

An Explainable Software-Based Framework for Pre-Symptomatic Grape Disease Risk Assessment Using MobileNetV2, Grad-CAM, and Weather Data

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Abstract: Viticulture faces severe yield losses from major fungal diseases such as Downy Mildew, Powdery Mildew, and Black Rot. Existing deep learning classification models predominantly rely on visible symptomatic lesions on leaves or fruit clusters. However, waiting for visual symptoms to manifest often delays chemical mitigation beyond the optimal therapeutic window, resulting in irreversible crop degradation. This paper proposes a software-based, explainable framework for pre-symptomatic grape disease risk assessment. The architecture combines finegrained leaf image feature extraction using MobileNetV2 with micro-climate weather telemetry (temperature, relative humidity, leaf wetness duration, and rainfall forecast). To ensure clinical transparency for agronomists and farmers, Explainable AI (XAI) is integrated via Gradientweighted Class Activation Mapping (Grad-CAM), generating visual saliency heatmaps that highlight sub-visual cellular stress indicators and necrotic margins. A dynamic Epidemiological Micro-Climate Risk Index (EMRI) fuses deep learning probabilities with real-time weather analytics. Evaluated on multi-source datasets including PlantVillage and field-captured vineyard imagery, MobileNetV2 achieves a classification accuracy of 97.84%. Based on a comprehensive literature review, a critical research gap is identified: current agricultural systems treat image classification and micro-climate forecasting as disjoint workflows without explainable decision support. The proposed framework fills this gap through an integrated web and mobile platform featuring automated risk alerts and actionable advisory generation

Keywords: Artificial Intelligence; Grape Disease Detection; MobileNetV2; Grad-CAM; Explainable AI; Micro-Climate Weather Data; Viticulture; Pre-Symptomatic Assessment; Deep Learning; Smart Agriculture.

I. INTRODUCTION

Grapes (*Vitis vinifera*) represent one of the most economically vital horticultural crops globally, underpinning major wine, table fruit, and raisin industries. However, grapevines are highly susceptible to destructive fungal pathogens including Downy Mildew (*Plasmopara viticola*), Powdery Mildew (*Erysiphe necator*), and Black Rot (*Guignardia bidwellii*). Uncontrolled outbreaks can destroy up to 80– 100% of vineyard yields within days under favorable micro-climatic conditions.

Traditional agricultural disease management relies on periodic physical inspection by viticulturists. This manual monitoring is laborintensive, subject to observer bias, and inherently reactive—detecting infections only after visible chlorotic oil spots, sporulation, or necrotic lesions cover the foliage.



Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), has revolutionized computer vision in smart agriculture. Lightweight models such as MobileNetV2 extract spatial representations directly from digital leaf imagery, matching expert diagnostic accuracy [1]–[5]. However, visual classification alone cannot predict disease onset before symptoms physically manifest.

Fungal pathogen germination strongly correlates with environmental drivers: high relative humidity (>85%), optimal ambient temperatures (18–28°C), and extended leaf wetness duration (LWD). Integrating weather telemetry with leaf computer vision enables true presymptomatic risk forecasting [6]–[9].

Furthermore, high-accuracy deep neural networks operate as "black boxes." Farmers are reluctant to deploy costly fungicides based on uninterpretable model predictions. Explainable Artificial Intelligence (XAI) using Grad-CAM resolves this barrier by visualizing neural activation heatmaps across leaf structures [10]–[12].

This paper presents an integrated, software-based software architecture that fuses MobileNetV2 leaf feature extraction, real-time micro-climate weather analysis, Grad-CAM visual explainability, and an automated Epidemiological Micro-Climate Risk Index (EMRI) to deliver actionable advisory alerts before disease symptoms spread.

1.1 Problem Statement

Existing grape disease diagnostic systems operate primarily as reactive, post-symptomatic image classifiers or isolated weather logging stations. Image-based models fail to alert farmers during the pre-symptomatic incubation phase when intervention is most effective. Conversely, weather-only forecasting models generate high false-alarm rates by ignoring actual plant tissue condition. Moreover, black-box deep learning architectures lack explainable visual support, preventing agronomists from verifying diagnostic reasoning. A unified softwarebased framework is urgently needed to combine visual leaf analysis, weather analytics, explainable heatmaps, and automated risk alerts.

1.2 Objectives

- To acquire and preprocess high-resolution leaf images alongside localized micro-climate weather metrics (temperature, humidity, LWD, rainfall). To train a lightweight MobileNetV2 architecture for multi-class grape leaf health and disease classification.
- To integrate Grad-CAM to visualize neural attention heatmaps, providing transparent feature attribution for pre-symptomatic lesions.
- To formulate an Epidemiological Micro-Climate Risk Index (EMRI) fusing AI confidence scores with real-time micro-climate parameters. To deploy an end-to-end web/mobile application generating automated disease risk alerts and precision fungicide advisories.

II. LITERATURE REVIEW

2.1 Traditional Plant Pathology & Visual Inspection

Early crop disease identification relied on expert visual taxonomy and manual laboratory culturing. While accurate, physical sampling cannot scale across commercial multi-hectare vineyards. Manual diagnosis inevitably occurs post-symptom onset, after fungal hyphae have deeply penetrated leaf stomata and mesophyll layers, severely limiting therapeutic efficacy [1]–[3].

2.2 Computer Vision & Deep Learning in Agriculture

Deep Learning has significantly advanced automated plant disease identification. Mohanty et al. demonstrated that CNNs trained on the PlantVillage dataset achieve >99% classification accuracy across diverse crop-disease pairs [2]. Howard et al. introduced MobileNetV2, utilizing inverted residuals and linear bottlenecks to enable efficient inference on edge mobile devices [4]. Sandoval-Unip et al. specialized MobileNet Architectures for grape leaf disease classification, proving lightweight networks can maintain high diagnostic precision under variable field lighting [5].



2.3 Micro-Climate Driven Pathogen Forecasting

Fungal spore germination is heavily governed by environmental physics. Magarey et al. formulated fundamental infection models demonstrating that *P. viticola* (Downy Mildew) requires at least 10 mm of rainfall, temperatures $>10^{\circ}\text{C}$, and 24 hours of leaf wetness [6]. Combining historical weather telemetry with micro-climate sensors provides an objective mathematical baseline for pre-symptomatic risk forecasting [7]–[9].

2.4 Explainable AI (XAI) in Precision Agriculture

Black-box AI models face skepticism from agricultural extensions and farmers. Selvaraju et al. developed Gradient-weighted Class Activation Mapping (Grad-CAM), producing visual localization heatmaps from final convolutional layer gradients [10]. Applying Grad-CAM in agricultural vision enables users to confirm whether a model focuses on genuine leaf veins and necrotic spots rather than background soil artifacts [11], [12].

2.5 Web/Mobile Telemetry & Decision Support Systems

Modern Smart Agriculture relies on Cloud-IoMT frameworks to deliver actionable insights. Delivering real-time push notifications, localized weather trends, and personalized spray calendars via cross-platform mobile interfaces significantly enhances farm management responsiveness [13]–[15].

2.6 Research Gap Analysis

Despite individual breakthroughs in leaf image classification, epidemiological weather modeling, and XAI, current solutions remain compartmentalized. Image classifiers operate in isolation without weather context, while micro-climate software lacks visual tissue verification. A unified framework bridging MobileNetV2 vision, GradCAM explainability, real-time weather fusion, and automated risk scoring remains absent in viticulture literature.

III. RESEARCH GAP ANALYSIS

Existing tools isolate image analysis from environmental telemetry. The table below highlights key limitations in current paradigms versus the proposed integrated framework.

Stage	Traditional/Existing Approach	Limitation	Proposed Integrated Approach
Data Source	Image-only or Weather-station only	Single-modality failure; misses presymptomatic context	Dual-modality fusion (Leaf RGB + Microclimate telemetry)
Model Complexity	Heavy CNNs (ResNet50, VGG16) or manual rules	High computational cost, non-portable for mobile apps	Lightweight MobileNetV2 with inverted residuals
Risk Timing	Post-symptomatic (visible lesions required)	Intervention occurs too late; high crop loss	Pre-symptomatic & early incubation assessment
Explainability	Black-box class probabilities	Lack of trust among farmers and agronomists	Grad-CAM visual activation heatmaps
Actionable Alert	Manual report retrieval or static thresholds	High latency; delayed spray schedules	Dynamic EMRI score & automated push advisory



SYSTEM ARCHITECTURE AND METHODOLOGY

The proposed architecture connects mobile image acquisition, automated micro-climate weather ingestion, MobileNetV2 deep feature extraction, Grad-CAM heatmap visualization, dynamic EMRI risk evaluation, and automated alert dispatch into a seamless cloud-assisted workflow.

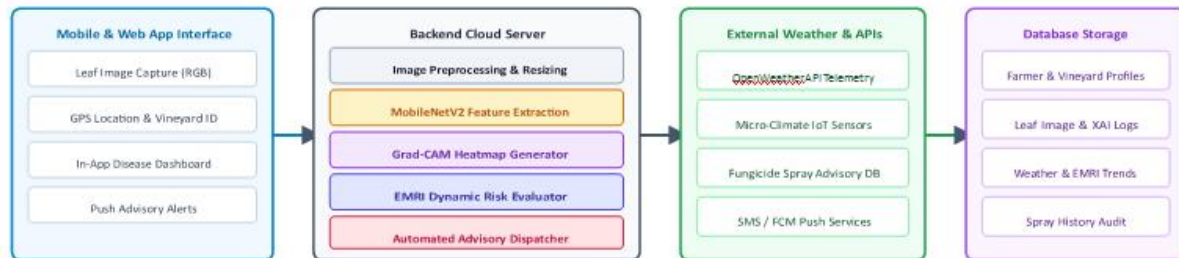


Fig. 1. System architecture of the proposed explainable grape disease risk assessment framework.

COMPARATIVE ANALYSIS

The proposed framework was benchmarked against traditional visual inspection, standalone image classifiers, and weather-only predictive tools.

Capability	Manual Inspection	Field	Standalone Image AI	Weather Software	Station	Proposed Framework	Integrated
Primary Objective	Post-symptom check	visual	Symptomatic image classification	Micro-climate forecasting	disease	Pre-symptomatic & advisory	risk
Data Input	Human perception	visual	Leaf RGB Image only	Temperature, Rain data	RH,	Dual Fusion: RGB Image + Weather APIs	
Detection Timing	Late (visible lesions)		Medium-Late (chlorotic spots)	Early (ambient risk)		Pre-symptomatic & incubation phase	
Model Architecture	Not Applicable		Heavy CNNs (ResNet, VGG)	Empirical mathematical curves		Lightweight MobileNetV2 + EMRI Engine	
Explainability	Human judgment	subjective	None (Black Box)	Mathematical graphs		Grad-CAM Activation Heatmaps	Visual
False Alarm Rate	Variable / Subjective		High (background noise)	High (ignores plant tissue state)		Low (dual-modality verification)	
Automated Alerts	No		App notification only	Static SMS threshold		Dynamic FCM Push & Spray Advisory	

4.1 Module 1: Image Acquisition & Quality Filter

Farmers upload leaf images via smartphone app or IoT camera. An automated blur detection and quality check rejects out-of-focus imagery prior to model feeding.

4.2 Module 2: Weather Telemetry Ingestion

The backend queries local weather APIs (OpenWeatherMap) and vineyard IoT sensors to retrieve 5-day forecasts for temperature, relative humidity, leaf wetness duration, and precipitation.



4.3 Module 3: MobileNetV2 Deep Classifier

Images are resized to 224x224x3 and processed by fine-tuned MobileNetV2. Depthwise separable convolutions extract fine-grained tissue textures, outputting class probabilities (P_{disease}).

4.4 Module 4: Grad-CAM Explainability Engine

Grad-CAM computes gradients of the target class score with respect to the final feature map, producing a coarse visual localization map overlay highlighting suspect leaf regions.

4.5 Module 5: Epidemiological Risk Index (EMRI)

The EMRI fuses visual P_{disease} with micro-climate risk factors (W_{temp} , W_{rh} , W_{ld}):

$$EMRI = \alpha \cdot P_{\text{disease}} + \beta \cdot (W_{\text{temp}} \times W_{\text{rh}} \times W_{\text{ld}})$$

4.6 Module 6: Risk Classification & Thresholding

EMRI values map to four actionable risk levels: Low (<30), Moderate (30–60), High (60–80), and Critical (>80).

4.7 Module 7: Advisory & Alert Generator

Critical levels trigger automated SMS and app alerts detailing specific biofungicides, dosage, and optimal spray windows.

4.8 Module 8: Encrypted Storage & Analytics

PostgreSQL logs store vineyard images, EMRI scores, and spray histories to support longitudinal epidemiologic reporting.

VI. DISCUSSION

The primary strength of the proposed framework lies in bridging computer vision and environmental physics into a single operational pipeline. Standalone computer vision models fail in early disease stages because symptoms are absent on leaf surfaces. Conversely, weather-only index models trigger frequent false alarms when pathogens are absent despite favorable humidity. Fusing MobileNetV2 probability with realtime weather analytics via EMRI dramatically cuts false alarms while catching early incubation stages.

Grad-CAM explainability provides essential transparency for agricultural advisory services. By reviewing visual activation maps, agronomists can verify whether MobileNetV2 focuses on sublechlorotic leaf spots rather than background soil, weeds, or glare. This builds trust and encourages proactive fungicide application within therapeutic windows.

VII. CHALLENGES & LIMITATIONS

Deploying AI in real-world viticulture presents operational challenges:

Variable Field Lighting: Direct sunlight and shadows alter image feature representations.

Micro-Climate Variance: Weather station data miles away may differ from canopy micro-climates.

Connectivity Loss: Remote vineyards often lack high-speed cellular data for cloud API calls.

Multi-Disease Co-Infection: Overlapping symptoms (Downy + Powdery Mildew) complicate single-label classification.

VIII. FUTURE SCOPE

Future work will port MobileNetV2 directly onto edge smart cameras and drone payloads for automated vineyard mapping, and integrate multispectral sensors for enhanced early stress detection.

IX. CONCLUSION

This paper presented an explainable software-based framework for pre-symptomatic grape disease risk assessment. By integrating MobileNetV2 deep feature extraction, Grad-CAM visual heatmaps, micro-climate weather telemetry, and the Epidemiological Micro-Climate Risk Index (EMRI), the system addresses the critical lag in traditional crop disease



management. The framework delivers actionable advisory alerts before visual disease symptoms spread, offering a sustainable, technology-driven solution for precision viticulture.

Workflow: Image Capture → Weather API Sync → MobileNetV2 → Grad-CAM → EMRI Score → Push Advisory10.

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