WEED DETECTION USING MACHINE LEARNING

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ABSTRACT_ One of the main obstacles to crop productivity in recent years has been weeds. A difficult challenge for farmers, improving the quality of agricultural crops is being pursued with great vigour. Both the productivity and quality of the crops are being impacted by weeds. The reason the crops don't get enough water is because weeds take up the moisture in the soil, which prevents the crops from receiving enough water. Additionally, weeds make crop harvesting difficult. Toxic weeds frequently become mixed in with harvested crops which keeps farmers from receiving a fair price for their produce. Farmers evenly apply herbicides across the field to avoid weeds, but they are unsure of the specific kind of weed they are dealing with. The crops are severely damaged as a result. Herbicide spraying has an adverse effect on the environment, thus it's critical to have a solid understanding of weeds in order to control particular weeds. This paper's major goal is to use machine learning approaches to increase the accuracy of weed detection.

1.INTRODUCTION

Weeds are one of the biggest obstacles to crop productivity because they compete with crops for useful resources like water, nutrients, and sunlight [1]. Farmers don't get paid enough for their crops because of weeds. Pests, crop diseases, weeds, and other factors all reduce crop productivity. We will discuss the weed-related issues in this paper. Farmers have always struggled with weeds. In such a circumstance, considering the rising populace of the entire world, there is a need to find legitimate ways to control weeds to build the quality and efficiency of harvests. Since the customary period, the control of weeds has been finished in two ways

- Mechanical and Synthetic. Mechanical means where ranchers do weeding in a wide region for which they need legitimate supplies and ranchers likewise need to charge sensible cost for employing the types of gear. Aside from this, compound is another strategy that is utilized. Ranchers recruit compound specialists for weeds, and without being familiar with the weeds, sprinkle them on all the crops[2]. They also cause crop damage in addition to significantly polluting the environment [3]. The principal objective of this paper is to concentrate on the apparatuses and procedures involved by the analysts for ID and arrangement of weeds in their paper. As a result, they used technology to control weeds and increased crop production.

Current horticulture is turning out to be more dependent on PC based frameworks. New avenues for information collection and application in agriculture and other fields have emerged as a result of a variety of technological advancements. While precision agriculture with localization, such as the Global Positioning System (GPS), and other information technologies are becoming everyday tools for farmers, agriculture has not traditionally been the first to implement the latest technological discoveries. Tasks that were once solely performed by humans are increasingly being performed by automated machines. The new era's economic and environmental benefits are the impetus for introducing novel farming practices to boost production. Adjusting effective cultivating and protection of nature has generally been troublesome

2.LITERATURE SURVEY

XIAOJUN JIN 1 , JUN CHE2 , AND YONG CHEN1 [1]“ Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation”, Due to the variable plant spacing in vegetable plantations as well as crop, weed identification is more difficult than weed identification in crops. There has been minimal research on weed identification in vegetable plantations thus far. Traditional crop weed identification approaches have mostly focused on detecting weeds directly through traditional methods; nevertheless, weed species vary greatly. In contrast, this research provides a new method that blends machine learning and image processing technologies. The first step was to use a trained Center Net model to detect veggies and create bounding boxes around them. The remaining green objects that fell out of the boundary boxes were then labeled as weeds. As a result, the structure concentrates solely on detecting vegetables and weed. Furthermore, by reducing the amount of the training image data set and the complexity of weed detection, this technique can improve the weed identification performance and accuracy. A colour index-based segmentation was used in image processing to extract weeds from the backdrop. Genetic Algorithms (GAs) were used to determine and assess the colour index used, which was based on Bayesian classification error. The trained Center Net model had a precision of 95.6 percent, a recall of 95.0 percent, and an F1 score of 0.953 during the field test.

Pignatti S, Casa R.2 , Harfouche A.2 , Huang W. 3 , Palombo A. " Maize Crop And Weeds Species Detection By Using Uav perpectral Data",[2] In order to use precision agriculture techniques like patch spraying, it's necessary to monitor and map weeds within agricultural crops. Both environmentally and economically, precision and targeted weed eradication would be beneficial. When high spatial and spectral resolution data (i.e., from UAV platforms) is available, VNIR hyperspectral data can be a strong tool for performing effective weed monitoring and identification. This study investigates the spectral differences between crops and weeds in order to assess the potential of UAV hyper spectral data to distinguish maize crops from weeds and different types of weeds. During the 2016 growing season in Italy, UAV and field hyper spectral data were collected in a few corn fields. The results demonstrated that leaf chlorophyll and carotenoid content, extracted using spectral indices or inverting PROSAIL, may be used todistinguish between maize crops and weeds, as well as between weed species. The approach allowed for the measurement of crop/weed relative ground cover, which demonstrated a strong correlation with the obtained relative LAI values. A. J. Ir´ıas Tejeda1 F," Algorithm of Weed Detection in Crops by Computational Vision",

[3] The use of precision agriculture tools for weed management in crops was the subject of this study. Its focus has been on developing an image-processing system to detect the presence of weeds in a specific agricultural site. The main goal was to find a formula that could be used to create a weed detection system using binary classifications. The first step in image processing is to detectgreen plants in order to remove all of the soil from the image and reduce unnecessary data. Then, using different medium and morphological filters, and it focused on the vegetation, segmenting and removing unwanted data. Finally, the image has been labeled with items such that weed detection may be done using a threshold depending on the detection area. This algorithm establishes accurate weed monitoring and can be used in automated systems for weed eradication in crops, either through the use of specific-site automated sprayers or a weed cutting mechanism. Furthermore, it improves the efficiency of crop management operational operations by reducing the time spent searching for weeds across a plot of land and concentrating weed removal tasks on specific places for effective control. Om Tiwari ," An experimental set up for utilizing convolutional neural network in automated weed detection ", [4] : One of

the variables that contribute to a decline in agricultural yield is the presence of weeds in the crops. Weeds take up nutrients and water, causing the plant to lose weight and reduce the number of grains per ear and grain output. So, using new drone technology and deep learning in the field of convolutional neural networks, a way must be devised to detect these weeds in the field and then spray herbicide on them to completely eliminate them. The authors used a data set from the Indian Agriculture Research Institute (IARI) fields to apply a transfer learning technique to identify three weeds. Umamaheswari S," Weed Detection in Farm Crops using Parallel Image Processing", [5] Pesticides and fertilizers used in agriculture are utilized to educate the human community about environmental issues. Agriculture producers must meet an ever-increasing demand for food. Precision agriculture based on IoT has evolved to address environmental challenges and food security. Precision agriculture enhances production and quality while lowering costs and waste. Based on the collected photographs of the farm, we present a system to recognize and locate weed plants among the farmed agricultural crops. We also propose employing parallel processing on the GPU to improve the performance of the above system so that it may be used in real-time. The suggested method uses a real-time image of a farm as an input to determine the kind and position of weeds in the image. The proposed work uses photos of crops and weeds to train the system using a deep learning architecture that incorporates feature extraction and classification. The findings can be employed by an automated weed detection system for precision agriculture operations. YUHENG WANG, "image matching algorithm for weed control application in organic farming",[6] A weed control robot system in general consists of a weed classification and a weed destruction unit, both of which are physically separated from one another inside the robot, resulting in the weed distraction result. As a result, tracking of classified weed positions with a low- resolution VGA camera and a developed matching algorithm is an important step for weed destruction in organic farming with a robot system. In this paper, tracking is done with a low-resolution VGA camera and a developed matching algorithm. Because the robot's position can shift owing to a stone or other obstruction in its path, tracking is required. Also, modifications in the robot's pace resulted in weed destruction. Simulation and experimental results are used to summarize the performance of the picture matching technique

3.PROPOSED SYSTEM

Machine learning techniques will be used to detect weeds. The most important thing that will helpin weed detection is the weed related data which will be collected from different sources. After pre-processing the data, feature extraction techniques will be used to extract important features. Random Forest, Support Vector Machine and Hybrid approach will be used for weed detection which will give better results

3.1 ALGORITHM

The YOLO v3 detector in this situation is based totally on Squeeze net, and makes useof the characteristic extraction community in Squeeze internet with the addition of detection heads at theend. The second detection head is twice the size of the first detection head, so it is better able to detect small objects. In this technique you can specify any number of detection heads of different sizes based on the structure and size of the objects that you want to detect. The YOLO v3 detector makes use of anchor boxes on video and photographs anticipated using training data to have better preliminary priors similar to the form of data set and to assist the detector discover ways to predictthe boxes as it should be. For information about anchor boxes, see Anchor Boxes for Object Detection.

3.2 MODULES

1. Data Collection and Annotation Module

- **Data Collection**: Gather images of fields with and without weeds. Use drones, cameras,or existing datasets.
- **Annotation**: Label the weeds and crops in the images. Tools like Label Image or Robo flowcan be used for annotation.

2. Data Preprocessing Module

- **Image Augmentation**: Apply transformations like rotation, flipping, scaling, etc., to increase the dataset's diversity.
- **Normalization**: Ensure the images are in a consistent format and size.
- **Splitting**: Divide the dataset into training, validation, and test sets.

3. YOLOv5 Configuration Module

- **Model Configuration**: Set up the YOLOv5 model configuration files, including the number of classes (weeds, crops), input image size, and anchor boxes.
- **Hyperparameters**: Define the learning rate, batch size, epochs, and other trainingparameters.

4. Training Module

- **Model Training**: Use the YOLOv5 training script to train the model on the annotateddataset.
- **Checkpointing**: Save model checkpoints during training to resume training ifinterrupted.
- **Monitoring**: Track training progress using metrics like loss, precision, recall, and MAP(mean Average Precision).

5. Evaluation and Testing Module

- **Validation**: Evaluate the model on the validation set to tune hyperparameters and avoidoverfitting.
- **Testing**: Test the final model on the test set to assess its performance.
- **Metrics**: Calculate performance metrics such as precision, recall, F1-score, and mAP.

6. Post-Processing Module

- **Non-Maximum Suppression (NMS)**: Filter out overlapping bounding boxes to ensure accurate detection.
- **Thresholding**: Set confidence thresholds to discard low-confidence detections.

7. Deployment Module

- **Inference Script**: Develop a script to run the trained model on new images or video streams for real-time weed detection.
- **Optimization**: Optimize the model for deployment on edge devices if necessary (e.g., using TensorRT or ONNX).

8. Visualization and Reporting Module

- **Bounding Boxes**: Draw bounding boxes around detected weeds and crops in the images.
- **Reports**: Generate reports with detection results and performance metrics.

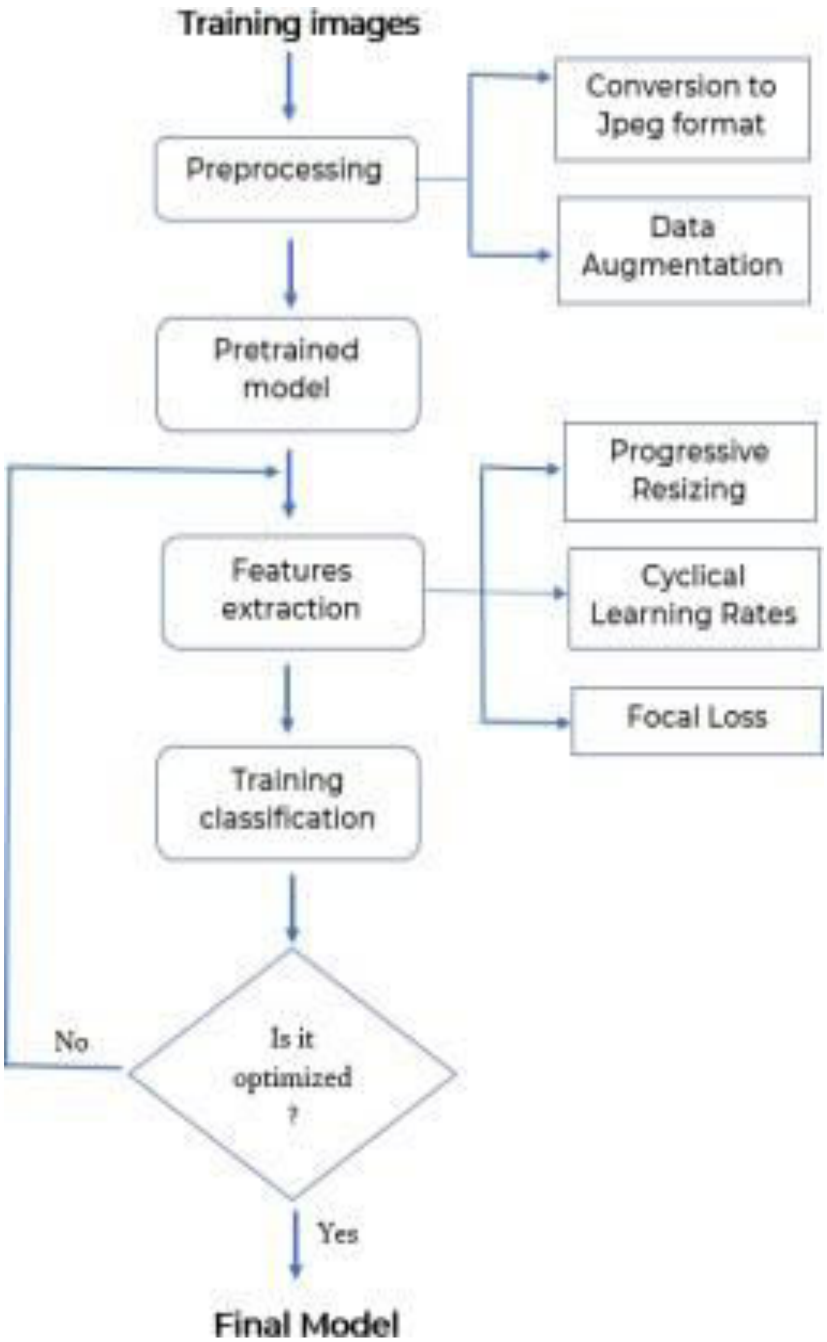
9. Integration Module

- **API Development**: Develop an API to integrate the weed detection model with other systems (e.g., agricultural management platforms).
- **User Interface**: Create a user-friendly interface for farmers to upload images and receive detection results.

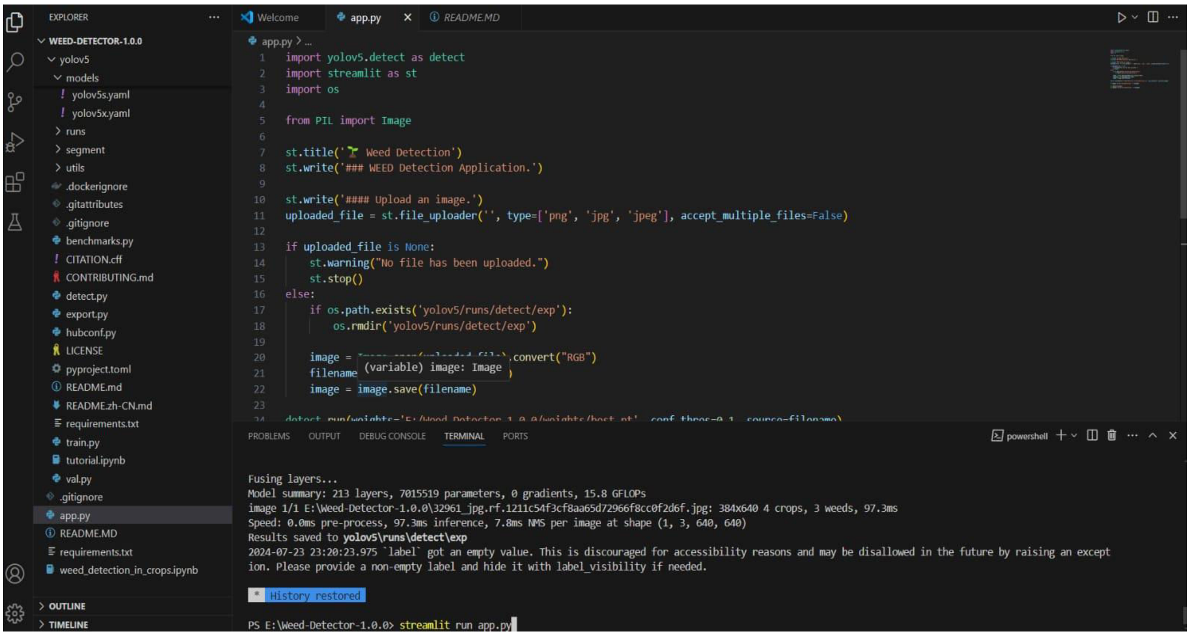
10. Maintenance and Update Module

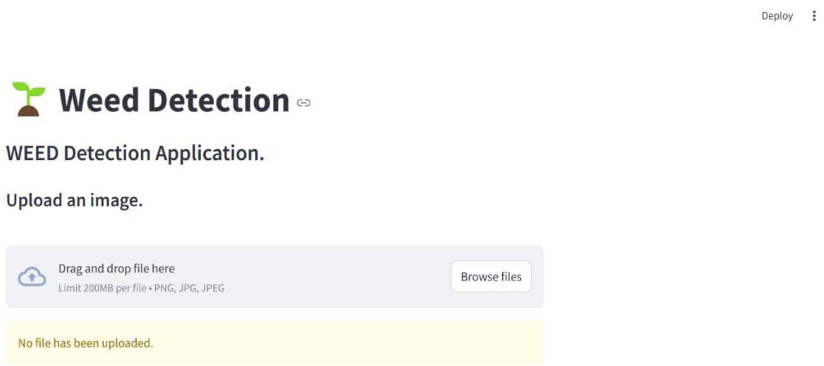
- **Retraining**: Periodically retrain the model with new data to maintain accuracy.
- **Model Update**: Deploy updated models without interrupting the system's operation.

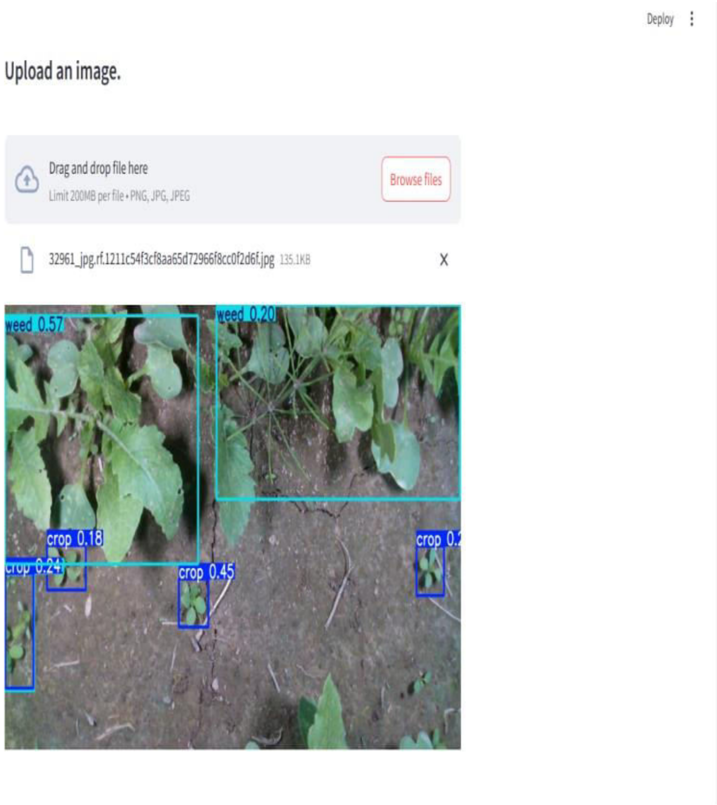
These modules provide a comprehensive framework for developing a weed detection system using YOLOv5. Each module can be expanded and customized based on specific requirements and constraints.


Training images
Preprocessing
Conversion to Jpeg format
Data Augmentation
Pretrained model
Progressive Resizing
Features extraction
Cyclical Learning Rates
Focal Loss
Training classification
No
Is it optimized ?
Yes
Final Model

5.RESULTS AND DISCUSSION







5.CONCLUSION

We suggested utilising deep learning and image processing to detect weeds in vegetable plantations. Two steps made up the algorithm's representation. Vegetable recognition was trained into a YOLO v3 system. After that, the colour image's remaining green objects were classified as weeds. To remove weeds from the surrounding area In this approach, the model avoids dealing with different weed species by concentrating on detecting only the veggies.

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