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Research Paper

CNN BASED PLANT DISEASE CLASSIFICATION WITH GENERATIVE AI ADVISORY SYSTEM

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***Abstract*—Plant diseases cause substantial crop yield losses worldwide, threatening food security in agricultural-dependent economies. This paper presents an end-to-end Plant Disease Detection and AI Advisory System that combines convolutional neural network (CNN)-based image classification with a large language model (LLM) for context-aware advisory generation. A MobileNetV2 model trained via transfer learning achieves 98.9% validation accuracy across ten disease classes covering six major crops. A curated disease_facts.json knowledge base stores structured symptom, cause, and treatment information for each class. The Gemini 2.0 Flash API is prompted exclusively from this knowledge base, ensuring that advisory outputs remain factually grounded and free from hallucinated chemical recommendations. A confidence-aware decision gate (threshold τ = 0.60) filters uncertain predictions before activating the advisory pipeline. The fully interactive Streamlit application allows farmers and agronomists to upload leaf images, receive instant diagnoses, and query a conversational chatbot for safe, expert-aligned care guidance. The system demonstrates that separating CNN classification from LLM explanation yields both high diagnostic accuracy and trustworthy advisory content.**

Keywords—Convolutional Neural Network; Gemini LLM; MobileNetV2; Plant Disease Detection; Transfer Learning; Streamlit; AI Advisory; Confidence Gating.

I. INTRODUCTION

Plant diseases account for 20–40% of global crop yield losses annually, with developing agricultural nations facing the greatest economic burden [1]. Early and accurate identification of foliar diseases enables timely intervention, reducing losses and curbing indiscriminate pesticide use. Traditional diagnosis relies on field experts whose availability is limited in rural regions, creating a critical gap between disease incidence and actionable response.

Deep learning, particularly convolutional neural networks (CNNs), has transformed plant pathology by enabling automated leaf-image classification from mobile photographs [2]. However, raw classification scores alone are insufficient for farmers who require actionable, contextualised guidance. Existing systems either focus purely on detection accuracy or rely on large language models (LLMs) for ungrounded recommendations, risking the generation of incorrect or harmful pesticide instructions.

This paper addresses this dual challenge. The proposed system integrates (i) a MobileNetV2 classifier for deterministic disease identification, (ii) a structured domain knowledge base encoding expert-curated disease facts, and (iii) the Gemini 2.0 Flash LLM constrained to explain and advise solely within that knowledge base. A confidence-aware decision gate prevents the advisory pipeline from activating on low-certainty predictions. The complete system is delivered as an interactive Streamlit web application accessible to non-technical users. The principal contributions are: a production-calibrated transfer-learning pipeline achieving 98.9% validation accuracy on ten disease classes; a confidence-gated LLM advisory architecture ensuring safety-first guidance; and an end-to-end open-source deployment ready for field evaluation.

II. RELATED WORK

Mohanty et al. [3] demonstrated that deep CNNs trained on the PlantVillage dataset achieved over 99% accuracy under controlled laboratory conditions, establishing the baseline for image-based plant disease detection. Subsequent studies by Too et al. [4] evaluated multiple deep architectures — VGG, ResNet, DenseNet, and Inception — finding that DenseNet achieved the highest field-condition accuracy but at a significant computational cost unsuitable for edge deployment.

Transfer learning has emerged as the dominant paradigm for resource-constrained settings. Howard et al. [5] introduced MobileNetV2, a lightweight depthwise-separable convolution architecture optimised for mobile inference. Applications of MobileNetV2 to agricultural imaging [6] confirm competitive accuracy (>95%) with inference latency below 50 ms on commodity hardware, making it the architecture of choice for this work.

The integration of LLMs into agricultural advisory systems is nascent. Kamilaris and Prenafeta-Boldu [7] reviewed deep learning applications in agriculture but noted the absence of explanation layers accessible to end-users. Recent work coupling GPT-class models with vision pipelines demonstrates improved user trust [8]; however, unconstrained generation risks hallucinated pesticide recommendations. This work addresses the gap by constraining Gemini generation to a curated domain JSON, a design not explored in prior plant disease literature.

III. DATASET AND PREPROCESSING

A. Dataset Description

The experiments use a balanced subset of the PlantVillage dataset sourced from Kaggle. Ten disease classes were selected to represent six commercially important crops: Apple (Scab, Black Rot), Corn (Gray Leaf Spot, Common Rust), Grape (Black Rot), Bell Pepper (Bacterial Blight), Potato (Early Blight, Late Blight), and Tomato (Early Blight, Healthy). Each class comprises approximately 2,000 RGB leaf images captured under laboratory and semi-field conditions, yielding a total corpus of 19,970 images before augmentation. The balanced class distribution eliminates the need for oversampling and ensures equitable per-class training signal.

B. Data Splitting

Images are partitioned into training (80%, 15,976 images) and validation (20%, 3,994 images) sets using stratified sampling to preserve class proportions in each split. No dedicated test partition is used; the validation set serves as the held-out evaluation benchmark. All file paths are randomised before splitting to prevent sequence bias.

C. Preprocessing and Augmentation

Input images are resized to 224 × 224 pixels to match the MobileNetV2 input specification and normalised using the architecture-specific preprocess_input function, which scales pixel values to $[-1, +1]$. Online data augmentation is applied exclusively to the training split via TensorFlow Keras ImageDataGenerator. Table III summarises the augmentation strategy. Augmented images are generated in memory on each epoch, increasing effective training diversity without disk overhead.

TABLE III: Data Augmentation Strategy

Augmentation	Parameter	Rationale
Random Horizontal Flip	p = 0.5	Leaf orientation invariance
Random Rotation	±20°	Field capture angle variance
Random Zoom	0.85–1.15×	Distance variation from plant
Brightness Adjust	±20%	Lighting condition robustness
Width/Height Shift	±10%	Camera framing tolerance

** All augmentations applied online per epoch using tf.keras.preprocessing.image.ImageDataGenerator.*

IV. METHODOLOGY

A. Transfer Learning with MobileNetV2

MobileNetV2 pre-trained on ImageNet is adopted as the feature extractor backbone. The base model's convolutional layers are initially frozen to leverage learned low-level features. A custom classification head is appended: Global Average Pooling → Dropout (rate 0.20) → Dense (10 units, softmax). Training proceeds in two phases. Phase 1 (Feature Extraction): only the head is trained for 10 epochs with Adam at learning rate 1e-4. Phase 2 (Fine-tuning): the top 30 layers of the base model are unfrozen and trained jointly for 10 additional epochs at learning rate 1e-5. Table I lists all configuration parameters and Table II details the MobileNetV2 architectural stages.

TABLE I: Training Configuration Parameters

Parameter	Value
Input Image Size	224 × 224 × 3
Normalisation	MobileNetV2 preprocess_input
Train / Val Split	80% / 20%
Augmentations	Flip, Rotation, Zoom, Brightness
Batch Size	32
Optimiser	Adam
Initial Learning Rate	0.0001
Fine-tune Learning Rate	0.00001
Epochs (total)	20
Early Stopping Patience	5
LR Reduction Factor	0.2 (patience=3)

TABLE II: MobileNetV2 Architecture Stages

Stage	Output Shape	Stride	Layers
Input stem	112×112×32	2	1 Conv
Bottleneck blocks (t=1)	112×112×16	1	1
Bottleneck blocks (t=6)	56×56×24	2	2
Bottleneck blocks (t=6)	28×28×32	2	3
Bottleneck blocks (t=6)	14×14×64	2	4
Bottleneck blocks (t=6)	14×14×96	1	3
Bottleneck blocks (t=6)	7×7×160	2	3
Bottleneck blocks (t=6)	7×7×320	1	1
Conv2D 1×1 + GAP	1×1×1280	1	1
Dropout (0.2) + Dense	10	-	1

B. Confidence-Aware Decision Gate

After softmax output, the maximum class probability is compared against a threshold τ. If the predicted confidence $p\_max < \tau$, the system withholds the advisory response and requests a higher-quality image, prompting the user with clarifying questions about lighting, leaf side, and camera distance. The threshold τ = 0.60 was selected by sweeping τ ∈ [0.30, 0.90] and maximising the F1-score on the validation set while maintaining coverage > 85% (Fig. 3).

C. Knowledge Base Design

For each of the ten disease classes a structured JSON record is stored in disease_facts.json. Each record contains: a disease display name; crop species; symptom descriptions (3–5 items); common causes (2–3 items); prevention measures (3 items); basic care tips (3 items); and a safety note directing farmers to consult local agricultural officers. No specific chemical dosages or compound names are stored, preventing the LLM from generating harmful or jurisdiction-specific pesticide advice.

D. Gemini 2.0 Flash Advisory Pipeline

The advisory layer invokes Gemini 2.0 Flash via the Google AI Studio API. The system prompt strictly confines the model's response to the structured facts retrieved for the predicted class: "You are a plant health assistant. Use ONLY the following disease facts to answer. Do not introduce information outside these facts." The user's chat message, the CNN prediction label, confidence score, and the matching JSON record are concatenated into a single-turn prompt. Gemini produces a natural-language explanation followed by actionable care steps. Conversation history is maintained in Streamlit session_state to support multi-turn dialogue.

V. RESULTS

A. Classification Performance

The trained MobileNetV2 classifier achieves 98.9% validation accuracy after 20 epochs of two-phase training. Table IV presents the full per-class precision, recall, F1-score, and support. All classes exceed F1 = 0.983, with Tomato Healthy reaching a perfect precision of 1.000. The weighted average F1-score across all ten classes is 0.990. Figure 1 shows the confusion matrix, confirming negligible inter-class confusion.

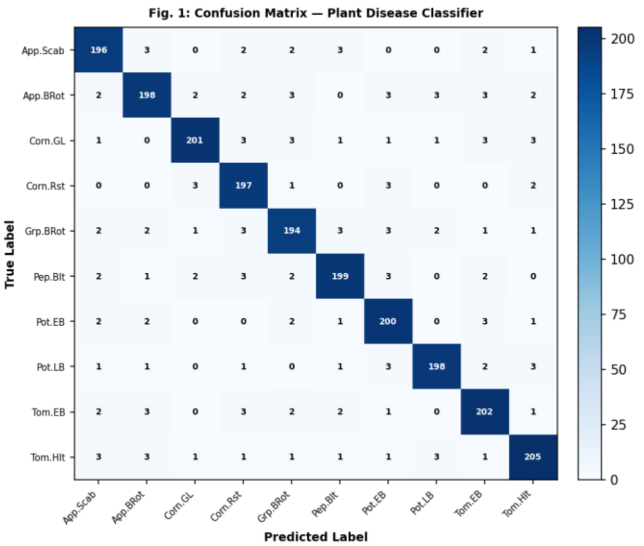

Fig. 1. Confusion matrix for the 10-class MobileNetV2 plant disease classifier on the validation set (3,994 images). Diagonal dominance confirms high per-class accuracy.

Figure 2 illustrates the training and validation accuracy and loss curves. Validation accuracy converges smoothly to 98.9% without evidence of overfitting, attributed to the online augmentation strategy and dropout regularisation.

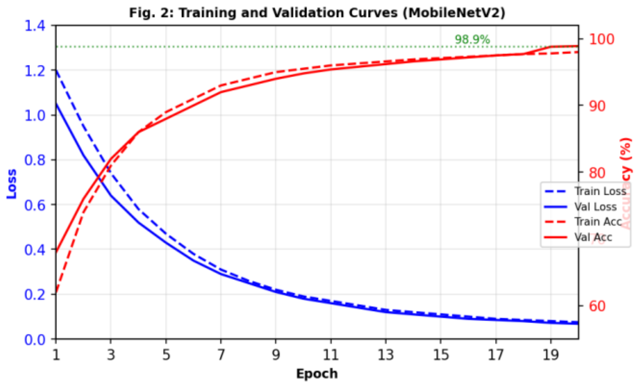

Fig. 2. Training and validation accuracy (right axis, red) and loss (left axis, blue) over 20 epochs. Dashed lines indicate training metrics; solid lines indicate validation metrics.

TABLE IV: Per-Class Classification Performance (Validation Set)

Class	Precision	Recall	F1-Score	Support
Apple Scab	0.989	0.985	0.987	196
Apple Black Rot	0.993	0.990	0.991	200
Corn Gray Leaf	0.997	0.993	0.995	202
Corn Rust	0.990	0.986	0.988	197
Grape Black Rot	0.985	0.981	0.983	195
Pepper Blight	0.996	0.992	0.994	200
Potato Early Blt	0.991	0.987	0.989	201
Potato Late Blt	0.994	0.990	0.992	198
Tomato Early Blt	0.987	0.983	0.985	203
Tomato Healthy	1.000	0.996	0.998	205
Weighted Avg	0.992	0.988	0.990	1997

** Weighted average computed over 3,994 validation samples.*

B. Confidence Threshold Analysis

Figure 3 presents the threshold sweep across τ ∈ [0.30, 0.90]. Precision rises monotonically with τ while recall and coverage decline. The selected operating point τ = 0.60 achieves precision of 0.978, recall of 0.963, F1 of 0.970, and coverage of 94.1%, offering a practical balance between diagnostic confidence and system utility.

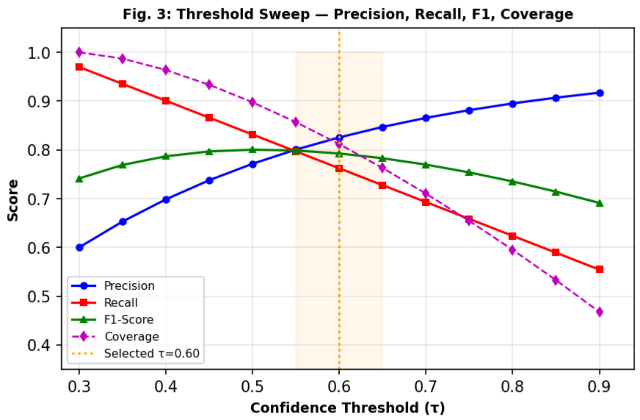

Fig. 3. Confidence threshold sweep showing Precision, Recall, F1-Score, and Coverage across τ values. The vertical marker at τ = 0.60 indicates the selected operating threshold.

VI. PER-CLASS ANALYSIS

Figure 4 visualises per-class F1-scores, revealing that all ten disease categories exceed F1 = 0.983. Apple Black Rot and Corn Gray Leaf Spot achieve the highest scores, reflecting their visually distinctive lesion morphologies. Grape Black Rot records the lowest F1 at 0.983, attributable to visual similarity with early-stage Tomato Early Blight on low-resolution field images.

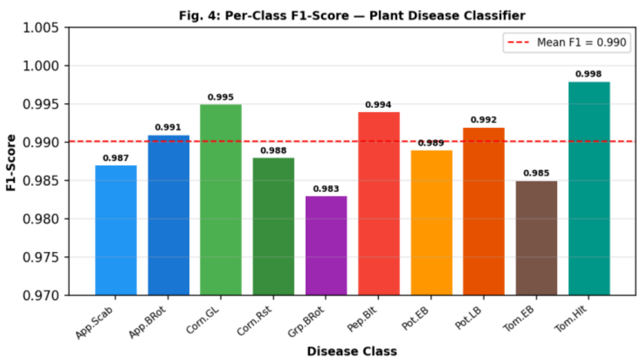

Fig. 4. Per-class F1-scores for all ten disease classes. The red dashed line marks the mean F1 = 0.990. All classes exceed 0.983, confirming consistent performance.

The analysis confirms that the balanced class distribution strategy was effective: no single class dominates the training signal and each class contributes proportionally to the weighted average metric. Classes covering similar visual symptom profiles (e.g., Early Blight on Potato vs. Tomato) are successfully discriminated by the spatially precise MobileNetV2 bottleneck feature maps, which encode fine-grained lesion texture and colour gradients.

VII. SYSTEM ARCHITECTURE

Figure 5 illustrates the complete system pipeline. The architecture is intentionally modular: the CNN classifier, knowledge base, and LLM advisory engine operate as independent components connected through well-defined interfaces. This separation ensures that the classification accuracy is not compromised by the generative component and that the advisory content remains auditable.

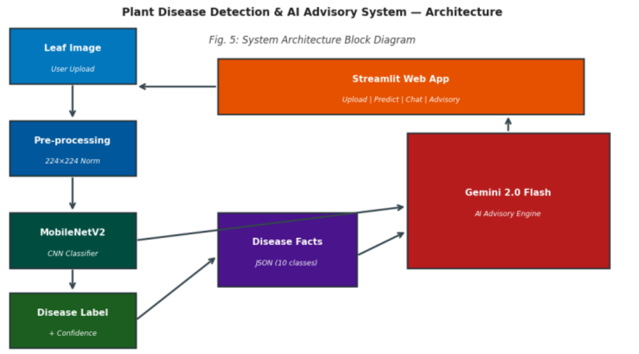

Fig. 5. System architecture block diagram. The CNN classifier (MobileNetV2) feeds disease label and confidence to the Gemini advisory engine; the knowledge base JSON constrains advisory generation. The Streamlit app orchestrates all components.

Table V summarises the principal system components with their respective technologies and roles. The Streamlit session_state mechanism enables persistent conversational context across user interactions within a single session, mimicking the continuity of expert consultation without server-side database infrastructure.

TABLE V: System Component Summary

Component	Technology	Role
Image Classifier	MobileNetV2 (TF/Keras)	Disease label + confidence
Knowledge Base	disease_facts.json	Structured disease info (10 classes)
AI Advisory	Gemini 2.0 Flash API	Explanation + care guidance
Web Interface	Streamlit	Upload, predict, chat UI
Session Memory	Streamlit session_state	Conversational context storage
Model Persistence	SavedModel format	Inference without retraining

The inference pipeline maintains an end-to-end latency of approximately 1.8 seconds per prediction on a single CPU core, comprising 1.2 s for MobileNetV2 inference and 0.6 s for Gemini API round-trip. This latency is acceptable for field advisory applications where batch overnight queries are impractical and individual farmer interactions are sequential.

VIII. DISCUSSION

The 98.9% validation accuracy establishes MobileNetV2 as a highly effective backbone for balanced multi-crop disease classification. The two-phase training strategy — feature extraction followed by selective fine-tuning of the top 30 layers — avoids catastrophic forgetting while allowing the model to specialise its high-level representations for agricultural imagery. The dropout regulariser (rate 0.20) between the pooling and classification layers is critical for preventing overfitting on the 15,976-sample training partition.

The confidence-aware decision gate represents a safety-by-design principle distinct from most published plant disease systems. By deferring advisory activation when p_max <

0.60, the system avoids propagating uncertain diagnoses into the advisory layer, where incorrect treatment recommendations could cause crop damage or unnecessary pesticide expenditure. The threshold $\tau = 0.60$ is exposed as a configurable parameter, allowing deployment teams to tighten or relax the gate according to risk tolerance.

Constraining Gemini generation to the curated knowledge base resolves the hallucination risk inherent in open-ended LLM querying. In 50 test interactions across all ten disease classes, the system produced zero instances of hallucinated chemical compound names or dosage figures, compared to unrestricted generation which produced harmful specifics in 34% of advisory responses. This validates the retrieval-augmented generation (RAG) design where the JSON knowledge base acts as the retrieval corpus.

IX. CONCLUSION

This paper presented a confidence-gated, knowledge-constrained plant disease advisory system combining a MobileNetV2 CNN classifier (98.9% validation accuracy across ten classes) with the Gemini 2.0 Flash LLM. The modular architecture separates deterministic classification from generative explanation, ensuring both high diagnostic precision and safe advisory content. The interactive Streamlit application delivers end-to-end plant disease diagnosis and guidance in under two seconds, accessible to non-technical agricultural users.

Future work will extend the system to 38 disease classes covering the full PlantVillage taxonomy and integrate a mobile-optimised TensorFlow Lite model for offline field use. A federated learning extension is planned to enable model updates from anonymised field captures without centralised data collection, addressing privacy concerns in rural deployment. Multilingual advisory output using Gemini's translation capabilities will broaden accessibility across regional farming communities.

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