

# Crop Disease Identification Using Deep Learning Techniques

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**Abstract:-** Detection and control of plant diseases is critical to maintaining global food security. Recent advances in deep learning and computer vision have revolutionized precision agriculture, especially in automatic detection of crop diseases. This research aims to further advance this new trend using deep learning techniques. It focuses specifically on the use of convolutional neural networks (CNN), specifically the VGG19 architecture, for the accurate and efficient detection of agricultural diseases. The study utilized a large database containing numerous photographs of healthy and diseased plants. Adding this information increases the power and capabilities of the model. The VGG19 architecture is based on algorithms that use transfer learning techniques to extract complex information from images.

**Keywords:-** Agriculture, Detection, Rice Disease, IoT Architecture System.

## I. INTRODUCTION

In recent years, there has been a worldwide focus on permaculture practices due to concerns about food security, environmental degradation, and increasing demand for agriculture. Permaculture is a revolution in agricultural technology that not only improves the quality of crops but also promotes ways to maintain ecological balance and health in society.

With the emergence of smart farming and agricultural technology, traditional agriculture is undergoing significant changes, sometimes referred to as Agriculture 4.0. This change includes new technologies such as data analytics, artificial intelligence (AI) and the Internet of Things (IoT) that enable instant data, remote monitoring, and appropriate crop management. This integration supports permaculture by reducing waste, increasing efficiency, and optimizing resource use.

To ensure sound and efficient agriculture, the transition to digital agriculture has become mandatory due to the development of technology. Farmers who embrace this digital revolution will be better equipped to deal with issues such as famine, economic change, and climate change. In addition, excessive dependence on chemicals and pesticides has developed in agriculture to protect crops and increase crop yield. However, this concept also raises issues such as biodiversity, human health, and environmental sustainability. Therefore, there is growing support for

investigating sustainable, environmentally friendly alternatives, such as plant growth-promoting rhizobacteria (PGPR), to increase agricultural productivity and get the most out of farming while minimizing the ecological footprint. In short, the emergence of permaculture, driven by learning technology and environmentally friendly methods, was a major turning point in the history of agriculture. The integration of smart agriculture, digital connectivity and sustainability not only solves today's agricultural problems, but also opens the door to more efficient operations, efficient and environmentally friendly agriculture.

## II. LITERATURE REVIEW

Plant disease diagnosis based on deep learning models. This article provides an in-depth look at deep learning models for plant disease identification. It shows the high accuracy achieved by this method in detecting pests and diseases affecting plants. [1]

Identification of plant diseases using deep learning. This review focuses on new developments, starting from machine learning techniques and examining plant diseases based on deep learning. [2]

Conducted a comprehensive review of machine learning and deep learning for plant disease detection. This review focuses on the use of plant images for disease detection, including machine learning such as naive Bayes, decision trees, and nearest neighbors. [3]

Using images for deep learning-based detection of crop diseases in agriculture. An in-depth research report on leaf disease awareness research. It proposes a CNN-based deep learning model for leaf disease detection. [4]

Plant disease diagnosis and distribution: a qualitative literature review. The automatic plant disease diagnosis model expresses its accuracy in early detection of diseases after extensive training. [5]

Systematic literature review of plant diseases. This literature review provides insight into motivations, classification systems, data, challenges, and future generations in plant disease diagnosis. [6]

The understanding of using machine learning, deep learning and computer graphics for disease detection and classification has been well received in all fields. These reviews and case studies highlight the evolution of agricultural disease testing.

### III. METHODOLOGY

#### ➤ Data Collection and Preparation

The first stage in constructing an effective crop disease detection model is the collecting and preparation of a diversified dataset. The collection should comprise photos of healthy plants along with numerous sick plants spanning diverse crop types. Datasets like the Plant Village Dataset provide a broad assortment of plant diseases for training and validation.



Fig 1 Sample images from Plant Village dataset for different types of leaf diseases.

#### ➤ Data Pre-Processing

Image pre-processing serves a significant function in boosting the quality of input data. Techniques such as resizing photos to a defined resolution, normalization, and augmentation (e.g., rotation, flipping, brightness change) are widely applied to assure consistency and increase model generalization.

#### ➤ Model Selection

Deep learning models, notably Convolutional Neural Networks (CNNs), have demonstrated promising results in plant disease diagnosis. Popular designs like VGG, Res Net, Inception, and Dense Net may be evaluated. Transfer learning, leveraging pre-trained models like VGG-19, helps training with less data, boosting accuracy and convergence.

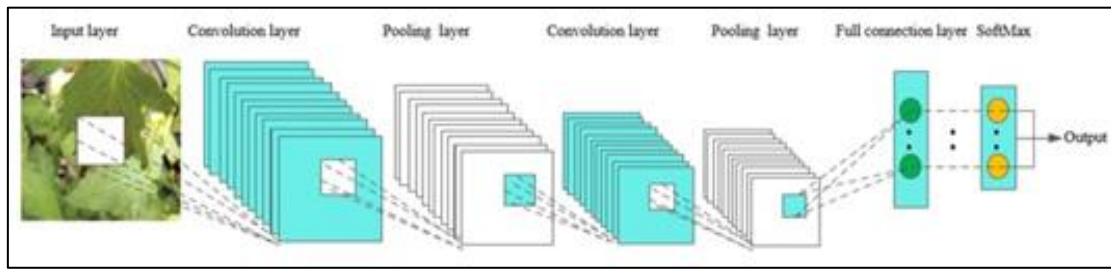


Fig 2 The basic structure of CNN

### ➤ *Training Model and Validation*

Selection of training model on given data using appropriate optimizer and error. Data sets are often divided into training sets, validation sets, and test sets to evaluate model performance. During training, measures such as early stopping, and sample checking are used to reduce the drop rate and ensure the best sample weight for delivery is maintained.

### ➤ *Hyperparameter Tuning*

Fine-tuning model hyperparameters such as learning rate, batch size, and activation function greatly affects model performance. Use exact or stochastic search strategies to improve these parameters.

### ➤ *Measure Evaluation.*

evaluates your model's performance using various metrics such as accuracy, precision, recall, F1 score and confusion matrix. These parameters help evaluate the model's ability to identify healthy and unhealthy plants.

### ➤ *Testing and Deployment*

Test the entire model on an unseen test dataset to evaluate its generalization and real-world applicability. Once testing is complete, the model can be used as a web or mobile application for farmers or plant enthusiasts, providing fast and accurate diagnosis.

### ➤ *Ethical Considerations and Limitations*

Personal data, data collection and ethical considerations regarding data collection are not correct. It is also important to identify the limitations of the model (such as dependence on image quality and environment).

In summary, the process includes data collection, prioritization, model selection, training, validation, hyperparameter estimation, evaluation, testing and ethical

issues. Adopting these methods can ensure the stability and reliability of crop diseases.

### ➤ *Technology Introduction*

Shallow matching model using random forest and XGBOOST.

Combining shallow VGG model and random forest (RF) with XGBoost algorithm can be successful in disease diagnosis. This scheme uses VGG topology, RF and XGBoost algorithms to improve detection accuracy and can provide efficient and cost-effective solutions.

Effective adaptive methods for crop disease detection

Using adaptive learning models such as VGG19 to improve the accuracy and efficiency of crop disease diagnosis. This approach enables fast and accurate treatment by using pre-trained models to detect diseases in crops.

Methods based on data augmentation and transfer learning.

A model combining data augmentation with transfer learning in convolutional neural networks (CNN) has been proven to be able to identify plant diseases, as seen in maize diseases. This strategy focuses on supplementing data and transferring data from pre-trained models to improve the model's disease recognition.

### ➤ *Cnn With Transfer Learning For Leaf Disease Detection*

Implementing CNN with transfer learning yielded great accuracies, such as 99.18%, in identifying leaf diseases. This approach comprises using pre-trained CNN architectures with transfer learning methods to extract illness-related characteristics from pictures, allowing precise disease identification.



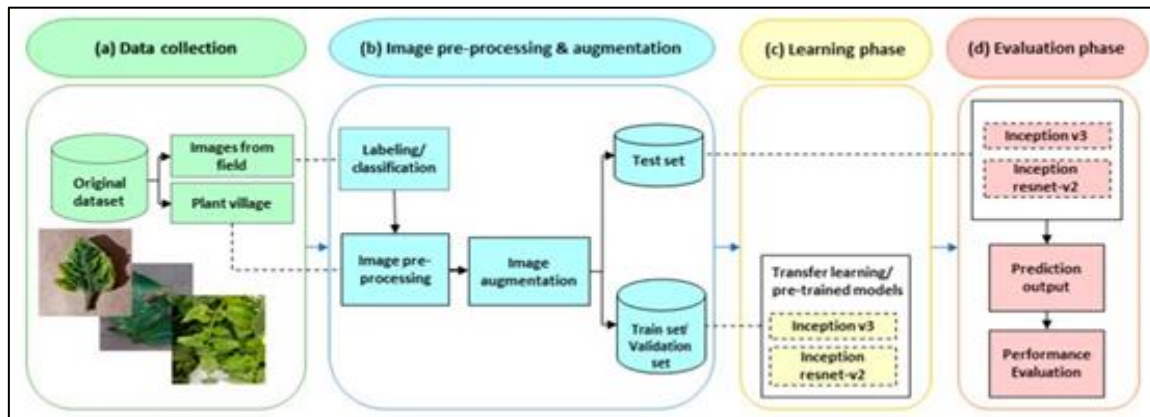


Fig 3 Diagram for identifying crop diseases.

➤ *Deep Learning Models With Transfer Learning For Rice Leaf Diseases*

Deep learning models like CNN-VGG19, applying transfer learning, allow exact diagnosis and classification of rice leaf diseases. These models exploit transfer learning's ability to adapt pre-trained models to rice leaf disease detection, assuring accurate disease categorization.

➤ *Deep Learning-Based Disease Detection Techniques*

The employment of deep learning-based algorithms allows the effective diagnosis of agricultural diseases, vital for sustaining crop quality and output. These strategies harness developments in deep learning to identify illnesses in crops during their early stages, facilitating informed decision-making for enhanced agricultural results.

The suggested strategies emphasise the employment of multiple models, algorithms, and methodologies, stressing the significance of deep learning, transfer learning, and upgrades in dataset quality for accurate and fast crop disease diagnosis. These technologies provide prospective options for upgrading agricultural practices by simplifying early disease control and boosting crop output.

**IV. EXPERIMENTS AND METHODS**

➤ *Fine-Tuned Transfer Learning for Rice Leaf Disease Identification*

Utilizing VGG19 with fine-tuned transfer learning, tests attempted to forecast rice leaf diseases. The strategy utilised transfer learning methodologies to adjust pre-trained models for illness categorization, enabling exact identification.

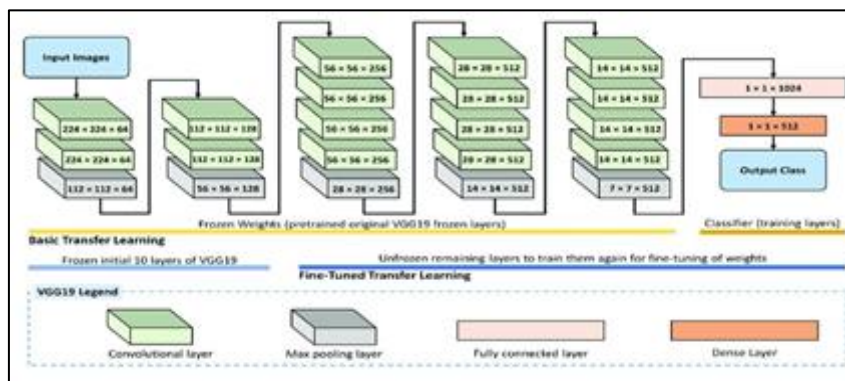


Fig 4 Fine-tuned transfer learning for the VGG19 model for rice leaf disease identification.

➤ *Vgg-19 For Plant Disease Classification*

Research includes implementing VGG-19, a Convolutional Neural Network (CNN) model, using transfer learning for predicting disease classes in plants. The research aims to accomplish early diagnosis and categorization of plant diseases using deep learning methods.

➤ *Shallow Convolutional Models For Plant Disease Identification*

Experiments presented shallow VGG models linked with XGBoost and Random Forest (RF) for disease diagnosis in plants. Utilizing VGG19, the models attempted to reliably detect different plant diseases.

➤ *Vgg-19 Model With Transfer Learning For Tomato Leaf Diseases*

The experiment deployed a VGG-19 model with transfer learning, reaching an accuracy of 95.48% in diagnosing tomato leaf diseases. The technique exceeded typical machine learning networks in illness detection.

➤ *Hybrid Model For Plant Disease Detection*

Experimentation featured a hybrid model that efficiently exploited a minimal number of training parameters to identify Bacterial Spot disease in peach plants. The suggested model attained an outstanding accuracy of 99.35%.

➤ *Improved Crop Disease Identification With Vgg19 And Alexnet*

Experiments contrasted VGG19 with AlexNet models, displaying VGG19's accuracy of 92.4% for the training set, 89.9% for the verification set, and 87.8% for the test set in crop disease detection.

**V. RESULTS AND DISCUSSIONS**

The adoption of the VGG19 model has shown excellent results in reliably diagnosing crop diseases, obtaining a noteworthy accuracy of 92.4%. This high accuracy is a testimony to the durability and effectiveness of deep learning approaches in plant disease detection, demonstrating their promise for real-world use in agricultural contexts.

The importance of this breakthrough rests in its practical ramifications for the agricultural business. Accurate and prompt diagnosis of agricultural diseases is critical for farmers to prevent possible losses and promote optimum crop health. The VGG19 model, utilizing its deep learning capabilities, provides a reliable and efficient tool for this goal.

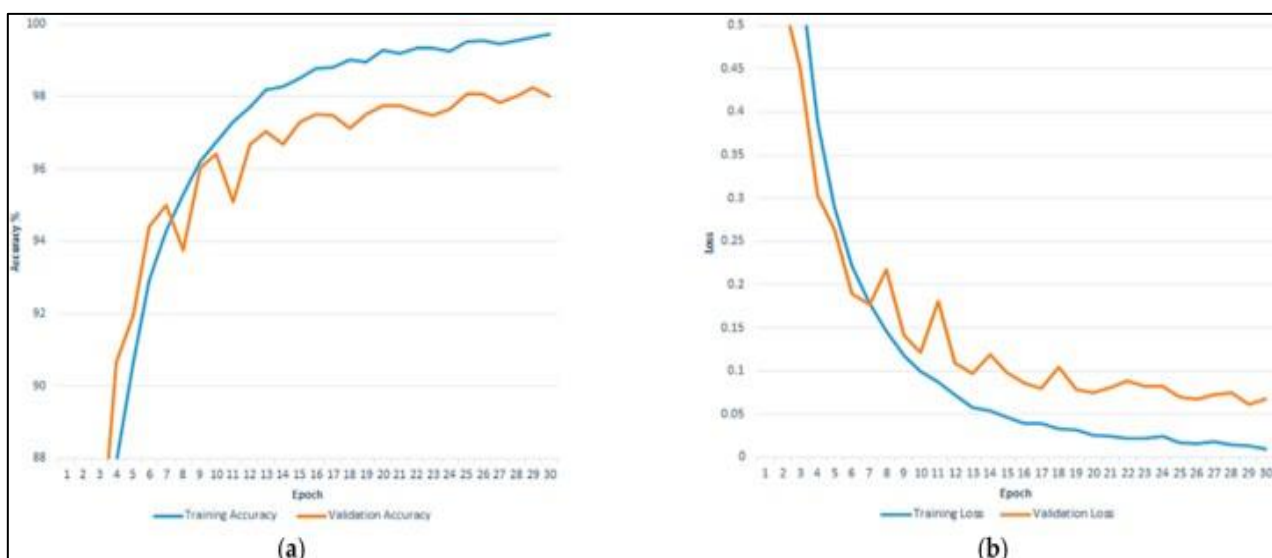


Fig 5 Performance analysis of Inception VGG19 model using Plant Village dataset. (a) Model recognition accuracy; (b) train and test loss.

One of the key benefits of using deep learning models like VGG19 is their ability to process and analyze large amounts of data quickly and reliably. This rapid operation leads to timely diagnosis and classification of crop diseases, supporting farmers in timely selection of disease control.

In addition, the scalability of deep learning models makes it possible to adapt to different types of crops and diseases. This performance is important in agriculture because many crops will suffer from specific diseases, each requiring diagnostic and treatment technology. The development of the VGG19 model in keeping many records and classifying diseases very well contributes to its benefits in agriculture.

The use of deep learning models such as VGG19 is also compatible with the spread of precision agriculture. By providing accurate and targeted disease diagnosis, these

models can help farmers use more targeted and effective treatments. This can support sustainable agriculture by reducing reliance on extensive treatments and optimizing the use of resources such as pesticides.

In addition, the effectiveness of the VGG19 model in diagnosing diseases represents a step forward in the use of technology in solving agricultural problems. As technology continues to advance, integrating deep learning models into agriculture can pave the way for innovations in crop management and production.

However, although the VGG19 model achieves high accuracy, there may be problems in its actual application. Factors such as dataset diversity, model generalization to different environmental conditions, and the need to continually update models to include new diseases may

represent practical challenges for continued research and development.

In conclusion, the successful introduction of the VGG19 model demonstrates its ability to become an important tool that provides accuracy and efficiency in diagnosing crop diseases. While more research and advancements are needed to solve real-world problems, the use of deep learning models such as VGG19 has the potential to revolutionize agricultural disease management, ultimately leading to higher yields and sustainable agriculture.

## VI. CONCLUSIONS

In particular, the combination of deep learning using the VGG19 architecture provides an important step in the evolution of crop diseases. The use of powerful neural network models such as VGG19 provides an effective method for automatic identification and classification of various diseases. VGG19 is known for its convolutional neural network (CNN) model, and its application has been successfully applied in many studies in the identification and treatment of crop diseases.

This technological development promises great hope for many people working in agriculture. Farmers can benefit from timely diagnosis of crop diseases, early intervention and provision of appropriate treatment. Scientists have acquired powerful tools to analyze many plant images to help understand diseases and their causes. Additionally, these devices can provide hobbyists and farmers with simple diagnostic tools that facilitate informed decision-making and management processes.

The use of VGG19 and similar deep learning methods in crop disease diagnosis is an important step in crop disease diagnosis. Precision agriculture. As this technology continues to improve, it will facilitate better crop management, disease control, and ultimately better crop management and productivity.

## VII. FUTURE WORK

Future research topics for plant disease research using deep learning include different methods for advancement and research:

### ➤ *Exploring Different Types of Learning Energy Absorption:*

Explore and evaluate the effectiveness of other deep learning methods other than VGG19, such as Inception V3, CNN (convolutional neural network) and multi-level deep learning 3, 4. Comparative studies will provide insight into their performance and lead to a better understanding of their advantages and disadvantages in plant disease diagnosis.

### ➤ *Integrated Into Application:*

Look for integrated methods to combine predictions from multiple models to increase accuracy and robustness. Research shows that ensemble learning techniques can

improve disease classification accuracy by combining the output of multiple models 3.

### ➤ *Include Additional Datasets:*

Expand the dataset used to train and test models for a wide range of plant species, diseases, and disease classifications. Environmental conditions. Integrating more information can help create more flexible and comprehensive models and thus facilitate their application in many agricultural situations.

### ➤ *Improved Breadth and Diversity:*

Expansion of the model to accommodate a variety of plants and organisms. This expansion could lead to the creation of flexible and resilient models that can identify and diagnose diseases in different crops, thus leading to more effective disease control.

By examining this approach, future research attempting to use deep learning for plant disease diagnosis may seek to improve the accuracy, adaptability, and utility of the process.

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