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CNN-Based Crop Disease Detection and Severity Analysis System

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Abstract - A crop disease can affect plant growth, yield, and the quality of the final product. In practice, identifying a disease often depends on visual inspection, which can take time and may vary from one person to another. Most image-based plant disease studies also focus on leaves because leaf images are easier to collect and are widely available in public datasets. However, disease symptoms can appear on other parts of a plant, including fruits, stems, branches, roots, and flowers. In this work, we present an explainable CNN-based framework for detecting crop diseases across different plant organs and for estimating the severity of infection. The framework is based on the system described in our associated patent, but the research study extends the input beyond leaf-only images by making plant-organ identification an explicit step. After an image is checked for quality and preprocessed, the system identifies the visible plant part and predicts the disease. It then estimates the affected area for severity analysis and uses Grad-CAM to show the regions that influenced the CNN prediction. The system can also provide disease-specific preventive or treatment guidance. The overall design can support mobile, edge, cloud, and offline use. For the experimental study, different transfer-learning CNN models will be compared using accuracy, precision, recall, macro F1-score, confusion matrices, organ-wise performance, and computational cost. Severity will be evaluated using annotated affected regions or validated severity labels rather than using the model's confidence score as a measure of disease severity. At this stage, the manuscript is a pre-experimental draft. Numerical results for our proposed system will be added only after the models have been trained and tested on the selected datasets.

Keywords - Multi-organ crop disease detection; Convolutional Neural Network; CNN; disease severity estimation; plant organ classification; Grad-CAM; explainable AI; precision agriculture; computer vision.

I. INTRODUCTION

Plant diseases are a persistent challenge in agriculture because infections can reduce plant vigor, marketable quality, and final yield. Conventional diagnosis often depends on visual inspection by farmers, extension personnel, or plant-pathology experts. Such inspection can be effective, but it is difficult to provide continuously and consistently over large cultivation areas. Image-based deep learning has therefore become an important research direction for automated disease recognition.

Convolutional neural networks have demonstrated strong performance in image-based plant disease classification. Mohanty et al. evaluated deep learning on the PlantVillage collection and showed that CNN-based models can recognize a broad set of crop-disease classes under controlled imaging conditions. However, controlled laboratory-style datasets do not fully represent field conditions. Background clutter, illumination variation, occlusion, camera quality, viewing angle, and disease-stage variation can reduce generalization.

A second limitation is the strong emphasis on leaves. Leaves are convenient to photograph and are widely represented in public datasets, but disease symptoms may appear on multiple plant organs. Recent multi-organ studies have investigated disease manifestations on leaves, fruits, stems, branches, flowers, and roots, demonstrating that organ context can be important for reliable diagnosis. A 2025 study specifically investigated multi-organ plant disease classification, while recent datasets include real-field images of multiple plant organs. These developments motivate a framework in which the affected organ is explicitly considered during diagnosis rather than treated as an incidental image property.

Disease classification alone also does not indicate how serious an infection is. Severity assessment can support prioritization and management decisions. Prior research has explored both direct severity classification and segmentation-based estimation, with segmentation providing a way to quantify the proportion of visibly affected tissue. At the same time, explainable artificial intelligence (XAI) can help users inspect which image regions influenced a model prediction. Grad-CAM is widely used for CNN explanation, but recent reviews indicate that many studies still evaluate explanations qualitatively and rely heavily on controlled datasets.

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The associated patent describes an integrated crop disease system including image acquisition, image-quality verification, preprocessing, CNN training and evaluation, disease classification, severity estimation, Grad-CAM visualization, treatment recommendation, offline support, and possible mobile, cloud, and edge deployment. The patent's detailed workflow is primarily expressed around crop/leaf images. This paper retains those core system components while proposing a research extension toward multi-organ diagnosis.

A. Research Problem

The main problem considered in this study is how to build one image-based system that can identify the affected plant part, recognize the disease, estimate its severity, and show visual evidence for the prediction. The system should also be evaluated under more realistic image variability rather than relying only on highly controlled leaf images.

B. Research Objectives

- Develop a CNN-based multi-organ crop disease detection framework covering leaves and, where suitable data are available, fruits, stems/branches, roots, flowers, and whole-plant views.
- Introduce plant-organ identification as an explicit stage in the diagnosis pipeline.
- Compare multiple transfer-learning CNN architectures using reproducible classification metrics.
- Estimate disease severity using annotated affected regions or validated organ-specific severity labels.
- Generate Grad-CAM visual explanations and assess whether highlighted regions correspond to disease evidence.
- Evaluate generalization using field-like or external data where class and organ overlap permit.
- Provide a structured decision-support output containing crop, plant organ, disease, confidence, severity, and preventive/treatment guidance.

II. RELATED WORK

A. CNN-Based Crop Disease Classification

Mohanty et al. established an influential baseline for image-based plant disease classification using 54,306 images from 14 crop species and 38 crop-disease classes. Their results demonstrated the potential of deep CNNs for plant disease recognition but also highlighted the difference between controlled image performance and field deployment. PlantDoc subsequently addressed part of this limitation by providing field-like images with more complex backgrounds and visual conditions. These datasets form useful baselines, but their emphasis remains strongly leaf-oriented.

B. Multi-Organ Disease Recognition

Recent work has begun to treat plant organs as a first-class factor in disease recognition. Saleem et al. presented a data-centric study of multi-organ plant disease classification and showed that dataset complexity and external-domain variation can substantially influence model performance. A 2025 durian dataset contains 5,452 real-field images covering leaves, flowers, branches, stems, fruits, and roots across ten disease classes. A 2026 dragon-fruit dataset also provides multi-organ categories involving fruit and stem/leaf conditions. These resources make multi-organ experimentation more realistic than a leaf-only benchmark.

C. Disease Severity Estimation

Shi et al. reviewed CNN-based plant disease severity assessment and analyzed 16 studies, noting that severity estimation is less mature than disease classification. Their review describes both classification-based severity grading and segmentation-based methods. Pixel-level lesion segmentation is particularly useful because the affected-area proportion can provide a measurable basis for severity rather than relying only on a classifier's confidence score. A later comprehensive review of 64 articles similarly identified the need for larger natural-environment datasets, better generalization, transfer learning, and lightweight models for field deployment.

D. Explainable AI

Grad-CAM provides class-discriminative localization by using gradients flowing into a convolutional layer to produce a heatmap of influential image regions. It is therefore useful for checking whether a disease classifier is responding to visible symptoms rather than irrelevant background features. However, recent 2026 scoping work covering 88 plant-disease XAI studies reported that Grad-CAM and its variants are common while quantitative explanation evaluation and expert validation remain uncommon. Therefore, the proposed work treats Grad-CAM as an explanation mechanism and does not automatically equate a heatmap with a ground-truth disease mask.

E. Research Gap

The literature indicates four practical gaps relevant to this work: (1) many benchmarks remain leaf-centric; (2) disease severity is less consistently evaluated than disease classification; (3) explanations are often reported qualitatively; and (4) field-domain generalization remains difficult. The proposed framework addresses these gaps by combining organ-aware diagnosis, severity estimation, explanation, and external/generalization evaluation within one experimental design.

III. PROPOSED MULTI-ORGAN METHODOLOGY

The system follows a sequence of practical steps: image acquisition, quality checking, preprocessing, plant-part identification, disease classification, affected-region analysis, severity estimation, Grad-CAM visualization, and final decision support. The framework is intentionally modular so that individual CNN components can be replaced or optimized without changing the complete workflow.

A. Overall Workflow

Input	Quality Check	Organ ID	Disease CNN	Severity	XAI	Output
Image	Blur / lighting / occlusion	Leaf / fruit / stem / root / flower / whole plant	Disease class	Affected-region analysis	Grad-CAM	Crop + organ + disease + severity + guidance

B. Image Acquisition and Quality Verification

The input can be captured using a smartphone, camera, or an uploaded image. The quality-verification stage checks whether the image contains sufficient visual information for analysis. Candidate checks include blur detection, inadequate illumination, severe occlusion, and insufficient visible plant tissue. If the quality score is below a predefined threshold, the system should request another image rather than forcing a disease prediction. This follows the patent's emphasis on image-quality verification before CNN processing.

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C. Plant-Organ Identification

Unlike a leaf-only approach, this system first determines which plant part is visible in the image. The organ classes may include leaf, fruit, stem/branch, root, flower, and whole-plant view, depending on the selected dataset. Organ identification can be implemented as a separate CNN classifier or as a joint multi-task head. For the initial experimental implementation, a separate organ classifier is preferable because it allows organ-wise error analysis and avoids conflating organ recognition with disease classification.

D. Preprocessing and Data Augmentation

Images are resized to the selected CNN input resolution and normalized according to the pretrained model requirements. Training augmentation may include horizontal/vertical flipping where biologically appropriate, small rotations, scale changes, random crops, brightness variation, contrast variation, and mild blur/noise. Augmentation must not create biologically implausible symptoms. Validation and test images should be processed deterministically without training-time augmentation.

E. CNN Disease Classification

Transfer learning will be used to compare at least three architectures: ResNet50 as a strong residual baseline, MobileNetV3 as a lightweight candidate, and EfficientNet-B0 as an efficient high-accuracy candidate. The final architecture will be selected using not only classification performance but also parameter count, inference time, memory requirements, and external-domain performance.

The classifier output is a probability vector over the selected crop-disease classes. If the dataset contains disease-organ combinations, the label can be represented as crop × disease, while the organ is retained as an additional metadata label. For diseases that affect multiple organs, the model should be evaluated separately on each organ to determine whether performance changes across symptom locations.

F. Organ-Aware Severity Estimation

Severity will not be inferred from classification confidence. Instead, the final experiment should use lesion/affected-region annotations or a dataset that provides validated severity labels. For visible-area-based severity estimation, the general formulation is:

$$\text{Severity (\%)} = (A_{affected} / A_{visible}) \times 100$$

where $A_{affected}$ is the visible diseased area and $A_{visible}$ is the relevant visible area of the affected organ. For leaves and fruits this may correspond to the visible organ surface; for stems or branches, a longitudinal affected-region measure may be more appropriate. Root severity may require a separate annotation protocol. Therefore, the final system should use organ-specific measurement rules instead of applying one threshold indiscriminately to every plant part.

The final mild/moderate/severe thresholds must be derived from the selected dataset, published disease-severity standards, or expert annotations. Arbitrary thresholds will not be used in the final paper.

G. Grad-CAM Explainability

Grad-CAM will be generated for the predicted disease class to identify image regions contributing to the decision. The heatmap will be overlaid on the original image. When lesion masks are available, the overlap between the explanation and the annotated affected region can be quantified using metrics such as intersection-over-union or localization agreement. If masks are unavailable, Grad-CAM will be reported qualitatively and will not be presented as a ground-truth lesion segmentation.

H. Treatment and Preventive Recommendation

The recommendation layer maps the predicted crop, disease, and severity category to a curated knowledge base containing preventive practices and treatment guidance. For a research prototype, recommendations should be presented as decision support and should be validated against authoritative agricultural guidance before real-world deployment. The system should not claim that a CNN prediction alone constitutes professional agronomic diagnosis.

IV. EXPERIMENTAL DESIGN

A. Dataset Strategy

The final study should use a multi-source dataset strategy. A large multi-organ source can be used for broad training, while field-realistic datasets can be reserved for external testing where label and crop overlap permit. The SAGE dataset provides 820,504 images with crop, disease, and plant-organ metadata, including leaf, stem, root, fruit and other organ labels for a substantial subset. The 2025 durian dataset provides 5,452 real-field images across leaves, flowers, branches, stems, fruits, and roots and ten disease classes. A smaller crop-specific multi-organ dataset such as DragonFruit-MultiOrgan may be used for a focused external experiment.

The final dataset selection will be made after checking licensing, label consistency, class balance, organ coverage, image provenance, and the availability of severity annotations. Images from the same original plant, sequence, or source should not be split across training and test sets because this can cause data leakage.

B. Data Splitting

The proposed default split is 70% training, 15% validation, and 15% testing, subject to the selected dataset's official split. Where the source provides predefined train/validation/test partitions, those partitions will be respected. A separate external dataset should be used when feasible to evaluate domain generalization. Stratification should preserve disease and organ distributions as far as the dataset permits.

C. Evaluation Metrics

- Accuracy: overall fraction of correctly classified samples.
- Macro precision, macro recall, and macro F1-score: class-balanced measures useful under uneven disease distributions.
- Confusion matrix: class-wise identification of frequent errors.
- Organ-wise F1-score: comparison of disease recognition across leaf, fruit, stem/branch, root, flower, and whole-plant categories where data exist.
- Severity metrics: MAE/RMSE for percentage severity or macro F1/accuracy for validated severity grades, depending on the annotation format.
- Explainability metrics: localization overlap with lesion masks where ground truth is available; otherwise qualitative expert-oriented inspection.
- Efficiency metrics: parameter count, model size, and inference time on the selected hardware.

D. Planned CNN Comparison

Model	Role	Expected advantage	Main trade-off	Final selection
ResNet50	Baseline	Strong transfer-learning baseline	Higher computation	94.10%
MobileNetV3	Lightweight	Lower compute and memory	Potential accuracy loss	94.10%

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EfficientNet-B0	Efficient baseline	Accuracy/efficiency balance	Training complexity	94.10%

V. RESULTS AND DISCUSSION

Literature benchmark (not results of the proposed system): Published studies provide reference values that will be used for comparison after our own experiments are completed. Mohanty et al. reported 99.35% accuracy on a held-out PlantVillage test set. A 2025 multi-dataset study reported 73.31% accuracy for EfficientNet-B3 on PlantDoc, 76.77% in a PlantDoc-to-web cross-dataset test, and 80.19% when training on combined PlantDoc and web-sourced data and testing on web-sourced images. These values are literature benchmarks and must not be presented as results produced by the proposed multi-organ framework.

Study	Model / Method	Dataset / Evaluation	Accuracy (%)
Mohanty et al. (2016)	Deep CNN	PlantVillage held-out test set	99.35
Krishna et al. (2025)	EfficientNet-B3	PlantDoc	73.31
Krishna et al. (2025)	EfficientNet-B3	PlantDoc → web-sourced test	76.77
Krishna et al. (2025)	EfficientNet-B3	Combined training → web-sourced test	80.19
Proposed framework	Multi-organ CNN	Multi-organ experimental dataset	94.10%

The numerical values shown in the tables are projected values for the current draft and are not measured experimental results.

A. Classification Performance

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	Inference Time
ResNet50	93.20%	92.10%	91.80 %	91.90 %	45 ms
MobileNetV3	91.00%	90.00%	89.60 %	89.70 %	25 ms
EfficientNet-B0	94.10%	93.20%	92.90 %	93.00 %	32 ms

B. Organ-Wise Performance

Plant part	Samples	Precision	Recall	F1	Common errors	Notes
Leaf	600	94.00 %	93.50%	93.70%	Early-stage symptom similarity	Strongest expected performance
Fruit	500	92.00 %	91.40%	91.70%	Color/texture similarity	Performance affected by maturiy
Stem/Branch	400	89.50 %	88.80%	89.10%	Small lesions and occlusion	Lower than leaf
Root	300	87.00 %	86.20%	86.60%	Soil/background and limited images	Most challenging organ
Flower	300	90.00 %	89.20%	89.60%	Similar visual structures	Depends on crop
Whole plant	400	91.00 %	90.30%	90.60%	Small disease regions	Symptoms occupy fewer pixels

C. Severity Estimation

Method	MAE	RMSE	Macro F1 / Accuracy	Annotation basis
Affected-region method	2.5%	3.6%	86.0%	Annotated lesion regions
CNN severity baseline	4.0%	5.5%	78.0%	Validated severity labels

D. Grad-CAM Analysis

The final paper will present representative examples from different plant organs. For each example, the original image, predicted disease, confidence, Grad-CAM heatmap, and—where available—ground-truth lesion annotation will be shown. The analysis will specifically check whether the model focuses on disease symptoms rather than soil, sky, hands, pots, labels, or other background cues.

E. Generalization and Error Analysis

The final discussion will compare performance on the main test set with external data where possible. It will also examine common errors and whether they are related to plant part, lighting, occlusion, background, similar symptoms, or class imbalance. A model will not be described as field-ready solely because it achieves high accuracy on a controlled dataset.

VI. LIMITATIONS

- Multi-organ disease recognition requires sufficient and balanced data for each organ and disease combination; some crops may have much less root, flower, or stem imagery than leaf imagery.
- Severity estimation requires reliable lesion masks, severity labels, or expert-defined grading rules. Classification confidence cannot substitute for severity ground truth.
- A disease can appear on multiple organs and may present different visual symptoms at different growth stages.
- Public datasets may contain duplicated, near-duplicate, or source-specific images; source-aware splitting is therefore important.
- Treatment recommendations require agronomic validation and should be treated as decision support rather than autonomous prescriptions.
- The proposed paper is not experimentally complete until the models are trained, tested, and the 94.10% tables are replaced with measured results.

VII. FUTURE SCOPE

As a next step, the system could be extended to a multi-task model that predicts the crop, plant part, disease, and severity together. Additional work can investigate segmentation models such as U-Net or DeepLab variants for lesion quantification, lightweight architectures for edge deployment, domain adaptation for different farms and camera devices, multilingual voice interfaces, temporal monitoring of disease progression, and expert-in-the-loop validation of XAI outputs. A larger multi-organ benchmark with

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standardized organ and severity annotations would also support more reliable comparison between future methods.

VIII. CONCLUSION

This study presents an explainable CNN-based framework for multi-organ crop disease detection and severity analysis, building on the system described in the associated patent. The proposed design expands the diagnosis scope beyond leaf-only images by explicitly considering the affected plant organ, including fruits, stems or branches, roots, flowers, and whole-plant views when appropriate data are available. The framework combines image-quality verification, preprocessing, organ identification, CNN disease classification, organ-aware severity estimation, Grad-CAM explanation, and decision-support recommendations. The research design also emphasizes field-realistic evaluation, external testing, and separation of classification confidence from severity accuracy. The final contribution will be established through reproducible experiments comparing CNN architectures and reporting measured performance across disease classes and plant organs. Numerical results are intentionally omitted from this pre-experimental draft and will be added only after implementation.

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