

Multi-Class Grapevine Disease Detection Using Convolutional Neural Networks with RAG-Based Knowledge Integration

Bindushree S^{1*}, Keerthi Vardhan M², Hema E³

Rakshitha S⁴, Vani V⁵

²UG students, Department of Computer Science and Engineering, BGS College of

³Engineering and Technology, VTU, Bengaluru, Karnataka, India

⁴Associate Professor, Department of Computer Science and Engineering, BGS College of

⁵Engineering and Technology, VTU, Bengaluru, Karnataka, India

^{1*}Corresponding Author: 1mp24cs400@gmail.com

Abstract

Grape downy mildew, caused by the oomycete pathogen *Plasmopara viticola*, is one of the most devastating fungal-like diseases affecting vineyards worldwide. Early and accurate detection of this disease is critical to minimize crop losses and reduce excessive pesticide use. In this study, we propose a hybrid deep learning framework that combines Convolutional Neural Networks (CNN) for visual feature extraction from grape leaf images with a Large Language Model (LLM) for semantic interpretation and decision-level reasoning. A real-world dataset of grape leaf images was collected directly from vineyards at Gandhi Krishi Vigyan Kendra (GKVK), Bengaluru, encompassing both healthy and downy mildew-infected samples under diverse field conditions. The CNN module extracts spatial and textural disease features from raw leaf images, while the LLM component provides contextual reasoning and generates human-readable diagnostic outputs. This integrated approach not only improves classification accuracy but also enhances interpretability, making the system practical for deployment in agricultural settings. Experimental evaluations are currently in progress, and preliminary results indicate the proposed framework holds significant promise for automated plant disease detection in real-world agricultural environments.

Keywords— Grape Downy Mildew, Plant Disease Detection, Convolutional Neural Network, Large Language Model, Deep Learning, GKVK Dataset, Image Classification, Precision Agriculture, viticulture.

1. Introduction

Agriculture plays a vital role in the Indian economy, and viticulture — the science, study and practice of cultivation of grapes — represents a significant segment of the horticultural sector. India ranks among the top grape-producing nations globally, with Karnataka being one of the major contributing states. However, grape cultivation is severely threatened by

Grape downy mildew, caused by *Plasmopara viticola*, manifests as yellowish-green oil spots

on the upper leaf surface and a characteristic white cottony growth on the underside. If left undetected, this disease can cause yield losses of up to 75% in a single growing season. Traditional disease management relies on manual scouting by agronomists, which is labour-intensive, time-consuming, and prone to human error, particularly in large-scale vineyards.

The rapid advancement of artificial intelligence and computer vision has

opened new avenues for automated crop disease detection. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification tasks including plant disease identification. More recently, Large Language Models (LLMs) have emerged as powerful tools capable of natural language reasoning and contextual understanding, adding a layer of explainability that is critical for agricultural end-users such as farmers and extension workers.

In this work, we present a novel hybrid framework that integrates CNN-based visual feature extraction with LLM-driven semantic reasoning for the detection of grape downy mildew. The dataset used in this study was collected from real vineyard fields at Gandhi Krishi Vigyan Kendra (GKVK), Bengaluru — a premier agricultural research institution — ensuring that the data reflects authentic field conditions including varying lighting, angles, and disease severities.

The primary objectives of this study are: (i) to collect and curate a real-world grape leaf image dataset from GKVK, (ii) to develop a CNN model capable of extracting discriminative disease features, (iii) to integrate an LLM for contextual reasoning and diagnostic explanation generation, and (iv) to evaluate the combined framework's performance under real-world conditions.



2. Related Work

Significant research has been conducted on automated plant disease detection using machine learning and deep learning techniques. Mohanty et al. [1] demonstrated that deep convolutional

neural networks trained on the plant diseases under controlled conditions. However, performance drops considerably when models are evaluated on real-world field images due to variability in background, lighting, and disease stage.

Ferentinos [2] explored various CNN architectures including AlexNet and GoogLeNet for plant disease classification and reported high accuracy under laboratory settings. Similarly, Tm et al. [3] applied transfer learning using pre-trained VGG16 and ResNet models for grape disease identification, showing that fine-tuned models significantly outperform training from scratch on limited agricultural datasets.

For grape-specific diseases, Jha et al. [4] proposed a lightweight CNN model for detecting black rot, Esca, and downy mildew in grape leaves. Their work highlighted the challenge of differentiating diseases with overlapping visual symptoms. Kaya et al. [5] used data augmentation strategies to improve model robustness on small datasets, which is highly relevant given the limited availability of labeled disease images in specific regional settings.

The integration of language models with vision systems, often referred to as Vision-Language Models (VLMs), represents an emerging frontier. OpenAI's GPT-4V and models such as LLaVA [6] have demonstrated the ability to interpret visual inputs and generate descriptive textual outputs, enabling not just classification but contextualized explanations. Such capabilities are particularly valuable in agriculture, where end-users benefit more from actionable diagnostic information than from mere class labels.

Despite these advances, no prior work has specifically combined CNN feature extraction with LLM reasoning for grape downy mildew detection using field-collected data from Indian agricultural research stations. This study addresses this gap by leveraging a real-world dataset from GKVK, Bengaluru, and proposing an integrated CNN-LLM pipeline.

3. Materials and Methods

3.1 Dataset Collection

The dataset used in this study was collected from the experimental vineyards at Gandhi Krishi

Vigyan Kendra (GKVK), University of Agricultural Sciences, Bengaluru, Karnataka, India. Field visits were conducted across multiple sessions during the grape growing season to capture images at varying stages of disease progression. Images were captured using smartphones with 12MP cameras under natural outdoor lighting conditions, resulting in a diverse and representative collection.

The dataset comprises two primary classes: (i) Healthy grape leaves and (ii) Grape leaves infected with downy mildew. Images were captured from multiple leaf surfaces, angles, and under different ambient light conditions to ensure dataset diversity. All collected images were reviewed and annotated in consultation with plant pathology experts at GKVK to ensure labeling accuracy.

3.2 Data Preprocessing

All images were resized to a uniform resolution of 224×224 pixels to conform to standard CNN input requirements. Data augmentation techniques were applied to increase dataset size and improve model generalization. Augmentation operations included random horizontal and vertical flipping, rotation (up to ±30 degrees), brightness and contrast adjustments, and Gaussian noise addition. Image normalization was performed using ImageNet mean and standard deviation values. The dataset was split into training (70%), validation (15%), and testing (15%) subsets using stratified sampling to maintain class balance.

3.3 CNN Architecture

The visual feature extraction module is based on a pre-trained ResNet-50 architecture fine-tuned on the grape leaf dataset. ResNet-50 was selected for its proven performance on agricultural image classification tasks and its ability to capture multi-scale spatial features through residual connections. The final fully connected layer was replaced with a custom classification head consisting of a dropout layer ($p=0.5$) followed by a dense layer with softmax activation for binary classification. Training was performed using the Adam optimizer with an initial learning rate of 0.0001, and categorical cross-entropy was used as the loss function.

3.4 LLM Integration

The LLM component serves a dual purpose in the proposed framework: (i) receiving the CNN's extracted feature representations and predicted class probabilities, and (ii) generating a structured natural language diagnostic report. A prompt engineering strategy was employed to pass disease prediction confidence scores, leaf condition descriptors, and contextual metadata (such as crop variety and season) as input to the LLM. The LLM then generates a comprehensive textual diagnosis including probable cause, severity estimation, and recommended management actions.

This design ensures that the system is not only accurate but also interpretable and actionable for farmers and agricultural extension officers who may not be familiar with AI classification outputs.

3.5 System Architecture

The overall pipeline operates as follows: (1) A grape leaf image is captured in the field; (2) the image is preprocessed and passed through the fine-tuned ResNet-50 CNN, which outputs a class prediction and associated confidence score;

(3) these outputs along with image metadata are structured into a prompt; (4) the prompt is fed to the LLM, which generates a diagnostic report; and (5) the final output is presented to the user in both structured and natural language form.



The experimental evaluation of the proposed CNN-LLM hybrid framework is currently in

progress. Preliminary tests conducted on a subset of the GKVK dataset have demonstrated the system's ability to correctly distinguish between healthy and downy mildew-infected leaves across varying field conditions. The ResNet-50 CNN component has shown strong feature discrimination capability, particularly in identifying the characteristic yellowish lesions and white sporulation patterns associated with downy mildew infection.

Table 1 presents a summary of the preliminary performance metrics obtained during initial testing phases. Final metrics will be reported upon completion of full-scale experimental evaluation.

A key observation from preliminary testing is that the LLM integration significantly enhances the output interpretability. While the CNN alone provides a binary classification output, the combined CNN-LLM system produces a structured diagnostic report specifying the disease name, estimated severity level, likely causal factors based on visual symptoms, and recommended agrochemical or cultural control measures. This level of output is directly actionable by farmers without requiring intermediate technical interpretation.

The use of real-world data from GKVK introduces realistic challenges such as image blur, partial leaf occlusion, shadows, and mixed healthy-diseased regions within a single leaf. These complexities reflect actual field conditions and provide a more rigorous evaluation environment compared to controlled laboratory datasets. The model's ability to handle such variability will be a key determinant of its practical applicability.

5. Conclusion

This paper presents a hybrid CNN-LLM framework for the detection of grape downy mildew disease using real-world leaf images collected from the vineyards at Gandhi Krishi Vigyan Kendra (GKVK), Bengaluru. The proposed approach leverages the spatial feature extraction capabilities of a fine-tuned ResNet-50 CNN combined with the contextual reasoning and natural language generation capabilities of a Large Language Model to produce accurate, interpretable, and actionable disease diagnoses.

The use of a real-world dataset ensures that the system is evaluated under genuine field conditions, making the results more representative of actual deployment scenarios. The integration of LLM-generated diagnostic reports addresses a critical gap in existing plant disease detection systems — the lack of human-readable, actionable output for non-technical end-users such as farmers and field extension workers.

Experimental evaluation is currently ongoing, and full performance metrics will be reported in the final version of this paper. Future work will explore multi-class disease detection extending beyond downy mildew to include other common grape diseases such as powdery mildew and black rot. Additionally, the framework will be optimized for deployment on mobile devices to enable in-field real-time diagnosis, further enhancing its practical utility for the Indian viticulture sector.

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