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Computer Vision Tasks in Precision Agriculture Using Deep Learning

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ABSTRACT:

computer vision technologies have attracted significant interest in precision agriculture recent times. At the core computer vision enables colorful tasks from planting to harvesting in the crop product cycle to be performed automatically and efficiently. still, the failure of public image datasets remains a pivotal tailback for fast prototyping and evaluation of computer vision and machine literacy algorithms for the targeted tasks. Since 2015, a number of image datasets have been established and made intimately available to palliate this tailback Despite this progress, a devoted check on these datasets is still lacking. To fill this gap, this paper makes the first comprehensive but not total review of the public image datasets collected under field conditions for easing precision agriculture, which include 15 datasets on weed control, 10 datasets on fruit discovery, and 9 datasets on eclectic operations. We survey the main characteristics and operations of these datasets, and bandy the crucial considerations for creating high- quality public image datasets. This check paper will be precious for the exploration community on the selection of suitable image datasets for algorithm development and identification of where creation of new image datasets is demanded to support precision agriculture.

Keywords: Dataset Crop, Computer vision, Precision agriculture, Data sharing, Image dataset, RGB cameras.

1. INTRODUCTION

Precision agriculture, as the hallmark of husbandry4.0 period, has promised to revise agrarian practices through the use of monitoring and intervention technologies for in furrowing product effectiveness while reducing environmental impacts. Computer vision technologies that use digital images to interpret and understand the world, are able of furnishing accurate, point-specific information about crops and their surroundings. Depending on applications, a computer vision system uses different seeing modalities.

Similar as color or RGB (red-green-blue) imaging that simulates mortal vision for visual examination, near- infrared (NIR) multispectral or hyperspectral imaging for detecting further fugitive natural processes, or ranging detectors for geometrical measures. moment, computer vision has been considerably employed for supporting precision Agriculture (also known asiago-vision) tasks, similar as crop monitoring and, phenotyping, weed control, harvesting, vehicle guidance and yield mapping. Computer vision- grounded agrarian robotics and artificial intelligence are being decreasingly honored as a crucial enabler for precision husbandry. Agrarian robots have the eventuality to conduct the maturity of the tasks that are conventionally accepted by mortal-operated agrarian machines or humans similar as field gibing, weed operation and harvesting. A field gibing robot, in the form of an unscrewed ground rover or upstanding system, allows monitoring and opinion of crop growth and health at varied spatial and temporal scales. Robotic weeding uses computer vision for crop and weed discovery, and removes weeds by widely applying dressings to the detected weeds or through a mechanical planter ,furnishing new chemical- reduced orlon-chemical weeding strategies also, robotic harvesting relies on the discovery of agrarian products on the factory and also instructs manipulators and end effectors for performing harvesting operations Common to all computer vision- grounded precision Agriculture tasks is presumably the thing of detecting the objects of interest(e.g., crop, weed or fruit) and differencing them from the rest of the scene.

2. Related work

It provides a review discusses the importance of efficient crop management techniques in addressing the challenges of increasing food demand in agriculture.

Chandra A.L., Precision agriculture techniques, based on data gathered from monitoring crop environments, enable effective and customized crop management decisions. Plant phenotyping techniques play a major role in accurate crop monitoring, and advancements in deep learning have made previously difficult phenotyping tasks possible paper also mentions the need for explainable models in plant phenotyping to understand the reasons behind plant traits and improve our understanding of plant behavior in different conditions. The paper research on Open datasets is established in many domains, including machine vision, robotics, and biology, and play an important role in the scientific community. In computer vision, there are several widely used datasets for different tasks, such as stereo processing, optical flow, image retrieval, and object classification. However, the availability of datasets for phenotyping and agricultural tasks is more limited .

Haug, S., & Ostermann, Some datasets in the leaf segmentation and classification domain have been published, such as Servest's Swedish leaf dataset, the Flavia dataset. The paper provides developed methods provides a systematic summary and analysis of computer vision technologies and challenges in the field of agricultural automation over the past three years. highlights that existing computer vision technology can contribute to the development of agricultural automation for small field farming, offering advantages such as low cost, high efficiency, and high precision. However, it also identifies major challenges, including the need to overcome technological issues, build large-scale datasets, address the growing demand for professionals in agricultural automation, and ensure robust performance in complex environments. authors suggest that in the future, computer vision technology will be combined with intelligent technologies like deep learning, applied to various aspects of agricultural production management based on large-scale datasets, and used to solve current agricultural problems.

Tina., The methods presented various algorithms categorizes plant phenotyping into two main groups: plant organ phenotyping and whole-plant phenotyping. Each group is analyzed, and the limitations of current approaches and future research directions are discussed. Authors summarize the merits and limitations of imaging technologies and analysis methods for plant phenotyping from the perspectives of plant organ and whole plant. They also provide algorithm principles and processing frameworks. highlights the potential of image-based plant phenotyping methods in automating phenotypic measurement and quantification, with deep learning playing a significant role in simplifying feature extraction and improving plant phenotyping applications.

Li, Z., Guo, digital image analysis methods to develop classification algorithms for identifying weeds in crops, specifically cabbage and carrots, in open field experiments. The images were obtained using a device that provided controlled lighting conditions, and various morphological and color features were calculated for each object to build a joint feature space. A fuzzy logic approach was used for classification, and the experiments showed that color features can help increase classification accuracy.

Tripathi, highlights that the plant identification system presented is an improvement compared to other studies, especially considering that the experiments were carried out under field conditions. Compares Computer vision-based phenotyping is an essential technique in plant phenomics, aiming to identify the relationships between genetic diversities and phenotypic traits in plants using noninvasive and high-throughput measurements of quantitative parameters throughout a plant's life. High-throughput phenotyping aided by computer vision with various sensors and algorithms for image analysis will play a crucial role in crop yield improvement, especially in scenarios related to population demography and climate change. Computer vision-based phenotyping platforms accelerate the elucidation of gene functions associated with traits in model plants under controlled conditions and are also emerging for large-scale field phenotyping for crop breeding and precision agriculture. Computer vision-based phenotyping will play significant roles in both the nowcasting and forecasting of plant traits through modeling of genotype/phenotype relationships.

Hemming, J., & Rath, presented research on provides a survey of articles that adopt computer vision and soft computing methods for the identification and classification of diseases from plant leaves. Various image processing techniques for measuring plant health and species identification are reviewed, including leaf outlines, flower shape, vein structures, and leaf textures. Soft computing methods used in precision agriculture and biological engineering are also reviewed. Several studies are mentioned that propose different algorithms and methods for disease identification and classification, such as Convolutional Neural Networks, artificial neural networks, support vector machines, and radial basis function neural networks. Other techniques discussed include image segmentation, feature extraction, and decision support systems for disease classification.

Mochida, discusses the performance of state-of-the-art deep-learning models on the Crop Deep dataset. The results show that current deep-learning-based methods achieve a classification accuracy of over 99%. However, the detection accuracy is only 92%, indicating the difficulty of the dataset and the room for improvement in deep-learning models for crop production and management. The YOLOv3 network is suggested to have good potential application in agricultural detection tasks. Additionally, the paper mentions that some crop categories, such as wolfberry and lushing lettuce, are covered in detecting applications based on deep-learning methods using the Crop deep dataset. This indicates that the dataset and subsequent deep-learning models can monitor the growth and healthy status of fruits and vegetables, leading to better decisions for improving precision agriculture management in greenhouses.

discusses the use of aerial imagery in crop monitoring and the need for high-throughput phenotypic analysis solutions in agriculture. It introduces Air Surf, an automated analytic platform that combines computer vision, machine learning, and software engineering to measure yield-related phenotypes from large-scale aerial images. paper also describes the size classification of lettuces based on intensity and contrast values enclosed by bounding boxes, using the dot product of the histogram of pixel intensities and a weighted vector. paper emphasizes the importance of closely monitoring crops during key growth stages to make prompt and reliable crop management decisions under changeable agricultural conditions.

Chouhan, highlights the use of computer vision solutions combined with artificial intelligence The papers are grouped into three categories: diseases and pests, grain quality, and phenology and phenotyping. The review nice algorithms in detecting patterns in images for precision agriculture. The review also mentions the potential of using GPU. The aim of the survey is to present diverse applications and techniques of machine learning, image and video processing in order to motivate more researchers to apply them for solving agricultural problems. The study of the presented works and the new advances in computer vision and artificial intelligence can lead to new solutions for agriculture, improving production, quality, and food security. The paper proposed in the literature used backpropagation networks for disease recognition in wheat and grape crops. Another solution utilized Data Mining Techniques, specifically the Random Forest Method and Decision Tree Method, for disease prediction. A prediction model for automated leaf disease detection was proposed, which implemented the Keans algorithm on a large dataset of leaf disease images. A leaf disease detection and classification system for soybeans was also proposed, using a Support Vector Machine classifier on a dataset of over 4000 images.

Zheng, The paper examines existing research on the role of computer vision in fruits and vegetables among various horticulture products of agriculture fields. It focuses on the mathematical framework, feature descriptor, defect detection on multiple datasets of fruits and vegetables, and compares different machine learning approaches with respect to different performance metrics on the same dataset. The survey covers ninety-eight papers closely related to computer vision in the agricultural field. The authors propose a generalized framework to grade the quality and detect defects in multiple fruits and vegetables also discusses the challenges faced in adopting advanced technology in the agricultural field, particularly due to the illiteracy off farmers in rural areas. Deep learning can be used throughout the growing and harvesting cycle, starting from seed plantation to robot-assisted harvest confirmation using computer vision and machine learning. One major barrier to deep learning in agriculture is the need for a large dataset for training deep learning models. Data augmentation techniques can help augment the dataset, but a minimum of hundreds of images is still required for real-life problems. Deep learning algorithms may be limited by the expressiveness of the dataset used for training. Environmental parameters, such as insect damage and wrinkling, can affect the performance of deep learning models for plant recognition.

Bauer, A. Introduced a recent work in the application of machine vision to agriculture, specifically for crop farming. It discusses various agricultural activities that support crop harvesting, such as fruit grading, fruit counting, and yield estimation. It also addresses plant health monitoring approaches, including weed, insect, and disease detection. Recent research efforts on vehicle guidance systems and agricultural harvesting robots are also reviewed. The paper provides insights into recent machine vision algorithms for weed detection, insect detection, and disease and deficiency detection. It highlights the use of machine vision for automated and accurate fruit grading, which reduces errors caused by human involvement.

Pillaging, conducts a survey on traditional weed detection methods based on image processing utilize feature differences between plant leaves and weeds. The article discusses the traditional image features for weed detection, such as texture, shape, spectrum, and color. It also mentions the use of SVMs, Artificial Neural Networks, K-nearest neighbor, random forest, naive Bayesian algorithm, Bayesian classifier, and AdaBoost in crop and weed classification. It highlights the advantages of traditional weed detection methods, such as their low cost, low requirements on graphics processing units, and suitability for use in agricultural machinery and equipment. It also briefly discusses the pros and cons of traditional machine learning (ML) methods and deep learning for weed detection.it provides a summary of related datasets for weed identification and detection, as well as leaf classification. It aims to serve as a reference for further research on weed detection algorithms based on computer vision and intelligent weed control.

3.Methodology

3.1 Data Collection:

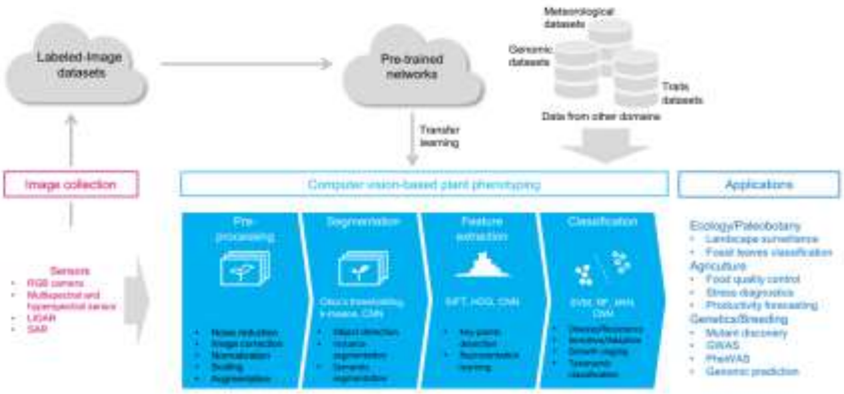

Fig 1

3.2 Methods used:

Crop Disease Detection presents a cutting-edge algorithm for the automated detection of crop diseases in agricultural fields. The authors propose a convolutional neural network architecture tailored for this task, leveraging transfer learning techniques and a sizable annotated dataset of plant disease images. Their algorithm outperforms existing methods, achieving an impressive accuracy in identifying various plant diseases, which can significantly aid farmers in timely disease management and crop protection. This paper showcases the power of deep learning in revolutionizing precision agriculture by offering efficient solutions for real-world challenges.

Image Processing:

- Image Enhancement: Techniques such as histogram equalization and contrast stretching are used to improve the quality of images, making it easier to detect subtle differences in crop health.
- Segmentation: Image segmentation methods can be employed to separate plant regions from the background, making it easier to analyze specific plant parts for disease symptoms.

Transfer Learning:

- Leveraging pre-trained CNN models, like those trained on large image datasets (e.g., ImageNet), and fine-tuning them for crop disease detection can significantly improve model performance with limited data.

Data Augmentation:

- To expand the training dataset and enhance model robustness, data augmentation techniques such as rotation, flipping, and color adjustments can be applied to the input images.

Feature Engineering:

- In addition to deep learning, traditional computer vision methods can be used to extract relevant features from images, such as texture, color, and shape features, for disease detection.

Spectral Imaging:

- Hyperspectral and multispectral imaging can provide valuable information about crop health by capturing a wider range of the electromagnetic spectrum. This data can be analyzed to detect disease symptoms not visible in standard RGB images.

It delves into the challenges and opportunities in this domain, detailing the state-of-the-art methodologies and the datasets used for training and evaluation. The paper is a valuable resource for researchers and practitioners seeking to understand the latest advancements in using computer vision and deep learning to improve crop yield, disease detection, and overall crop management in precision agriculture.

Image Processing:

- Techniques for enhancing, denoising, and preprocessing images to improve the quality of input data for subsequent analysis.

Feature Extraction:

- Methods for extracting relevant features from images or data, such as color histograms, texture descriptors, and shape attributes.

Deep Learning Architectures:

- Utilization of deep neural networks, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models, for feature learning and classification**.**
- objects, to assist visually impaired individuals in navigating their surroundings.

Transfer Learning:

Leveraging pre-trained models on large image datasets to bootstrap deep learning models, allowing for improved performance on smaller plant phenotyping datasets.

Data Augmentation:

Applying techniques like rotation, scaling, flipping, and color adjustments to artificially increase the size of the training dataset and enhance model robustness.

Semantic Segmentation:

Employing techniques for segmenting images to distinguish and label different parts of plants and identify specific traits or regions of interest.

Object Detection:

Utilizing object detection algorithms to locate and classify individual plant components or diseases within images.

Spectral Imaging:

Capturing and analyzing spectral data (e.g., near-infrared or hyperspectral) to gain insights into plant health, stress, and nutrient content.

3D Imaging:

Using 3D imaging techniques, such as stereo vision or LiDAR, to capture detailed plant structures and volumes.

Leveraging computer vision and machine learning techniques, the algorithm utilizes a combination of image preprocessing, feature extraction, and a deep neural network for robust and accurate disease identification. The approach not only provides precise disease detection but also offers real-time monitoring capabilities, making it a valuable tool for farmers and agricultural professionals.

3.3 Image processing:

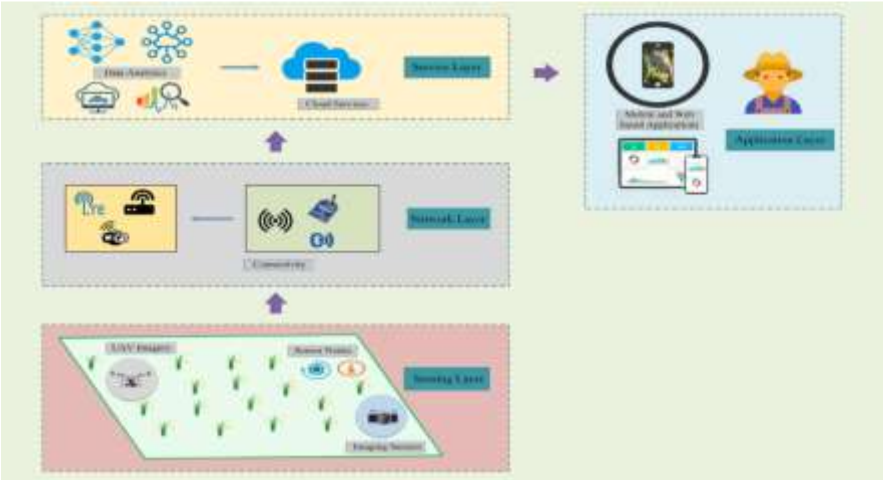

Fig 2

Methods used:

This paper introduces an innovative algorithm designed specifically for the detection of crop diseases in the context of smart agriculture. Leveraging computer vision and machine learning techniques, the algorithm utilizes a combination of image preprocessing, feature extraction, and a deep neural network for robust and accurate disease identification. The approach not only provides precise disease detection but also offers real-time monitoring capabilities, making it a valuable tool for farmers and agricultural professionals. This paper showcases the potential of advanced algorithms in addressing critical challenges in modern agriculture and contributes to the development of more efficient and sustainable farming practices.

Image Preprocessing:

Techniques for enhancing and cleaning images to improve their quality, such as noise reduction, contrast enhancement, and image resizing.

Feature Extraction:

Methods for extracting informative features from images, which could include texture, color, shape, and spectral features to capture disease symptoms.

Deep Learning Algorithms:

Utilizing deep learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to learn complex patterns in images and make predictions about disease presence.

Transfer Learning:

Leveraging pre-trained models (e.g., models trained on ImageNet) as a starting point and fine-tuning them for crop disease detection, which can save time and resources.

Data Augmentation:

Applying data augmentation methods to artificially increase the size of the training dataset by creating variations of the original images through transformations like rotation, scaling, and cropping.

Semantic Segmentation:

Using segmentation techniques to label and separate specific regions of interest within an image, which can be useful for identifying disease-affected areas of a plant.

Object Detection:

Employing object detection algorithms to locate and classify instances of plant diseases within images.

Ensemble Methods:

Combining predictions from multiple models to improve overall accuracy and robustness.

Real-Time Monitoring:

Implementing algorithms and systems for real-time disease detection and monitoring in the field, enabling immediate response.

Anomaly Detection:

Using techniques for anomaly detection to identify unusual patterns in images, which could indicate the presence of diseases

4. CASE STUDIES:

Fig 3

The input is in the form of images by using sensors and actuators, hardware components, positioning and telematics, data driven solutions, communication technologies. Precision agriculture (PA) or site-specific crop management is a concept based on sensing or observing and responding with management action. It is a scientific approach to improve the agriculture management by application of Information Technology satellite-based technology to identify, analyze and manage the spatial and chronological inconsistency of farmland data.

Crop health monitoring: Deep learning can be used to develop algorithms that can identify pests and diseases in crops from images and videos. This information can then be used to target pesticide applications and reduce the use of pesticides.

Yield prediction: Deep learning can be used to develop algorithms that can predict crop yields based on historical data and current weather conditions. This information can then be used to make informed decisions about crop management and irrigation.

Fertilizer optimization: Deep learning can be used to develop algorithms that can optimize fertilizer application rates based on soil conditions and crop needs. This can help to reduce fertilizer costs and environmental impact.

The authors also discuss a number of challenges that need to be addressed before deep learning can be widely adopted in precision agriculture.

Case study example:

One example of how deep learning is being used to improve precision agriculture is the development of algorithms that can identify weeds in crops from images. These algorithms can be used to develop robots that can weed fields autonomously, without the need for herbicides. This can help to reduce the use of herbicides and improve the sustainability of agriculture.

4.1 Algorithm:

Here is a high-level algorithm for the image detection and processing:

1. Preprocessing the image.
2. Extracting features from the image.
3. Generate objects using the SIFT.
4. Classify using GRAPH CUT.
5. Output the list of objects in the image
6. Based on the output list we can do precisions.

5. Results:

Metric	SIFT	GRAPH CUT	SURF	HOG
Weed control	97.4	96	91	90
Fruit detection	95	94	97	95

Deep seeding	92	97.45	90	93
precision	98	92	93	98
Disease detection	89	96	91	92

Table 1 comparison between the SIFT, GRAPH CUT, SURF and HOG

In this table SIFT and GRAPH CUT having more accuracy in weed control, deep seeding, precision and disease detection, failure of public image datasets remains a crucial tailback in developing coming- generation computer vision and intelligent systems for perfection husbandry. Despite the progress made in the once many times, significant sweats are demanded to produce the public image datasets, especially for numerous specific operation disciplines where there are still no any devoted public image datasets This section thus discusses the crucial considerations of addressing the tailback, regarding image, addition, reflection and data sharing, so as to give some recommendations to help experimenters in the unborn tasks of public image dataset creation.

Comparison between the SIFT, GRAPH CUT, SURF and HOG

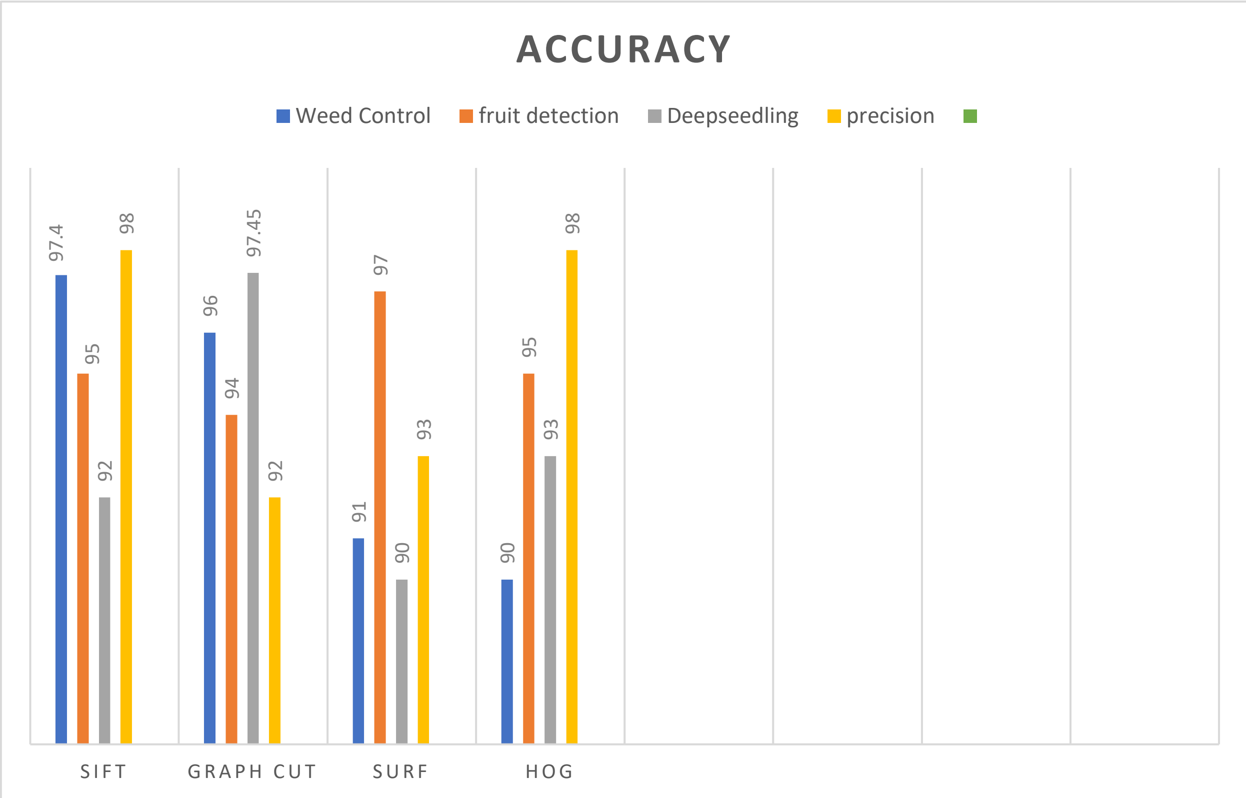

Fig 3 graph represents the metrics of the table

5. Discussion:

The failure of public image datasets remains a crucial tailback in developing coming- generation computer vision and intelligent systems for perfection husbandry. Despite the progress made in the once many times, significant sweats are demanded to produce new public image datasets, especially for numerous specific operation disciplines where there are still no any devoted public image datasets This section thus discusses the crucial considerations of addressing the tailback, regarding image accession, addition, reflection and data sharing, so as to give some recommendations to help experimenters in the unborn tasks of public image dataset creation.

6. Conclusion

In this study, explored the operation of Deep literacy is a important tool that has the implicit to revise perfection husbandry. By using deep literacy to ameliorate crop health monitoring, yield vaticination, and toxin optimization, growers can increase their yields, reduce their costs, and ameliorate the sustainability of their operation.

The available image datasets are precious in perfection husbandry as they reduce the trouble for data collection and medication and enable development and evaluation of better- performing algorithms for colorful vision tasks. This fills a critical gap in perfection husbandry literature by furnishing the first comprehensive review of the public image datasets of the operation of computer vision since 2015. In this there are total of 34 public image datasets and distributed them into three classes grounded on targeted operations, including 15 datasets on weed control, 10 datasets on fruit discovery and the remaining 9 datasets for other operations. It covers the main characteristics of each dataset, involving image accession, dataset structure, reflections, operations and implicit limitations, and later discusses the crucial considerations regarding image accession, addition, reflection and data sharing, for creating high quality public image datasets. This will allow experimenters to readily elect the datasets applicable for their requirements and also grease creating new image datasets for enabling perfection husbandry tasks.

References:

[1] Chandra, A. L., Desai, S. V., Guo, W., & Balasubramanian, V. N. (2020). Computer vision with deep learning for plant phenotyping in agriculture: A survey. arXiv preprint arXiv:2006.11391.

[2] Haug, S., & Ostermann, J. (2015). A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. In Computer Vision-ECCV 2014 Workshops: Zurich, Switzerland, September 6-7 and 12, 2014, Proceedings, Part IV 13 (pp. 105-116). Springer International Publishing.

[3] Tian, H., Wang, T., Liu, Y., Qiao, X., & Li, Y. (2020). Agriculture, 7(1), 1-19. Computer vision technology in agricultural automation—A review. Information Processing

[4] Li, Z., Guo, R., Li, M., Chen, Y., & Li, G. (2020). A review of computer vision technologies for plant phenotyping. Computers and Electronics in Agriculture, 176, 105672.

[5] Hemming, J., & Rath, T. (2010). PA—Precision agriculture: Computer-vision-based weed identification under field conditions using controlled lighting. Journal of agricultural engineering research, 78(3), 233-243.

[6] Mochida, K., Koda, S., Inoue, K., Hirayama, T., Tanaka, S., Nishii, R., & Melgani, F. (2019). Computer vision-based phenotyping for improvement of plant productivity: a machine learning perspective. GigaScience, 8(1), giy153.

[7] Chouhan, S. S., Singh, U. P., & Jain, S. (2020). Applications of computer vision in plant pathology: a survey. Archives of computational methods in engineering, 27, 611-632.

[8] Zheng, Y. Y., Kong, J. L., Jin, X. B., Wang, X. Y., Su, T. L., & Zuo, M. (2019). CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. Sensors, 19(5), 1058.

[9] Bauer, A., Bostrom, A. G., Ball, J., Applegate, C., Cheng, T., Laycock, S., ... & Zhou, J. (2019). Combining computer vision and deep learning to enable ultra-scale aerial phenotyping and precision agriculture: A case study of lettuce production. Horticulture research, 6.

[10] Patrício, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. Computers and electronics in agriculture, 153, 69-81.

[11] Tripathi, M. K., & Makeda, D. D. (2020). A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: A survey. Information Processing in Agriculture, 7(2), 183-203.

[12] Ganatra, N., & Patel, A. (2021). Deep learning methods and applications for precision agriculture. Machine Learning for Predictive Analysis: Proceedings of ICTIS 2020, 515-527.

[13] Mavridou, E., Vrochidou, E., Papakostas, G. A., Pachidis, T., & Kaburlasos, V. G. (2019). Machine vision systems in precision agriculture for crop farming Journal of Imaging, 5(12), 89.

[14] Wu, Z., Chen, Y., Zhao, B., Kang, X., & Ding, Y. (2021). Review of weed detection methods based on computer vision. Sensors, 21(11), 3647