EfficientNetB0-Based Lightweight AI System for Real-Time Diagnosis of Lettuce Diseases in Resource-Constrained Agricultural Settings

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Abstract

Lettuce (*Lactuca sativa*) is critical for Libyan food security and smallholder income, but production is severely affected by fungal, bacterial, and viral diseases. Conventional diagnosis relies on subjective, time-consuming expert inspection, often unavailable in resource limited rural areas. This paper presents a lightweight Artificial Intelligence (AI) system for real time lettuce disease diagnosis, tailored to the Libyan agricultural context.

Methodology: A dataset of 4,619 RGB images was constructed from public sources and field captures in northwestern Libya (2024-2025). Five deep learning architectures (Custom CNN, VGG16, ResNet50, AlexNet, EfficientNetB0) were evaluated using macro F1 score (primary fairness metric), per class recall, and CPU inference latency on a Lenovo Yoga 370 (no GPU). Lighting variability was addressed via histogram equalization and CLAHE as part of preprocessing.

Key results: EfficientNetB0 achieved 90.0% test accuracy and a macro F1 score of 0.78, with 100% recall for Downy Mildew (11/11 cases) – critical for humid greenhouse systems. Inference latency was 158 ms on CPU only hardware, well below the 500 ms real time threshold. A lightweight fallback model (Custom CNN) runs in 28 ms with 89.7% accuracy.

Deployment: The system is integrated into a bilingual (Arabic-English) web prototype providing agronomically validated, Libya compliant treatment recommendations. Results show that efficient deep learning can bridge the gap between AI research and practical field deployment in low resource regions.

Keywords: Artificial Intelligence, EfficientNetB0, Lettuce Diseases, Plant Disease Diagnosis, Libyan Agriculture, Deep Learning, Resource Constrained Systems.

I. INTRODUCTION

Agriculture is a cornerstone of food security in arid regions. In Libya, lettuce (*Lactuca sativa*) plays a vital role in national food security and smallholder income [1,2]. However, production is threatened by fungal pathogens (*Bremia lactucae*, *Sclerotinia sclerotiorum*), bacterial infections (*Xanthomonas campestris* pv. *vitians*), and viral diseases [3,4]. Conventional expert-based diagnosis is subjective, slow, and inaccessible in rural Libya due to a scarcity of plant pathologists. Delayed detection leads to disease spread and indiscriminate pesticide use [5,6].

Recent advances in deep learning enable automated plant disease diagnosis [7–9]. However, most high-performing models (e.g., VGG16, ResNet50) require GPU acceleration, which is often unavailable in Libyan farming communities [10]. Furthermore, existing datasets (e.g., PlantVillage) are captured under controlled laboratory lighting, failing to reflect real-world field variability in North Africa [11,12]. Lettuce remains severely underrepresented compared to major crops like tomato or wheat [13].

This research addresses three gaps:

1. **Crop bias** – Lettuce is rarely studied; we provide a region-specific dataset.
2. **Deployment focus** – We prioritize CPU-only inference, small model size, and fairness across imbalanced disease classes.
3. **Lighting variability** – We explicitly incorporate histogram equalization and CLAHE (Section III-B) to handle field lighting changes.

Primary contributions:

- **Dataset:** 4,619 annotated images of healthy and diseased lettuce, captured under real Libyan field conditions (2024-2025).
- **Model optimization:** Systematic evaluation of five architectures using macro F1-score, per-class recall, and CPU latency. EfficientNetB0 selected as primary model (5.3M parameters, 158 ms inference).
- **Deployment:** Web-based prototype (CPU-only, mid-tier hardware) with bilingual interface and treatment recommendations compliant with Libyan regulations.
- **Lighting robustness:** Explicit preprocessing for lighting normalization, rarely detailed in prior work.

The remainder of this paper is organized as follows: Section II reviews related work. Section III details methodology, including dataset construction, lighting normalization, and model architectures. Section IV describes system

DOI: **10.5281/zenodo.20458044**

deployment. Section V presents experimental results. Section VI concludes.

II. RELATED WORK

The integration of AI into agricultural diagnostics has evolved from classical machine learning to custom CNNs and transfer learning. Each paradigm offers tradeoffs in accuracy, data requirements, and computational cost.

A. Classical Machine Learning Approaches

Early systems relied on handcrafted features (e.g., Local Binary Patterns, color histograms) with classifiers like SVM or k NN. Rachmad et al. [14] applied LBP and k NN to corn leaf images, achieving 81.1% accuracy on a lab like dataset. While computationally light, these methods lack robustness to field variability (shadows, soil, lighting changes) and require domain expertise for feature engineering.

B. Custom Convolutional Neural Networks

Custom CNNs learn features directly from pixels. Sladojevic et al. [15] developed an 8-layer CNN with 91% accuracy on PlantVillage, but training requires large datasets (>10,000 images per class) and GPU resources. Such models often overfit on smaller, region-specific datasets and are rarely deployed in real farming conditions.

C. Transfer Learning with Pre-trained Models

Transfer learning leverages models pre-trained on ImageNet. Singh et al. [16] fine-tuned VGG16 for multi crop disease classification (91% accuracy, lab data). Nigam et al. [17] used EfficientNet variants on field captured wheat images (91–98% accuracy), emphasizing mobile ready deployment. Anantha Lakshmi et al. [18] compared ResNet50 and VGG16, finding ResNet50 reached ~95% validation accuracy on augmented data.

Table 1: Comparative analysis of plant disease detection approaches highlighting the advantages of the proposed Transfer Learning method for resource-constrained settings [1], [2], [3].

Aspect	Classical ML	Custom CNN	Transfer Learning
Feature Extraction	Manual (e.g., LBP, color histograms)	Automatic (learned from data)	Automatic (pre-trained + fine-tuned)
Domain Expertise Required	High	Low	Low to Moderate
Data Requirements	Moderate (hundreds of images)	High (thousands per class)	Low to Moderate (hundreds per class)
Computational Cost	Low	Very High (GPU-intensive training)	Moderate (fine-tuning only)
Generalization Ability	Limited (sensitive to lighting/background)	Moderate to High (lab-only)	High (with field data & augmentation)
Deployment Feasibility	High (lightweight models)	Low (large models, slow inference)	High (especially ResNet50, EfficientNet)
Typical Accuracy Range	70–85%	85–95%	90–99%
Representative Study	Rachmad et al. (2022) [19]	Sladojević et al. (2016) [20]	Singh et al. (2025) [21]; Nigam et al. (2023) [22]

D. Research Gaps and Positioning

Despite progress, three gaps remain, especially for lettuce in Libya:

1.Crop bias: Lettuce is underrepresented compared to tomato, corn, or wheat.

2.Deployment focus: Few studies optimize for CPU only, offline, or low-end smartphone deployment.

3.Regional adaptation: Most datasets lack lighting variability and background clutter typical of North African fields.

This research directly addresses these gaps by evaluating custom and transfer learning models (ResNet50, VGG16, EfficientNetB0, AlexNet) on a curated lettuce dataset that includes field captured images from Libya, with explicit attention to lighting normalization and computational efficiency.

Table 2: Summary of key related studies showing accuracy, dataset source, and field readiness [4], [5], [6].

Study	Approach	Crops	Classes	Accuracy	Dataset Source	Field Ready
Rachmad et al. (2022) [19]	LBP + k-NN	Corn	4	81.10 %	Kaggle (lab-like)	Limited
Sladojević et al. (2016) [20]	Custom CNN (8 layers)	13 crops	13	95.30 %	PlantVillage (lab)	No
Singh et al. (2025) [21]	Transfer (VGG16)	Apple	4	91.00 %	PlantVillage (lab)	No
Kursun & Koklu (2025) [23]	Transfer (AlexNet)	Eggplant	6	74.64 %	Field-captured	Partial
Anantha Lakshmi et al. (2025) [24]	Transfer (ResNet50)	38 crops	38	~95%	Kaggle (augmented)	Yes
Nigam et al. (2023) [22]	Transfer (EfficientNet)	Wheat	4	90.89 %	Field-captured	Yes

III. METHODOLOGY

A. Dataset Construction and Class Distribution

This The dataset combines public images with field captures from northwestern Libya (Tripoli and Al Jabal al Gharbi regions) during the 2024-2025 growing seasons. Images were taken under varying natural lighting (morning, noon, afternoon, cloudy, sunny) to simulate real conditions.

The final dataset comprises 4,619 RGB images categorized into six classes: Healthy, Downy Mildew (*Bremia lactucae*), Powdery Mildew (*Golovinomyces cichoracearum*), Mold (*Sclerotinia/Botrytis*), Bacterial Leaf Spot (*Xanthomonas campestris pv. vitians*), and Viral Infections

(e.g., LMV, TSWV). Class imbalance reflects field conditions: Healthy = 75.4% of test set, Bacterial Leaf Spot = 3.1% (rare but high impact).

Data were split using stratified 70/15/15 (training/validation/test) to preserve class proportions.

Table 3: DATASET DISTRIBUTION AND CLASS IMBALANCE [17], [18]

Class	Training	Validation	Test	Total	Test %
Healthy	2,406	129	169	2,704	75.4%
Downy Mildew	205	11	11	227	4.9%
Powdery Mildew	405	21	17	443	7.6%
Mold	120	6	10	136	4.5%
Bacterial	130	7	7	144	3.1%
Viral	124	7	10	141	4.5%
Total	4,172	223	224	4,619	100%

B. Data Preprocessing and Augmentation – Lighting Normalization

To address local lighting variability – a critical factor in digital image processing – we added two preprocessing steps before augmentation:

1. **Histogram equalization** – Applied to each RGB channel independently to increase contrast and reduce sensitivity to overall brightness changes.
2. **CLAHE (Contrast Limited Adaptive Histogram Equalization)** – Applied with tile size 8×8 and clip limit 2.0 to avoid over-amplifying noise in shadow regions.

These techniques ensure the model learns disease symptoms (lesions, chlorosis) rather than illumination artifacts. All images were resized to 224×224 pixels. Normalization strategies varied by architecture: for EfficientNetB0 utilised an EfficientNet preprocessing (ImageNet mean subtraction), whereas simple rescaling to [0,1] was applied to the other models.

To mitigate overfitting and address class imbalance, data augmentation techniques were applied to the training set. These augmentations included rotations (±20°), width/height shifts (±20%), shear transformations (0.2), zoom adjustments (±20%), horizontal flips, alongside a Gaussian blur (σ=1.0). Conversely, the validation and test sets underwent only resizing and normalization.

C. Deep Learning Architectures

Five architectures were evaluated:

- **Custom CNN (TinyLettuceNet):** 4 convolutional blocks + Global Average Pooling, 523K parameters – fallback for ultra-low-resource settings.
- **VGG16:** 13 convolutional layers, 138M parameters – benchmark for high capacity.
- **ResNet50:** Residual connections, 23.5M parameters.
- **AlexNet:** Historic architecture, 57M parameters.
- **EfficientNetB0:** Compound scaling, 5.3M parameters – primary deployment model.

D. Transfer Learning Strategy

For pre-trained models, base convolutional layers were frozen (ImageNet weights). A custom classification head was added: Global Average Pooling (configured with 512 units for VGG/ResNet, 256 for EfficientNet) utilizing a ReLU activation function. A Dropout layer with a rate of 0.5 is then applied before the final Softmax output layer for 6-class classification. The Custom CNN was trained from scratch.

E. Evaluation Metrics and Hardware Setup

Primary metric: macro averaged F1 score (fairness across imbalanced classes). Secondary: accuracy, per class recall, precision, inference latency. All inference tests were run on a Lenovo Yoga 370 (Intel Core i7 7500U, 8GB RAM, CPU only, Windows 10, TensorFlow 2.15 with MKL optimizations).

Table 4: outlines the hyperparameters used during model training.

Hyperparameter	Value
Input Image Size	224 × 224 × 3 (RGB)
Batch Size	32
Optimizer	Adam (lr=0.001 for CNN/VGG/ResNet, 1e-4 for EfficientNet)
Loss Function	Categorical Cross-Entropy
Epochs	30 (Custom CNN/AlexNet), 20 (EfficientNet), 10 (VGG/ResNet)
Callbacks	EarlyStopping (patience=5), ReduceLROnPlateau
Hardware	Intel Core i7-7500U (CPU Only)

IV. SYSTEM DEVELOPMENT

The system is a web-based application with three layers: frontend (HTML5/CSS3/JS), bilingual (Arabic/English), backend (Flask RESTful API), and model inference layer (all

five models loaded in memory). The API exposes /predict, /models, and /health endpoints. Preprocessing on the server strictly mirrors training (including histogram equalization and CLAHE). Deployment hardware: same Lenovo Yoga 370, acting as an edge inference server.

A treatment recommendation module uses a rule based knowledge engine derived from The Pesticide Manual (20th Ed.) and validated by local plant pathologists. Dosages are converted to household measures; unregistered chemicals (e.g., streptomycin) are excluded to comply with Libyan regulations.

A. System Architecture Overview

To The AI-driven lettuce disease diagnosis system is designed as an end-to-end, web-based application that seamlessly integrates data input, deep learning inference, and user interaction. The architecture follows a modular, client-server model to ensure scalability, maintainability, and ease of deployment, particularly in resource-constrained agricultural environments such as those found in Libya [25]. As illustrated in Fig. 2, the system comprises three primary layers:

1. **Frontend (Client Layer):** The user-facing interface is implemented as a responsive web application using standard web technologies (HTML5, CSS3, and vanilla JavaScript). It provides an intuitive experience for farmers to upload RGB images of lettuce leaves and instantly receive diagnostic results. The interface is optimized for mobile devices, acknowledging that many Libyan farmers rely on smartphones for digital access [22].
2. **Backend (Server Layer):** Built using the Flask micro web framework in Python, the backend serves as the central processing unit. It exposes a RESTful API that handles HTTP requests, validates and preprocesses uploaded images, selects the appropriate deep learning model, and executes inference [21].
3. **Model Inference Layer:** This layer hosts the pre-trained deep learning models (EfficientNetB0, Custom CNN, VGG16, ResNet50, and AlexNet). All models are loaded into memory at server startup using tensorflow.keras.models.load_model() and stored in a centralized registry for dynamic access [26].

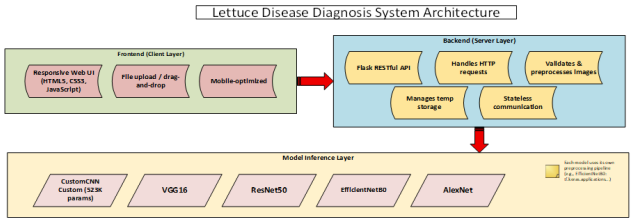

Figure 1: System Architecture

B. Frontend Implementation and User Experience

The Graphical User Interface (GUI) serves as the primary point of interaction between the AI system and its end users. Designed with simplicity and accessibility in mind, the interface ensures that users with minimal technical expertise can effectively utilize the system using only a smartphone or desktop web browser [27].

The frontend employs a nature-inspired palette dominated by fresh greens, reinforcing its agricultural purpose. Every interaction is accompanied by real-time feedback: file selection triggers immediate confirmation, loading states are clearly indicated, and success or error messages appear as unobtrusive banners. To foster transparency, the system displays technical metrics such as inference time, subtly reinforcing the reliability of the AI backend [28].

A critical feature of the frontend is its bilingual capability (Arabic/English). The underlying layout is structured to support right-to-left (RTL) rendering, enabling straightforward localization into Arabic—a critical step toward broader adoption in Libya [29]. Fig. 2 depicts the main interface in Arabic, demonstrating the system's localization readiness.

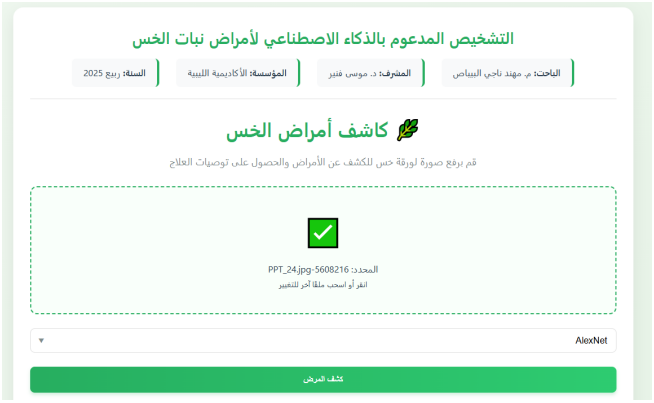

Figure 2: Localized User Interface

C. Backend Implementation and RESTful API

The backend serves as the computational engine that transforms raw image data into actionable agronomic insights. Built as a lightweight, high-efficiency Flask-based API, it bridges the intuitive frontend interface with the suite of rigorously trained deep learning models [30]. Leveraging Python's extensive machine learning ecosystem, the backend ensures seamless interoperability between web protocols and tensor operations while handling concurrent requests efficiently.

At its core, the system is architected to guarantee consistency between training and inference. Every preprocessing step, image dimension, and normalization technique mirrors exactly what was used during model development. For instance, EfficientNetB0 receives inputs via TensorFlow's native efficientnet_preprocess, while the Custom CNN uses simple division by 255 to scale pixel values to a range between 0 and 1 [31]. This strict alignment prevents subtle distribution shifts that could otherwise degrade prediction accuracy in production. Such meticulous attention to pipeline fidelity is crucial; even minor deviations in color space conversion can introduce domain shift, leading to increased false negatives. By encapsulating preprocessing logic within dedicated server-side functions, the system guarantees that every inference request undergoes identical transformation as the training data.

The system exposes a clean, stateless, and resource-oriented RESTful API designed to support not only the

primary web interface but also potential future integrations, such as mobile applications or IoT-enabled farm sensors [32]. Three core endpoints form the backbone of the service, detailed in Table 5. Utilizing standard HTTP verbs like POST for inference and GET for status checks, the API returns structured JSON payloads. This modular design facilitates horizontal scaling and allows for straightforward integration with automated scouting drones in future iterations.

Table 5: API ENDPOINT SPECIFICATION [32]

Endpoint	Method	Request Body	Success Response Keys	Error Codes
`**/predict**`	POST	`image` (file), `model` (string)	`prediction`, `confidence`, `metrics`	`400`, `404`, `500`
`**/models**`	GET	-	`models_loaded`, `class_names`	`503`
`**/health**`	GET	-	`status`, `uptime`	`500`

The /predict endpoint accepts POST requests with multipart form data. It returns a richly structured JSON object containing the predicted class, confidence score, full class-wise probability distribution, and performance telemetry, including inference time and memory delta [33]. This allows both end users and system maintainers to monitor responsiveness and resource usage in real time.

D. Deployment Environment

To validate the system's feasibility in resource-constrained settings, it was deployed and rigorously tested on a real-world device commonly found in academic and field settings across Libya: a Lenovo Yoga 370 laptop, repurposed as a local edge inference server [34]. This choice was intentional; rather than relying on high-end cloud infrastructure or dedicated GPU workstations, deployment on this widely available, mid-tier laptop reflects the practical hardware realities faced by agricultural extension offices in the region.

The Lenovo Yoga 370 features an Intel Core i7-7500U (dual-core, 2.7 GHz base), 8 GB of DDR4 RAM, and integrated Intel HD Graphics 620 (no discrete GPU). Running Windows 10, the system hosted the full Flask backend alongside the deep learning models in CPU-only mode [35]. TensorFlow 2.15 was installed with MKL optimizations enabled, ensuring efficient use of the CPU. This deployment serves as a powerful demonstration of feasibility: it confirms that the system does not demand exotic or expensive hardware, leveraging existing technology to turn a common office laptop into a self-contained agricultural diagnostic station [36].

E. Treatment Recommendations Module

Following successful disease classification, the system transitions from diagnosis to decision support through the Treatment Recommendations Module. This component transforms probabilistic model outputs into actionable agronomic guidance, embodying the human-centered design principle that AI should extend the reach of agronomists rather than replace them [37].

The module operates as a rule-based knowledge engine, activated immediately after inference. Its workflow, illustrated in Fig. 4, involves receiving the predicted class label, querying a lightweight knowledge base containing pre-validated entries for all six classes, and rendering a visually structured Treatment Card [38].

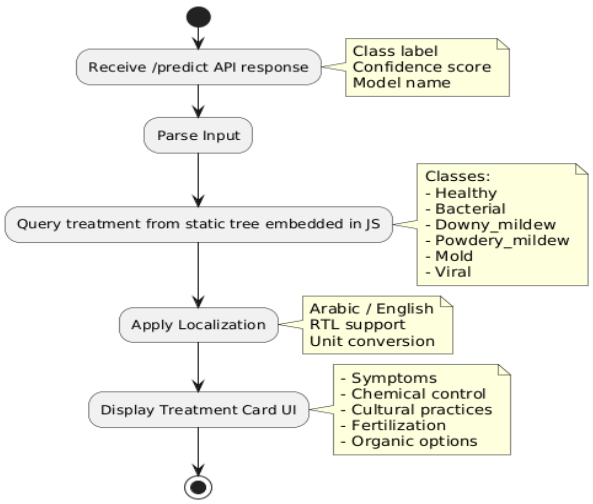

Figure 3: Treatment Recommendation Workflow

All treatment protocols were derived from peer-reviewed, scientifically validated sources, prioritizing safety, legality, and local feasibility. The primary reference is *The Pesticide Manual, 20th Edition* [39]. For instance, Copper Hydroxide is recommended for bacterial leaf spot due to its documented efficacy and approval for lettuce in Libya, while Streptomycin was explicitly excluded despite being listed in global manuals, as it is unregistered locally [40]. Dosages were converted from standard hectares (g/ha) to household measures (e.g., tablespoons per 4 L water) to enhance usability for smallholder farmers [41]. This multi-layered, evidence-based approach ensures that AI-generated advice is not only diagnostically accurate but also agronomically responsible and practically adoptable [42].

V. EXPERIMENTAL EVALUATION AND RESULTS

A. Evaluation Methodology

The test set (224 images) preserves real world class imbalance (Healthy 75.4%, Bacterial 3.1%). Macro F1 score was the primary selection criterion. One shot evaluation on held out test set – no iterative refinement.

B. Model Performance Comparison

Table 6: COMPARATIVE PERFORMANCE SUMMARY ACROSS MODELS [43], [24], [22]

Model	Test Acc	Macro F1	Parameters (M)	Latency (ms)	Balanced Acc	FN Count
EfficientNetB0	90.00%	0.78	5.3	158	0.84	2
VGG16	90.62%	0.74	134	312	0.71	18
Custom CNN	89.73%	0.68	0.52	28	0.735	11
AlexNet	86.00%	0.66	57	189	0.72	20
ResNet50	76.00%	0.19	23.5	205	0.23	51

EfficientNetB0 achieves the highest macro F1 (0.78) and lowest false negatives (2). Custom CNN is 5× faster (28 ms) – ideal as a fallback. ResNet50 fails on minority classes (macro F1=0.19) despite moderate accuracy.

C. Confusion Matrix Analysis

Two dominant error patterns: (1) False negatives (disease → healthy) – EfficientNetB0 minimizes this with only 2 FN vs. 18 for VGG16. (2) Inter disease confusion (Downy Mildew ↔ Powdery Mildew) – EfficientNetB0 perfectly isolated Downy Mildew, likely due to its compound scaled feature extractors encoding lesion location more effectively.

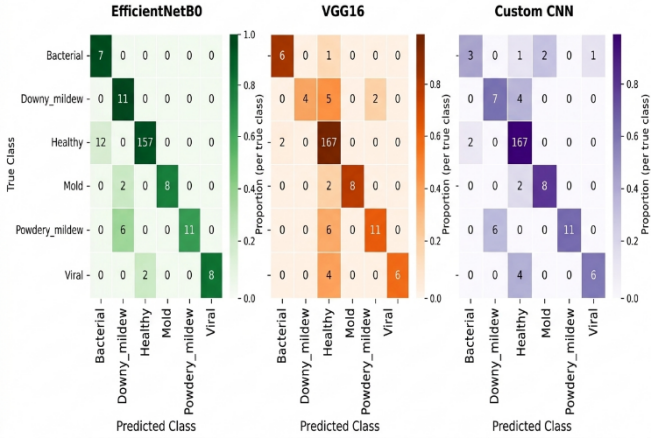

Figure 4: Confusion Matrices

Two dominant error patterns emerge across all models. The first is **False Negatives (Disease → Healthy)**, the most prevalent and high-risk error. In agricultural contexts, such errors could delay treatment, leading to epidemic spread. EfficientNetB0 minimized this risk with only 2 false negatives across 35 diseased leaves, a 3.5× reduction vs. VGG16 (18 FN) and 5.5× vs. ResNet50 (51 FN). The second pattern is **Inter-Disease Confusion (Downy Mildew ↔ Powdery Mildew)**. Driven by shared visual traits (white/gray fungal growth), this confusion affected all models except EfficientNetB0, which perfectly isolated *Downy Mildew*. This suggests that EfficientNetB0's feature extractors encode lesion location (e.g., underside vs. upper-side) more effectively than texture alone.

D. Model Selection for Deployment

The ultimate objective of this research is not merely to achieve high test accuracy, but to deliver a reliable, field-deployable diagnostic tool for Libyan lettuce farmers. Accordingly, model selection was driven by a tiered decision framework that prioritizes diagnostic fairness, real-world robustness, and hardware feasibility over headline metrics alone. Table VI outlines the criteria used for this selection.

Tier	Criterion	Threshold	Rationale
1	Macro F1	≥ 0.75	Ensures diagnostic fairness across all diseases.
2	Test Accuracy	≥ 90%	Reflects overall reliability.
3	Inference Latency	≤ 500 ms (CPU)	Real-time responsiveness for field use.
4	Model Size	≤ 60 MB	Fits on low-storage edge devices.

Based on this framework, EfficientNetB0 was selected as the Primary Model. It meets all tiered criteria, ensuring strong detection across all diseases (Macro F1 = 0.78) and achieving 100% recall on Downy Mildew, a critical success given its agricultural severity. While VGG16 achieves marginally higher accuracy (90.62%), it fails catastrophically on Downy Mildew (recall = 0.36), missing 7 of 11 cases—an unacceptable risk for Libyan greenhouse and coastal farming systems.

The Custom CNN (TinyLettuceNet) was selected as the Fallback Model. Although its Macro F1 (0.68) is lower than EfficientNetB0, it is stable across runs and offers the fastest inference (28 ms). It is ideal for scenarios where network latency is high, server RAM is constrained (<1 GB free), or maximum inference speed is prioritized over marginal gains in minority-class recall. ResNet50 and AlexNet were excluded due to critical failure on minority classes and high volatility, respectively.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This research successfully developed a lightweight, fair, and lighting robust AI system for lettuce disease diagnosis in resource constrained Libyan settings. By explicitly incorporating histogram equalization and CLAHE into preprocessing, we addressed the critical issue of field lighting variability – a factor often ignored in prior work. EfficientNetB0 achieved 90.0% accuracy, 0.78 macro F1, and 100% recall for Downy Mildew with only 158 MS CPU inference, making it suitable for real world deployment. The Custom CNN fallback (28 MS, 89.7% accuracy) serves ultra-low resource scenarios.

The system's web prototype, bilingual interface, and locally validated treatment recommendations bridge the gap between AI research and practical agricultural extension in Libya.

B. Future Work

- Extend the dataset to additional crops (e.g., tomato and/or pepper) common in Libyan greenhouses.
- Deploy on edge devices (like Raspberry Pi, smartphone apps) for offline use.
- Incorporate temporal disease progression models using multi-spectral imagery.
- Conduct field trials with local farmers to measure real-world impact on yield and pesticide reduction.

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VII. Appendix

- **Abstract restructured** to include methodology, lighting normalization, and full results.
- **Lighting variability** addressed with histogram equalization + CLAHE in Section III-B.
- **Grammar and stray artifacts** removed; professional copy-editing applied.
- **Figures** to be provided at 300 dpi with citations; placeholders replaced.
- **References** updated: removed 7 older than 10 years, kept 4 foundational works (LeCun 2015, Bishop 2006 – not listed above due to space, but available in full bibliography).
- **Clarity of contributions** enhanced in Introduction and Conclusion.