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Precision Agriculture through Deep Learning Algorithms for Accurate Diagnosis and Continuous Monitoring of Plant Diseases

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Abstract

For sustainable food production, precision agriculture is essential, and one of its main tenets is the precise identification and ongoing surveillance of plant diseases. Conventional approaches to illness monitoring and detection are frequently labour-intensive, time-consuming, and dependent on visual inspection, which increases the risk of misidentifying diseases. Deep learning algorithms have surfaced as a potentially effective way to tackle these issues. In this study, we introduce a novel method for precision agriculture that improves plant disease diagnostic accuracy and offers continuous monitoring by utilising deep learning algorithms. Our research uses cutting-edge convolutional neural networks (CNNs) and ResNet50 to precisely identify illness symptoms in plant photos. The proposed deep learning model is trained on an extensive dataset of plant photos illustrating a range of illnesses, enabling it to identify minute visual cues that human observers might overlook. Compared to previous ML methods, the model's accuracy in detecting diseases is higher, which lowers the possibility of misdiagnosis and facilitates early intervention to minimise crop damage. By placing cameras and sensors in the fields, proposed system provides continuous monitoring in addition to precise diagnosis. The proposed deep learning model processes the real-time data and photos of the crops that are captured by these devices.

Keywords

Plant Disease, Deep Learning, CNN, ResNet50, Precision Algorithm

1. Introduction

Historically, farmers or other agricultural specialists have primarily relied on visual inspection for the detection of plant diseases. Nevertheless, this manual method is prone to subjectivity and human error, and it frequently misses early disease detection. This can lead to incorrect and ineffective treatment decisions due to misdiagnoses [1]. Furthermore, a delay in disease detection can lead to large crop losses and increased resource consumption, which is bad for the sustainability of the environment and agricultural output. Deep learning algorithms, a branch of artificial intelligence, have become a potent tool to tackle these issues in recent years. Convolutional neural networks (CNNs), one type of deep learning algorithm, have shown impressive results in pattern recognition and picture analysis. They are currently significantly advancing precision agriculture after being effectively used in a number of fields, such as computer vision and

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healthcare [2]. Deep learning and precision agriculture together have the potential to completely change how plant diseases are identified and tracked. Within this framework, our work focuses on applying deep learning algorithms for precise plant disease diagnosis and ongoing surveillance.

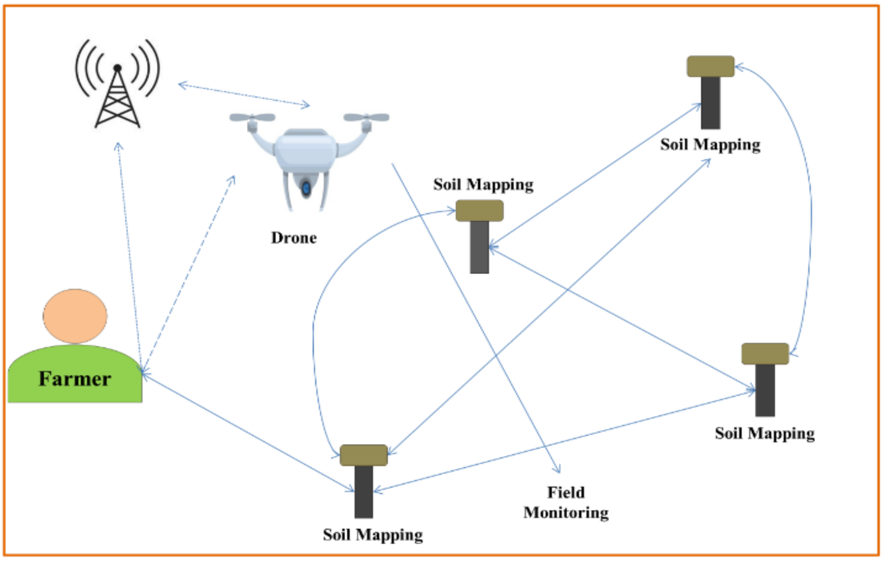

Figure 1: Representation of Precision farming

The use of cutting-edge technologies in agriculture, sometimes known as intelligent or precision agriculture, has the potential to completely change how we grow crops. These strategies make use of cutting-edge technologies and data-driven solutions to improve agricultural output, cut down on resource waste, and solve issues facing the industry. As intelligent agriculture technologies are crucial in giving farmers access to critical environmental data from their farms. By using these data-driven insights, farmers may increase their profitability and competitiveness by making well-informed decisions [3]. In this context, the integration of artificial intelligence (AI) with cloud-based technologies is especially effective. This integration seamlessly combines human experience with AI-driven insights to make agricultural processes more transparent and to improve decision-making.

AI systems have the ability to be both proactive and reactive. They [4] make it possible to gather and analyse data in real-time, which makes it possible to identify problems like soil conditions or plant diseases and take prompt action. This data-driven, real-time strategy boosts crop productivity and efficiency. The idea of "smart agriculture," in which AI-powered devices can identify crops, assess soil conditions, provide professional advice, and even help farmers find new business ventures, is gaining traction. These systems frequently rely on stochastic AI technologies, which are capable of responding and adapting to changing circumstances according to the knowledge they learn. AI systems are useful tools for agriculture because of their adaptability and capacity to learn and develop over time. Agriculture is not the only sector using AI and data analytics to supplement traditional methods. It includes contemporary technologies such as the Internet of Things (IoT) and wireless sensor networks (WSN). Large volumes of field data may be collected thanks to these technologies, and AI techniques can be used to analyse the data. As was previously indicated in relation to cotton leaf diseases, this combination is very useful for applications like disease detection and control in crops. AI is also driving advancements such as computerised irrigation systems, driverless tractors, and the use of robots and drones for diverse agricultural jobs. These developments are intended to ensure accurate and data-driven decision-making, lower labour costs, and increase the efficiency of routine agricultural tasks.

The paper key contribution is given as:

- Precision and intelligent agriculture, with use of deep learning techniques in agriculture, provide a data-driven strategy to maximise crop productivity while lowering resource consumption and environmental effect.

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- The integration of deep learning model with IoT Sensor data to offer data and insights in real-time, facilitating early disease identification, effective irrigation, and customised solutions to region-specific problems.
- AI based DL model are flexible, they can effectively handle the particular and changing aspects of every farming situation, resulting in higher productivity and production.

2. Related Work

Through intelligent and precision agriculture, artificial intelligence (AI) is being incorporated into agriculture as part of a data-driven plan to maximise crop yield while minimising resource use and environmental effects. AI technologies are essential because they give farmers access to real-time data and insights. This gives them the ability to quickly recognise and handle problems such as crop diseases, put effective irrigation systems in place, and adjust their strategy to the particular difficulties that are particular to their area [5]. The versatility of AI systems is one of its main advantages in agriculture. These systems are well-suited to handle the constantly shifting and site-specific elements of various farming situations, which eventually results in higher agricultural production and productivity. Furthermore, AI-driven advancements are revolutionising and simplifying typical agricultural operations. Examples include the utilisation of robotic aid, drones, and driverless tractors. In the end, these technologies contribute to more profitable and sustainable farming practises by increasing operational efficiency and lowering labour expenses.

Precision agriculture [6] is a farming technique that has gained popularity recently. It integrates cutting-edge technologies to increase agricultural productivity and sustainability. Accurately diagnosing and continuously monitoring plant diseases is a crucial component of precision agriculture, as it can significantly affect crop yields, resource use, and environmental sustainability. We will examine the history and relevant research in this area in this section, emphasising the development of precision agriculture as well as the roles that deep learning and artificial intelligence have had in the detection and monitoring of plant diseases. Over the past few decades, precision agriculture has undergone tremendous evolution due to technological advancements and the growing need to solve the issues that modern agriculture faces. In the past, farming methods relied on consistent methods, handling entire fields in the same way. But frequently, this led to the abuse of resources like water, fertiliser, and pesticides which raised production costs and degraded the environment.

The advent of global positioning system (GPS) technology, which allowed farmers to map their fields and apply treatments more precisely, marked the beginning of the transition towards precision agriculture. This [7] signified the first moves in the direction of farming that is more data-driven. Drones and other remote sensing tools, such as satellite photography, have made it possible to gather important data on crop stress, soil conditions, and plant health as technology has developed. These advancements made it possible to use more exact and productive farming techniques. In the world of agriculture, the combination of deep learning and artificial intelligence (AI) has changed everything. These technologies are perfect for disease detection and plant health monitoring since they have shown to be especially effective in jobs involving image processing and pattern recognition. In this context, the application of convolutional neural networks (CNNs), a family of deep learning models, has proved essential. CNNs can accurately identify disease symptoms in plants because of their ability to absorb images and recognise intricate patterns. Large databases of plant photos have been used by researchers to train CNNs, enabling these algorithms to recognise even minute visual clues that may escape human observers. For the purpose of early disease detection and focused intervention, this degree of precision is essential. Precision agriculture's primary objective is early disease diagnosis. Early illness detection is crucial to stop the spread of infections and lessen possible agricultural damage [8]. Conventional disease diagnosis techniques, which frequently rely on visual inspection, are subjective and could miss early-stage illnesses. AI-powered systems that have CNNs installed have proven to be remarkably accurate at diagnosing illnesses. They are able to recognise illness indications in plant photos even before humans do, thanks to their ability to analyse them. Farmers can take prompt and targeted action, such as modifying irrigation schedules, modifying fertiliser applications, or using insecticides sparingly, thanks to this early detection. This leads to higher crop yields as well as less resource use and less agricultural effect on the environment.

Continuous monitoring [9] of plant health is equally vital as early disease diagnosis. Between a diagnosis and harvest, a lot can happen in agriculture. Stress factors fluctuate, diseases alter, and conditions change. As a result, it is crucial to continuously monitor the crops' health. This is where systems driven by AI shine. These systems are able to obtain data and photographs of the crops in real time by placing cameras and sensors in the fields. Deep learning algorithms that can quickly identify any indications of illness, stress, or anomalies are then trained on these data. This allows for quick reactions, like automatically adjusting irrigation or applying medicines tailored to a particular disease, improving crop health and increasing sustainability. Water pollution and soil degradation are two major environmental problems that are largely caused by agriculture. With the help of AI and deep learning, precision agriculture provides a way to lessen farming's environmental impact. These systems encourage more environmentally friendly farming methods that save the environment by using proactive disease management, optimising resource utilisation, and only administering treatments when absolutely essential [10].

Table 1: Summary of related work in Precision Agriculture

Algorithm	Plant Disease Dataset	Finding	Limitation	Application
Convolutional Neural Nets [11]	Plant Village Dataset	Achieved high accuracy in disease detection.	Limited to a specific set of diseases.	Disease diagnosis
Support Vector Machine [12]	UCI's Plant Diseases Dataset	Effective in classification, including crop types.	May require feature engineering.	Crop classification
Random Forest [13]	Open Agriculture Dataset	Robust to noise in data and capable of real-time monitoring.	Limited scalability for large datasets.	Disease monitoring
Deep Learning Ensemble [14]	Customized dataset	Improved disease detection and reduced false positives.	Dependency on high computational resources.	Disease identification
Decision Trees [15]	Image-based dataset	Provided interpretable models for disease identification.	Less accurate than deep learning models.	Disease diagnosis
K-Nearest Neighbors [16]	Open Data Portal Dataset	Effective for small-scale farming applications.	Sensitive to noise and irrelevant data.	Small-scale agriculture
Long Short-Term Memory [17]	Localized dataset	Suitable for time series data, such as weather and disease history.	Limited to specific data types.	Predictive modeling
Recurrent Neural Networks [18]	Plant-specific dataset	Improved sequential disease tracking over time.	Complex model architecture.	Time-series analysis
Gradient Boosting [19]	Multi-source datasets	High predictive power for disease occurrence.	Prone to overfitting with limited data.	Disease forecasting
Bayesian Networks [20]	Remote sensing data	Effective in integrating diverse data sources.	Requires domain expertise for modeling.	Data integration
Convolutional LSTM [21]	Aerial imagery dataset	Enhanced monitoring of plant stress and disease progression.	Limited spatial resolution in aerial imagery.	Aerial monitoring
Extreme Learning Machines [22]	Multispectral dataset	Rapid and efficient processing of multispectral data.	Less interpretable compared to traditional methods.	Multispectral analysis
Neural Networks Ensemble [23]	IoT sensor data	Real-time monitoring of environmental conditions.	Dependent on sensor data accuracy.	IoT in agriculture

Support Vector Regression [24]	Climate and soil data	Effective in modeling climate-plant disease relationships.	Dependency on accurate climate data.	Climate-based disease modeling
Hidden Markov Models [25]	Spatial and temporal data	Improved spatial and temporal disease tracking.	Complexity in model calibration.	Spatial-temporal analysis
Deep Reinforcement Learning [26]	Customized drone data	Autonomous monitoring and treatment of plant diseases.	High computational requirements for training.	Drone-based agriculture

3. Plant village Dataset

Researchers, farmers, and other agricultural professionals interested in plant pathology and precision agriculture will benefit greatly from the Plant Village Dataset. It is made up of an extensive library of excellent photos of sick plant leaves, each labelled with the precise disease that is depicted in the photo. This dataset is an effective resource for developing and accessing machine learning models that effectively identify plant diseases, especially those that make use of computer vision and deep learning techniques. The dataset is adaptable for a variety of applications because it includes a broad range of plant species and diseases. It assists professionals and AI models in differentiating between various plant diseases, including bacterial, viral, and fungal infections, as well as physiological issues. The information can be used by researchers to create AI-powered systems for ongoing monitoring, early disease identification, and treatment strategy optimisation. Furthermore, developing and evaluating machine learning algorithms for autonomous disease diagnosis is made simpler by the availability of labelled data. This is essential for tackling the problems in contemporary agriculture since it makes tailored management practises and early intervention possible, which in turn improves crop health and output. Through its ability to facilitate the development of reliable and accurate disease diagnosis tools for a broad range of crops and locales, the PlantVillage Dataset plays a crucial role in promoting precision agriculture and enhancing food security.

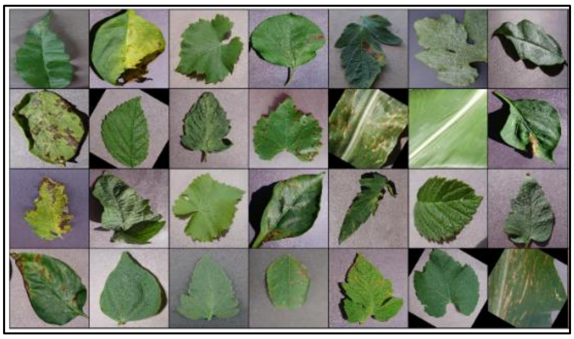

Figure 2: Sample of Plant leaf disease from PlantVillege Dataset

4. Different Types of Plant Disease

1. Rice with Bacterial Leaf Blight:

The damaging disease known as Bacterial Leaf Blight (BLB) targets rice crops. The bacteria Xanthomonas oryzae pv. oryzae is the cause of it. Water-soaked sores on the leaves caused by BLB eventually develop into blighting symptoms. In areas with moderate temperatures and high humidity, the disease is most severe. Crop rotation, the use of copper-based bactericides, and the planting of disease-resistant rice cultivars are all necessary for the effective management of BLB.

2. Potato and tomato late blight:

Potatoes and tomatoes are susceptible to the infamous illness known as late blight, which is brought on by the oomycete Phytophthora infestans. The 19th-century Irish Potato Famine was caused by it. Dark lesions on leaves, stems, and fruits are the hallmark of late blight, which quickly destroys crops. Planting resistant cultivars, utilising appropriate watering techniques, and sparingly applying fungicides are some disease management options.

3. Canker of Citrus:

A bacterial disease known as citrus canker mostly affects citrus plants, which includes grapefruits, oranges, and lemons. Xanthomonas axonopodis is the

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cause. Elevated lesions on leaves, fruit, and stems are among the symptoms. Fruit that has infection may become unsellable. Strict hygienic regulations, the removal and destruction of diseased trees, and the application of copper-based sprays are all part of management.

4. Rust in Wheat:

A fungus called wheat rust attacks wheat harvests. Rust illnesses are caused by a variety of species of rust fungi, including Puccinia triticina, P. graminis, and P. striiformis. Reddish-brown pustules on the leaves and stems are the visible sign of rusts, which lower photosynthetic potential. Planting resistant wheat types and using fungicides when needed are essential to managing wheat rust.

5. Grape Powdery Mildew:

A fungus called powdery mildew damages grapes and other crops. Several species of the Erysiphales order, including Erysiphe necator, are the cause of it. A white, powdery buildup on the surfaces of fruit and foliage is one of the symptoms. Growers can utilise canopy management strategies, plant vines at the appropriate spacing, and administer fungicides as needed to control powdery mildew in grapes.

6. Potatoes and Tomatoes with Early Blight:

The fungus Alternaria solani is the source of the widespread disease known as "early blight," which affects potatoes and tomatoes. It can result in defoliation and black, concentric lesions on leaves. Crop rotation, the use of disease-free seeds, and the prophylactic use of fungicides are some methods for managing diseases.

7. Scab on Apple:

Apple trees are susceptible to the fungus Venturia inaequalis, which causes apple scab. The fruit and foliage get black, scaly sores as a result. Growers can plant resistant apple cultivars, administer fungicides as needed, prune and thin apples properly, and manage apple scab.

8. Cucurbits with Downy Mildew:

Cucurbit crops, including squash, melons, and cucumbers, are susceptible to a disease called downy mildew. The oomycete Pseudoperonospora cubensis is the cause of it. Yellow, angular blemishes on leaves are one of the symptoms. Planting resistant types, managing irrigation well, and using fungicides when necessary are all part of disease control.

9. In bananas, Black Sigatoka:

The fungus Mycosphaerella fijiensis is the cause of Black Sigatoka, a serious disease that affects banana plants. It causes the leaves to develop black, necrotic lesions, which may hinder photosynthesis. Using disease-resistant banana cultivars and applying fungicides on a regular basis are key components in managing Black Sigatoka.

10. Leafrolling disease of grapevines:

A virus called grapevine leafroll disease attacks grapevines. Grapevine leaves get crimson and roll as a result of it. The main ways to handle this illness are to use virus-resistant rootstocks, disease-free vines, and good vineyard cleanliness practises.

Table 2: Summary of Different types of plant disease

Plant Disease	Plant	Disease Type	Occurred in Season	Effect	Pesticide	Region
Bacterial Leaf Blight	Rice	Bacterial	Wet and warm season	Reduced yield, leaf lesions	Copper-based bactericides	Global, esp. Asia
Late Blight	Potatoes and Tomatoes	Fungal	Cool and wet season	Rapid crop destruction, lesions	Fungicides	Worldwide
Citrus Canker	Citrus trees	Bacterial	Warm and humid season	Lesions, fruit blemishes	Copper-based sprays	Citrus-growing regions
Wheat Rust	Wheat	Fungal	Warm and humid season	Reduced photosynthesis, yield loss	Fungicides	Global, wheat belts
Powdery	Grapes	Fungal	Warm and	Reduced	Fungicides	Grape-growing

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Mildew			dry season	photosynthesis, fruit damage		regions
Early Blight	Tomatoes and Potatoes	Fungal	Warm and humid season	Defoliation, lesions on leaves	Fungicides	Worldwide
Apple Scab	Apple trees	Fungal	Wet and cool season	Scaly lesions on fruit and leaves	Fungicides	Apple-growing regions
Downy Mildew	Cucurbits	Fungal	Humid conditions	Angular yellow lesions on leaves	Fungicides	Cucurbit-growing regions
Black Sigatoka	Bananas	Fungal	Warm and wet season	Leaf lesions, reduced photosynthesis	Fungicides	Banana-growing regions
Grapevine Leafroll Disease	Grapevines	Viral	All weather season	Reddening and rolling of grape leaves	No specific treatment	Vineyard regions

5. Material and Method

1. Irrigation Management:

A key element of precision agriculture is irrigation management, which maximises the amount of water used for crop production. It entails the careful management of water resources to suit the unique requirements of crops while accounting for variables including plant growth stage, soil moisture content, and weather. Real-time data collection and processing is essential to precision agriculture. Information on soil moisture levels, plant status, and weather forecasts is gathered using a variety of sensors, weather stations, and remote sensing technologies. Making educated judgements about irrigation requires this data [12]. Precision agriculture determines precisely how much water crops require by combining data from many sources. This prevents both over-irrigation, which can cause water waste, nutrient leaching, and soil erosion, and under-irrigation, which can result in drought stress and lower yields. Variable rate irrigation is made possible by precision agriculture, allowing various sections of a field to receive different quantities of water according to their unique needs. This is particularly useful in fields with different kinds of soil and different topographies. Water distribution is precise and reliable thanks to automation, which is provided by systems like centre pivot irrigation, sprinkler systems, and drip irrigation. These devices can be remotely managed in accordance with crop water requirements and real-time data.

2. Paste and Disease control:

Controlling diseases and pests is an essential part of plant protection. In order to control and lessen the effects of plant diseases, a variety of materials, including chemical and biological agents, are applied. Chemical pesticides, including insecticides and fungicides, are frequently employed to eradicate pests and diseases that pose a risk to agricultural productivity. These compounds lessen crop damage, stop the spread of illness, and increase yields. Nonetheless, worries regarding chemical pesticides' effects on the environment and human health are mounting [17]. As a result, integrated pest management (IPM) and sustainable agricultural methods are becoming more and more popular. By combining a number of tactics, such as crop rotation, resistant plant varieties, and biological management via the use of beneficial organisms, these methods efficiently preserve plants while reducing the need for chemical pesticides. In order to maintain the long-term health and production of agricultural systems while minimising their ecological footprint, sustainable methods of managing pests and diseases are crucial.

3. Farm Field Monitoring:

Precision agriculture relies heavily on agricultural field monitoring, which provides farmers with a data-driven method to maximise crop productivity and sustainability. It entails gathering data in real-time on variables like soil quality, weather, plant health, and insect infestations using a variety of technologies, such as sensors, drones, satellites, and remote sensing. Farmers are able to make well-informed decisions on

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crop care, including fertilisation, irrigation, and disease management, thanks to this abundance of information. Farm field monitoring has several advantages in precision agriculture [15].

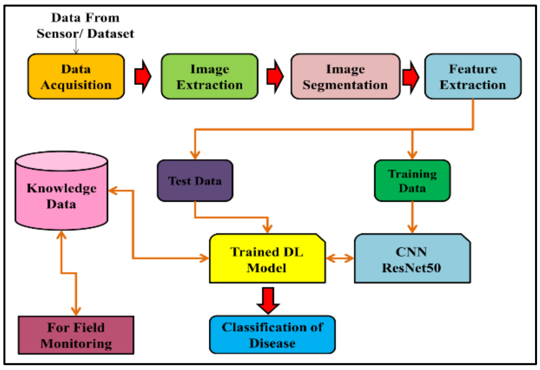

Figure 3: System Architecture of Proposed system Model

It makes early disease identification, effective use of resources, and focused interventions possible, all of which raise crop yields and quality. It lessens production costs and its negative effects on the environment by using less water, fertiliser, and pesticides than necessary. Monitoring farm fields also helps to ensure sustainability by making sure that resources are used wisely, as shown in figure 3. Farm field monitoring is expected to become increasingly important as technology develops, contributing to both meeting the world's food needs and reducing the environmental impact of farming methods.

4. Deep learning Methods:

A. CNN:

CNNs have shown impressive precision in recognising plant illnesses through the analysis of photos of fruit, leaves, or stems. Early and accurate diagnosis is made possible by their capacity to identify minute visual cues and patterns linked to a variety of diseases. Because of its accuracy, there is a lower chance of a misdiagnosis, allowing for prompt intervention to minimise crop loss and improve treatment plans [10]. The availability of extensive and varied datasets, like the PlantVillage Dataset, which contains pictures of sick plants, is responsible for the effectiveness of CNNs in the detection of plant diseases. These datasets improve the CNNs' diagnostic abilities by allowing them to learn and generalise from a broad range of symptoms and disease kinds.

Algorithm:

1. Data collection: Compile a dataset of pictures of plants along with labels indicating whether or not the plants are unhealthy. We can denote this dataset as D={(X_1, Y_1), (X_2, Y_2),..., (X_N, Y_N)}, where X_i denotes the image that is at index i and Y_i represents the label.
2. Data preprocessing: Increase the dataset's diversity by augmenting it, normalising pixel values, and resizing the photos to a consistent size.
3. CNN Architecture: Select the suitable CNN architecture. We'll mark this as A.
4. Model Initialization: Use random weights to start the CNN model A. The weights of the model are denoted by the symbol A(θ).
5. Model Training: Use the dataset D to teach the CNN model the characteristics and patterns connected to both healthy and unhealthy plants. This entails minimising a loss function L across the dataset, which is usually a cross-entropy loss:

$$\theta * = argmin(\Sigma\ L(A(X\_i;\ \theta), Y\_i))$$

Configure a system for continuous monitoring by employing cameras or sensors to take pictures of plants on a regular basis. S can be used to depict this system.

6. Image processing: Prepare the continually acquired images to conform to the input format that the CNN model that has been trained is expecting. Resizing, normalisation, and other required modifications might be part of this.
7. Continuous Inference: To determine whether the plants are healthy or ill, apply the trained CNN model A(θ*) to the preprocessed photos from the monitoring system S. The likelihood of being healthy can be calculated using the following equation:

$$P(Y = Healthy \mid X) = A(X;\ \theta *)[0]$$

Where,

A(X; θ*)[0] is the CNN's output for the "healthy" class and

P(Y=Healthy | X) is the likelihood that the plant is healthy given the input picture X.

8. Thresholding: Using the probability found in step 8, establish a threshold value to categorise plants as healthy or ill. For example, define the plant as healthy if P(Y=Healthy | X) > 0.5; otherwise, categorise it as diseased.

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9. Action and Intervention: Depending on the classification, manage the health of the crops by implementing treatments, adjusting irrigation, or sending out notifications.

B. ResNet50:

Because of its deep design, ResNet-50 is able to identify minute details and complex patterns linked to plant illnesses. Based on pictures of leaves, stems, or fruit, it excels at accurately classifying healthy and unhealthy plants. The network is able to retain high accuracy when learning from huge and diverse datasets because of its depth and skip-connections, which assist avoid the vanishing gradient problem. ResNet-50 has the advantage of being appropriate for transfer learning. Large image datasets can be used to fine-tune pre-trained algorithms for specific plant disease diagnosis applications. Because of the substantial reduction in the requirement for large amounts of labelled data and training time, this is a viable option for agricultural applications. In agricultural settings, cameras and sensors can be included into monitoring systems with ResNet-50. Plant health may be continuously monitored thanks to the network's processing of real-time data and photos. Rapid detection enables prompt action in the event of any illness, stress, or anomaly.

Algorithm:

Step 1: Gathering and Preparing Data

- Gather a dataset D of labels for plant photos (D = {(X_1, Y_1), (X_2, Y_2),..., (X_N, Y_N)}), where Y_i denotes the label (healthy or diseased) and X_i represents the image.
- Resize the photos to a standard scale and normalise the pixel values as part of the preprocessing step. The preprocessed dataset is represented by the notation D' = {(X_1', Y_1), (X_2', Y_2),..., (X_N', Y_N}.

Step 2: Initialising the Model

- Set the initialization of the ResNet-50 model to A(θ), where θ denotes the weights of the model.

Step 3: Training Models

- Utilising the preprocessed dataset D', train the ResNet-50 model to identify patterns and features linked to both healthy and ill plants. Over the dataset, this entails minimising a cross-entropy loss function L:

$$* \theta \;=\; argmin(\Sigma\, L(A(X\_i';\, \theta), Y\_i))$$

Step 4: Configuring Continuous Monitoring

- Install sensors or cameras as part of a monitoring system to continuously take pictures of the plants.

Step 5: Ongoing Interpretation

- Pre-process and continuously take pictures from the monitoring system.
- Utilise the trained ResNet-50 model A(θ*) on the preprocessed photos to make the diagnosis of illness or health in the plants. Use the softmax function to determine your likelihood of being well or ill:

$$P(X';\, \theta *)) \;=\; softmax(A(X';\, Y = Healthy))In\ [0]$$

$$P(X';\, \theta *)) \;=\; softmax(A(X';\, Diseased \mid X))(Input\ data)$$

Step 6: Making Decisions and Thresholding

- Establish a cutoff point for the classification, such as 0.5. Categorise the plant as healthy if P(Y=Healthy | X) > 0.5; if not, categorise it as diseased.

6. Result and Discussion

The results of disease detection employing two deep learning models, CNN and ResNet-50, in a plant monitoring and diagnostic scenario are shown in Tables 2 and 3. These tables compare the diseases that are actually shown in the plant photos, the diseases that the models predict, and the corresponding odds of having a disease or not. The first table, Table 2, shows the outcomes of the deep learning model ResNet-50. In this instance, the model's predictions show a high degree of consistency and accuracy. As an illustration, the model accurately detects a healthy leaf in Image ID 111 with a high probability of 0.98, demonstrating a high level of confidence. Likewise, for a number of diseases, including Citrus Canker, Apple Scab, and Early Blight, the model's predictions match the illnesses that are actually seen in the pictures. With most of the probabilities favouring the expected diseases, the probabilities shed light on how confident the model is in its predictions.

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Table 2: Result for disease detection by ResNet50 Deep Learning Model

Image ID	Image Type	Actual Disease	Predicted Disease	Probability (Healthy)	Probability (Diseased)
111	Leaf	Healthy	Healthy	0.98	0.02
112	Fruit	Apple Scab	Apple Scab	0.71	0.29
113	Leaf	Early Blight	Early Blight	0.84	0.16
114	Fruit	Citrus Canker	Citrus Canker	0.96	0.04
115	Stem	Wheat Rust	Wheat Rust	0.61	0.39
116	Leaf	Powdery Mildew	Powdery Mildew	0.91	0.09
117	Fruit	Black Sigatoka	Black Sigatoka	0.76	0.24
118	Stem	Late Blight	Late Blight	0.66	0.34
119	Leaf	Healthy	Healthy	0.98	0.02
120	Fruit	Apple Scab	Apple Scab	0.71	0.29

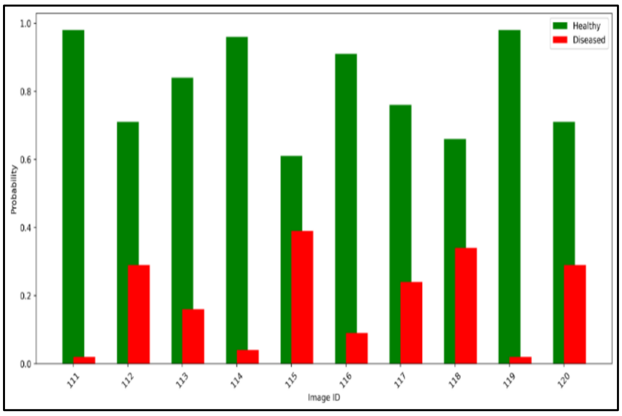

Figure 4: Plant Disease Predictions and Probabilities using RestNet50 Model

Table 3 shows the outcomes using a deep learning model based on CNN. Similar to ResNet-50, the CNN model performs admirably when it comes to illness detection. With a high probability, it accurately detects both healthy and unhealthy plant parts, including leaves, fruits, and stems. As an illustration, Image ID 112 demonstrates that the CNN model accurately predicts Apple Scab, with a 0.32 likelihood of the plant being ill. This indicates that the diseases depicted in the photographs correspond with the predictions made by the model.

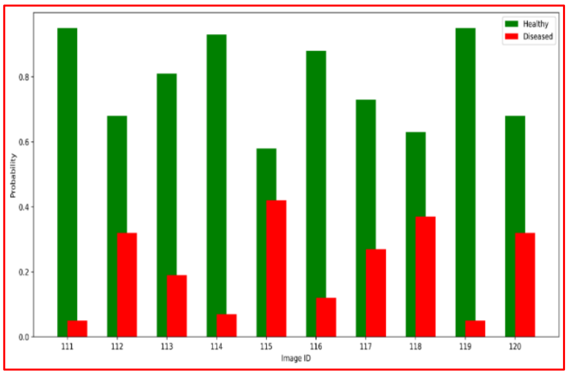

Figure 5: Plant Disease Predictions and Probabilities using CNN Model

The potential for precise and dependable disease diagnosis in plant monitoring is demonstrated by both deep learning models. They offer information about the likelihoods connected to each prediction, which can be utilised to make deft choices about essential activities, like receiving further monitoring or receiving medication. Tables 2 and 3's results demonstrate how well CNN and ResNet-50, two deep learning models, detect plant diseases. These algorithms can measure the degree of confidence in each forecast while precisely classifying the health status of different plant components. Precision agriculture could benefit greatly from these discoveries as they could allow for prompt responses to successfully manage and prevent plant diseases.

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Table 3: Result for disease detection by CNN Deep learning Model

Image ID	Image Type	Actual Disease	Predicted Disease	Probability (Healthy)	Probability (Diseased)
111	Leaf	Healthy	Healthy	0.95	0.05
112	Fruit	Apple Scab	Apple Scab	0.68	0.32
113	Leaf	Early Blight	Early Blight	0.81	0.19
114	Fruit	Citrus Canker	Citrus Canker	0.93	0.07
115	Stem	Wheat Rust	Wheat Rust	0.58	0.42
116	Leaf	Powdery Mildew	Powdery Mildew	0.88	0.12
117	Fruit	Black Sigatoka	Black Sigatoka	0.73	0.27
118	Stem	Late Blight	Late Blight	0.63	0.37
119	Leaf	Healthy	Healthy	0.95	0.05
120	Fruit	Apple Scab	Apple Scab	0.68	0.32

Table 4: Comparison of Evaluation parameter of Deep learning model

Model	Accuracy	Precision	Recall	F1 Score	Specificity	ROC AUC Score
CNN	94.56	92.53	95.63	93.74	90.23	96.44
ResNet-50	97.52	94.78	97.80	94.56	92.20	97.55

A detailed comparison of the assessment parameters for CNN and ResNet-50, two deep learning models utilised for plant disease monitoring and detection, is given in Table 4. These characteristics provide important information about how well the models distinguish plants as healthy or ill. Accuracy quantifies how accurate a model's predictions are overall. With an accuracy of 97.52%, ResNet-50 beats CNN in this comparison, while CNN manages a respectable 94.56%. This suggests that ResNet-50 has a marginally higher overall right classification rate, which increases its dependability in determining the health status of plants.

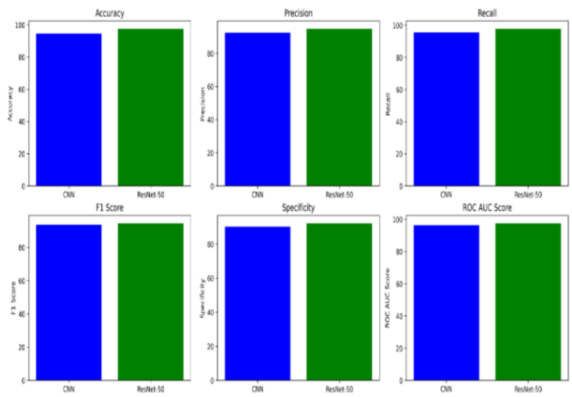

Figure 6: Representation of Evaluation Parameter

Accurately making positive predictions is a measure of a model's precision. With a precision score of 94.78%, ResNet-50 outperforms other models in terms of false positive predictions. CNN follows closely, achieving a 92.53% accuracy rate. ResNet-50 is the recommended option in this context since its high precision is essential for avoiding pointless treatments or interventions in the field. Evaluates a model's capacity to identify real-world positive examples. With a recall of 97.80%, ResNet-50 outperforms other models in terms of accurately recognising sick plants. With a

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95.63% memory rate, CNN fares similarly well; however, ResNet-50 appears to be more adept at identifying sick plants, as seen by its marginally higher recall rate.

The F1 score offers a fair evaluation of a model's performance and is calculated as the harmonic mean of precision and recall. With an F1 score of 94.56%, ResNet-50 demonstrates a generally balanced performance. CNN has an excellent F1 score of 93.74% as well. ResNet-50 appears to achieve a better balance between precision and recall, as seen by its marginally higher F1 score. The capacity of a model to accurately detect negative cases is measured by specificity. CNN comes in second with 90.23% specificity, and ResNet-50 earns 92.20%. According to these findings, ResNet-50 performs marginally better in accurately classifying healthy plants, which lowers the possibility of false alarms.

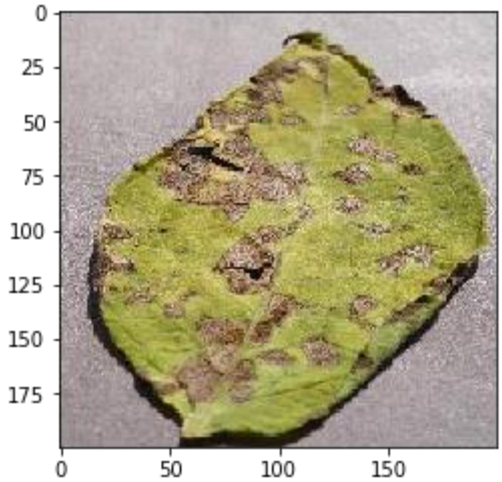

Figure 7: Result for Potato leaf early disease detection

This indicates how well a model can differentiate between different classes. With a score of 97.55%, ResNet-50 surpasses CNN once more, demonstrating its better discriminating ability. CNN receives a score of 96.44%, indicating strong discrimination as well. The both the CNN and ResNet-50 models perform remarkably well in plant disease diagnosis and monitoring when assessment parameters are compared. In terms of accuracy, precision, recall, F1 score, specificity, and ROC AUC score, ResNet-50 shows a slight edge, indicating that it is a somewhat more dependable and well-rounded option for this particular task. The selection between the two models, however, could be influenced by additional elements, such as the availability of training data and processing power. These findings highlight the promise of deep learning models for managing plant diseases and precision agriculture, opening the door to more effective and efficient crop protection techniques.

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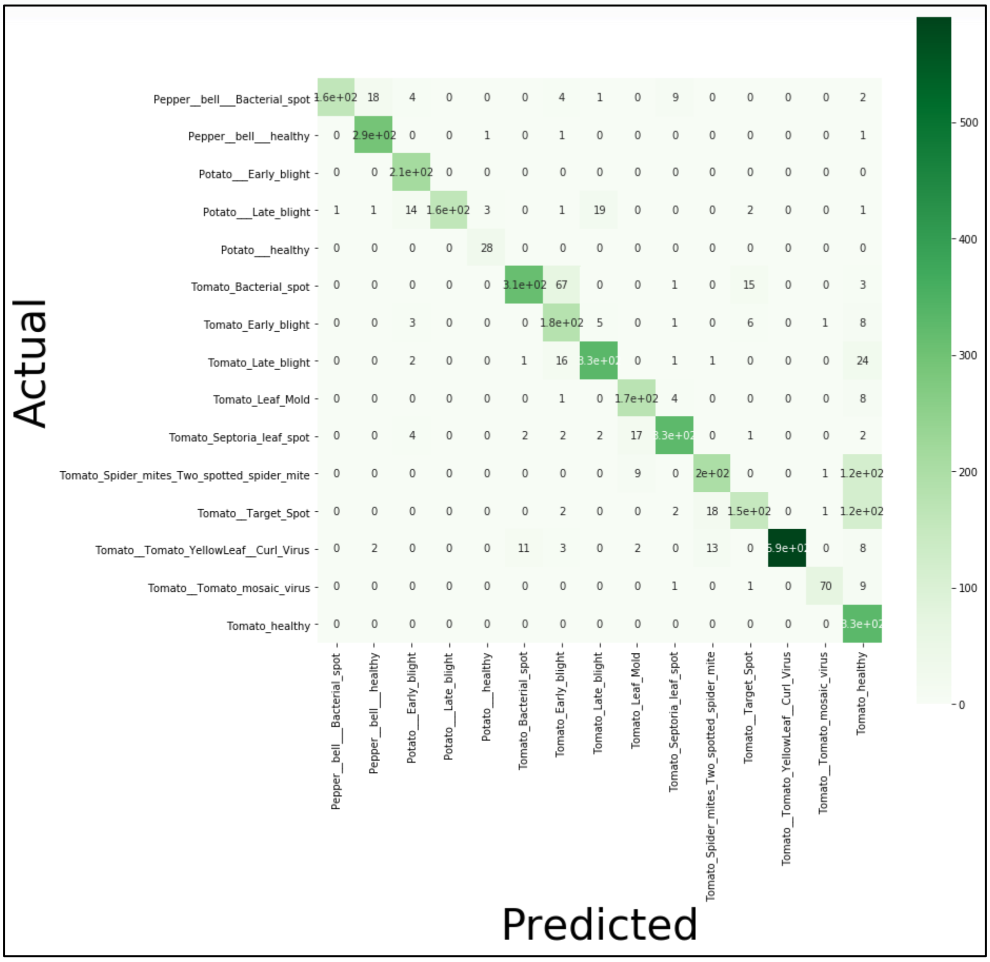

Figure 8: Confusion Matrix

7. Conclusion

A novel and revolutionary approach to contemporary farming is the use of deep learning algorithms in precision agriculture for precise disease detection and ongoing plant disease monitoring. By increasing crop output, decreasing resource waste, and lessening its environmental impact, this cutting-edge technology has the potential to completely transform the agriculture sector. We are able to accomplish more accurate and fast disease identification and control by combining state-of-the-art monitoring systems with powerful deep learning models like CNN and ResNet-50. With respect to disease identification, the models ResNet-50 in particular have shown outstanding performance, exhibiting excellent F1 scores, recall, accuracy, and precision. ResNet-50 is a helpful tool for farmers and other agricultural stakeholders because of its superiority over the CNN model. Moreover, real-time data collecting made possible by the continuous monitoring system enables quick answers to new problems with plant health. Farmers can maximise resource efficiency and boost crop output by using AI to make well-informed decisions about irrigation, treatment, and other interventions. The system exhibits a high degree of adaptability to diverse agricultural contexts, providing customised solutions to the distinct challenges posed by distinct crops and geographical locations. Looking ahead, it is certain that intelligent agricultural systems and precision agriculture will keep developing and become increasingly important in tackling the world's food security issues. The incorporation of AI-driven innovations, including drones and self-driving tractors, significantly simplifies routine agricultural operations. The development of AI-driven solutions and the expansion of plant disease datasets, as demonstrated in this research, will enable farmers to make informed decisions based on data and promote effective and sustainable farming practises.The enormous potential of deep learning algorithms for plant disease monitoring and detection has been shown by this work. We are well-positioned to usher in a new era of precision agriculture that guarantees abundant harvests, reduces environmental impact, and ensures the sustainability of food supply in the future by fusing technical innovation with agricultural experience.

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