J. Integr. Sci. Technol. 2024, 12(2), 734

Journal of Integrated
SCIENCE & TECHNOLOGY

Leaf analysis based early plant disease detection using Internet of Things, Machine Learning and Deep Learning: A comprehensive review

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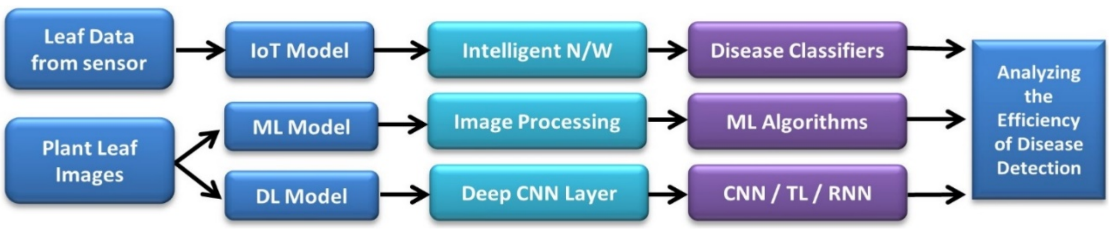
Received on: 26-Aug-2023, Accepted and Published on: 04-Oct-2023

Review

ABSTRACT



In the agricultural sector, timely identification of plant diseases is crucial to mitigate crop losses, ensure quality yields, and promote sustainable farming practices. Recent years have witnessed declining agricultural incomes due to the pervasive presence of bacterial, viral, and fungal infections, which progressively affect plants, resulting in crop loss, reduced fruit quality, and plant mortality. This paper investigates the application of IoT, Machine Learning, and Deep Learning techniques to detect disease symptoms at various stages, enabling proactive interventions to prevent extensive crop losses and disease propagation within agricultural plots. The primary objective of this study is to explore diverse approaches for early plant disease detection, addressing a critical gap in current research that predominantly focuses on leaves and fruits. Furthermore, this study extends its scope to include diseases originating from soil, offering a comprehensive approach to disease management in agriculture. This research holds significant implications by empowering farmers with predictive capabilities, reducing pesticide use, and fostering sustainable farming practices, ultimately contributing to food security and economic stability in the agricultural industry.

Keywords: Deep Learning, Machine Learning, IoT, Digital Image Processing, Recurrent Neural Networks, Transfer Learning, CNN

INTRODUCTION

A significant portion of the world's population depends on agriculture for their livelihood. However, factors such as untimely rains, weather fluctuations, lack of soil fertility, and unscientific farming practices have hindered the farmers' ability to cultivate successful crops.[1,2] The continuous reduction in agricultural income is a concerning trend, primarily as a consequence of the adverse impact of diseases and pests on agricultural products. While pest control measures such as pesticides and advanced techniques like ultrasonic pest repellents exist, diseases have emerged as a major problem in recent times.[3] Some diseases lack effective medications for treatment, and many go undetected in their early stages. Infectious plant diseases, caused by bacteria, fungi, or viruses, can range in severity from mild leaf or fruit damage to plant death.[4]

Unfortunately, farmers often struggle to detect the primary symptoms, spreading diseases across more than 50% of the total plant area. Observing plant leaves, fruits, and stems, and conducting soil testing can aid in disease identification.[5] Soil-borne diseases are particularly prevalent, as environmental conditions and improper plot maintenance promote the growth of pathogenic fungi and viruses.[6] Common plant diseases, such as blight, cankers, rust, wilts, rots, and anthracnose, are caused by bacteria or fungi.[7] Technological enhancements have substantially improved the ability to identify plant diseases at early stages.[8]

The main goal of this research is to investigate different methods and techniques for the early detection of plant diseases. This is crucial because there is a notable gap in the current body of research, which tends to concentrate primarily on detecting diseases in plant leaves and fruits. Our study aims to fill this gap by exploring a wider range of approaches to identify diseases in plants at an earlier stage of their development. In addition to addressing the existing gap in research, this study goes a step further by broadening its scope. It doesn't limit itself solely to diseases that manifest in leaves and fruits. Instead, it includes diseases that

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Cite as: *J. Integr. Sci. Technol., 2024, 12(2), 734. URN:NBN:sciencein.jist.2024.v12.734*

 ISSN: 2321-4635
http://pubs.thesciencein.org/jist

originate from the soil. This comprehensive approach means that the research covers the entire spectrum of disease management in agriculture. It takes into account not only the diseases that visibly affect the above-ground parts of plants but also those that may stem from the soil, which is an essential aspect of ensuring plant health and overall crop management. The study's primary objective is to diversify and improve early plant disease detection methods while extending its focus to encompass a broader array of potential disease sources, ultimately contributing to more effective disease management in agriculture.

Research Questions:

1. What novel approaches and technologies can be employed to enhance the early detection and management of plant diseases, and how do these strategies compare to traditional methods focused on leaf and fruit symptom recognition?
2. How can sensor-based technologies be employed to monitor and manage soil-borne pathogens, ensuring plant health and sustainable, disease-free crop cultivation in agriculture?

Challenges:

Data Collection and Quality: Gathering a diverse set of plant images with diseases can be tough, especially for rare diseases or less common plant types. Labeling these images for training takes time and can lead to errors. Also, having an uneven mix of healthy and diseased samples can bias machine learning models.[9]

IoT Device Integration: Placing IoT sensors correctly on plants to collect accurate data is crucial. In agriculture, IoT devices often have power constraints, making data transmission and maintenance challenging.[10]

Environmental Variability: Weather conditions, lighting, and other environmental factors can affect image quality and sensor readings. Disease symptoms may vary by season, so these changes need to be incorporated into the dataset.[11]

Model Generalization: Machine learning models, especially deep learning ones, trained on one plant type or region may not work well on different plants or regions. They might become too specialized in the training data.[12]

Scalability: Going from small experiments to large farms is hard due to issues with hardware, data management, and scaling up the detection system.[13]

Education and Training: Farmers and workers might need special training to use and understand AI-based disease detection systems effectively.[14]

Addressing these challenges requires a collaborative effort among experts in agriculture, machine learning, IoT, and data management. Additionally, there's a need to develop strong, adaptable models that fit the specific needs and limitations of different agricultural situations.[15] In the following sections, this paper will delve into various aspects of plant disease detection. First, the paper will explore IoT-based methods for identifying plant leaf diseases, shedding light on the benefits and challenges associated with this approach. Next, it will delve into the realm of image processing and machine learning techniques, specifically focusing on their application in plant leaf disease detection. Following that introduces deep learning methods tailored for plant disease detection. The paper will then present the results of the survey, highlighting key findings that address existing research gaps and propose a hybrid solution. Finally, the paper will conclude by summarizing the implications of the research and its contribution to the field.

Note: *Deep Learning (DL), Machine Learning (ML), Digital Image processing (DIP), Internet of Things (IoT)*

LITERATURE REVIEW

PLANT LEAF DISEASE DETECTION USING THE INTERNET OF THINGS:

The IoT encompasses various fields of application, including Industry, Health, Agriculture, and Automation. In the Agricultural domain, IoT plays a significant role by contributing to its development and efficiency.[16] Several applications utilize IoT technology to enhance agricultural practices, such as Agricultural Drones, Livestock Monitoring, Smart Greenhouses, Remote Sensing, Smart Irrigation Systems, and Plant Health Monitoring systems [17]

Plant leaf disease detection using the IoT involves the use of connected devices and sensors to monitor and detect diseases in plants.[18] It combines the power of IoT technology with data analysis techniques to identify and determine plant diseases at an early stage. IoT devices are infused with sensors to sense and also actuators to bring change in the real world.[19] Through the utilization of IoT sensors, it becomes possible to monitor essential parameters related to crops, including physical, chemical, environmental, and biomolecular aspects.[20] These parameters serve as indicators for plant diseases or abiotic stress factors. Furthermore, IoT sensors enable the tracking of plant growth rate, changes in plant health, fruit quality, and soil fertility levels, as well as the identification of viruses, bacteria, and soil-borne fungi.[21]

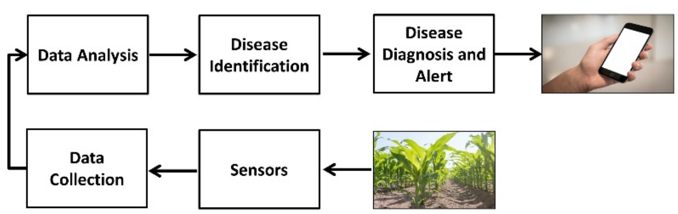

Figure 1 Plant Disease Detection using IoT

The data collected by plant-wearable sensors are transmitted wirelessly to a centralized cloud platform. This cloud-based approach facilitates the consolidation of information and enables intelligent decision-making processes. By analyzing the collected data, it becomes feasible to detect infections or other critical factors affecting plant health. These insights can then be utilized to implement timely interventions or adjustments to ensure optimal agricultural outcomes.[22] Figure 1 shows the fundamental stages involved in the plant disease detection system using IoT.

The following is the introduction to the fundamental stages of plant disease detection using IoT.

Sensor deployment: Involves the strategic placement of IoT devices equipped with a wide array of sensors, including humidity, temperature, light, and moisture sensors, in and around the plants or fields. These sensors work tirelessly to continuously monitor and collect precise data pertaining to environmental conditions.[23]

Data collection: Gathering data related to various factors is the responsibility of the sensors, such as light intensity, soil moisture, temperature, humidity levels, and other pertinent parameters. Afterwards, the data is forwarded to a central system or cloud platform for subsequent processing and analysis.[23]

Data analysis: The gathered data undergoes processing and analysis through the utilization of machine learning algorithms, statistical models, or image processing techniques. These advanced methods aid in the recognition of patterns, anomalies, and potential indications of plant diseases within the collected dataset.[23]

Disease identification: Effectively discerning the existence of diseases in plants is achieved through the system's utilization of either the collected data's comparison with predefined disease patterns or the application of machine learning models trained on historical disease data. This identification relies on symptoms like leaf discolouration, growth patterns, or other observable characteristics.[23]

Disease diagnosis and alerts: Upon detecting a disease, the model can offer a diagnosis or generate alerts to promptly inform farmers or plant experts about its presence. These alerts are conveyed through mobile apps, emails, or SMS messages, guaranteeing the prompt distribution of information to facilitate the implementation of required measures.[23]

Plant Disease Detection using Temperature Sensor:

Leaf pigments contribute to leaf colouring, and different pigments like chlorophyll, carotenoids, and anthocyanins create various colours in leaves. In autumn, leaves change colours due to the breakdown of chlorophyll and the existence of additional pigments. Environmental factors such as daylight, temperature, and soil dampness influence leaf appearance in fall. Sunlight and low temperatures promote chlorophyll breakdown, leading to vibrant colours. To detect plant diseases, first, establish baseline temperature values for healthy plants using the DHT11 sensor. Monitor the temperature of healthy plants over time. Different diseases cause specific symptoms, including changes in leaf temperature. Correlate known disease symptoms, like wilting or discolouration, with temperature variations detected by the DHT11 sensor. Once baseline temperatures are set, the DHT11 sensor continuously monitors plant temperature. Considerable deviations from the baseline benchmarks may indicate potential diseases or plant stress. The sensor data is directed to a cloud platform via a WiFi shield connected to an Arduino UNO board and recorded for analysis. If a leaf's temperature falls outside the healthy range, it is considered unhealthy.[24]

Plant Disease Detection Using Colour Sensor:

Colour changes in plant tissue can signal the existence of plant disease, particularly when green tissue turns yellow due to the loss of chlorophyll. The degree of colour change varies, ranging from partial to complete repression of leaf colour. To discriminate between healthy and diseased leaves, a colour sensor like the TCS3200 RGB colour sensor is used. It measures the "RED," "Green," and "Blue" components of the leaf's colour. The colour values are then directed to a cloud platform through an Arduino board for analysis. In the cloud platform, values of RGB are compared to a threshold value stored in a dataset. This threshold value serves as a reference point for determining leaf health. By comparing the recorded values with the threshold, the analysis identifies if the leaf is fit or suffering from a disease based on its colour characteristics.[25]

Table 1 Assessment Criteria for IoT Models

Paper	Data Collection	Robustness to Environmental Variability	Scalability	Accuracy
Nawaz et al., (2020)[24]	Data is collected from a DHT11 temperature sensor and a TCS3200 colour sensor to gather information about the leaves.	While the DHT11 is a waterproof sensor suitable for use during the monsoon and all other seasons, the TCS3200 is not water-resistant, which means it may not maintain robustness in all weather conditions.	Implementing on a large scale can be challenging due to hardware limitations and the need to deploy a substantial number of sensors.	Temperature and colour alone are insufficient for accurately predicting diseases, making the prediction less accurate.
R.Yakkundimath et al., (2018)[25]	Data is extracted from the leaf using both a DHT11 humidity and temperature sensor and a TCS3200 colour sensor.	The model lacks robustness for real-time deployment due to the absence of wireless communication between the sensor and Arduino UNO.	Enabling wireless communication between the cloud and an Arduino requires deploying a package consisting of Arduino boards and sensors in the field to achieve automation, resulting in an increased overall cost.	The model achieved an overall accuracy of 85.33% by employing three distinct algorithms to analyse the data.
Absar et al., (2023)[26]	Greenhouse data is collected by a DHT-11 temperature and humidity sensor, while a soil moisture sensor measures the levels of soil moisture.	The sensors employed for monitoring crops within greenhouses are designed to withstand controlledrenders climate conditions and remain robust in varying environmental conditions.	Sensor models have the potential to communicate, making them suitable for deployment over large areas, which render them scalable.	Encouraging manual control of greenhouse environments may hinder the attainment of higher accuracy due to the potential for human errors.

Table 2 Challenges Faced by IoT Models

Paper	Challenges
Nawaz et al., (2020).[24]	The placement of sensors, power supply, and interfacing with a large number of sensors.
R.Yakkundimath et al. 2018 [25]	Continuous monitoring of plant leaves is challenging due to the necessity of collecting leaf samples for reference and testing, which involves manual efforts in sample collection.
Absar et al., (2023)[26]	The model does not support automated environment settings; the only option available is manual control through the Blynk App. Additionally, the investment cost will be higher because the model utilizes a soil moisture sensor for controlled irrigation, restricting the application of sprinklers and making drip irrigation the sole viable option.

Plant Disease Detection using Humidity Sensor:

The DHT11 sensor is an affordable and user-friendly digital humidity sensor. It integrates "a capacitive humidity sensor and a thermistor" to measure the surrounding air's humidity and temperature. The "capacitive humidity sensor" detects changes in capacitance caused by moisture absorption, allowing it to determine relative humidity. The thermistor, a temperature-sensitive resistor, measures temperature changes. In this context, the DHT11 sensor measures humidity on a leaf's surface. Monitoring surface humidity helps assess the leaf's health. Different plants or leaves may need specific humidity levels to thrive, and discrepancies from the ideal range could indicate disease or stress. The sensor data is directed to a cloud platform via a Wi-Fi shield connected to an Arduino UNO board, where it is recorded for analysis.[26]

Table 1 outlines the assessment criteria for evaluating IoT models.[24–26] Data Collection, Robustness to Environmental Variability, Scalability and Accuracy, These assessment criteria are critical for assessing and improving IoT models. Data collection ensures the availability of relevant information, robustness ensures reliability in varying conditions, scalability supports deployment at different scales, and accuracy determines the efficacy of IoT applications. Together, they contribute to the success and efficiency of IoT solutions.

Table 2 specifies the challenges and limitations faced by the IoT models.[24–26]

Research Gap: Assessing whether a plant is afflicted with a disease by considering factors such as temperature, humidity, leaf colour, and the surrounding environment poses a significant challenge for precision agriculture. Climate change can introduce substantial variances in plant conditions, which may not always indicate the presence of a disease accurately. However, the implementation of hybrid techniques has shown potential for improving the accuracy of disease prediction, facilitating early intervention and reducing potential crop losses. While advancements have been achieved in harnessing hybrid methods, there remains a notable research gap in effectively integrating advanced sensor technologies, including biosensors, spectroscopic sensors, soil conductivity sensors, and soil pH sensors, into the monitoring and management of soil health. These sensors offer a wealth of data about the plant's immediate environment, potentially enabling more precise early prediction of diseases.

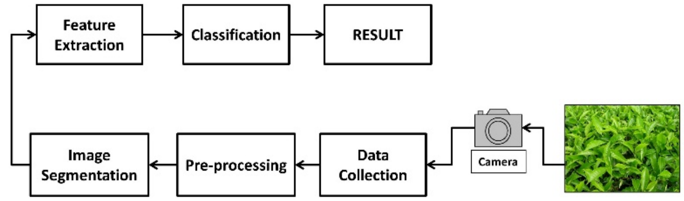

Figure 2 Plant Infections Recognition using DIP

Plant disease detection using Digital Image Processing (DIP) and Machine Learning (ML):

Digital Image Processing (DIP) is a cutting-edge computer technology that revolves around working with images to derive valuable insights. By analysing and processing images, DIP finds utility in diverse domains like visualization, pattern recognition, classification, and segmentation.[27] Digital image processing focuses on using computers to manipulate digital images. The outcomes often involve extracting valuable insights from the images, such as data on features, characteristics, bounding boxes, or masks. These outputs provide valuable facts and aid in understanding the content and context of the images.[28]

Machine learning (ML) algorithms operate through a well-defined process to Attain knowledge from data. For accurate learning and prediction, they depend on abundant, high-quality data. When analyzing image data, DIP techniques are employed, aiding ML algorithms in extracting crucial patterns and information.[29]

The integration of DIP and ML finds its application in diverse fields. Medical Imaging/Visualization, Self-Driving Technology, Image Restoration and sharpening, and Pattern Recognition are among the areas where these combined techniques prove invaluable. They enable advanced analysis, decision-making, and automation in image-based tasks, revolutionizing various industries.[30]

A blend of DIP and ML techniques can identify plant infections and also achieve higher accuracy in the prediction. Figure 2 shows the typical process of plant disease detection using DIP and ML.[31] The following is the introduction to the fundamental stages of plant disease detection using DIP and ML:

Data collection: Assemble an extensive dataset of images featuring both healthy and diseased plants. This dataset should encompass diverse plant species and a wide range of diseases. To achieve this, utilize an appropriate imaging device, such as a camera or smartphone, to capture the images effectively.[32]

Pre-processing: Pre-process the gathered images to elevate their quality, eliminate noise, and optimize the image processing algorithm's efficacy. Standard pre-processing techniques entail resizing, cropping, normalization, filtering, and image enhancement. Additionally, this step involves clipping the selected region of images and applying image smoothing techniques.[33]

Image segmentation: Conduct image segmentation to distinctively separate the plant region from the backdrop. This crucial step aids in isolating the plant and directing the analysis toward the pertinent areas. Employ well-known clustering-based segmentation algorithms like k-means, and enhanced versions such as K-means++, Kernelized K-means, and Fuzzy K-means (FCM) to achieve accurate results.[34]

K-means: - is a renowned clustering method frequently employed for dividing an image into separate segments based on pixel resemblances. K-means is a straightforward algorithm that aims to minimize the within-cluster sum of squared distances. The steps involved are Pre-processing the image, Converting the image to feature vectors, Defining the number of clusters, Initialising the cluster centres, Assigning pixels to clusters, Updating cluster centres, and Generating the segmented image.[35]

Fuzzy C-means (FCM):- is a popular technique for segmenting an image into distinct regions by examining pixel similarities and dividing it accordingly. FCM extends the traditional K-means clustering algorithm by introducing a fuzzy membership function, enabling each pixel to be associated with multiple clusters, having varying degrees of membership. The steps involved are Pre-processing the image, Defining the FCM parameters, Initialising the cluster centres, Calculating membership values, Updating cluster centres, and Generating the segmented image.[35]

Feature extraction: Obtain pertinent features from the segmented plant regions, incorporating colour-based attributes, texture attributes, shape attributes, and other pertinent characteristics. These captured attributes provide measurable indications of the plant's health condition.[36] Several methods of feature extraction can be employed to develop the system, like grey-level co-occurrence matrix (GLCM), colour co-occurrence method, spatial grey-level dependence matrix, and histogram-based feature extraction. The GLCM method is specifically a statistical approach employed for texture classification.[37] Using GLCM texture features like Contrast, Dissimilarity, Homogeneity, Energy and Correlation can be extracted.[38] Two types of features, colour texture, and space features, were extracted, a total of 17 in number. Comprising 13 colour features and 4 shape features, the shape features, including area, perimeter, circularity, and complexity, were derived from the binary segmentation images.[39] Simultaneously, colour and texture characteristics were derived from the picture obtained through colour segmentation. The image examination method utilized for this process is the Colour Co-occurrence Matrix (CCM).[40]

Classification: Using the extracted features, a correlation plot can be generated to classify plant diseases. The classification is performed using a Random Forest classifier, Random forest combines multiple decision trees trained on different subsets of the dataset.[41] This helps reduce overfitting and enhances classifier accuracy, achieving 93% accuracy. Another option is to employ a Support Vector Machine (SVM) classifier for plant disease classification. This involves training the model on labelled data containing images of robust and ailing plants, yielding an impressive 96% accuracy.[42] Table 3 shows the comparison between different methods of DIP and ML.

Research Gap: image-based disease classification might not be suitable for all scenarios, due to seasonal factors, the colour and gesture of plants and leaves may vary. Biological and Molecular factors are crucial for a final conclusion which is not possible with the combination of DIP and ML. So along with DIP if biological sensors are used, then disease prediction accuracy can be improved.[43,44]

Plant disease detection using Deep Learning (DL) Techniques:

Plant disease detection using DL has received considerable focus in the current era as a promising approach for early and accurate diagnosis of plant diseases.[45] Deep learning, a subfield of machine learning, makes use of Neural Networks (NNs) with deep architectures to extract complex features, enabling it to learn patterns and make predictions.[46] Figure 3 shows a Multi-layered architecture of neural networks.

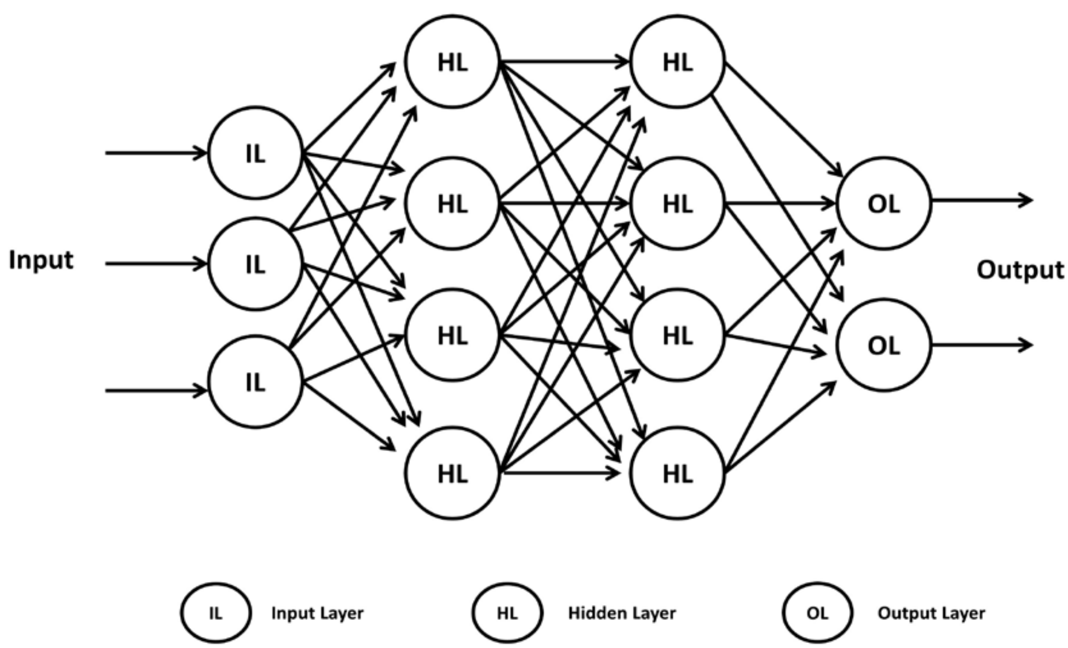

Figure 3 Multi Layered Architecture of Neural Network

Table 3 Comparison of Methods for Leaf Disease Identification using DIP and ML

Reference	Data Collection	Applied Technique	Crop	Accuracy	Future Perspective
Vijai Singh et al., 2017 [35]	Data is acquired by using a digital camera to capture images of leaf samples.	Image Segmentation and SVM	Banana Lemon and Rose	95.71%	To enhance accuracy, alternative methods such as Artificial Neural Networks, Bayes classifiers, Fuzzy Logic, and hybrid algorithms can be considered for utilization.
Manjunatha Badiger et al., 2022 [42]	The input for this model is an image, which can be obtained from a physical camera, an existing folder with sample images, or from an online image library accessible in the cloud.	K-means and SVM	Tomato	96%	The model could be enhanced to support a real-time video access system, allowing for continuous monitoring and care of plants without the need to upload images from various sources.
Hu YH et al,201 [44] 6	The data was acquired by a hyperspectral imaging system capable of capturing spectral information over a wavelength range spanning from 374 to 1,018 nanometres (nm).	Hyperspectral Imaging	Potato	94.87%	Creating advanced ML and DL models can significantly enhance disease identification accuracy by analysing hyperspectral data in real-time, allowing for prompt disease management recommendations.
Seyed Mohamad Javidan et al., 2023 [43]	Images of grape leaves, encompassing both healthy and diseased specimens, are obtained using an intelligent machine vision system. These images are acquired in real field conditions, where the leaves naturally thrive.	K-means clustering and SVM	Grape	97.68%	Exploring the utilization of transfer learning involves fine-tuning pre-trained models specifically for targeted diseases or crops.

The processes involved in plant disease detection using DL are:

Data Collection: The initial stage is to gather a large dataset of plant images that includes both healthy and diseased plants. These images can be gathered from multiple avenues like field surveys, digital plant pathology databases, or by taking pictures in controlled environments.[47]

Data Pre-processing: The collected images need to be pre-processed to assure their appropriateness for deep learning. This pre-processing step may include resizing images, normalizing pixel values, and augmenting the dataset by applying transformations such as rotations, flips, and blurring to increase its diversity.[48]

Model Training: Deep learning models, such as convolutional neural networks (CNNs), are extensively applied to detect plant disease. CNNs are particularly effective at extracting spatial features from images. The training process involves feeding the pre-processed images into the network by tagging them with their relevant labels (healthy or diseased). The model learns to associate particular image features with disease classes through an iterative optimization process.[49]

Model Evaluation: After training, the model's performance needs to be evaluated using a separate test dataset. The trained model predicts disease classes for unseen images, and the predictions are compared with the legitimate labels to calculate various evaluation metrics like accuracy, recall, precision and F1 score.[50]

Deployment and Application: Once the model has demonstrated satisfactory performance, it is feasible to deploy for real-world applications. This may involve developing a user-friendly interface where users can upload plant images and receive predictions about the existence or non-existence of diseases. The model can aid farmers, agronomists, or researchers in recognising plant diseases early, allowing timely intervention and preventing widespread crop damage.[51]

Table 3 Challenges of Deep Learning Methods

Challenges	Solutions
Data Requirements: DL models often require a large scale of labelled data for training, which can be expensive and time-consuming to collect.	Use pre-trained models on huge datasets and fine-tune them for specific tasks with smaller datasets. Combine a small amount of labelled data with a huge pool of unlabelled data to improve model performance.
Overfitting: DL models are prone to overfitting, especially when the model is complex and the dataset is small.	Monitor the model's performance on a validation set and stop training when performance starts to degrade. Apply techniques like dropout, and L1/L2 regularization to prevent overfitting.
Data Bias: DL models can inherit biases present in training data, leading to unfair or discriminatory outcomes.	Use techniques to identify and mitigate biases in data and model predictions. Ensure that training data is diverse and representative of the target population.
Interpretability: Deep learning models are often considered "black boxes," making it challenging to understand their decision-making process.	Develop and use Explainable AI (XAI) techniques to provide insights into model predictions.

Table 4 states the challenges of DL.[52]Addressing these challenges often involves a combination of techniques and a thorough understanding of the specific problem and dataset.[53] The choice of approach will depend on the nature of your deep learning task and the resources available for data collection and model development

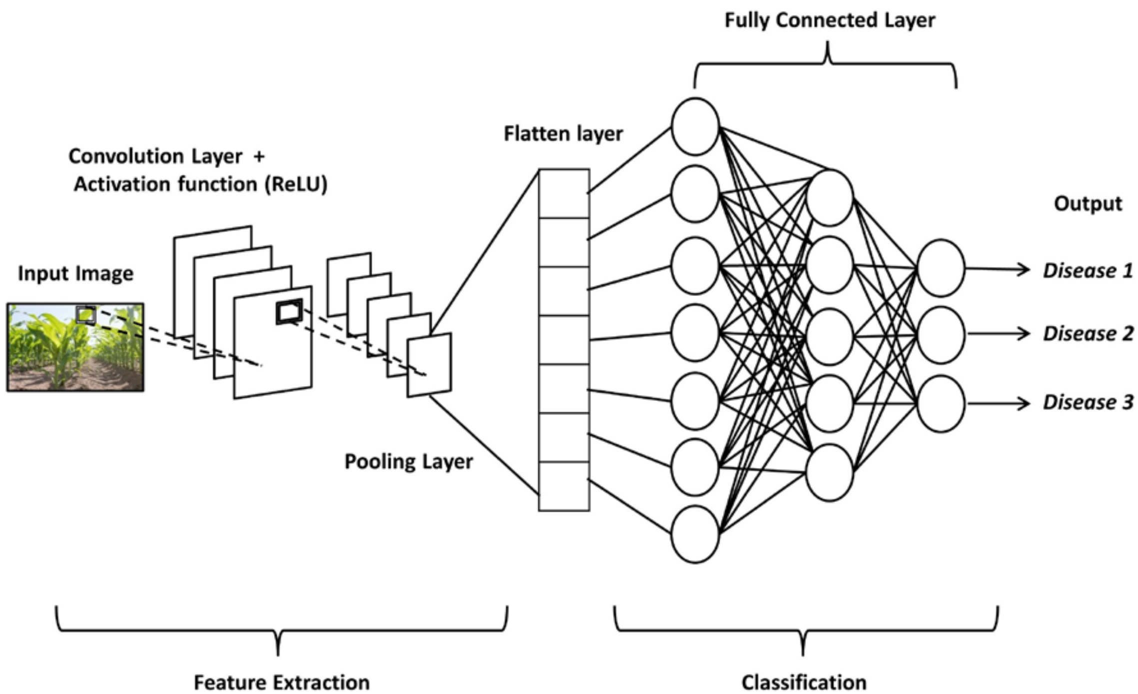

Figure 4 Architecture Diagram of CNN

Numerous DL techniques can be utilized for the detection of plant disease. In this study, it is concentrated on CNNs, Transfer Learning and Recurrent Neural Networks (RNNs).

Convolutional Neural Networks (CNNs) for plant disease detection:

CNNs are extensively employed for image-related tasks, including the identification of plant diseases. CNNs are effective at learning and extracting hierarchical features from images, enabling them to capture intricate patterns that indicate plant diseases.[54] The CNNs comprise four layers: input image, convolutional layer, pooling layer, fully connected layers, and output.[55] Figure 4 represents the architecture diagram of CNN.

Layers of Convolutional Neural Networks are as follows:

Input Layer: This layer receives an image or data as input and forwards this information to the successive layers.[56]

Convolutional layers: In a neural network, the outputs gained by applying kernels (filters) to the previous layer's data are stored. These convolutional layers contain two aspects: one is weights and the second is biases, which are required to be learned during the period of training. This process captures local patterns and features present in the input. To achieve this, a series of mathematical operations are performed within the convolutional layer.[57] These operations are intended to extract the feature map of the input image. The objective is to optimize the network by generating kernels that accurately depict the data without any error. In the following example, an image of 5*5 serves as the input and the filter used is 3*3. Finally, 5*5 images will be reduced to 3*3 by the convolution layer. From the right top corner, the filter is multiplied with the original values of an input image, and later they will be added together to generate a single value among 3*3 resulting output. Then the filter will move sequentially across the remaining portions of an image.[58] Figure 5 displays the filter operations in the convolution layer.

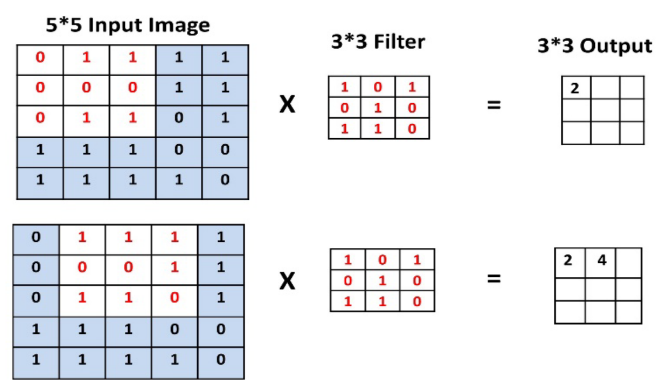

Figure 5 Filter Operations in Convolution Layer

Activation Layer: The activation layer, popularly known as the activation function, plays a very important role in CNNs. It introduces non-linearities into the network, allowing CNNs to learn and represent complex patterns and relationships in the input data.[59] The activation function computes the aggregated sum of inputs from the previous layer and applies a non-linear transformation to produce the output. The resulting output is then forwarded to the successive layers of the network. Rectified Linear Unit (ReLU) is a widely used activation function, due to its simplicity and effectiveness. It converts all negative values into zeros and keeps the positive values unchanged, effectively introducing non-linearity.[60]

Pooling Layer (PL): The main task of this layer is to down-sample the feature maps produced by convolutional operations. This down-sampling process reduces the size of the feature maps while preserving crucial information or features.[61] Similar to the convolutional operation, the PL is defined by the stride and kernel size. Various types of pooling methods are available, including tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max pooling. The frequently employed pooling methods include GAP pooling, min pooling, and max pooling. [62]

However, the PL can sometimes decrease the overall efficiency of the CNNs. Its main drawback is that it helps the CNNs identify whether a particular feature is present in the input image, but it focuses solely on determining the location of that feature. As a result, the CNNs may miss relevant information. Figure 6 demonstrates an instance of the pooling operation. The filter used here is 2*2 Maximum Pooling.

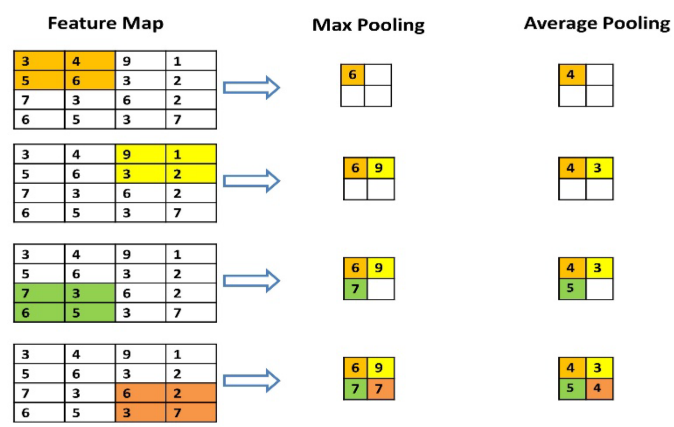

Figure 6 Pooling Operation

Fully Connected Layer (FC Layer): A fully connected layer, alternatively referred to as a dense layer, is commonly used in CNNs for applications such as semantic segmentation, image classification, and object detection. Unlike convolutional layers, which operate locally, FC layers establish links between all neurons from the previous layer to the current layer, forming a fully connected network.[63] After convolutional and pooling layers in CNNs, the output is flattened or reshaped into a vector before entering the FC layers. The FC layers capture high-level features and make predictions.[64] To improve generalization and reduce overfitting, the dropout layer is enabled in these layers.

It randomly drops out neurons during training. Softmax Classifier and Sigmoid Classifier are the commonly used classifiers in the FC layer in a neural network. Sigmoid activation is frequently utilized in binary classification tasks, where the goal is to categorize input data into one of two classes. Softmax is often used for multi-class classification tasks; it transforms the output values of the neurons into a probability distribution over multiple classes.[65]

Output Layer: The output layer produces the final predictions or outputs of the network, depending on the particular task. For example, in image classification, in a CNN, the output layer is composed of neurons representing various classes, and class with the greatest activation value is regarded as the predicted class for the input image.[66]

DEEP TRANSFER LEARNING FOR PLANT DISEASE DETECTION:

Transfer learning (TL) simplifies the process of solving a new problem by using knowledge gained from a pre-trained model on a different task.[67] For instance, a model trained to identify helmets in images can also be used for the recognition of bikes by applying the knowledge learned during its training.[68] Figure 7 shows the working of Transfer Learning.

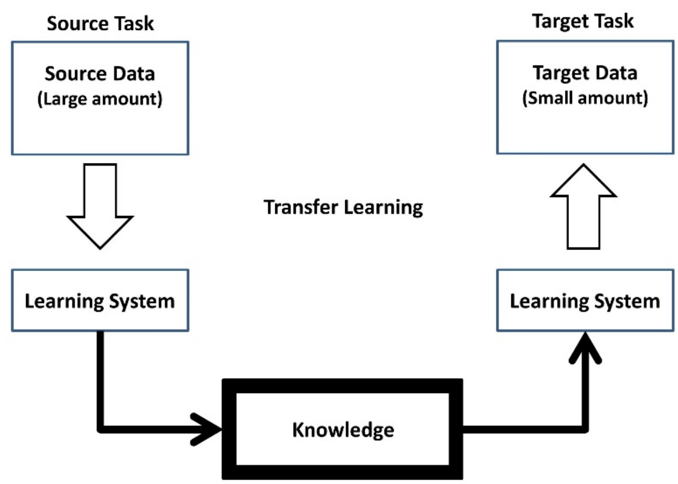

Figure 7 Transfer Learning

The main aim of deep TL is to enhance performance on the new task by transferring the learned weights from one network (task A) to another (task B). This way, the model starts with patterns learned from a related task with abundant labelled data, avoiding the need to start from scratch.[69] In the context of plant disease detection, TL involves leveraging pre-trained models, such as those trained on ImageNet, and adapting them to detect plant diseases. The pre-trained model's convolutional layers can serve as feature extractors and specific layers for plant disease detection can be added and trained, leading to improved performance even with limited plant disease datasets.[70] Figure 8 shows the Pre-trained Deep TL Model for Feature Extraction.

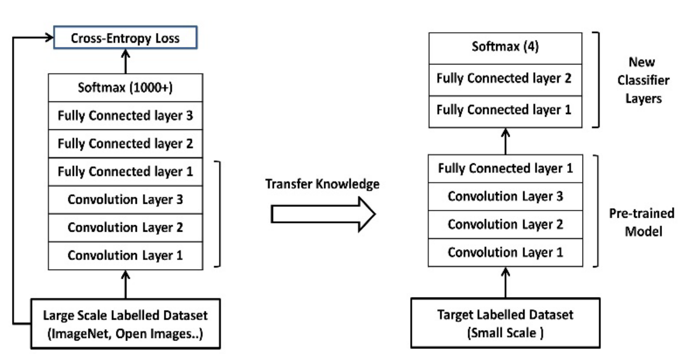

Figure 8 Pre-trained Deep TL Model for Feature Extraction

Deep learning systems are structured with multiple layers that extract features, refining them as we dive deeper into the neural network. To speed up training, Deep Transfer Learning is employed. This technique utilizes pre-trained models, trained on extensive datasets to recognize patterns or objects. By integrating these pre-trained models into the initial layers of a multi-layered CNN, the need to train from scratch is greatly reduced. Pre-trained models are highly effective as they possess knowledge of various patterns and objects.[71]

Incorporating them in the early layers of the target model, the training process for pattern detection can be bypassed.[72] During this process, the pre-trained model layers are frozen, preventing their weights from being updated. Instead, they are fine-tuned using new and enriched datasets, adapting to the specific task. The final target model is created by discarding the final classification layers of the pre-trained model and replacing them with a new classifier.[73] The new classifier has undergone training on a limited yet high-quality dataset, further enhancing its ability to identify specific patterns or objects relevant to the task. In summary, Deep Transfer Learning optimizes the training effort by leveraging pre-trained models and fine-tuning them with focused data, resulting in more efficient and accurate deep learning systems.[74] The main aim of using a loss function (*Cross-Entropy Loss*) in machine learning, particularly in supervised learning tasks, is to quantify the disparity between the model's predictions and the true ground-truth labels (discrepancy between the predictions and the true labels). The loss function serves as a measure of how well the model is performing on the given task.[75]

Steps involved in Deep Transfer Learning:

Obtain the Pre-trained Model: To start, the initial step is to carefully choose a pre-trained model that aligns with our training objective and the specific task we want to accomplish. When employing transfer learning, it is vital to ensure a strong relationship between the pre-existing knowledge of the selected model and the target task domain. This compatibility between the source model and the desired task domain is vital for the success of the transfer learning process. Some examples of commonly used pre-trained models are VGG-16, VGG-19, and Inception V3.[76]

Create a Base Model: In the initial step, we carefully select a base model that is best suited for our task requirements, considering options like VGG-16, VGG-19, Inception V3, ResNet, or Xception. If the base model has more or fewer neurons in the final output layer than required for our specific use case, we can easily modify the output layer by either removing or adding neurons as needed.[77]

Freeze Layers: It is essential to freeze the initial layers of the pre-trained model to avoid relearning basic features. If these layers are not frozen, the model would lose its existing knowledge, necessitating a restart of the training process from scratch. This would be time-consuming, resource-intensive, and counterproductive.[78]

Add New Trainable Layers: When using a base model, we only reuse its feature extraction layers. To address specific tasks, we add extra layers on top, typically as the final output layers, enabling our model to make predictions tailored to our objectives.[79]

Train the new layers on the Dataset: Pre-trained models are trained on large datasets, covering various classifications. However, our target model is designed for a particular task, requiring a specific pattern or object recognition. After freezing the pre-trained model, we train the new classifier layers using an enhanced and limited dataset.[80]

Fine-Tuning: Fine-tuning involves two steps: first, unfreezing certain sections of the base model, and then retraining the entire model on the complete dataset with a minor learning rate. This approach enhances the model's performance on the new dataset while avoiding overfitting.[81] Table 5 summarises the various research results.[82]

Table 4 Summary of Various Researches works

Ref	Dataset	Model	Accuracy
100	Potato leaf from PlantVillage dataset	VGG-19 + Logistic Regression	97.8%
101	PlantVillage	ResNet-50 and SVM	98%
102	PlantVillage	VGG-19	98.3%
82	PlantVillage	CAE and CNN	98.38%
103	Banana leaf images from banana field	ResNet-152	99.2%
104	PlantVillage	GoogLeNet	99.3%
105	PlantVillage	VGGNet	99.5%

Recurrent Neural Network (RNN) for plant disease detection:

RNN is a specialized form of ANN that leverages sequential data or time series information. At each step, an RNN takes an input vector and combines it with the previous hidden state, producing an output and updating its internal hidden state. This hidden state serves as the memory of the network and influences the computation at subsequent steps. A common set of weights is utilized consistently across all time steps, allowing the network to process input sequences of varying lengths.[83]

“RNNs have found extensive application in diverse fields, such as natural language processing (NLP), speech recognition, machine translation, sentiment analysis, and numerous other domains”.[84] RNNs can be employed for the identification of plant diseases by analysing sequential data, such as time-series measurements or sequences of images, related to plant health.[85]

CNN models typically don't exclusively concentrate on the visible portions impacted by a plant disease for classification. Sometimes, they might consider unrelated backgrounds or unaffected plant parts. CNNs are a feed-forward network which concentrates on the current input state and these states remain devoid of loops within the hidden layers. CNNs don’t have any memory to store the previous input state so it is unable to handle the sequential data. Recurrent Neural Networks (RNNs) technique enables automatic identification of infected regions and extraction of pertinent features, which aids in disease classification.[86] An RNN is a neural network type that employs connections between nodes to establish a directed graph along a sequence of variables, such as a temporal sequence. These recurrent connections allow for capturing the relationship between the current state of a variable and its previous states. RNNs have captured substantial interest for their adeptness in managing sequential data in tasks like language translation and action recognition.[87] Figure 9 states the unfolded hidden layers of RNN.

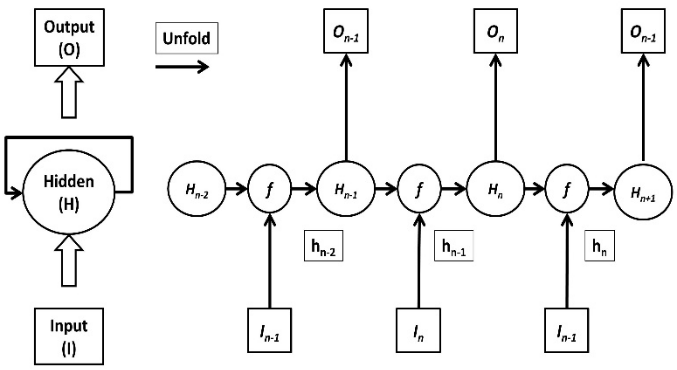

Figure 9 RNNs Unfolded Hidden Layers

Improved RNN models, including LSTMs and GRUs, have overcome issues like vanishing gradients and can effectively train on long sequences. GRU can efficiently model dependencies between different images of plant observations and LSTM can be utilised to capture discriminating regions of images for fine-grained classification. Several recent publications have showcased the effectiveness of RNN approaches in processing variable-length data of fixed sizes, such as images.[88] RNN possesses a memory mechanism for retaining the previous hidden state, which serves as the basis for generating the subsequent hidden state in the subsequent time step.[89] The same activation function can be utilized a repeated number of times in the hidden layer to generate the current hidden state so it is called Recurrent. At the initial input time step, the hidden state of the previous state is initialized to zero. i.e. H_{n-1}.

In the first time step, H_n, the hidden state of the previous time step (Hn-1) and the current input time step (In) will be the input for activation function f.

The Activation function is responsible for computing the current hidden state at time step t.[90]

$$h_n = f\,(h_{n-1}, I_n)$$

where h_n is the hidden state for time step n, f is the activation function with two parameters, h_{n-1} is the hidden state from the previous time step $n-1$, and I_n is the current input for time step n.

The activation function (f) is *tanh*

$$h_n = \tanh\,(W_{n-1} \cdot h_{n-1} + W_n I_n)$$

W_{n-1} – Weight in the previous hidden state,

W_n – Weight in the current time-step.

The output state O_n is computed at each time step through the utilization of the following process:

$$O_n = W_{no} \cdot h_n$$

W_{no} – Weight at the output state

Attention operates as a formidable mechanism that, when fused with an RNN, enhances its performance. This integration allows the network to focus selectively on specific input regions, enabling the prioritization of relevant information for improved learning and higher-quality output. By combining RNNs with an attention mechanism, specifically Gated Recurrent Units (GRUs), salient characteristics of plant diseases are dynamically emphasized, strengthening the model's ability to learn disease characteristics for accurate identification.[91]

The approach aims to harness the strengths of CNNs for visual feature extraction and RNNs with attention mechanisms to effectively analyze and classify plant diseases. Leveraging local CNN features and the attention mechanism facilitates a comprehensive understanding of the image, resulting in enhanced disease classification accuracy.

In this method, a CNN is trained to recognize plant diseases and extract visual features from plant images. These features create a smaller image of activations with channels corresponding to the number of filters used. Subsequently, to capture local activations in different sections of the image, the smaller image is partitioned into sub-sections. The extracted local features are subsequently employed to form a sequence, which is fed into an RNN with GRUs. The RNN's attention mechanism identifies crucial parts of the features, and by extending the pixel neighbourhood in each sub-part, the model maximizes information across multiple sub-parts, improving its overall performance.[92]

Throughout the process, the model is optimized to minimize prediction errors, leading to better disease identification outcomes. Figure 10 shows the combination of attention mechanisms with CNN-RNN hybrid models offers a promising approach for precise plant disease analysis and holds practical applications in agriculture and plant disease management.[93]

It's very important to consider that the choice of DL technique relies on the specific requirements of the plant disease identification task, available datasets, computational resources, and other constraints.[94] Experimentation and fine-tuning are often necessary to identify a very effective approach for a given scenario. Overall, the remarkable potential of DL is evident in its ability to automate plant disease detection effectively and enable timely interventions to prevent crop losses.[95] Table 6 states the comparison between CNN, TL and RNN.

Table 5 Operational Comparison of CNN, TL and RNN

Aspects	CNN	Transfer Learning	RNN
Architecture	Specialized for image data	Pre-trained models	Sequential data processing
Data Requirements	Large labelled datasets	Smaller labelled datasets	Sequential labelled data
Training Speed	Computationally intensive	Faster fine-tuning	Slower convergence
Feature Extraction	Hierarchical features	Features from pre-trained	Temporal dependencies
Efficiency in Image Processing	More efficient with large dataset	More efficient with less dataset	Not an efficient choice
Efficiency in Sequential Data Processing	Not an efficient choice	Highly efficient when pre-trained models are available	Highly efficient , Explicitly for sequential data processing
Applications in Plant Disease Detection	Image-based symptom recognition	Fine-tuning pre-trained models	Sequence-based disease progression

Compared to CNNs, Transfer learning is suitable for plant disease detection because it leverages pre-trained CNNs to extract relevant image features, significantly reducing the necessary of extensive labelled data, while improved RNNs like LSTM and GRU are apt for modelling temporal dependencies and capturing disease progression patterns, making them effective in monitoring plant health over time, thereby combining the strengths of both approaches to enhance the accuracy of plant disease detection systems.

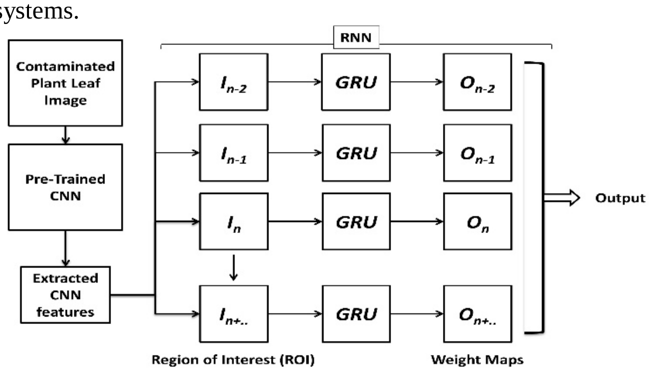

Figure 10 CNN-RNN Hybrid Models for Plant Leaf Disease Detection

Result of Survey

In comparison to traditional methods such as visual observation and costly laboratory tests, the utilization of novel approaches like IoT-based models, machine learning algorithms, and DL methods demonstrates enhanced efficiency in the early detection of plant diseases at various stages.

Table 6 Research Findings

Research Questions	Status
Enhancing early detection and management of plant diseases - Novel approaches and technologies vs. traditional methods	Addressed
Dynamics and mechanisms of the soil-borne pathogen population - Changes over time and impact on plant health	Not Addressed

This study found a missing area in current research on plant disease detection. Most of the focus has been on spotting disease symptoms on leaves and fruits while ignoring diseases that come from the soil. Detecting diseases early is crucial for farmers to effectively manage them. To bridge this gap, the authors suggest a solution called the "Hybrid Model of IoT and DL for Early Plant Disease Detection". This approach combines IoT technology with DL techniques. It involves using sensors in the fields to continuously monitor soil conditions that can lead to disease-causing pathogens.[96,97,99] At the same time, a Deep Learning system (utilising both RNN and Pre-Trained CNN model) examines sensor data, and images of leaves and fruits to identify initial signs of diseases.

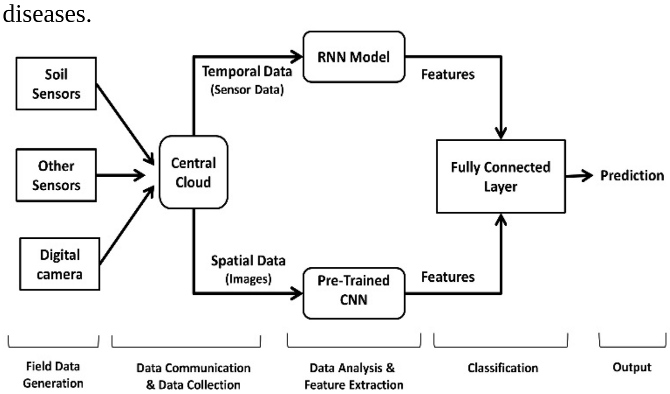

Figure 11 Simulated Hybrid Architecture aims to Bridge the Research Gap

This combined approach aims to provide a comprehensive way of detecting plant diseases early.[98] This integrated approach offers better disease management and support for farmers, enabling proactive measures to combat plant diseases and enhance crop productivity. Figure 11 shows the simulated hybrid architecture aims to bridge the research gap.

Conclusion

In agriculture, where people rely on successful crops for their livelihoods, plant diseases pose a persistent threat to food security and economic stability. Despite advancements in farming and technology, these diseases harm crop yields, and fruit quality, and even lead to plant death. This review focuses on efficient methods for early plant disease detection, revealing a gap in research that mainly looks at diseases in leaves and fruits, ignoring soil issues. To address this gap, we introduce the "Hybrid Model of IoT and

DL for Early Plant Disease Detection," combining Internet of Things (IoT) sensors and Deep Learning (DL) techniques. IoT sensors monitor the environment and soil, identifying disease risks, while a sophisticated DL system with Recurrent Neural Networks (RNN) and Pre-Trained CNN analyzes sensor data and images to spot disease signs. This innovative approach empowers farmers with early warnings, aiding precise disease management, reducing pesticide use, and enhancing food security. Challenges like data collection, IoT integration, and model adaptation require collaboration among experts. In essence, this review promotes more resilient and sustainable agriculture, expanding disease detection methods and promoting a holistic approach for a brighter future in farming.

Acknowledgement

We express our heartfelt gratitude to the farmers and agricultural experts who generously shared their knowledge and experiences, shaping our research.

Conflict of Interest

The authors would like to affirm that there are no known conflicts of interest associated with this publication, and there has been no substantial financial or non-financial support for this research that could have potentially influenced its outcomes.

References

1. R. Baghel, P. Sharma. Evaluating agricultural activity dynamics over the Uttar Pradesh state of India using satellite-based datasets. *Trop Ecol* **2023**, 1–14.
2. T.N. Liliane, M.S. Charles. Factors Affecting Yield of Crops.
3. B. Wang. Identification of Crop Diseases and Insect Pests Based on Deep Learning. **2022**.
4. T. Wang, H. Xu, Y. Hai, Y. Cui, Z. Chen. An Improved Crop Disease Identification Method Based on Lightweight Convolutional Neural Network. *Journal of Electrical and Computer Engineering* **2022**, 2022.
5. A. Nair, G. J, M. James, S.M. Shibu, S. H. Smart Farming and Plant Disease Detection using IoT and ML. *International Journal of Engineering Research & Technology* **2021**, 9 (13).
6. V. Bhatnagar, R. Chandra. IoT-Based Soil Health Monitoring and Recommendation System. **2020**, 1–21.
7. T.A. Shaikh, W.A. Mir, T. Rasool, S. Sofi. Machine Learning for Smart Agriculture and Precision Farming: Towards Making the Fields Talk. *Archives of Computational Methods in Engineering* **2022**, 29 (7), 4557–4597.
8. V. Goswami. Soil Health Monitoring System. *Int J Res Appl Sci Eng Technol* **2020**, 8 (5), 1536–1540.
9. A.E. Franț. Forensic challenges regarding the Internet of Things. *SHS Web of Conferences* **2023**, 177, 03002.
10. J.G.A. Barbedo. A review on the main challenges in automatic plant disease identification based on visible range images. *Biosyst Eng* **2016**, 144, 52–60.
11. H.M. Abdullah, N.T. Mohana, B.M. Khan, et al. Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. *RSASE* **2023**, 32, 100996.
12. Y. Liu, Y. Song, R. Ye, et al. High-Precision Tomato Disease Detection Using NanoSegmenter Based on Transformer and Lightweighting. *Plants 2023, Vol. 12, Page 2559* **2023**, 12 (13), 2559.
13. N. Zhang, G. Yang, Y. Pan, et al. A Review of Advanced Technologies and Development for Hyperspectral-Based Plant Disease Detection in the Past Three Decades. *Remote Sensing 2020, Vol. 12, Page 3188* **2020**, 12 (19), 3188.
14. A. Salman. Internet of Things (IoT) and its Applications: A Survey. *Int J Comput Appl* **2020**, 175 (21), 22–27.
15. C.H. Bock, J.G.A. Barbedo, E.M. Del Ponte, D. Bohnenkamp, A.-K. Mahlein. From visual estimates to fully automated sensor-based measurements of plant disease severity: status and challenges for improving accuracy. *Phytopathology Research 2020 2:1* **2020**, 2 (1), 1–30.
16. F. Pan, B. Zhang, X. Zhao, et al. A Lightweight, Secure Authentication Model for the Smart Agricultural Internet of Things. *Agronomy 2023, Vol. 13, Page 2257* **2023**, 13 (9), 2257.
17. W.S. Kim, W.S. Lee, Y.J. Kim. A Review of the Applications of the Internet of Things (IoT) for Agricultural Automation. *Journal of Biosystems Engineering* **2020**, 45 (4), 385–400.
18. S. Kumar, P. Tiwari, M. Zymbler. Internet of Things is a revolutionary approach for future technology enhancement: a review. *J Big Data* **2019**, 6 (1), 1–21.
19. P. Sarma, A. ul Islam, T. Bayan. IoT-Based Agriculture Environment and Security Monitoring System. *Periódico Tchê Química* **2023**, 20 (44), 15–31.
20. A. Kumar, S. Jain. Upscaling Living Standards with Internet Of Things. *International Journal of Engineering Applied Sciences and Technology* **2023**, 8, 2.
21. S.S. Shanto, M. Rahman, J.Md. Oasik, H. Hossain. Smart Greenhouse Monitoring System Using Blynk IoT App. *Journal of Engineering Research and Reports* **2023**, 25 (2), 94–107.
22. S. Islam, S. Jamwal, M.H. Mir, Q.R. Khan. IoT-Smart Agriculture: Comparative Study on Farming Applications and Disease Prediction of Apple Crop using Machine Learning. *Iraqi Journal of Science* **2022**, 63 (12), 5520–5533.
23. S. Sankaran, A. Mishra, R. Ehsani, C. Davis. A review of advanced techniques for detecting plant diseases. *Comput Electron Agric* **2010**, 72 (1), 1–13.
24. M.A. Nawaz, T. Khan, R.M. Rasool, et al. Plant Disease Detection using Internet of Thing (IoT). *International Journal of Advanced Computer Science and Applications* **2020**, 11 (1), 505–509.
25. R. Yakkundimath, G. Saunshi, V. Kamatar. Plant Disease Detection using IoT; **2018**.
26. G.H.; F.; Mirza, W.; Zakai, Y.; John, et al. Novel IoT-Based Plant Monitoring System. *Engineering Proceedings 2023, Vol. 32, Page 12* **2023**, 32 (1), 12.
27. C. Luo, Y. Hao, Z. Tong. Research on Digital Image Processing Technology and Its Application. **2018**, 587–592.
28. H. Mayatopani, N. Handayani, R.S. Septarini, R. Nuraini, N. Heriyani. Implementation of Self-Organizing Map (SOM) Algorithm for Image Classification of Medicinal Weeds. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)* **2023**, 7 (3), 437–444.
29. I.H. Sarker. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Comput Sci* **2021**, 2 (3), 1–21.
30. R. Egipto, A. Aquino, J.M. Costa, J.M. Andújar. Predicting Crop Evapotranspiration under Non-Standard Conditions Using Machine Learning Algorithms, a Case Study for Vitis vinifera L. cv Tempranillo. *Agronomy* **2023**, 13 (10), 2463.
31. L. Mohammed, Y. Yusoff. Detection And Classification Of Plant Leaf Diseases Using Digital Image Processing Methods: A Review. *Asean Engineering Journal* **2023**, 13 (1), 1–9.
32. Meyyappan, Senthilkumar, Chandramouleeswaran, et al. Plant Infection Detection Using Image Processing. International Journal of Modern Engineering Research 2018, 8. 2249-6645.
33. G.N. Rani, R. Divya Darshini, S.P. Monirhithikka, et al. Image-Based Plant Disease Classification with Cause and Severity Analysis and Remedial Action. *Proceedings of the 2023 International Conference on Intelligent Systems for Communication, IoT and Security, ICISCoIS 2023* **2023**, 550–555.
34. Sahebgouda, M. Sumana. Disease Detection In Pomegranate Plant Using Image Processing Techniques. **2023**, 1–6.
35. V. Singh, A.K. Misra. Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture* **2017**, 4 (1), 41–49.

36. P. Malarvizhi, R. Dayana, D. Srivathsan, S.R. Keerthi Varman, V. Shashank. Integrated Smart Farming Technique Using IOT and AI-ML. *International Interdisciplinary Humanitarian Conference for Sustainability, IIHC 2022 - Proceedings* **2022**, 1444–1446.
37. V Suresh, Mohana Krishnan, M Hemavarthini, K Jayanthan, D Gopinath. Plant Disease Detection using Image Processing. *International Journal of Engineering Research and* **2020**, V9 (03).
38. S.D. Khirade, A.B. Patil. Plant disease detection using image processing. *Proceedings - 1st International Conference on Computing, Communication, Control and Automation, ICCUBEA 2015* **2015**, 768–771.
39. M.G. Lanjewar, J.S. Parab. CNN and transfer learning methods with augmentation for citrus leaf disease detection using PaaS cloud on mobile. *Multimed Tools Appl* **2023**.
40. Md. Nahiduzzaman, M.E.H. Chowdhury, A. Salam, et al. Explainable deep learning model for automatic mulberry leaf disease classification. *Front Plant Sci* **2023**, 14, 1175515.
41. M. Li, Y. Liao, Z. Lu, M. Sun, H. Lai. Non-destructive monitoring method for leaf area of Brassica napus based on image processing and deep learning. *Front Plant Sci* **2023**, 14, 1163700.
42. M. Badiger, V. Kumara, S.C.N. Shetty, S. Poojary. Leaf and skin disease detection using image processing. *Global Transitions Proceedings* **2022**, 3 (1), 272–278.
43. S.M. Javidan, A. Banakar, K.A. Vakilian, Y. Ampatzidis. Diagnosis of Grape Leaf Diseases Using Automatic K-Means Clustering and Machine Learning. *SSRN Electronic Journal* **2022**.
44. Y.H. Hu, X.W. Ping, M.Z. Xu, W.X. Shan, Y. He. Detection of late blight disease on potato leaves using hyperspectral imaging technique. *Guang Pu Xue Yu Guang Pu Fen Xi/Spectroscopy and Spectral Analysis* **2016**, 36 (2), 515–519.
45. D. Abdelhafiz, C. Yang, R. Ammar, S. Nabavi. Deep convolutional neural networks for mammography: Advances, challenges and applications. *BMC Bioinformatics* **2019**, 20 (11), 1–20.
46. L. Alzubaidi, J. Zhang, A.J. Humaidi, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data 2021 8:1* **2021**, 8 (1), 1–74.
47. I.H. Sarker. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. *SN Comput Sci* **2021**, 2 (6), 1–20.
48. A. V. Panchal, S.C. Patel, K. Bagyalakshmi, et al. Image-based Plant disease detection using Deep Learning. *Mater Today Proc* **2023**, 80, 3500–3506.
49. A. Kounani, N. Lavazos, A. Tsimpiris, D. Varsamis. Sustainable Smart Agriculture: Plant disease detection with deep learning techniques in cotton cultivation. *International Conference on Environmental Science and Technology Proceedings* **2023**, 18.
50. M. Shoaib, B. Shah, S. EI-Sappagh, et al. An advanced deep learning models-based plant disease detection: A review of recent research. *Front Plant Sci* **2023**, 14, 1158933.
51. Y. Kumar, R. Singh, M.R. Moudgil, Kamini. A Systematic Review of Different Categories of Plant Disease Detection Using Deep Learning-Based Approaches. *Archives of Computational Methods in Engineering* **2023**, 1–23.
52. M. Shoaib, B. Shah, S. EI-Sappagh, et al. An advanced deep learning models-based plant disease detection: A review of recent research. *Front Plant Sci* **2023**, 14, 1158933.
53. D. Abdelhafiz, C. Yang, R. Ammar, S. Nabavi. Deep convolutional neural networks for mammography: Advances, challenges and applications. *BMC Bioinformatics* **2019**, 20 (11), 1–20.
54. H. Wang, J. Ding, S. He, et al. MFBP-UNet: A Network for Pear Leaf Disease Segmentation in Natural Agricultural Environments. *Plants 2023, Vol. 12, Page 3209* **2023**, 12 (18), 3209.
55. L. Ale, A. Sheta, L. Li, Y. Wang, N. Zhang. Deep learning-based plant disease detection for smart agriculture. *2019 IEEE Globecom Workshops, GC Wkshps 2019 - Proceedings* **2019**.
56. J. Andrew, J. Eunice, D.E. Popescu, M.K. Chowdary, J. Hemanth. Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications. *Agronomy 2022, Vol. 12, Page 2395* **2022**, 12 (10), 2395.
57. S. Journal, U. Journal. International Journal of Recent Technology and Engineering (IJRTE). **2020**.
58. M.T. M -Ap, / Ece. Plant Leaf Disease Detection using Deep Learning.
59. M.-I. Georgescu, R.T. Ionescu, N.-C. Ristea, N. Sebe. Non-linear Neurons with Human-like Apical Dendrite Activations. *Applied Intelligence* **2020**.
60. S.R. Dubey, S.K. Singh, B.B. Chaudhuri. Activation functions in deep learning: A comprehensive survey and benchmark. *Neurocomputing* **2022**, 503, 92–108.
61. N. Marini, S. Otálora, H. Müller, M. Atzori. Semi-supervised training of deep convolutional neural networks with heterogeneous data and few local annotations: An experiment on prostate histopathology image classification. *Med Image Anal* **2021**, 73, 102165.
62. M. Rana, M. Bhushan. Machine learning and deep learning approach for medical image analysis: diagnosis to detection. *Multimed Tools Appl* **2023**, 82 (17), 1.
63. R. Yamashita, M. Nishio, R.K.G. Do, K. Togashi. Convolutional neural networks: an overview and application in radiology. *Insights Imaging* **2018**, 9 (4), 611–629.
64. M. Aljalal, S.A. Aldosari, K. Alsharabi, A.M. Abdurraqeeb, F.A. Alturki. Parkinson's Disease Detection from Resting-State EEG Signals Using Common Spatial Pattern, Entropy, and Machine Learning Techniques. *Diagnostics* **2022**, 12 (5).
65. A.J. Belay, A.O. Salau, M. Ashagrie, M.B. Haile. Development of a chickpea disease detection and classification model using deep learning. *Inform Med Unlocked* **2022**, 31, 100970.
66. V.G. Dhanya, A. Subeesh, N.L. Kushwaha, et al. Deep learning-based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture* **2022**, 6, 211–229.
67. K. Weiss, T.M. Khoshgoftaar, D.D. Wang. A survey of transfer learning. *J Big Data* **2016**, 3 (1), 1–40.
68. R. Ribani, M. Marengoni. A Survey of Transfer Learning for Convolutional Neural Networks. *Proceedings - 32nd Conference on Graphics, Patterns and Images Tutorials, SIBGRAPI-T 2019* **2019**, 47–57.
69. A. Hosna, E. Merry, J. Gyalmo, et al. Transfer learning: a friendly introduction. *J Big Data* **2022**, 9 (1), 1–19.
70. S.J. Pan, Q. Yang. A survey on transfer learning. *IEEE Trans Knowl Data Eng* **2010**, 22 (10), 1345–1359.
71. J. Ramon, K. Driessens, T. Croonenborghs. Transfer learning in reinforcement learning problems through partial policy recycling. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* **2007**, 4701 LNAI, 699–707.
72. Y. Xu, J. Su, F. Xiang, et al. Deep convolutional neural network transfer learning optimization based on visual interpretation. *2021 IEEE International Conference on Real-Time Computing and Robotics, RCAR 2021* **2021**, 527–532.
73. K. He, X. Zhang, S. Ren, J. Sun. Deep residual learning for image recognition. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* **2016**, 2016-December, 770–778.
74. B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, A. Torralba. Learning Deep Features for Discriminative Localization. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* **2016**, 2016-December, 2921–2929.
75. Q. Wang, Y. Ma, K. Zhao, Y. Tian. A Comprehensive Survey of Loss Functions in Machine Learning. *Annals of Data Science* **2022**, 9 (2), 187–212.
76. What Is Transfer Learning? [Examples & Newbie-Friendly Guide] https://www.v7labs.com/blog/transfer-learning-guide (accessed Sep 30, 2023).
77. R. Khan, G.L. Masala. Detecting Breast Arterial Calcifications in Mammograms with Transfer Learning. *Electronics 2023, Vol. 12, Page 231* **2023**, 12 (1), 231.

78. A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications in Deep Learning | by Dipanjan (DJ) Sarkar | Towards Data Science https://towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a (accessed Oct 1, 2023).
79. M.E. Taylor, P. Stone. Transfer Learning for Reinforcement Learning Domains: A Survey. *Journal of Machine Learning Research* **2009**, 10, 1633–1685.
80. S. Khairy, P. Balaprakash. Multifidelity Reinforcement Learning with Control Variates. **2022**.
81. J. Chen, J. Chen, D. Zhang, Y. Sun, Y.A. Nanehkaran. Using deep transfer learning for image-based plant disease identification. *Comput Electron Agric* **2020**, 173.
82. P. Bedi, P. Gole. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. *Artificial Intelligence in Agriculture* **2021**, 5, 90–101.
83. H.E. David, K. Ramalakshmi, R. Venkatesan, G. Hemalatha. Tomato leaf disease detection using hybrid CNN-RNN model. *Advances in Parallel Computing* **2021**, 38, 593–597.
84. M. Nandhini, K.U. Kala, M. Thangadarshini, S. Madhusudhana Verma. Deep Learning model of sequential image classifier for crop disease detection in plantain tree cultivation. *Comput Electron Agric* **2022**, 197.
85. N. Kakran, P. Singh, K. P. Detection of Disease in Plant Leaf using Image Segmentation. *Int J Comput Appl* **2019**, 178 (35), 29–32.
86. Z.C. Lipton, J. Berkowitz, C. Elkan. A Critical Review of Recurrent Neural Networks for Sequence Learning. **2015**.
87. D. Garg, M. Alam. Integration of Convolutional Neural Networks and Recurrent Neural Networks for Foliar Disease Classification in Apple Trees. *International Journal of Advanced Computer Science and Applications* **2022**, 13 (4), 357–367.
88. Mr V, I. V, N. R, M. B, S. V. Plant Disease Prediction Using Hybrid Model. *International Journal of Engineering Research & Technology* **2023**, 11 (3).
89. A. Das, P.K. Kumawat, N.D. Chaturvedi. A Study to Target Energy Consumption in Wastewater Treatment Plant Using Machine Learning Algorithms. *Computer Aided Chemical Engineering* **2021**, 50, 1511–1516.
90. W. Yin, K. Kann, M. Yu, H. SchützeSch, L. Munich. Comparative Study of CNN and RNN for Natural Language Processing. **2017**.
91. S. Nosouhian, F. Nosouhian, A.K. Khoshouei. A Review of Recurrent Neural Network Architecture for Sequence Learning: Comparison between LSTM and GRU. **2021**.
92. S.H. Lee, H. Goëau, P. Bonnet, A. Joly. Attention-Based Recurrent Neural Network for Plant Disease Classification. *Front Plant Sci* **2020**, 11, 601250.
93. D. Garg, M. Alam. Integration of Convolutional Neural Networks and Recurrent Neural Networks for Foliar Disease Classification in Apple Trees. *International Journal of Advanced Computer Science and Applications* **2022**, 13 (4), 357–367.
94. M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, D. Stefanovic. Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection. *Symmetry 2019, Vol. 11, Page 939* **2019**, 11 (7), 939.
95. J. Liu, X. Wang. Plant diseases and pests detection based on deep learning: a review. *Plant Methods* **2021**, 17 (1), 1–18.
96. K. Dyussembayev, P. Sambasivam, I. Bar, et al. Biosensor Technologies for Early Detection and Quantification of Plant Pathogens. *Front Chem* **2021**, 9, 636245.
97. Z. Yu, R. Fischer. Light sensing and responses in fungi. *Nature Reviews Microbiology 2018 17:1* **2018**, 17 (1), 25–36.
98. A. Daood, E. Ribeiro, M. Bush. Sequential Recognition of Multifocal Image Pollen-Grain Sequences by Combining CNN and RNN.
99. K. Shibani, K.S. Sendhil Kumar, G. Siva Shanmugam. An Effective Approach for Plant Monitoring, Classification and Prediction Using IoT and Machine Learning. *Advances in Intelligent Systems and Computing* **2020**, 1056, 143–154.
100. D. Tiwari, G. Kangri Vishwavidyalaya, M. Ashish, et al. Potato Leaf Diseases Detection Using Deep Learning. *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* **2020**.
101. F. Mohameth, C. Bingcai, K.A. Sada. Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village. *Journal of Computer and Communications* **2020**, 08 (06), 10–22.
102. J. Chen, J. Chen, D. Zhang, Y. Sun, Y.A. Nanehkaran. Using deep transfer learning for image-based plant disease identification. *Comput Electron Agric* **2020**, 173, 105393.
103. S.L. Sanga, D. Machuve, K. Jomanga. Mobile-based Deep Learning Models for Banana Disease Detection. *Engineering, Technology & Applied Science Research* **2020**, 10 (3), 5674–5677.
104. S.P. Mohanty, D.P. Hughes, M. Salathé. Using deep learning for image-based plant disease detection. *Front Plant Sci* **2016**, 7 (September), 215232.
105. K.P. Ferentinos. Deep learning models for plant disease detection and diagnosis. *Comput Electron Agric* **2018**, 145, 311–318.