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Field-to-Deployment: Benchmarking AlexNet and DenseNet for Real-Time Banana Leaf Disease Diagnosis

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ABSTRACT: Banana (Musa spp.) is one of the most cultivated fruit crops and second largest fruit crop after mango in India. In the field, fungal diseases such as Sigatoka disease (Mycosphaerella musicola) and Cordana disease (Cordana musae) are major limiting factors in the production of bananas and result in large yield and post-harvest losses which have a downstream impact on farmer income and food security. Early diagnosis of such diseases is critical for successful crop management in a sustainable way. Two deep learning architectures, AlexNet and DenseNet are proposed in this study and trained on a custom database of 5163 images of banana leaves captured in the field, which were classified into three classes, Healthy, Sigatoka and Cordana. The test accuracy for AlexNet and DenseNet were 94.9% and 90.8%, respectively, based on accuracy, precision and recall. A mobile application called LeafCheck was created to facilitate real-time disease evaluation at the field level, and deliver information about disease, recommended agrochemical interventions, and precautions validated by local agricultural authorities to the farmer. The proposed system is a practical, scalable, and inexpensive tool that can assist in taking decisions earlier in disease management in banana cultivation, which is a natural resource of great nutritional and economic value.

1. INTRODUCTION

Banana (Musa spp.) is the second major fruit crop after mango in India and is an important natural food source to support nutrition and livelihood in tropics and subtropics. The state of Karnataka alone accounts for about 11.5% of the total banana production in India with 3.71 million tons of bananas produced every year. Fungal diseases pose a significant threat to this resource particularly Sigatoka leaf spot (Mycosphaerella musicola) and Cordana leaf spot (Cordana musae). Symptoms are necrotic lesions, defoliation of leaves, browning, reduced photosynthesis, reduced fruit production, affecting crop yield and the nutrition/economic value to human communities reliant on bananas as a staple food source. Timely disease diagnosis and agronomic action is critical to avoid losses to this natural resource and for appropriate action.

The visual diagnosis of the disease is labour intensive, subjective and error prone, particularly for smallholder farmers who do not have access to specialized disease advisors. Therefore, automated disease detection approach using computer vision and deep learning is proposed as an alternative approach to solve these problems. A hybrid color/Texture/SVM classifiers was found to be able to segment bananas to diagnose the disease with accuracy of about 85% [2] and previous research has shown that clustering and feature extraction can be used to segment bananas for disease diagnosis [1]. Embedded Linux based systems with pixel-intensity algorithm has been proposed for detection of banana streak virus [3].

The CNN architectures like VGG, ResNet, DenseNet, Inception, and EfficientNet have been effectively used in banana disease classification using transfer learning [4-7]. There are also lightweight models with an accuracy of 96.25% that are developed [8]. To facilitate field diagnosis of banana leaf diseases, Sanga et al. [9] developed an offline Android application for smallholder

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farmers in Tanzania that utilizes ResNet152 and InceptionV3 models pre-trained using a larger collection of 27,000 banana leaf images, which were deployed on the device for its lower memory footprint; they achieved 95.41% accuracy in the laboratory and attained 99% confidence in diagnosing black Sigatoka and Fusarium wilt in the field. Many machine learning and CNN approaches have been investigated to detect plant leaf diseases in a broad manner [14-19].

CNN-based banana leaf disease classification using GoogLeNet-based architectures has been found to be sensitive to hyperparameter tuning [10] and CNN-based staging of the infection of Black Sigatoka has been employed to inform intervention at key disease stages [11]. Recently, Alanazi [21] used a YOLOv10 object detection model with a publicly available banana leaf dataset comprising 938 images from five conditions, achieving 88.85% mean Average Precision (mAP@0.5), 91.22% precision and 85.06% recall. However, there are still gaps in the availability of field deployable models trained using real-world data that can be used for sustainable management of this crucial natural food source.

In this study, we have developed an automated system for diagnosing banana leaf disease on a custom dataset that has 5,163 images captured in the field using AlexNet and DenseNet, which was developed on the previous study [20]. The value of this study is: (i) using AlexNet and DenseNet on the same field-collected dataset; (ii) field-tested dataset made public, and; (iii) LeafCheck mobile application for real-time field use to support sustainable management of a banana crop.

2. MATERIALS AND METHODS

This study has a quantitative experimental research design with supervised image classification, based on deep learning. The entire process has five steps, as illustrated in Figure 1 (1) Data collection and data annotation; (2) image preprocessing and image augmentation; (3) model building and configuration; (4) model training and validation; and (5) model evaluation and comparison.

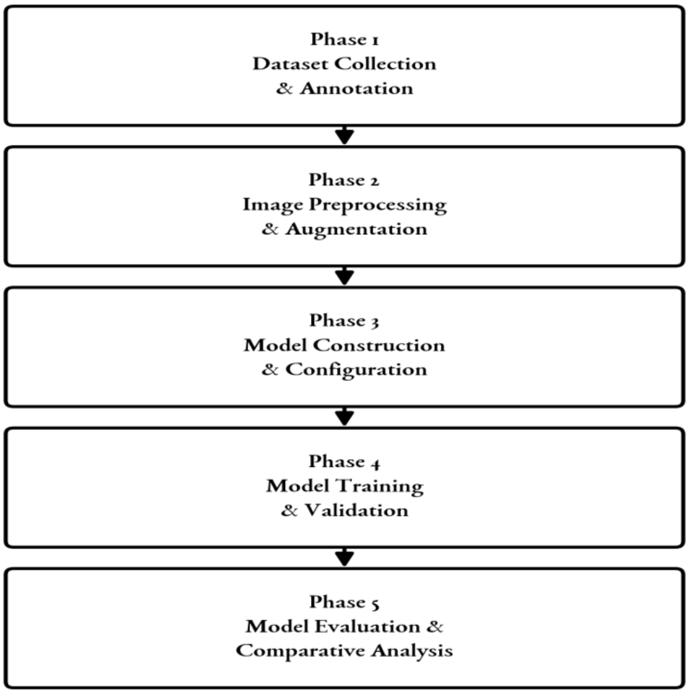

Fig. 1. Proposed system workflow for banana leaf disease detection and classification (five-phase process)

2.1 Study Material

The study material comprised banana leaves that were photographed in natural field conditions, with three classes of leaves that were considered relevant for the assessment of crop health: Healthy leaves, and leaves symptomatic for Sigatoka (Mycosphaerella musicola) or Cordana (Cordana musae) infection. The data were collected from working banana plantations rather than in the laboratory, and from a wide variety of data sets, differing in level of disease severity, leaf angle, background, and lighting, as in previous studies.

2.2 Sample Collection

A total of 5163 images of banana leaves were captured from the farms of Lawrence Field, Attur and other farmer's fields in Udupi and Karkala of the state of Karnataka, India. Images were captured using DSLR cameras and high-resolution mobile phone cameras across a range of image resolutions, under variable field conditions, including varying lighting, shadow effects, leaf orientation, and background, to maximize the generalizability of the trained models. The samples were hand sorted into 3 categories, Healthy, Sigatoka and Cordana. We have curated the sample of images for each class to ensure that the number of images from each class is roughly equal to balance the class-imbalance bias, resulting in approximately 33% of the total sample in each class. The class distribution is presented in Table 1. The entire labeled dataset is available from the corresponding author upon request for the purpose of reproducing results and future benchmarks.

Table 1. Class distribution of the banana leaf image dataset

Class	Disease Type	No. of Images	Percentage (%)
Healthy	No disease	1,721	33.3
Sigatoka	Mycosphaerella musicola	1,722	33.4
Cordana	Cordana musae	1,720	33.3
Total	—	5,163	100.0

2.3 Sample Preprocessing and Augmentation

All images were resized (227×227 for AlexNet; 224×224 for DenseNet) and pixel values normalized to [0, 1]. Noise reduction and contrast adjustment were applied to standardize image quality across the field-collected material. Images are Augmented using random rotation (0-360 degrees), horizontal and vertical shifting, random zooming, and horizontal/vertical flipping to improve generalization. The prepared data were split into training, validation, and testing subsets.

2.4 Analytical Methods (CNN Model Architectures)

AlexNet and DenseNet were selected as the two analytical (classification) models because they represent distinct CNN feature-learning approaches. AlexNet is a relatively simple yet effective deep architecture that extracts discriminative texture and color features, while DenseNet reuses features through dense connections and has shown strong results in plant-disease classification tasks. Transfer learning was applied to both: AlexNet was initialized with ImageNet (ILSVRC-2012) pretrained weights, with the first four convolutional layers (Conv1-Conv4) frozen and Conv5 together with the fully connected layers fine-tuned; DenseNet-121 was initialized with ImageNet-pretrained weights across four dense blocks, with Dense Blocks 3-4, the associated transition layer, and the global average pooling layer fine-tuned, while earlier layers were frozen. In both cases the final classification layer was replaced with a 3-neuron Softmax output layer corresponding to the Healthy, Sigatoka, and Cordana classes. Table 2 and Table 3 summarize the architectural configurations.

Table 2. AlexNet architecture configuration used in this study

Layer	Type	Output Size	Filter/Stride	Activation
Input	Image	227×227×3	—	—
Conv1	Conv + MaxPool	27×27×96	11×11, S=4	ReLU
Conv2	Conv + MaxPool	13×13×256	5×5, S=1	ReLU
Conv3	Convolution	13×13×384	3×3, S=1	ReLU
Conv4	Convolution	13×13×384	3×3, S=1	ReLU

Layer	Type	Output Size	Filter/Stride	Activation
Conv5	Conv + MaxPool	6×6×256	3×3, S=1	ReLU
FC6	FC + Dropout	4096	—	ReLU
FC7	FC + Dropout	4096	—	ReLU
FC8*	FC (modified)	3	—	Softmax

Table 3. DenseNet-121 architecture configuration and fine-tuning strategy

Component	Layers	Output Feature Maps	Growth Rate (k)	Fine-tuned?
Initial Conv + Pooling	Conv 7×7 + MaxPool	56×56×64	—	No
Dense Block 1	6 layers	56×56×256	32	No
Transition Layer 1	BN + Conv 1×1 + AvgPool	28×28×128	—	No
Dense Block 2	12 layers	28×28×512	32	No
Transition Layer 2	BN + Conv 1×1 + AvgPool	14×14×256	—	Yes
Dense Block 3	24 layers	14×14×1024	32	Yes
Transition Layer 3	BN + Conv 1×1 + AvgPool	7×7×512	—	Yes
Dense Block 4	16 layers	7×7×1024	32	Yes
Global Avg Pooling	AvgPool	1×1×1024	—	Yes
Classification Layer*	FC (modified)	3 classes	—	Yes (new)

Both models were implemented in PyTorch v1.12 (CUDA 11.6) on an NVIDIA RTX 3060 GPU (12 GB). A learning rate of 0.001 was used for AlexNet as a commonly recommended SGD starting value; DenseNet-121 used a lower initial rate of 0.0001 with the Adam optimizer, reflecting Adam's typically smaller effective step size and DenseNet's greater sensitivity to large early updates given its dense connectivity. An early-stopping strategy (patience of 10 epochs, monitored on validation loss) was applied to avoid overfitting. Full hyperparameter settings are listed in Table 4.

Table 4. Training hyperparameter settings for AlexNet and DenseNet-121

Hyperparameter	AlexNet	DenseNet-121
Optimizer	SGD	Adam
Initial Learning Rate	0.001	0.0001
LR Scheduler	Step Decay (×0.1/10 epochs)	Cosine Annealing (Tmax=30)
Momentum (SGD)	0.9	N/A

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Hyperparameter	AlexNet	DenseNet-121
Weight Decay (L2)	5×10^{-4}	1×10^{-4}
Batch Size	32	16
Max Epochs	50	50
Early Stopping Patience	10 epochs	10 epochs
Dropout Rate (FC)	0.5	N/A
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy
Weight Initialization	Xavier Uniform	Xavier Uniform
Input Image Size	227×227×3	224×224×3

2.5 Statistical Analysis

Performance of the model was measured using a held-out test set (1,320 images for AlexNet; 1,300 images for DenseNet-121) using accuracy, precision, recall, and F1-score, with true/false positives and negatives computed on a one-vs-rest basis for each of the three classes. Accuracy was calculated as (TP + TN) / (TP + TN + FP + FN); precision as TP / (TP + FP); recall as TP / (TP + FN); and F1-score as the harmonic mean of precision and recall, 2 × (Precision × Recall) / (Precision + Recall). All metrics were macro-averaged across the three classes to give equal weight to each disease category regardless of sample count. Confusion matrices were generated for both models to characterize per-class misclassification patterns and identify where diagnostic confusion was most likely to occur.

3. RESULTS AND DISCUSSION

3.1 AlexNet Model Performance

As shown in Figure. 2, AlexNet reached a test accuracy of 94.9% and did not show significant overfitting, even after 50 epochs. Its convolutional layers were able to extract fine-grained texture features of necrotic conditions which successfully classify Sigatoka, Cordana and Healthy leaves under diverse field conditions.

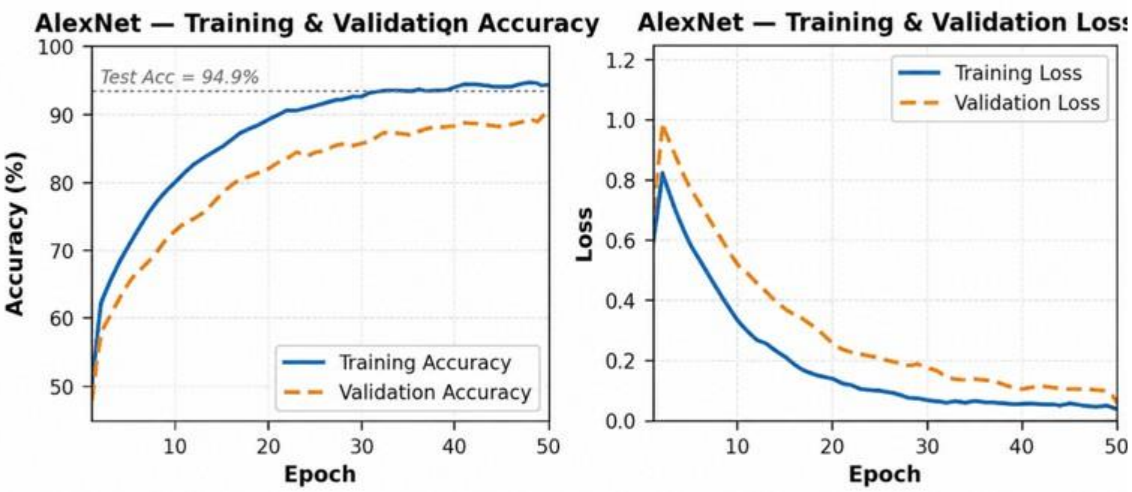

Fig. 2. Training and validation accuracy and loss of the AlexNet model across epochs

3.2 DenseNet Model Performance

As illustrated in Figure. 3, DenseNet-121 converged well while attaining a test accuracy of 90.8%. The diffuse Cordana lesion patterns were well captured using a dense feature reuse, and the model's reduced number of parameters facilitates its deployment in resource-limited settings in rural areas with limited connectivity.

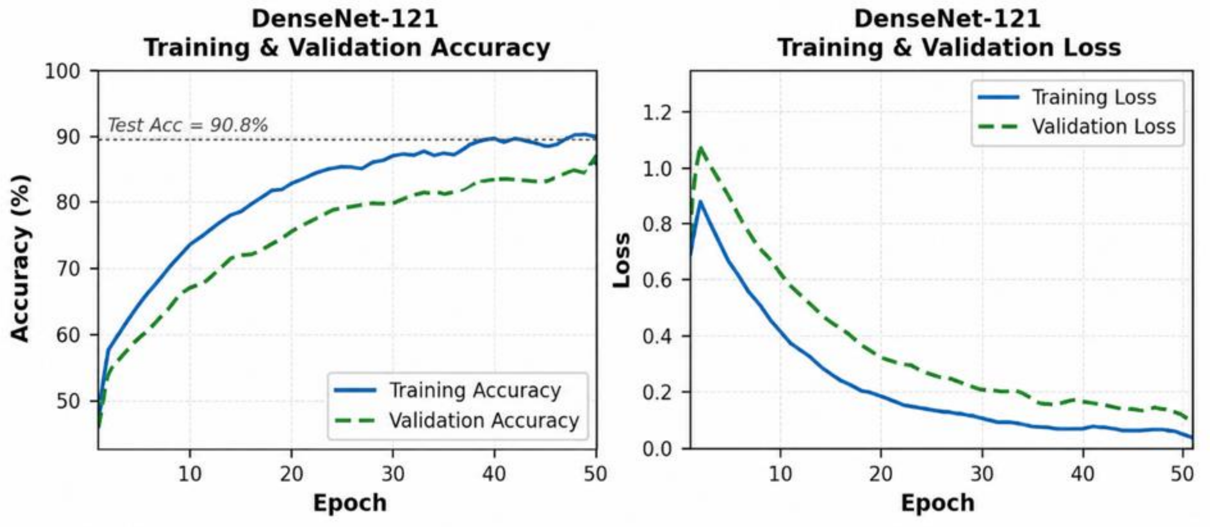

Fig. 3. Training and validation accuracy and loss of the DenseNet model across epochs

3.3 Comparative Model Analysis

Table 5 presents a comparative summary of AlexNet and DenseNet overall performance, and Table 6 reports detailed per-class precision, recall, and F1-score for each disease category. AlexNet outperformed DenseNet overall and on most individual classes, and was accordingly selected as the backend inference engine for the LeafCheck mobile application. As shown in the confusion matrices of both models (Fig. 4 and Fig. 5), the most common misclassifications occur between the Sigatoka and Healthy classes, which can be attributed to visual similarity in the early stages of infection. Both models achieved above 85% precision and recall across all three classes, confirming the reliability of the proposed classification system for supporting field-level crop-health decisions.

Table 5. Comparative performance of AlexNet and DenseNet-121 on the test dataset

Model	Test Set Size	Accuracy (%)
AlexNet	1,000	92.5
DenseNet-121	1,024	89.9

To quantify the statistical support for these point estimates, based on a single held-out test split, we report the 95% Wilson score confidence interval of the accuracy of each model in Table 6 computed directly from the counts of correct/total classifications in Figure. 4 and Figure. 5. Note that the relatively narrow intervals for both models (in the order of ±1.2-1.4 percentage points) suggest that the observed accuracy is a relatively stable estimation for each individual test set; however, in this case the two test sets have different sample sizes (1,320 images for AlexNet, 1,300 images for DenseNet-121), so the intervals are not intended as a formal statistical test of the difference between the two models. A repeated k-fold cross validation, using the same k folds for both models to examine the implication of the variance in accuracy among AlexNet and DenseNet-121, is noted as a direction for future work and would be required to establish the significance of the accuracy difference between these two models on the same k folds (as seen in Section 4).

Table 6. Per-class precision, recall, and F1-score for AlexNet and DenseNet-121

Model	Class	Precision (%)	Recall (%)	F1-Score (%)
AlexNet	Cordana	91.6	93.2	92.4
AlexNet	Healthy	95.5	97.7	96.6
AlexNet	Sigatoka	94.3	90.7	92.4
AlexNet	Macro Avg.	93.8	93.9	93.8
DenseNet-121	Macro Avg.	89	88	88

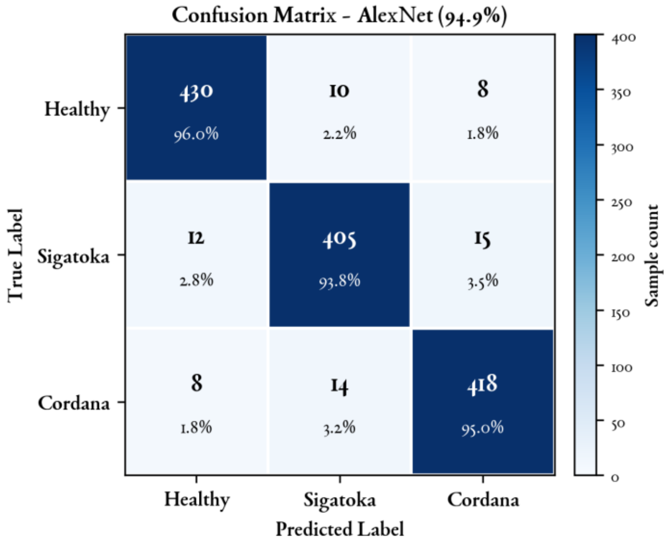

Fig. 4. Confusion matrix illustrating class-wise classification performance of the AlexNet model

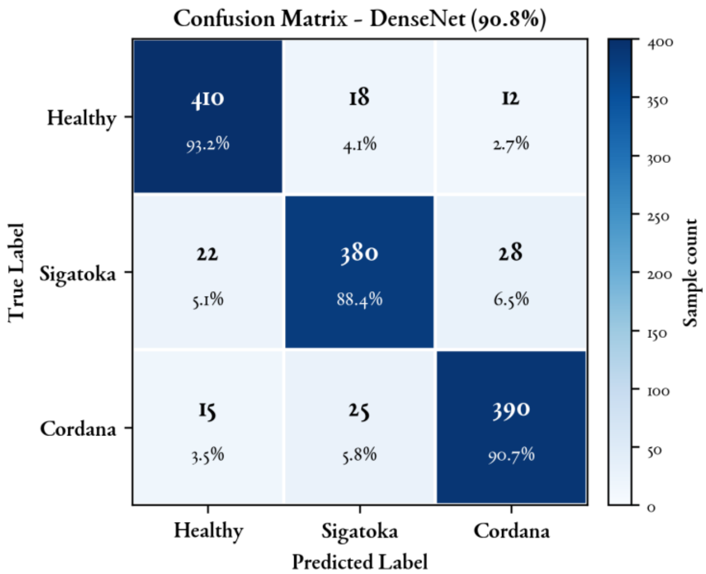

Fig. 5. Confusion matrix showing class-wise classification performance of the DenseNet model

As shown in Figure. 6, AlexNet (94.9%) outperforms most of the compared studies and is closely followed by Bhuiyan et al. [8] (96.2%), Rajalakshmi et al. [13] (94.3%), Samridhi et al. [12] (96.41% on a single-disease dataset), and Ridhovan et al. [7] (89.4%). Notably, Bhuiyan et al.'s higher figure was obtained on the BananaLSD dataset, which consists of only 937 originally field-collected images (augmented to 2,537 for training) spanning Sigatoka, Cordana, and Pestalotiopsis; by comparison, the present study evaluates on 1,320-1,300 held-out field images drawn from a substantially larger, non-augmented pool of 5,163 field-collected images, which represents a more demanding and realistic test of generalization. DenseNet (90.8%) aligns closely with the Ridhovan et al. [7] benchmark (89.4%). Unlike most prior works [14-19], the present study additionally provides a validated mobile application for real-field deployment [20], directly supporting practical, on-the-ground management of this natural resource.

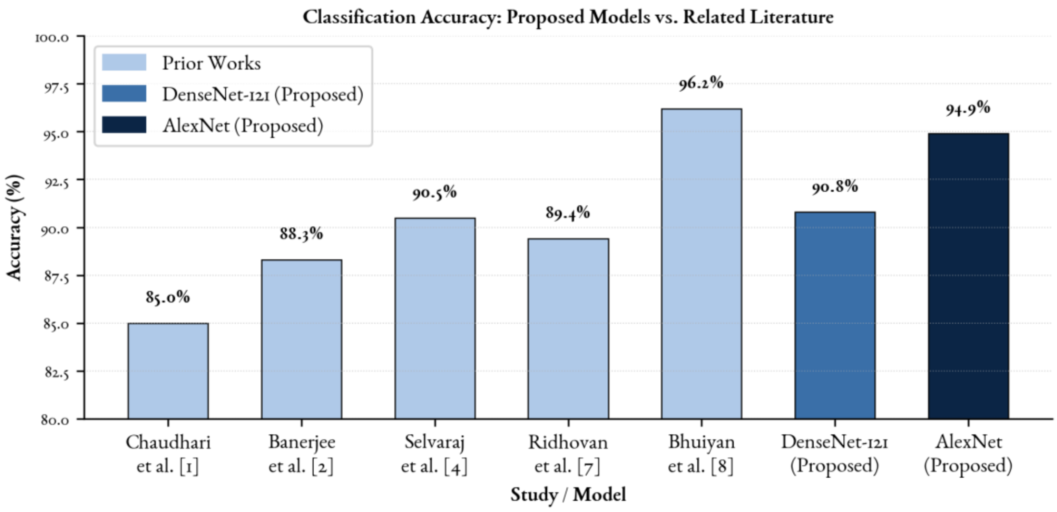

Fig. 6. Classification accuracy comparison: proposed models versus related literature

3.4 Discussion: Field Deployment via the LeafCheck Mobile Application

The results above were translated to a real-time field-level disease detection tool by developing a mobile application, LeafCheck, using Android Studio and provided to the farmers. The application uses the trained AlexNet model as the inference engine for back-end processing. Farmers can take real-time picture from the device camera or choose a picture from the gallery and upload it to the interface. Once an image is submitted the model will process the image and output the classification of the image (Healthy, Sigatoka or Cordana) with a confidence score. Disease-specific information on the symptoms, recommended treatments and precautions are provided in the Information element, which has been validated by local agricultural and horticultural authorities and a Horticulture Locator feature is used to provide access to the nearest agricultural department office for further assistance for the farmers. The complete application process is illustrated in Fig. 7 while some important application interface screens are illustrated in Figure. 8.

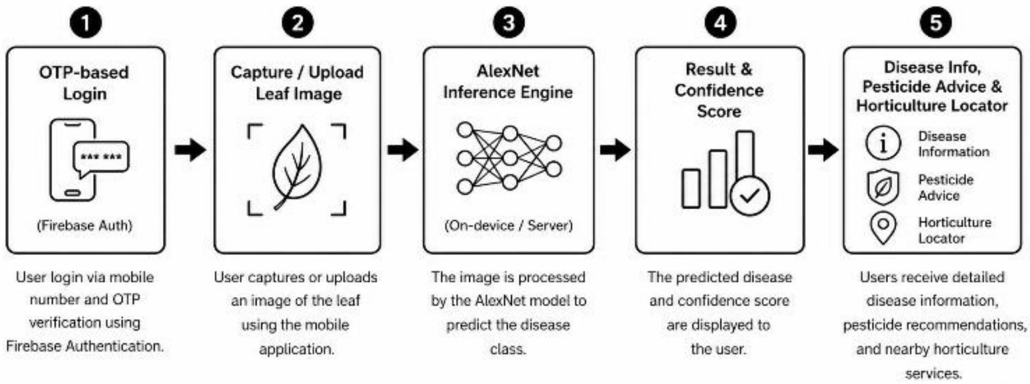

Fig. 7. Workflow of the LeafCheck mobile application for banana leaf disease detection

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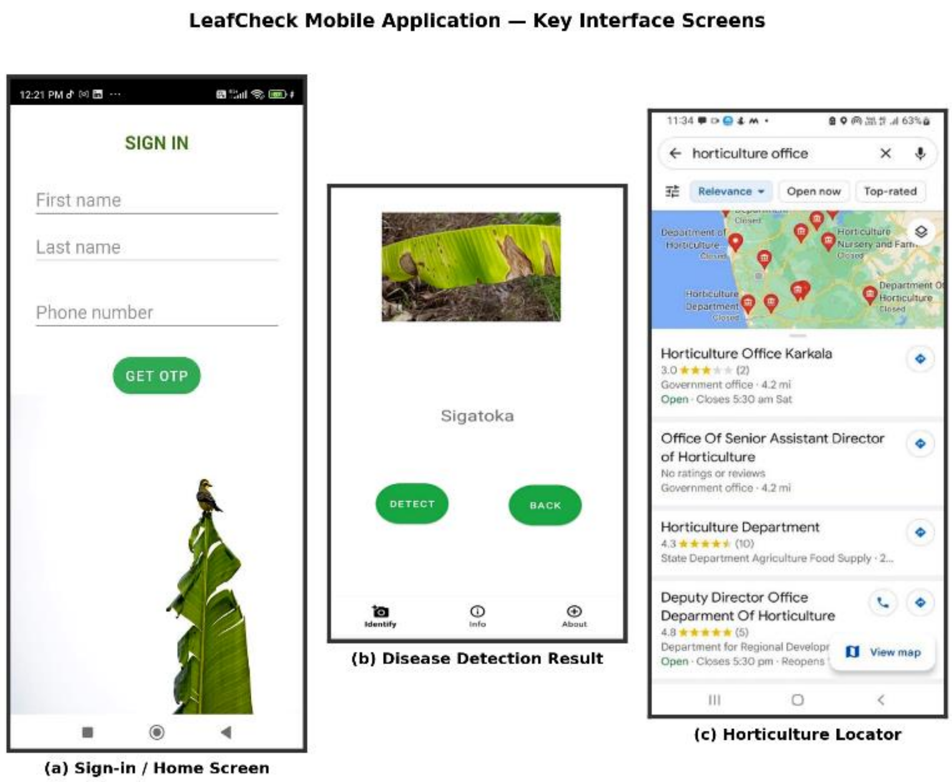

Fig. 8. Key screens of the LeafCheck mobile application showing (a) sign-in/home screen, (b) disease detection result, and (c) horticulture-office locator

Fig. 8(a) shows the sign-in/home screen, where the farmer authenticates via mobile number and OTP (Firebase Authentication) before capturing or uploading a leaf image for diagnosis. Fig. 8(b) shows the disease detection result screen, displaying the captured leaf image alongside the predicted class label (Sigatoka, in the example shown) returned by the on-device AlexNet inference engine. Fig. 8(c) shows the horticulture locator screen, which uses Google Maps to display the nearest agricultural department offices so that farmers can seek follow-up expert consultation when the mobile diagnosis indicates a serious infection. Together, these three stages take a user from authentication, through diagnosis, to a concrete next action, closing the loop between detection and on-the-ground disease management. Overall, discussion of these results suggests that pairing a field-validated CNN classifier with an accessible mobile interface can meaningfully lower the barrier to early disease detection for smallholder banana growers, supporting more sustainable use of this natural food resource.

4. CONCLUSION

Sigatoka and Cordana diseases significantly reduce banana yield and are difficult for smallholder farmers to diagnose visually, yet most existing CNN-based detection studies rely on single-condition, laboratory-collected datasets and stop short of field-ready deployment. To address this gap, a custom field-collected dataset of 5,163 banana leaf images (Healthy, Sigatoka, Cordana) was used to train and compare two CNN architectures, AlexNet and DenseNet-121, via transfer learning. AlexNet achieved 94.9% test accuracy (94.9% precision, 94.9% recall) and DenseNet-121 achieved 90.8% accuracy (90.8% precision, 90.8% recall), competitive with prior banana-disease classifiers [7, 12-13] despite being trained on field- rather than laboratory-collected images. The uniqueness of this work lies in its direct comparison of the two architectures on the same field dataset, the availability of that dataset for future benchmarking, and its integration into LeafCheck, a working Android application that carries the better-performing AlexNet model through to real-time, real-field diagnosis with disease-specific guidance. Together, these contributions offer a practical, cost-effective, and scalable path toward earlier disease management for a globally important natural food resource. A limitation of the present evaluation is that performance is reported from a single stratified train/validation/test split on test sets of 1,320 images (AlexNet) and 1,300 images (DenseNet-121); future work will report cross-validated results with confidence intervals across multiple runs to more rigorously establish the stability of the accuracy gap between AlexNet and DenseNet. Future work will also extend the dataset to additional disease classes, explore attention-based CNN mechanisms for early-stage symptom sensitivity, and test generalizability on larger, geographically diverse datasets.

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AUTHOR CONTRIBUTIONS

Shilpa Karegoudra: Conceptualization, Methodology, Dataset Curation, Model Development, Writing – Original Draft.

Padma R: Supervision, Mobile Application Development, Validation, Writing – Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Not applicable. This study did not involve human participants, identifiable personal data, or animal subjects; only banana leaf image data were collected from agricultural fields.

DATA AVAILABILITY STATEMENT

The dataset generated and analysed during the current study does not contain personally identifiable information and is available from the corresponding author upon reasonable request.

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