experimental setup, methodologies, results, and conclusions.
- Procedure:

1.Record Keeping: Maintain detailed records of all experimental procedures, data, and observations.

2. Reporting: Prepare comprehensive reports, including methodology, results, discussion, and recommendations.
3. User Guidelines: Develop guidelines for deploying and using the weed detection system in various agricultural settings.

Conclusion

This experimental setup outlines the comprehensive process required to develop, train, and deploy an AI-based weed detection system. By following these steps, the project aims to create a robust, efficient, and scalable solution for weed management in agriculture, ultimately contributing to improved crop yields and sustainable farming practices.

4.2. Representation of Data

1. **Dataset Visualization**

a. Sample Images: Displaying sample images of crops and weeds helps to provide a clear understanding of the dataset's content.

b. Annotated Images: Show images with annotated regions highlighting crops and weeds.

2. **Data Distribution**

a. Class Distribution: Pie charts or bar graphs showing the distribution of crop and weed images in the dataset

3. **Model Training Visualization**

a. Training and Validation Curves: Plotting loss and accuracy curves to monitor the training process.

4. **Model Evaluation**

a. Confusion Matrix: Visualizing true positives, false positives, false negatives, and true negatives.

b. Precision-Recall and ROC Curves: Evaluating model performance in distinguishing between classes.

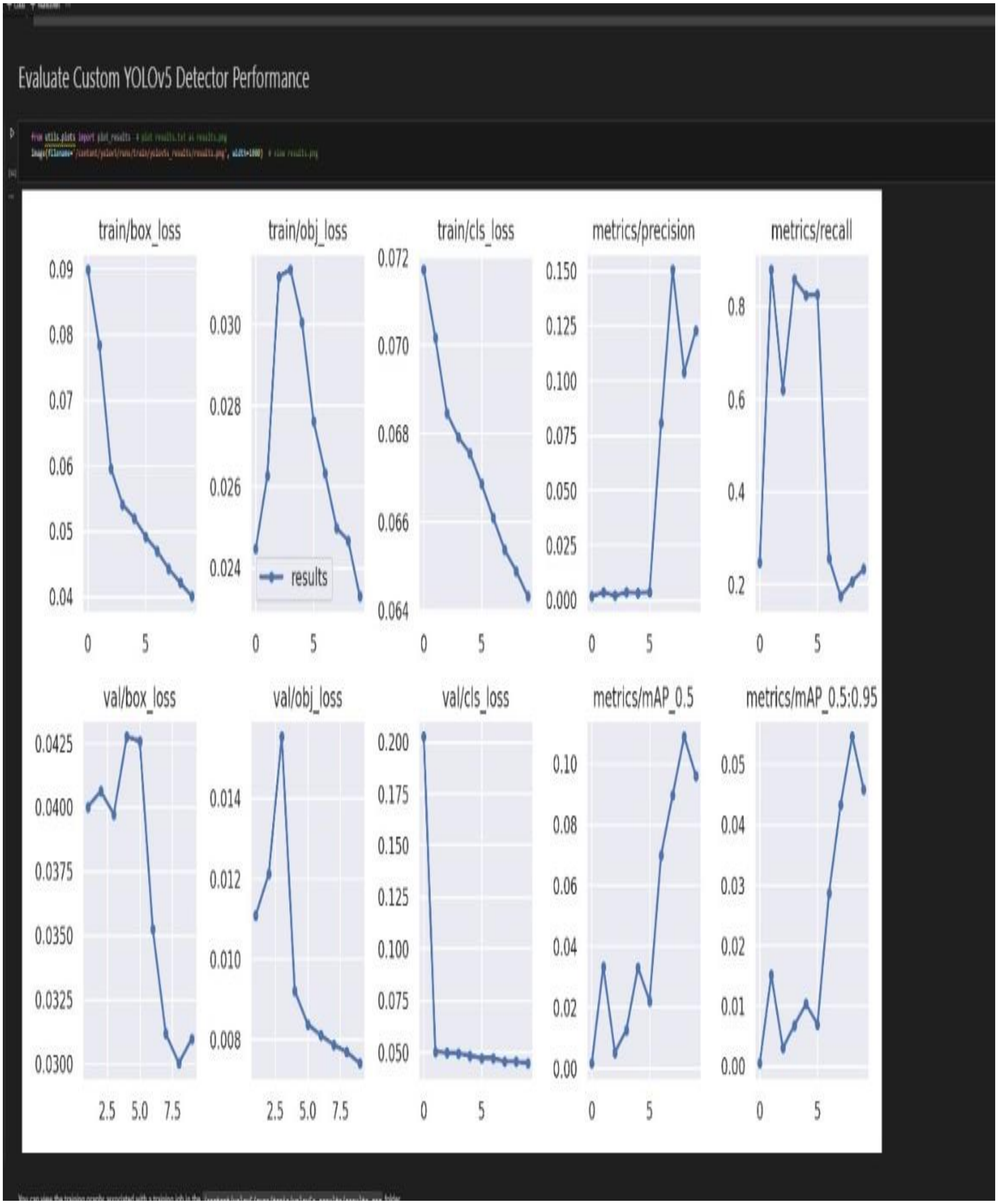
5. **Real-Time Implementation Visualization**

a. Detection Results: Displaying results of real-time weed detection on sample images or video frames.

1

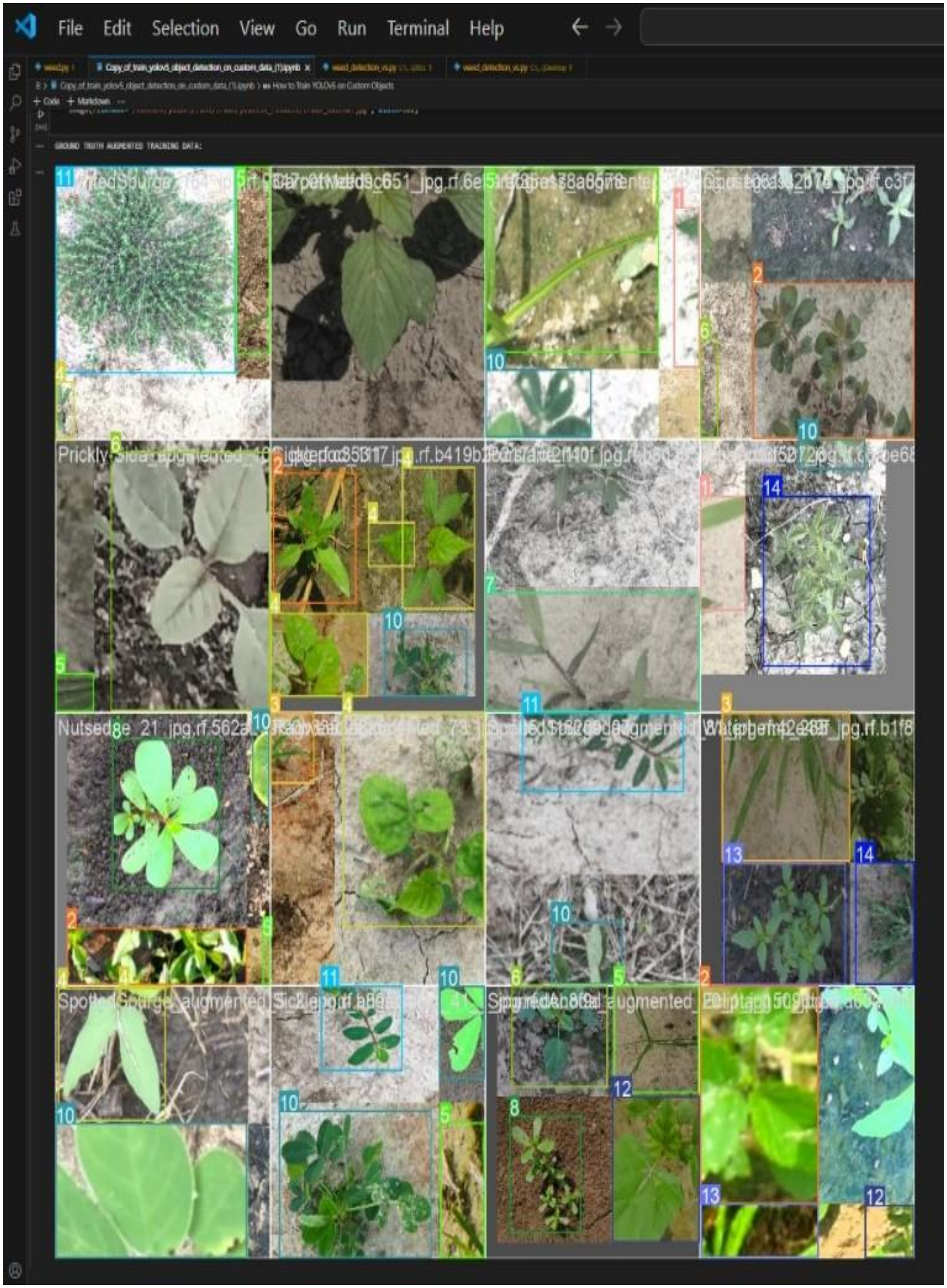
Outcomes:

Evaluate Custom Yolov5 Detector Performance:

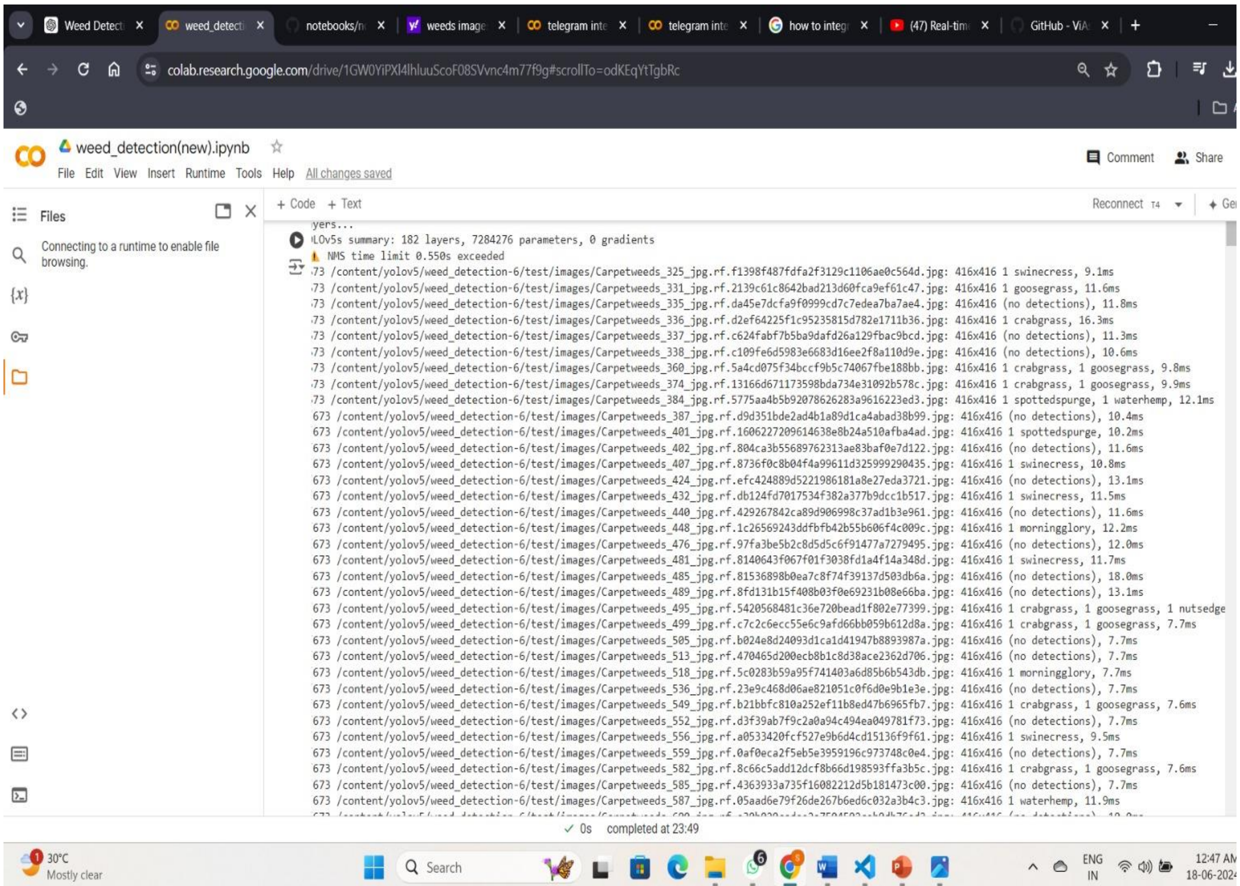


Visualizing our training data with labels:

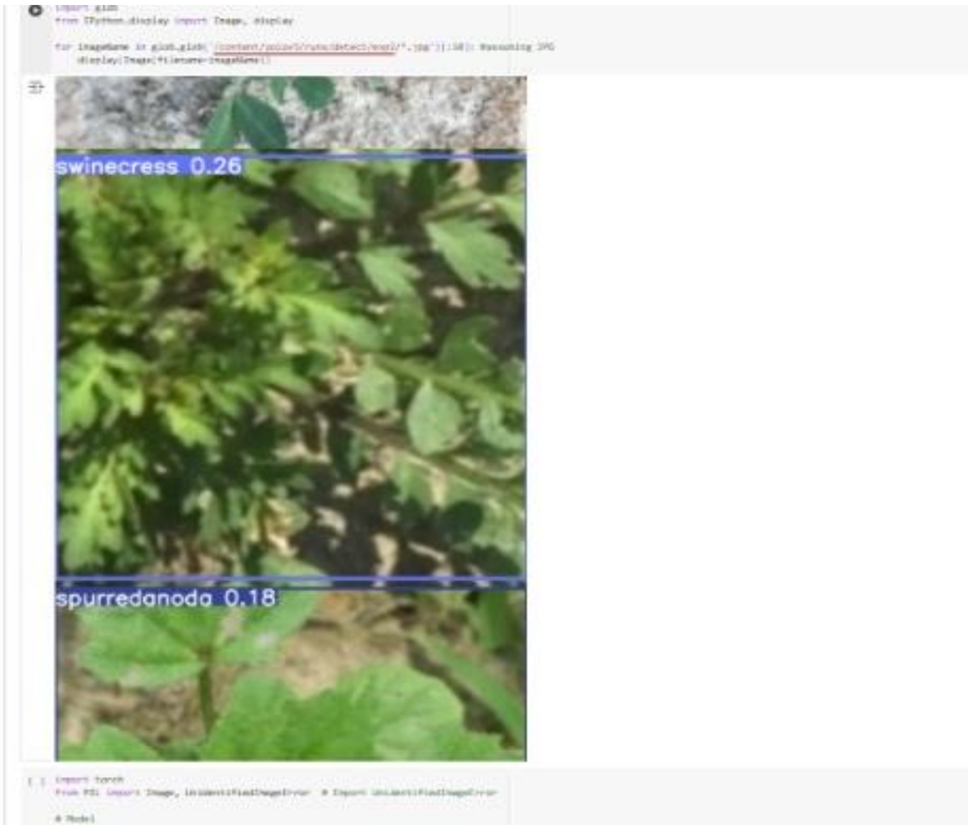
Ground truth and agumented training data:

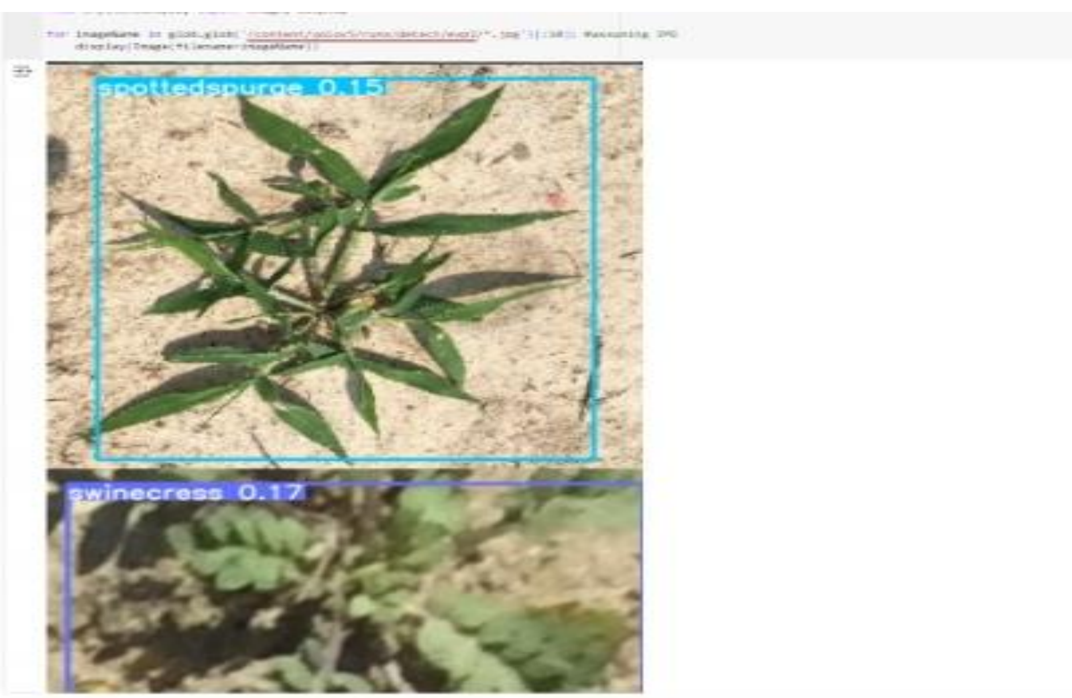


Running inference with trained weeds:



Detected weeds with Labels:


swinecress 0.26
spurredanoda 0.18


spottedspurge 0.15
swinecress 0.17

4. CONCLUSION AND FUTURE SCOPE

5.1. Conclusion

In conclusion, the integration of artificial intelligence (AI) for weed detection in agriculture represents a pivotal advancement, offering high efficiency and accuracy in distinguishing between crops and weeds. Through robust data collection, preprocessing, and model development, AI models such as convolutional neural networks (CNNs) have proven capable of effectively addressing challenges like varying lighting conditions and diverse weed species. By reducing dependence on manual labor and chemical herbicides, these systems promote sustainable farming practices while enhancing crop yield and health. Future research should focus on expanding datasets, refining real-time processing capabilities, and fostering collaborative efforts between AI experts and agricultural stakeholders to maximize the potential of automated weed management technologies.

5.2. Future Scope

The future scope for AI-based weed detection in agriculture is promising, with several avenues for further exploration and development:

1. Enhanced Model Performance: Continued research can focus on improving the accuracy and efficiency of AI models through advancements in deep learning architectures, such as integrating attention mechanisms and reinforcement learning techniques. This will enable models to adapt better to diverse environmental conditions and achieve higher precision in weed detection.

2**. Integration with IoT and Edge Computing**: Leveraging Internet of Things (IoT) devices and edge computing platforms can enhance real-time data acquisition and processing capabilities.

This integration will enable faster decision-making and proactive weed management strategies in the field, minimizing crop yield losses.

3**. Multi-sensor Fusion:** Incorporating data from multiple sensors, including RGB, multispectral, and thermal cameras, can provide richer information about crop and weed characteristics. Fusion of these data sources using machine learning algorithms can improve detection accuracy and enable more comprehensive agricultural monitoring.

4**. Autonomous Systems**: Developing autonomous robotic systems equipped with AI-powered weed detection capabilities will revolutionize weed management practices. These systems can autonomously navigate fields, identify weeds, and apply targeted treatments, reducing the need for human intervention and further optimizing resource use.

5. **Scalability and Adaptability**: Scaling AI-based weed detection systems across different crop types, geographical regions, and farming practices requires robust adaptation and generalization capabilities. Future research should focus on developing adaptable models and frameworks that can accommodate diverse agricultural settings.

6**. Data Sharing and Collaboration**: Establishing collaborative platforms and datasets for AI researchers, agronomists, and farmers will facilitate knowledge sharing and accelerate innovation in weed detection technologies. Open-access datasets and benchmarks will promote transparency and encourage the development of benchmarking standards for performance evaluation.

7. Environmental Impact Assessment: Conducting comprehensive studies to evaluate the environmental impact of AI-based weed detection systems compared to traditional methods will be crucial. Assessing factors such as chemical usage reduction, soil health preservation, and biodiversity conservation will support the adoption of sustainable agricultural practices.

8**. Policy and Adoption**: Addressing regulatory and policy considerations surrounding the deployment of AI in agriculture will be essential for widespread adoption. Collaborating with policymakers and industry stakeholders to establish guidelines and standards for AI applications in weed management can promote responsible and ethical use of technology.

In summary, the future of AI-based weed detection in agriculture lies in advancing technology capabilities, integrating with IoT and robotic systems, ensuring scalability and adaptability, fostering collaboration, assessing environmental impacts, and navigating regulatory frameworks. These efforts will collectively contribute to sustainable agriculture practices, improved crop productivity, and enhanced food security globally.

6.REFERENCES

1. Wang A., Zhang W., Wei X. A review on weed detection using ground-based machine vision and image processing techniques. *Comput. Electron. Agric.* 2019; **158**:226–240. doi: 10.1016/j.compag.2019.02.005. [CrossRef] [Google Scholar]

2. Castrignanò A., Buttafuoco G., Khosla R., Mouazen A., Moshou D., Naud O. *Agricultural Internet of Things and Decision Support for Precision Smart Farming.* Academic Press; Cambridge, MA, USA: 2020. [Google Scholar]

3. Cho S., Lee D., Jeong J. AE—Automation and Emerging Technologies: Weed–plant Discrimination by Machine Vision and Artificial Neural Network. *Biosyst. Eng.* 2002;**83**:275–280. doi: 10.1006/bioe.2002.0117. [CrossRef] [Google Scholar]

4. Aitkenhead M., Dalgetty I., Mullins C., McDonald A., Strachan N. Weed and crop discrimination using image analysis and artificial intelligence methods. *Comput. Electron. Agric.* 2003;**39**:157–171. doi: 10.1016/S0168-1699(03)00076-0. [CrossRef] [Google Scholar]

5 .J. Yu, A. W. Schumann, Z. Cao, S. M. Sharpe, and N. S. Boyd, "Weed detection in perennial ryegrass with deep learning
convolutional neural network," Frontiers in Plant Science, vol. 10, Oct. 2019, doi: 10.3389/fpls.2019.01422.

6. K. Osorio, A. Puerto, C. Pedraza, D. Jamaica, and L. Rodríguez, "A deep learning approach for weed detection in lettuce crops
using multispectral," AgriEngineering, vol. 2, no. 3, pp. 471–488, Aug. 2020, doi: 10.3390/agriengineering2030032.

6. O. Tiwari, V. Goyal, P. Kumar, and S. Vij, "An experimental set up for utilizing convolutional neural network in automated weed
detection," in 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), Apr. 2019, pp. 1–
6, doi: 10.1109/IoT-SIU.2019.8777646.

7. S. Umamaheswari, R. Arjun, and D. Meganathan, "Weed detection in farm crops using parallel image processing," in 2018 Conference on Information and Communication Technology (CICT), Oct. 2018, pp. 1–4, doi: 10.1109/INFOCOMTECH.2018.8722369.

8. S. Badhan, K. Desai, M. Dsilva, R. Sonkusare, and S. Weakey, "Real-time weed detection using machine learning and stereo-vision," in 2021 6th International Conference for Convergence in Technology (I2CT), Apr. 2021, pp. 1–5, doi: 10.1109/I2CT51068.2021.9417989.