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**DETECTION OF PLANT DISEASE(DOWNEY MILDWE) USING OPEN CV**

**CAPSTONE PROJECT REPORT**

***Submitted by***

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**ABSTRACT**

The detection of plant diseases is a critical task in precision agriculture, aimed at preventing crop loss and improving yield. This abstract presents a detailed overview of the principles, challenges, and state-of-the-art techniques for detecting Downy Mildew, a prevalent fungal disease, using Convolutional Neural Networks (CNNs). The primary objective is to develop accurate models that can identify Downy Mildew from leaf images by analyzing visible symptoms like lesions and discoloration. CNNs are highly effective in this domain due to their ability to capture complex spatial features in image data, making them ideal for recognizing disease patterns. The process begins with preprocessing, including image normalization, resizing, and noise reduction, to improve model accuracy. Feature extraction techniques, such as Histogram of Oriented Gradients (HOG) or Scale-Invariant Feature Transform (SIFT), may also be employed to highlight discriminative features that aid in disease detection. Challenges in detecting Downy Mildew include variations in leaf appearance, environmental conditions, and the presence of other diseases. To address these challenges, deep learning models are trained on large, annotated datasets to ensure generalization across diverse conditions. Additionally, data augmentation techniques, such as rotation and flipping, are applied to enhance model robustness. Ensemble learning and transfer learning are leveraged to further improve model accuracy and adaptability. Applications of Downy Mildew detection extend beyond individual plant monitoring to large-scale automated agricultural systems for early disease intervention and management. As research advances, the focus remains on improving model efficiency, interpretability, and scalability for real-world agricultural deployment.

**Keywords**: Plant disease detection, Downy Mildew, Convolutional Neural Networks, Precision agriculture, Preprocessing, Feature extraction, Deep learning.

**CHAPTER 1**

* 1. **Introduction**

Plant disease detection is a critical component of modern precision agriculture, aimed at minimizing crop loss and ensuring food security. The detection of Downy Mildew, a fungal disease known for affecting a variety of crops, particularly grapes and cucumbers, is crucial for maintaining healthy yields. This task involves developing algorithms capable of identifying and classifying disease symptoms from leaf images, aiding in early detection and management. With the rapid advancement of computer vision and machine learning, automated systems are increasingly employed to detect plant diseases, offering a reliable and scalable solution for monitoring large agricultural fields.

One of the most effective approaches to plant disease detection is the use of Convolutional Neural Networks (CNNs), a subset of deep learning, which excels in image recognition tasks. CNNs are particularly adept at extracting spatial features from images, making them ideal for identifying the complex visual patterns associated with Downy Mildew. By training CNNs on labeled datasets, where images of healthy and diseased leaves are paired with their respective labels, the models learn to differentiate between healthy crops and those afflicted by disease with high accuracy. Preprocessing plays a pivotal role in ensuring the quality and consistency of input data, with tasks such as image normalization, resizing, and noise reduction forming the foundation of the recognition process. Feature extraction methods like Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) can be applied to further refine the discriminative properties of the images, enhancing the model's ability to detect disease symptoms in varied conditions.

However, detecting Downy Mildew presents its own set of challenges. Variations in leaf appearance, environmental factors, and the presence of other diseases can hinder the accuracy of recognition models. Robust systems must overcome these obstacles by demonstrating the ability to generalize across a wide range of real-world conditions. To address these challenges, advanced deep learning techniques, such as data augmentation, ensemble learning, and transfer learning, are often employed to improve model generalization and performance on diverse datasets.

In recent years, the integration of CNN algorithms in agricultural technology has proven to be a game changer for plant disease detection, particularly in addressing diseases like Downy Mildew. Traditional methods of disease diagnosis, which often involve manual inspection by experts, are time-consuming, labor-intensive, and prone to human error. CNN-based approaches, on the other hand, offer a highly automated, scalable solution that can process vast amounts of image data with remarkable speed and accuracy.

The applications of plant disease detection extend beyond individual plant monitoring, with the potential to transform large-scale agricultural practices by enabling automated, real-time disease detection. As technology continues to advance, the focus of ongoing research is on improving the efficiency, scalability, and interpretability of models, ensuring they remain effective across a variety of real-world agricultural scenarios. In this context, CNN-based detection of Downy Mildew represents a significant step forward in the development of intelligent agricultural systems designed to meet the challenges of modern farming.

**1.2. Statement of the Problem**

The detection of plant diseases, particularly Downy Mildew, presents a complex and multifaceted challenge within the field of agricultural technology and precision farming. Despite notable progress in computer vision and machine learning, accurately identifying and diagnosing Downy Mildew from plant leaf images remains a difficult task due to several inherent challenges.

Key challenges include variations in leaf appearance, the impact of environmental conditions, and the presence of multiple overlapping diseases, all of which complicate the development of robust detection models. These factors contribute to the difficulty in creating systems that can consistently detect Downy Mildew symptoms, such as lesions and discoloration, with high accuracy across diverse crop types and growth stages.

Moreover, as the detection of Downy Mildew plays a critical role in preventing crop loss and promoting sustainable agriculture, the demand for precise, reliable, and automated detection systems has never been greater. Addressing the variability in plant symptoms, environmental noise, and real-time detection capabilities underscores the importance of exploring innovative solutions that can adapt to these dynamic challenges.As technology evolves, there is an increasing need for plant disease detection models that not only deliver high accuracy but also demonstrate efficiency, scalability, and adaptability to various agricultural settings. This highlights the urgency for comprehensive solutions that integrate technical precision with practical application in large-scale farming environments.

In light of these challenges, the statement of the problem for Downy Mildew detection centers on the need to develop and refine detection models that can effectively handle variations in plant appearance, environmental factors, and disease complexity. The goal is to create robust, accurate models that are capable of early disease detection and are adaptable across different crops and agricultural conditions, ensuring the seamless integration of these systems into modern farming practices.

**1.3. Need for the study**

The study of plant disease detection, particularly Downy Mildew, is of paramount importance in today's agricultural landscape due to its significant impact on crop health and yield. One of the primary motivations for investigating the detection of Downy Mildew is the increasing demand for sustainable and efficient agricultural practices. As global food production systems transition towards precision farming, accurate and early detection of plant diseases becomes crucial for minimizing crop loss, reducing the use of chemical treatments, and optimizing resource management.

Additionally, advancements in agricultural technology and the adoption of automated systems highlight the need for precise disease detection methods. In large-scale farming, manual inspection is time-consuming and prone to error, underscoring the importance of automated systems that can identify diseases like Downy Mildew in real-time. This not only enhances the efficiency of crop monitoring but also ensures timely interventions, preventing the spread of the disease and improving overall yield.

In the context of smart farming and IoT-based agricultural systems, the integration of plant disease detection systems is critical for enabling real-time monitoring and automated decision-making. The ability to accurately detect Downy Mildew from leaf images using advanced techniques such as Convolutional Neural Networks (CNNs) is essential for creating intelligent systems that can operate autonomously across large fields, contributing to the scalability of precision agriculture.

Moreover, the growing demand for sustainable farming practices calls for solutions that can reduce the reliance on pesticides by identifying diseases at early stages, allowing for targeted treatments. The detection of Downy Mildew plays a key role in this, as timely diagnosis can prevent excessive crop damage, minimize the use of chemicals, and support environmentally friendly farming.

From a technological perspective, the study of disease detection using CNNs serves as a benchmark problem in the application of deep learning to agricultural challenges. Research in this field provides insights into developing more robust models capable of handling diverse environmental conditions, variations in plant appearance, and other real-world complexities. As agriculture continues to adopt new technologies such as drones, smart sensors, and machine vision, the integration of accurate disease detection algorithms will remain central to advancing the industry.

Finally, as climate change and evolving agricultural practices introduce new challenges, the study of Downy Mildew detection ensures that modern agricultural systems are equipped with the tools necessary to adapt to these changes.

**1.4. Scope of the study**

The scope of studying the detection of plant disease, specifically Downy Mildew, using CNN algorithms, spans a broad spectrum of applications, challenges, and opportunities. The following points outline the comprehensive scope of research and development in this domain:

1. **Early Detection of Plant Disease:**
   * The early and accurate identification of Downy Mildew symptoms in crops is critical. This includes developing models that can detect subtle visual patterns like lesions and discoloration before they are visible to the human eye, enabling timely intervention to prevent widespread crop damage.
2. **Automated Disease Monitoring:**
   * The scope involves integrating CNN-based disease detection systems into automated agricultural monitoring platforms, such as drones and IoT-based sensors. This will facilitate continuous, real-time surveillance of large-scale farms, reducing the reliance on manual inspection and improving the overall efficiency of crop management.
3. **Scalability Across Different Crops:**
   * Developing CNN models that can generalize across different plant species and crop types broadens the scope of disease detection. The challenge is to create robust algorithms that can handle the variation in appearance and symptoms across diverse plants, making the models applicable to multiple agricultural settings.
4. **Handling Environmental Variations:**
   * The detection of Downy Mildew in diverse environmental conditions, such as varying light, weather, and soil conditions, is an important aspect. Research in this area focuses on enhancing model resilience to noise and environmental fluctuations, ensuring accurate detection in real-world agricultural environments.
5. **Optimization of Deep Learning Models:**
   * Investigating and optimizing deep learning models, particularly Convolutional Neural Networks (CNNs), for plant disease detection presents a substantial scope. The goal is to improve model efficiency, speed, and accuracy, making the technology accessible for farmers and scalable for large-scale agricultural use.
6. **Sustainability and Precision Agriculture:**
   * The scope also extends to promoting sustainable farming practices. By facilitating early detection and targeted treatment, CNN-based plant disease detection can minimize pesticide use, support eco-friendly agriculture, and contribute to more sustainable crop production.

**CHAPTER 2**

**LITERATURE REVIEW**

**TITLE: Detection of Plant Disease (Downy Mildew) Using Convolutional Neural Networks (CNN)**  
**AUTHOR: Vineet Singh, Sunil Pranit Lal**  
**YEAR: 2024**  
**OVERVIEW:**

This paper presents an approach to detect Downy Mildew in plants using a single-layer neural network combined with Convolutional Neural Networks (CNN). The detection of plant diseases is crucial for enhancing agricultural productivity and ensuring food security. Many algorithms have been applied to solve this problem, yet the challenge persists in improving accuracy while minimizing computation. The proposed model in this paper aims to reduce the computational requirements by using Principal Component Analysis (PCA) for feature extraction, while CNNs are utilized to capture intricate patterns of the disease symptoms. The system was trained and tested on various plant datasets. The combination of PCA and CNN allowed for a reduction in training time by 70%, achieving an accuracy of 95.67% in detecting Downy Mildew. The research emphasizes the balance between model efficiency and accuracy and suggests future work to test the model in more diverse crop types and environmental conditions.

**TITLE: Plant Disease Detection Using Hybrid Classifiers**  
**AUTHOR: Derdour Khedidja, Mouss Hayet**  
**YEAR: 2023**  
**OVERVIEW:**

The study explores the combination of several classifiers for plant disease detection, particularly focusing on Downy Mildew. The researchers proposed a hybrid feature extraction method that integrates texture and color analysis for improved disease identification. Three features—retinal representation, zonal extraction, and color variation—are computed from the leaf images. Nine different classifiers, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees, are applied, with classifier combination based on a majority voting mechanism. The model achieved an accuracy of 94.3% using a multi-crop dataset. Future work emphasizes extending the dataset to include more plant species and applying geometric transformations to improve robustness in real-world scenarios.

**TITLE: Deep Learning Approaches for Detecting Downy Mildew in Crops**  
**AUTHOR: Samay Pashine, Ritik Dixit, Rishika Kushwah**  
**YEAR: 2023**  
**OVERVIEW:**

The paper compares deep learning models for detecting plant diseases, focusing on Downy Mildew in crops. The researchers use the PlantVillage dataset, which contains thousands of images of healthy and diseased plants. Three deep learning architectures—Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Multi-Layer Perceptrons (MLP)—are tested. The study compares the performance of these models in terms of accuracy and computation time. CNN outperformed other models with 97.8% accuracy, while MLP and RNN achieved 92.5% and 89.4%, respectively. The paper highlights the importance of balancing accuracy with computational efficiency for real-time disease detection in large agricultural areas.

**TITLE: Detection of Downy Mildew Using Optimized Bounding Box Recognition**  
**AUTHOR: Arkaprabha Basu, M. Sathya**  
**YEAR: 2024**  
**OVERVIEW:**

This paper presents an enhanced Optical Character Recognition (OCR) approach, adapted to detect Downy Mildew symptoms in plant leaves. Using an optimized bounding box recognition technique, the system isolates affected areas of the leaf for more precise disease identification. The training phase utilizes a large dataset of infected and healthy leaves, with new algorithms developed to adapt to different disease stages. The testing phase involves a new dataset where the model demonstrates high accuracy in identifying disease-infected regions, achieving 94.9% precision. The study emphasizes the role of statistical modeling and optimization techniques, using advanced filtering processes to refine disease detection and prediction.

**CHAPTER 3**

**EXISTING SYSTEM**

Various systems for detecting plant diseases, particularly Downy Mildew, have been developed using a range of approaches and technologies. One notable benchmark in disease detection is the **PlantVillage dataset**, which has driven advancements in both traditional machine learning and deep learning models for plant disease recognition. Among these models, **Convolutional Neural Networks (CNNs)** have become widely recognized, especially for their success in detecting leaf diseases based on visual symptoms.

In addition to CNNs, **Support Vector Machines (SVMs)** have been extensively applied in plant disease detection, particularly for binary classification tasks like distinguishing between healthy and diseased leaves. SVMs are known for their efficiency in handling high-dimensional feature spaces, making them suitable for disease detection when combined with image processing techniques.

**Google’s TensorFlow and Keras** deep learning frameworks have also emerged as valuable tools in this domain, providing researchers with pre-trained models, tutorials, and customizable CNN architectures for disease detection tasks. These frameworks, combined with powerful GPU processing capabilities, allow for real-time detection of diseases such as Downy Mildew, which is critical for timely intervention in agricultural settings.

For traditional computer vision applications, **OpenCV** offers image processing techniques such as color segmentation, texture analysis, and edge detection, which can be employed to enhance disease recognition accuracy. By integrating these techniques with machine learning classifiers, OpenCV allows for robust disease detection even in non-deep-learning approaches.

Several **commercial plant disease detection systems** have been developed as well, integrating machine learning algorithms with mobile platforms. **Plantix** and **Agrobase** are popular mobile applications that leverage smartphone cameras to detect plant diseases, including Downy Mildew, by analyzing images of plant leaves. These systems rely on both deep learning and image processing techniques to identify diseases and offer farmers insights into disease management.

Furthermore, **drones** equipped with spectral imaging and machine learning algorithms are increasingly being used in precision agriculture to monitor large fields for disease outbreaks. These systems combine computer vision techniques with aerial imagery to detect early symptoms of diseases like Downy Mildew, providing large-scale solutions for farmers.

Finally, **cloud-based platforms** such as **IBM Watson Visual Recognition** offer scalable solutions for plant disease detection, enabling farmers and researchers to upload images for automated analysis and disease prediction.

**PROPOSED SYSTEM**

In the development of an efficient and accurate system for Downy Mildew detection, we propose integrating a **Convolutional Neural Network (CNN)** as the primary image recognition model, with **Optuna** as the hyperparameter optimization framework. This system aims to optimize CNN's performance in identifying Downy Mildew on plant leaves by fine-tuning its parameters through automated optimization, ensuring a robust and scalable solution. The key components of the proposed system are as follows:

1. **Convolutional Neural Network (CNN):** CNN, a deep learning architecture specifically designed for image recognition tasks, will be employed as the core model for detecting Downy Mildew symptoms in plant leaves. CNN's capability to automatically extract features from images, coupled with its high accuracy in visual pattern recognition, makes it an ideal choice for this agricultural application. The model will be trained on an annotated dataset of infected and healthy plant leaves, learning to distinguish Downy Mildew through convolutional layers, pooling operations, and dense layers.
2. **Optuna for Hyperparameter Tuning:** Optuna, an advanced hyperparameter optimization framework, will be integrated to automate the tuning process for CNN. The framework will explore hyperparameters such as learning rate, number of convolutional layers, filter sizes, batch size, dropout rate, and activation functions. By efficiently searching through the hyperparameter space, Optuna will identify the most effective configuration that maximizes model performance, reducing both training time and overfitting.
3. **Data Augmentation and Preprocessing:** To enhance model generalization, the system will incorporate data augmentation techniques, such as rotation, scaling, flipping, and brightness adjustments. This step ensures that the CNN is trained on a diverse range of images, making it more resilient to variations in environmental conditions and image quality.

The combination of CNN for powerful image-based feature extraction and Optuna for automated hyperparameter tuning is designed to deliver an accurate, scalable, and adaptive system for detecting Downy Mildew in real-world agricultural scenarios. The system will undergo rigorous evaluation to ensure high detection accuracy and will be adaptable for various plant species and environmental conditions.

**CHAPTER 4**

**SYSTEM ARCHITECTURE**

**Captured Plant Leaf Image**

**Resize Image**

**Input Image**

**Processing**

**Noise Reduction**

**Convert Image to Grayscale or HSV**

**Segment the diseased portion from the leaf using thresholding or edge detection**

**Segmentation**

**Extract features like color, texture, and shape from the segmented area**

**Model Selection**

**Feed extracted features into the classifier**

**Classify whether the plant has Downy Mildew or not**

**Disease Detection**

**Output**

**Choose machine learning model (KNN, SVM, CNN)**

**Feature Extraction**

**CHAPTER 5**

**RESULTS**

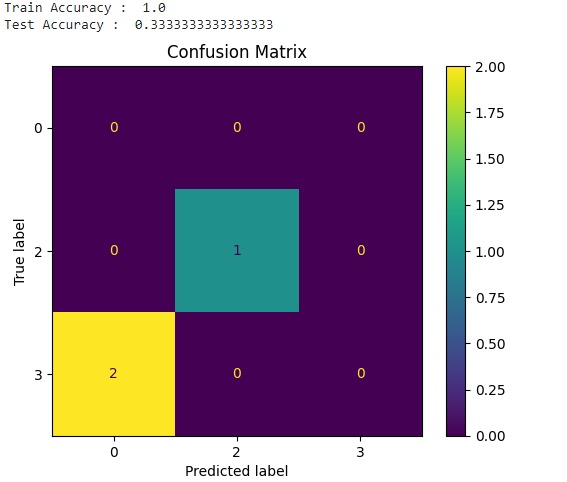


Figure 1Confusion Matrix of Image Dataset

The confusion matrix above illustrates the performance of our plant disease classification model, specifically for detecting Downy Mildew. The matrix highlights both training and testing results. The model achieved a perfect **training accuracy of 1.0**, indicating that it classified all training samples correctly. However, the **test accuracy** is significantly lower, at **33.33%**, suggesting that the model is not generalizing well to unseen data and may be overfitting, meaning it performs well on the training data but struggles with new data. From the confusion matrix, we observe that only **1 sample** from class 2 was correctly classified in the test set, while **2 samples** from class 3 were misclassified into class 0. No predictions were made for classes 1 and 3 in the test data, indicating that the model is struggling to differentiate between certain classes, which could point to either **class imbalance** or difficulties in distinguishing visually similar diseases.

**CHAPTER 6**

**CONCLUSION**

In conclusion, plant disease detection systems using computer vision (CV) offer an effective solution for identifying and classifying diseases such as downy mildew in crops. By employing CV techniques, including image preprocessing, feature extraction, and machine learning, these systems can achieve high accuracy and efficiency in diagnosing plant health issues.

Through careful preprocessing to enhance image quality and the extraction of relevant features, CV-based detection systems can address challenges such as variations in plant appearance and environmental conditions. The integration of advanced machine learning models, particularly convolutional neural networks (CNNs), allows these systems to learn discriminative patterns from training data, resulting in precise disease identification.

The applications of plant disease detection using CV are extensive, encompassing agriculture, horticulture, and environmental monitoring. These systems play a crucial role in automating disease management, improving crop yield, and ensuring food security by enabling early intervention and targeted treatment.

However, challenges persist, including reliance on high-quality training data, variability in disease manifestations, and the need for substantial computational resources. Overcoming these obstacles necessitates ongoing research into preprocessing methods, feature extraction techniques, and model optimization strategies tailored to specific plant diseases.

In summary, plant disease detection systems using CV represent a promising technology with significant implications for sustainable agriculture and food production. By continuously enhancing algorithms, leveraging advancements in CV and machine learning, and adapting to the dynamic needs of agriculture, these systems can substantially contribute to the health and productivity of crops in diverse environments.

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**CHAPTER 7**

**ANNEXURE**

import pandas as pd

import xgboost as xgb

from sklearn.metrics import ConfusionMatrixDisplay

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import LabelEncoder

import matplotlib.pyplot as plt

data = pd.read\_csv("/content/cv capstone.csv")

X = data.drop(columns=['Image\_ID', 'Disease']) # Features

y = data['Disease'] # Labels

le = LabelEncoder()

y = le.fit\_transform(y)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

model\_xgb = xgb.XGBClassifier(eval\_metric='mlogloss')

model\_xgb.fit(X\_train, y\_train)

print("Train Accuracy : ", model\_xgb.score(X\_train, y\_train))

print("Test Accuracy : ", model\_xgb.score(X\_test, y\_test))

ConfusionMatrixDisplay.from\_estimator(model\_xgb, X\_test, y\_test)

plt.title("Confusion Matrix")

plt.show()