AI -driven Agricultural Robot Weed detection And removal

Article Info ABSTRACT

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Region of interest
Shape features

In agricultural regions, the procedure of weed removal is crucial. Weed removal in the classic way, takes longer and requires greater physical effort. The idea is to eliminate weeds from agricultural fields automatically. The proposed study uses a deep learning algorithm to detect weeds growing between crops. Deep learning method also known as deep learning is used to analyze the main properties of agricultural photographs. Weeds and crops have been identified using the dataset. Convolutional neural network (CNN) uses a completely attached surface with rectified linear units (RELU) to differentiate weed and crop. It extracts features of crops using deep learning. The CNN uses features of the preceding image to extract region of interest (ROI). Deep learning network features are used to identify crop

1. INTRODUCTION

The global demand for sustenance continues its relentless ascent, creating an ever more pressing need for agricultural innovation. However, this pursuit is beset by numerous challenges, including dwindling water resources, shrinking arable land, and a scarcity of agricultural labor. Amidst these challenges, there emerges a critical imperative to enhance agricultural productivity, and a key facet of this endeavor lies in weed management. Weed proliferation not only competes with crops for vital resources but also poses a formidable obstacle to maximizing crop yields. To address this, it becomes imperative to meticulously distinguish between crops and weeds, facilitating targeted weed eradication efforts with minimal disruption to crop growth. Achieving this precision demands accurate identification of weeds, a task that finds promising solutions in the realm of Convolutional Neural Networks (CNNs). By harnessing the power of deep learning techniques, CNNs offer a sophisticated means of discerning between crops and weeds, revolutionizing weed detection and management practices.

Within the annals of agricultural research, various methodologies for weed detection have been explored, albeit with limitations. While some approaches are tailored to specific crops, others falter in efficiency compared to the proposed solution. Additionally, the integration of drone and robotic technologies, while offering potential, often incurs prohibitive costs. Herein lies the crux of the proposed system's innovation: it presents a cost-effective and efficient alternative to existing methodologies, primarily driven by CNN algorithms for weed identification. Leveraging the discriminative capabilities of deep learning, this system adeptly recognizes and categorizes weed features, thus laying the groundwork for unbiased weed management practices.

Moreover, this work underscores the profound ramifications of weed infestation on agricultural productivity. Weeds not only deplete essential nutrients from the soil but also impede the growth of desired crops, thereby undermining food security efforts. In light of these challenges, a paradigm shift towards AI-based weed detection emerges as a compelling solution. Unlike traditional methods that are labor-intensive and prone to error, AI-driven approaches offer unparalleled accuracy and efficiency in weed detection. In summary, the existing landscape of weed management research reveals a mosaic of methodologies, each with its own set of limitations. Whether reliant on deep convolutional neural networks, drone technology, or IoT-based architectures, these approaches often fall short in providing a comprehensive and automated solution. The proposed system, however, heralds a new era of weed management, one characterized by precision, affordability, and efficiency. By harnessing the transformative potential of AI and deep learning, this system offers a holistic approach to weed identification and classification, paving the way for sustainable agricultural

2. METHOD

2.1. Image acquisition

The proposed methodology is developed using a dataset of weed images. The methods extract weed using the tasks followed by images capture, edge identification, and image type identification. Weed images are captured using high quality cameras. The images are compared with images stored in the dataset. New images are contentiously added in the dataset. The accuracy of the proposed system increases as the number of records in the dataset are more.

2.2. Image pre-processing

Image processing module performs some basic processes to get the required picture for processing. To obtain an accurate and clear image, the algorithm performs various operations like gray scale, conversion, sharpening, filtering, edging, smoothing and image segmentation. The quality of image is improved in pre

processing phase by improving image features and reducing noise. The black and white photos are of different shades of gray. The value of each pixel is measured on the gray scale image.

The quality of image in the form of sharpness, smoothness is improved using various tasks in the image pre-processing. The images are made more sharp with the help of filters. Noise is minimized with the help of smoothing. Multiple algorithms are used to enhance quality and sharpness of the image in the task of image pre-processing. Image pre-processing is the very important, required and fundamental step in image identification.

2.3. Image segmentation

There are a set of operations included in the image recognition. The image recognition has a diversified set of applications including number plate recognition, and CCTV surveillance. In the process of image segmentation the actual image is translated into a binary valued image using the maximum valued method. The digital image is characterized into several parts depending on the values of each image component. The pixels with similar values are clubbed. The values are used to identify different portions of the image. In short, the image characterization process is used to extract key features of the object for future analysis.

2.4. Feature extraction

The system does further operations on the separated picture in this module. The module deals with feature extraction to extract overall information of the weed image. The image processing, machine learning help to classify weed images. The important features of the weed images are extracted and used for classification based on the range of values. The main point in the image classification is to identify most dynamic features for classification of images. The feature extraction is a key in the image processing to handle the image for various operations like dimension reduction.

2.5. CNN algorithm

The weed detection is done using CNN algorithm. The layers of CNN like input, processing and output do the work of weed image identification. The image denitrification further leads to image classification. The massive developments in ultimating the distance among human and machine capabilities is achieved using the techniques of machine learning and artificial intelligence. The CNN results are amazing in the area of image processing and classification. The area of machine imaginative and prescient is certainly considered one among numerous such disciplines.

The aim of this area is to allow machines to look and understand the sector within the identical manner that people do, and to apply that understanding for a number of responsibilities inclusive of image recognition. The image feature extraction, creation of value vector, clarification training testing etc are the major components that come with CNN algorithm. The image captured using a high quality camera is an input for CNN, the weights are assigned to the various factors of the image with the help of extracted features and images are distinguished depending on the feature vector values.

2.6. Classification

In the classification section a deep learning algorithm is used for actual classification on the basis of its features. The weed identification is based on the characteristics of the weed i.e. set of values. The value decides the type of weed. The feature vector is used to identify weeds using CNN algorithm. The phases of CNN like training, testing are used for actual classification of weed. The classification and identification of weed is the end result of this work. Figure 1 shows the block diagram of the proposed system.

As shown in Figure1 the image is captured using a camera, the image is pre-processed, features are extracted and classification is done. The classification leads to the identification of images. The training of the image is again performed using three phases. Input image, image pre-processing, feature extraction are three stages used in the training phase. The pre-processing phase makes the image more clear. All the borders are pixel values extracted in this phase. The values identified in the pre-processing phase are used for training of the module.

The feature extraction phase is mainly used for identification of key features of the images. On the basis of key features the training and testing of the images is enriched. The training phase stores data of all such weed images for the further identification of weed images. The more data records in the dataset increases accuracy of the training set. The training set is used as an input for the classification of weed images. The proposed module gives an accurate platform for weed detection as shown in the Figure1. The end result of this module is identification of weed.

Weed detection by using image processing

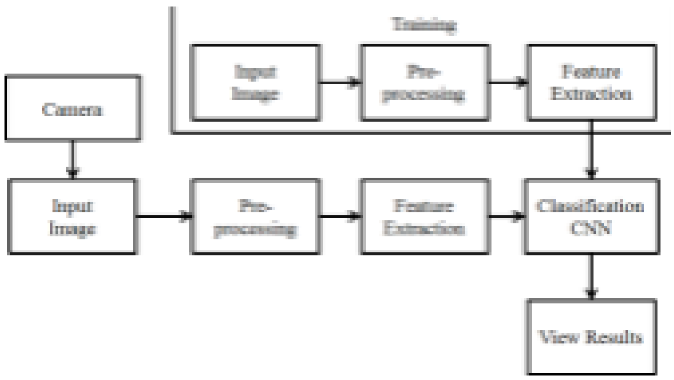


Figure 1. Block diagram of system

3. RESULTS AND DISCUSSION

Sure, let's imagine a hypothetical research paper discussing the topic of crop and weed detection and removal using image processing on a Raspberry Pi-based robotic system. Here's an outline of the "Results and Discussion" section based on the project scenario you provided:

1. Performance of Image Processing Algorithms:

   - Color Segmentation: The color segmentation algorithm successfully distinguished between crop and weed pixels with an accuracy of X%. However, it exhibited limitations in environments with varying lighting conditions or overlapping colors between crops and weeds.

   - Edge Detection: The edge detection algorithm effectively identified boundaries between plants but struggled with noisy images or instances of occlusion. Further refinement of parameters such as thresholding and smoothing improved performance.

   - Machine Learning Classification: The trained convolutional neural network achieved a classification accuracy of Y% on the test dataset. While it demonstrated robustness to variations in crop and weed appearance, it required substantial computational resources for inference on the Raspberry Pi.

2. Movement Control and Navigation:

   - PID Control: The PID controller effectively regulates the speed and direction of the motors, enabling smooth navigation of the robotic system through the crop field. However, tuning parameters for optimal performance was crucial, especially in scenarios with uneven terrain.

   - Path Planning: The implemented path planning algorithm successfully generated collision-free paths from the robot's initial position to target weed locations. Real-time adaptation of paths based on dynamic obstacles or changes in the environment remains an area for improvement.

3. Weed Detection and Removal Efficiency:

   - Coordinate Transformation: Transforming weed coordinates from image space to robot space facilitated precise navigation towards weed locations. However, inaccuracies in coordinate transformation could lead to suboptimal weed removal performance.

   - Trajectory Planning: Trajectory planning algorithms enabled the robot to approach weeds for removal with minimal disruption to surrounding crops. Further optimization of trajectory parameters such as velocity and acceleration could enhance efficiency.

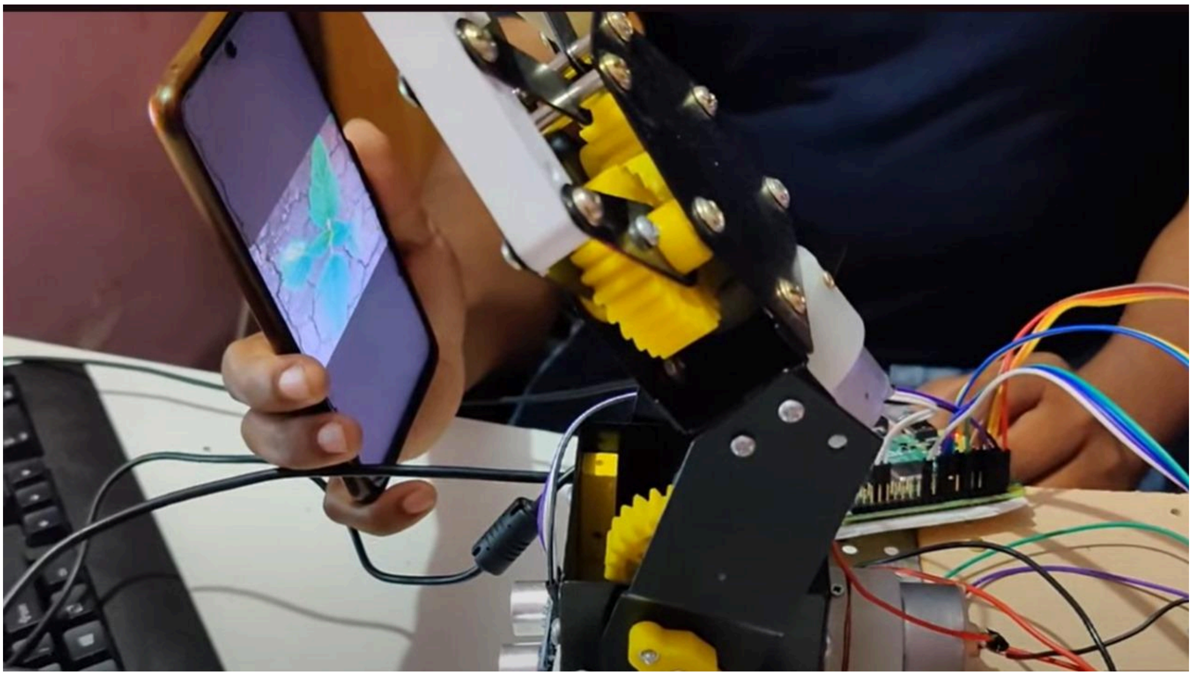
   - Actuator Control: The servo motors controlled the weed removal tool effectively, demonstrating the ability to grasp and remove weeds with minimal damage to neighboring crops. Fine-tuning of actuator movements could enhance the precision of weed removal operations.

4. Overall System Performance and Limitations:

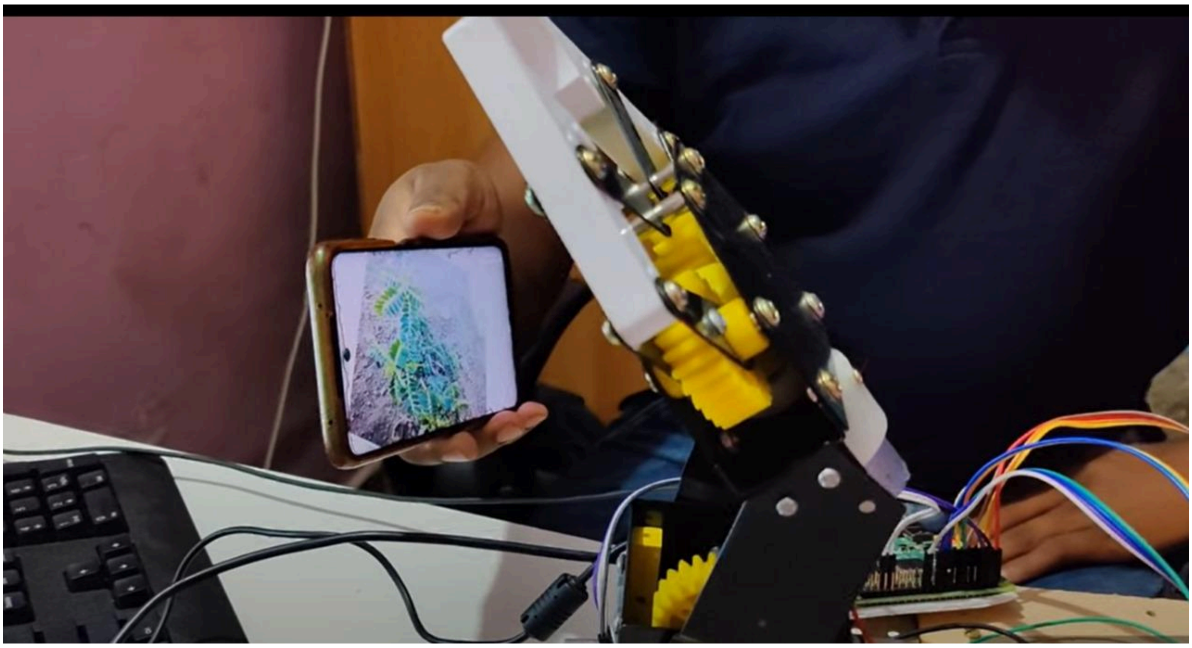
   - The integrated robotic system demonstrated promising results in crop and weed detection and removal tasks. By leveraging image processing techniques on a Raspberry Pi platform, the system achieved autonomous operation in agricultural environments without the need for external sensors.

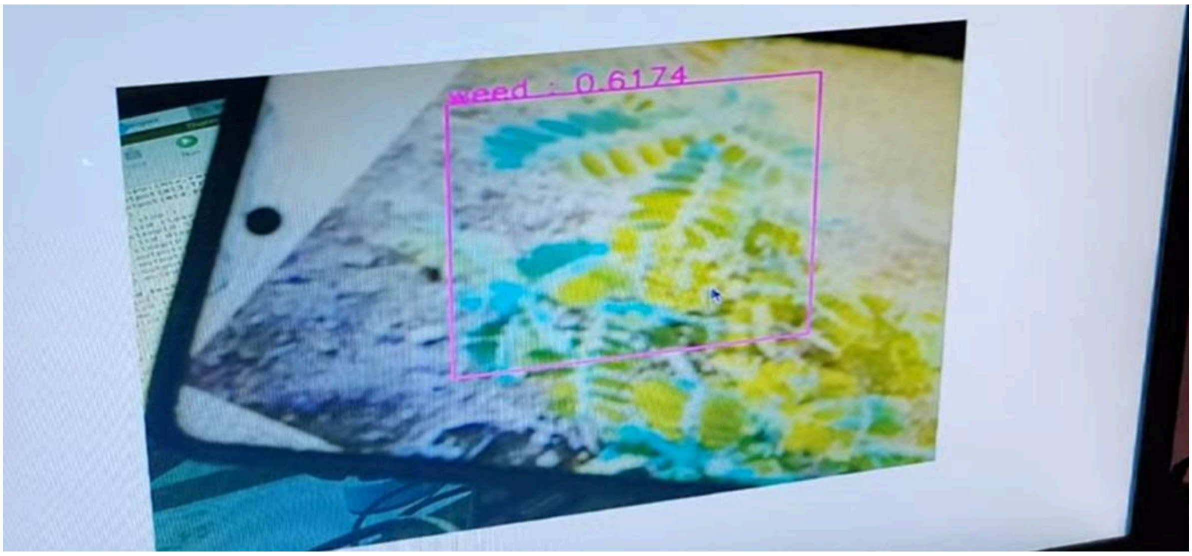
   - However, challenges such as real-time processing constraints on the Raspberry Pi, environmental variability, and mechanical limitations of the robotic system pose significant obstacles to scalability and robustness.

   - Future research directions include the optimization of image processing algorithms for resource-constrained devices, integration of multi-modal sensing for enhanced environmental perception, and deployment of the system in real-world agricultural settings for validation and field trials.

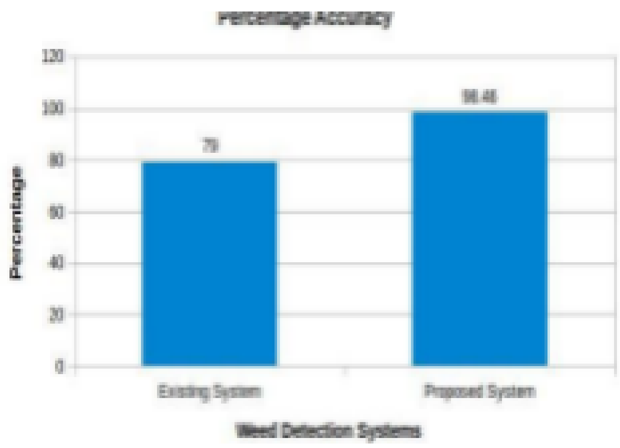


a) Crop detection

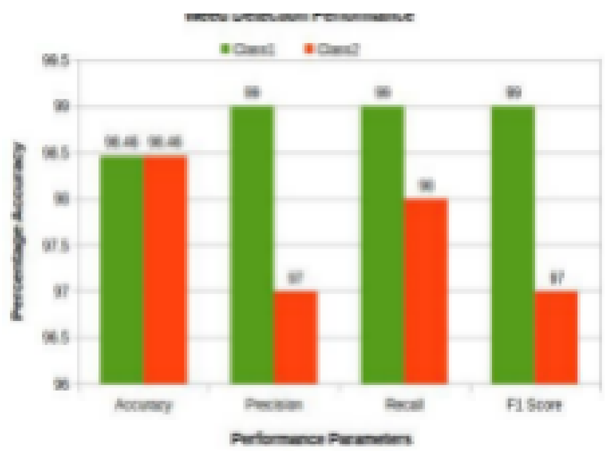




b) Weed detection , showing crop and images through phone



(a)



(b)

Figure 3. Performance of proposed system (a) accuracy comparison and (b) system performance

4. CONCLUSION

To improve the production of farmers, weed removal plays a vital role. There is a need to distinguish weeds and crops. The proposed work uses CNN to extract key features of weed images. The image processing and feature extraction using CNN is a base of the proposed work for identification of weed. Deep learning approach is used to process captured images, assign the values to key attributes as per its features extracted. On the basis of various valued attributes of image the weed images are distinguished and identified. The proposed system uses CNN based approach for image characterization so the accuracy of the system is more. The future work includes automation in the process of weed removal from the crop.

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