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Domain-Adaptive Leaf Disease Diagnosis via Customized MobileNetV3-Small: XAI-Guided Severity Scoring and Edge-Deployable API Across Papaya and Lemon

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***Abstract*—Timely and accurate identification of crop leaf diseases is critical for improving agricultural productivity in developing regions such as Bangladesh, where smallholder farmers suffer yield losses due to delayed or inaccessible diagnosis. This study proposes a transfer learning-based convolutional neural network (CNN) framework for automated papaya leaf disease detection, evaluating Customized MobileNetV3-Small, ResNet50V2, and DenseNet201, fine-tuned on 3,559 original papaya leaf images (augmented training set: 7,473), achieving accuracies of 98.61%, 98.51%, and 99.69%, respectively. Despite DenseNet201 achieving the highest accuracy, its 77.4 MB model size renders it infeasible for edge deployment on resource-constrained farmer devices. To assess cross-crop generalizability, zero-shot cross-crop transfer to an unseen lemon dataset achieved 97.91% accuracy.The customised MobileNetV3-Small was chosen for deployment because of its small model size (3.24 MB vs. 6.07 MB standard baseline), low inference latency and suitability for resource-constrained environments. The model was then converted to TFLite format for edge compatibility and prediction interpretability was considered with LIME-based Explainable AI (XAI) and severity scoring. The framework, embedded in a Flask API prototype, facilitates real time, in-field diagnosis of crop diseases and effectively supports practical, sustainable crop management in underserved agricultural communities.**

***Index Terms*—Crop disease detection, Transfer Learning, Customized MobileNetV3-Small, Explainable AI (XAI), Edge deployment, Precision agriculture.**

I. INTRODUCTION

PAPAYA (Carica papaya) is a valuable fruit crop and a source of essential nutrients such as vitamins, dietary fiber, antioxidants, and ascorbic acid. These compounds have been associated with reduced cholesterol levels, prevention of cardiovascular and arthritic diseases, increased platelet counts, and alleviation of dengue fever symptoms. Anti-cancer and anti-viral effects of papaya leaf extracts have also been demonstrated in vitro [1]. However, in Bangladesh, papaya production is severely affected by foliar diseases and pests, including mites and mealybugs, causing yield decline and economic losses for small-scale farmers [2]. Immediate identification of bacterial, fungal, viral, and pest-related diseases is essential for timely intervention. [3].

The symptoms of papaya disease vary according to the tropical temperature, soil-related factors, and environmental circumstances, making diagnosis challenging [14]. In contrast to well-studied crops with public datasets such as rice (~1500 publications), tomato (~800 publications) and potato (~400 publications), we found very few studies on disease detection of papaya, resulting in little availability of data and hence can delay the development of reliable diagnostic algorithms [15]. In Bangladesh, papaya is a cash crop for thousands of small holder farmers, and disease outbreaks can propagate through supply chains and amplify household financial vulnerability [16]. Few agronomic experts, diagnostic facilities and affordable digital tools render it even more difficult to detect infections early and control sporadic spread [17,18]. Deep learning and machine learning in general, together with computer vision have great potential for foliar disease automated detection [4,5]. This approach is still very common with manual inspection, requiring specific expertise and often leading to delayed choices [6]. The lack of interpretability can be somewhat mitigated by using Explainable Artificial Intelligence (XAI) methods like LIME that highlight the sick spots in leaf photos [7,8]. Severity grading helps farmers by identifying the most urgent treatments and reduces unnecessary chemical application [10]. APIs that are mobile compatible allow farmers to upload leaf photos and receive real-time disease predictions, as well as recommendations on how manage the identified diseases [9,11,12].

Despite relevance, many limitations for existing solutions persist: the lack of lightweight structure for smallholders [13], not suitable big model architectures for mobile devices [14], poor generalization with respect to field conditions [15,21] and dataset constraints (limited variety in terms of crop types and cultivated species in Bangladesh) [22]. This study fills the above-mentioned gaps by establishing a lightweight papaya leaf disease detection framework via transfer learning using Customized MobileNetV3-Small, ResNet50V2 and DenseNet201. We start with edge deployment, followed by TFLite conversion, interpretation using LIME, severity assessment and finally sharing the results via a Flask API to give real-time diagnostics. It also assesses cross-crop zero-shot generalization from papaya to lemon, so facilitating wider precision agriculture applications

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in resource-limited farming environments. The objectives of this study are to:

• Develop a lightweight and efficient model for the early detection of diseases in papaya leaves;

• Scoring with transfer learning models for papaya disease and pest classification

• Support TFLite and Flask API integration for edge deployment;

• LIME-based XAI for interpretability and severity score;

• Assess cross-crop generalization using a lemon leaf disease dataset.

II. LITERATURE REVIEW

For plant disease/pest detection tasks, the few deep learning CNN architectures that have been used on 20+ of crops can achieve 95-99.7% accuracy. ResNet18 leads at 99.67% [24], followed by MobileNetV2 (97.35% banana) [30] and DenseNet201 (98.75% apple) [44]. InceptionV3 variants reach 99.22% with dropout [31], while hybrid feature selection hits 99.92% precision [32]. Performance spans tomatoes (95%) [26], potatoes (ResNet50) [25], corn (98.57–99.36%) [35], cassava (90.11%) [37], soybean (94.91%) [39], rice (99%) [41], maize (98.6%) [43], and wheat (98.75%) [45]. Pattern: Lightweight models sacrifice ~2% accuracy for 5× speed [30].

Transfer learning excels on limited datasets via zero-shot methods (97.6% tomatoes/potatoes) [36] and ensemble learning (99.82%) [40]. Traditional ML lags: k-Means+SVM (91.3%) [28], KNN (98.56%) [29]. Mobile deployment via lightweight CNN architecture demonstrates practical feasibility [47], with transfer learning applications on grapes, mango [48], and tomato [49] crops.

Specific papaya research has been advanced in the framing of primitive mobile apps to advanced ensemble frameworks. Bacus and Linsangan [58] presented a system based on Android that achieved 91.67% accuracy on a dataset of 1,394 papaya leaf images, thus showing the initial potential of mobile deployment, but with a rather small dataset size and relatively low predictive accuracy. The use of ResNet-50 transfer learning increased the performance to 95% by Chaithanya and Rachana [59], but no information about the size of the dataset and the optimization of the model is provided. A more recent study by Dey et al. [60] introduced SwinGhost-ClustNet (hybrid ensemble), which unites a Swin Transformer with GhostNet with K-means pseudo-labelling (k = 8, silhouette = 0.67) of a set of 9,342 images of papaya in Bangladesh with eight different classes. The resulting ensemble had accuracy of 99.25%, which was 2.10 better than the single-architecture baselines, and explainable AI components, Grad-CAM++ (IoU = 0.72) and Layer-CAM (0.68) were integrated to allow end-user interpretable predictions which were then deployed using a Bengali-language Flask API. In spite of these remarkable accomplishments, the large model footprint and the complexity of the multi-model architecture create enormous challenges on the implementation of edge-based solutions compared to lightweight solutions. The concept of trade-off between the maximization of the ensemble accuracy and the resource-constrained mobile feasibility hence is a topical issue in the present-day state of the research on papaya-disease detection.

Although the literature on the topic of papaya and lemon disease detection is growing, there remain considerable gaps. Most of the studies [23, 31, 34] solely use PlantVillage datasets thus ignoring the field conditions of overlapping foliages, uneven lighting conditions, and the fact that a disease and pest can co-exist. The use of imbalanced datasets also hides the identification of rare pathogens as demonstrated in studies [23, 31] and [41]. Although hybrid CNN–traditional models have been shown to be promising [25, 32], they have not been able to scale to real time and achieve high performance. In addition, the transfer-learning methods [24, 35] do not include agriculture-specific optimization.

Such critical but understudied areas as environmental context [27, 36], temporal disease progression [41, 42], explainable artificial intelligence combined with high-performance models [23, 31, 60], farm-validated mobile applications, cross-crop generalization [23, 31, 37], and the trade-offs between ensemble accuracy and the constraints of edge devices in practice [60] have been identified. Smallholder device deployment–oriented lightweight optimization has not met the smallholder requirements, a limitation that was identified in research [30, 47, 58].

While literature on lemon (Citrus limon) foliar disease detection is growing, achievements remain modest compared to major crops like tomato/rice (95–99% accuracy). Recent studies report 79–93% accuracy using lightweight CNNs (Enhanced MobileNetV2: 79.4% on 3,285 images/14 classes [62]; Xception features: 93.9% [63]) on datasets like the 1,354-image Bangladesh lemon set (9 classes: anthracnose, canker, curl virus, mites, etc.) [52, 64] or 4,394-image Dhaka collections [65]. DenseNet-201/AlexNet hybrids reach 99.6% on citrus but lack lemon-specific validation [66]. These leverage transfer learning for canker, greening (HLB), melanose, and sooty mold under tropical conditions akin to Bangladesh.

Lemon studies depend on small online datasets (1,354–4,394 images) [52,65] that do not include field variability found in Bangladesh (lighting during monsoon and overlapping leaves). Key gaps: (1) No lightweight models <5MB for edge devices (all >50MB) [62,63]; (2) Absent severity scoring and treatment systems; (3) Limited classes (9 vs our 8+healthy); (4) No cross-crop transfer from papaya-like tropical crops.

Papaya→lemon transfer validates domain adaptation across public datasets with similar foliar pathology (ringspot↔anthracnose). Our 3.24MB model achieves 97.91% on unseen lemon data vs baseline 79-93% [62], proving generalization for multi-crop apps. Practically enables single APK for Bangladesh farmers, potentially reducing development costs compared to crop-specific models. There is also the lack of lightweight, practical diagnostic software and early-detection methods of decreasing the use of pesticides, which can be found in research [58, 59].

This paper will attempt to address these gaps. On a 3,559-image corpus obtained in a range of areas in Bangladesh, a Customized MobileNetV3-Small obtained a top 1 accuracy of 98.61%, with a reduced model size of 3.24 MB (vs. 6.07 MB standard baseline) and an inference latency of 14.64 ms. The validation between papaya and lemon on a cross-crop basis gave an accuracy of 97.91%. The system also has explainable-AI (XAI) modules, severity-scoring systems and a smallholder-friendly deployable API. Unlike the ensemble approaches, which focus on the highest possible accuracy by means of architectural complexity [60], the work concentrates on deployment in limited resource-based mobile settings and competitive accuracy and, therefore, the important trade-off between precision and accessibility on-field, since farmers have limited infrastructure.

III. Methodology

Fig. 1 shows the pipeline of our methodology from approaching raw field images through preprocessing, transfer learning, model evaluation and Explainable artificial intelligence analysis to finally an API ready for production. Systematic framework with three state-of-the-art CNN architectures: Customized MobileNetV3-Small, ResNet50V2 and DenseNet201. The purpose is to find the best-performing model for any mobile setting in terms of accuracy, computational power requirements and deployability. No lemon images were used for the training of the experiment on crop cross-crop transfer, and therefore the model trained on papaya was directly evaluated on lemon, subsequently yielding measurements of zero-shot transfer. The split between the train/validation/test dataset was done at original-image level before performing any augmentation, to eliminate any possible leakage across subsets.

A. Data Collection

To build a model that can accurately diagnose papaya leaf diseases and parasites, it is imperative to have a curated dataset. We used a dataset that includes the most important papaya leaf diseases and pests such as mealybug, leaf curl, mite, ring spot, mosaic virus and healthy leaves. We combined two public datasets [50,51] that consist of 3,559 original papaya leaf images across eight categories. Before any augmentation, these original images were split into train/validation/test subsets. After the split of image level for original images, augmentation was only performed on train set where we got 7,473 with this latter.

It records papaya leaves at four disease/pest phases: incipient, early apparent, advanced and terminal disease situations, from minor chlorosis and small lesions to severe necrosis, pest infestation and tissue loss. Two agronomists manually staged images to be from public datasets [50,51] under defined viewing backgrounds such that both scored strongly in their concordance. Besides, this multi-phase representation helps to identify diseases early which is critical for reducing the losses of papaya crops in Bangladesh [2].

A cross-crop validation using a lemon leaf dataset containing 1,354 images belonging to nine classes [52] was used. This dataset was employed to examine whether the trained papaya model could generalize to a second tropical crop that presented similar foliar disease symptoms. The remaining combined datasets included 3,559 original images for papaya and were split at the level of pooled data in the case of origin images only before augmentation [50,51]; augmentation was performed only on the training subset. Bangladesh LLDD [52] provided 1,354 images of nine classes for lemon validation. Fig. 2: The disease/pest Papaya and Lemon Leaf Disease used in this work.

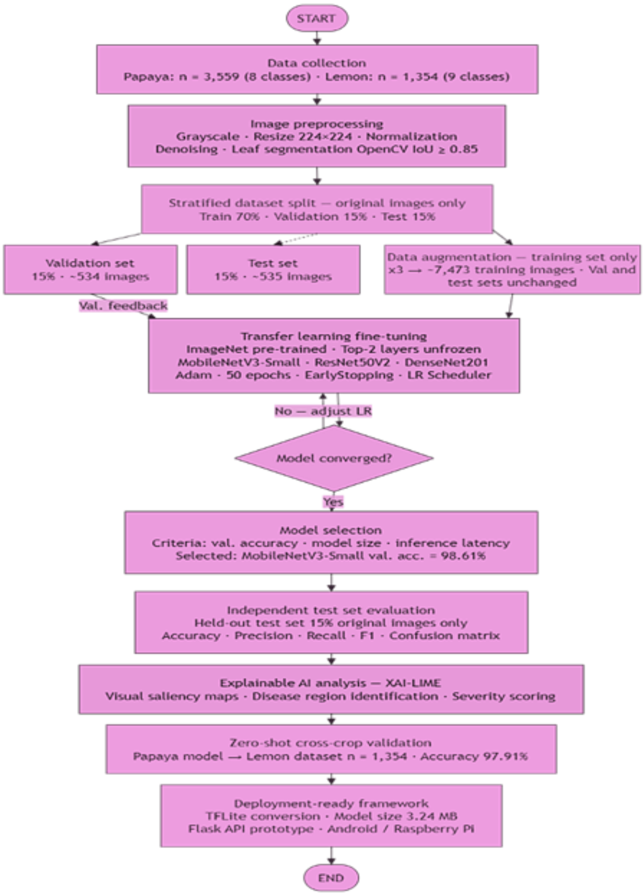


Fig. 1. Flowchart of the proposed methodology.

B. Data Preprocessing

Preprocessing of prepared papaya leaf images as per (resize, normalize, denoise, segment and augment shown in Figure 3). The images were specially preprocessed to match the shape, normalize for evaluation in constant lighting conditions, denoise because they contain fast disease characteristics, and segment use of RGB-to-HSV conversion, Otsu's simple thresholding and morphological operations with contour detection methods using OpenCV algorithm to isolate a leaf region. To avoid data leakage, we performed the stratified split at the original-image level before augmentation, and augmentation was applied only to the training subset. Augmentation (rotation, flipping, brightness, zoom, translation, shearing, contrast) was then applied to the training images only, expanding the training set while preserving leakage-free validation and test splits.

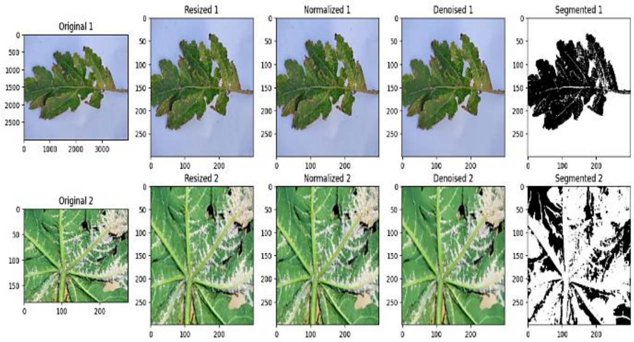


Fig. 3. Images after Preprocessing.

C. Description of Models

This research utilized three CNN models: Customized

Fig. 2. Papaya and Lemon Leaf Disease/Pest Classes Used in This Study

MobileNetV3-Small, ResNet50V2, and DenseNet201. These models were employed to categorize papaya leaf diseases and pests, as well as to facilitate severity assessment via a transfer learning and explainable artificial intelligence framework.

MobileNetV3-Small is a very efficient convolutional neural network tailored for mobile phones, IoT devices, and edge computing contexts. This allows mobile models to be trained with robust performance while significantly reducing the compute cost by utilizing depth-wise separable convolutions, inverted residual blocks, squeeze-and-excitation modules and hard-swish activation [54]. Because of its compact memory footprint and minimal latency, it was regarded as a promising candidate for real-time deployment. This study utilized domain-specific fine-tuning to customize MobileNetV3-Small for the detection of agricultural diseases. The result was a reduced parameter count (1.34M vs. 2.54M baseline) and model size (3.24 MB vs. 6.07 MB) achieved by The backbone (Stem Conv + MBConv Layers 1–9) was kept frozen with ImageNet weights, while the standard classification head was replaced with a domain-specific head comprising Conv1×1 + AvgPool, Dense-256 (ReLU), Dropout-0.3, and 8-class Softmax — reducing parameters from 2.54M to 1.34M. Fig. 4 depicts the architecture of the proposed Customized MobileNetV3-Small, consisting of a frozen ImageNet-pretrained backbone and a trainable domain-specific classification head fine-tuned on the papaya leaf disease dataset.

ResNet50V2 is a 50-layer residual network that uses pre-activation residual blocks to improve the flow and stability of gradients during training [55].

It is favorable because it strikes a balance between computational complexity and classification accuracy which allows comparison with lightweight models. DenseNet201 is a deep convolutional network with densely connected layers, where each layer is connected to all following layers into dense blocks [56].

This architecture facilitates feature reuse and exhibits robust classification performance, while necessitating greater computational resources than MobileNetV3-Small.

Transfer learning was applied by using pre-trained versions of these CNN models. The early layers were retained for feature extraction, while the top classification layers were modified and fine-tuned for papaya disease/pest classification. This approach allowed effective training with a relatively smaller agricultural dataset while reducing overfitting and improving generalization. The best-performing model was further validated on the lemon leaf dataset to assess cross-crop generalization.

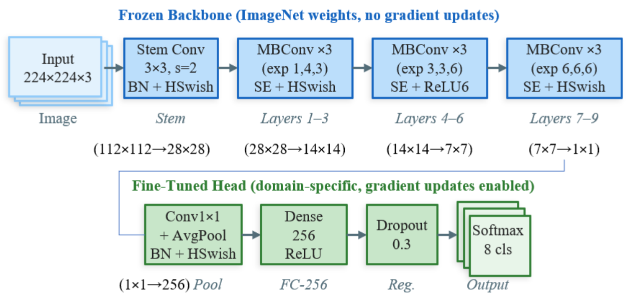


Fig. 4. Architecture of the proposed Customized MobileNetV3-Small with frozen backbone and fine-tuned classification head incorporating dense and dropout layers.

D. *Performance Matrices*

Confusion Matrix, True Positive, True Negatives, False Positive, False Negatives, accuracy, precision, F-measure, specificity, and recall are metrics for classification used for the performance analysis of the suggested models. These are defined as follows:

1) *Confusion Matrix*

The confusion matrix is among the easiest approaches to judge the accuracy and proficiency of the model. The confusion matrix is a table with each dimension's "Actual class" and "Predicted class".

• True Positive (TP): Cases when the actual data point classes are True and the expected is likewise True are known as True positives.

• True Negatives (TN): Cases when the actual classes of the data point are False, and the projection is likewise False, are known as true negatives.

• False Positive (FP): False positives are situations where the anticipation is also true, although the real class of the data points is False.

• False Negatives (FN): Cases when the expected is also False, but the actual class of the data item is True are known as true positives.

2) *Accuracy*

The quantity of the total correct disease predictions divided by the complete dataset determines accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

3) *Precision*

It indicates the proportion of positive class predictions that really indicate illness. The great accuracy guarantees consistent or repeated values of the reading, thus defining the outcome of the measurements; reduced precision results in different measuring values.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

4) Recall

Recall is the ability of a test to mark one as positive for illness. Few false negative findings from a highly sensitive test translate into fewer cases of disease being missed. Another name for it is the True Positive Rate (TPR).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

5) F1-Score

The FI-Score is like the mean between recall and precision. A higher Fl-score indicates perfect accuracy and recall of the suggested model.

$$F1\_Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (4)$$

6) ROC Score

ROC score (AUC) is used to tabulate the performance of the model regarding differentiating positive and negative classes by defining the bounds under the ROC curve. When the AUC is near 1, then it means that the model would perform well in identifying the difference between the two groups.

7) Kohen's Kappa

Cohen's Kappa is used to measure the agreement between two raters or classifiers, accounting for the possibility of agreement occurring by chance. It is commonly used in situations where two different people or models are classifying data, and you want to know how well their judgments agree.

$$k = \frac{(Po - Pe)}{(1 - Pe)} \quad (5)$$

Where:

P_o is the observed agreement between the two raters.

P_e is the expected agreement by chance.

8) Mathews Correlation Coefficient (MCC)

MCC is a more robust measure for evaluating the quality of binary classification models, especially when the classes are imbalanced. It considers all four elements of a confusion matrix; true positives, (TP), true negatives, (TN), false positives (FP), and false negatives (FN).

E. Model Interpretability and Deployment Strategy

To provide transparency and usability for Bangladeshi smallholder farmers, the proposed Customized MobileNetV3-Small was enhanced via (1) LIME-based XAI generating disease-specific saliency maps (Section 5), and (2) deployment optimization with 3.24 MB size (vs. 77.4 MB ensembles) and TFLite compatibility (~2.8 MB post-quantization). The Flask API prototype (14.64 ms localhost inference, Section 8) estimated 25–45 ms on entry-level Androids (Samsung A10, Raspberry Pi 4, 2GB RAM, Snapdragon 3xx/4xx) — not empirically validated on physical hardware, delivering real-time interpretable predictions, severity scores, and treatment recommendations from the high-accuracy CNN (98.61% papaya, 97.91% lemon).

F. Severity Score Method

Disease severity was computed from the segmented leaf mask by measuring the proportion of diseased pixels relative to the total leaf area. Let A_ddenote the number of diseased pixels and A_ldenote the total number of leaf pixels. The continuous severity score was calculated as:

$$\text{Severity } (\%) = \left(\frac{A_d}{A_l}\right) \times 100 \quad (6)$$

The resulting value represents the percentage of the leaf area that is visibly diseased. In Fig. 10, the values reported are continuous severity in percent of segmentation masks.

IV. Result Analysis

The papaya leaf disease detection of Customized MobileNetV3-Small was systematically compared with that of ResNet50V2 and DenseNet201 on the cross-crop validation on lemon leaves. In addition, confusion matrices, training curves and interpretability analysis were performed to determine the predictive reliability of the models and their readiness for clinical adoption, alongside accuracy, precision recall, F1-score, Cohen's Kappa and Matthews Correlation Coefficient (MCC).

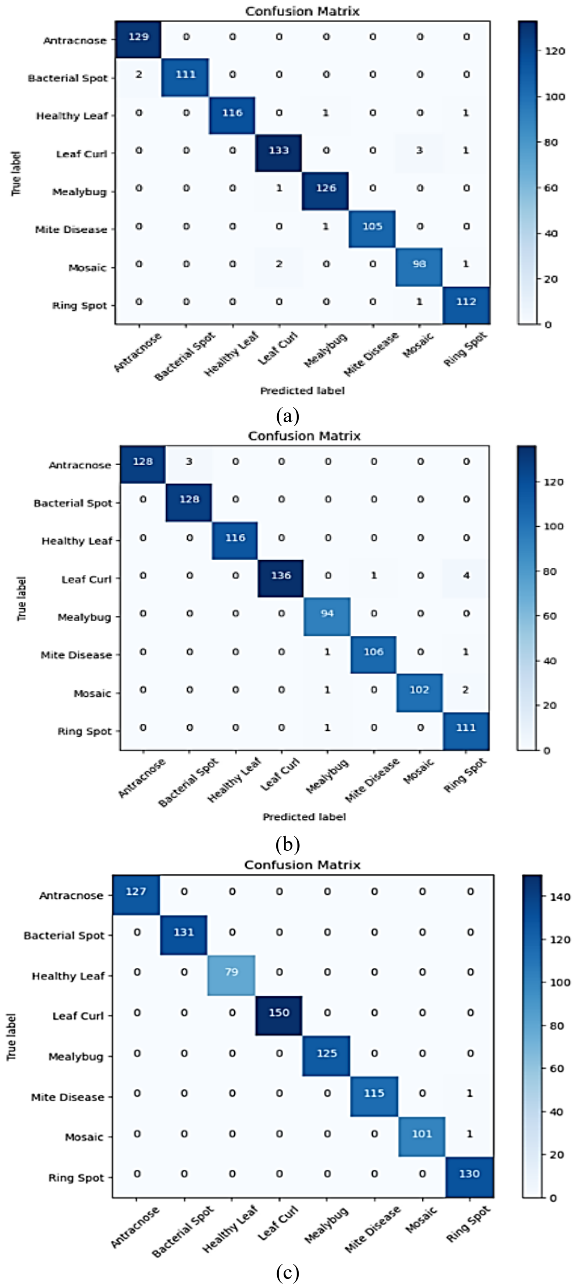


Fig. 5. Confusion Matrix for (a) Customized MobileNetV3-small Model, (b) ResNet50V2 Model and (c) DenseNet201 Model.

A. Hyperparameter Optimization

The hyperparameter ablation experiments varied one parameter at a time: optimizer, learning rate, batch size or epochs, keeping (224×224) image resolution, 0.2 dropout, threefold data augmentation and train-validation-test split

(70/15/15). categorical cross-entropy loss with SoftMax output, early stopping (10 epochs) and learning rate reduction (7 epochs). To ensure stable convergence and generalization, for each model several optimal configurations were identified.

B. *Papaya Leaf Disease Classification*

DenseNet201 had 99.69% accuracy but needed significantly more resources to train and hence it was unsuitable for edge deployment. Fig. 5 presents accuracy and loss curves for the Customized MobileNetV3-small Model, ResNet50V2 Model, and DenseNet201 Model. While Fig. 6 compares training accuracy and loss across all models, confirming stable convergence without overfitting. Fig.7 shows training accuracy and loss comparison across all models.

TABLE I
CLASS-WISE PERFORMANCE OF CUSTOMIZED MOBILENETV3-SMALL MODEL

Class	Precision	Recall	F1-Score
Anthracnose	1.00	0.98	0.99
Bacterial Spot	0.98	1.00	0.99
Healthy Leaf	1.00	1.00	1.00
Leaf Curl	1.00	0.96	0.98
Mealybug	0.97	1.00	0.98
Mite	0.99	0.98	0.99
Mosaic	1.00	0.97	0.99
Ring Spot	0.94	0.99	0.97

TABLE II
COMPARATIVE PERFORMANCE OF EVALUATED MODELS

Model	Accuracy	Precision	Recall	F1 Score	ROC Score	Cohens' kappa	MCC
Customized MobileNetV3 -Small (Proposed)	98.61%	98.56%	98.50%	98.51%	99.96%	98.08%	98.09%
MobileNetV3 -Small (Baseline)	98.50%	98.51%	98.50%	98.50%	99.96%	98.51%	98.56%
ResNet50V2	98.52%	98.53%	98.52%	98.52%	99.92%	98.52%	98.98%
DenseNet201	99.69%	99.79%	99.79%	99.78%	100%	99.06%	99.63%

C. *Explainable AI and Severity Assessment*

Activation maps from Customized MobileNetV3-Small hidden LIME visualizations (Fig. 9) offer interpretable saliency maps to foster farmer trust, while layers (Fig. 8) emphasize the effective feature extraction for disease regions. The continuous severity score (Ad/Al × 100) derived from segmentation masks is reported directly as a percentage (Fig. 10), facilitating prioritized interventions and minimizing pesticide use in smallholder contexts in Bangladesh. The reported values in Fig. 10 represent continuous severity percentages calculated from the ratio of diseased pixels to total leaf pixels.

D. *Cross-Crop Validation: Lemon Leaves*

The papaya-trained Customized MobileNetV3-Small demonstrated remarkable Zero-shot setting to the 1,354-image lemon dataset, with an accuracy of 97.91% with per-class precision, recall, and F1-scores ranging from 0.94 to 1.00 across nine classes (Table 3) without any lemon-domain fine-tuning. The following results were obtained by directly applying the papaya-trained model to the lemon test set. The confusion matrix (Fig. 11) indicates minimal misclassifications.

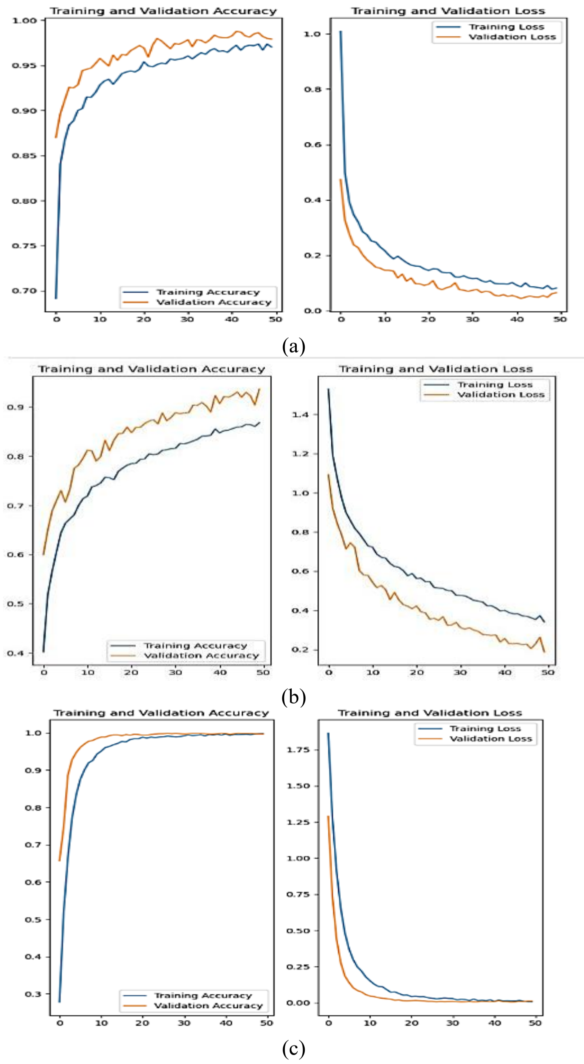
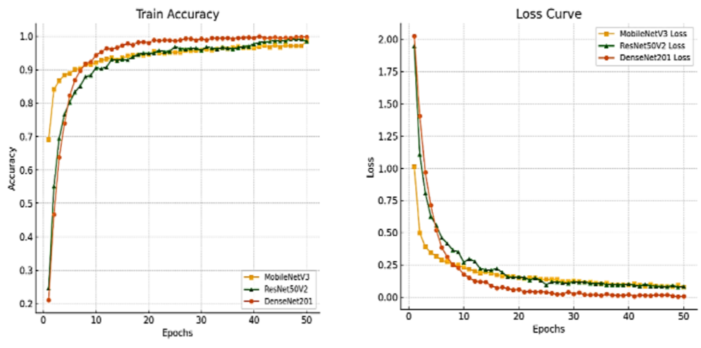


Fig. 6. Accuracy and Loss Curve for Customized MobileNetV3-small Model, ResNet50V2 Model, DenseNet201 Model.



(a) (b)

Fig. 7. (a) Training Accuracy and (b) Loss Comparison Across All Models.

TABLE III
CLASS-WISE PERFORMANCE ON THE LEMON LEAF DATASET UNDER ZERO-SHOT CROSS-CROP EVALUATION

Class	Precision	Recall	F1-Score	Support
Anthracnose	1.00	1.00	1.00	6
Bacterial Blight	0.94	1.00	0.97	15
Citrus Canker	1.00	1.00	1.00	9
Curl Virus	1.00	1.00	1.00	16
Deficiency Leaf	1.00	1.00	1.00	22
Dry Leaf	1.00	1.00	1.00	17
Healthy Leaf	0.94	1.00	0.97	15
Sooty Mould	1.00	0.91	0.95	22
Spider Mites	1.00	1.00	1.00	14

Note: Classes with fewer than 20 test samples (Anthracnose n=6, Citrus Canker n=9, Spider Mites n=14) should be interpreted as exploratory due to limited support.

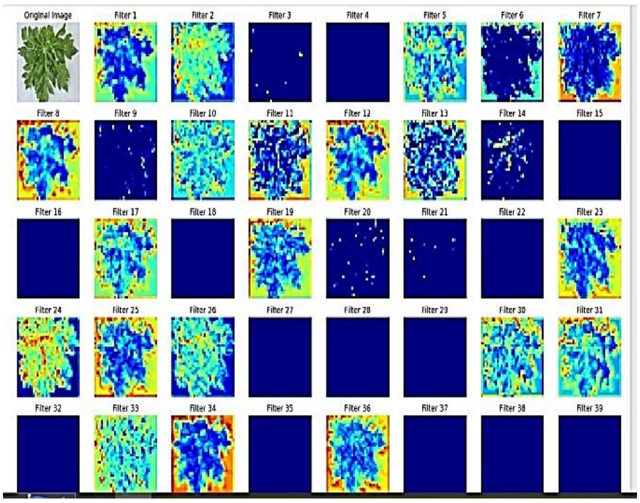


Fig. 8. Representing the hidden layer output activation maps of the Customized MobileNetV3 Small Model.

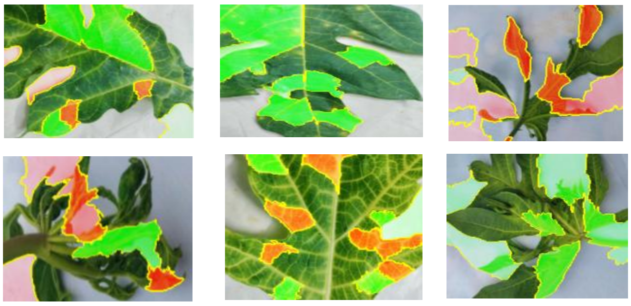


Fig. 9. Visualization with LIME.

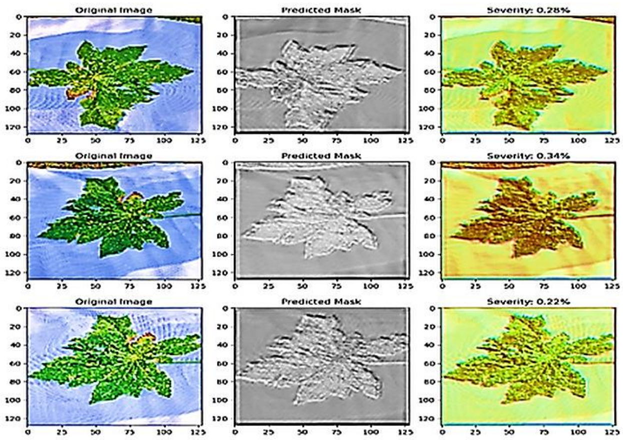


Fig. 10. Disease severity (%) computed from diseased-pixel ratio.

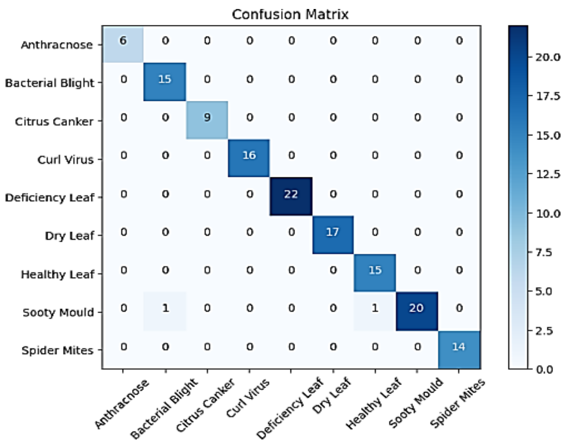


Fig. 11. Confusion Matrix of lemon leaf dataset.

The parameter count was reduced from 2.54M to 1.34M by replacing the standard classification head with a lightweight 8-class domain-specific head, resulting in 47% model size reduction (6.07 MB → 3.24 MB) without sacrificing classification performance. Inference time on local host; edge device benchmarks pending field validation. Custom MobileNetV3-Small provides top accuracy with best size/speed analysis on edge for deployment. More params, but accurate as with EfficientNet-B0 ShuffleNetV2/SqueezeNet trade off accuracy for speed This establishes Customized MobileNetV3-Small as a better option for resource-constrained environments (Raspberry Pi/Android).

TABLE IV
PERFORMANCE COMPARISON OF LIGHTWEIGHT CNN MODELS (SIMILAR PARAMETER RANGE)

Model	Parameters (M)	Accuracy (%)	Model Size (MB)	Inference Time (ms)
MobileNetV3-Small (Customized)	**1.34**	**98.61**	**3.24**	**14.64**
MobileNetV3-Small (Baseline)	2.54	98.50	6.07	14.01
EfficientNet-B0	5.3	97.42	20.5	18.2
ShuffleNetV2	2.3	97.92	6.04	12.1
SqueezeNet	1.2	96.34	8.5	10.5

E. Deployment Readiness

A customized MobileNetV3-Small was the model deployed in a RESTful API prototype built using Flask (Fig. 12), using images of 224×224, and achieving real-time 8-class prediction probabilities, confidences, severities and treatment recommendations at a latency of 14.64 ms. TFLite conversion (~2.8 MB post-quantization) enables offline edge compatibility on resource-constrained devices to support precision agriculture for papaya-lemon farmers in Bangladesh.

Papaya leaf disease and pest detection: Customized MobileNetV3-Small model deployment as a Flask API prototype, verified locally through Postman. At the top, predict receives 224×224 image types and outputs 8-class predictions along with confidence scores and treatment recommendations in the Bengali language, treatment recommendations collated from existing agronomic practices for managing papaya diseases in Bangladesh (the treatment guidelines are among established practices supported by BARI & DAE). The recommendation module is coded as a static Bengali language JSON knowledge base that maps each of the eight predicted classes to a corresponding disease description and three curated treatment steps, whereby, upon classification, the predicted class label queries this lookup table and responds with the respective Bengali description and treatment recommendations via the Flask API.

Dynamic HTML visualizations include confidence bar charts, icons, and timestamps. Lightweight architecture (3.24 MB, 14.64 ms/image) enables real-time inference on edge devices such as low-RAM smartphones and Raspberry Pi. TensorFlow Lite conversion (~2.8 MB) allows offline mobile deployment, eliminating cloud dependency and costs.

V. DISCUSSION

Despite DenseNet201 attaining a slightly superior accuracy of 99.69%, its 77.4 MB model size renders it entirely unsuitable for edge deployment in resource-limited settings. By contrast, the proposed Customized MobileNetV3-Small achieves 98.61% accuracy with a model size of merely 3.24 MB, approximately 119 times smaller, establishing it as the most viable solution for real-

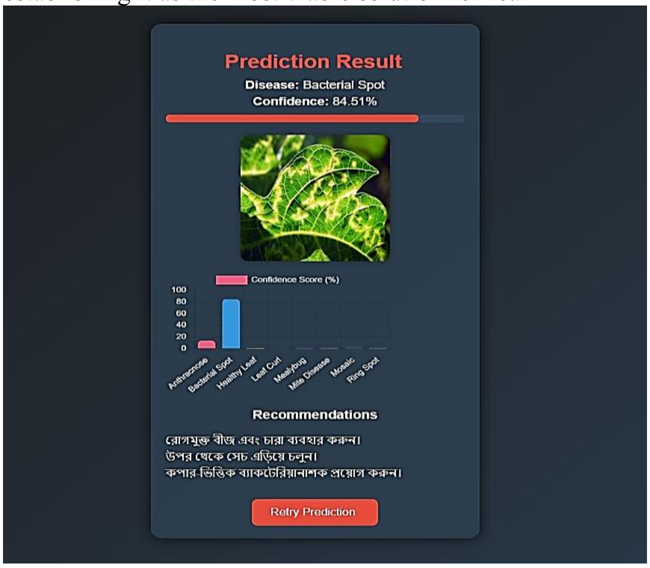


Fig. 12. API for Papaya Leaf Disease/pest Detection with Bengali Recommendation Output.

TABLE V
COMPARISON WITH EXISTING WORK

Study	**Model**	**Dataset**	**Accuracy (%)**	**Model Size (MB)**	**Inference Time (ms)**	**Target Crop**	**Dissimilarities**
Proposed Framework	MobileNetV3-Small	3,559 (aug. training: 7,473)	98.61 (Papaya), 97.91 (Lemon)	3.24	14.64	Papaya, Lemon	Lightweight for edge devices (Raspberry Pi), XAI integration (LIME), and Severity Score analysis.
Bacus et al. [58]	MobileNet	1,394	91.67	Not Reported	Not Reported	Papaya	Smaller dataset, lower accuracy, no model size or inference time data, limited edge optimization.
Chaithanya et al. [59]	ResNet-50	Not Reported	95	Not Reported	Not Reported	Papaya	Lower accuracy, fewer classes, no edge device focus, and unreported size/time.
Emmanuel et al. [37]	MobileNet V2, VGG16	9,302	90.11	Not Reported	Not Reported	Cassava	Lower accuracy, different crop, no edge device or XAI focus.
k et al. [46]	InceptionResNetV2	5,200	95.67	Not Reported	Not Reported	Rice	Moderate accuracy and dataset, no edge device or lightweight focus.
Dey et al. [60]	SwinGhost-ClustNet	9,342	99.25	385	34.15	Papaya	Larger dataset, XAI (Grad-CAM++), but a heavy model, unsuitable for edge devices

world, resource-constrained agricultural deployment. Specifically, Customized MobileNetV3-Small has a high level of performance, thus, making it possible to run it on resource-constrained devices in real-time. This performance is made possible by the depth-wise separable convolutions specifically formulated to execute on mobile and edge hardware, which is given the necessity to provide low-cost diagnostics to the farmers in such countries as Bangladesh. The interpretability of the decision-making process of Customized MobileNetV3-Small can be achieved through explainable AI (XAI) approaches such as LIME to visualize what areas of the leaf related to diseases are being used by the model to make its predictions and hence develop trust in the end-users. In addition, severity scoring also lends support to practical decision-making by quantifying injury, helping farmers to rank interventions and decrease the abuse of pesticides, and thereby contributing to sustainable farming. The Flask-based API supports real-time diagnosis and pesticide recommendation, and is proven by a Postman test, with the potential being amenable to field use. There are several limitations still; the use of curated datasets may not reflect the full complexity as in actual scenarios (overlapping leaves, diverse external settings) and the need for more tuning when it comes to multi-disease. The high generalizability of this framework, demonstrated on lemon datasets, provides an inexpensive and scalable tool for precision agriculture in low-income areas. Nonetheless, per-class support is still too small in some categories (e.g., Anthracnose n=6, Citrus Canker n=9) for lemon cross-crop validation so these per-class results should be considered as exploratory pending evaluation on larger lemon test sets. Results are reported for a single train/Val/test split and training run per model. In this case, it would be necessary to compare each model using cross-validation experiments due to the very small differences in accuracy (e.g., 98.50% vs 98.61%).

VI. CONCLUSION

We conclude the work, which illustrates the optimal Customized MobileNetV3-Small (2.0 process, 98.61% accuracy to size 3.24 MB with 14.64 ms inference). Cross-crop generalizability zero-shot across lemons (97.91%) confirms transferability of the underlying model without prior training on lemon-rich datasets here, this reinforces generalizability to other important tropical crops. We realized an end-to-end offline deployable TFLite-ready prototype1 capable of providing XAI visualizations, severity scoring and pesticide recommendations on widely available farmer devices (Samsung A10/Nokia C01) to help farmers tackle the crop yield loss epidemic in Bangladesh.

The key limitations are as follows: Table IV latency (14.64 ms) is for localhost only, since physical benchmarking against target edge hardware (Raspberry Pi 4, Samsung A10) is still to be conducted and prioritized in respect of field trials in 2026; restricted dataset coverage (3,559 original images; augmented training set: 7,473); lemon validation was based on a limited number of images (1,354), and there is further work needed to produce a larger field dataset; Flask API testing was performed locally on localhost; recommendations were currently delivered as Bengali text based on BARI/DAE guidelines but with future plans to provide Bengali voice guidance after implementing the native Android version. These gaps will be filled in future work, including 100+ farmer field trials in 2026 and targeting mango and banana crops, a native app for Android with camera integration and Bengali voice guidance, hardware acceleration using Google Coral TPU (1–3 ms inference) and sensor fusion with environmental data for predictive severity scoring.

This work combines high accuracy, relative light weight and farmer-centric design to lay the groundwork for practical precision agriculture with scalable, affordable and actionable disease detection of tropical crops in resource-limited environments.

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The writers used "ChatGPT," "Grammarly," and "QuillBot" to improve the language and readability of this work. The authors take full responsibility for the content of the published paper and have reviewed and revised it as needed after use.

Author contributions

Shourav was primarily responsible for data curation, methodology development, visualization, and preparation of the original manuscript draft. Kamrul conceptualized the study, supervised the research activities, contributed to methodological design, validated the findings, and critically reviewed and edited the manuscript. Rifat conducted the formal analysis and contributed to both the original draft preparation and manuscript revision. Mahbub participated in the validation of the research outcomes and contributed to manuscript review and editing. Ayshi and Ashraful contributed to visualization, preparation of the original draft, and manuscript review and editing. All authors reviewed and approved the final version of the manuscript.

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