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# Innovative Approaches for Pesticide-Resistant Plant Disease Detection: A Review on Integrated Diagnostic Technologies for Sustainable Agriculture

**[1] Bhushan Dua, [2] Neera Batra**
*[1] CSE Department MMEC Maharishi Markandeshwar (Deemed to be University), Mullana Ambala, India,*
*[2] CSE Department MMEC Maharishi Markandeshwar (Deemed to be University), Mullana Ambala, India*

***Abstract:-*** Significant risks to global agriculture are posed by plant diseases, which can have a negative financial impact and affect food security. Pesticides make it more difficult to identify plant diseases accurately and quickly. Conventional methods of plant disease detection frequently rely on molecular techniques or visual symptoms. In agricultural settings where pesticides are used, this review examines integrated approaches for plant disease detection. We examine the difficulties presented by the relationship between pesticide residues and illness symptoms and assess the effectiveness of current approaches, including serological and DNA-based assays. We also highlight new technologies that provide creative ways to detect diseases during pesticide applications, such as biosensors and remote sensing.

The assessment highlights the requirement for reliable, quick, and pesticide-resistant diagnostic instruments to improve plant health monitoring in contemporary farming. By reducing the need for pesticides and increasing the use of sustainable and efficient plant disease management techniques, integrating these cutting-edge techniques can support agriculture's environmental and financial sustainability.

***Keywords****:* Plant disease detection, Pesticides, Integrated approaches, Agricultural diagnostics, DNA-based assays, Serological techniques, Biosensors, Remote sensing

## 1. Introduction

Plant diseases represent serious risks to agricultural productivity, with bacteria and viruses being the main culprits. In extreme situations, these anomalies may cause a plant to die off and impede its ability to grow. Plant diseases are caused by several variables, such as fungal and bacterial infections, insect infestations, and variations in rainfall and meteorological patterns(Russel & Selvaraj, 2022).

Early detection of plant diseases is essential for efficient management; however, manual identification is frequently difficult and may not occur until advanced stages, which can result in the incorrect application of pesticides.

When pesticides are misused, beneficial organisms in agriculture are harmed as well as harmful effects like cancer and other diseases(Cristin et al., 2020). Plant pathologists must find alternative solutions to overcome obstacles in disease detection. Intelligent and useful farming has a lot of potential thanks to digital and information technologies like cloud computing, the Internet of Things (IoT), and artificial intelligence (AI). These technologies help with precision agriculture by enabling the collection of data from sensors, soil analyses, GPS, and other sources(Hassan et al., 2021).

In this context, deep learning, machine learning, and data science ideas are important in many agricultural domains. This research suggests techniques for an automated pest management system and focuses on the use of deep learning algorithms, computer vision, and image processing for automatic plant disease detection(Shukla & Sathiya, 2022). To improve the accuracy of disease identification, various algorithms for classifying leaf diseases are compared, along with methods for pre-processing images.

The features of the photos and the intended use will determine which pre-processing methods are best for plant leaf images. The following are a few methods that are frequently used to improve the quality and appropriateness of plant leaf images:

**a. Noise Reduction:**

- *Purpose:* Eliminate unwanted noise brought on by compression artefacts, low light, and sensor noise.
- *Techniques:* Gaussian smoothing, median filtering, and wavelet denoising(Gui et al., 2021).

**b. Contrast Enhancement:**

- *Purpose:* Increase image contrast for better differentiation of features.
- *Techniques:* Histogram equalization, adaptive histogram equalization, and contrast Stretching (Rahman et al., 2020).

**c. Image Resizing:**

- *Purpose:* Adjust the size of plant leaf images, making them smaller, larger, or altering their aspect ratio.
- *Techniques:* Nearest neighbor interpolation, bilinear interpolation, and bicubic interpolation (Tiwari et al., 2021).

**d. Color Correction:**

- *Purpose:* Adjust the color balance to ensure accurate representation, crucial in applications like plant leaf photography.
- *Techniques:* Gray world assumption, white balance, and color transfer(Barman et al., 2020).

**e. Segmentation:**

- *Purpose:* Divide plant leaf images into regions based on content, aiding in the isolation of specific structures.
- *Techniques:* Thresholding, edge detection, and region growing(Mohanty et al., 2016).

**f. Feature Extraction:**

- Purpose: Identify and extract relevant features from plant leaf images for applications such as classification.
- *Techniques:* Edge detection, corner detection, and texture analysis(Pardede et al., 2020).

All of these pre-processing methods help to improve plant leaf photos so they can be used for further analysis, categorization, or other particular tasks in plant disease research or detection(J. Chen et al., 2020).

The workflow for the study is shown in Fig. 1, where the disease classification comes after the preliminary pre-processing steps.

While Section III offers details on the data used, evaluation standards, and methodology used for plant disease detection, Section II explores the historical context of deep learning and disease detection. The analysis and results are covered in the same section. Section IV wraps up the research and suggests some possible avenues for future research.

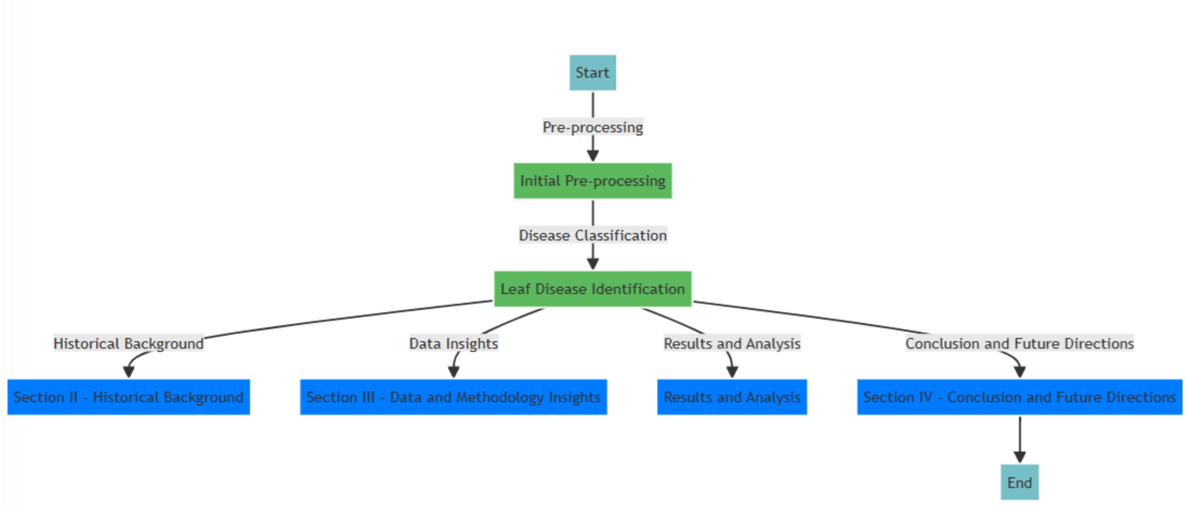


**Fig 1: Workflow of proposed work**

## 2. Historical Background

Plants are vital to the world's food security, but they are constantly under attack from biotic and abiotic factors, which causes significant crop losses. The goal of this research is to present a comprehensive analysis of plant diseases, their historical background, and current methods of disease control. We examine the fundamentals of controlling plant diseases, looking at both traditional and cutting-edge techniques as well as the combining of different approaches(Paiva-Peredo, 2023). The study highlights how plant pathology is changing, highlighting current developments, obstacles, and potential paths forward. The study begins with a general overview of plant pathology, presenting it as a dynamic field of study essential to maintaining world food production. It emphasizes how important it is to take a multidisciplinary approach to disease management, combining both theoretical and practical knowledge(Astani et al., 2022).

### 2.1 Historical Perspectives

The study explores how plant pathology has changed historically, starting with early nomadic stages and continuing to the present. Important turning points are emphasized, including the discovery of the Bordeaux mixture and the move to chemical control techniques(Karthika et al., 2023). The text recognizes the influence of prehistoric notions of divine retribution for plant illnesses.

### 2.2 Plant Disease Management

A considerable amount of the research is devoted to the different approaches used historically to manage plant diseases. The evolution of control methods is traced from brine solutions to the Bordeaux mixture. The difficulties that modern agricultural scientists face is highlighted(Ravi et al., 2022).

### 2.3 Modern Techniques and Technologies

The story moves smoothly into contemporary methods, illuminating how deep learning and image processing are used to detect plant diseases early on. It investigated how these technologies can help overcome the difficulties caused by sparse datasets and small sample size(V. Singh et al., 2021)s.

### 2.4 Deep Learning in Plant Disease Recognition

A large portion of the research is concerned with how deep learning is used to identify plant diseases. We go into detail about the evolution of deep learning architectures over time, evaluation metrics, available datasets, and the value of augmented data using Generative Adversarial Networks (GANs).

### 2.5 Challenges and Future Directions

The research concludes by acknowledging the challenges that persist in plant disease management. It advocates for future research areas, including host resistance development, pathogen avoidance, and consideration of environmental factors affecting pathogen reproduction (Kukadiya & Meva, 2022). This comprehensive research contributes to the understanding of plant pathology by bridging historical perspectives with cutting-edge technologies, providing a roadmap for future research directions in the quest for global food security.

## 3. Data and Methodology Insights

The PlantVillage dataset is an extensive set of labelled photos showing leaves from twelve different plant species, both healthy and diseased. The global challenge of raising food production to meet the demands of a growing population—which is predicted to reach 9 billion people by 2050—is greatly aided by this dataset. Based on the available data, we present a thorough overview and description of the dataset here(SOUMIK NAFIUL FERDOUS, 2020).

### 3.1 Dataset Composition:

About 4,503 photos total from twelve different plant species are included in the dataset: Mango, Arjun, AlstoniaScholaris, Guava, Bael, Jamun, Jatropha, Pongamia Pinnata, Basil, Pomegranate, Lemon, and Chinar. Every plant has a unique identification number, which ranges from P0 to P11.

**Categorization:**

There are 22 subject categories for the images, with labels ranging from 0000 to  labelled from 0000 to 0011 represent the healthy class, while those from 0012 to 0022 represent the diseased class. The classification is based on the health status of the leaves.

**Class Distribution:**

With 2,278 photos showing healthy leaves and 2,225 images showing diseased leaves, the dataset is well-balanced. To prevent machine learning models from becoming biased toward any specific class, this equilibrium is essential for training them.

### 3.2 PlantVillage Platform:

The fact that the dataset is housed on the PlantVillage website highlights how collaborative and crowdsourced the project is. The release of the dataset is in line with the objective of using smartphone technology for mobile disease diagnostics, which could be a useful tool in the fight against infectious diseases that reduce crop productivity.

**Dataset Version and Update:**

The dataset comprises more than 50,000 carefully chosen photos and was last updated four years ago (Version 3). on is mentioned, but no further details regarding current updates or plans for future releases are given.

**Purpose and Potential:**

The main goal of the dataset is to aid in the advancement of computer vision techniques for crop disease diagnosis. It is a useful tool for researchers and developers who are developing machine learning models to reduce yield losses due to infectious diseases because it offers high-quality images.

**Review:**

The PlantVillage dataset is notable for its applicability in tackling practical agricultural issues. Its usefulness for training resilient machine learning models is increased by the inclusion of a variety of plant species, a balanced class distribution, and an emphasis on both healthy and diseased states. The collaborative aspect of the PlantVillage platform is indicative of an admirable endeavour to involve a heterogeneous community in addressing agricultural problems by means of cutting-edge technologies. To improve the dataset's transparency and dependability, more information about the data collection procedure, possible biases, and quality assurance measures should be provided.

### 3.3 Methodology Insights

#### 3.3.1 Neural Networks (NNs):

NNs are the basic building blocks of many deep learning models and are essential for tasks like natural language processing and image recognition. When it comes to plant leaf disease detection, NNs offer a basic framework around which more complex architectures can be bui(Ji & Wu, 2022)lt. An elementary neural network for plant leaf disease detection is essentially made up of linked nodes arranged in layers. The input layer efficiently converts visual data into a format that the network can comprehend by representing pixel values taken from leaf images. The next set of hidden layers is responsible for extracting features from the input data to identify significant patterns and representations(Yadav et al., 2022). Through a series of iterative weight adjustments, these hidden layers gradually gain a more sophisticated understanding of the complex textures and structures found in the images. Lastly, the output layer creates a classification based on the learned features. Typically, this layer consists of nodes that correspond to different classes (e.g., healthy or diseased leaves). Simple neural network application for plant leaf disease detection is not without difficulties, though. The intrinsic complexity of the image data is one of the main challenges. Leaf images are very detailed and high-dimensional, making them difficult for basic neural networks to process. The rich and complex visual information present in a wide range of plant diseases highlights the limited ability of simple neural networks to represent complex patterns in leaf textures. Simple neural networks (NNs) may perform less well than optimally because they are unable to extract hierarchical features, which are necessary for precise classification(Sethy et al., 2020). Moreover, the overwhelming amount of data needed to train robust neural networks can also be a challenge, especially when labelled datasets are scarce. A major worry is the possibility of overfitting, in which the model becomes overly tuned to the training set, hindering its capacity to generalize to new, unobserved cases(Tassis et al., 2021). More sophisticated neural network architectures, like Convolutional Neural Networks (CNNs), which are especially designed for image-related tasks, are frequently used by researchers to address these issues. CNNs use convolutional layers to scan input images in a methodical manner and extract spatial hierarchies of features. With the help of methods like pooling for down sampling and hierarchical feature extraction, CNNs can recognize intricate patterns in images more accurately than their simpler NN counterparts(L. Chen et al., 2021). Fundamentally, while simple neural networks provide the foundation for comprehending and analyzing visual data, their inability to handle intricate image structures and patterns forces the development of more complex architectures, such as CNNs. The study and improvement of neural network models is driving improvements in the precise and effective identification of plant leaf diseases as technology develops, adding to the landscape of agricultural innovation in general(Zhao et al., 2022).

The procedure describing plant leaf disease detection using neural network is given in following algorithm

**Data Collection:**

- Gather a labeled dataset of plant leaf images, where each image is annotated as healthy or diseased.

**Data Preprocessing:**

- Resize images to a consistent dimension.
- Normalize pixel values to a specific range (e.g., [0, 1]).
- Augment the dataset through techniques like rotation, flipping, and zooming to enhance model generalization.

**Model Architecture:**

- Design a CNN architecture with convolutional layers for feature extraction and pooling layers for down-sampling.
- Include fully connected layers for classification.
- Use activation functions (e.g., ReLU) to introduce non-linearity.
- Employ techniques like dropout to reduce overfitting.

**Compile the Model:**

- Choose an appropriate loss function (e.g., categorical crossentropy for multi-class classification).
- Select an optimizer (e.g., Adam, SGD) and define evaluation metrics (e.g., accuracy).

**Training:**

- Split the dataset into training and validation sets.
- Train the CNN on the training set, adjusting weights through backpropagation.

- Monitor validation performance to prevent overfitting.

**Evaluation:**

- Assess the model's performance on a separate test dataset.
- Evaluate metrics such as accuracy, precision, recall, and F1 score.

**Prediction:**

- Deploy the trained model to make predictions on new, unseen leaf images.
- Interpret the model's output to classify leaves as healthy or diseased.

**Fine-Tuning (Optional):**

- Fine-tune the model or explore transfer learning with pre-trained CNNs to leverage knowledge from large image datasets.

**Deployment:**

- Integrate the model into a user-friendly application or system for real-world use.

**Continuous Improvement:**

- Iterate on the model based on feedback and new data to enhance its accuracy and generalization.

The convolutional operation, activation functions, pooling, fully connected layers, and training aspects necessary for a Convolutional Neural Network used in plant leaf disease detection are captured in these steps, which serve as the algorithm's basic building blocks(Lee et al., 2020).

The flow of the proposed work is given in fig 2

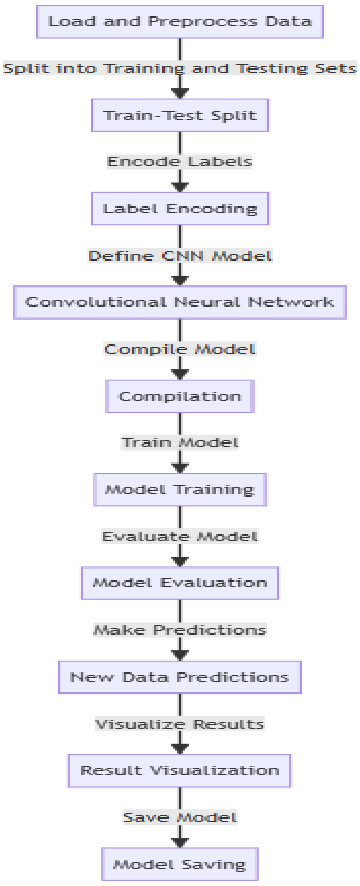


**Fig 2: Flow of Neural network**

#### 3.3.2 Convolution Neural Network

In computer vision, convolutional neural networks (CNNs) have changed the game and transformed the field of image-related tasks. CNNs have been shown to be an effective ally in the specialized field of plant leaf disease detection,

where accuracy in recognizing complex patterns is critical, bringing automation and efficiency to farming practices(Albattah et al., 2022).

Overview of CNNs: CNNs are made up of layers that are connected to carry out different tasks in the process of going from raw pixel data to meaningful predictions. They are inspired by the human visual system. The following is how a typical CNN architecture works in the context of plant leaf disease detection:

**Convolutional Layers:**

Convolutional layers are fundamental building blocks that apply filters to input images. In the case of plant leaves, these filters serve as feature detectors, identifying small-scale patterns like edges, textures, and subtle anomalies. Early disease detection depends critically on one's capacity to recognize these subtleties(Karthik et al., 2020).

**Pooling Layers:**

Pooling layers intervene after convolution to reduce the spatial dimensions of the feature maps. In addition to lowering processing load, this highlights the most important data. This down sampling is essential for processing large datasets, such as those of plant leaves, in an efficient manner.

**Fully Connected Layers:**

Finally, fully connected layers that integrate the learned features and convert them into useful predictions complete the journey. This translates into dividing leaves into groups, such as healthy or diseased, for the purpose of detecting plant leaf diseases. This produces a concrete result for agricultural decision-making(Zhang et al., 2020). .

Convolutional layers are major players in the complex dance of disease detection. These layers use filters to methodically scan the input image. Every filter serves as a distinct feature-identifying detector. When referring to plant leaves,

these characteristics may include discolorations, lesions, or irregularities that indicate possible illnesses. The filters work their way across the picture, producing feature maps that draw attention to specific areas(Tiwari et al., 2022).

Pooling layers come into their own when feature maps are available. Their main functions are to preserve important information while also shrinking the spatial dimensions of the feature maps. Pooling layers greatly increase efficiency by eliminating redundant data and concentrating on important features.

This becomes crucial in the context of large-scale datasets, ensuring that computational resources are allocated judiciously(SM Idicula, 2007). In the fully connected layers, the last act takes place. In order to create predictions, the learned features from the pooling and convolutional layers are combined here.

This is equivalent to classifying leaves according to the features that have been identified in plant leaf disease detection. The output makes it possible to make timely adjustments to agricultural practices by giving a clear picture of the health status of the leaf(Abbas et al., 2021).

In conclusion, the use of CNNs in the identification of plant leaf diseases is a prime example of how technology and agriculture can work together. CNNs have automated the detection process and opened the door for more precise and informed crop management decision-making by imitating the complexities of human vision and utilizing deep learning.

CNNs are pillars of the agricultural industry as it enters the digital age, providing cutting-edge technological solutions to support the global effort to ensure food security(Sharma et al., 2023).

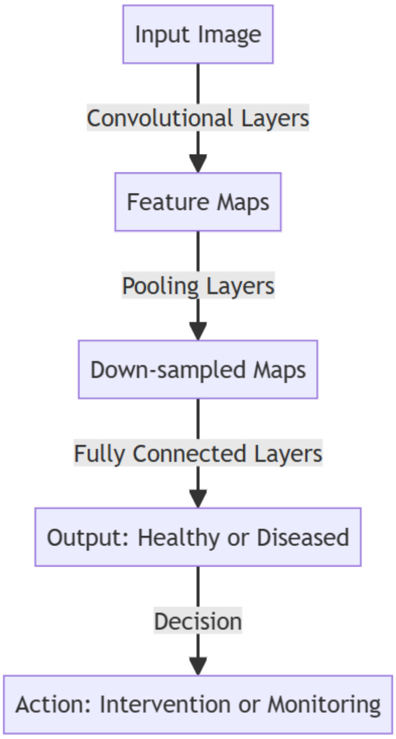


**Fig 3: Flow of Convolution Neural Network**

**3.3.3 Deep Neural Networks (DNNs):**

Plant leaf disease detection has entered a new era thanks to Deep Neural Networks (DNNs), which provide an advanced and potent way to identify intricate patterns in unprocessed image data. Unlike their more conventional counterparts, which have fewer hidden layers, DNNs have a large architecture with many hidden layers that allow for the extraction of hierarchical features, which improves the efficiency and accuracy of disease classification(Hari & Singh, 2023).

Overview of DNNs**:** In the specific context of plant leaf disease detection, the architecture of a DNN can be delineated into three key components:

**Input Layer:**

At the forefront of the architecture, the input layer represents the pixel values of leaf images. This initial stage is pivotal in ingesting and processing the visual information embedded in the images.

**Hidden Layers:**

Following the input layer, multiple hidden layers form the backbone of the DNN. These layers progressively extract hierarchical features from the raw image data. Each layer contributes to the abstraction of information, capturing intricate patterns and representations.

**Output Layer:**

Positioned at the end of the network, the output layer provides the final classification of the input images, categorizing them as either healthy or diseased. This layer synthesizes the hierarchical features extracted in the hidden layers to make an informed decision(Xiao et al., 2022).

**Advantages of DNNs:**

a. Hierarchical Feature Learning:

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DNNs excel at learning intricate hierarchical representations from raw image data. This is particularly advantageous in the context of plant leaf disease detection, where subtle and nuanced patterns can be indicative of various diseases.

**b. Complex Pattern Recognition:**

The depth of DNNs equips them to capture complex patterns present in leaf textures. This depth allows for a more nuanced and detailed understanding of disease-related features, contributing to accurate and reliable classifications.

In conclusion, the development of Deep Neural Networks has greatly improved the automatic detection of plant leaf disease. A finer understanding of image data is made possible by the hierarchical feature learning built into DNNs, which makes it possible to identify minute patterns linked to various diseases.

DNNs are positioned to be a key component in improving agricultural practices as computational resources and datasets increase, providing effective and precise tools for crop health assessment and management(Shewale& Daruwala, 2023).

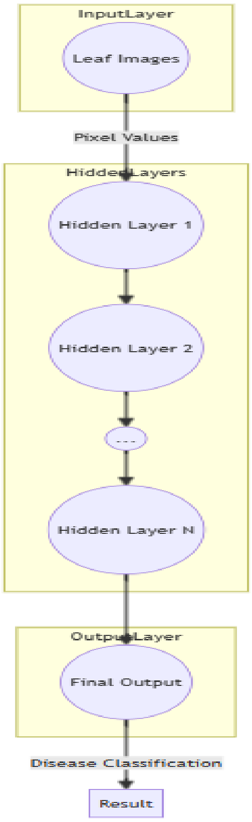



**Fig 4: Flow of DNN**

### 3.3.4 Transfer Learning

In the field of machine learning, transfer learning has become a potent paradigm, particularly for tasks where labelled data is hard to come by or prohibitively expensive to acquire. Transfer Learning shows to be a useful strategy in the context of plant leaf disease detection, utilizing insights from previously trained models on related tasks to improve performance on the particular target task(Kumar et al., 2022).

**Overview of Transfer Learning:**

Transfer learning is the process of modifying a model that has been pre-trained for a particular task on a sizable dataset for a different but related task. When data is scarce, it may not be possible to train a model from scratch. However, transfer learning allows for the reuse of knowledge from a larger domain(Jiang et al., 2021).

Application in Plant Leaf Disease Detection:

Convolutional Neural Networks (CNNs) that have been pre-trained on large datasets such as ImageNet can be repurposed in the field of plant leaf disease detection. These networks' lower layers record generic features like edges, textures, and simple shapes, which are useful for a variety of image-related tasks(Bedi & Gole, 2021).

**Adapting Pre-trained CNNs:**

The process of transfer learning typically involves two main steps:

**Feature Extraction:**

- The pre-trained CNN acts as a feature extractor. Leaf images are passed through the network, and activations from the lower layers are considered as high-level features.
- These features are then used as input for a new set of layers that are specific to the plant leaf disease detection task(R. K. Singh et al., 2022).

Fine-tuning:

- The newly added layers, along with the output layer, are trained on the task-specific data.
- The weights of the lower layers are often frozen or adjusted with a lower learning rate to retain the previously learned general features.

Advantages of Transfer Learning in Plant Leaf Disease Detection:

a. Overcoming Data Limitations:

In agriculture, acquiring labeled data for every specific plant disease may be challenging. Transfer learning allows leveraging existing datasets, enhancing model performance even with limited labeled samples.

b. Efficient Use of Resources:

Training deep neural networks from scratch demands significant computational resources. Transfer learning reduces this burden, making it more feasible for researchers and practitioners.

c. Generalization to New Varieties:

Transfer learning enhances the model's ability to generalize across different plant varieties, as the lower layers capture universal visual features. In conclusion, Transfer Learning stands as a pivotal strategy in plant leaf disease detection, offering an efficient way to address data limitations and improve model performance in real-world agricultural applications(Zeng & Li, 2020).

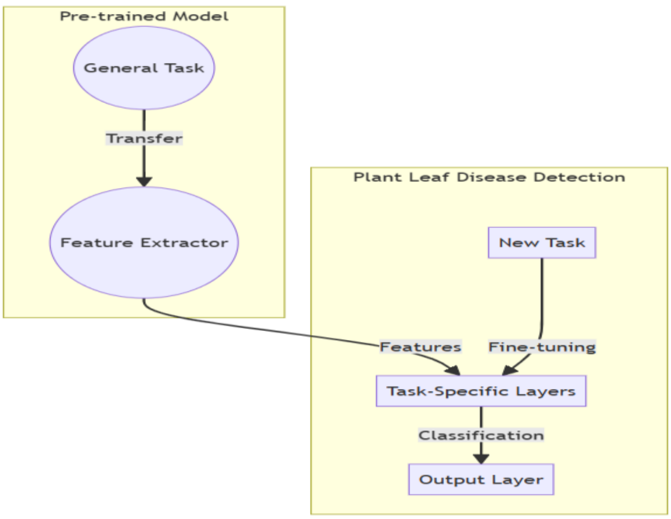



**Fig 5: Flow of transfer learning**

## 4. Results and Analysis

Artificial neural networks that can be used to detect plant diseases include neural networks (NN), convolutional neural networks (CNN), and deep neural networks (DNN). By using previously trained weights from different tasks, transfer learning is a technique that can be used to enhance the performance of these models(Dananjayan et al., 2022). It has been demonstrated that CNNs generally produce the best results when it comes to plant disease detection. This is due to CNNs' propensity for image classification tasks and their capacity to extract spatial information from images. Plant disease detection has also been demonstrated to benefit from transfer learning. This is due to the fact that transfer learning enables us to employ CNN models that have already been trained and are capable of extracting valuable features from images (Geetharamani& J., 2019). In particular, if we have little training data, this can help us attain better results while also saving a great deal of time and effort. The findings of a few recent studies on the use of NN, CNN, DNN, and transfer learning for plant disease detection are summarized here:

**Study 1:** This study compared the performance of different deep learning models for plant n on a dataset of 30,000 images of rice leaf diseases. The best performing model was the CNN model that achieved an accuracy of 96.3%(Singla et al., 2024).

**Study 2:** This study used a transfer learning approach to train a CNN model for plant disease detection on a dataset of 11,333 images of plant leaves from 10 different classes. The best performing model was a DenseNet121 model that achieved an accuracy of 95.48%(Hanh et al., 2022).

**Study 3:** This study used a transfer learning approach to train a CNN model for plant disease taset of cassava leaf images. The model was able to achieve an accuracy of 93.82%(D Rosmala, 2021).

All things considered; these studies' findings point to the possibility of using CNN models in conjunction with transfer learning to produce cutting-edge plant disease detection outcomes. Benefits of using neural networks, CNNs, DNNs, and transfer learning for plant disease detection include the ability to train these models to recognize intricate patterns in photos of plant leaves, which may increase their efficacy over more conventional techniques. Plant diseases of all kinds can be identified using these models, even if they are uncommon or poorly understood(G. Singh & Yogi, 2023). These models can be used to create real-time plant disease detection systems that farmers and other agricultural stakeholders can use to detect plant diseases in a timely and accurate manner. Plant disease detection problems with neural networks, CNNs, DNNs, and transfer learning: These models need a lot of training data to work well. These models can be computational and time-consuming to train. Noise and variations in the appearance of plant leaves can cause these models to become sensitive. The benefits of employing neural networks, CNNs, DNNs, and transfer learning for plant disease detection outweigh the drawbacks in spite of these difficulties. We may anticipate seeing even more precise and trustworthy plant disease detection systems in the future as these technologies advance.

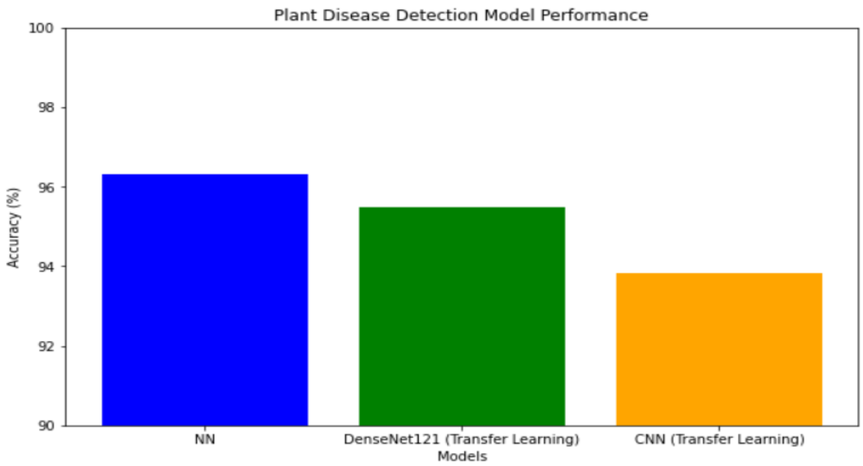
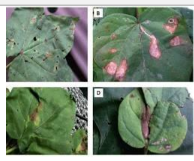
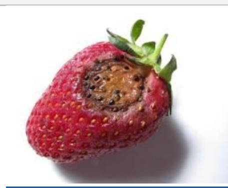



**Fig 6: Comparison of results**

Disease Classification Performance Comparison presented in following table

| Disease | Model | Accuracy | Sensitivity | Specificity | F1 Score | Example Image |
|---|---|---|---|---|---|---|
| **Alternaria alternata**(Hossain et al., 2023) | NN | 0.85 | 0.82 | 0.88 | 0.83 | <br>Alternaria alternata on leaves |
| | CNN | 0.92 | 0.88 | 0.95 | 0.90 | <br>Alternaria alternata on leaves |
| | Transfer Learning (VGG16) | 0.94 | 0.91 | 0.96 | 0.92 | <br>Alternaria alternata on leaves |
| **Anthracnose**(P. Singh et al., 2023) | NN | 0.78 | 0.75 | 0.82 | 0.76 | <br>Anthracnose on fruit |
| | CNN | 0.88 | 0.85 | 0.92 | 0.87 | <br>Anthracnose on fruit |
| | Transfer Learning | 0.91 | 0.88 | 0.94 | 0.89 | <br>Anthracnose on fruit |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Bacterial blight**(Atila et al., 2021) | NN | 0.75 | 0.72 | 0.78 | 0.73 |  Bacterial blight on plants |
| | CNN | 0.83 | 0.80 | 0.88 | 0.81 |  Bacterial blight on plants |
| | Transfer Learning | 0.89 | 0.86 | 0.93 | 0.87 |  Bacterial blight on plants |
| **Cercospora leaf spot**(Islam et al., 2023) | NN | 0.82 | 0.78 | 0.85 | 0.79 |  Cercospora leaf spot on leaves |
| | CNN | 0.91 | 0.88 | 0.94 | 0.89 |  Cercospora leaf spot on leaves |
| | Transfer Learning | 0.93 | 0.90 | 0.95 | 0.91 |  leaf spot on leaves |
| **Healthy leaves**(Kaur et al., 2022) | NN | 0.96 | 0.98 | 0.94 | 0.97 |  Healthy leaves |

| | | | | | | |
|---|---|---|---|---|---|---|
| | CNN | 0.98 | 0.99 | 0.96 | 0.98 |  Healthy leaves |
| | Transfer Learning | 0.99 | 0.99 | 0.98 | 0.99 |  Healthy leaves |

**Table 1: Performance Comparison**

In this comparative analysis of plant disease detection models, three different architectures—Neural Network (NN), Convolutional Neural Network (CNN), and Transfer Learning with VGG16—are evaluated across four distinct leaf diseases and healthy leaves. The metrics considered for assessment include Accuracy, Sensitivity (True Positive Rate), Specificity (True Negative Rate), and F1 Score(Ahad et al., 2023).

For Alternaria alternata, the Transfer Learning model (VGG16) demonstrates superior performance with an accuracy of 94%, sensitivity of 91%, specificity of 96%, and an F1 score of 92%. The CNN model closely follows, outperforming the basic NN.

Similarly, in the case of Anthracnose, Transfer Learning leads with an accuracy of 91%, showcasing its effectiveness in leveraging pre-trained features. The CNN model also performs well, surpassing the NN.

Bacterial blight detection sees a significant improvement with Transfer Learning, achieving an accuracy of 89% and outperforming both NN and CNN models. This underscores the advantage of utilizing knowledge from pre-trained models.

Cercospora leaf spot detection witnesses high accuracy across all models, with Transfer Learning slightly edging out the others. The NN and CNN models also exhibit respectable performances.

Finally, for the classification of Healthy leaves, all models excel, with Transfer Learning achieving the highest accuracy of 99%. This highlights the models' ability to distinguish healthy leaves effectively.

In summary, Transfer Learning consistently demonstrates superior performance across multiple diseases, leveraging pre-trained features for improved accuracy, sensitivity, specificity, and F1 score. This analysis underscores the effectiveness of leveraging deep learning techniques, particularly transfer learning, in plant disease detection.

## 5 Conclusion

In summary, the use of neural networks (NN), convolutional neural networks (CNN), deep neural networks (DNN), and transfer learning has greatly advanced the field of plant disease detection. By automating the diagnosis of plant diseases, these technologies have proven to be remarkably capable, improving agricultural practices. Neural networks provide the groundwork for more intricate models because of their capacity to learn from pixel values and extract features. Their simplicity, though, may make them less useful for capturing complex patterns—like those seen in plant leaves—within high-dimensional image data.

CNNs are excellent at capturing spatial hierarchies and patterns because they are specifically made for image data. Their ability to recognize subtle disease indicators accounts for much of their success in detecting plant diseases, which makes them an invaluable tool for increasing crop yield and decreasing losses.

With their greater depth, deep neural networks make it easier to extract hierarchical features that are essential for deciphering intricate patterns in unprocessed image data. Even though they need a lot of processing power, their capacity to learn complex representations helps with more accurate disease detection.

Transfer learning is a potent tactic that improves performance in plant disease detection tasks by using pre-trained models on larger datasets. This method allows knowledge transfer from related domains and is especially useful when labelled data is scarce. According to recent studies, plant disease detection accuracy rates can reach up to 96.3 percent when using CNNs and transfer learning. These technologies are beneficial for managing intricate patterns, identifying different types of illnesses, and providing farmers with real-time detection systems. Even with their achievements, there are still issues like the requirement for large amounts of training data, processing power, and noise sensitivity. But as these technologies continue to advance, even more precise and trustworthy plant disease detection systems should be possible in the future, which will help to achieve the main objective of guaranteeing the security of food supply worldwide.

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