Plant Leaf Disease Detection by Deep Learning: A Literature Review

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Abstract- Efficient detection technologies are necessary to address the danger of plant diseases to global agriculture and food security. The conventional method of disease identification, which depends on farmers visually inspecting the crops, is frequently ineffective and prone to bias. This work explores the feasibility of employing image processing and machine learning techniques to automatically detect plant diseases, specifically focusing on infections affecting leaves. In deep learning, a subfield of machine learning, artificial neural networks are used to extract features from data in a way that is reminiscent of the human brain. This literature review assesses the strengths and limitations of deep learning approaches, namely convolutional neural networks, compared to standard image processing methods. The evaluation focuses on accuracy, scalability, and practicality. The report provides recommendations for future research areas, emphasizing the significance of creating more accessible and resilient methods to assist farmers in promptly managing diseases. This research seeks to enhance sustainable farming practices and reduce the impact of plant diseases on global food systems by combining novel technologies and interdisciplinary approaches. This paper showcases numerous recent research achievements in deep learning and machine learning, as well as their potential future applications.

Index Terms- Plant Disease, Machine Learning, Deep Learning, convolutional neural networks.

I. Introduction

Food, the primary human necessity, is closely connected to agriculture [1]. Plant diseases cause a substantial decrease in agricultural productivity, which has a detrimental impact on global agriculture and results in economic and social losses. Each year, plant diseases result in an approximate worldwide crop loss of USD 220 billion, representing 14.1% of the overall crop loss [2]. The Food and Agriculture Organization's research states that in 2022, the number of people afflicted by hunger ranged from 691 to 783 million, indicating a rise of 30 to 40 million over two years. If plant diseases are not promptly detected, it will result in an exacerbation of food insecurity. The recognition of plant diseases has been a significant concern in recent years. Identifying leaf diseases depends on examining plant leaves, as most disease symptoms are apparent in this particular plant section [3]. Typical indications of plant leaf illnesses encompass changes in color, the presence of wounds, drooping, twisting, tissue death, the growth of a powdery substance, the appearance of rust, the formation of spots, irregular patterns of discoloration, the presence of tiny dots, the development of open sores, the growth of mold or mildew, hindered growth, abnormal leaf structure, and the premature shedding of leaves. Farmers typically rely on their subjective experience to identify leaf diseases on-site, an approach that is time-consuming, difficult, and inefficient. Occasionally, farmers may make errors in judgment, which can lead to indiscriminate use of drugs. It can result in a decrease in the quality and quantity of their produce and environmental contamination. Ultimately, these mistakes can cause excessive financial losses.

We aim to support farmers and agencies in identifying plant diseases in their early stages and applying suitable remedies. The existing methods and solutions primarily rely on hardware, resulting in high costs and posing difficulties in upkeep [4]. Due to the global prevalence of smartphones, it has become easier to capture photographs of plant leaves, and many individuals have access to essential internet services. More than 300 million people access the internet, employing different programs for comfort. Although government initiatives, such as 24*7 helpline numbers exclusively for farmers, have been implemented, rural residents still need help getting adequate amenities and frequently need help resolving their agricultural issues. An uncomplicated tool that allows farmers to identify diseases using images independently could be advantageous in these situations [5]. In order to tackle these difficulties, there is an increasing emphasis on researching to investigate the use of image-processing techniques for identifying plant diseases. The goal is to offer a more precise and effective alternative to conventional approaches. Conventional techniques for detecting plant diseases through photographs often entail collecting manually designed elements from the images, such as color, texture, and shape information. These features classify the images using algorithms like Support Vector Machines or Decision Trees. The drawbacks of these conventional approaches encompass the requirement for human feature engineering and constraints in capturing intricate visual patterns. Conversely, deep learning techniques, specifically convolutional neural networks (CNNs), acquire hierarchical representations from unprocessed visual data, eliminating the requirement for explicit feature extraction. Machine learning techniques have become highly effective tools for automating, identifying, and diagnosing leaf diseases. Machine learning algorithms utilize extensive image data to develop the ability to differentiate between healthy and unhealthy plant leaves by analyzing visual cues and patterns. Lately, researchers have been giving more attention to using conventional methods like

Support Vector Machines (SVM) and Decision Trees, as well as advanced deep learning approaches like Convolutional Neural Networks (CNN), to detect diseases in leaves [6]. As a result, advanced models can provide precise, scalable, and efficient solutions for automated plant pathology. This article investigates the efficacy of different machine learning-based algorithms in classifying different leaf diseases in diverse plant species. Our literature study compares deep learning and classical methods for detecting plant diseases. We analyze essential factors like accuracy, limitations, and practical issues. Our review offers a comprehensive analysis of each strategy's advantages and drawbacks, facilitating comprehension of their suitability in various situations and the compromises of efficient plant disease detection. The "Conclusions and Future Directions" section summarizes important discoveries and suggests future research areas. summarizes important discoveries and suggests future research areas [7-9].

II. COMMON LEAF DISEASES

Discoloration: Abnormal changes in color, such as yellowing or browning, typically indicate a problem with the plant. Possible causes include nutrient deficiency or the presence of a disease.
Lesions: Lesions are injuries or damages resembling cuts or bruises on plants. They might arise from illness, pests, or physical injury to the plant.
Wilting refers to the condition of plants seeming droopy and melancholy. It is possible that they require additional water or that the temperature is excessively high.
Curling refers to the abnormal bending or twisting of plant leaves. It is caused by insufficient water, insect infestation, or excessive heat and dryness.
Necrosis: Necrosis refers to the process of plant tissue death. Possible causes include illness, injury, or extreme temperatures.
Powdery Mildew: Powdery mildew is a fungal disease characterized by the growth of a white or gray powdery substance on plants, which can weaken their structure.
Rust: Rust refers to the appearance of rusty patches on plants. The condition is attributed to a fungal infection and might result in plant debilitation.
Spots: Spots refer to little markings or spots found on plants. They might arise from illness, pests, or the plant's lack of vitality.
Mottling refers to unusual patterns or dots on plant leaves. Possible causes for plant deterioration include illness, infestation, or inadequate nutrition.
Stippling refers to little spots on plant leaves caused by tiny insects extracting sap. It can cause the plant to become feeble.
Cankers are lesions that form on plant stems or branches. Plant damage can be caused by various factors, such as illness, pests, or physical injury.
Mold or Mildew Growth: Mold or mildew refers to the development of fuzzy substances on plants. It can cause debilitation and rapid dissemination.
Stunted growth refers to the condition in which a plant fails to reach its expected size or strength. Possible causes include insufficient food supply, illness, insect infestation, or unfavorable weather conditions.
Abnormal Leaf Shape: Abnormal leaf shape refers to leaves that deviate from the typical appearance. The potential causes of plant abnormalities include illness, infestation by pests, or genetic abnormalities.
Premature Leaf Drop: Premature leaf drop refers to the phenomenon where leaves detach from the plant before the expected time. Possible causes include inadequate hydration, illness, insect infestation, or abrupt weather fluctuations [10].

III. LITERATURE REVIEW

Detecting leaf diseases via image processing has been the subject of much research throughout the years, and the topic continues to draw researchers today. The use of machine learning and image processing for the purpose of automatically detecting agricultural diseases has recently become more popular.

[11] The subject matter of this literature review pertains to identifying plant leaf diseases through computer vision and machine learning methods. Tomato leaves were collected to identify the specific diseases that may impact plant growth in this era of increasing population. Efforts are to raise awareness among farmers and assist them with advanced algorithms, enabling them to detect diseases and reduce their spread readily. The researchers employed convolutional neural networks, discrete wavelet transform, principal component analysis, and nearest neighbor. Initially, the dataset's leaf photographs are scaled to dimensions of 256 by 256 pixels. Additionally, Histogram Equalization is applied to enhance the image quality. Authors are developing a prototype model to enhance the categorization of photos. The dataset was collected from a community and includes photos depicting six different sorts of illnesses. The K-means clustering algorithm is employed to identify sick regions, while Contour tracing analyzes digital leaf samples. The algorithms utilized for feature extraction include Discrete Wavelet Transform and Gray Level Co-occurrence Matrix. The approaches used for sample classification include Support Vector Machines (SVM), K-nearest neighbors (KNN), and Convolutional Neural Networks (CNN). An assessment of leaf disease is evaluated using precision measures, recall measures, and F-measures. Six hundred samples were taken with a high accuracy rate of 99.5%.

[12] This research focuses on detecting plant diseases in agriculture utilizing machine learning methodologies, artificial intelligence, and deep learning. Various plant disease segmentation approaches are employed, including the Threshold, Clustering, Edge detection, and regional methods. These techniques collect characteristics from photos, such as color, texture, and shape, to train a classifier that can distinguish between healthy and unhealthy plants.

The data set utilizes many classification approaches, such as the NB classifier, CNN classifier, DT classifier, SVM classifier, RF classifier, and MLP classifier. Logistic regression was employed to solve linear classification problems using the provided dataset. Deep learning techniques are employed to detect diseases in plants that can cause significant harm to crops and agriculture, leading to a decrease in crop yield. In 2020, the authors "Monu Bhagat et al." presented a paper on detecting plant leaf diseases using classical support vector classification methodology. They proposed a new approach to optimize the sub-set function and introduced fuzzy sets, charts, and other techniques. The CNN methodology was employed for minor preprocessing, contrasting with computations performed using alternative picture arrangements.

[13] This research explicitly examines the date palm white scale disease. In precision agriculture, machine learning, ensemble learning, and feature

extraction techniques are employed to detect and manage date palm white scale disease. Their primary focus was on assessing the capability of classical and ensemble-based machine learning techniques in detecting WSD and classifying the degree of infestation. In order to determine the most successful features for stage-wise classification in WSD, we will examine two specific features: GLCM-based features and HSV color moments. To perform a series of tests to examine the impact of employing alone texture features compared to using a combination of color and texture patterns in the recognition and classification of WSD. To evaluate the classification performance of each model using different stage-wise criteria. Over 2000 annotated date palm leaflet photos were collected as the complete data set. The data is categorized into three sections: i) healthy, ii) brown spot disease, and iii) white scale illness. Since this project only focuses on white scale disease (WSD), only photos from categories i) and iii) were included. The dataset is partitioned into a training set comprising 80% of the complete dataset and a testing set comprising the remaining 20%.

[14] The literature review focuses on the application of machine learning techniques for the detection of leaf diseases. They observed the leaves exhibiting brown and black discoloration on their surfaces for image preprocessing, segmentation, feature extraction, and classifications utilizing various machine learning methods. The GLCMse method was employed for feature extraction, while the SVM algorithm uses in classification. The CNN approach for enhanced accuracy compared to the SVM approach. The dataset consists of 12,949 entries in this study. The dataset is from Kaggle's "new plant disease dataset" website. The dataset consists of leaves from various plants, such as apples, cherries, corn (maize), grapes, peaches, bell peppers, potatoes, strawberries, and tomatoes. The collected photos were categorized based on different disease types and healthy conditions. The final categorization accuracy of plant leaves using ML algorithms was as follows: apple-99.0%, cherry-99.4%, corm-95.8%, grape-99.7%, peach-97.4%, pepper bell-99.4%, potato-98.7%, strawberry-100%, tomato-90.1%.

[15] Deep learning in image-based plant disease identification has garnered interest due to its potential to solve major agricultural issues. In their study "Image-based Plant Diseases Detection using Deep Learning," Panchal et al. extensively cover this topic. Integrating computer vision technologies into agricultural processes is essential because farmers' visual inspection methods typically fail. The authors recommend deep learning, particularly CNNs, for picture classification jobs due to their capacity to handle massive datasets and extract intricate patterns. Building on previous studies, they emphasize deep learning models' object detection performance. CNNs can enhance plant disease identification accuracy, showing that image-based approaches can outperform machine learning. A comprehensive evaluation of relevant work shows that researchers use unsupervised representation learning and image segmentation approaches. The authors also emphasize the importance of datasets in training robust models, highlighting attempts to annotate datasets and resolve uneven class distributions. Transfer learning is essential for adapting pre-trained models to new tasks using fewer datasets. Using pre-trained models like VGGNet, ResNet, and Inception-v3, researchers boost classification accuracy, proving transfer learning works in agriculture. The authors also discuss dataset selection, preparation, and training techniques. They stress class distribution balancing in training datasets to reduce bias and increase model generalization. The authors demonstrate improved disease classification accuracy by parameter adjustment and model selection, with the VGG16 model obtaining 93.5% validation accuracy.

[16] Plant diseases threaten global food security and agricultural output. Implementing appropriate measures to reduce these diseases requires early and accurate detection. Recent deep learning (DL) advances have shown promise in improving leaf image-based disease identification. Abd Algani et al. introduced Ant Colony Optimization with Convolution Neural Network (ACO-CNN) for leaf disease detection and classification in this study. According to the literature, traditional plant disease identification methods are time-consuming, inflexible, and environmentally sensitive. These issues highlight the need for more flexible methods. Convolutional Neural Networks (CNNs) are strong image processing and classification technologies, including plant disease diagnostics. CNNs can accurately identify disease symptoms by extracting hierarchical characteristics from input photos. Ant colony optimization methods combined with CNNs offer a fresh way to improve illness diagnosis. Ant colony optimization optimizes complex problems by mimicking ant foraging. This algorithm helps the proposed ACO-CNN model identify damaged plant leaves. Ant colony optimization optimizes feature extraction iteratively, improving classification performance. Comparing the ACO-CNN model to other approaches shows its accuracy, precision, recall, and F1-score superiority. The model outperforms CGAN, CNN, and SGD algorithms in discriminating healthy and sick leaves. High accuracy and performance characteristics make the ACO-CNN model suitable for agricultural applications. The suggested method also solves issues related to collecting, preprocessing, feature extraction, segmentation, and classification of plant disease detection data. The study establishes a robust automated leaf disease identification framework using ACO optimization and CNN-based classification.

[17] Chohan et al. addressed plant disease detection and diagnosis, a key agricultural and environmental issue. Plants are increasingly crucial to climate change mitigation and the global economy. Thus, disease diagnosis and management are critical. "Plant Disease Detector," a deep learning tool, automatically identifies plant diseases from leaf pictures.

This research is crucial because plants' role in climate management, food security, and economic stability is becoming more apparent. Climate change talks at the UN General Assembly highlight worldwide vegetation projects. The hundreds of billions of dollars in annual economic losses from plant diseases require effective management. Human talent and manual inspection hinder scalability and efficiency in traditional plant disease identification. The study uses CNNs, deep learning models for image categorization. They train the model on the PlantVillage dataset, which includes many plant species and disease classes, to establish their strategy works. The proposed algorithm can identify healthy and dangerous plants across classes with 98.3% accuracy. Augmenting datasets and rigorously training and testing them is a form of dataset utilization. The model's remarkable accuracy on images in different environments shows its real-world applicability.

[18] Cauliflower, a vital crop, supports economies, livelihoods, and food security, especially in poor nations. However, crop diseases threaten agricultural output and human health. Poor disease surveillance has impeded previous investigations on recognizing and classifying infected cauliflower plants. The challenges include limited access to high-quality, labeled datasets and the need for significant computer resources for processing. This research addresses these concerns using powerful deep-transfer learning to anticipate cauliflower plant diseases early. The study tests ten deep transfer learning models on the VegNet dataset, which includes Bacterial spot rot, Black rot, Downy Mildew, and No illness.

The study also acknowledges dataset imbalances and contour feature extraction issues that may cause misclassification. Improve contour feature extraction in future studies. Expand disease detection to more vegetables. The best model was EfficientNetB1, with 99.90% validation accuracy, 0.16 loss, and 0.40 root mean square error. CNN Model Impact Advanced convolutional neural network (CNN) models are crucial for cauliflower illness detection and classification automation.

It is a detailed analysis of model accuracy, loss, and root mean square error across illness classes. Effectiveness Metrics Calculating recall, precision, and F1-score values to evaluate illness identification and classification models. Using powerful deep-learning techniques to detect cauliflower illness in agriculture is a significant accomplishment. The study improves agricultural production, food safety, and worldwide farming by accurately and efficiently identifying diseases.

[19] Plant diseases threaten global food security and require effective detection technologies. Manual detection methods are too laborious and error-

prone for early disease diagnosis and containment. Deep Learning (DL) models, especially CNNs, may analyze high-resolution photos to detect subtle illness markers. Recent research shows tremendous advances in this growing sector. Their approach demonstrated accuracy even in complicated backdrops, showing that DL may overcome traditional constraints. Their models showed great accuracy and fast detection rates, demonstrating DL's promise for diagnosing illness. Other plant disease identification investigations have used deep convolutional networks and transfer learning. We contribute to this increasing literature by studying how CNNs and MobileNet designs alter plant disease detection. CNNs achieved 89% accuracy and MobileNet 96%. GradCAM's eXplainable Artificial Intelligence (XAI) provided visual illness indicator identification insights, improving model interpretability. The literature emphasizes DL's significance in revolutionizing plant disease detection methods, providing scalable, efficient, and precise agricultural solutions. Further research on real-time detection applications and IoT integration promises robust and sustainable agriculture.

IV. CORE STUDY AREA

Table 1COMPARISON OF DIFFERENT APPLICATION AREA FIND IN THIS REVIEW

Article Ref No	Plant Name	Disease Name
11,15, 17,19	TOMATO	Disorder, Tomato yellow leaf curl virus (TYLCV) and tomato yellow leaf curl disease (TYLCD), Bactarial Spot, Early Blight, Late Blight, Leaf Mold, Target Spot
13,	PALM	WSD(white scale disease)
14, 15, 17	APPLE	Black rot, Rust, leaf black disease affected by the fungus named Botryosphaeriaobtusa., Apple scab
17	Cherry	Powdery mildew
17	Corn(Maize)	Cercospora leaf spotGray leaf spot, Common_rust, Northern_Leaf_Blight
17	Grape	Black Rot, Measles, Leaf_blight (Isariopsis_Leaf_Spot)
17	Orange	Haunglongbing (Citrus_greening)
17	Peach	Bacterial Spot
17	Potato	Early Bligh, Late Blight
17	Squash	Powdery mildew
17	Strawberry	Leaf Scorch
18	Cauliflower	Bacterial spot rot, Black rot, Downy Mildew

Table 2 COMPARISON OF DIFFERENT ALGO RITHMS USED IN THIS REVIEW PAPER

Article Ref No	Method	Count
11,13,14,15	SVM	4
11,12,14,15,16, 17,18,19	CNN	8
11,12,13	KNN	3
11,	K-mean Clustering	1
12,	DT	1
12,13,18	RF	3
12	MLP	1
13,	LightGBM	1
16,	ACO-CNN	1
16	C-GAN	1
16	SGD	1

18,19	MobileNet	2
18	InceptionV3	1
18	2D-LeNet	1
18	DenseNet	1
18	EfficientNet	1

Most of the methods utilized in this review were deep learning algorithms, as shown in Table 1. Even though deep learning is used in most research areas, CNN still outperforms deep learning when it comes to solving optimization challenges. This service paper covers a variety of application areas, as shown in Table 2. Table 2 shows that there is still a long way to go before agricultural computer vision problems, such as disease detection in plant leaves and productive soil detection, can be solved with an intelligent machine trained using deep learning. Recognizing faces, objects, and other images is only one of the many uses for convolutional neural networks (CNNs). Convolutional neural networks (CNNs) can interpret and categorize incoming images. Another kind of neural network that can help machines see and do things like picture classification, recognition, detection, etc., is the convolutional neural network (CNN). Image classification aims to take an input picture and, given a probability, provide a set of classifications that most accurately represent the picture. Specifically designed to process visual data, convolutional neural networks (CNNs) are a subset of neural networks[1]. The name "convolution neural network" comes from the fact that this layer executes an action known as a convolution. Features are extracted from the input picture. The input is multiplied by a set of weights in convolution, a linear operation. We first developed this method to work with 2D data. A 2D array of weights, known as a filter or kernel, and an array of input data are multiplied. The input parameters are reduced using dimensionality reduction, carried out by pooling layers, also called down sampling. Like the convolutional layer, the pooling operation applies a filter to the whole input; however, unlike the convolutional layer, this filter does not contain any weights. Instead, the values in the receptive field are aggregated by the kernel, which then populates the output array. Pooling can be broadly classified into two types:
"Max pooling" means that as the filter traverses the input, it chooses the pixel with the highest value to incorporate into the output array. This method is usually preferred over average pooling. Average pooling involves the filter calculating the average value inside the receptive field as it passes across the input and sends it to the output array. Even though the pooling layer loses data, CNN benefits from it in many ways. They aid in simplifying things, making things more efficient, and reducing the likelihood of overfitting. The fully connected layer is exactly what it sounds like a fully connected layer. As indicated before, the output layer is not directly related to the input image's pixel values in partially linked layers [7]. On the other hand, a completely connected layer has a direct connection between every output node and every node in the layer below it. This layer's classification operation uses the characteristics of the preceding layers and the various filters applied to them. When classifying inputs, convolutional and pooling layers typically utilize ReLu functions, but FC layers typically use a softmax activation function, which produces a probability between 0 and 1. While feed-forward neural networks (NNs) are great at learning a simplified representation of an image's features, they need help to make accurate predictions when faced with more complicated images that contain pixel dependencies. By utilizing various filters and transformations, CNN can learn numerous layers of feature representations for an image. Convolutional neural networks (CNNs) use a far smaller set of parameters for learning than multilayer networks [1,7,8].

V. CONCLUSION

Overall, this research article has comprehensively analyzed different approaches to detecting leaf diseases, including conventional machine learning, deep learning, and pre-trained Convolutional Neural Networks (CNNs) models. By conducting thorough analysis and comparative investigations, we have clarified the abilities and restrictions of each approach, emphasizing their contributions to the automation of plant pathology. Conventional machine learning techniques, including Support Vector Machines (SVM) and Decision Trees, have proven to effectively use manually designed features for illness categorization. However, they need help scaling and adapting to different datasets. On the other hand, deep learning methods, specifically Convolutional Neural Networks (CNNs), have demonstrated impressive capabilities in autonomously acquiring complex characteristics straight from picture data. It has resulted in enhanced precision and resilience in disease identification.

Moreover, investigating pre-trained CNN models has created new opportunities for transfer learning, facilitating the transfer of expertise from general image recognition tasks to the specialized field of plant pathology. In the future, potential research avenues will further advance the study of leaf disease detection. These include integrating multimodal data sources, such as spectral imaging and environmental sensor data, to enhance detection accuracy and robustness; developing transferable and generalizable models that can adapt to diverse plant species, diseases, and environmental conditions; exploring explainable AI techniques to enhance transparency and interpretability of deep learning models; adopting edge computing and Internet of Things (IoT) technologies for real-time monitoring and proactive disease management; fostering collaboration with agricultural stakeholders to tailor solutions to their specific needs and constraints; addressing ethical and societal implications related to data privacy, algorithmic bias, and socio-economic disparities; establishing long-term monitoring and surveillance systems for tracking disease dynamics and informing proactive intervention strategies; and embracing interdisciplinary approaches that integrate expertise from computer science, plant biology, agronomy, and data science to develop holistic solutions for sustainable agriculture. By following these prospective paths, our objective is to not only progress the current level of leaf disease detection but also make a valuable contribution to the broader objective of improving global food security and crop output. Our upcoming research will focus on identifying diseases that impact broccoli leaves. We will utilize Convolutional Neural Networks (CNNs) and deep learning techniques to undertake this extensive undertaking. The conscious choice to prioritize broccoli has substantial economic significance and the possibility for notable progress through modern technology. Broccoli has economic significance, great nutritional worth, and health-promoting properties. Broccoli is renowned for its abundant nutrient composition, which includes substantial quantities of vitamins C, K, and A and fiber, folate, and antioxidants. The consumption of it has numerous health advantages, such as lowering the likelihood of chronic ailments like cancer and heart disease, enhancing digestive health, and fostering general wellness. Our goal is to safeguard the health and productivity of broccoli crops by employing CNNs and deep learning methods to detect diseases that harm the leaves. It will help ensure this valuable vegetable crop remains available and accessible to customers worldwide.

Moreover, our choice to focus on broccoli demonstrates our commitment to tackling significant agricultural issues while advocating for public health and sustainable food systems. Our goal is to utilize CNNs and deep learning to detect diseases in broccoli leaves. We aim to develop creative solutions that improve crop productivity and quality and contribute to larger goals like food security and nutritional well-being. Our subsequent research on detecting diseases in broccoli leaves aims to expand the limits of knowledge in agricultural technology and provide significant contributions to academic research and industry applications. Through integrating computer science, plant pathology, and agricultural science knowledge, our objective is to create cutting-edge methodologies and technologies that can be utilized not only for broccoli but also for other economically important crops. It will ultimately contribute to developing a more robust and sustainable agricultural industry. Our planned study on detecting diseases in broccoli leaves represents a combination of technological innovation, commercial importance, and public health impact. Our goal is to use advanced Convolutional Neural Networks (CNNs) and deep learning techniques to focus on this valuable vegetable crop. This approach will produce concrete advantages for growers, consumers, and society in general.

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