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WEED IDENTIFICATION USING DEEP LEARNING AND IMAGE PROCESSING

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ABSTRACT

In recent years weeds are responsible for agriculture losses. To overcome this, the farmers have uniformly spray whole field with herbicides. But, the process of spraying herbicides affects the environment. The identification and classification of weeds are of major technical and economical importance in the agriculture industry. To control and prevent specific weeds, deep learning techniques are used. The classification is done by fully connect layers of CNN model. The main aim is improving accuracy of weed detection by applying deep learning techniques.

This project proposes a method, which combines deep learning and image processing technology. Firstly, a trained CenterNet model was used to detect vegetables and draw bounding boxes around them. Afterwards, the remaining green objects falling out of bounding boxes were considered as weeds. Furthermore, this strategy can largely reduce the size of training image dataset as well as the complexity of weed detection, thereby enhancing the weed identification performance and accuracy.

1. INTRODUCTION OF THE PROJECT

This chapter gives data with respect to the collection of a dataset, pre- processing, division, and classification calculation committed to accomplishing the objective of the venture. Trim generation is an basic figure of the farming framework and is dependable for worldwide nourishment administration. It is hence obligatory to design modern patterns and logical methods to appropriately arrange and oversee them. Agreeing to later considers, it has been found that weed development and thickness essentially impacts the horticulture framework, which leads to trim abdicate misfortune.

There have been different activities by the subsidizing offices that cultivate innovative rural improvement ventures which successfully help agriculturists .Most of the work has been carried out in the computer science space of horticulture applications utilizing the Web of Things (IoT) and Manufactured Insights (AI) .Other than, a assortment of Deep Learning (DL) approaches have been displayed and prescribed by diverse analysts over the past a few a long time, concocting distinctive weed distinguishing proof and discovery techniques.

The datasets included in weed discovery, classification, weed/crop development, and thickness gauge are portrayed in this chapter. Firstly, we give data with respect to the dataset, pre- preparing, and division procedures. The diverse sorts of CNN models are moreover clarified in this chapter. The information has been collected from a standard information store as Edit Weed Field Picture Dataset (CWFID). There are eleven diverse sorts of information in this category. A isolated portion depicts the characteristics of the dataset gotten for the inquire about crevice. The quality of information is kept up by evacuating clamor, and improvement utilizing pre-processing. Encourage upgraded and normalized to accomplish the ideal execution when utilizing the Deep Learning method. Fig 4.1 appears the steps included in the location and classification of weeds.

Image Data Pre-processing

Data Pre-processing is a procedure for moving forward the quality of the

picture. It has been control of crude picture information comes beneath the picture pre-processing portion some time recently the Deep learning calculation forms it, the reason of which is to upgrade the quality of the information .Building a high- performing demonstrate requires a exhaustive examination of both the arrange design and the input datasets. Hence, in this work, the dataset has been pre-processed to permit a savvy determination to be performed by the proposed show to extricate appropriate highlights from.

There are seven sub-steps included for picture pre-processing Picture Securing, Picture Improvement, Picture Rebuilding, Morphological Handling, Color Picture Handling, Wavelet Multi-Resolution Preparing, and Picture Compression. The total depictions are portrayed in fig

Image Acquisition

Image procurement is the prepare of changing over optical pictures into numerical information that can be handled on a computer. There is a few picture procurement hardware such as charge-coupled gadgets (CCDs), charge infusion gadgets (CIDs), etc.

Image Upgrade of weed/crop image

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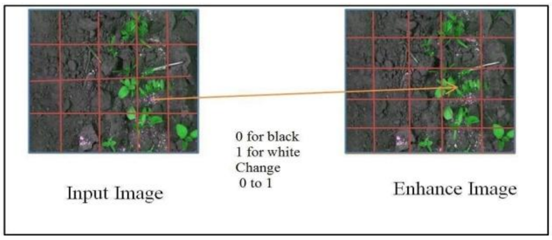
To improve the productivity and precision of the CNN show require to upgrade the quality of the picture. Picture information improvement incorporates sharpness, brightness, etc. This work has been utilizing spatial and recurrence spaces.

Spatial and recurrence spaces are the methods utilized to upgrade the quality of the picture. The spatial space alter pixel esteem agreeing to the change condition and gives way better exactness. The upgraded weed picture utilizing the spatial space procedure is given in condition appears the improved weed/crops image.



g(i, j) T(g(i, j))

Where i and j are the axis and T is the transformed equation that has changed the pixel value 0 to1 or 1 to 0 in a grey-scale image. In this work, we change the pixel intensity according to thebrightness of the image using the constant value

(k) of the RGB image which has a valuebetween 0-255. The $g(i, j)$ is the function of image enhancement. T is a transpose function that has use K constant value (0 to 255). From equation 4.2 we increase the brightness of the image.

g(i, j) T(g(i, j) k

The Strong Foremost Component Examination (RPCA) picture handling is another strategy that has been utilized to analyze and improve the quality of the field

,and to perform picture upgrade for the likely weed area and thickness ranges calculation in the soya bean field. The inadequate and low-rank network is isolated by RPCA. The picture acknowledgment and measurement decrease on tall measurement picture information utilized by RPCA strategy will perform direct transformation operations with the greatest include vector.

As normal, the picture has contained slight clamor and is unstructured so utilizing RPCA will break down the input lattice and change over it into two lattices so the liner calculation of the inadequate framework (counting commotion) can be communicated as condition

In this study, RPCA decomposition has been performed in the pre-processing phase of the image and performed in some of the components of the image and absolute values of the coefficients. The position of non-zero elements and a sparse matrix is extremely identified $object\_toq$ which is the positionof

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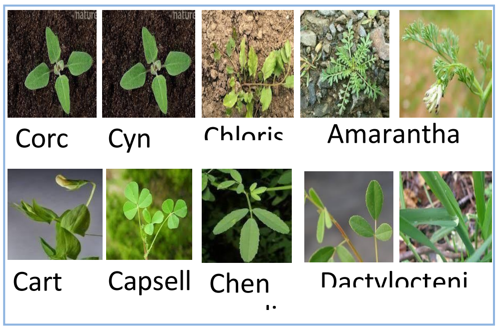
a non-zero element means a relatively larger absolute value in S (sparse matrix). Fig 4.3 shows the enhanced image of weed leaf.



c. Image Restoration

Image reclamations are the handle of reestablishing the harmed picture and returning the unique picture. Moreover, this prepare moreover employments the picture upgrade method which has been examined in the sub-section.

d. Morphological Processing

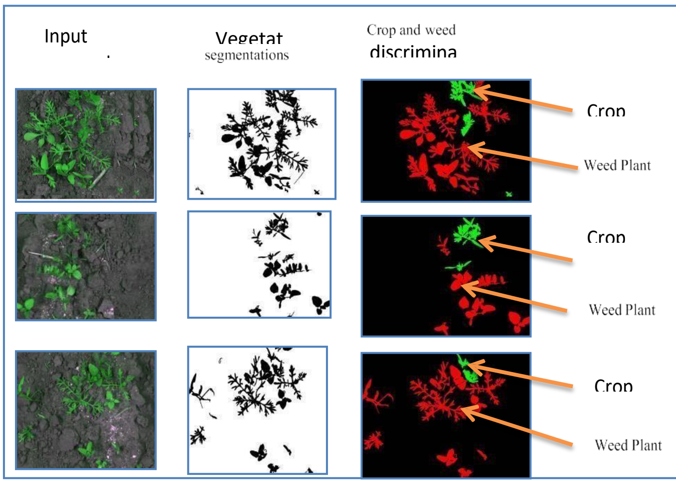
Morphology alludes to a bunch of picture preparing strategies that work with pictures depending on their shapes. Morphological operations apply a organizing component to an input picture and deliver a similar-sized yield image.

e. Color Picture Processing

In color picture preparing, an unique numerical show known as color space is utilized to characterize the color in terms of escalated values.

DATA SEGMENTATIONS OF WEED AND TRIM PICTURE DATA

After pre-processing of a picture, picture division is done for segregating the weed and edit plant from field picture information. Picture division is a strategy in which a advanced picture is broken down into different subgroups called Picture sections which makes a difference in diminishing the complexity of the picture to make encourage preparing or investigation of the picture less complex.'Segmentation in simple words is doling out names to pixels. There are a few division strategies included in information division such as Edge base division, Edge base division, Locale Base division, Semantic division, Occasion division, and Vegetation segmentation.These division methods have been utilized to assess plant and weed segregation and area estimation.



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2. LITERATURE SURVEY

Later thinks about and investigate in the field of farming anticipate that the abdicate of a trim is influenced by distinctive variables. The weeds are the preeminent figure that may hurt trim surrender. Subsequently, this is the most critical assignment to distinguish and control weeds at an early arrange of weed development investigate holes in the setting of weed recognizable proof, location, development rate, and thickness estimation are surveyed in this chapter, which incorporates a comparison of distinctive sources. To reach any conclusion, much exertion is vital to select a valid source. This writing overview has been gathered as appeared

2.1 Based on types of weed and their identification

To improve the efficiency of weed-infected ranges, weed area, and thickness estimation the analysts begun making utilize of Deep Learning. In this manner, it is imperative to learn the changes in morphological, properties of clears out. The creator proposes a few optimization procedures, which are talked about in the chapter. This segment talks about the different sorts of weed, recognizable proof, and discovery procedures in terms of picture handling strategies.

This writing incorporates recognizable proof, location, and thickness estimation of weed based on the Deep learning approach.

Mishra et al. (2022) have examined the diverse sorts of biennial and perennials, a monocot, and wide takes off weeds species and too portrayed organic control strategies. It has moreover depicted the morphological and surface property of common lasting weeds such as “Paspalum Distichum”, “Cynodon Dactylon”, “Scirput Maritimus”, and “Cyperus Rotundus” in Paddy trim farming. Moreover, they have too portrayed the weed control method such as Natural, Social, Physical, and Chemical control strategies. The creators utilize occurrence and semantic division procedures for protest location, and Gray Level Co-occurrences Framework (GLCM), Tint, Immersion, Esteem (HSV) are utilized for include extraction. The creator has connected diverse CNN strategies for picture information classification and compares the procedure based on the execution of the show. There are a few execution parameters that have been examined by the creator in terms of Exactness, Review, F1-score, Exactness, Supreme Mistake (AE), and Cruel Outright Blunder (MAE) .

Xu et al. (2020) have examined the Positive Empower (PE) strategy for finding the correct area of plant objects and classifying the information utilizing the Encoder- Decoder Customary Neural Organize (ED-CNN) demonstrate. The creators have utilized 4000 weed pictures and it has been collected from the "Deep weed dataset" for the test. There are five distinctive families of weeds such as "Cronopus Didymium", "Fumaria Parvilfora', "Lathyrus Aphaca", and "Medicago polymorpha" that have been utilized for information distinguishing proof and discovery. The creator has connected a distinctive CNN show for picture information classification; they compare their proposed strategies based on the distinctive execution matric. After comparing the distinctive CNN models, the ED- CNN has accomplished 94.03% exactness .

Chechlinski et al.(2019) have proposed robotized weeding called agro mechanical autonomy. In this method, Weeds can be distinguished utilizing mechanical technology innovation. The creator has portrayed the Web of Things (IoT) and Deep Learning (DL) based method which has naturally recognized weed distinguishing proof and discovery. The creator utilized 10 FPS on the Raspberry Pi 3B and a computer framework for computerization of weeding. This method has been utilized by the Warsaw College of Innovation and MCMS Warka Ltd. The demonstrate has accomplished 47-67% weed discovery precision. It has been tried in four distinctive plants in a stadium and beneath medium lighting conditions. The mechanical technology framework has utilized the custom semantic division CNN utilizing U-Net, DenseNet, and ResNet design. Out of this CNN design, ResNet pre-trained demonstrate accomplished way better 87% information exactness. The creator proposed that weed pictures can effectively exchange to computer vision to another agro-robotic errand.

Rastiet al. (2019) have examined segregating the weeds from the soya bean trim plant. They utilized pre-trained DL models such as AlexNet, SqueezeNet, GoogLeNet, ResNet-50, SqueezeNet- MOD1, and SqueezeNet-MOD2 for preparing the show. Moreover, 11,600 weed pictures have been collected from Edit Weed Field Picture Dataset (CWFID) and prepared in the models.

The ResNet-50 has accomplished more than 92% information precision. AlexNet, SqueezeNet, GoogLeNet, SqueezeNet-MOD1, and SqueezeNet-MOD2 has been accomplished 94%, 91%, 87%, 90%, 95% information exactness continuously. The creator calculated the handling time of the ResNet CNN show and accomplished

40.73 s, to handle 11,600 pictures. In any case, the creator recommended that it can moreover execute in biotic and abiotic leaf infection distinguishing proof and discovery

Nieuwenhuizen et al. (2010) have talked about the weed discovery procedure in sugar beet plants utilizing CNN. The creator has been classifying the work into four diverse sub-modules Information pre- handling, Information Division, Include Extraction, and classification. They separate the weed and sugar beet plants utilizing CNN. Firstly creator has collected the dataset from the standard information store as the Deep Weed dataset and pre-processed the picture as 224 × 224 × 3.

The moment is division, the execution of division strategy for weed and edit plant segregation based upon morphological and surface properties of clears out. The third is weed/ trim include extraction. The creators utilized 52 surface properties of takes off and they classify the weed and trim. The creators have utilized the Initiation V4 pre-trained CNN show for the explore and accomplished 95.40% exactness.

Gardhe et al. (2018) have suggested a new architecture of RCNN for classification and detection of weed where weed leaf images were classified by PU learning technique; weed characteristic extricates using positive negative problem technique. The development of remark the broadleaf was typical in a crop, VGGNet model useful for various multiclass broad leaf identification such as “Amaranths Viridis”, “Boerhavia Diffua”, “Anagallis Arvenisis”, “Argemone Mexicana”.

There weeds data is unstructured so it has been resized from 255×255×3 to 224×224×3. The author uses the U-Net CNN model for data classification. This model has been compared with SegNet, VGG-19, and ResNet-151. Finally, achieve 94% maximum data accuracy. The SegNet, VGG-19, and ResNet-151 CNN models have achieved 91%, 92%, and 90% image data accuracy respectively but the U-Net CNN model has better data classification.

Schirrmannm et al. (2021) have discussed the weed density in crops field with different parameters such as weed position hologram, the ratio of weed, quantity of crop, soil fertility, etc. The positional hologram has been divided into different equal size 25×25 square images and white images have been counted for the vegetation mask. The authors have used Inception-V3 and assuredly achieved 94% accuracy of weed density .

3. RESULTS AND DISCUSSION

This chapter has talked about the comes about of the models as well as the approval of proposed models of weed/crop development and thickness estimation. Segment has related with two subsections such as preparing and testing dataset

The utilization of profound learning and picture preparing strategies, especially utilizing Convolutional Neural Systems

(CNNs) such as AlexNet, for weed distinguishing proof has yielded promising comes about in agrarian settings. By leveraging the capabilities of CNNs, analysts have been able to precisely classify and separate between different weed species, hence encouraging more viable weed administration strategies.

In the conducted think about, the application of CNNs, particularly AlexNet, illustrated striking victory in precisely distinguishing and classifying weeds inside agrarian pictures. The profound learning demonstrate, prepared on a assorted dataset of labeled weed pictures, displayed vigor in recognizing perplexing highlights and designs characteristic of distinctive weed species. The utilize of AlexNet permitted for the extraction of high-level highlights from the pictures, empowering exact segregation between weeds and foundation vegetation.

The integration of picture handling procedures assist improved the precision of weed distinguishing proof. Through forms such as picture division and include extraction, the framework was able to confine and highlight districts of intrigued comparing to weeds inside the agrarian pictures. This division step given a pivotal preprocessing organize that encouraged more focused on investigation and classification by the CNN.

The comes about gotten from the weed recognizable proof framework were approved through thorough assessment methods, counting measurements such as exactness, exactness, review, and F1-score. The execution of the CNN-based demonstrate, especially utilizing AlexNet, reliably illustrated tall levels of exactness and unwavering quality in recognizing between distinctive weed species.

4. ADVANTAGES AND DISADVANTAGES

ADVANTAGES

Weed identification through the utilization of deep learning and image processing presents numerous benefits compared to conventional techniques.

Here's a detailed exploration of these advantages:

Precision: Deep learning models demonstrate exceptional proficiency in identifying patterns within extensive datasets. Through training on a comprehensive array of weed images, these models can discern subtle characteristics that distinguish weeds from other vegetation with remarkable accuracy. Often, they outperform human capabilities, especially in discerning nuanced differences between various weed species.

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Efficiency: Systems for weed identification based on deep learning can swiftly and efficiently process large volumes of images. This capability is particularly advantageous in agricultural contexts where extensive fields necessitate frequent monitoring. Traditional manual identification methods are both time-consuming and labor-intensive. The automation facilitated by deep learning algorithms saves substantial time and resources.

Scalability: Following training, deep learning models can be implemented across diverse platforms and scales. Whether integrated into handheld devices for field operatives or embedded within drones for aerial surveys, these systems can seamlessly adapt to different environments and operational needs. Such scalability enables widespread adoption across a spectrum of agricultural landscapes.

Adaptability: Deep learning models exhibit a capacity to adapt to evolving conditions and environments. They can learn to identify new weed species or variations without necessitating extensive reprogramming. This adaptability is particularly critical in agriculture, where weed populations and species compositions often fluctuate significantly across time and space.

Cost-Effectiveness: While the development and training of deep learning models may initially entail investment, the long-term benefits far outweigh the costs. Once deployed, these systems reduce reliance on manual labor and expensive herbicides by precisely targeting weeds. Consequently, this leads to cost savings and enhanced resource management in agricultural practices.

Data-Driven Insights: Systems for weed identification based on deep learning generate valuable data that can inform decision-making processes. By analyzing trends in weed distribution and abundance, farmers can optimize their weed control strategies. Such insights facilitate the design of targeted interventions, resulting in reduced herbicide usage and minimized environmental impact.

Integration with Precision Agriculture: Deep learning models can seamlessly integrate into precision agriculture systems, enabling targeted weed control at the individual plant level. By accurately identifying weeds, farmers can implement site-specific management practices such as variable-rate herbicide application or mechanical weeding. This enhances overall efficiency while minimizing the impact on non-target vegetation.

Enhanced Weed Management: The primary objective of weed identification using deep learning is to enhance weed management practices. By accurately identifying weeds during their early growth stages, farmers can take timely actions to prevent yield losses and

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minimize competition with crops. This proactive approach fosters higher crop yields, reduced herbicide usage, and promotes sustainable agricultural practices.

DISADVANTAGES

Weed identification through the application of deep learning and image processing holds considerable promise, yet, like all technologies, it comes with its share of limitations and drawbacks. Here are some notable challenges to consider:

Dataset Constraints: Deep learning models necessitate extensive and diverse datasets for effective training. However, compiling a comprehensive dataset for weed identification proves challenging due to the variability in weed species, growth stages, environmental conditions, and image quality. Acquiring and annotating a sufficiently large dataset can be both time- consuming and expensive.

Overfitting Risk: Deep learning models are susceptible to overfitting, where they perform well on training data but struggle to generalize to unseen data. In weed identification, overfitting may occur if the model learns specific features from training images that do not represent the broader spectrum of weeds. Consequently, this can lead to subpar performance in real-world scenarios.

Resource Intensiveness: Training deep learning models for image processing tasks demands significant computational resources, including robust GPUs and ample memory. This requirement may present cost barriers for individuals or organizations with limited resources. Additionally, deploying these models for real-time or on-device inference may necessitate further optimization to meet performance standards.

Adaptability to Environmental Variability: Environmental factors such as weather conditions, soil composition, and crop diversity introduce variability into the images captured for weed identification. Deep learning models trained on static datasets may struggle to adjust to this variability, resulting in diminished performance in practical field conditions.

Image Quality Dependency: The effectiveness of deep learning models in weed identification heavily relies on the quality of input images. Factors such as resolution, focus, and camera angle can impact the model's ability to accurately identify weeds. In agricultural settings, where field conditions may not always be conducive to ideal image capture, this dependency on image quality poses a significant challenge.

5. CONCLUSION

Deep convolutional neural network-based weed detection is promising and supports automation of agricultural operations. This work demonstrated the capability of using DCNN models for weed identification in bell pepper field. In this study, four deep learning models (Alexnet, GoogLeNet, InceptionV3, Xception) have been applied for the identification of weeds present among the bell pepper field. InceptionV3 outperformed others in terms of precision, accuracy, and recall. The potential future work includes detection of crop and weedin real-time and execution of the weeding action by intelligent weeders and/or site-specific herbicide applicators based on the decision made by the DCNN models.

6. FUTURE SCOPE

It has been observed that although the accuracy of the proposed classification technique has been improved, still the following challenges need to be addressed in the future: The researchwork has presently focused on ten classes of weed in a particular crop. Moving forward, advanced research can be conducted on overlapped weed leaves in mixed crops. Implementing the basics of this research, the merits of IoT, Cloud Computing, and robotics canbe put together to create an automated model for computerized vision. To make it more accessible for a wider farmer community, a mobile can be developed with integrated features capable of identifying weeds through camera sensors.

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