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A SURVEY ON PLANT DISEASE DETECTION AND FERTILIZER RECOMMENDATION

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ABSTRACT: **As the world's population continues to rise and the importance of maintaining food security grows, early identification of crop leaf diseases is essential for improving agricultural productivity. Automated, accurate, and efficient alternatives are required because existing sickness detection methods are usually labor-intensive and time-consuming. [1] In this research, a novel real-time strategy for identifying crop leaf illness utilizing machine learning and the YOLO model is proposed. A sizable image collection showing a range of crop diseases is used to train the model.[2] The ability of the YOLO model to recognize objects is useful for locating diseased areas on leaves. Providing a wide range of crop varieties, agriculture is the backbone of the Moroccan economy and provides a living for millions of farmers. However, farmers find it challenging to correctly diagnose plant diseases due to a lack of resources and experience. As a result, trying to salvage sick crops frequently wastes important time and money. [8]A ground-breaking approach that leverages the most recent developments in deep learning and computer vision technology to detect plant diseases in real-time has been presented to address this problem. Using an advanced object identification technique called Yolov8 (You Only Look Once), our system analyzes leaf images at a pace of 70 frames per second.**

KeyWords: **YOLO , Plant disease, Deep learning**

1. INTRODUCTION

Plant diseases can result in large agricultural losses annually and represent a serious danger to the world's food security. Reducing these losses and increasing the efficacy of disease control need the timely diagnosis of crop illnesses. Conventional disease detection techniques, like the manual assessment of spot color, size, and form, take a lot of time and demand a high level of expertise, which reduces job productivity. Research on object detection technologies is one of the hottest topics right now. It was created to get around the drawbacks of traditional disease diagnosing techniques. By identifying and forecasting an object's location within a picture or video, it is able to classify and determine the category of items.

2. LITREATURE SURVEY

2.1: Plant leaf Disease detection by CNN

Jahnavi Kolli, Fellow, IEEE, Manikandan, Fellow, IEEE, D. Mohana Vamsi, Fellow, IEEE [2021]

The detection of plant leaf disease examines the efficacy of two methods: conventional image processing techniques and convolutional neural networks (CNN). This study evaluates their capacity to recognize plant illnesses using photos of leaves. The research entails gathering various datasets, putting CNN models into practice, and using image processing techniques. Evaluation measures are employed to juxtapose the precision and efficacy of the two methodologies. Results help determine which method works best and under what circumstances, providing information for automated plant disease diagnosis in agriculture. [10]

The paper addresses the advantages and disadvantages of each approach while comparing the accuracy, robustness, and efficiency of the two approaches. The results help determine which strategy works better in different situations and offer insightful information for automating plant disease identification in agriculture, which can have a big impact on crop management and yield optimization.[20] For precise image differentiation-based plant disease diagnosis, develop a CNN model. Create a comprehensive collection of plant photos with details about the health, intensity, and diversity of plant species. Boost in order to gain strength. Verify generality across species, diseases, and environments by examining the CNN model's accuracy, sensitivity, specificity, and F1 score.CNNs are particularly good at correctly diagnosing plant diseases based on their visual symptoms because of their high accuracy in image classification.[11] CNN-based systems are able to quickly assess a huge number of plant images, which makes it possible to diagnose diseases early and implement successful agricultural interventions.[15] CNNs are frequently less useful in resource-constrained agricultural settings since they are computationally demanding and require sophisticated equipment for training and inference.

2.2: Plant Disease Detection and Recognition using KNN Algorithm

Surbhi Garg, Fellow, IEEE, Divya Dixit, Fellow, IEEE, Sudeept Singh Yadav, Fellow, IEEE [2022]

Using technology to automatically detect and classify diseases in plant leaves is known as plant leaf disease prediction using KNN and image processing. A dataset of plant leaf photos, comprising both healthy and diseased samples, is usually the starting point for this kind of research.[7] The first step in the project is to gather a large collection of photos of plant leaves, including both healthy and diseased leaves for comparison.

Using image data, a deep learning model (KNN) is utilized to identify and extract patterns specific to diseases, enabling automated disease prediction. Method of Image Processing: traits are extracted from leaf images using conventional image processing techniques including colour and texture analysis, and these traits are then utilized to forecast disease. Construct and execute a plant disease detection system that use the K-Nearest Neighbours (KNN) algorithm as its principal classification technique. For the purpose of training and assessing the KNN algorithm, an accurate detection model, create and optimize a dataset with features related to plant health and illness. [5]Analyze the KNN-based plant disease detection system's effectiveness. For strength, increase. Verify generality across species, diseases, and environments by examining the CNN model's accuracy, sensitivity, specificity, and F1 score.[10] In order to provide insights into automated disease prediction in agriculture for early disease management and enhanced crop health, this study compares the efficacy and accuracy of the two approaches. Grayscale conversion of input images is done for consistent processing. uses the Grey Level Co-occurrence Matrix to measure the correlations between pixel intensity. quantifies pixel value permutations and highlights comparable grey levels. trains a dataset and applies the K-Nearest Neighbours (KNN) algorithm to test photos.

2.3: Plant Disease Detection Using Machine Learning

Shima Ramesh, Fellow, IEEE, R. Hebbar, Fellow, IEEE, Pooja R, Fellow, IEEE [2018]

The increase in population worldwide has resulted in a scarcity of food and raw materials. The primary and most important source to get past this specific obstacle is now the agricultural sector. However, pests and several crop diseases are a problem for the sector as a whole. The industry has spent decades putting a lot of effort into combating this. However, there was a limitation on the mass identification of the damaged crops because of the prior technological gap. Nevertheless, the issue of identification can now be swiftly answered because to advancements in technology. Machine learning-based plant disease detection uses image analysis to identify visual clues that indicate disease on plant leaves. Algorithms are trained on large datasets that contain photos of both healthy and diseased plants, and this allows them to extract pertinent traits that are essential for identifying diseases. These characteristics could include discoloration patterns, lesions, or abnormalities typical of particular illnesses. This technique facilitates early intervention and reduces crop losses by precisely and quickly categorizing illnesses. Prompt disease management techniques help farmers maintain production and ensure food security. Moreover, focused treatment methods that are based on accurate illness diagnosis lessen the need for broad-spectrum insecticides, supporting environmentally friendly farming methods and environmental health. Essentially, plant disease detection powered by machine learning not only increases output but also ensures the long-term viability of food production systems by fostering an environmentally friendly and resilient agricultural ecosystem.

2.4: Plant leaf disease detection by Image processing techniques

Sachin D. Khirade, Fellow, IEEE, A.B. Patil, Fellow, IEEE [2015]

Preventing reductions in agricultural product productivity and quantity can be achieved by early detection of plant diseases. The study of plant diseases refers to the study of patterns on plants that are visible to the human eye. Plant disease identification and health monitoring are essential for sustainable agriculture. Manually keeping an eye on plant diseases is really challenging. It calls for an extreme amount of labor, knowledge of plant diseases, and lengthy processing times. Therefore, plant disease detection uses image processing. A number of processes are involved in disease detection, including feature extraction, classification, segmentation, pre-processing, and image acquisition. This study examined techniques for identifying plant illnesses using photos of their leaves. Additionally, this paper also discussed some segmentation and feature extraction algorithm used in the plant disease detection.

Plant disease identification that is accurate and uses algorithms to reduce false positives. Developing early plant disease detection algorithms for intervention is essential for management. Gather a variety of plant photos, encompassing habitats, lighting, different crops, and health and disease states. To isolate plant regions, standardize photos by cropping, resizing, improving quality, reducing noise, and segmenting them. Utilizing feature selection, extract pertinent features such as texture, shape, and colour histograms, then optimize for efficiency. Train the chosen model, adjusting hyper parameters, and using augmented data to increase robustness. Reliable diagnosis is essential for efficient illness management, and image processing guarantees this.

Before a disease manifests itself, image algorithms can identify it, allowing for prompt treatment, stopping its spread, and lowering crop losses. The installation of image processing, which involves cameras, software, and hardware, can be expensive. It's possible that agricultural environments lack the technological know-how to maintain picture processing. We then use image processing techniques to extract pertinent features from these photos, including segmentation, texture analysis, and color analysis. Plant diseases can be identified and classified using these characteristics. This method offers an accessible and affordable way to identify diseases in agriculture, enabling prompt management and action to safeguard crop harvests.

It Develop labour savings, continuous monitoring, automatic disease detection, and effective image processing. Traditional computer vision techniques are used in plant leaf disease detection through image processing techniques to identify and diagnose illnesses in plant leaves. Usually, this procedure begins with gathering a dataset of leaf photos that includes both healthy and diseased samples.

3. RESULTS

The report concludes with a thorough review of the suggested scheme and the model's output. Convolutional Neural Networks (CNN) are a tool for plant leaf disease detection that use deep learning to automatically detect and categorize diseases in plant leaves. It starts with a collection of photos of plant leaves, including both healthy and unhealthy examples. Following this, these images are analyzed using CNN models, which identify and extract patterns and features unique to each disease. The model is able to categorize leaves as healthy or ill thanks to these learned patterns. CNN techniques are a potent tool for precision agriculture because they provide great accuracy in disease diagnosis. They aid in the early detection and treatment of diseases, enhancing crop health and productivity in the farming industry. Plant disease detection has generally improved significantly as a result of the combination of cutting-edge technologies, extensive datasets, and cooperative efforts. This has given farmers useful tools for managing diseases and protecting their crops. Continuous investigation keeps improving current methods and investigating fresh ideas to further improve the precision and expandability of plant disease detection systems.

4. ADVANTAGES

Plant leaf disease detection offers several advantages:

1. Early Detection: Identifying diseases in their early stages allows for prompt intervention, preventing further spread and minimizing crop damage.
2. Increased Yield: Early detection and timely treatment of diseases help maintain plant health, leading to higher crop yields and better quality produce.
3. Cost Reduction: By detecting diseases early, farmers can reduce the need for extensive pesticide or fungicide use, saving on input costs and minimizing environmental impact
4. Precision Management: Disease detection enables targeted treatment, optimizing resource allocation and minimizing wastage of agricultural inputs.
5. Data-driven Decision Making: Disease detection systems provide valuable data on disease prevalence and severity, empowering farmers to make informed decisions about crop management strategies.
6. Improved Sustainability: By reducing the reliance on chemical inputs and promoting targeted interventions, disease detection contributes to more sustainable farming practices.
7. Efficiency: Automated detection systems, such as those based on computer vision and machine learning, offer efficient and rapid disease identification, saving time and labor for farmers.

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