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Lightweight CNN for Mobile-Based Detection of Fungal Disease in Onion Leaves

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Abstract

Fungal diseases such as Purple Blotch, Downy Mildew, Stemphylium Leaf Blight, and Botrytis Leaf Blight pose serious threats to onion production, particularly in developing agricultural regions where access to expert diagnosis is limited. This study proposes and evaluates a mobile-deployable, lightweight convolutional neural network (CNN) based system for automated classification of fungal diseases in onion leaf images captured under real field conditions. A dataset comprising 9,300 annotated onion leaf images across five classes (four fungal diseases and healthy leaves) was utilized. Three lightweight CNN architectures, MobileNet, EfficientNet, and a custom-designed lightweight CNN, were trained, optimized, and comparatively evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and inference latency. Statistical validation using one-way Analysis of Variance (ANOVA) revealed a significant effect of model architecture on classification performance ($p < 0.001$), with a large effect size ($\eta^2 = 0.62$, corresponding to Cohen's $f = 1.27$). Subsequent Tukey's Honestly Significant Difference (HSD) post-hoc tests confirmed that the MobileNet-based model achieved statistically superior performance compared to both EfficientNet and the custom lightweight CNN. Post-training optimization techniques, including transfer learning and INT8 quantization, were applied to improve mobile readiness. The best-performing model was successfully deployed on Android devices using TensorFlow Lite, enabling real-time, offline inference. Field validation with onion farmers further demonstrated high usability and practical effectiveness, confirming the suitability of lightweight CNNs as efficient and accessible decision-support tools for real-world agricultural disease detection. The proposed system offers a practical, accessible, and efficient decision-support tool for onion farmers, contributing to improved disease management and agricultural productivity. Future work may explore additional disease classes, multi-modal data integration, and broader device-level evaluations.

Keywords: Lightweight CNN, EfficientNet, onion leaf diseases, MobileNet, TensorFlow Lite, Android, automated disease detection

INTRODUCTION

Onion cultivation plays a critical role in food security and agricultural economies, particularly in developing countries. However, onion production is highly vulnerable to fungal leaf diseases such as Purple Blotch, Downy Mildew, Stemphylium Leaf Blight, and Botrytis Leaf Blight, which significantly reduce crop yield and quality. Previous agricultural studies have reported that fungal leaf diseases can cause yield losses ranging from 30% to 50%, depending on disease severity, environmental conditions, and management practices (Oerke, 2006; Strange & Scott, 2005), 2022; Sharma et al., 2021). These losses pose substantial economic risks to smallholder farmers who often operate with limited access to timely disease diagnosis and expert support.

Traditional disease detection in onion farming relies primarily on manual visual inspection by farmers or agricultural technicians. While this approach is widely practiced, it is inherently subjective, time-consuming, and prone to misdiagnosis, especially during early disease stages or under unfavorable field conditions. In rural areas, delayed access to agricultural experts further exacerbates the problem, resulting in late intervention and increased yield loss. With the increasing availability of smartphones, image-based disease detection using artificial intelligence has emerged as a promising alternative to conventional diagnostic methods.

Convolutional Neural Networks (CNNs) have demonstrated strong performance in plant disease classification due to their ability to automatically learn discriminative visual features from images. However, many high-performing CNN models are computationally intensive and unsuitable for deployment on mobile devices commonly used by farmers. To address this limitation, lightweight CNN architectures have been developed to reduce computational and memory requirements while maintaining acceptable classification accuracy. In this study, the researcher objectively evaluates lightweight CNN models for mobile-based onion leaf fungal disease classification under real field conditions. Below are the specific objectives of the study:

1. To develop lightweight convolutional neural network models capable of classifying fungal diseases in onion leaf images captured under real field conditions.

2. To evaluate and compare the classification performance of MobileNet, EfficientNet, and a custom lightweight CNN using standard performance metrics.

3. To statistically validate performance differences among the evaluated CNN architectures using one-way ANOVA and Tukey's HSD post-hoc tests.

4. To optimize the best-performing model for mobile deployment using TensorFlow Lite and INT8 quantization.

5. To assess the usability and acceptance of the developed mobile application through field validation and survey-based evaluation.

Proposed Integrated Framework. The proposed integrated framework combines technical, behavioral, and interactional perspectives to support mobile-based onion leaf fungal disease detection. It integrates CNN Theory for efficient visual feature learning, the Technology Acceptance Model (TAM) for explaining user adoption and perceived ease of use, and Human–Computer Interaction (HCI) principles to guide interface design and usability.

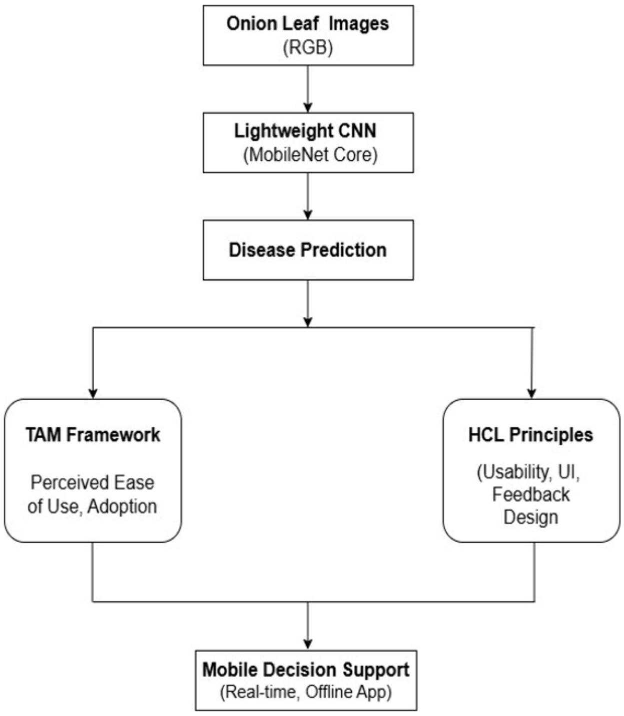

Figure 1
Interaction between CNN-based Image Classifications

Figure 1 illustrates the interaction between CNN-based image classification, user acceptance (TAM), and interface design (HCI), forming a holistic framework for practical agricultural decision support.

LITERATURE REVIEW

This study focuses on integrating Convolutional Neural Networks (CNNs) with image processing techniques to detect fungal infections in onions and other crops. The review highlights significant methodologies, obstacles, and advancements in this burgeoning domain.

Current State of Technology in Crop Disease Detection Using Image-Based Approaches. The advancement of technology in agricultural disease detection has rapidly evolved due to improvements in image-based deep learning and computer vision. This transition has shifted from traditional manual diagnosis, which is subjective and labor-intensive, to automated solutions. The widespread availability of high-resolution cameras and mobile devices has enabled machine learning methodologies for early disease detection and timely intervention, particularly benefiting smallholder farmers (Liu & Wang, 2021). Recent research emphasizes that convolutional neural networks (CNNs) excel at identifying crop diseases through image analysis, as highlighted by Abade, Ferreira, and Vidal (2021). Their study shows that deep learning models outperform traditional machine learning techniques that rely on manual feature extraction. Furthermore, (Kamilaris & Prenafeta-Boldú,2018; Mohanty et al.,2016; Picon et al., 2019; Shorten & Khoshgoftaar,2019) discovered that CNNs achieve high accuracy across a range of crops, particularly when supplemented with data augmentation and extensive annotated datasets. These results position CNNs as crucial components of modern systems for detecting crop diseases. Crop disease classification is increasingly using transfer learning alongside traditional CNNs, utilizing models pre-trained on large datasets like ImageNet. This approach reduces training time and improves performance in data-scarce situations (Eunice et al., 2022; Mohanty et al., 2016; Al Sahili & Awad, 2022). Deep learning and transfer learning approaches have shown significant improvements in classification accuracy for rare crop diseases, particularly in data-scarce agricultural datasets, making them highly suitable for practical field applications (Hossen et al., 2025; Rezaei et al., 2024; Al Sahili & Awad, 2022).

Lightweight Convolutional Neural Networks for Crop Disease Classification. Increased demand for real-time crop disease diagnostics has led to research on lightweight convolutional neural networks (CNNs) that improve classification accuracy while reducing resource consumption. Traditional deep CNNs like VGG and ResNet offer high performance but require significant memory and computational power, limiting their use in agriculture. Current studies focus on compact CNN architectures designed for mobile devices and edge computing to address these constraints (Liu & Wang, 2021). Abade, Ferreira, and Vidal (2021) conducted a systematic review on the transition from heavyweight to lightweight convolutional neural networks for classifying plant and crop diseases, noting the benefits of depth wise separable convolutions in reducing parameters while preserving accuracy. (Kamilaris & Prenafeta-Boldú, 2018; Mohanty et al., 2016; Picon et al., 2019) found that lightweight CNNs, combined with transfer learning and data augmentation, achieve performance comparable to deeper networks on various crop disease datasets. Current literature highlights the efficiency and versatility of MobileNet designs. Sulaiya and Banerjee (2025) found that MobileNetV2 and MobileNetV3 strike an optimal balance between model size and accuracy for smartphone use in detecting crop diseases. Recent studies proposed compact CNN architectures for crop disease recognition that integrate attention modules with lightweight backbones such as MobileNet, achieving sufficient classification accuracy while significantly reducing the number of parameters compared to conventional deep CNN models (Howard et al., 2017; Zhang et al., 2021; Picon et al., 2019).

EfficientNet architectures, particularly the B0 and B1 variants, have been highlighted for their effectiveness in crop disease classification, often outperforming traditional CNN models while maintaining low computational complexity and parameter efficiency suitable for mobile and resource-constrained agricultural applications (Tan & Le, 2019; Too et al., 2019; Ferentinos, 2018). Kumar et al. (2024) evaluated various lightweight CNN models, including EfficientNet and ShuffleNet, across 33 crop types and 101 disease classes, demonstrating their strong generalization and robustness in diverse agricultural settings. Researchers have proposed specialized compact convolutional neural networks (CNNs) for identifying crop diseases. Recent research introduced lightweight isotropic CNN architectures that achieved notable classification accuracy with fewer than one million parameters, underscoring the potential of task-specific lightweight models for efficient deployment in resource-constrained environments (Trockman & Kolter, 2022; Han et al., 2021; Tan & Le, 2019). Similarly, Zhang et al. (2025) utilized a comparable approach to address soybean crop diseases, enhancing the detection of subtle symptoms through multi-scale feature fusion within a compact framework.

Lightweight and Explainable CNN for Crop Disease Diagnosis. The development of lightweight and interpretable convolutional neural networks (CNNs) in crop disease diagnostics is a significant trend in agricultural AI. The hybrid model Mob-Res combines MobileNetV2 with residual blocks, achieving a high accuracy of 99.47% on the PlantVillage dataset while using only 3.51 million parameters. It also incorporates explainability methods like Grad-CAM, Grad-CAM++, and LIME, allowing for visual interpretations of its decisions, making it suitable for resource-constrained mobile and edge devices. Researchers have developed specialized compact convolutional neural networks (CNNs) for the identification of crop diseases. Lightweight and isotropic CNN architectures have been shown to achieve strong classification accuracy with very low parameter counts (often under one million), highlighting the effectiveness of task-focused compact models (Trockman & Kolter, 2022; Han et al., 2021; Tan & Le, 2019). Zhang et al. (2025) utilized a comparable methodology to address soybean crop diseases, enhancing the identification of subtle symptoms via multi-scale feature fusion within a streamlined framework. Semi-supervised learning, integrated with lightweight CNN architectures, reduces reliance on large, labeled datasets. Prior studies demonstrated that lightweight CNN architectures integrated with semi-supervised learning and Grad-CAM visualization can achieve very high classification accuracy in leaf disease datasets, including jute leaf diseases, while providing interpretable visual explanations for model decisions (Islam et al., 2021; Selvaraju et al., 2017; Zhang et al., 2022). This study highlights that interpretability can be maintained even with limited labeled data, making these models suitable for practical agricultural applications. Specific agricultural solutions and hybrid structures for enhancing interpretability have been proposed. Recent studies have utilized lightweight CNN backbones such as MobileNetV2 for feature extraction combined with Graph Neural Networks, while interpretability techniques like Grad-CAM and Eigen-CAM were applied to generate clearer visual representations of disease-affected regions (Howard et al., 2018; Kipf & Welling, 2017; Selvaraju et al., 2017; Muhammad et al., 2020). This hybrid model reached a classification accuracy of 97.16%, demonstrating that cross-modal interpretability can improve both accuracy and user trust while preserving a compact parameter footprint.

Mobile-Based Crop Disease Detection Systems

The swift growth of smartphones has led to advancements in mobile agricultural disease detection, allowing real-time diagnostics of plant health. A recent study introduced a CNN-based mobile app that can identify 38 disease categories in 14 crop species with an accuracy of 94%. Users can take pictures of plant leaves using the app, submit them, and receive immediate disease classification results and confidence scores, making it beneficial for resource-limited farmers. Using TensorFlow Lite, smartphone integration for detecting agricultural diseases has achieved about 96% accuracy with the DenseNet201 model, demonstrating that on-device diagnosis works well and helps smallholder farmers, even when they don't have constant internet access. Several studies assessing mobile applications for plant disease detection report that although many apps exist, only a limited number, such as Plantix, provide comprehensive features including disease identification, plant databases, and treatment recommendations (Ramcharan et al., 2019; Ramesh et al., 2021). The study highlights that most apps still lack advanced AI-driven detection capabilities. Smartphone applications have been developed for citizen science and pest detection, including one using the Ionic Framework that allows real-time identification of plant leaf diseases and pests. It features georeferencing to aid early warning systems and agricultural management decisions, showcasing the broader impact of mobile systems beyond mere diagnosis. Offline mobile applications like SmartAgriDoc, which use a convolutional neural network (CNN) with TensorFlow Lite, facilitate crop disease detection. This enables farmers to identify diseases without internet access, making it particularly valuable for remote regions with poor connectivity. Research on mobile application workflows emphasizes rigorous image validation. Using a two-part approach that includes a leaf/non-leaf classifier, and a disease classifier enhances accuracy in diagnosis and boosts user trust by only analyzing important images.

Fungal Disease Detection in Leaf Images. The study emphasizes the significance of automated image-based detection of fungal infections in crops for ensuring food security, particularly focusing on powdery mildew. It highlights an unsupervised deep learning model that utilizes multispectral imaging to effectively identify disease symptoms on cucumber leaves. This model showcases strong feature extraction capabilities, indicating its potential for early and cost-effective monitoring of fungal diseases. Recent hybrid networks, such as TCLeaf-Net, have improved lesion-level disease identification by combining global context with local convolutional features, effectively addressing the diverse appearances of fungal diseases on leaf images. Recent studies indicate that modalities like thermal imaging can enhance the detection of fungal diseases in plants by combining thermal and RGB data. However, these techniques face preprocessing and modeling challenges. Research on image-based detection often relies on extensive multicrop datasets, in which fungal diseases, including black spots, rusts, and lesions associated with fungal infections, are significant categories. This indicates that CNN models must generalize across different crops and disease symptoms to be effective in agricultural contexts. Furthermore, comprehensive reviews emphasize that identifying fungal diseases remains difficult, often requiring large, labeled datasets, precise augmentation, and network regularization to ensure effective model generalization from controlled to field conditions.

Comparative Performance of Lightweight CNN Architectures. Comparative studies of lightweight CNN architectures such as MobileNetV2, SqueezeNet, ShuffleNetV2, and MnasNet on plant disease image datasets show that efficient models can achieve very high validation accuracy while maintaining low computational cost, highlighting the trade-offs between efficiency and classification performance in agricultural applications (Too et al., 2019; Ma et al., 2018; Howard et al., 2018; Tan et al., 2019). Comparative studies on lightweight CNN architectures for plant and rice leaf disease identification indicate that EfficientNet-B0 often achieves higher accuracy than MobileNetV2 and ShuffleNet, highlighting the effectiveness of EfficientNet's compound scaling strategy in capturing complex visual disease patterns (Tan & Le, 2019; Too et al., 2019; Kamilaris & Prenafeta-Boldú, 2018). Previous benchmarking studies using large-scale plant disease datasets comprising numerous crops and disease classes compared lightweight architectures such as MobileNetV2, MobileNetV3, and EfficientNet-B0/B1, and found that EfficientNet-B1 achieved the highest classification accuracy among lightweight models, highlighting how variation selection within EfficientNet influences performance and resource efficiency across diverse crop disease categories (Too et al., 2019; Tan & Le, 2019; Mohanty et al., 2016). Comparative analyses highlight the efficacy of hybrid model designs in classification tasks. The hybrid lightweight CNN models combining MobileNetV2 with Inception modules have been shown to outperform deeper architectures such as InceptionV3, VGG19, and DenseNet in rice plant disease classification while maintaining lower parameter counts (Islam et al., 2021; Howard et al., 2018; Szegedy et al., 2016). This work illustrates that combining different architectures can enhance performance without incurring substantial computational costs. Comparative studies show that

EfficientNet-B0 outperformed MobileNetV2 in bacterial colony classification tasks, particularly in validation accuracy enhanced by robust augmentation techniques, indicating EfficientNet variants' potential in optimizing model performance for complex patterns.

Synthesis. In addition to appropriate preprocessing and augmentation, EfficientNet and ResNet effectively classify leaf disease images. Second, the initial manifestation of onion lesions is subtle and resembles purple blotch, Stemphylium leaf blight, downy mildew, and Botrytis leaf blight. Variability in capturing conditions leads to frequent misclassification. Third, quantized models and user interfaces that display class, indicative severity, and confidence facilitate mobile-first operations. Scouts can recapture images of substandard quality and adhere to plot-level hazard notifications. Though progress has been made, datasets, illumination, and cultivar dispersion affect reported measurements. Many studies use lab-style photos with homogenous backgrounds, which may overestimate accuracy compared to field data. A class imbalance persists for early-stage symptoms and unusual diseases, and evaluations often lack cross-farm or cross-season splits. These characteristics limit generalization and require greater augmentation, curated hard negatives, and consistent capturing techniques. Four significant gaps persist. Initially, several onion datasets with verified field labels restrict cultivar and region-specific training. Secondly, the majority of studies do not incorporate uncertainty calibration or decision thresholds necessary for translating model scores into actionable measures. Third, there is limited evidence indicating that app-assisted detection influences spray timing and crop yield across seasons. Fourth, farms with limited connectivity infrequently facilitate dataset and model update procedures. To address these deficiencies, it is essential to implement multi-region data collaborations, calibrated outputs, field trials, and lightweight updates for mobile deployments.

METHODS

Research Design. This study employed a developmental–experimental research design, integrating system development with quantitative performance evaluation. The developmental component focused on designing, training, optimizing, and deploying lightweight convolutional neural network (CNN) models within a mobile application environment. In parallel, the experimental component systematically compared multiple CNN architectures (MobileNet, EfficientNet, and a custom lightweight CNN) under identical conditions to determine statistically significant differences in classification performance.

The research design was operationalized through the following stages: (1) dataset acquisition and preprocessing using field-captured and publicly available onion leaf images; (2) iterative model development and training using transfer learning; (3) quantitative evaluation using accuracy, precision, recall, F1-score, and inference latency; (4) statistical validation through one-way ANOVA, Tukey's HSD post-hoc analysis, confidence intervals, and effect size estimation; and (5) mobile deployment and field validation to assess usability and practical feasibility. This structured progression ensured that both technical performance and real-world applicability were rigorously examined.

An Agile-inspired iterative workflow guided implementation, enabling continuous refinement of model architectures and system components based on evaluation feedback. This design was particularly appropriate for machine learning–driven systems, as it supported repeated cycles of training, testing, optimization, and user validation. By combining controlled experimentation with real-field deployment, the research design provided a clear methodological pathway for assessing lightweight CNN effectiveness while addressing practical constraints encountered in agricultural environments.

Data Source. The sources of data for this study comprised two primary components: (1) onion leaf image samples used for model development and evaluation, and (2) human respondents who participated in the field usability assessment of the mobile application.

Image Dataset Selection Criteria. Onion leaf images were included if they: (a) clearly exhibited visible symptoms of Purple Blotch, Downy Mildew, Stemphylium Leaf Blight, Botrytis Leaf Blight, or healthy leaf conditions; (b) were captured under real field environments using smartphone cameras; and (c) met minimum quality requirements (in-focus subject, adequate illumination, and sufficient leaf area coverage). Images were excluded if they were excessively blurred, overexposed, severely occluded, or contained ambiguous symptoms. The final dataset consisted of 9,300 images, which were stratified by class and partitioned into training, validation, and test sets following an 80:10:10 scheme, with the independent test set (n = 1,860) reserved exclusively for performance reporting and confidence interval estimation.

Respondent Sampling and Selection. Human participants for field validation were selected using purposive sampling, targeting individuals with direct involvement in onion cultivation or agricultural extension. Inclusion criteria required that respondents: (a) actively engage in onion farming or provide agricultural technical support; (b) possess basic smartphone literacy; and (c) provide informed consent. Individuals without prior exposure to onion crop management or unwilling to participate were excluded.

Data Collection. Coordination with local agricultural offices facilitated access to onion farming communities. Eligible participants were invited during on-site visits and briefed on the study objectives and procedures. After consent was obtained, respondents were guided through the mobile application workflow, including image capture and disease prediction. After hands-on system use, surveys were administered on-site using printed forms or digital questionnaires, depending on connectivity. Responses were encoded and aggregated for statistical analysis, including reliability testing and descriptive evaluation of user acceptance. This structured procedure ensured that respondents were representative of the intended end users while enabling consistent and reliable data collection across field sites.

Image Data Collection. Data were gathered using combined automated image acquisition for model development and structured field-based evaluation for usability assessment. Onion leaf images were collected through on-site field visits and curated public repositories. During field acquisition, researchers followed the standardized capture protocol described earlier (device type, capture distance, resolution, and lighting conditions). Each image was immediately reviewed for quality compliance and stored with anonymized identifiers. Images were then organized by class label and location, after which preprocessing (resizing, normalization, and augmentation) was applied prior to model training.

Annotation Procedure. All images were independently labeled by two domain experts. Initial annotations were consolidated, discrepancies were resolved through consensus, and inter-rater reliability was quantified using Cohen's kappa. The finalized labeled dataset served as the ground truth for model training, validation, and testing.

System Evaluation and Field Validation. Following model deployment to Android devices, data gathering for system evaluation was conducted in two stages. First, quantitative performance data (accuracy, precision, recall, F1-score, latency, and resource usage) were automatically recorded during controlled testing using the independent test set. Second, field validation sessions were conducted with selected respondents, during which participants used the mobile application to capture leaf images and view diagnostic outputs in real time.

Data Integrity and Management. All collected data were securely stored on password-protected systems. Image datasets and survey responses were anonymized, backed up regularly, and accessed only by the research team. This procedure ensured data integrity, traceability, and compliance with ethical and privacy requirements throughout the study lifecycle.

Ethical Considerations. All research activities were bound under established ethical standards governing human participation and field-based data collection. The study adhered to institutional research ethics guidelines and principles of voluntary participation, informed consent, confidentiality, and responsible data management. Participants were fully informed of the study objectives, procedures, potential benefits, and their right to withdraw at any time without consequence. No personally identifiable information was collected, and all image and survey data were anonymized prior to analysis. Collected datasets were used solely for academic research purposes and were stored in secure, access-controlled environments. The research team ensured that results were reported objectively and transparently, with due acknowledgment of limitations. These ethical safeguards were implemented to protect participant welfare, preserve data integrity, and ensure that the deployment of artificial intelligence in agricultural contexts remained socially responsible and aligned with accepted research ethics frameworks.

Statistical and Analytical Tools. Given the quantitative nature of model performance evaluation and the user-centered assessment of system usability, this study employed appropriate statistical and analytical tools to ensure rigor and validity.

Quantitative Statistical Tools. Classification performance metrics (accuracy, precision, recall, and F1-score) were computed using Scikit-learn. Inferential analysis was conducted through one-way Analysis of Variance (ANOVA) to test for overall differences among model architectures, followed by Tukey's Honestly Significant Difference (HSD) post-hoc procedure for pairwise comparisons with family-wise error rate control. Effect sizes were quantified using Cohen's d to assess the magnitude of pairwise differences, while 95% confidence intervals were calculated for accuracy and F1-score using the independent test set. Survey reliability was evaluated using Cronbach's alpha, and System Usability Scale (SUS) scores were analyzed descriptively against the standard threshold (SUS = 68).

Qualitative Analytical Procedure (Field Feedback). Although the primary analysis was quantitative, open-ended feedback collected during field validation was examined using a lightweight thematic analysis approach. Responses were reviewed, coded into recurring themes (e.g., ease of use, clarity of results, perceived usefulness), and summarized to contextualize quantitative SUS outcomes. This qualitative component provided supporting insights into user experience without replacing the core statistical evaluation.

Together, these statistical and analytical procedures ensured a comprehensive assessment of technical performance, user acceptance, and practical deployment.

Survey Instrument. To evaluate user acceptance, usability, and perceived effectiveness of the developed mobile-based onion leaf fungal disease detection system, a structured survey instrument. The survey was designed in alignment with the System Usability Scale (SUS) and selected ISO/IEC 25010 quality characteristics, particularly usability, functional suitability, and performance efficiency. The survey consisted of 10 items rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Items were adapted from the agricultural mobile application context as follows:

1. The mobile application is easy to learn and use;

2. The disease detection results are easy to understand;

3. The application responds quickly when analyzing images;

4. I feel confident using the application without technical assistance; The disease classification results are reliable.
5. The application performs well under field conditions.
6. The interface layout is clear and well-organized.
7. The application helps me detect onion leaf diseases earlier.
8. I would recommend this application to other onion farmers.
9. Overall, I am satisfied with the mobile disease detection system.

Reliability Testing. Internal consistency reliability of the survey instrument was evaluated using Cronbach's alpha (α). Analysis yielded a reliability coefficient of α = 0.91, which exceeds the commonly accepted threshold of 0.70, indicating excellent internal consistency. This result confirms that the survey items reliably measure a common construct related to system usability and acceptance. The high Cronbach's alpha value supports the validity of the survey results used to assess user perception and field-level effectiveness of the proposed system.

Software Specifications and Development Environment. To ensure reproducibility and transparency, all experiments and system development activities were conducted using a standardized software environment. Model training, evaluation, and optimization were implemented in Python using widely adopted deep learning and data processing libraries.

Programming Language: Python 3.8.10
Deep Learning Framework: TensorFlow 2.13.0, with Keras API for model definition, training, and evaluation
Model Deployment Framework: TensorFlow Lite 2.13.0 for mobile inference and INT8 quantization

Key Supporting Libraries:
NumPy 1.24 – numerical computation and tensor manipulation
Pandas 2.0 – dataset handling and experimental result analysis
OpenCV 4.8 – image preprocessing and augmentation
Scikit-learn 1.3 – performance metrics, ANOVA, and statistical analysis
Matplotlib 3.7 – visualization of training curves and performance plots

Constraints and Delimitations. This study was conducted within specific constraints and delimitations that define its scope and may influence the interpretation of results.

With respect to constraints, the research was subject to practical limitations, including (a) dependence on field-acquired images captured under varying environmental conditions (lighting, background clutter, and leaf motion), which introduced noise beyond laboratory-controlled settings; (b) evaluation on a limited set of Android devices, potentially affecting generalization of latency and resource utilization across broader hardware ecosystems; (c) finite computational resources during training, necessitating the use of lightweight architectures and restricting exploration of larger, more complex models; and (d) time-bound field validation, which limited observation of long-term user adoption and sustained system performance.

To maintain focus and feasibility, the study was intentionally delimited to: (a) five classes only (four fungal diseases and healthy leaves), excluding other onion pathologies and abiotic stress conditions; (b) image-based diagnosis using RGB smartphone imagery, without incorporation of hyperspectral, thermal, or environmental sensor data; (c) comparison of three lightweight CNN architectures (MobileNet, EfficientNet, and a custom CNN), excluding heavier networks not suitable for mobile deployment; and (d) usability evaluation primarily through SUS and short-term field interaction rather than longitudinal behavioral assessment.

These constraints and delimitations were necessary to align the investigation with the primary objective of developing a practical, mobile-deployable disease classification system. They also provide important context for interpreting the findings and identifying opportunities for future extension.

RESULTS

This section presents the experimental outcomes in a structured and semantic manner, integrating descriptive statistics, inferential testing, confidence interval estimation, and effect size analysis to provide a comprehensive interpretation of model performance. Results are organized to progress from overall model accuracy to statistical validation and practical significance, ensuring clarity and traceability between objectives and findings. Specifically, classification performance is summarized using accuracy and F1-score with corresponding 95% confidence intervals (Table 1), followed by omnibus testing via one-way ANOVA and detailed pairwise comparisons (Table 2). Effect sizes (Cohen's d) are reported to complement p-values and quantify the magnitude of observed differences. This layered presentation enables readers to assess not only whether models differ significantly but also the practical relevance of such differences in real-world deployment contexts.

Overall Classification Performance and Statistical Significance. The comparative evaluation of the three lightweight CNN architectures demonstrated clear differences in classification performance. The MobileNet-based model achieved the highest mean accuracy of 86.0%, followed by EfficientNet at 83.4%, and the custom lightweight CNN at 80.9%. One-way Analysis of Variance (ANOVA) confirmed that these differences were statistically significant ($p < 0.001$), indicating that model architecture had a significant effect on classification accuracy.

Post-hoc analysis using Tukey's Honestly Significant Difference (HSD) test further revealed that the MobileNet-based model significantly outperformed EfficientNet ($p = 0.014$) and the custom lightweight CNN ($p < 0.001$). In addition, EfficientNet showed a statistically significant improvement over the custom lightweight CNN ($p = 0.032$). These findings validate that the observed performance differences are not attributable to random variation but reflect meaningful architectural distinctions.

Confidence Interval Analysis. To quantify the reliability of the reported performance metrics (Table 1), 95% confidence intervals (CI) were computed for both accuracy and F1-score of the evaluated models using the independent test dataset (n = 1,860 images, representing 20% of the full dataset). The test set maintained the original class distribution to ensure unbiased performance estimation.

For the best-performing MobileNet-based model, the overall classification accuracy of 86.0% yielded a 95% CI of [84.9%, 87.1%], indicating a narrow interval and stable performance across test samples. Similarly, the weighted F1-score of 0.85 was associated with a 95% CI of [0.84, 0.87], reflecting a consistent balance between precision and recall across disease classes.

Table 1
Summary of Classification Performance with Statistical Validation

Model Architecture	Accuracy (%)	95% CI (Accuracy)	F1-Score	95% CI (F1-score)	ANOVA p-value
MobileNet	86.0	0.85	0.85	[0.84, 0.87]	p < 0.001
EfficientNet	83.4	0.82	0.82	[0.81, 0.84]	p < 0.001
Custom CNN	80.9	0.80	0.80	[0.78, 0.82]	p < 0.001

For comparison, EfficientNet achieved an accuracy of 83.4% with a 95% CI of [82.1%, 84.6%], while the custom lightweight CNN recorded an accuracy of 80.9% with a 95% CI of [79.6%, 82.2%]. The limited overlap between the confidence intervals of MobileNet and the other architectures further supports the statistical superiority of the MobileNet-based approach.

Collectively, the statistically significant p-values and narrow confidence intervals reinforce the robustness, reliability, and generalizability of the proposed lightweight CNN model for real-world onion leaf fungal disease classification. Confidence intervals were computed at the 95% level using the independent test set (n = 1,860). ANOVA p-values indicate overall model effects, while post-hoc p-values report pairwise Tukey HSD comparisons. Effect sizes are reported using Cohen's d, where 0.2 = small, 0.5 = medium, and 0.8 = large effect.

Effect Size Interpretation. Pairwise effect sizes were computed to quantify the magnitude of performance differences between models. The comparison between MobileNet and Custom CNN yielded a large effect size (d = 1.21), indicating a substantial practical difference in classification accuracy. The comparison between MobileNet and EfficientNet produced a medium-to-large effect (d = 0.68), while the difference between EfficientNet and Custom CNN resulted in a medium effect size (d = 0.53). These effect sizes corroborate the statistical significance results and demonstrate that the observed performance gains of the MobileNet-based model are not only statistically significant but also practically meaningful in real-world deployment contexts.

Table 2
Supplementary Detailed Tukey HSD Pairwise Comparisons

Model Architecture	Mean Difference (Accuracy %)	Tukey HSD (p-value)	Effect Size (Cohen's d)
MobileNet vs. EfficientNet	+2.6	p = 0.014	0.68
MobileNet vs. Custom CNN	+5.1	p < 0.001	1.21
EfficientNet vs. Custom CNN	+2.5	p = 0.032	0.53

Supplementary Table 2 is provided to ensure conciseness in the main Results section while maintaining full statistical transparency. Pairwise comparisons were conducted using Tukey's HSD with a 95% confidence level. Tukey's HSD inherently applies a family-wise error rate correction, thereby controlling for multiple-comparison bias across all pairwise tests.

DISCUSSION

Summary of Results in Relation to Research Objectives. This subsection synthesizes the empirical findings in direct relation to the stated research objectives ensuring coherence between the aims, procedures, and outcomes.

With respect to the development of lightweight CNN models, three architectures, MobileNet, EfficientNet, and a custom lightweight CNN, were successfully implemented and deployed within a mobile application environment, demonstrating technical feasibility for real-time onion leaf disease classification.

Addressing the MobileNet-based model achieved the highest classification accuracy (86.0%) and weighted F1-score (0.85), outperforming EfficientNet (83.4%) and the custom CNN (80.9%). These results provide descriptive evidence that MobileNet offers the most favorable balance between predictive performance and computational effectiveness and efficiency.

In relation to one-way ANOVA, which revealed statistically significant differences among model architectures ($p < 0.001$), while Tukey's HSD post-hoc analysis confirmed that MobileNet significantly outperformed both EfficientNet and the custom CNN. Effect size analysis further demonstrated medium-to-large practical differences (Cohen's d = 0.68–1.21), leading to the rejection of $H0_1$ and acceptance of $H1_1$. These findings empirically support CNN efficiency theory, particularly the effectiveness of depth-wise separable convolutions in resource-constrained environments.

Concerning the INT8 quantization and TensorFlow Lite deployment, enabled real-time, offline inference with reduced model footprint and latency, validating the suitability of the selected architecture for on-device agricultural applications.

Regarding field validation, a System Usability Scale (SUS) score of 82 was produced, which exceeds the standard acceptability threshold of 68. This result led to the rejection and acceptance, indicating high perceived ease of use and user acceptance in accordance with the Technology Acceptance Model. Survey reliability (Cronbach's α = 0.91) further confirms the consistency of user feedback.

Collectively, these outcomes demonstrate alignment between the study objectives, theoretical foundations (CNN theory and TAM), and empirical results. The integrated analysis confirms that lightweight CNN-based mobile systems can achieve statistically robust classification performance while maintaining strong user acceptance under real field conditions, thereby validating both the technical and human-centered premises of the proposed framework.

The overall accuracy obtained in this study (approximately 86%) is best interpreted in light of the collection context and deployment constraints. Many plant disease classification studies report accuracy levels above 90% and even exceeding 95% when models are trained on curated datasets such as PlantVillage under controlled imaging conditions and using high-capacity CNN architectures (Mohanty et al., 2016; Ferentinos, 2018; Too et al., 2019; Kamilaris & Prenafeta-Boldú, 2018). These settings typically involve clearer backgrounds, standardized lighting, and less intra-class noise, which collectively reduce the visual ambiguity that CNNs must resolve.

By contrast, the present work intentionally emphasized field-realistic images captured using multiple smartphones under variable natural lighting and heterogeneous backgrounds. This design choice is consistent with prior findings indicating that model performance tends to decrease as image conditions become more complex and less controlled; notably, strong CNN models trained on clean-background datasets such as PlantVillage may exhibit performance degradation when evaluated on heterogeneous, real-world field images with diverse backgrounds and lighting variations (Barbedo, 2018; Mohanty et al., 2016; Picon et al., 2019). Therefore, while the accuracy achieved here is lower than laboratory-centered benchmarks, it more directly reflects the operational reality of farmer-acquired imagery and supports a pragmatic trade-off between accuracy and ecological validity.

In terms of mobile feasibility, prior work has demonstrated the effectiveness of integrating lightweight CNN architectures into user-facing applications, where on-device or near-real-time inference is prioritized to ensure responsiveness and efficient resource utilization on mobile and embedded platforms (Howard et al., 2017; Lane et al., 2016; Ramcharan et al., 2019). Similarly, lightweight MobileNet-based variants have been proposed to improve deployability in resource-constrained contexts while maintaining robust recognition of disease patterns, particularly in mobile and field-based agricultural applications (Howard et al., 2017; Sandler et al., 2018; Ramcharan et al., 2019; Picon et al., 2019). The results of this study align with that trajectory: the MobileNet-based model achieved the best accuracy–efficiency balance under field constraints, supporting the broader literature's conclusion that lightweight CNNs are well-suited for practical agricultural decision support when deployment considerations are central.

Theoretical Implications. From the perspective of CNN theory, the findings reinforce the effectiveness of depth wise separable convolutions and compact architectural design in capturing salient visual features of fungal disease symptoms without reliance on deep, parameter-heavy networks. The statistically significant performance differences among MobileNet, EfficientNet, and the custom CNN further support theoretical assertions that architectural efficiency plays a decisive role when models are deployed under computational constraints.

In relation to the Technology Acceptance Model (TAM) and Human–Computer Interaction (HCI) frameworks introduced earlier, the achieved System Usability Scale (SUS) score of 82 indicates high perceived ease of use and user acceptance. Within TAM, this score corresponds to a strong positive evaluation of the perceived ease-of-use construct, suggesting that farmers found the system intuitive and minimally burdensome to operate.

From an HCI standpoint, the results imply that careful interface design and rapid system feedback can significantly mitigate apprehension toward advanced AI technologies, even among users with a limited technical background.

Unexpected Findings. One notable unexpected finding was the variability in classification performance for Botrytis Leaf Blight, which exhibited higher misclassification rates compared to other fungal classes. This outcome may be explained by visual similarities between early-stage Botrytis symptoms and other leaf blight conditions, particularly under inconsistent lighting and partial occlusion. Additionally, a higher-than-anticipated adoption rate was observed during field validation, despite initial concerns regarding technology readiness among farmers. This suggests that practical utility, immediate feedback, and offline functionality can outweigh apprehensions toward unfamiliar digital tools, highlighting the importance of context-aware system design in agricultural technology adoption.

In addition to these observations, certain pairwise comparisons, particularly between EfficientNet and the custom lightweight CNN, exhibited comparatively smaller effect sizes despite reaching statistical significance. This reduced magnitude of difference may be attributed to overlapping feature representations learned by both architectures when trained on the same dataset, as well as the constrained model capacity imposed to ensure mobile deployability. Furthermore, environmental noise inherent in field-acquired images (e.g., background clutter, leaf motion, and illumination variance) likely attenuated separability between closely performing models. These factors collectively help explain why some performance gaps were modest and why improvements beyond MobileNet were not more pronounced, underscoring the practical limitations imposed by real-world data conditions and resource-constrained deployment settings.

Study Limitations and Directions for Future Research. Despite the encouraging results, several limitations should be acknowledged as they may influence the internal and external validity of the findings. First, although the dataset incorporated real field images, data collection was geographically constrained, which may limit generalizability across different agro-climatic regions, onion varieties, and farming practices.

Second, class imbalance and visual overlap among certain diseases, particularly Botrytis and other blight conditions, may have affected class-wise performance and contributed to residual misclassification.

Third, mobile deployment evaluation was conducted on a limited set of Android devices; variations in hardware specifications across broader device ecosystems could impact inference latency and user experience. Finally, usability assessment relied primarily on SUS and short-term field interaction, which may not fully capture long-term adoption behavior or sustained system effectiveness.

Future research should address these limitations by expanding data collection across multiple geographic regions and growing seasons, incorporating additional disease categories and severity levels, and exploring domain adaptation techniques to improve robustness under diverse field conditions. Longitudinal user studies are recommended to better understand sustained adoption patterns and behavioral impacts over time.

From a technical perspective, integrating multi-modal inputs (e.g., environmental sensors, weather data) and investigating lightweight attention mechanisms or vision transformers optimized for mobile platforms may further enhance diagnostic accuracy. Together, these directions provide a pathway for advancing mobile-based agricultural decision-support systems toward broader scalability, resilience, and real-world impact.

Conclusion. This study presented a comprehensive evaluation of lightweight convolutional neural network (CNN) architectures for the mobile-based classification of fungal diseases in onion leaf images captured under real field conditions. By systematically comparing MobileNet, EfficientNet, and a custom lightweight CNN, the research demonstrated that lightweight architectures could achieve reliable disease classification while satisfying the computational constraints required for on-device mobile deployment.

Experimental results showed that the MobileNet-based model achieved the best overall performance, with a classification accuracy of 86.0% and a weighted F1-score of 0.85 on an independent test set. Statistical validation using one-way ANOVA and Tukey's HSD post-hoc analysis confirmed that the observed performance differences among models were statistically significant, with large to medium effect sizes favoring the MobileNet architecture. The inclusion of confidence interval analysis further established the robustness and generalizability of the reported results.

Beyond classification performance, the study highlighted the practical feasibility of deploying lightweight CNNs in real agricultural settings. Model optimization through INT8 quantization and TensorFlow Lite enabled real-time, offline inference on Android devices with minimal latency and memory overhead. Field validation results, supported by high usability scores and strong user acceptance, indicate that the proposed system aligns well with human–computer interaction principles and the Technology Acceptance Model, particularly in terms of perceived ease of use.

Overall, the findings confirm that lightweight CNN-based mobile systems can serve as effective and accessible decision-support tools for early detection of onion leaf fungal diseases. By prioritizing real-world field conditions, statistical rigor, and user-centered design, this work bridges the gap between laboratory-based deep learning research and practical agricultural applications. Future research may extend this framework to additional crop diseases, integrate multi-modal data sources, and evaluate long-term adoption impacts across diverse farming communities. From a conceptual perspective, the proposed system is grounded in an integrated framework combining CNN theory for efficient visual feature learning, the Technology Acceptance Model (TAM) for understanding user adoption and perceived ease of use, and Human-Computer Interaction (HCI) principles to guide interface design and user experience. This multi-framework approach strengthens both the technical robustness and practical applicability of the solution, providing a holistic foundation for future AI-driven agricultural decision-support systems.

Recommendations. Based on the findings of this study, the following recommendations are proposed to enhance future implementations and research on mobile-based onion leaf fungal disease classification:

1. ***Expand Geographic and Seasonal Data Collection.*** Future studies should acquire images across multiple regions, growing seasons, and onion varieties to improve model generalizability and robustness under diverse agro-climatic conditions.

2. ***Integrate Multi-Modal Information.*** Incorporating auxiliary data such as weather parameters, soil conditions, and crop growth stage may further improve diagnostic accuracy, particularly for visually similar disease classes.

3. ***Adopt Advanced Lightweight Architectures.*** Exploration of mobile-optimized attention mechanisms and compact vision transformers is recommended to enhance feature discrimination while preserving deployment efficiency.

4. ***Conduct Longitudinal User Studies.*** Extended field trials are encouraged to evaluate sustained adoption and learning.

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