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Plant Health Analysis using IOT

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ABSTRACT: Machine learning techniques, particularly object recognition and image classification, are revolutionizing plant disease and weed management in agriculture. We propose an integrated approach using YOLOv4 and convolutional neural networks for efficient weed and crop detection, as well as disease diagnosis. This method addresses critical challenges in agricultural productivity, including weed competition for resources and water wastage. By accurately identifying plants, weeds, and diseases, the system enables targeted interventions. Additionally, the technology estimates plant water requirements, facilitating automated irrigation systems that optimize water usage. This comprehensive solution promises to enhance crop yields, reduce resource waste, and improve overall agricultural sustainability.

KEYWORDS: YOLOv4, CNN, Machine leaning, Imageprocessing, Arduino, Soil sensors, DHT11 sensor.

I.INTRODUCTION

In the realm of agriculture, the age-old battle between cultivated crops and unwanted plants, known as weeds, continues to challenge farmers worldwide. These persistent invaders compete for vital resources, potentially diminishing crop yields and increasing production costs. However, the definition of a weed is not always fixed, as some plants once considered undesirable have later revealed beneficial properties, leading to their intentional cultivation.

Weeds pose multiple threats to agricultural productivity. They deplete soil moisture and nutrients, leaving crops struggling in less hospitable conditions. This competition can render fields more prone to drought, further compromising crop health. The removal of weeds, whether through chemical means or manual labor, adds a significant financial burden to farmers. Moreover, certain weeds can pose health risks to humans, causing skin irritations, allergies, or even more severe reactions. Simultaneously, plant diseases present another formidable challenge to the agricultural sector, causing substantial economic losses and reduced crop yields. The management of these diseases is complex, often requiring swift and accurate identification for effective treatment. Traditionally, farmers have relied on visual inspection to detect disease symptoms, such as discolored spots on leaves. However, this manual approach is time-consuming and prone to errors, particularly when symptoms are subtle or mimic those of other conditions.

The machine learning (ML) techniques offers promising solutions to these agricultural challenges. In the realm of disease detection, ML algorithms can analyze images of plant leaves to identify and classify various diseases with greater speed and accuracy than human observation. This technology uses convolutional neural networks to process segmented images, extracting key features that indicate the presence and type of disease. By automating this process, farmers can receive early warnings and precise diagnoses, enabling them to take targeted action with appropriate treatments.

The application of ML in agriculture extends beyond disease detection. These advanced tools have the potential to revolutionize farming practices, optimizing resource use while maximizing productivity. From predicting optimal planting times based on weather patterns to fine-tuning irrigation systems, ML can provide data-driven insights that empower farmers to make more informed decisions.

As agriculture faces mounting pressures from climate change, population growth, and resource scarcity, the integration of ML and other innovative technologies becomes increasingly crucial. These smart farming approaches offer the promise of a more sustainable and efficient agricultural system, capable of meeting global food demands while minimizing environmental impact.

The journey from traditional farming methods to a technologically enhanced agricultural landscape is ongoing. While challenges such as weed management and disease control persist, the tools to address them are evolving rapidly. Machine learning stands at the forefront of this agricultural revolution, offering sophisticated solutions to age-old

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problems. As these technologies continue to develop and integrate into farming practices, they pave the way for a more resilient, productive, and sustainable future in agriculture.

II.LITERATURE REVIEW

In'es Barbero-García [1] This paper, the author sees about the YOLO algorithm for bulldozer detection on coastal video data. The suggested method is a combination of PCA change detection and YOLO object detection. The algorithm was found to give good results with an accuracy of 0.94 and a recognition of 0.81 for the CoastScan images. Preprocessing of the change detection improved the detection by slightly increasing the recognition and greatly reducing the number of false positives compared to using YOLO directly on the original images. First, the video frames were extracted and preprocessed using principal component analysis (PCA), a well-known method for highlighting moving or changing objects in images. YOLOv5 was specifically trained to detects the bulldozers on this type of imagery. The change detection calculation removes most of the standard features or background from the images, reducing areas that can be misclassified as bulldozers. Change detection also allows for the automatic removal of static bulldozers that may be parked on the beach for some time but are not performing work in the sand. Later, detection was performed for the two months of CoastScan imagery dataset, and the detected sand movements performed by bulldozers were validated against the suspected anthropogenic changes detected from the 3D data.

Peiyuan Jiang [2] This paper gives us an outlook of the YOLO versions. The YOLO structure is extremely straightforward. The artificial neural network may immediately output the position and category of the bounding boxes. The pace of YOLO is quick since all that is required to complete real-time detection of videos is the feeding of an image for final recognition. To recognize objects, YOLO directly leverages the global picture, which may encode global information and lower detection error for backgrounds as objects. 24 convolutional layers are followed by two fully linked layers in the original YOLO architecture. In order to suppress non-maxima, YOLO predict the several bounding boxes for each grid cell.

Najmeh Razfar [3] This paper proposes a weed detection system leveraging advanced imaging techniques and Convolutional Neural Networks (CNNs). The approach utilizes established architectures like MobileNet and ResNet50, alongside three custom-designed CNNs. These machine learning systems identify weed species based on structural and textural features, with wavelet texture characteristics employed for validation. The process involves applying a discriminating method to each image before feeding it into the neural network. Recent advancements in deep learning have significantly improved real-time weed detection systems, enhancing both model performance and computational efficiency. To maximize effectiveness, the study explores hybrid machine learning models that combine multiple methodologies, potentially offering a more robust and versatile approach to weed identification in agricultural settings.

Sachin Dahiya [4] The PlantVillage dataset is used in this work to identify the suitable hyper-parameters for evaluating most deep learning techniques for plant disease diagnosis. The plant leaves dataset is employed in the study, which employs the GoogleNet architecture. It is discovered that 30 epochs and a learning rate of 0.0001 are acceptable for plant disease identification. The creation of knowledge-based agricultural systems that may boost crop output and so address all issues has numerous challenges. Deep learning, a branch of machine learning that belongs to artificial intelligence, promises to overcome these challenges

Sumita Mishra [5] This paper presents a real-time deep Learning model for identification and classification of major cereal diseases without the need of internet. The performance analysis of the developed Deep CNN has shown an average accuracy of 98.40%. Artificial Neural Networks (ANN) with intelligent disease detection algorithms are the need of the hour to reduce the severity of losses and minimize crop health problems. While the results obtained are promising, the detection accuracy of the NCS can be further improved by adjusting and optimizing hyperparameters and increasing the diversity of the pooling operation; data augmentation can also be used. For further adaptation, we plan to diversify the data set by including additional maize diseases to increase the effectiveness of the method.

Jesús María Domínguez-Niño [6] The outcomes of this experiment demonstrate the viability of sensor-based automated irrigation in feilds. The program supplied exact irrigation dosages throughout the season. It was based on the balancing technique of water and locally controlled by data from sensors. The study looks how the autonomous system operated in areas with different types of trees and if it could deliver differential watering when the design was the same. In the same orchard, real evapotranspiration was ascertained using a weighted lysimeter, and the automatic method was contrasted with human scheduling using a traditional water balance. Capacity sensors have been successfully employed to give the scheduling algorithm automated feedback

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S. Akwu [7] The proposed model is the irrigation system is controlled by the soil moisture sensor which detects the percentage of water in the soil and updates to the microcontroller for irrigation and sends a notification to the owner, this project focuses on reducing excessive human intervention in the process of irrigation, also reduces water wastage and informs the owner about the situation in operation. This work aims to replace the manual method of irrigation with an automated one and promote human capital development and capacity building opportunities. A simple automated technique is used to control plant irrigation with GSM notification is proposed.

R. S. Ghumatkar [8] In this paper, an IoT-based smart irrigation architecture along with a hybrid machine learning-based approach for soil moisture prediction is proposed. Soil moisture is a critical parameter for developing a smart irrigation system. Soil moisture is affected by several environmental variables: air temperature, humidity, and soil temperature. The accuracy of weather forecasting has substantially increased because to technology advancements, and soil moisture variations may now be predicted using weather prediction data.

S. S. Harakannanavar [9] The model was developed based on the IP and ML approaches to foliar disease detection and is presented in this section. The proposed model (DWT+PCA+GLCM+CNN) uses computer vision and machine learning algorithm for leaf disease detection. To evaluate the accuracy and to detect the leaf disease as healthy or unhealthy, the tomato samples with six diseases are considered. As part of the image processing, the tomato samples are reduced to 256 × 256 pixels to keep their size the same throughout the experiment. HE and K-means clustering are used to maximize the quality and segment the leaf samples. Based on the K-means clustering response, it can be predicted at an early stage of the operation whether the leaf is diseased or not. The boundaries of the leaf samples can be extracted using contour tracking.

Revanth Yenugudhati [10] This paper is about automatic detection of plant diseases using plant leaves, which is a major breakthrough. Moreover, early and timely detection of plant diseases improves agricultural production and quality. The results obtained with models such as SVM architecture, logistic regression and KNN classifier have been helpful in detecting the health status of plants. Since we have limited data at the moment, we worked with the images that were available to us. In most studies, a dataset was used to test the performance of the deep learning models. Although this dataset contains many photos of different plant species and their diseases, it was created in a laboratory. Consequently, alarge data set of plant disease is predicted under real conditions.

P. Kulkarni [11] Using statistical machine learning and an image processing technique, the study claims for plant disease identification is computationally less expensive and needs less time for prediction than existing deep learning-based approaches. To quickly identify plant illnesses, the editors employ a robotic vehicle with artificial intelligence and a powerful CPU. On farmland, this system can find sick plants. Such robots can also automate the application of fertiliser. Because our suggested algorithm requires little computational effort, it can effectively identify plant diseases. Additionally, it occasionally occurs that the farmer is unable to find the plant disease.

J. Chen [12] This paper is about the YOLO sesame model, which is proposed to improve the efficiency and accuracy of sesame weed identification. Based on the above research, machine vision based on Deep Learning can achieve some accuracy and speed in weed identification. However, in complex sesame cultivation areas, problems such as the similar morphology of sesame plants and weeds, inconsistent size and specifications can lead to lower accuracy of detection models and overlooking of small targets. Therefore, an improved model based on YOLOv4, YOLO-sesame, is proposed to realize object recognition of sesame weeds and improve the identification process.

B. Ying [13] This paper targets the various weeds in the growth environment of carrot seedlings and improves YOLOv4 into a lightweight weed detection model YOLOv4- weeds. This means that the proposed model can effectively detect the carrot seedlings and various weeds in the complex scene of carrot field and can be easily applied to embedded devices. However, the recognition effect of our model on a few images is limited by the fact that there are relatively few targets of some weed species in the images of our dataset, i.e., the training examples are unbalanced, with a difference between image features; as a result, the features of some targets are not sufficiently extracted during model training.

F. Dang [14] This paper shows about weed detection tasks can be divided into three basic categories: 1) classification of images as crops/weeds, 2) detection or localization of weeds in the images, and 3) segmentation of images into semantic weed maps, which corresponds to three basic problems of computer vision, namely image classification, object detection, and segmentation, respectively. DL Methods are most used to train weed classification models using labelled image-level datasets. However, the resulting models do not provide information about the location of specific

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weeds in an image and are therefore suboptimal for accurate weed control. In contrast, object recognition, which requires the localization of objects of interest within an image, would predict the locations of weeds in images and be more beneficial for high precision weed removal.

III.METHODOLOGY

Plant Health Analysis

With the advancement in computer vision, deep learning and CNN algorithm for comparing the plant with the trained data, new promising solutions for identifying overall health status of the plants were introduced. The dataset of plant leaves dataset are collected from the Kaggle PlantVillage dataset. The intelligent decision support system for identifying crop diseases would lead to timely control of the panic situations and eradicating the huge losses, ultimately leading to improved plant quality.

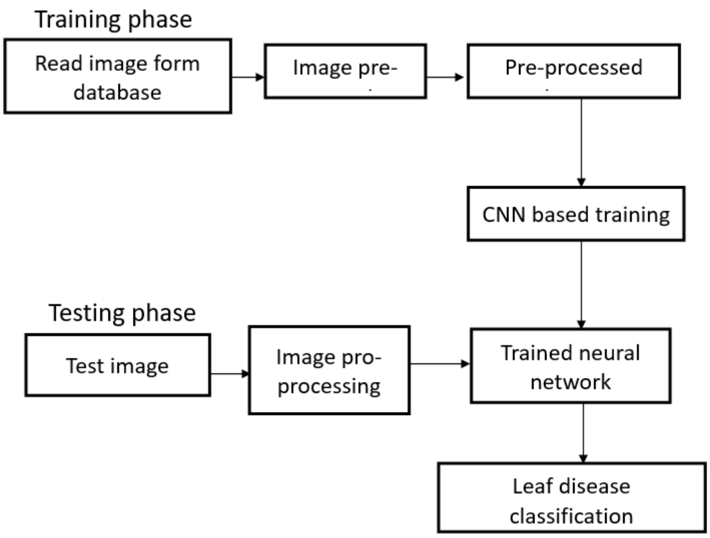

Fig. 1. Plant health analysis.

Weed detection

The weed in the farms is detected using computer vision and alert farmers. This method helps farmers to eradicate the confusion between a crop and a weed. The weed and plant are determined by the Yolov4 machine learning algorithm which will be used to object detection, data collected will be trained first or the data which needs to be compared with the real time data is stored. The picture captured is compared with the trained data using image processing and then the classification of weed and crop is done. Training a YOLOv4 model on weed and crop detection using Colab and then using the trained weights to detect weed and crop in real-time video feed from a camera. To start, first we collected and label a dataset of images containing weed and crop. We used OpenCV to display the processed video on the screen with bounding boxes around detected weed and crop instances.

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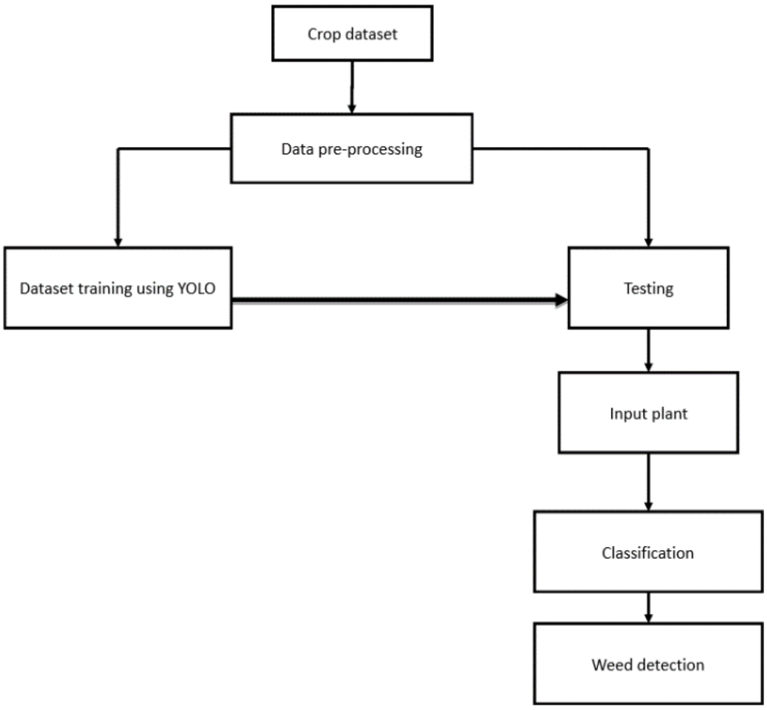

Fig. 2. Weed and Crop detection.

Soil analysis and Irrigation technique:
The preservation and improvement of dynamic soil characteristics is the main emphasis of soil management in agriculture for increasing crop productivity by including the hardware soil moisture sensor. This will help farmers to grow crops in less amount of water by smart irrigation by analysing the soil moisture content. Arduino is used as the controller and all the sensors and motor pump is connected to the Arduino. When the moisture content in the soil is less the Arduino will send the message to turn on the motor pump and irrigate the field and sends moisture percentage and pump status as text message to the user through LCD display. When the moister content satisfies the soil sensor the Arduino will automatically turn off the motor pump. Form this the user can save water and time by automatic irrigation.

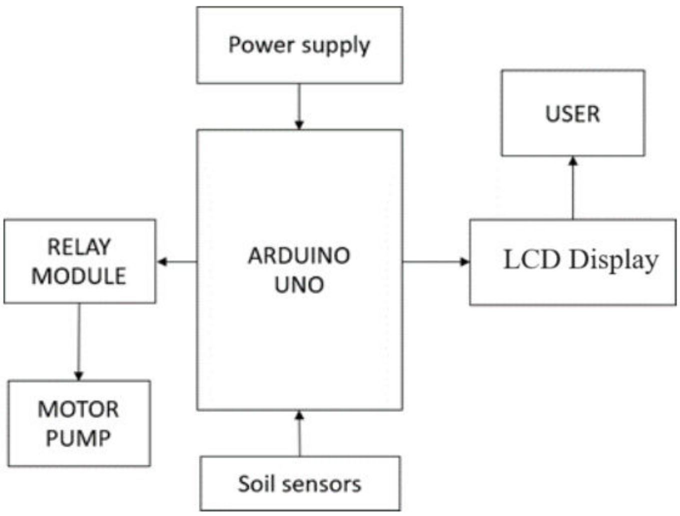

Fig. 3 Soil analysis and irrigation technique.

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IV.RESULTS

After the training of the model using the plant leaf dataset and a trained model is generated. When the user uploads the image to the trained model the code will execute, the uploaded image will be classified and the name of the leaf is shown asoutput.

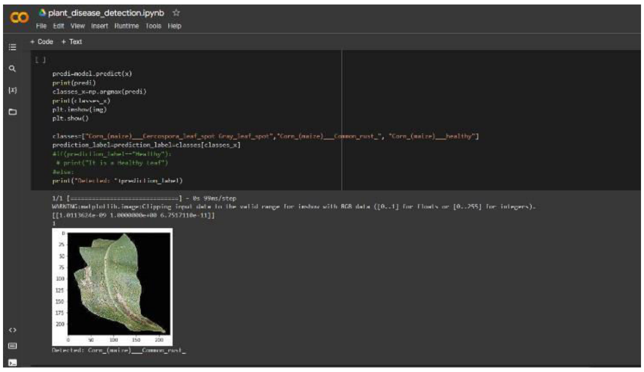

Fig. 4. Plant health analysis.

We used the Yolov4 model to recognise crops and weeds in new photos once it has been trained on the dataset of crop and weed. To carry out the inference technique on the brand-new photos, we must employ the trained Yolov4 model. Theoutcome of the inference procedure will be the bounding boxes and classes of the detected objects.

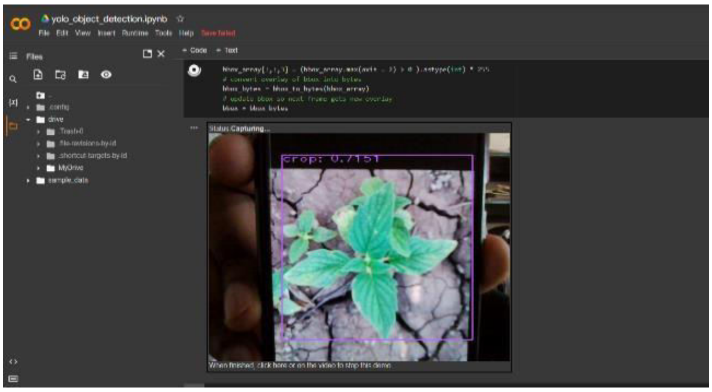

Fig.5. Weed Detection.

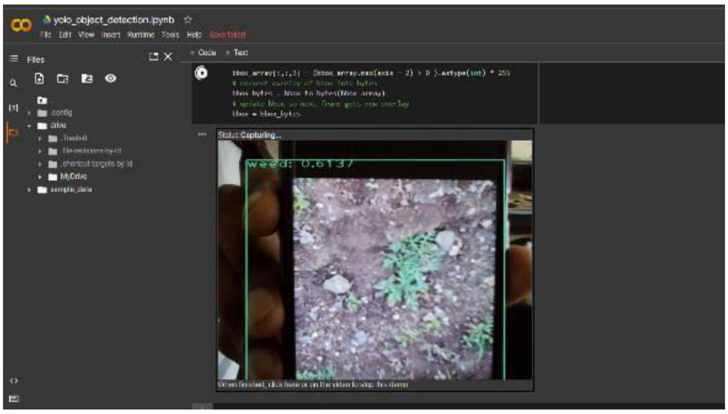

Fig.6. Crop Detection.

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The soil moisture sensor analyses the soil's moisture content, and when it falls below the predicted level, the motor automatically turns on and waters the plant. And the engine will stop after the plant has received the necessary amount of water. Arduino is used to regulate this procedure.

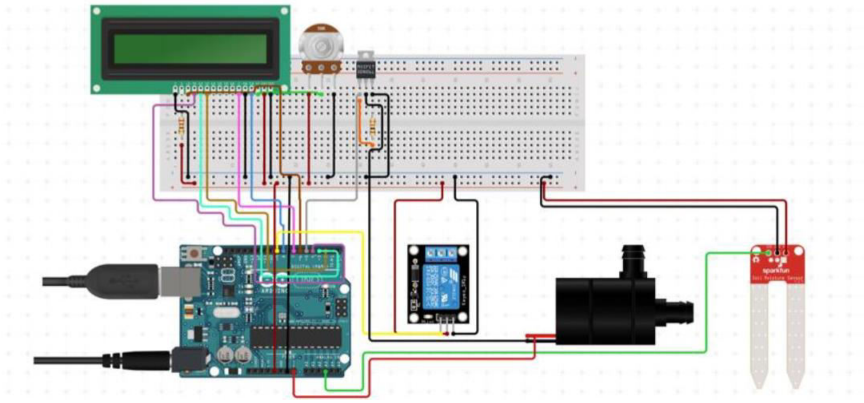

Fig.7. Soil Analysis circuit

V. CONCLUSION

With the aid of the CNN-based model for tracking the health of plants and the YoloV4 algorithm for real-time weed and crop recognition including the use of machine learning architecture and artificial engineering, weed detection will be useful for the user in detecting the weed more quickly. The user may classify the plant illness with great aid from the plant leaf disease detection. We can reduce further water loss and manage the excess of water in the fields by automating soil irrigation. The soil moisture sensor senses the percentage of water in the soil and updates the percentage if it goes below the threshold value for that crop/plant to the microcontroller unit for the start of the watering and updates to the user in this design. The Arduino is the main control of the system that coordinates the control to other system components.

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