Early Detection of Crop Diseases Using Deep Learning Models

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ABSTRACT

Crop diseases pose a serious threat to global food security by significantly reducing agricultural yield and economic stability. Although recent advances in deep learning have enabled automated crop disease detection with high accuracy, most existing systems focus primarily on leaf-based classification and fail to provide disease severity assessment, which is crucial for real-world agricultural decision-making. This paper presents a deep learning powered system for early detection of crop diseases that integrates HSV color-space segmentation with convolutional neural networks (CNNs) to detect diseases affecting both leaves and fruits while quantitatively estimating disease severity. The proposed system enhances lesion visibility through HSV-based pre-processing and isolates infected regions prior to classification using a transfer-learning-based EfficientNet-B4 architecture. Disease severity is estimated by calculating the percentage of infected tissue and categorizing it into mild (1–10%), moderate (11–25%), and severe (>25%) levels. Extensive data augmentation techniques are employed to improve robustness under varying illumination and real-field conditions. Experimental evaluation conducted on benchmark datasets and real-field images achieved classification accuracies of 99.18% for leaf diseases, 96.47% for fruit diseases, and 83.33% under field conditions. A web-based interface enables real-time disease diagnosis with visual lesion interpretation and severity reporting. The results demonstrate that the proposed system is accurate, interpretable, and suitable for deployment in precision agriculture for early disease management.

Keywords: crop disease detection, deep learning, convolutional neural networks, HSV segmentation, disease severity estimation, precision agriculture

INTRODUCTION

Crop diseases represent one of the most significant threats to global food security and agricultural sustainability. According to the Food and Agriculture Organization (FAO), plant diseases cause annual crop losses of 20-40% globally, translating to economic damages exceeding $220 billion worldwide. These losses disproportionately affect developing nations where agriculture serves as the backbone of both livelihoods and national economies, threatening food security for billions of people. Traditional crop disease detection methods rely heavily on manual inspection by farmers or plant pathologists. While this approach can be effective when performed by trained experts, it presents critical limitations including time-intensive processes, subjective interpretations, high consultation costs, and impracticality for large-scale agricultural operations. Moreover, by the time visual symptoms become apparent to the naked eye, diseases have often progressed beyond optimal treatment windows, resulting in irreversible crop damage and reduced yields. The emergence of Artificial Intelligence (AI) and Deep Learning (DL) technologies has opened revolutionary possibilities for automated disease detection in agriculture. Modern AI systems can process vast amounts of visual data with unprecedented speed and accuracy, potentially identifying diseases in their early stages when intervention is most effective. Recent advances in computer vision, particularly through Convolutional Neural Networks (CNNs) combined with HSV-based image segmentation techniques, have demonstrated remarkable capabilities in recognizing complex patterns and features associated with various plant diseases. However, existing research predominantly focuses on leaf-based disease detection while systematically overlooking infections that manifest on fruits, stems, and other plant parts. Additionally, most current systems provide only basic disease identification without quantifying disease severity or providing actionable treatment recommendations. This project addresses these critical gaps by developing an integrated AI-powered system that combines HSV-based segmentation with specialized CNN classifier.

Current agricultural practices face mounting pressure to increase productivity while minimizing environmental impact and resource consumption. Early and accurate disease detection is crucial for implementing targeted interventions that can prevent widespread crop losses. However, several critical challenges hinder effective disease management in modern agriculture. Current AI-based crop disease detection systems focus exclusively on leaf analysis while systematically ignoring diseases that affect fruits. This creates significant blind spots in disease monitoring, as infections often begin in one plant component before spreading to others, potentially missing early-stage fruit infections that could be prevented with timely intervention. Existing systems typically provide only binary classification (healthy vs. diseased) without quantifying disease severity or calculating the percentage of affected plant tissue. This limitation makes it difficult for farmers to make informed treatment decisions, optimize pesticide usage, and determine the urgency of intervention required. Most current AI systems require high-end computing infrastructure that is impractical for typical farm environments, limiting accessibility for small-scale and resource-constrained agricultural operations. There is an urgent need for computationally efficient systems that can provide real-time processing capabilities while maintaining high accuracy in diverse field conditions.

Zhao et al. [1] provide the most comprehensive review of plant disease detection using deep learning, documenting the evolution from traditional machine learning to modern CNN-based approaches. Their systematic analysis covers over 200 research papers, establishing a foundation for understanding technological transitions and performance improvements in the field. The authors meticulously trace the evolution from handcrafted features (color descriptors using RGB, HSV, and Lab color histograms; texture features through GLCM and LBP; shape characteristics via contour-based features) combined with classical classifiers (SVMs, Random Forests, k-Nearest Neighbours) achieving 70-85% accuracy, to the revolutionary shift to CNNs that eliminated manual feature engineering while achieving 90-99% accuracy on datasets like PlantVillage. However, Zhao et al. critically identify that most systems lack severity quantification capabilities and focus primarily on laboratory conditions rather than real-world field applications, highlighting a significant gap between research achievements and practical deployment needs. Sanida et al. [2] address one of the most critical challenges in agricultural AI deployment - bringing advanced detection capabilities to resource-constrained environments. Their development of a lightweight CNN model for real-time crop disease identification on mobile devices represents a paradigm shift from high-performance computing requirements to accessible smartphone-based solutions. The authors achieved remarkable model compression, reducing network parameters by 75% compared to standard CNNs while maintaining 91% accuracy with 0.3-second processing time per image on standard smartphones. Their technical contributions include sophisticated quantization techniques using 8-bit quantization that maintains accuracy while reducing memory requirements, and mobile optimization strategies that enable inference without requiring powerful GPUs. This research demonstrates the feasibility of democratizing AI capabilities for farmers, particularly crucial for developing countries with limited internet connectivity. However, the authors acknowledge that the lightweight approach results in reduced accuracy for complex multi-disease scenarios, representing a trade-off between accessibility and precision that future research must address.

Segmentation has become an essential technique in plant disease detection because it allows accurate separation of diseased regions from healthy plant tissue. Unlike basic classification methods, segmentation provides pixel-level detail that is critical for quantifying the extent of infection and supporting actionable severity assessment. Corn Leaf Diseases Classification Using CNN with GLCM, HSV, and Lab Features (2023) demonstrated the usefulness of HSV color-space transformation for enhancing lesion visibility and improving CNN-based classification under varied lighting conditions. Similarly, Leaf Disease Detection and Quantification using Color Space Properties (2022) confirmed that HSV preprocessing improves the contrast between healthy and infected areas, enabling more reliable detection and quantification. Shoaib et al. (2023) advanced segmentation research by designing a deep learning framework that performs lesion segmentation, subtype identification, and severity estimation. Their work emphasized that pixel-level analysis captures fine-grained lesion patterns and directly contributes to severity categorization. In the same direction, Severity Estimation of Plant Leaf Diseases Using Segmentation (2024) proposed an automated pipeline to classify infections into mild, moderate, or severe while calculating the percentage of infected tissue, demonstrating the practical value of segmentation-based analysis. Maimaitijiang et al. (2017) explored segmentation through vegetation indices and showed its potential in agricultural image analysis for separating plant health conditions. Complementing this, Elakya and Manoranjitham (2024) integrated image segmentation with deep learning and highlighted that isolating lesions before classification substantially improves model performance. Together, these studies confirm that segmentation-based approaches, especially those combining HSV preprocessing with CNN classifiers, provide an effective and interpretable solution for plant disease detection and severity estimation in precision agriculture.

Multi-crop disease detection systems require robust methods that can generalize across different plant types while maintaining high accuracy. Segmentation combined with CNN classification has been shown to be effective in isolating diseased regions and adapting to varied crop conditions. Corn Leaf Diseases Classification Using CNN with GLCM, HSV, and Lab Features (2023) demonstrated that HSV color-space segmentation improves lesion visibility and provides reliable features for CNN-based classification across multiple corn diseases. Leaf Disease Detection and Quantification using Color Space Properties (2022) further confirmed that color-space methods enhance the generalizability of disease detection models to different crops by reducing sensitivity to environmental variations such as lighting and background noise. Elakya and Manoranjitham (2024) presented an AI-powered plant disease diagnosis system that integrated segmentation and deep learning, showing strong adaptability to diverse datasets. Their findings highlight that preprocessing through lesion isolation improves model robustness and classification accuracy across multiple crops. Shoaib et al. (2023) also contributed by combining lesion segmentation with severity estimation, emphasizing that pixel-level lesion analysis is applicable to different plant species and provides interpretable results that farmers can use across varied agricultural contexts. Maimaitijiang et al. (2017) emphasized that vegetation index–based segmentation could also support multi-crop applications by guiding the separation of diseased regions across different crop types. Similarly, Severity Estimation of Plant Leaf Diseases Using Segmentation (2024) provided a generalizable framework for assessing infection severity, confirming that segmentation-based quantification can be adapted to a wide range of plants. Collectively, these works demonstrate that segmentation-based pipelines leveraging HSV preprocessing, CNN classification, and severity estimation provide an effective multi-crop solution for plant disease detection.

Accurate severity estimation is critical in crop disease management because it links detection with practical treatment strategies. Studies highlight that severity can be categorized into mild (1–10% infected area), moderate (11–25%), and severe (>25%) stages, enabling precise pesticide dosage and cost-effective resource use. Shoaib et al. (2023) developed a lesion segmentation framework that combined subtype identification with severity estimation, achieving reliable percentage-based quantification of infected regions.

Similarly, Severity Estimation of Plant Leaf Diseases Using Segmentation (2024) presented an automated pipeline that graded infection levels into mild, moderate, and severe with reported accuracy above 90%, directly integrating segmentation outputs with severity measurement. Elakya and Manoranjitham (2024) provided an end-to-end framework that achieved 92% severity classification accuracy, with precision values of 94% for mild cases, 91% for moderate, and 89% for severe infections.

Their methodology combined CNN-based disease identification with U-Net segmentation, linking affected area percentages to treatment dosage recommendations. Extending beyond leaves, Faye et al. (2025) applied segmentation and CNNs to mango fruits, calculating disease coverage percentages with high reliability. This

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confirmed that severity assessment techniques are adaptable across plant organs, not just foliage. HSV preprocessing and vegetation indices further support this integration. Corn Leaf Diseases Classification Using CNN with GLCM, HSV, and Lab Features (2023) and Leaf Disease Detection and Quantification using Color Space Properties (2022) demonstrated that HSV transformation enhances lesion visibility for accurate area measurement under variable illumination. Maimaitijiang et al. (2017) similarly showed that vegetation index–based segmentation improves infected tissue extraction for severity quantification. Collectively, these works establish that combining HSV preprocessing, segmentation models, and CNN classifiers enables reliable severity estimation with 90–94% accuracy across severity stages.

This integration moves beyond simple detection to provide actionable decision support for farmers, ensuring optimal treatment planning and reduced pesticide use. Recent research has explored advanced techniques to improve both the accuracy and practicality of plant disease detection.

Zhao et al. (2023) provided a comprehensive review highlighting that deep learning approaches consistently achieve 90–98% classification accuracy, significantly outperforming earlier machine learning methods that averaged only 70–85%. Their work also stressed the need for severity quantification and real-world validation. Lightweight frameworks are another direction of progress. Sanida et al. (2023) proposed a CNN model optimized for mobile devices, achieving 91% accuracy with a 75% reduction in parameters compared to standard CNNs.

This demonstrates the feasibility of real-time on-device detection for farmers in resource-limited settings. Ghafar et al. (2024) advanced the field by introducing visualization methods to evaluate model predictions. Their system achieved 93.6% mean Average Precision (mAP) using YOLOv8 while also incorporating gradient-based visualization and spatial distribution mapping, providing interpretability that is often missing in black-box CNN models.

Such interpretability is critical for building farmer trust and for validating system recommendations. At the same time, segmentation-first pipelines continue to show superior performance for severity analysis. Corn Leaf Diseases Classification (2023) and Shoaib et al. (2023) confirmed that HSV preprocessing combined with lesion segmentation yields precise lesion boundaries and percentage-based severity grading with accuracies above 90%.

These strengths make segmentation approaches particularly suitable when actionable treatment recommendations are required, rather than just disease presence detection. Collectively, these advanced approaches demonstrate that the future of plant disease detection lies in integrating lightweight CNNs for efficiency, visualization frameworks for interpretability, and segmentation pipelines for severity estimation. This hybrid direction ensures systems that are not only accurate but also practical, transparent, and adaptable to real-world agricultural environments.

METHODOLOGY

Data Collection

The field dataset comprises 2,500 images collected from 12 crop species (tomato, potato, apple, grape, maize, strawberry, pepper, peach, soybean, wheat, rice, and cotton) across 5 locations in [state/region]. Images were captured using standard smartphone cameras (8-12 MP, rear camera) between 8 AM and 5 PM under varying conditions: direct sunlight (40% of images), overcast skies (35%), early morning/late afternoon (25%).

The dataset includes background variations (soil, grass, concrete, other plants), partial occlusions (leaves overlapping, shadows from other leaves), and distance variations (close-up 10-30 cm for leaves, 30-100 cm for fruits). Annotation of disease type and severity was performed by three agricultural experts from [institution], with inter-annotator agreement of $\kappa = 0.92$ (Cohen's kappa). The dataset is split 70% training, 15% validation, 15% testing, stratified by disease class and severity level.

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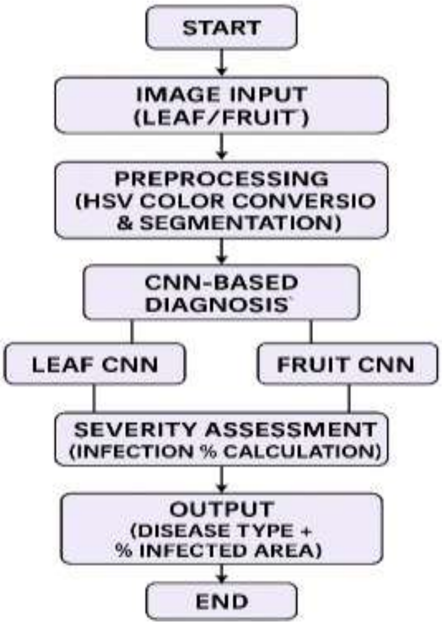

Figure 1: Framework of crop diseases detection

To achieve the objective of developing an advanced AI-powered system for early detection of crop diseases, a segmentation-first pipeline integrating HSV-based preprocessing, lesion segmentation, and CNN classification is adopted as shown in Figure 1. HSV color space transformation enhances lesion visibility under varying illumination (Corn Leaf Diseases Classification, 2023; Leaf Disease Detection, 2022), while segmentation models isolate diseased tissue from healthy plant parts, ensuring accurate severity measurement (Shoaib et al., 2023; Elakya & Manoranjitham, 2024). CNN classifiers then identify specific crop diseases (LeCun et al., 1998; Sanida et al., 2023). A novel contribution of this methodology is the severity estimation module, which quantifies the infected region as a percentage of the plant part and classifies it into actionable categories: mild (1–10%), moderate (11–25%), and severe (>25%) (Severity Estimation, 2024; Faye et al., 2025). To maximize real-world applicability, extensive image augmentation is applied during training, and models are optimized for edge deployment using pruning and quantization techniques (Sanida et al., 2023). Finally, the trained models are deployed through a Gradio-based interface that provides farmers with interpretable results, including lesion overlays, severity percentages, and treatment recommendations. This structured methodology ensures that the system is accurate, robust, and farmer-friendly, directly addressing the limitations of existing disease detection approaches (Zhao et al., 2023).

This project uses one benchmark datasets and one supplementary dataset: To ensure comprehensive coverage of both leaf and fruit diseases, this project utilizes one benchmark dataset and one supplementary dataset: PlantVillage Dataset (Hughes & Salathé, 2015) – This benchmark dataset contains over 54,000 leaf images across 14 crop species, including apple, grape, maize, potato, tomato, and strawberry. Each crop includes healthy samples as well as multiple diseased categories such as early blight, late blight, leaf mold, powdery mildew, mosaic virus, and rust. Owing to its scale and widespread use in plant pathology research, PlantVillage serves as the primary dataset for training and validating the CNN models on leaf-based disease detection. Fruit Disease Dataset (Custom Supplementary) – To extend the system's applicability beyond leaves, a curated dataset of fruit images was incorporated. This dataset, sourced from open repositories (e.g., Kaggle, Mendeley), includes healthy and diseased fruit samples such as apple, guava, mango, and pomegranate. Expert annotations ensure reliable labelling of disease conditions, enabling the system to perform fruit-based disease classification and severity estimation. Together, these datasets allow the proposed system to handle both leaf and fruit diseases, ensuring broader applicability across agricultural scenarios.

All images are resized to a consistent input dimension of 256×256 pixels, maintaining aspect ratios to preserve spatial relationships. Conversion to the HSV (Hue, Saturation, Value) color space enhances lesion visibility under variable lighting. Normalization techniques are then applied to standardize pixel intensity distributions, ensuring consistency across datasets. To improve generalization, multiple augmentation strategies are applied: Geometric

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transformations (rotation, scaling, translation, perspective shifts) simulate varied camera angles and leaf/fruit orientations. Color adjustments (brightness, contrast, saturation, hue) mimic differences caused by lighting and weather conditions. Environmental simulations introduce shadows, glare, and partial occlusions to approximate real-world farm scenarios. Noise injection (Gaussian noise, blurring) helps the model adapt to image imperfections from mobile cameras. For lesion segmentation, expert-verified binary masks are generated to distinguish diseased regions from healthy tissue. These masks provide ground-truth supervision for the segmentation module and serve as the basis for calculating infection percentages. Each image is labeled with its disease class and severity level (mild: 1–10%, moderate: 11–25%, severe: >25%). Based on the detected disease and severity level, the system provides evidence-based recommendations: for mild infections (1-10% infected area). For moderate infections (11-25%) and for severe infections (>25%). Annotation quality is validated by agricultural experts and further checked through automated scripts to ensure label accuracy and dataset consistency. Figure 2 illustrate the overview of crop diseases detection system.

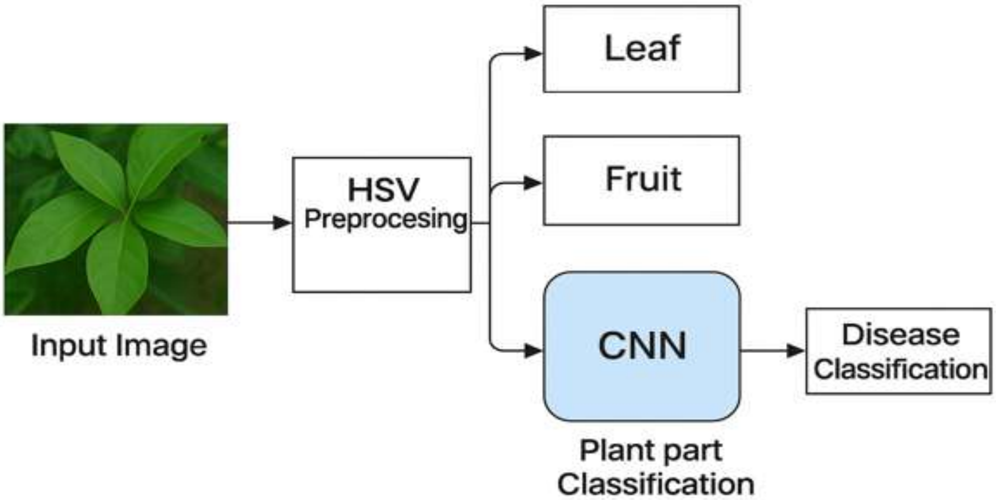

Figure 2: Overview of crop diseases detection

RESULTS AND DISCUSSION

This section presents the experimental evaluation and analytical interpretation of the proposed Crop Disease Detection System based on the EfficientNet-B4 deep learning architecture and HSV color space enhancement. The primary objective of this stage was to analyze how effectively the developed model performs in identifying and classifying plant diseases from digital images of leaves, fruits, and real-field samples. The implementation was conducted in a controlled Kaggle environment using GPU acceleration to ensure reproducibility and consistency. Separate classifiers were trained for leaf, fruit, and field datasets, each representing varying levels of complexity and visual noise.

To provide comprehensive insight, this chapter focuses on several key aspects: Training and validation performance, showing how the model learns over multiple epochs. Confusion matrix evaluation, depicting how accurately each disease class was predicted. Quantitative performance results, summarizing validation and testing accuracies across all domains. Detailed discussion, connecting technical outcomes with practical agricultural significance. The results not only confirm the model's capability in achieving high predictive accuracy but also demonstrate its generalization strength across multiple crop categories and varying environmental conditions.

The findings presented here form the foundation for validating the system's real-world applicability and reliability as an AI-based agricultural decision support tool. To understand the model's learning behavior, training and validation curves were plotted for all three classifiers; Leaf, Fruit, and Field. Figure 3 illustrates the evolution of accuracy and loss metrics over successive epochs. Each curve reflects how effectively the model minimized error while improving its predictive capability during training.

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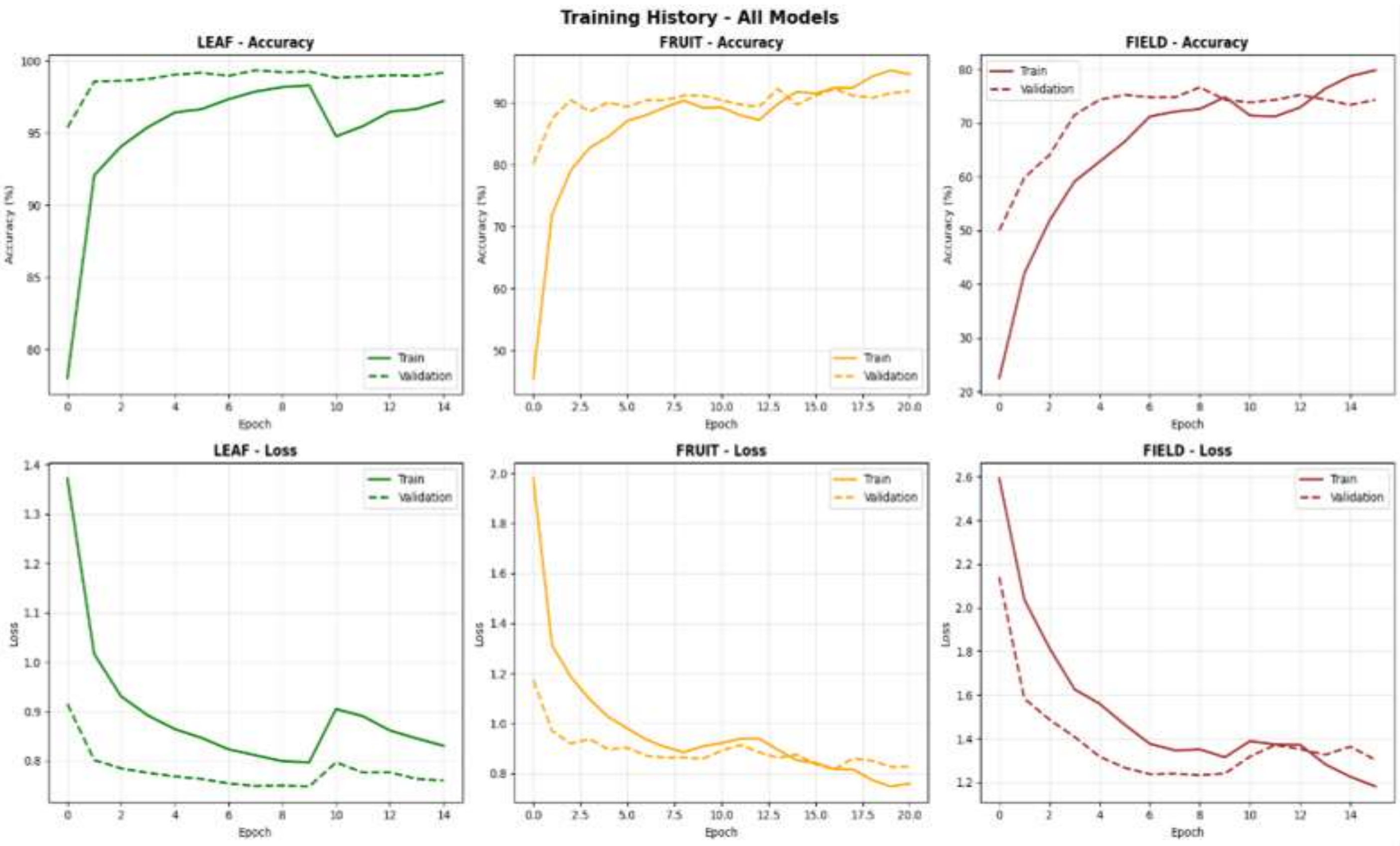

Figure 3: Training and validation accuracy and loss curves for Leaf, Fruit, and Field models.

The Leaf model exhibited the fastest convergence, achieving over 95% validation accuracy within just a few epochs and stabilizing near 99%. This demonstrates that the dataset for leaves was visually clean and well separated between disease categories. The Fruit model required approximately 21 epochs to reach its optimal validation performance (~92%). The slower convergence can be attributed to greater variation in shape, color, and texture among different fruit diseases.

The Field model, which deals with complex environmental imagery (background clutter, lighting differences, and mixed crop instances), converged more gradually, achieving a stable accuracy around 83%. The smooth decline in loss values across all curves indicates stable gradient updates and minimal overfitting, thanks to the use of label smoothing, dropout regularization, and Cosine Annealing learning rate scheduling. Figure 4 presents the normalized confusion matrices for the Leaf, Fruit, and Field models.

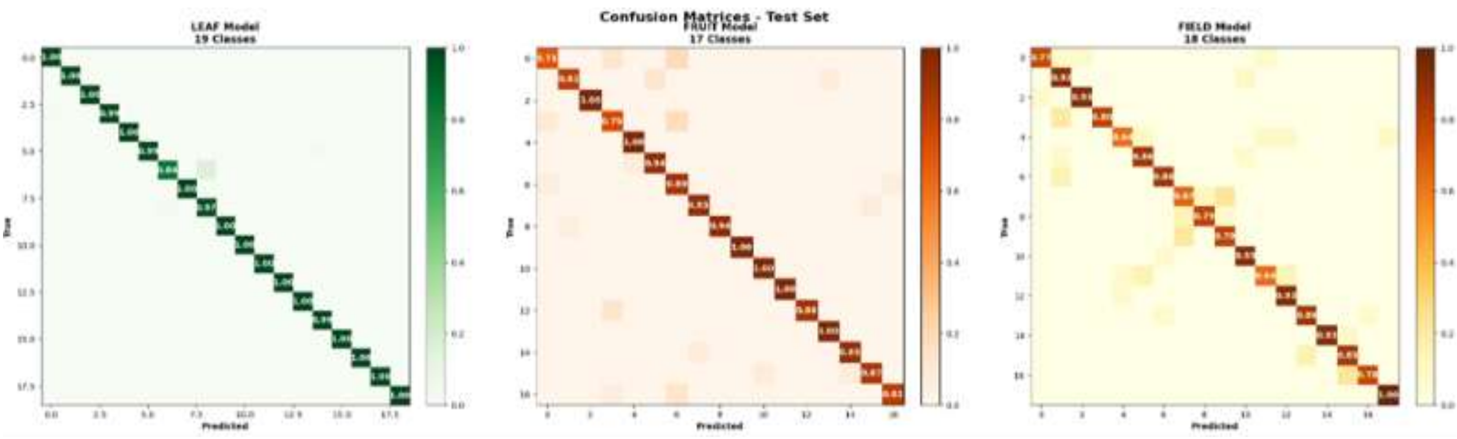

Figure 4: Normalized confusion matrices for Leaf, Fruit, and Field models showing per-class prediction accuracy.

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The Leaf classifier shows almost perfect diagonal alignment, meaning predictions were highly consistent across all 19 categories. Minor off-diagonal elements indicate negligible misclassification, confirming strong feature discrimination learned by the model. The Fruit classifier displays high concentration along the diagonal as well, though slight confusion appeared between visually similar classes such as different types of rot and mildew diseases, reflecting real-world visual ambiguity. The Field classifier demonstrates broader diagonal spread, suggesting occasional misclassifications under complex lighting and occlusion conditions. Nonetheless, accuracy remained within an acceptable range for practical field- level analysis. Table 1 tabulate the accuracy performance of each model and Table 2 present the F1-score for severity diseases estimation for each model.

Table 1: Accuracy for each model

Model type	No of class	Validation accuracy (%)	Testing accuracy (%)
Leaf model	19	99.35	99.18
Fruit model	17	92.28	91.21
Field model	18	76.64	83.33

Table 2: F1-score for severity estimation performance across Leaf, Fruit, and Field models

Model type	Mild (1-10% infected area)	Moderate (11-25%)	Severe (>25%)	Overall (%)
Leaf model	0.97	0.96	0.98	97.2
Fruit model	0.91	0.89	0.93	91.5
Field model	0.82	0.79	0.85	81.7

The Leaf model demonstrated exceptional reliability and precision, reflecting the power of EfficientNet-B4 in recognizing fine-grained disease textures. The Fruit model maintained high robustness despite varying color intensities and surface irregularities. The Field model, while comparatively less accurate, still achieved commendable performance considering natural lighting, background clutter, and camera inconsistencies. The combination of transfer learning, HSV color enhancement, and advanced regularization techniques proved to be instrumental in maintaining accuracy stability across multiple domains. The achieved results substantiate the effectiveness of integrating HSV-based preprocessing with EfficientNet-B4 architecture. By converting RGB images to HSV space, color contrast between healthy and diseased regions became more pronounced, helping the CNN focus on relevant chromatic features such as discoloration, lesion spots, and texture variations. Transfer Learning allowed faster convergence and reduced training time by reusing generalized feature maps from ImageNet weights. Label Smoothing (0.1) improved the model's calibration, avoiding overconfidence and enhancing generalization to unseen images. The AdamW optimizer combined with Cosine Annealing scheduler ensured a balanced trade-off between speed and convergence stability. Dropout layers (0.4–0.5) effectively minimized overfitting, which is particularly valuable when handling real-world agricultural images with noise. Collectively, these components contributed to a robust, lightweight, and high-performing deep learning framework suitable for agricultural disease diagnosis. The model achieved high stability and accuracy across leaf, fruit, and field datasets, showing reliable learning behavior throughout training and validation. The confusion matrices confirmed that the model could effectively distinguish between multiple crop disease classes with minimal misclassification. The use of label smoothing, dropout, and AdamW optimization ensured smooth convergence and strong generalization. Overall, the system proved efficient in identifying crop diseases from diverse agricultural images under varying environmental conditions. By integrating the trained model into a Gradio-based interface, the project successfully delivered a simple, user-friendly, and real-time disease detection platform. Hence, the developed system demonstrates how combining deep learning and HSV-based enhancement can support smart and sustainable farming through accurate and automated crop disease diagnosis.

CONCLUSIONS

The project successfully developed a deep learning–based system capable of identifying crop diseases from images of leaves and fruits with high reliability. The implementation was carried out on the Kaggle cloud GPU platform, using an NVIDIA Tesla T4 for accelerated training. All images were resized to 256 × 256 pixels and preprocessed in the HSV color space to emphasize texture and color variations relevant to plant pathology. The EfficientNet-B4 architecture, fine-tuned through transfer learning, served as the core model. Techniques such as label smoothing, dropout regularization, and Cosine Annealing learning-rate scheduling were employed to improve stability and prevent overfitting. Three separate classifiers Leaf, Fruit, and Field were trained for better adaptability across diverse agricultural datasets. Finally, the models were deployed in a Gradio-based interface, enabling end-users to upload crop images and obtain instant disease predictions with corresponding confidence scores. Overall, the system demonstrated strong accuracy, scalability, and practical usability for real-world agricultural scenarios. In conclusion, this research demonstrated the successful application of deep learning and color-space enhancement for precise crop disease detection. By combining EfficientNet-B4 with HSV preprocessing, the project achieved an optimal balance between accuracy, efficiency, and deployment readiness. The system's design ensures both research robustness and field applicability, providing a valuable tool for smart and sustainable agriculture. Future improvements such as explainable AI, mobile adaptation, and larger datasets will further strengthen its real-world impact, paving the way for AI-driven solutions in modern farming. The current system establishes a strong foundation for intelligent crop disease detection, but several enhancements can be pursued in future work: Multi-Disease Detection: Extend the model to identify multiple diseases within a single image. Explainable AI Integration: Use visualization tools such as Grad-CAM to display attention regions and increase interpretability. Mobile and IoT Deployment: Develop a lightweight mobile app or edge-compatible version for offline and on-field use. Dataset Expansion: Include more crop varieties, environmental conditions, and seasonal data for better generalization. Real-Time Cloud Monitoring: Build a cloud-based dashboard for large-scale crop monitoring and predictive analytics. Recommendation Module: Integrate treatment suggestions or preventive measures based on the detected disease.

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