Smart Monitoring System for Enhancing Plant Health and Sustainable Growth

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Abstract. As agriculture plays a vital role responsible for sustaining the growing population, it is important to enhance crop health monitoring to ensure food security and maximize farming methods. This paper presents an extensive review of crop health monitoring systems, with the integration of artificial intelligence (*AI*), computer vision, and the Internet of Things (*IoT*). The efficacy of several approaches, such as sensor-based networks, data-driven prediction models, and image processing techniques, in predicting plant diseases and improving agricultural yield is explored. Key deep learning architecture models for image classification, such as -- *Convolutional Neural Networks* (*CNNs*), *Data Augmentation, Transfer Learning,* and *You Only Look Once* (*YOLO*), for plant disease identification are discussed. Using an image classification process via CNN, the images of a few leaves and other plant traits are analyzed to distinguish between healthy and unhealthy crops. Further, key parameters such as temperature, humidity, soil moisture, and pH levels are continuously monitored through sensor networks integrated into agricultural systems, in order to get the details of crop health. For optimal crop growth, the soil needs to be nutrient-rich with a pH level between 6.5 and 7.5 to increase the soil's fertility. In conclusion, crop health monitoring using *AI* and *computer vision* has proven highly effective, with a 92% accuracy in plant disease detection. Through this integration, farmers are empowered to take preventive measures, reduce losses, and maximize their crop yields. This study paves the way for future advancements in sustainable farming by utilizing innovative technologies.

1 Introduction

Agriculture is one of the most important sectors globally, responsible for sustaining the growing population [1]. The alarming rate at which the world's population is growing raises concerns about global food security. The population of the world is expected to increase to 8.5 billion people by 2030 and then to 9.7 billion people by 2050, according to UN estimates. Thus, Global food consumption is anticipated to rise proportionately with this predicted development, growing between 36% and 59% between 2010 and 2050 [2].

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However, a number of issues, such as plant diseases, pollinator decline, and climate change, continue to pose a danger to food security. Each year, plant diseases contribute losses ranging from 10-16%, with an estimated cost of $220 billion. Numerous agroecosystems are suffering as a result of the widespread use of pesticides to manage plant diseases [3].

Currently, mechanical cultivation, the removal of diseased plant leaves, and the use of different pesticides are some methods for reducing plant disease. Nonetheless, disease identification manually or traditionally involves intensive labor, time-consuming, tedious processes, and error-prone [4].

Thus, plant disease identification using machine learning (ML) and deep learning (DL), as shown in Fig. 1, has become more popular and has demonstrated promising results in accurately identifying plant diseases from digital images. Plant disease detection has made use of machine learning techniques, including feature extraction and classification. Utilizing techniques such as color, texture, and form extraction, these methods train a classifier to distinguish between plants that are healthy and diseased plants.

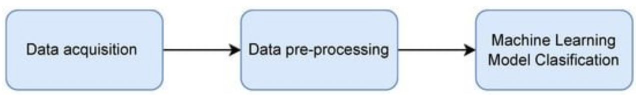

Fig. 1. Simplification of the ML pipeline [5].

This paper presents a literature review of the advanced crop health monitoring systems, with an emphasis on the state-of-the-art techniques. This study looks at several methods of disease detection in order to find the important patterns, assess how well existing solutions work, and recommend possible directions for further research. The goal is to present a thorough grasp of ways AI and computer vision may be leveraged to create more effective and resilient agricultural methods.

2 Detection Techniques for Plant Disease Detection

Deep Learning (DL) has made major advances in the detection of diseases from images in a variety of industries, like Agriculture. DL models may automatically extract relevant features from raw image data and categorize it into distinct categories, such as healthy and unhealthy. These developments in deep learning have revolutionized the way diseases are identified and diagnosed in agriculture, offering accuracy, scalability, and speed with conventional techniques [6]. Fig. 2 shows plant disease detection in three different diseased leaves using DL models.

Fig. 2. Sample images of plant disease detection of 3 different leaves [5].

There are several steps involved in the detection of diseases in crops. Fig. 3 is a flowchart that shows how plant health is classified using a collection of plant images. A CNN or YOLOv5 model is used to train after the dataset is split, and the performance is assessed using metrics.

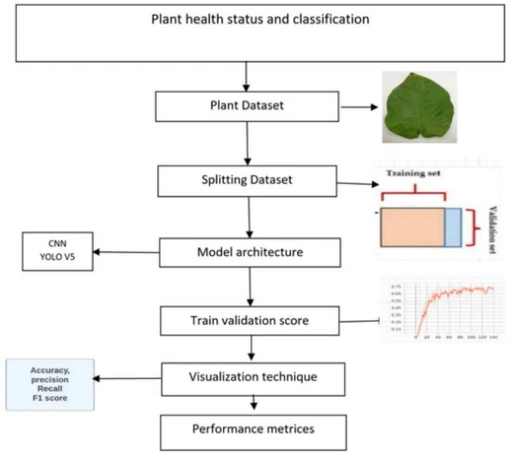

Fig. 3. Plant disease identification step-by-step process [5].

2.1 Convolutional Neural Networks (CNNs)

CNNs have transformed the categorization of plant diseases and have become the industry standard in this area by utilizing their potent feature extraction capability. In CNNs, the input picture is passed through a number of layers, including convolutional, pooling, and fully connected layers.

In order to identify characteristics like edges, forms, textures, and colors linked to diseased symptoms, the convolutional layers apply a filter. Pooling layers make the operation computationally efficient by reducing the dimensionality of the data. The fully connected layers at the end of the network are in charge of categorizing the picture according to the features that were extracted, as shown in Fig. 4.

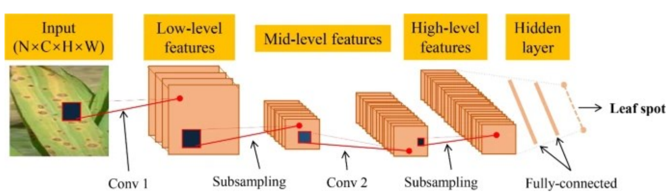

Fig. 4. CNN-based plant disease classification networks [5].

2.2 Data Augmentation for Expanding Datasets

The process of producing altered versions of pre-existing photographs is known as data augmentation, and it is used artificially to expand the size of the training dataset. This is particularly helpful in the agricultural industry, where seasonal variations, restricted to fields, and expensive data collection expenses all make gathering huge datasets difficult. Using data augmentation techniques, pre-existing photos are transformed by adding noise, rotating, flipping, scaling, cropping, and adjusting brightness. By subjecting the model to changes in illumination, direction, and size that it could experience in real-world situations, these transformations aid in making the model more resilient [7].

As depicted in Fig. 5, there are three different versions of two leaves, where (a) Leaf 1 color, (b) Leaf 1 grayscale, (c) Leaf 1 segmented, (d) Leaf 2 color, (e) Leaf 2 grayscale, (f) Leaf 2 segmented [8].

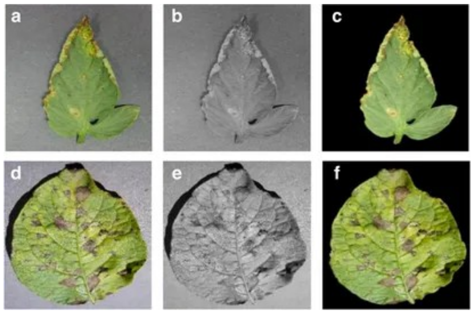

Fig.5. Sample images of 3 different versions of two leaves [8].

2.3 YOLOv5 Model for Real-Time Detections

On the basis of variations in network width and depth, YOLOv5 may be divided into four network model versions: YOLOv5s, YOLOv5m, YOLOv5I, and YOLOv5x. The Backbone, Neck, and Head are the three primary parts of the YOLOv5 network, as shown in Fig. 6. The backbone is a CNN or a collection of layers that have already been trained. The neck is a set of layers that connect the backbone to the head.

After the image is taken as input, Backbone aggregates and creates features for the image at different granularities. Subsequently, the image features are stitched by Neck and sent to the prediction layer, where Head makes predictions based on the image characteristics to provide predicted categories and bounding boxes.

Equation (1) illustrates the usage of $GIOU$ as the network loss function in the YOLOv5 network.

$$GIOU = IOU - \frac{|C - (A \cup B)|}{|C|} \tag{1}$$

Let A and B be two arbitrary boxes such as A, B $\subseteq$ S $\subseteq$ R^n. Let C be the smallest convex box enclosing both A and B, where $C \subseteq S \subseteq R^n$. The Intersection over Union (IOU) is defined as $IOU = |A \cap B| / |A \cup B|$.

To refine the predicted bounding boxes, the model uses a combination of non-maximum suppression and GIOU loss, helping it identifies the optimal target frame based on visual feature predictions [9].

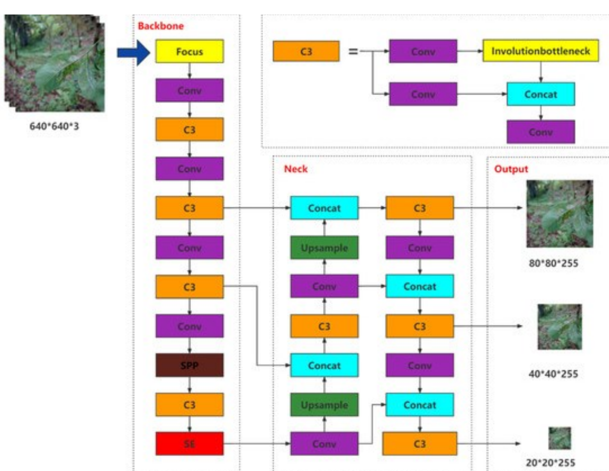

Fig. 6. YOLOv5 network model structure [9].

2.4 Applying Transfer Learning

Transfer Learning enables deep learning models to leverage pre-trained models for disease identification tasks, significantly reducing training time and computational resources, as shown in Fig. 7. A CNN model that has been pre-trained on a sizable dataset is refined for crop disease diagnosis by transfer learning. While the higher layers of the model are retrained using a domain-specific dataset of crop photos, the bottom levels of the model, which have been previously trained to recognize fundamental characteristics like edges and forms, are reused [10].

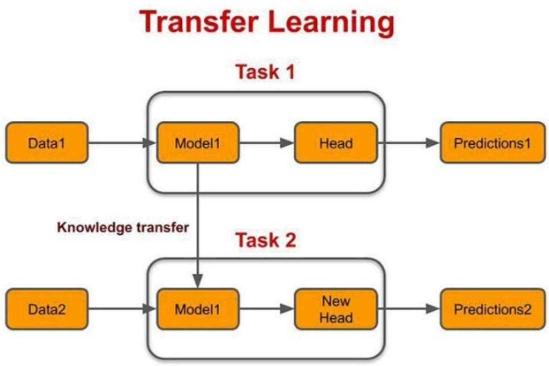

Fig. 7. Transfer Learning [11].

Table 1. Task Description for Crop Disease Detection.

Task	Description
System Design	Develop a crop disease detection system using computer vision and a deep learning model.
Data Collection	Use a ROSbot to take images of crop leaves and then process them to find diseases.
Real-time Detection	Implement the infrastructure in place to identify illness instantly and give consumers the results of their diagnoses through a user interface.

3 Integrating Disease Detection and Soil Monitoring for Crop Health Management

Plant diseases pose a significant threat to crops that result in large financial losses, making them a serious danger to horticulture and agriculture. These diseases arise from two main types of stressors: abiotic and biotic stress. Abiotic stressors include environmental factors, nutrient deficiencies, chemical imbalances, and physical injuries; and biotic stressors are those that include living organisms like fungi, bacteria, and viruses, as shown in Fig. 8 [12]. Thus, in addition to plant disease detection, soil monitoring also plays an equally important role in ensuring effective crop health management.

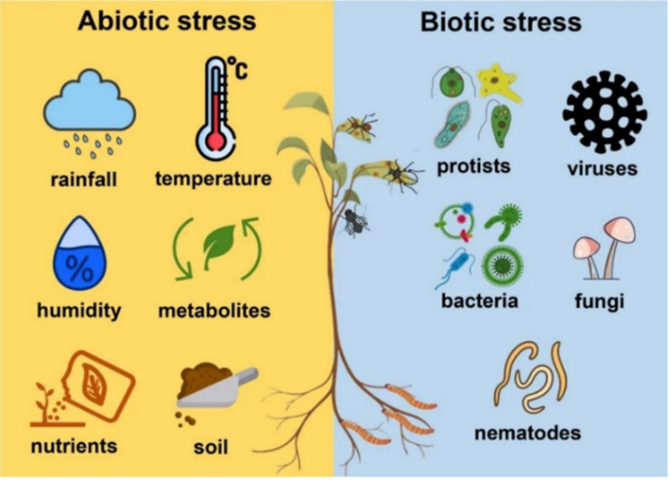

Fig. 8. Visualization of abiotic and biotic stresses that cause crop disease [12].

Soil Monitoring is one of the fundamental needs for farming [13]. Soil health assessments frequently involve extensive field sampling and laboratory analysis. Although this method yields trustworthy results, it is frequently too expensive and time-consuming to be applied for real-time soil monitoring. Due to the time-consuming process and lack of knowledge of soil nutrients and needs, farmers require a portable soil nutrient analyzer [14].

The Internet of Things (IoT) is a network of virtual devices that store and distribute data to consumers. The main motto of IoT is reducing human error and the workforce. Both the front-end and back-end devices are under control [15]. The primary factor influencing the field work to flourish is the nutrients in the soil [16]. The main nutrients found in soil are known as the soil's NPK value, N-nitrogen, K-potassium, and P-phosphorus [17].

Table 2. Explanation of NPK.

Nutrients	Description
N (Nitrogen)	Nitrogen encourages the development and the green color of leaves. Too little leads to yellowing and stunted development, while too many produce too much foliage, delayed blooming, and low-quality fruits [18].
P (Phosphorus)	Phosphorus is essential for plant genetics, seed development, maturity, and disease resistance [18].
K (Potassium)	Potassium strengthens stems, promotes early development, and improves the flavor and color of the fruit [18].

4 Advanced Soil Monitoring Techniques

Key soil characteristics that impact the crop yields are water content, temperature, and amounts of nutrients like nitrogen, phosphorus, and potassium. Thus, a monitoring system aids in maintaining soil parameters at their ideal levels [19]. Fig. 9 shows the block diagram for identifying soil nutrients and suggesting a suitable crop.

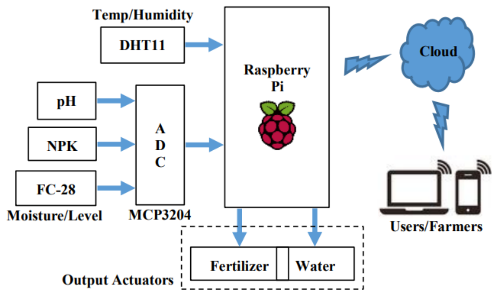

Fig. 9. IoT for Soil Monitoring [18].

4.1 DHT11 Sensor Module

DHT11 sensors are chosen to monitor the soil sample's composite temperature and humidity levels. This sensor is proven to be reliable and stable. The DHT11 sensor is suitable to be use as a drought monitoring sensor due to its compact size, low power consumption, and versatility in handling tough application situations, such as high humidity, dusty environment, cold or moderate weather [18].

Fig. 10. DHT11 Sensor [18].

4.2 pH Value Sensor

The soil's ability to support crop growth is determined by using a digital soil pH sensor. The pH of well-nutrient-rich soil typically falls between 6.5 and 7.5. The pH sensor's measured value can be used to assess the soil's acidity and alkalinity. A pH value between 6.5 and 7.5 is ideal for increasing soil fertility, and soil nutrient deficit is indicated if the pH value of the soil deviates from the neutral range [20].

Fig. 11. pH Sensor [18].

4.3 Soil Moisture Sensor

Soil moisture is essential as it has a direct impact on plant development and health. It promotes photosynthesis, permits the intake of vital nutrients, and aids in the general growth of plants. Proper moisture levels help maintain robust root systems and avoid wilting. The soil moisture sensor is an excellent passive tool that measures the soil's volumetric water content, with data read by the Node MCU through the digital pin [20]. By preventing excessive watering and off-site filtration of compost and other chemicals, remote soil moisture detection increases the effectiveness of water system frameworks [18].

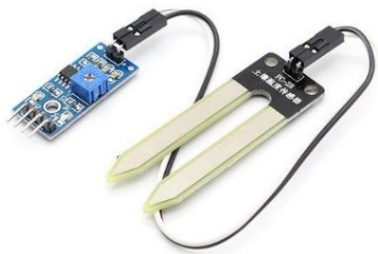

Fig. 12. Soil Moisture Sensor [18].

4.4 Soil NPK Sensor

The Soil NPK sensor measures the soil's levels of potassium (K), phosphorus (P), and nitrogen (N). NPK is required for soil health, and the soil must contain a certain amount of these nutrients. If they increase or decrease, it will have a direct impact on the crop health and yield. Fertilizers are labelled using the NPK rating, also known as N-P-K, which takes into account the proportions of the chemical components nitrogen (N), phosphorus (P), and potassium (K) that are commonly found in fertilizers [21]. The three nutrient elements promote plant development in diverse ways.

The functions of the NPK sensors are as follows:

- NPK sensors measure the soil nutrient levels by measuring the nitrogen, potassium, and phosphorus levels in the soil.
- They employ optical or electrochemical sensors to determine the concentrations in the soil.
- Information about soil fertility is obtained by converting data into understandable numbers.
- This encourages robust plant development and maximizes fertilization.

By monitoring the soil's NPK levels, farmers can apply fertilizers more precisely, avoiding overuse or underuse. This, in turn, reduces the expenses and minimizes the impact on the environment. These sensors aid in resource optimization by determining nutrient concentrations by optical or electrochemical sensors, which guarantees that fertilizers are administered only when required.

Fig. 13. Soil NPK Sensor [18].

Table 3. Task Description for Soil Monitoring.

Task	Description
System Design	Develop a sensor-equipped soil monitoring system to measure temperature, moisture content, pH levels, and NPK levels.
Data Collection	Utilize embedded sensors to get data from the soil in real-time.
Data Processing	Process and analyze the data to produce insightful information on the state of the soil.
User Feedback	Display the results to users on a display or through a mobile application to guide soil optimization for crop development.

5 Experimental Results

To evaluate the performance of the plant disease detection system, a simulation was run using a pre-processed image dataset combined with trained deep learning models. With an emphasis on different crops, the simulation was run on a subset of the dataset that included images of both healthy and diseased crops.

The DL model CNN was implemented as the core DL model, where images from the dataset were supplied into the system for analysis.

Table 4. Description of the Chosen Dataset.

Task	Description
Model Name	CNN
Accuracy	0.92
No. of Images	1K+
Precision	0.93
Dataset Name	Plant disease recognition dataset

Table 5. Simulation Results.

Input Image	Prediction
	
	
	

A remarkable 92% accuracy rate was attained by the model in identifying a variety of illnesses, including powdery mildew and rust disease. Feedback was provided for each identified ailment by presenting the anticipated disease name for every input image.

The plant disease detection CNN model was trained over five epochs to progressively improve its capacity to distinguish between healthy and diseased plants.

The model processed the plant image dataset at each epoch, modifying its internal weights to reduce classification errors. The model performed well despite using a comparatively small number of epochs, which was done to prevent overfitting. Fig 14 below shows the epochs done to train the model.

```
Epoch 1/5
42/42 ━━━━━━━━━━━━━━━━━━━━ 200s 5s/step - accuracy: 0.4484 - loss: 4.1224 - val_accuracy: 0.7667 -
val_loss: 0.6562
Epoch 2/5
42/42 ━━━━━━━━━━━━━━━━━━━━ 171s 4s/step - accuracy: 0.8106 - loss: 0.5071 - val_accuracy: 0.7833 -
val_loss: 0.6143
Epoch 3/5
42/42 ━━━━━━━━━━━━━━━━━━━━ 176s 4s/step - accuracy: 0.8662 - loss: 0.3445 - val_accuracy: 0.8667 -
val_loss: 0.4048
Epoch 4/5
42/42 ━━━━━━━━━━━━━━━━━━━━ 176s 4s/step - accuracy: 0.8946 - loss: 0.3207 - val_accuracy: 0.8500 -
val_loss: 0.4241
Epoch 5/5
42/42 ━━━━━━━━━━━━━━━━━━━━ 197s 4s/step - accuracy: 0.9209 - loss: 0.2444 - val_accuracy: 0.8000 -
val_loss: 0.4684
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Fig. 14. Five epochs for training the model.

A model accuracy graph was generated to visualize the accuracy by epoch for training and validation data. The graph was created by Matplotlib and Seaborn, which shows the evolution of the model's accuracy over the course of the five training epochs. Effective learning was demonstrated by the 92% training accuracy, while the model's capacity to generalize to new data was demonstrated by the 85% validation accuracy.

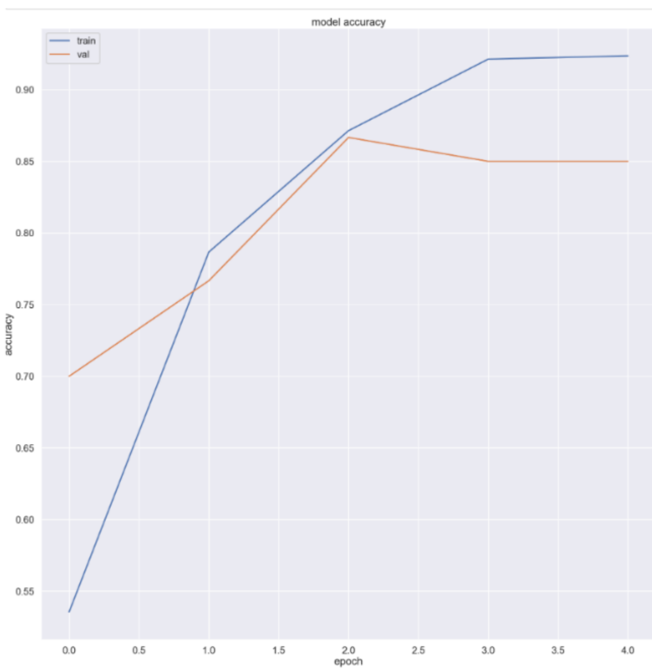

Fig. 15. Model's Accuracy Graph.

The model's efficacy in categorizing plant illness is clearly shown by the confusion matrix in fig. 16, which is produced after the prediction. It distinguishes between three classes, which are healthy, rust, and powdery. It also enables a thorough examination of the model's performance by displaying the proportion of accurate and inaccurate predictions for every class. The model's capacity to categorize plant health using the visual characteristics taken from the input image is clearly demonstrated.

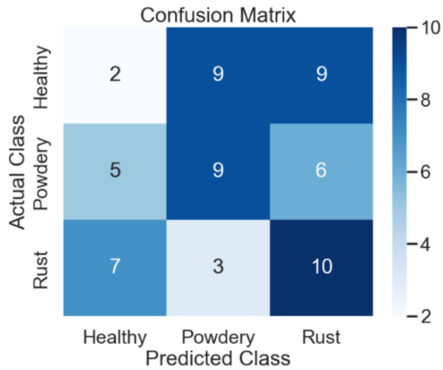

Fig. 16. Confusion Matrix.

Table 5 shows the input images of healthy and diseased leaves chosen, and each image is accompanied by the model's predictions. The predictions determine if the plant is healthy or diseased, such as powdery or rust. This evaluation helped provide valuable insights into the system's ability and accuracy to detect plant diseases across multiple crop types.

6 Discussion

The performance of convolutional neural networks has advanced significantly in the last few years in terms of their ability to classify images and object recognition [22]. Previously, the conventional method for classifying images has relied on manually created features, followed by the application of a learning algorithm in these feature spaces. Therefore, the underlying predetermined qualities had a key role in determining how well these techniques performed. The process of feature engineering itself is intricate and time-consuming, and in itself requires a review each time the problem at hand or related datasets undergo significant changes. All previous attempts to use computer vision to identify plant diseases have this issue since they rely mostly on labor-intensive and sophisticated methods, such as image enhancement techniques and labor-intensive methodologies [8]. Furthermore, as soil directly affects the plant growth conditions and might increase susceptibility to disease, efficient soil monitoring is essential.

6.1 Datasets for Detecting Crop Diseases

It is crucial to keep in consideration that, depending on the stage of crop development, the traits of insects or plant diseases may vary. Furthermore, images of various species of plants could change depending on the area. As such, the majority of recent research findings may not be generalizable to all circumstances. Even if a single test has a high recognition rate, the reliability of data collected at different times or locations cannot be guaranteed. Data from several sources, such as visible, near-infrared, and multispectral data, must be integrated to produce a comprehensive collection on plant diseases [8].

6.2 Early Detection of Plant Diseases

It might be challenging to identify different plants and pests at an early stage, due to the fact that symptoms are not always visible, even when examined through visual inspection or by digital image analysis. However, from a research and requirements perspective, early detection plays a crucial role as it aids in the prevention and control of diseases and the growth of pests. Taking pictures in bright, sunny weather improves the clarity of the image; nevertheless, taking pictures on cloudy days makes preprocessing more difficult and reduces the precision of identification. Furthermore, even high-resolution images may be hard to interpret in the initial stages of plant diseases. To effectively identify and forecast diseases, temperature, humidity, and other meteorological and plant health data must be included [8].

6.3 Data Processing

Noise reduction and contrast enhancement are common pre-processing stages required by the manual feature extraction process. The choice of feature extractors that are most suitable must be made by researchers. When using DL, pre-processing usually concentrates on techniques such as data augmentation, enriching the training set to improve model generalization. When comparing the outcomes of deep learning with the use of images converted to grey-scale or subjected to the removal of the background, the obtained images are analyzed more successfully. This is a helpful discovery, since backdrop removal for photos that are shot outdoors with complicated and variable backgrounds can be a difficult and challenging process [5].

6.4 Practical Implications of the Study

The research highlights how well plant diseases can be detected using ML and DL algorithms, which can increase the efficiency and accuracy of disease detection when compared to manual methods.

- Farmers and plant disease experts may detect infections early on and lower the risk of crop losses by avoiding further spread of the diseases by implementing this innovative technology.
- The study emphasizes how important it is to have more publicly accessible datasets for ML and DL model evaluation and training in the context of plant disease identification.
- Plant disease detection expenses and the necessity for manual work can be decreased by utilizing ML and DL approaches [5].

6.5 Sensor-Based Soil-Monitoring

Advanced sensor technologies are used by soil monitoring systems to measure vital characteristics, including temperature, moisture content, and nutrient levels. By optimizing soil conditions, these sensors offer real-time data that enhances crop health and agricultural yield. Such technologies allow for accurate water and fertilizer management by identifying changes in soil parameters, which minimizes resource waste and encourages sustainable agricultural practices. More effective decision-making is made possible by the incorporation of these sensors into smart agriculture, which improves environmental results. Thus, in order to improve crop health, soil monitoring is essential [19].

6.6 Limitations and Potential Challenges in Real Life.

While crop disease detection systems have a lot of potential to enhance crop health management, a number of restrictions and difficulties need to be addressed to optimize their effectiveness in real-world applications. One key limitation is the possibility of dataset biases during the training of machine learning models for disease detection. To accurately detect and categorize crop diseases or nutrient imbalances, these models rely on vast, varied datasets. Many datasets that are currently accessible do not accurately reflect the range of plant and crop species, environmental factors, or disease symptoms that exist in various geographical areas, leading to misclassifications or reduced accuracy.

Another limitation lies in the infrastructure and present another difficulty, especially in rural or isolated agricultural areas. Many farmers in these areas do not have access to sophisticated sensors, reliable internet connections, or even power sources needed to operate such systems. These can prevent their widespread use of these technologies, even if these technologies are shown to enhance crop health management.

Table 6 shows a comparison of various plant disease detection techniques. It draws attention to how, although being extensively utilized, traditional approaches have problems with scalability and reduced accuracy. While machine learning approaches like SVM and KNN enhance performance, their capacity to extend to extensive datasets and real-world scenarios is still restricted.

When trained on large, annotated datasets such as PlantVillage, deep learning models, and CNNs in particular, provide notable improvements in terms of efficiency and accuracy. Because transfer learning allows pre-trained models to be adjusted for particular crops and diseases, performance is further improved. These techniques are also more scalable and applicable in real-time, which makes them appropriate for incorporation into the farmer's mobile and web platforms.

Table 6. Comparisons of different kinds of methods.

Methods	Model/ Technique	Accuracy(%)	Processing Time	Scalability	Real-World Application
Traditional (Manual Inspection)	Visual/Manual	50-70%	High (slow process)	Low	Small farms, field experts
Transfer Learning [10]	Pre-trained CNNs	60-80%	Low (after training)	High	Mobile apps, large farms
Hybrid Approaches [17]	AI + IoT Sensors	85-95%	Moderate	Moderate	Smart agriculture systems
Support Vector Machines (SVM) [23]	Feature-based classification	70-85%	Moderate	Moderate	Niche application, early-stage research
K-Nearest Neighbors (KNN) [24]	Distance-based classification	65-80%	Moderate	Low to Moderate	Research, small-scale applications
Random Forest (RF) [25]	Ensemble learning	80-90%	Moderate	Moderate	Disease classification in specific regions

By adding environmental data, hybrid approaches, which integrate artificial intelligence (AI) with Internet of Things (IoT) sensors, offer a viable way to enhance real-time disease diagnosis. Precision agricultural decision-making is improved by this integration, which offers a more comprehensive perspective on crop health. Given the circumstances, the comparison shows that deep learning and hybrid approaches are setting the standard for innovative, scalable, and precise plant disease detection systems.

7 Conclusion

This paper examines the latest advances in the detection of plant-related diseases leveraging ML and DL approaches. It also highlights how crop health monitoring is being revolutionized by advances in AI and machine learning. Real-time monitoring of crop health and conditions is now provided via automated systems, allowing for optimal resource management and early disease identification. Advanced techniques such as AI and multispectral imaging algorithms offer accurate and data-driven insights to increase agricultural yields.

Crop and plant disease detection and control have significantly improved with the use of DL and ML technology. Identification of complex diseases and pests has become possible because of advances in image recognition. Nevertheless, the majority of this field's study is limited to lab-based research and relies mainly on pre-collected images of diseased plants. It is crucial to gather images that capture various plant growth phases, environmental conditions, and geographical areas in order to enhance the model's robustness and adaptability. For effective diagnosis and prediction, plant health and meteorological data, with environmental factors like humidity and temperature, must be included. Detection of plant disease at an early stage is crucial to controlling its progression and managing its development and spread.

DL model training and network learning can benefit from unsupervised learning and the integration of concepts inspired by brain-like computing and human visual perception. To fully utilize this technology, experts in plant protection and agriculture must work together, fusing their expertise with DL models and algorithms and incorporating the output into practical farming tools. By examining the advantages and disadvantages of various approaches and providing insights for both researchers and agricultural professionals, this research advances the diagnosis and prevention of plant diseases.

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