

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

PLANT DISEASE IDENTIFICATION USING VGG-16 - A DEEP LEARNING APPROACH

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ABSTRACT:

Agriculture has evolved beyond its primary purpose of sustaining growing populations. It is of paramount importance, especially in Asian countries where more than 70% of the population depends on it for their livelihoods. This means that agriculture plays a critical role in providing sustenance for a vast number of people. However, a significant challenge in agriculture is the occurrence of diseases that lead to reduced crop yields and quality. Detecting these diseases is crucial in preventing agricultural losses. The primary objective of this project is to develop a software solution that can automatically identify and categorize plant diseases. The process involves several key steps, including loading an image, pre-processing, segmentation, feature extraction, and disease classification. These steps collectively contribute to disease detection. In this project, leaf images are utilized for the purpose of identifying plant diseases. Therefore, the application of image processing techniques to detect and classify diseases in the context of agriculture proves to be highly beneficial.

Keywords: Agriculture, Plant disease detection, Image processing, Leaf images, Disease classification, Segmentation, Feature Extraction.

1. Introduction

Agriculture serves as the backbone of our nation, providing farmers with a wide array of crop choices for their fields. Nonetheless, the cultivation of crops for maximum profitability and consistent quality often requires a scientific approach. This can be achieved with the support of technical assistance. The ongoing management of crops, especially disease control, demands meticulous attention, as diseases can significantly affect the various factors of production and ultimately impact economic gains. Image processing has emerged as a powerful and transformative technique in the field of agriculture, particularly in the early detection and classification of plant diseases. By analyzing images of crops, this method enables the identification of various plant health issues that may otherwise go unnoticed, especially during the early stages of infection when symptoms are microscopic and not easily visible to the human eye. Manual inspection of plants is often labor-intensive, time-consuming, and prone to human error, underscoring the need for an automated system that can efficiently and accurately detect plant diseases. Automated plant disease detection systems, supported by modern agricultural development initiatives, are crucial in addressing the growing challenges of crop disease management. Such systems not only aid in early diagnosis but also contribute significantly to improving agricultural productivity and ensuring economic viability for farmers. Most plant diseases manifest themselves visibly on the leaves, stems, or fruits, often in the form of complex visual patterns. However, the task of accurately identifying and quantifying these symptoms remains a challenge due to the visual similarities between different disease types and the subtle variations in symptom expression.

In this context, deep learning and computer vision offer robust solutions by enabling automatic recognition, classification, and analysis of disease symptoms from images. Among the various deep learning architectures, VGG-16, a convolutional neural network (CNN) model, has demonstrated exceptional performance in image classification tasks. Its ability to extract deep hierarchical features from input images makes it particularly suitable for disease detection in crops, where fine-grained distinctions are essential. The proposed system leverages VGG-16 to perform image-based disease identification by classifying images of plant leaves into healthy or diseased categories. This approach eliminates the need for subjective human interpretation and provides consistent, high-accuracy results. The implementation begins with the acquisition of a dataset comprising both healthy and diseased plant leaf images. These images are then pre-processed to standardize size, remove noise, and enhance quality. Following this, the pre-processed images are passed through the VGG-16 network, where deep features are extracted and used for classification.

By utilizing VGG-16, the system aims to provide a reliable, scalable, and efficient solution for disease detection in large-scale agricultural fields. This method not only aids farmers in early and precise disease recognition but also supports timely intervention, thereby reducing crop loss and improving yield quality. The integration of such automated systems into agricultural practices marks a significant step toward smart farming and sustainable agricultural development.

1.1. Research Objectives

- 1. Develop an Automated Disease Detection System:
- To create a software solution capable of automatically identifying and classifying diseases in rice plants using digital leaf images. 2. Utilize Deep Learning (VGG-16) for Classification:

To implement the VGG-16 convolutional neural network for accurate and efficient classification of leaf images into categories such as Bacterial Blight, Leaf Blast, Brown Spot, Tungro, and Healthy.

- Apply Image Processing Techniques: To enhance and prepare leaf images using preprocessing techniques (resizing, noise removal, contrast enhancement) for more accurate classification.
- 4. Enable Early Detection and Timely Intervention:

To support farmers by detecting diseases at early stages, allowing for timely treatment and prevention of major crop loss.

 Build a Scalable and Cost-Effective System: To design a practical and accessible solution that minimizes manual labor and human error, aiming for broad adoption in agricultural practices.

6. Improve Accuracy Over Traditional Methods:

To demonstrate the superiority of deep learning over traditional manual or threshold-based methods in recognizing visually similar symptoms.

Generally, there are 3 forms of plant diseases. They're microorganism, Viral and fungal in Fig. 1

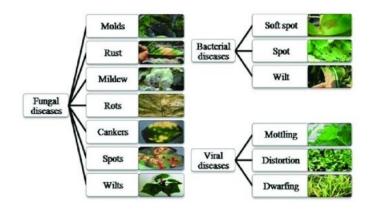


Fig1: Plant disease fundamental

Rice Blast (RB) is a major fungal disease that severely affects rice production. It appears on different parts of the plant such as leaves, nodes, and panicles, and can be observed in various stages of infection. In Fig. 2, the stages of Rice Blast — including early, spreading, and severe — are used to classify the disease. However, relying only on these visible stages can be challenging, especially when different diseases show similar symptoms. To address this, the VGG-16 deep learning model is used to improve disease detection. VGG-16 automatically learns important features from rice leaf images, helping to identify the disease more accurately. Unlike traditional methods, which depend on color thresholds or manual observation, this approach works well even when symptoms look alike. Using VGG-16 makes the system more reliable and efficient for detecting Rice Blast in real-world conditions.



Fig2: Rice Blast

This study focuses on the identification of leaf diseases in rice plants using image processing and deep learning techniques. The process involves a series of steps: image acquisition, preprocessing, feature extraction, classification, and disease identification. These steps help in accurately detecting the presence of disease from leaf images. In this approach, the VGG-16 convolutional neural network (CNN) is used to automatically extract deep

features from the input images and classify them into healthy or diseased categories. The model is trained using a dataset of rice leaf images, enabling it to recognize patterns and symptoms associated with different diseases. This method eliminates the need for manual observation and provides a faster, more reliable solution for disease detection.

By using this system, users can easily identify the disease affecting the crop in a straightforward and cost-effective manner. The model supports early detection, which is essential for timely treatment and improved crop health. This approach aims to assist farmers by offering a practical and efficient tool for monitoring plant health.

2. Literature Survey

The application of deep learning in agriculture, particularly in plant disease detection, has gained significant momentum in recent years. Identifying plant diseases at an early stage is vital for ensuring food security and minimizing crop losses. Traditional methods of disease identification, which rely on manual inspection and expert consultation, are often labor-intensive, time-consuming, and prone to human error. In response to these limitations, several studies have focused on automating the disease detection process through computer vision and artificial intelligence.

Recent advancements highlight the use of Convolutional Neural Networks (CNNs), which have become the cornerstone of image classification tasks due to their ability to learn complex features directly from raw images. Among these, VGG-16, a deep CNN architecture, has demonstrated outstanding performance in extracting hierarchical features that aid in precise classification of plant diseases. The model's robustness, simplicity, and transfer learning capabilities make it an ideal candidate for agricultural applications, especially in the classification of rice leaf diseases such as Bacterial Blight, Leaf Blast, Brown Spot, and Tungro.

Previous works, such as those by Islam et al. (2021) and Abhirami et al. (2021), have explored the use of automated CNN-based approaches for paddy disease identification. These models have shown high accuracy in distinguishing between healthy and infected leaves. Furthermore, studies by Sujatha et al. (2023) and Parasa et al. (2024) emphasize the integration of IoT and AI-driven tools for real-time disease prediction, supporting farmers in timely intervention and decision-making. Moreover, literature supports the use of image preprocessing techniques such as resizing, noise filtering, and contrast enhancement as essential steps in improving model performance. These preprocessing stages help normalize the input data and make the learning process more effective for neural networks. The use of transfer learning, especially with pretrained networks like VGG-16, enables models to perform well even with limited datasets, which is often a constraint in agricultural domains. This approach leverages knowledge gained from large-scale datasets like ImageNet, allowing the model to generalize better to specific tasks such as rice disease classification.

In conclusion, the existing literature demonstrates a growing consensus on the efficacy of deep learning techniques in plant disease detection. The adoption of VGG-16 for image-based disease classification aligns with current trends in smart agriculture, providing an efficient, scalable, and cost-effective solution for modern-day farming challenges.

3. Methodology and Processed Method

For the disease identification this is the process going to use. Fig3 shows the methods and techniques which were going to identify an disease by giving an input as a leaf image.

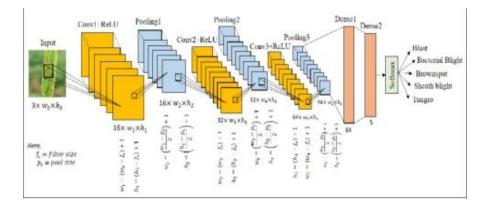


Fig3: Process of plant disease identification

IMAGE ACQUISITION

The initial step in digital image processing is the loading of an image, which involves capturing the image using a digital camera and storing it in digital media for subsequent PIL operations. This action also entails retrieving an image from hardware, enabling further processing. In our project, we get images of both healthy and diseased leaves as depicted in Figure 4, for utilization in the PIL image processing system.



Fig4: A sample disease leaf

IMAGE PREPROCESSING

The primary objective of image pre-processing is to improve the quality of the image by removing unwanted distortions or enhancing specific image features before further processing. Pre-processing techniques encompass a variety of methods such as resizing the image dynamically, noise filtering, image conversion, image enhancement, and morphological operations. In our project, we applied multiple PIL codes to resize the image, enhance contrast. These steps were undertaken to prepare the images for subsequent operations, including segmentation and cluster formation.

MODEL SELECTION

Model selection is a crucial step in designing an effective image classification system. In this study, we utilized the VGG-16 convolutional neural network (CNN) as our deep learning model. VGG-16 is known for its simplicity and strong performance in image recognition tasks. It consists of 16 layers, including multiple convolutional layers followed by fully connected layers that help in learning complex patterns from images. The model was chosen for its ability to automatically extract deep features from leaf images without the need for manual intervention. VGG-16 takes input images of size 224×224×3, making it suitable for leaf disease classification tasks. The architecture uses small 3×3 filters and ReLU activation functions to capture local patterns, followed by max-pooling layers to reduce dimensionality. Pretrained weights from the ImageNet dataset are used to enhance the model's learning efficiency and accuracy. This model selection approach allows the system to effectively distinguish between healthy and diseased leaves, even when symptoms are subtle or visually similar across categories.

CLASSIFICATION

The classification technique is employed for the training and testing of plant leaf images. In this context, the VGG-16 convolutional neural network is utilized for the classification process. It automatically extracts features from the input images and classifies them into categories such as healthy or diseased based on learned patterns.

4. Experimental Setup and Implementation

The Paddy Crop Disease Identification system follows a structured implementation process, covering image preprocessing, model training, and deployment. Below is the step-by-step breakdown:

1. Image Acquisition & Preprocessing

- User uploads a paddy leaf image via the web interface.
- Preprocessing Steps:
 - Resize the image to 224x224 for VGG-16 compatibility.
 - Normalize pixel values to enhance model performance.
 - o Convert the image to a suitable format for deep learning models

2. Feature Extraction

- VGG-16 CNN model extracts deep features from the input image.
 - Feature maps are generated to distinguish disease patterns.

3. Model Training

- Dataset of healthy and diseased paddy leaves is used.
- Pretrained VGG-16 network is fine-tuned for classification.
- Softmax classifier is applied for disease categorization.

4. Disease Classification

The trained model classifies the leaf as healthy or diseased.

• The system displays only the disease name and confidence score.

5. Prediction & Visualization

- The system outputs the disease category with a clear label.
- No confidence score is displayed to keep results simple.

6. Deployment (Web-Based Application)

- The trained VGG-16 model is integrated into a web-based system.
 - Users can:
 - Upload leaf images
 - Obtain disease classification results
 - o View the identified disease name and confidence score

This approach ensures efficient, accurate, and user-friendly disease identification for paddy crops.

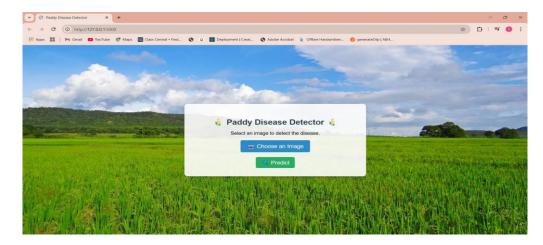
5. Result Analysis

Browse the Image File

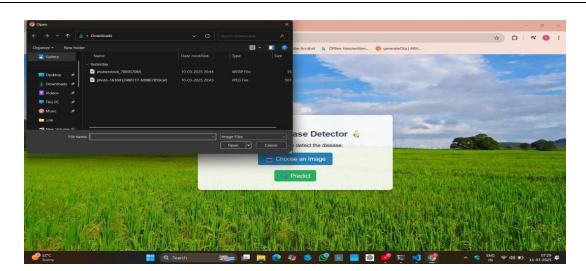
Upload your paddy leaf image to identify and classify diseases using the VGG-16 deep learning model. Ensure the image is clear and properly captured for accurate detection. Upon uploading, the system will process the image and provide a disease classification result.

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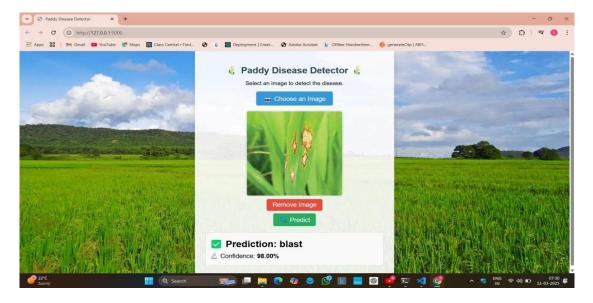
RUNNING A CODE



CLICK ON CHOOSE AN IMAGE



UPLOAD AN IMAGE



GET PROCESESSED AND GIVE RESULT

Conclusion and Future Scope

The Paddy Crop Disease Identification System successfully demonstrates the application of deep learning for detecting and classifying paddy leaf diseases using the VGG-16 model. By leveraging convolutional neural networks (CNNs), the system effectively extracts features from leaf images and identifies diseases with high accuracy. The integration of image preprocessing techniques ensures that input data is optimized for better classification performance.

Additionally, the system offers a user-friendly interface that allows farmers and researchers to upload paddy leaf images, process them, and receive disease classification results seamlessly. The use of deep learning ensures automated and efficient identification, reducing the time and effort required for manual disease detection.

While the system provides valuable insights, it is important to acknowledge that environmental factors such as lighting conditions, image quality, and variations in leaf texture may impact classification accuracy. Further improvements can be made by expanding the dataset, incorporating additional deep learning models, and integrating real-time field applications to enhance usability and reliability

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