INTERNSHIP PROJECT - II

Project Phase – 2

University of Windsor

Image Classification Model and Image Labelling Workflow for Powdery Mildew on Crops Through Machine Learning AI

Submitted To: Dr. Shafaq Khan

Submitted By: Manvir Singh Channa
Harjot Singh Saggu
Guneet Kaur

Introduction

Background

Powdery mildew is a pervasive fungal disease that affects a wide range of crops, leading to significant yield losses and economic impact.

Conventional methods of visual inspection for powdery mildew are subjective, labor-intensive, and prone to human error [1]. This limitation has spurred the need for a more sophisticated approach utilizing machine learning and image classification techniques.

The research aims to leverage machine learning algorithms to develop a robust image classification system. This system will be trained on a diverse dataset featuring the progression of powdery mildew symptoms over time. By employing advanced computer vision techniques, the model will be able to accurately identify the presence of powdery mildew on plant leaves and quantify the extent and progression of the disease.

By introducing a severity assessment component our project enables the classification of the disease's spread, providing growers with valuable information on the extent of the infestation.

This holistic approach holds the promise of significantly enhancing crop health, yield, and ultimately, the sustainability of agricultural practices.

Problem Statement

The commercial greenhouse industry grapples with the persistent challenge of accurately identifying and computing the severity of powdery mildew, a fungal infection which can profoundly impact crop health and yield [1]. The conventional approach of visual inspection proves to be time-consuming, subjective, and prone to errors, resulting in suboptimal outcomes for crop management.

Moreover, the rampant prevalence of powdery mildew, stands as a formidable threat to greenhouse crops [1]. The current absence of a reliable and efficient identification method hampers timely intervention, exacerbating the economic losses incurred due to infestations. Furthermore, the elusive nature of powdery mildew makes its severity evaluation particularly challenging.

By leveraging machine learning technology, we aim to address this critical issue. Through advanced algorithm such as CNN and image analysis, we seek to develop a robust model capable of accurately identifying and quantifying the extremity of powdery mildew, providing invaluable insights for targeted intervention strategies.

By addressing these challenges head-on, this research endeavor endeavors to revolutionize greenhouse management practices, ultimately leading to healthier and more productive crops, increased profitability for growers, and a sustainable future for the commercial greenhouse industry.

Research Motivation

The motivation behind this research project stems from the critical need to revolutionize crop management practices in the commercial greenhouse industry. This sector plays a pivotal role in ensuring a consistent and reliable food supply, making its efficiency and productivity paramount.

The challenges faced by greenhouse growers in accurately identifying and managing pests, nutrient deficiencies, and diseases are multifaceted. Conventional methods, relying heavily on visual inspection, are marred by subjectivity and inherent limitations. This leads to suboptimal outcomes, with potential consequences for crop health, yield, and economic viability [2].

Of particular concern is the pervasive threat posed by powdery mildew, a destructive fungal disease. Its insidious nature and propensity for rapid spread make timely intervention crucial. However, the absence of a reliable identification method exacerbates the economic losses associated with infestations.

The research project draws inspiration from the transformative potential of machine learning technology. By harnessing the power of advanced algorithms and image analysis, we aim to develop a model capable of accurately identifying powdery mildew. This technological leap addresses the inherent difficulty in visually detecting the disease, offering a precise and efficient solution [2].

Moreover, the integration of machine learning enables us to go beyond binary detection. It empowers us to assess the severity of powdery mildew infestations, providing growers with actionable insights for targeted intervention. This innovation stands to significantly enhance the effectiveness of disease management strategies.

The impact of this research extends far beyond the confines of the greenhouse. By empowering growers with accessible and advanced tools, we contribute to the broader effort of sustainable agriculture. The reduction of pesticide usage through targeted interventions and the optimization of resource allocation aligns with global goals of environmental stewardship.

Ultimately, the research motivation lies in the potential to transform agricultural practices, ensuring healthier crops, increased yields, and greater economic stability for growers. By pushing the boundaries of technology in service of agriculture, we pave the way for a more resilient and sustainable future in the commercial greenhouse industry.

Literature Study

The project on image classification and powdery mildew detection builds upon significant prior research efforts in agricultural disease management. One key area of focus in previous studies has been the detection of powdery mildew in crops using proximal images and machine learning techniques. This approach acknowledges the challenges posed by manual visual inspection, especially in large properties, and highlights the potential of combining digital images with machine learning for effective pest monitoring. The absence of a reliable identification method for powdery mildew has hindered timely intervention, resulting in substantial economic losses. The elusive nature of powdery mildew further compounds the challenge of accurate detection and measuring the extent of damage.

Due to the success of deep learning in target detection, many researchers try to apply it to crop disease detection. One such paper discusses about Powdery Mildew in wheat crop.

The study discerns that monitoring accuracy during the flowering stage surpasses that of the grain filling stage, owing to the relative stability of canopy structure in the former [3]. This observation underlines the importance of considering growth stages in disease monitoring. The research results of this study provide ideas and methods for realizing high-precision remote sensing monitoring of crop disease status [3]. In this paper they concluded that using the MC-CARS-SPA-RFR model algorithm enhanced the spectral response characteristics, extracted the characteristic bands more comprehensively and effectively, significantly improved the powdery mildew monitoring ability, and has a good prospect for application in the precise prevention and control of wheat powdery mildew [3]. To further evaluate the robustness of the model, it needs to be tested and perfected under different crop types and environmental conditions.

Another research done by S. Li, et al on detecting Powdery mildew on cucumber is very promising [4]. The research aimed to develop a deep learning-based system for the detection of powdery mildew in cucumber plants using convolutional neural networks (CNNs). They utilized leaf images to train and test their model [4]. The objective was to create an automated and accurate system to identify the presence of powdery mildew and classify it into different stages. The project aimed to develop a deep learning-based system for the detection of powdery mildew in cucumber plants using convolutional neural networks (CNNs) [4]. They utilized leaf images to train and test their model. The objective was to create an automated and accurate system to identify the presence of powdery mildew and classify it into different stages. However, the model's generalizability to other crops and environmental conditions might be limited. It may perform differently when applied to crops other than cucumbers or in different greenhouse settings.

Further work done in the same field by Huang et al. [5]embarked on a novel approach to quantify yellow rust disease severity in winter wheat by employing hyperspectral imaging, a method that captures and processes information across the electromagnetic spectrum. The research aimed to address the need for early, accurate disease detection and appropriate response measures, which are crucial for maintaining crop health and yields. The researchers categorized damage percentage into nine distinct classes, ranging from 0-3% (indicative of no disease) up to more than 70% (indicative of severe disease), based on the Disease Index (DI) levels. [5] The results demonstrated a promising correlation between the spectral data captured by the hyperspectral imaging and the disease severity levels. The classification model achieved satisfactory performance, highlighting hyperspectral imaging's potential as an efficient, non-destructive tool for early detection and quantification of plant diseases.

However, several challenges and limitations accompanied the study's findings. the research only focused on yellow rust in winter wheat, and whether this methodology is applicable to other diseases or crops warrants additional research and the study was conducted under controlled conditions, and the accuracy of this method in diverse, natural field conditions remains a subject for further exploration.

Similar work done by S. M. Omer, K. Z. Ghafoor, and S. K. Askar [6] for cucumber leaf disease diagnosis aims to develop an intelligent system for cucumber disease detection using CNN. The authors employ a tuned CNN algorithm as the core technology for image analysis and classification. Through extensive experimentation and tuning, they aim to enhance the system's performance in accurately identifying and diagnosing cucumber leaf diseases. The study presents results that demonstrate the effectiveness of their system in achieving precise disease diagnosis.[6] However, potential limitations and challenges related to the real-world application of the proposed system, such as performance in diverse environmental conditions, quantification of severity of disease and generalizability to diseases beyond cucumber leaves, should be further explored and addressed.

The research conducted by Y. Li, J. Wang, H. Wu, Y. Yu, H. Sun, and H. Zhang, titled "Detection of powdery mildew on strawberry leaves based on DAC-YOLOv4 model,"[7] focuses on the development of an effective system for the detection of powdery mildew on strawberry leaves.

Their approach leverages the DAC-YOLOv4 model, which is a variant of the YOLO (You Only Look Once) deep learning algorithm, renowned for its real-time object detection capabilities. In this context, the DAC-YOLOv4 model is fine-tuned to identify and classify powdery mildew on strawberry leaves. The study demonstrates promising results in terms of disease detection accuracy and efficiency, showcasing the potential of deep learning in agricultural disease management.
However, it is important to note that the paper did not specify the exact accuracy percentage achieved. Despite the achievements, limitations may include challenges related to model generalizability to varying environmental conditions, different types of plant diseases, and scalability to other crops. Further research might be necessary to validate the model's performance under diverse scenarios and to enhance its versatility for broader agricultural applications.

Table 1 represents few existing works done in the field of disease detection and severity quantification of the disease.

Paper Title	Algorithm Used	Main Focus	Limitations
Existing Literature:			
Hyperspectral Monitoring of Powdery Mildew Disease Severity in Wheat Based on Machine Learning	Machine Learning, Hyperspectral Monitoring	Disease detection, growth stage impact	Limited reliability, specific crop type, testing conditions
Deep Learning-Based Powdery Mildew Detection in Cucumber Plants Using Convolutional Neural Networks	Deep Learning (CNN)	Disease detection, cucumber-specific	Limited generalizability to other crops, greenhouse settings
Using Hyperspectral Imaging to Discriminate the Disease Severity of Yellow Rust on Winter Wheat Leaves	Hyperspectral Imaging	Disease severity quantification in winter wheat	Limited applicability to specific disease, uncertain generalizability
An Intelligent System for Cucumber Leaf Disease Diagnosis Based on the Tuned Convolutional Neural Network Algorithm	Tuned Convolutional Neural Network (CNN)	Cucumber leaf disease diagnosis	Potential challenges in generalizability to diverse conditions and diseases
Detection of powdery mildew on strawberry leaves based on DAC-YOLOv4 model	DAC-YOLOv4 Model	Powdery mildew detection on strawberry leaves	Potential limitations related to environmental conditions, disease types, and crop scalability
Proposed Model:			
Image Classification Model and Image Labelling Workflow for Powdery Mildew on Crops Through Machine Learning AI	Hyperspectral Imaging, Deep Learning, Convolutional Neural Network (CNN)	Powdery Mildew quantification on crops	

Table 1 Comparison of existing work

Proposed Model

Our proposed model leverages a comprehensive multi-metric approach to accurately detect and quantify powdery mildew severity in crops within commercial greenhouses. This model combines cutting-edge machine learning algorithm like CNN with image classification techniques, focusing on four key metrics: powdery mildew white spot size, spot color, leaf color, and the number of powdery spots.

Explanation:

Powdery Mildew White Spot Size: This metric evaluates the size of the white spots, a characteristic symptom of powdery mildew. Larger spots indicate more severe infections, providing a quantitative measure of disease progression.

Spot Color: The color of powdery mildew spots can vary, and our model analyzes this feature to discern differences in severity. Changes in coloration can indicate the stage of disease development.

Leaf Color Degradation: As powdery mildew progresses affected leaves often undergo color changes. By assessing these alterations, our model can gauge the severity of the infection.

Number of Powdery Spots: This metric counts the total number of powdery mildew spots on a leaf. A higher count signifies a more severe infection.

Differences from Existing Works:

Our proposed model distinguishes itself from existing works through its utilization of a multi-metric approach, incorporating a broader range of parameters for severity assessment. Prior research in powdery mildew detection has primarily focused on specific crops like wheat or tomato. While these studies have yielded valuable insights, our approach diverges in its aim for a more generic application across various crops. While previous studies have primarily focused on one or two metrics, our model comprehensively analyzes four distinct aspects of powdery mildew development. This allows for a more nuanced and accurate evaluation of disease progression.

Furthermore, the incorporation of machine learning algorithms enables our model to autonomously process and classify images, reducing reliance on manual, time-consuming assessments. This not only enhances the accuracy of severity quantification but also expedites decision-making for farmers and greenhouse managers.

In summary, our model stands out by employing a holistic approach to powdery mildew severity assessment, utilizing multiple metrics and advanced machine learning techniques. This comprehensive methodology promises to revolutionize disease detection and severity evaluation within commercial greenhouses, ultimately contributing to improved plant health, productivity, and sustainable farming practices.

System Architecture

Technology and Methodology

Technology Stack

Our project relies on the following technologies:

Python: The primary programming language for implementing the machine learning model and associated tasks.

TensorFlow and Keras: These libraries provide the framework for building and training neural networks.

Image Processing Libraries (PIL, OpenCV): Used for loading, preprocessing, and augmenting the image data.

VGG16 Pretrained Model: We employ a pre-trained VGG16 model for feature extraction, taking advantage of its robustness in image recognition tasks.

Methodology

Data Collection Process

The data collection process was thoroughly curated to ensure a comprehensive and diverse dataset for training the severity prediction model. The approach encompassed both the acquisition of original imagery and the utilization of existing datasets.

For the original data, a specialized dataset focusing on powdery mildew-affected plant leaves was obtained from Kaggle. This source was chosen due to its relevance to the research domain and the rich diversity of images available. The dataset, inspired by a notable research paper [1], provided a foundational repository for training the machine learning model.

To facilitate precise severity prediction, each image was meticulously annotated with corresponding severity percentages. This crucial step involved classifying the images into distinct stages based on predefined metrics, including spot size and color etc. These predefined metrics, such as spot size and color, were informed by comprehensive studies and research papers in the field [3]. This ensured that the classification process was founded on established methodologies, contributing to the accuracy and reliability of our severity assessment. These notes were really important because they helped the model to evaluate tiny differences in how severe the disease was in different hyperspectral images.

The data collection process heavily relied on Python, a versatile programming language well-suited for handling image data. Complementing Python, specialized image processing libraries were instrumental in tasks such as image augmentation and normalization. These libraries streamlined the preprocessing pipeline, ensuring the data was in a suitable format for training the model.

Data analysis and preprocessing

Following data collection, a systematic approach was undertaken to prepare and analyze the acquired dataset. The initial step involved meticulous data preprocessing to ensure uniformity and compatibility for subsequent analysis. To enhance dataset diversity and bolster the model's robustness, image augmentation techniques were applied. These included rotations, shifts, and flips, effectively introducing variations in perspective and orientation. Augmentation was a strategic decision aimed at mimicking real-world scenarios where the appearance of disease-affected leaves may differ in subtle ways.

The size of the dataset was a critical factor in training a robust and generalizable model. It comprised a curated selection of 1000 images, spanning various severity levels. This ensured that the model was exposed to a wide spectrum of disease presentations, enabling it to learn and generalize effectively.

Feature Extraction

A pre-trained VGG16 model is utilized as a feature extractor. It converts input images into a high-dimensional feature space while excluding the top layers responsible for classification.

The VGG16 model is a convolutional neural network (CNN) architecture that gained prominence for its exceptional performance in image classification tasks. Developed by the Visual Geometry Group (VGG) at the University of Oxford, VGG16 is characterized by its deep structure, consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. One of its key strengths lies in its uniform architecture, where the convolutional layers have a fixed 3x3 filter size, and the max-pooling layers follow every two convolutional layers. This regularity in design contributes to its ease of implementation and interpretability. VGG16 was originally trained on the ImageNet dataset, which enabled it to learn a rich set of features that are applicable to a wide range of visual recognition tasks. Due to its effectiveness, VGG16 has become a popular choice for transfer learning, where pre-trained weights from the model are utilized as a starting point for training on custom datasets, making it a valuable tool in various computer vision applications.

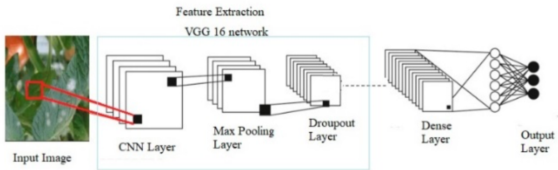

Figure 1 Model Architecture

In figure 1, the VGG16 model, pre-trained on the ImageNet dataset, was employed as a potent feature extractor. By removing its top classification layers, we retained the convolutional layers, which are adept at detecting intricate patterns and structures within images. Subsequently, these layers were utilized to transform our input images into a high-dimensional feature space. This feature space encapsulated rich representations of the visual characteristics present in the plant leaf images. These extracted features served as the basis for our severity prediction model, providing a compact yet information-rich representation of each image. This approach not only expedited training due to the reduced dimensionality of the feature space, but also bestowed the model with a heightened ability to discern subtle variations in disease severity. It effectively harnessed the collective knowledge embedded within the VGG16 model, fine-tuning its innate capacity to recognize complex patterns, and adapting it to the specific nuances of powdery mildew-affected plant leaves. The feature extraction process thus served as a transformative bridge, enabling us to harness the depth of knowledge ingrained in the VGG16 model and apply it judiciously to our domain of interest.

Model Architecture

A custom neural network is designed, incorporating flattened VGG16 features.

Dense layers with dropout for regularization are added to learn higher-level representations. Output layer with a single neuron for regression, predicting the severity percentage.

The model architecture designed for this study provides a comprehensive framework for predicting the severity percentage of powdery mildew-affected plant leaves. At its core, the feature extraction phase utilizes the VGG16 model's deep convolutional layers, which are fine-tuned for the specific domain of plant disease assessment. These layers form the foundation for learning intricate visual patterns in the input images, facilitating the extraction of disease-related features.

For the input to the model, RGB values represent the three primary color channels - Red, Green, and Blue - commonly used to represent and display images in computer vision tasks. In the context of the CNN network, each pixel in an input image is a combination of these three color channels, with intensities ranging from 0 to 255. Integrating these RGB values equips the network with the capability to process and analyze color information, a critical aspect in tasks where color variations convey significant meaning, as is the case in plant disease assessment.

However, it's imperative to acknowledge that while RGB images are effective in many scenarios, they may not capture all the nuances of spectral information that could be valuable in specific domains. This is where hyperspectral images come into play. Unlike RGB images, hyperspectral images capture information across a wide range of spectral bands, providing a much richer dataset. This wealth of spectral information proves particularly advantageous in tasks like plant disease assessment, where subtle changes in reflectance across different wavelengths may contain critical diagnostic information.

To leverage hyperspectral images, adjustments to the CNN architecture and preprocessing steps become necessary. The model must accommodate the increased dimensionality of hyperspectral data, and specialized preprocessing techniques are required to handle the additional spectral bands. Additionally, the use of hyperspectral images would likely entail a more complex network architecture capable of effectively extracting and utilizing the wealth of spectral information.

Following this, dense layers, coupled with dropout for regularization, are introduced to the architecture. These layers enable the model to learn higher-level representations, capturing complex relationships within the feature space. Moreover, the inclusion of dropout promotes model generalization and reduces overfitting. Ultimately, the model's output layer, consisting of a single neuron, is dedicated to regression tasks, predicting the severity percentage with precision. This streamlined architecture systematically combines the strengths of convolutional and dense layers, empowering the model to analyze images comprehensively, extract informative features, and make precise severity predictions. Each layer within the architecture plays a distinct role in enhancing the model's accuracy and adaptability to the intricacies of powdery mildew assessment, culminating in a powerful tool for disease management in agriculture.

Following the feature extraction and dense layers, the model culminates in the output layer, which is pivotal in generating predictions. In this architecture, the output layer consists of a single neuron, specifically designed for regression tasks. Unlike classification tasks where multiple neurons would represent different classes, this solitary neuron is adept at producing continuous values. In the context of this study, the output neuron computes the severity percentage of the powdery mildew infestation on plant leaves. This design choice aligns seamlessly with the regression nature of the task, allowing the model to precisely quantify the extent of disease severity. The output layer is integral in converting the learned representations and relationships from preceding layers into actionable severity predictions. Its singular focus on regression enhances the model's capacity to offer accurate assessments, thus solidifying its efficacy as a tool for disease management in agriculture.

Model Training

The model is trained using labeled data with a mean squared error loss function. The optimizer refines the model's weights to minimize the prediction error.

The training process is a pivotal phase in refining the model's predictive prowess. Leveraging a meticulously annotated dataset with severity percentages, the model undergoes rigorous training using a mean squared error (MSE) loss function. This loss function serves as a guiding metric, quantifying the disparity between the predicted severity percentages and the ground truth labels. Executed in a GoogleCollab environment with GPU acceleration, the training process benefits from enhanced computational resources, ensuring faster processing and efficient weight adjustments. Through an iterative process, the optimizer diligently refines the model's weights, systematically reducing the prediction error. This refinement process empowers the model to discern increasingly nuanced patterns and relationships within the data, enhancing its precision in predicting disease severity. The convergence towards minimal prediction error signifies the model's growing proficiency in accurately assessing the extent of powdery mildew infestation on plant leaves. This comprehensive training regimen ensures that the model attains a high level of accuracy and reliability, poised to make accurate severity predictions on unseen data in real-world scenarios.

Model Evaluation and Prediction

Model Evaluation is a critical step in gauging the effectiveness of the severity prediction model. This evaluation process entails subjecting the model to validation data, which it has not encountered during training. By assessing the model's performance on this unseen dataset, we gain valuable insights into its ability to generalize and make accurate severity predictions in real-world scenarios.

Following successful evaluation, the model is poised for practical deployment. When presented with new images of powdery mildew-affected leaves, the model swiftly processes the input and produces a continuous severity percentage. This output serves as a valuable tool for disease assessment, providing a precise quantification of the extent of infestation. Such granular information equips agricultural practitioners with a nuanced understanding of plant health, enabling timely interventions and effective disease management strategies.

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