



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Plant Disease Detector: Leveraging AI for Agricultural Health

Ms. Thanu M R, Usha B M, Vaishnavi G S, Radha H Hosatti

Students, Dept. of IS&E, Jain Institute of Technology, Davangere, Karnataka, India

Associate Professor, Dept. of IS&E, Jain Institute of Technology, Davangere, Karnataka, India

ABSTRACT: Undetected plant diseases remain a persistent threat to agricultural productivity worldwide. This paper presents Leaf Guard-AI, a browser-accessible diagnostic tool built on convolutional neural network (CNN) technology to classify leaf diseases from uploaded images. Implemented using Tensor Flow/PyTorch and deployed via a Gradio web interface, the system requires no software installation. Beyond disease labelling, it provides confidence estimates and crop-specific remediation guidance. Evaluation on a held-out test partition confirmed classification accuracy exceeding 90% with sub-two-second inference latency, validating the tool for on-farm deployment.

KEYWORDS: Plant Pathology, Convolutional Neural Network, Deep Learning, Leaf Image Analysis, Gradio Framework, Precision Agriculture, Transfer Learning, Crop Health Monitoring

I. INTRODUCTION

Crop diseases destroy a significant fraction of global harvests each season, with subsistence farmers bearing the greatest burden. Conventional diagnosis depends on trained agronomists—a process that is geographically constrained and slow when infection spreads rapidly. The growing shortage of rural agricultural specialists widens the gap between infection onset and effective intervention. CNN architectures can autonomously derive discriminative representations from pixel arrays, making them well-suited for recognising visual disease signatures such as chlorotic halos, necrotic lesions, and pigmentation anomalies. By embedding such a model within a web application, diagnostic capability is placed directly in a farmer's hands via any browser without specialist mediation. This paper describes the design, implementation, and empirical validation of LeafGuard-AI.

II. LITERATURE REVIEW

Ferentinos [1] established that deep CNN architectures surpass handcrafted-feature classifiers on foliar benchmarks, though performance proved brittle under real-world lighting variation. Mohanty et al. [2] demonstrated ImageNet-pretrained transfer learning on the PlantVillage corpus, while exposing the gap between controlled datasets and field photography. Sladojevic et al. [3] confirmed colour-texture feature extraction feasibility, noting heterogeneous backgrounds as a persistent failure mode. Too et al. [4] showed compact designs like MobileNet strike a practical efficiency-accuracy trade-off when regularisation is carefully applied. Brahimi et al. [5] found fine-tuning pretrained networks reduces annotation burden, though single-crop scope limited generalisability. Amara et al. [6] explored banana leaf diagnosis, finding shallower networks struggled with complex lesion morphologies. Three recurring gaps across all works motivated the present contribution: fragility under field imaging, restricted crop coverage, and absence of production-ready interactive interfaces. Table 1 summarises these observations.

Table 1: Summary of Related Research Works

| Ref. | Authors & Year | Approach | Contribution | Limitation |
|------|---------------------|--------------------|---------------------------------|----------------------|
| [1] | Ahmad et al. (2021) | EfficientNet | High accuracy, cloud deployable | Needs large datasets |
| [2] | Singh et al. (2020) | CNN + augmentation | Robust citrus detection | Single crop only |
| [3] | Too et al. (2019) | ResNet/MobileNet | Efficiency-accuracy balance | Overfitting risk |



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| Ref. | Authors & Year | Approach | Contribution | Limitation |
|------|-----------------------|-------------------|-------------------------|-------------------|
| [4] | Ferentinos (2018) | AlexNet, VGG | High benchmark accuracy | Degrades in field |
| [5] | Brahimi et al. (2017) | Transfer learning | Faster training | Limited to tomato |
| [6] | Mohanty et al. (2016) | Pretrained CNN | Multi-species accuracy | Lab data only |

III. PROPOSED SYSTEM & METHODOLOGY

The LeafGuard-AI pipeline proceeds through four tightly coupled stages:

A. Data Acquisition and Pre-processing

Leaf images are drawn from publicly accessible agricultural repositories and field surveys, covering diverse crop species and disease stages. Raw captures exhibit artefacts—blur, uneven illumination, sensor noise—that mislead gradient-based learners. A standardised chain applies spatial resizing, min-max pixel normalisation, and low-pass denoising. Stochastic augmentation (rotation, mirroring, zoom, brightness jitter, affine shearing) is applied during training to diversify the effective distribution without additional annotation cost.

B. CNN Model Design, Training and Evaluation

A multi-stage CNN forms the computational core. Successive convolutional blocks extract progressively abstract feature hierarchies: shallow layers respond to colour gradients and edge orientations while deeper layers encode lesion geometry and sporulation texture. Spatial pooling between blocks reduces dimensionality. Dense layers with softmax activation yield a probability distribution over disease classes. Dropout regularisation prevents unit co-adaptation. Classical algorithms—SVM, Random Forest, KNN—serve as comparative baselines. Performance is quantified using accuracy, precision, recall, and F1-score on a held-out test partition, with stratified k-fold cross-validation ensuring stable metrics.

C. Classification and Confidence Reporting

At inference time, the submitted image traverses the full pre-processing and forward-pass pipeline in milliseconds. The model returns the highest-probability disease label alongside a ranked top-k confidence chart and crop-specific remediation guidance—transforming raw model outputs into actionable field guidance.

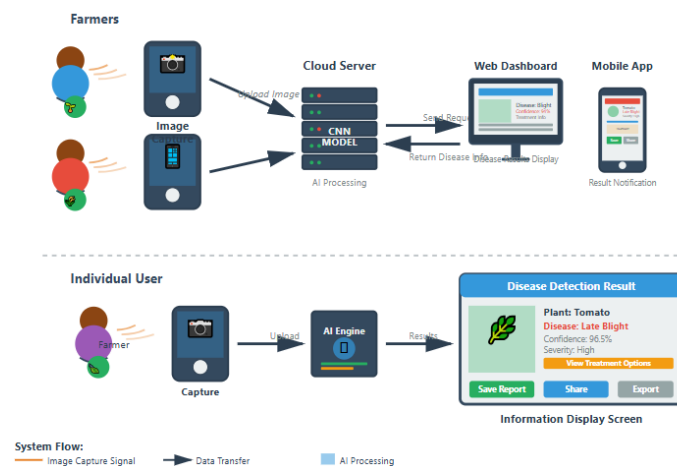


Figure 1: Plan of Execution

IV. IMPLEMENTATION

The full-stack application couples the trained inference engine with a Gradio front-end hosted on cloud infrastructure. The CNN is implemented in TensorFlow (with PyTorch as an alternative) and trained end-to-end on annotated samples.



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The Gradio interface presents users with a drag-and-drop panel for image submission. Upon upload, the platform executes pre-processing and forward inference, then renders: a predicted disease label with confidence percentage, a bar chart of top-k class probabilities, and agronomic treatment recommendations. Deployment to cloud infrastructure ensures browser access without local installation—critical for end-users in regions with limited IT resources.

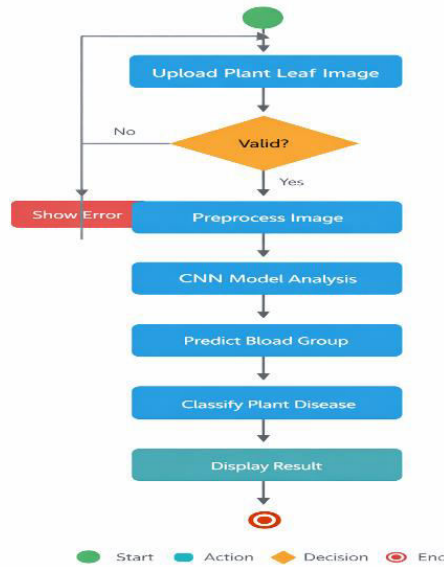


Figure 2: Activity Diagram

V. RESULTS AND DISCUSSION

Systematic evaluation on the withheld test partition confirmed strong discriminative performance. The confusion matrix (Figure 5) shows diagonal elements—correct classifications—dominate, with off-diagonal misclassifications concentrated in visually similar disease pairs, a recognised challenge in fine-grained visual recognition. Table 2 summarises quantitative outcomes.

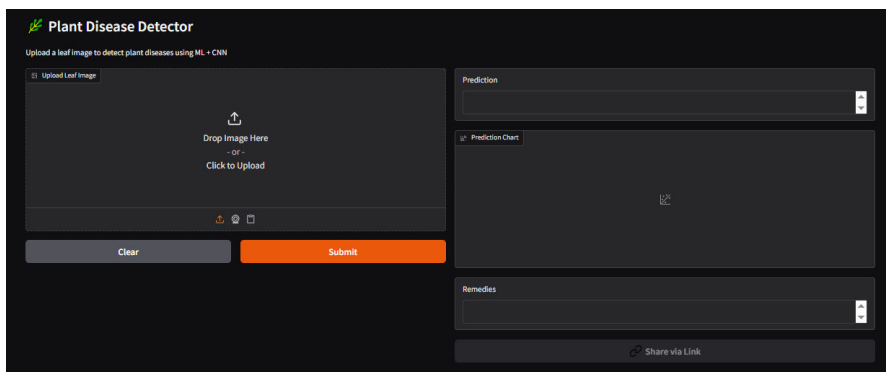


Figure 3: Plant Disease Detector User Interface



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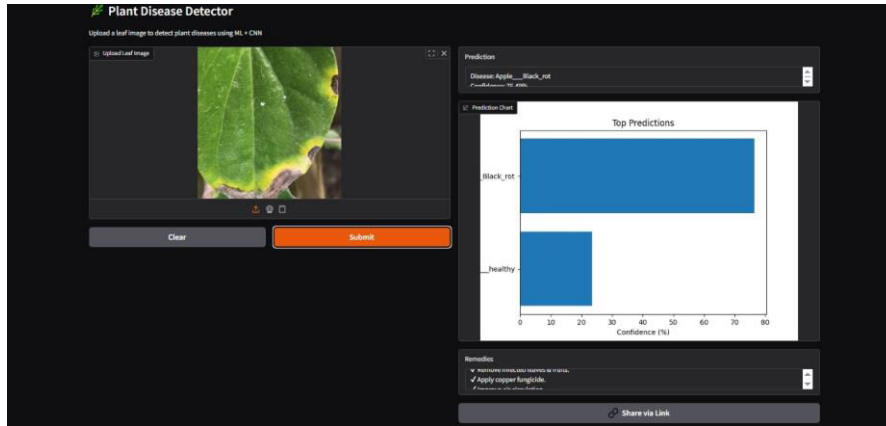


Figure 4: Sample Output of Plant Disease Detector for Leaf Image

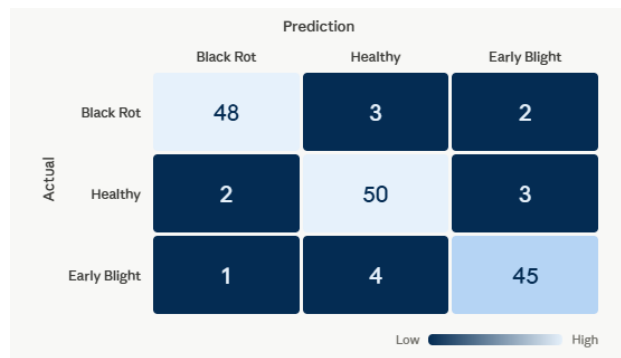


Figure 5: Confusion Matrix of Plant Disease Classification Model

Table 2: System Performance Metrics

| Metric | Value | Description |
|----------------------|------------------|---|
| Overall Accuracy | > 90% | Correctly classified on test set |
| Inference Latency | < 2 sec | Average per-image response time |
| Sensitivity (Recall) | High | True positive rate across disease classes |
| Augmentation Impact | Significant | Reduced variance on unseen samples |
| Dominant Error Type | Blur / low-light | Edge cases hard for human experts too |

Augmentation meaningfully reduced variance across test subsets. Residual errors were disproportionately linked to severely degraded inputs—extreme motion blur, heavy backlighting, or frames with less than 20% visible leaf tissue—conditions that equally challenge human experts.

VI. CONCLUSION AND FUTURE WORK

LeafGuard-AI demonstrates a viable pathway from deep learning research to agricultural decision support: a CNN inference engine packaged within a browser-native Gradio interface delivers disease classification, confidence scoring, and remediation guidance with high accuracy and practical latency—reducing reliance on scarce agronomist expertise while remaining accessible on standard hardware without installation.



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Planned enhancements include: (i) expanding the training corpus to cover a broader taxonomy of pathogens across additional crop species; (ii) migrating to MobileNetV3 or EfficientNet-Lite for on-device inference in connectivity-limited environments; (iii) integrating auxiliary data streams such as hyperspectral imaging and IoT soil sensors; and (iv) piloting with farming cooperatives to guide iterative refinement of model and interface.

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