Classification of Wilt Disease with an MLP Approach

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Abstract: **The MLP-based Wilt Disease Classifier is a Deep learning system designed to detect wilt disease in plants using a Multilayer Perceptron (MLP) neural network. Wilt disease, caused by various pathogens, significantly affects crop yield, making early detection crucial for effective intervention. This classifier processes input features such as environmental factors and plant health indicators to accurately predict the presence of wilt. The MLP model, with its multiple layers of interconnected neurons, is trained on a dataset of infected and healthy plants, learning patterns that distinguish disease symptoms. The classifier's performance is evaluated based on accuracy, precision, recall, and F1 score, demonstrating its potential as a reliable tool for farmers and agricultural experts to mitigate crop losses through timely diagnosis.**

Keywords: **Crop Images, Deep learning, CNN**

I. INTRODUCTION

Wilt diseases, caused by various pathogens, represent a significant challenge in agriculture due to their ability to rapidly affect plant health and reduce crop yields. Wilt disease is a severe fungal infection that affects trees, leading to extensive ecological and economic damage.

Early detection is crucial to controlling its spread, but traditional methods relying on manual inspections are time-consuming and expensive. With advancements in artificial intelligence, deep learning models like Convolutional Neural Networks (CNNs) combined with Multi-Layer Perceptron's (MLPs) offer a promising solution for automating disease classification.

CNNs are well-suited for extracting visual features from images, identifying patterns like color changes and leaf deformation associated with oak wilt. By integrating an MLP, which takes the features learned by the CNN to perform classification, this model achieves accurate detection of infected trees. A key aspect of this approach is its focus on sustainability, where techniques like model compression and pruning are employed to reduce computational overhead.

II. MOTIVATION

To enhancing food security, promoting sustainable agriculture, and empowering farmers with effective disease management tools. Wilt disease is a critical threat to tree populations, causing widespread damage to forests and ecosystems. Early and accurate detection of this disease is essential for managing its spread and reducing its impact. The growing availability of aerial and ground-based imagery offers an opportunity to leverage image-based machine learning techniques for faster and more accurate disease detection. Convolutional Neural Networks (CNNs), known for their powerful image-processing capabilities, can automatically identify visual features related to wilt, such as leaf discoloration and deformities, without the need for manual feature engineering.

III. LITERATURE SURVEY

[1] A Remote Sensing and Airborne Edge-Computing Based Detection System for Pine Wilt Disease. Et Al. Fengdi Li, Zhenyu Liu, Weixing Shen. The Pine Wilt Disease (PWD) is one of the most dangerous and destructive diseases affecting coniferous forests. The rapid spread and significant destruction it causes directly threaten forest security. The complex spread patterns and labor-intensive diagnosis process necessitate an effective method for detecting infected areas. This paper presents an airborne edge-computing and lightweight deep learning-based system designed for PWD detection using imagery sensors. Unmanned Aerial Vehicles (UAVs) are first utilized to achieve large-scale forest coverage, substantially reducing labor requirements. In addition to infected trees, a considerable number of irrelevant images are also acquired by the UAV, which overloads processing and transmission burdens. Subsequently, a lightweight improved YOLOv4-Tiny-based method (named as YOLOv4-Tiny-3Layers) is proposed to filter these irrelevant images by leveraging the computational capabilities of edge computing, enabling fast coarse-grained detection with a low missing rate. Finally, all

remaining images are transmitted to the ground workstation for detailed fine-grained detection. Experimental results demonstrate that the proposed system can perform rapid detection with superior performance compared to other methods, facilitating quick identification of infected pine trees.

[2] Deep Learning Meets Support Vector Machines: An Effective Hybrid Model for Banana Leaf Wilt Disease Severity Assessment. Et Al. Manish Kumar, Anuj Kumar. Bananas are grown worldwide as a staple crop, significantly contributing to the economy. However, diseases like Banana Leaf Wilt pose serious threats that, if left unchecked, can lead to devastating crop losses. This study introduces a novel method to address this issue by creating a model that combines features of both a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM). Our model utilizes Deep Learning (DL) to classify the severity of Banana Leaf Wilt, enabling farmers to take preventative measures as soon as the disease is detected. We began by compiling a large dataset of banana leaf images, labeled by domain experts according to severity. The quality and diversity of the dataset were ensured through data preprocessing and augmentation strategies. The selected pretrained CNN architecture serves as the feature extractor, capturing subtle patterns highly predictive of disease severity. Our hybrid model achieved an overall accuracy of 94.77% and provided sophisticated assessments of disease progression. To offer farmers precise insights regarding their crops' conditions, performance parameters such as precision, recall, and F1-score were calculated for each severity level. Additionally, comparisons with state-of-the-art models in the field confirmed the model's superiority, reaffirming its potential as a transformative tool for disease severity classification.

[3] A Multi-Agent System for Modelling the Spread of Lethal Wilt in Oil-Palm Plantations. Et Al. Conor Fahy, Fabio Caraffini, Mario Gongora. Lethal Wilt (Marchitez Letal) is a disease affecting Elaeis Guineensis, a plant used in palm oil production. The disease is increasingly prevalent, yet the spatial dynamics of its spread remain poorly understood. It is particularly dangerous due to the rapidity with which it spreads and the swift onset of symptoms in infected plants. Early identification, or ideally, accurate prediction of high-risk areas can slow the disease's spread and reduce crop waste. This study analyzes data collected over five years from an affected plantation in Colombia. The goal is to analyze the collected data to better understand the disease's spread and model its behavior. Based on insights from the initial analysis, a multi-agent-based system is proposed to model the infection pattern. The model comprises two steps: first, Kernel Density Estimation is used to create an estimation of the distribution from which newly infected plants are drawn, and this density estimation directs agents on a biased walk through the surrounding areas. Results indicate that the model can approximate the disease's behavior and predict areas at high risk for future infection.

[4] Detection of Fusarium Wilt on Phalaenopsis Stem Base Region Using Band Selection Techniques. Et Al. Meng-Chueh Lee, Kenneth-Yeonkong Ma, Yen-Chieh Ouyang. Phalaenopsis is a significant agricultural product with high economic value in Taiwan. However, Fusarium Wilt causes Phalaenopsis leaves to turn yellow, thin, lose water, and eventually die. This paper presents an emerging method for detecting Fusarium Wilt on the Phalaenopsis stem base. To build the detection models, hyperspectral databases are generated from two states of Phalaenopsis samples: healthy and diseased. We applied band selection (BS) processing based on Band Prioritization (BP) and Band Decorrelation (BD) to extract significant bands and eliminate redundant ones. Subsequently, three algorithms were employed: Orthogonal Subspace Projection (OSP), Constrained Energy Minimization (CEM), and Support Vector Machine (SVM) to detect Fusarium Wilt.

IV. GAP ANALYSIS

This lack of specialized models means that the unique visual characteristics of wilt disease are not being effectively addressed, limiting the accuracy of detection and identification. Existing deep learning models often focus on generic plant diseases, which do not capture the subtle, unique markers of wilt disease. As a result, current models may overlook specific features, leading to reduced precision and higher rates of false negatives. Additionally, while many models prioritize high performance and accuracy, they rarely account for the need for sustainability, particularly in terms of computational efficiency. High performance models tend to have elevated computational requirements, which limits their suitability for deployment in resource-constrained environments like forests or remote agricultural areas. Devices such as drones or edge computing units that operate in these environments often have limited battery capacity, making energy efficiency a critical factor. Furthermore, these models' high energy consumption rates pose a challenge for prolonged or large-scale monitoring efforts. Consequently, the gap in developing sustainable models that can balance accuracy with lower energy demands remains largely unaddressed, impacting the practical feasibility of widespread adoption in field conditions. The need for advanced yet sustainable detection models that cater to both specific visual characteristics of wilt disease and environmental constraints is essential for impactful deployment.

V. PROPOSED SYSTEM

The proposed system for a multilayer perceptron (MLP)-based wilt disease classifier uses Convolutional Neural Networks (CNNs) to detect and classify wilt disease in plants. It comprises an input layer, multiple hidden layers, and an output layer, with interconnected neurons in each layer. The input layer receives data, such as color, texture, and shape features from plant images. As data passes through the hidden layers, weights are adjusted using activation functions like ReLU or sigmoid to refine the classification. The training process utilizes labeled data, where the backpropagation algorithm minimizes errors by updating weights. The output layer indicates whether a plant is healthy or infected. This MLP-based system effectively generalizes and recognizes patterns from complex data, enabling accurate wilt disease identification under varying conditions.

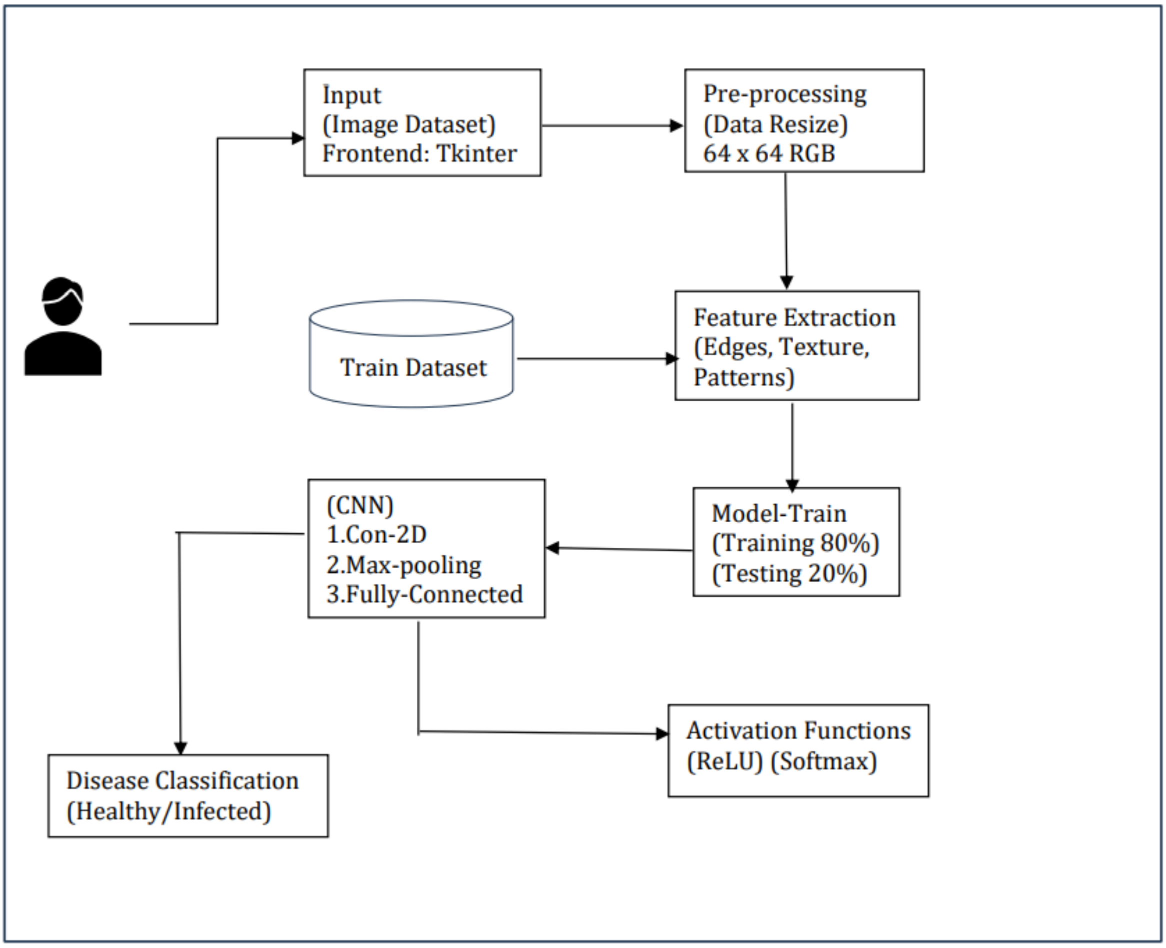

Fig. System Architecture Diagram

This system architecture is designed for disease classification using a CNN (Convolutional Neural Network). The process begins with an image dataset, with input handled by a Tkinter- based frontend. Images are pre-processed by resizing them to 64x64 RGB, followed by feature extraction of edges, textures, and patterns. The dataset is split, with 80% for training and 20% for testing. The CNN consists of Convolutional layers (Con-2D) for feature detection, Max- pooling for down- sampling, and Fullyconnected layers for classification. ReLU activation functions introduce non- linearity, while Softmax provides probabilities for classification. Finally, the model predicts the health status of the input images, categorizing them as either Healthy or Infected.

VI. CONCLUSION

The proposed hybrid model significantly improved classification accuracy by leveraging the feature extraction capabilities of CNNs and the pattern recognition strengths of Multi-Layer Perceptron's. This approach not only enhanced diagnostic performance but also addressed sustainability by optimizing computational efficiency and resource use. The model's ability to deliver rapid and precise disease detection has practical implications for early intervention and management of Oak Wilt, potentially reducing its impact on oak forests. Future research should aim to refine the model further and explore its application to other plant diseases, ensuring its adaptability and effectiveness in various agricultural and environmental contexts.

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