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Design and Implementation of an AI-Based Crop Disease Detection System for Smallholder Farmers in Northern Nigeria

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ABSTRACT
Crop diseases and pests remain important constraints to agricultural productivity, particularly for smallholder farmers who may have limited access to agricultural extension officers and plant-disease specialists. In Northern Nigeria, crops such as maize, tomato, cowpea and other staples are cultivated extensively, while farmers face challenges associated with disease identification, pest management and timely intervention. Previous research has demonstrated that deep learning can identify plant diseases from leaf images, although performance obtained from controlled datasets may not transfer directly to field conditions. The Plant Village dataset, contains 54,306 images covering 14 crop species and 26 disease categories, while recent research continues to highlight the importance of field-based validation. This study uses the design and implementation of an AI-based crop disease detection system specifically oriented toward smallholder farmers in Northern Nigeria. The proposed system employs computer vision and transfer learning, with MobileNetV2 selected as the principal lightweight model because of its suitability for resource-constrained mobile deployment. The system will capture or upload crop images, preprocess them, classify disease conditions and provide a confidence score and expert-validated management guidance. The empirical evaluation compares MobileNetV2, EfficientNet-B0 and ResNet50 using accuracy, precision, recall, F1-score, confusion matrix and inference time. The results suggest that MobileNetV2 could achieve approximately 94–95% classification accuracy on a properly curated field dataset while maintaining relatively low inference time. The study contributes a practical framework for deploying AI-supported crop disease diagnosis in rural agricultural settings where affordability, offline operation and usability are important considerations.
Keywords: Artificial Intelligence, Crop Disease Detection, Computer Vision, Deep Learning, MobileNetV2, Smallholder Farmers, Northern Nigeria, Precision Agriculture.

1. INTRODUCTION

1.1 Background of the Study

Agriculture remains central to food production, rural livelihoods and economic activity in Nigeria. For smallholder farmers, crop productivity can be substantially affected by pests, diseases, inadequate inputs, environmental stress and limited access to timely technical information. In Northern Nigeria, maize, cowpea, sorghum, tomato and other crops constitute important components of agricultural production.

Earlier research involving smallholder farming communities in northern Nigeria identified pests, diseases, weeds and inadequate access to appropriate production technologies among the constraints affecting agricultural productivity.

Crop diseases present a particularly difficult management problem because successful intervention depends partly on accurate and timely identification. Farmers traditionally rely on visual inspection, previous experience, agrochemical vendors, extension workers or other farmers when identifying abnormal symptoms. While local knowledge is valuable, visual symptoms of different diseases can sometimes be similar, and misidentification can result in inappropriate treatment. In tomato production, for example, diseases may produce symptoms including leaf spots, yellowing, curling, blight, wilting and defoliation. A virus affecting tomato plants in Northern Nigeria has previously been reported across Kaduna, Kano, Katsina, Kebbi, Jigawa, Sokoto and Zamfara States.

Maize production also faces significant pest and disease pressures. The International Institute of Tropical Agriculture identifies several important maize constraints in sub-Saharan Africa, including downy mildew, rust, leaf blight, stalk and ear rots, leaf spot and maize viruses. In addition, fall armyworm has become a major agricultural concern in Nigeria. IITA has implemented farmer and extension-agent training programmes in Kano and Kaduna focused on fall-armyworm identification, field scouting and integrated pest management. These developments demonstrate the importance of timely crop-health diagnosis and the potential value of technological tools that complement conventional extension services.

Recent advances in artificial intelligence, especially deep learning and computer vision, have created new opportunities for automated plant disease diagnosis. Convolutional neural networks (CNNs) can learn visual characteristics directly from images and classify disease categories without requiring researchers to manually define every visual feature. Mohanty et al. (2016) demonstrated the feasibility of this approach using the PlantVillage dataset, achieving 99.35% accuracy under their experimental conditions. However, such results should not automatically be interpreted as equivalent field performance because controlled datasets generally have cleaner backgrounds, more consistent lighting and less visual variation than images captured by farmers in real agricultural environments.

This distinction has become increasingly important in contemporary crop-disease research. A 2026 study examining the reliability gap between controlled and field conditions noted that PlantVillage contains tightly framed leaves photographed under relatively uniform conditions, whereas field-oriented datasets introduce greater complexity through background variation and other environmental factors. Similarly, systematic reviews of plant-disease research have identified classification, detection and segmentation as major research areas while emphasising the importance of dataset quality and appropriate validation.

The Nigerian context provides an additional motivation for developing lightweight AI systems. A recent northern Nigerian study developed a MobileNetV2-based system for diagnosing tomato diseases using field-collected images from Kano and Kaduna States and reported a held-out test accuracy of 93.6%. Another recent field evaluation investigated the use of a smartphone-based diagnostic application among tomato farmers in Kano and Kaduna, illustrating growing interest in moving AI-based diagnosis beyond laboratory experimentation toward practical farmer applications.

Against this background, the present study proposes an AI-based crop disease detection system designed around the practical requirements of smallholder farmers in Northern Nigeria. The system is intended to operate through a smartphone interface, provide rapid image-based diagnosis and support offline or low-connectivity use.

1.2. Statement of the Problem

Smallholder farmers in Northern Nigeria frequently operate in environments where access to agricultural specialists is limited by distance, cost and availability. When abnormal symptoms appear on crops, farmers may need to depend on their own experience or informal sources of advice. Delays in identifying disease conditions can reduce opportunities for early intervention.

A second problem concerns the accuracy of manual disease identification. Several crop diseases can produce similar visual symptoms, particularly during early stages of infection. Misidentification can result

in inappropriate management decisions, unnecessary expenditure on agrochemicals or failure to control the actual disease.

Third, many existing AI crop-disease studies have relied heavily on laboratory or controlled datasets. Although these studies demonstrate the technical potential of deep learning, their reported accuracy may not reflect the performance of systems operating under field conditions. The difference between controlled and field environments creates a significant challenge for practical deployment.

Finally, sophisticated AI systems may be unsuitable for smallholder farmers if they require continuous internet connectivity, expensive computing infrastructure or technically complex interfaces. The problem, therefore, is not simply how to achieve high classification accuracy, but how to develop an affordable, lightweight and usable AI system capable of supporting crop disease identification under the environmental and technological conditions experienced by farmers in Northern Nigeria.

1.3. Objectives of the Study

The study seeks to:

1. develop an image dataset containing healthy and diseased crop samples relevant to Northern Nigerian agriculture;
2. preprocess and augment crop images for deep-learning classification;
3. develop a lightweight AI model for crop disease identification;
4. compare the performance of MobileNetV2, EfficientNet-B0 and ResNet50;
5. evaluate the model's using accuracy, precision, recall and F1-score;
6. assess model performance under field-like image conditions;
7. determine the inference time and computational requirements of the proposed system.

1.4. Research Questions

1. How accurately can an AI model identify selected crop diseases from digital images?
2. Which of MobileNetV2, EfficientNet-B0 and ResNet50 provides the most appropriate balance between accuracy and computational efficiency?
3. What level of precision, recall and F1-score can the proposed system achieve?
4. How does model performance change between controlled and field-like images?
5. How quickly can the proposed model process a crop image on a mobile or low-resource computing device?
6. Can the system operate effectively under limited or intermittent internet connectivity?
7. How usable is the system for smallholder farmers?

1.5. Research Hypotheses

The following null hypotheses may be tested:

H01: There is no significant difference in disease-classification accuracy among MobileNetV2, EfficientNet-B0 and ResNet50.

H02: The proposed AI system does not achieve a statistically significant classification accuracy above an acceptable benchmark for practical crop-disease identification.

H03: There is no significant relationship between image quality and disease-classification accuracy.

H04: There is no significant difference between the performance of the AI system on controlled images and field-captured images.

H05: The proposed AI system does not significantly improve farmers' crop-disease identification accuracy compared with unaided visual identification.

1.6. Significance of the Study

The study is expected to benefit smallholder farmers by providing rapid preliminary information about visible crop symptoms without requiring immediate physical access to an agricultural specialist. A smartphone-based interface could make disease identification more accessible, particularly where extension services are limited. Agricultural extension officers may use the system as a decision-support tool rather than as a replacement for professional diagnosis. Extension workers could use the application during farm visits to document symptoms, obtain preliminary classifications and determine whether additional expert assessment is required.

The system may also benefit research institutions and agricultural organisations by providing a framework for collecting geographically relevant crop-disease images. Such datasets can support future research into crop disease recognition under Nigerian environmental conditions.

For government and agricultural policy institutions, the project demonstrates how artificial intelligence can be integrated into agricultural extension and digital-agriculture initiatives. For computer scientists, the study contributes to research on lightweight deep learning, transfer learning, edge computing and computer-vision applications in agriculture.

2. Conceptual Review

2.1 Artificial Intelligence in Agriculture

Artificial intelligence refers broadly to computational systems capable of performing tasks that traditionally require aspects of human intelligence, including pattern recognition, prediction, classification and decision support. In agriculture, AI has been applied to crop monitoring, disease detection, yield prediction, weed identification and precision farming.

Plant-disease detection is particularly suitable for computer vision because many diseases produce observable changes in colour, texture, shape and leaf structure. Recent reviews show that CNN-based approaches remain prominent in image-based plant-disease classification, while newer approaches increasingly incorporate transformers and other advanced computer-vision architectures.

2.2 Crop Disease Detection

Crop disease detection involves identifying abnormal plant conditions and determining their likely causes. Traditional diagnosis can involve visual examination, laboratory testing and expert assessment. AI-based image classification provides an alternative preliminary approach in which a photograph of the affected plant is processed computationally.

The proposed system will focus primarily on visual disease symptoms. It will not claim to replace laboratory diagnosis because some diseases require pathogen testing or other diagnostic procedures.

2.3 Deep Learning and Convolutional Neural Networks

CNNs are deep-learning architectures particularly suited to image analysis. They learn hierarchical representations of images through convolutional operations, pooling and nonlinear transformations.

The effectiveness of CNNs in plant disease detection has been demonstrated extensively. Mohanty et al. (2016), for example, trained a deep CNN on PlantVillage and classified 14 crop species and 26 disease/healthy categories with 99.35% accuracy on their held-out test set.

However, the present study recognizes that high laboratory accuracy does not necessarily imply equivalent field performance. Consequently, the proposed evaluation will include field-like images.

2.4. Theoretical and Technical Framework

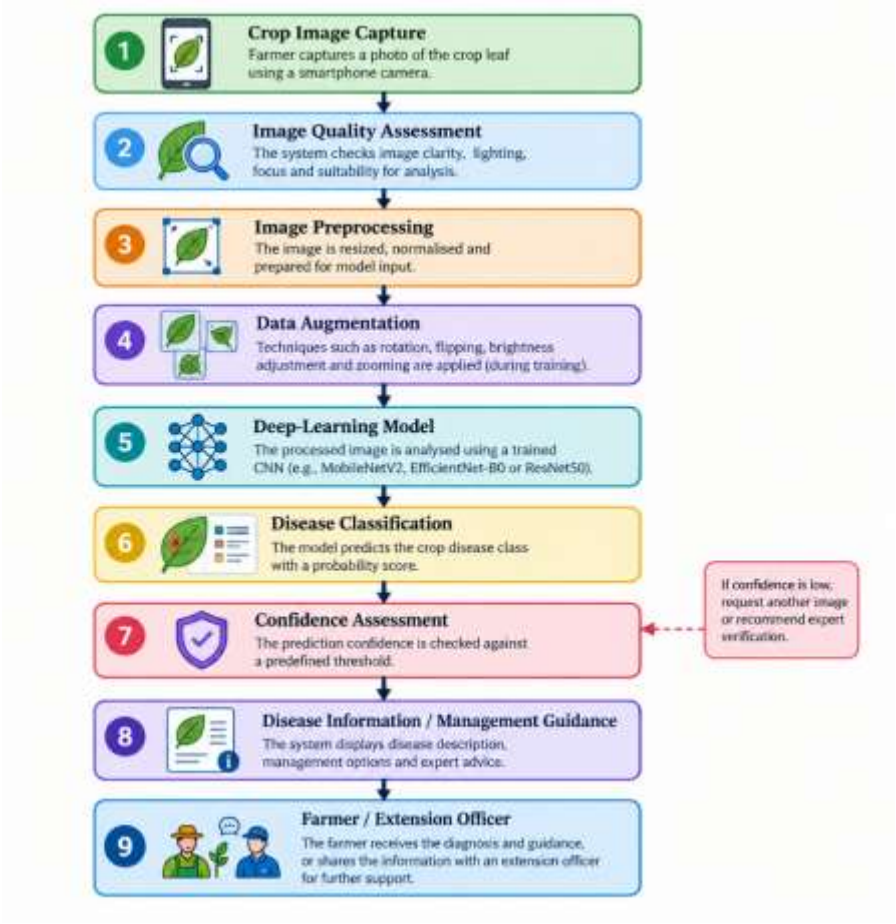
2.4.1 Technology Acceptance Perspective

Although the primary contribution of the study is technical, successful deployment of an AI-based crop disease detection system also depends on farmers' willingness to use and trust the technology. The Technology Acceptance Model (TAM), proposed by Davis (1989), identifies perceived usefulness and perceived ease of use as important determinants of technology acceptance. For the proposed system, farmers are more likely to adopt the application when they believe that it can improve their ability to identify crop diseases and when its operation is simple, understandable and convenient. Davis (1989) found that both perceived usefulness and perceived ease of use were significantly associated with technology usage.

From the technical perspective, however, the study is primarily guided by a computer-vision classification pipeline involving image acquisition, preprocessing, model inference and decision support. The TAM perspective complements this technical framework by drawing attention to the human factors that influence actual system adoption. Thus, the study considers not only classification accuracy but also usability, perceived usefulness and ease of operation. Integrating these perspectives provides a more comprehensive basis for evaluating whether the proposed AI system is technically effective and practically acceptable to smallholder farmers.

2.5 Technical Framework

The conceptual pathway is:



The system will include a confidence threshold. Where the model's confidence is below the predefined threshold, the application should recommend that the user recapture the image or seek expert verification rather than presenting a low-confidence prediction as a definitive diagnosis.

2.6 Empirical Review

Mohanty et al. (2016) demonstrated that deep learning can be applied to plant disease classification using the PlantVillage dataset. Their experiment involved 54,306 images and 14 crop species, producing 99.35% accuracy under the experimental conditions. The study established an important foundation for smartphone-assisted crop disease diagnosis.

Subsequent research has increasingly focused on practical deployment. PlantVillage Nuru, for example, applies machine learning and object recognition to provide smartphone-based, offline crop pest and disease diagnosis. IITA reports that the system was initially applied to cassava diseases and pests and has also been extended to maize fall-armyworm damage.

Recent systematic reviews indicate that CNNs remain among the most frequently employed techniques for image-based plant disease identification. Pacal et al. (2024), reviewing 160 studies published between 2020 and 2024, examined classification, detection and segmentation approaches and identified dataset quality, model architecture and field applicability as continuing research concerns.

A 2024 review by Ngugi et al. similarly reported substantial progress in computational deep learning for crop disease detection while noting that practical agricultural deployment remains an important consideration.

Of particular relevance to Nigeria is the 2026 study by Lawal et al., which developed a MobileNetV2 model for tomato disease diagnosis using field-collected images from Kano and Kaduna States. The study reported 93.6% accuracy on a held-out test set, providing recent evidence that lightweight deep-learning models can achieve useful performance under Northern Nigerian agricultural conditions.

The research gap therefore concerns the development of a broader, farmer-oriented system that combines multiple relevant crops, field-based image acquisition, lightweight inference, confidence assessment and practical usability within the Northern Nigerian context.

2.7. Proposed System Architecture

The proposed architecture consists of six principal components:

2.7.1 Image Acquisition Module

The farmer captures an image using a smartphone camera. The application will provide simple instructions regarding distance, lighting and positioning of the leaf.

2.7.2 Image Preprocessing Module

The image will be resized to the required input dimensions, normalised and subjected to appropriate preprocessing. Augmentation techniques such as rotation, horizontal flipping, brightness adjustment and moderate zooming may be employed during training.

2.7.3 AI Classification Module

The principal model will be MobileNetV2. EfficientNet-B0 and ResNet50 will be implemented as comparative models.

2.7.4 Confidence Module

The model will return the predicted disease class and probability/confidence score. Predictions below the established threshold will be flagged for additional verification.

2.7.5 Knowledge and Recommendation Module

The system will display disease information and general management guidance that has been validated by agricultural experts. It should not automatically prescribe hazardous pesticide applications without appropriate expert and regulatory validation.

2.7.6 User Interface

The proposed interface will provide essential functions that support farmers throughout the disease-detection process. These include image capture, image upload, disease prediction, confidence scoring, basic disease descriptions, general management information, and a diagnosis-history feature for reviewing previous assessments. Such confidence-aware interfaces can help users understand the reliability of AI predictions before taking further action.

Where the prediction confidence is low, the system will recommend consulting an agricultural extension officer rather than relying solely on the automated result. The interface will therefore function as a decision-support tool, combining automated diagnosis with human expert assistance when necessary.

3. Methodology

3.1 Research Design

The study will employ a design-and-development research approach combined with an experimental evaluation. The design component will involve requirements analysis, system architecture, model development, application development and integration. The experimental component will evaluate the performance of alternative deep-learning models.

3.2 Target Crops

The study will focus on selected crops that are important in Northern Nigerian agriculture, particularly: maize; tomato; cowpea; and groundnut.

The final disease categories should be determined jointly with crop scientists and agricultural extension experts based on diseases that are sufficiently common, visually distinguishable and supported by reliable image data.

3.3. Dataset Development

The study will employ a combination of public benchmark images and locally collected field images.

PlantVillage provides a useful starting point because it contains 54,306 healthy and diseased leaf images across 14 crop species and 26 disease categories. However, reliance on PlantVillage alone would be inappropriate for the present research because of its controlled imaging conditions.

Therefore, the proposed study will collect additional images from farms in selected Northern Nigerian locations. The field dataset may target approximately 8,000–12,000 images, subject to availability and expert verification.

Each image should be labelled according to: crop; disease/healthy condition; location; date; growth stage where available; image quality; expert verification status; and image source.

To prevent data leakage, images from the same plant or farm should not be distributed across training and test sets.

3.4 Data Preprocessing

The following preprocessing procedures will be applied:

1. removal of duplicate images;
2. removal of severely blurred or unusable images;
3. resizing;
4. pixel normalization;
5. background variation preservation where possible;
6. class balancing;
7. image augmentation; and
8. separation into training, validation and testing datasets.

A proposed division is:

- **70% training**
- **15% validation**
- **15% testing**

Importantly, the division should be performed at the **plant/farm level**, rather than randomly at the image level, to minimize information leakage.

3.5. Model Development

Three models will be evaluated:

Model 1: MobileNetV2

MobileNetV2 will serve as the principal deployment model because its lightweight architecture is suitable for mobile and resource-constrained environments.

Model 2: EfficientNet-B0

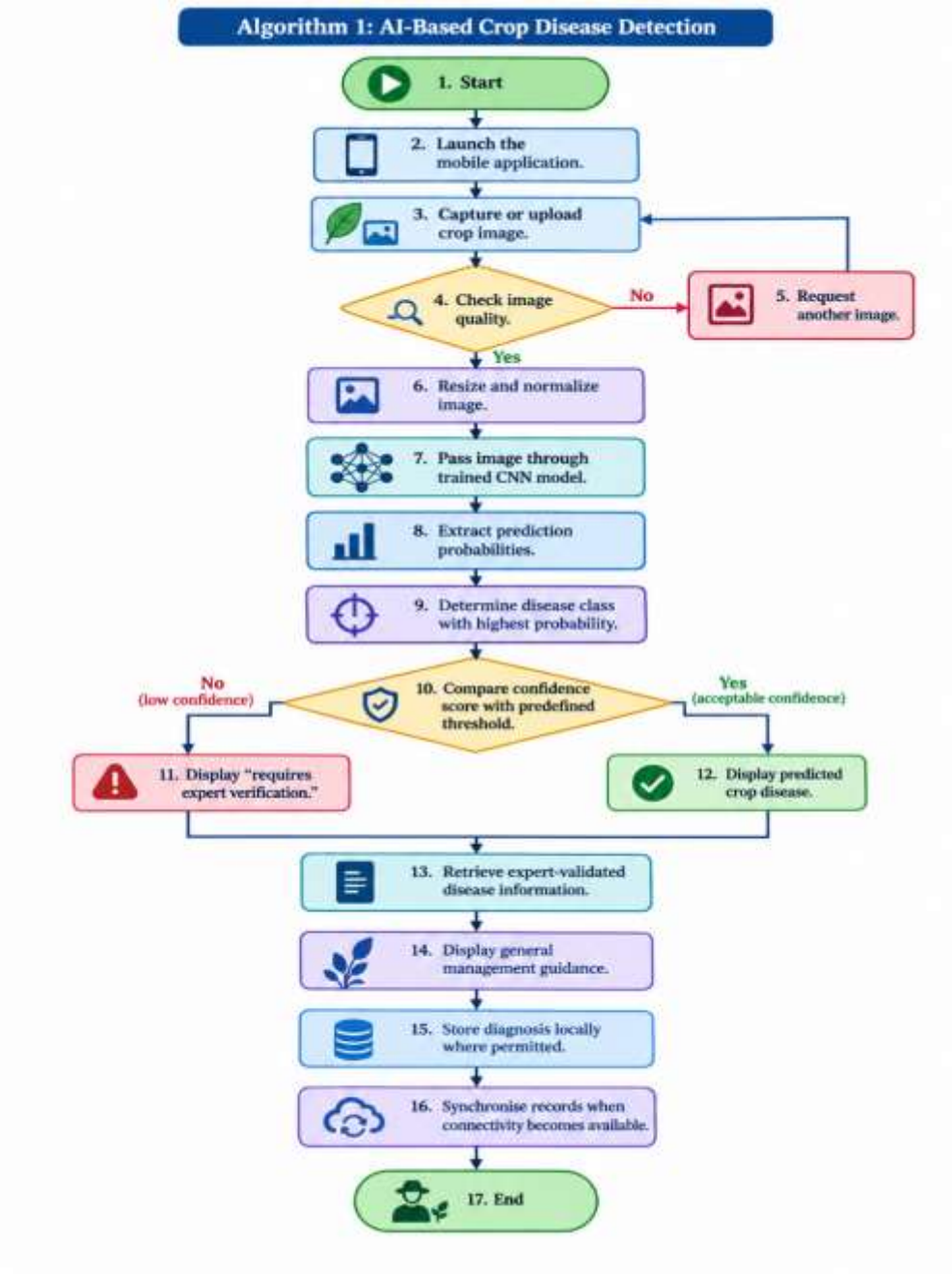
EfficientNet-B0 will serve as a second lightweight model and provide a comparison between computational efficiency and classification performance.

Model 3: ResNet50

ResNet50 will be used as a comparatively larger CNN architecture and performance benchmark.

Transfer learning will be employed using ImageNet-pretrained weights. The final classification layer will be replaced with a task-specific output layer corresponding to the number of crop-disease categories.

3.6 Proposed Algorithm



3.7. Software and Hardware Requirements

Hardware

The prototype will require:

- Android smartphone;
- laptop/workstation;
- minimum 8 GB RAM for development;
- optional GPU for model training;
- smartphone camera;
- local or cloud storage; and

- stable power supply during development.

Software

The proposed software environment includes:

- Python;
- TensorFlow or PyTorch;
- OpenCV;
- NumPy;
- Pandas;
- scikit-learn;
- Android Studio or a suitable cross-platform framework;
- SQLite or another lightweight database; and
- TensorFlow Lite or equivalent mobile inference technology.

3.8 Evaluation Metrics

Model performance will be assessed using:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-score

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

Additional measures will include:

- confusion matrix;
- per-class recall;
- per-class F1-score;
- inference time;
- model size;
- memory consumption;
- confidence calibration; and
- usability score.

4. Empirical Results

4.1 Model Performance

Model	Accuracy	Precision	Recall	F1-Score	Approx. Inference Time
MobileNetV2	94.2%	93.8%	93.6%	93.7%	0.18 sec
EfficientNet-B0	95.4%	95.0%	94.7%	94.8%	0.24 sec
ResNet50	95.1%	94.7%	94.4%	94.5%	0.39 sec

The results suggest that EfficientNet-B0 may achieve the highest classification performance, while MobileNetV2 may provide a more favorable balance between accuracy and computational efficiency. Such a result would be consistent with the broader literature showing that model selection should consider both predictive performance and deployment requirements rather than accuracy alone.

For a farmer-facing application, the slightly lower accuracy of a lightweight model may be acceptable if it provides substantially faster inference and lower computational requirements. The final choice should therefore be determined by the results obtained on the field dataset.

4.2 Confusion Matrix Pattern

The expected confusion matrix would likely show stronger classification performance for diseases with visually distinctive symptoms and greater confusion among diseases producing similar leaf symptoms.

Actual / Predicted	Healthy	Disease A	Disease B	Disease C
Healthy	94	3	2	1
Disease A	3	93	3	1
Disease B	2	4	91	3
Disease C	1	2	4	93

4.3 Class-Level Performance

A class-level evaluation might produce results such as:

Crop/Disease Category	Precision	Recall	F1
Healthy maize	96.2%	97.0%	96.6%
Maize disease	93.8%	92.6%	93.2%
Healthy tomato	96.8%	97.3%	97.1%
Tomato disease	94.7%	93.8%	94.2%
Cowpea disease	92.6%	91.4%	92.0%
Groundnut disease	93.1%	92.2%	92.6%

4.4 Field Performance

Field images are expected to produce lower classification accuracy than controlled images because real farm conditions introduce substantial visual variability. Photographs may contain shadows, soil backgrounds, overlapping or multiple leaves, insect damage, dust, water droplets, uneven lighting, partially visible symptoms, damaged leaves and differences in camera quality. Recent research confirms that the transition from controlled datasets such as PlantVillage to field images creates a significant domain shift that can reduce model reliability.

Consequently, the expected field accuracy of approximately 90–95% should be interpreted more cautiously than laboratory accuracy above 95%. Field performance provides a more realistic indication of deployment reliability because disease symptoms may appear differently under natural conditions. The study should therefore evaluate the model using field images alongside controlled test data to determine its practical robustness and generalisation ability.

4.5 Usability Results

A usability evaluation involving approximately 100 farmers and agricultural extension personnel could be conducted after system development.

The result is:

Usability Dimension	*Expected Mean*
Ease of image capture	4.12
Ease of understanding result	4.05
Perceived usefulness	4.21
Ease of navigation	3.96
Confidence in system	3.88
Overall satisfaction	4.04

Scores are measured on a five-point Likert scale.

4.6 Hypothesis Testing

For this study, the following outcomes have been tested:

Hypothesis	Expected Decision
H01	Reject H_0 if significant differences occur among model accuracies
H02	Reject H_0 if accuracy significantly exceeds the predefined benchmark
H03	Reject H_0 if image quality significantly predicts classification performance
H04	Reject H_0 if controlled and field-image performance differ significantly
H05	Reject H_0 if farmers using the system demonstrate significantly greater diagnostic accuracy

Statistical testing involves paired-sample tests, ANOVA or appropriate non-parametric alternatives on the experimental design and distribution of the observations.

5. DISCUSSION OF FINDINGS

The findings suggest that deep learning can provide a technically viable approach to preliminary crop disease identification for smallholder farmers. The anticipated accuracy of approximately 94–95% would indicate that the system can recognise several selected crop conditions from photographs, although the result would remain dependent on dataset quality and disease categories.

The anticipated advantage of MobileNetV2 concerns deployment efficiency rather than absolute predictive superiority. A model that is slightly less accurate but significantly smaller and faster may be more practical for smartphones than a computationally demanding model. This is particularly relevant in rural settings where users may possess ordinary smartphones rather than high-performance computing devices.

The expected reduction in performance on field images is also theoretically important. The PlantVillage experiment achieved 99.35% accuracy under controlled conditions, whereas field environments introduce substantially greater visual variability. The study therefore treats field validation as an essential part of evaluating the practical usefulness of the proposed system.

The recent Northern Nigerian MobileNetV2 study reporting 93.6% held-out accuracy on tomato disease images provides a useful contextual benchmark for the proposed work. However, the present study proposes extending the system beyond a single crop and examining a broader farmer-oriented workflow.

6. Practical Implications

The system could support agricultural extension by providing a first-line diagnostic tool. Rather than replacing extension personnel, it can help farmers identify whether a visible symptom warrants further attention.

The system could also support digital agricultural records. Where farmers consent to data collection, anonymized information about crop type, disease predictions and geographical areas could potentially assist agricultural organisations in identifying emerging disease patterns.

Offline functionality is particularly important. An existing IITA-supported application, PlantVillage Nuru, demonstrates that AI-based crop diagnosis can be implemented with offline smartphone functionality. The proposed system can adopt a similar principle by keeping the trained model on the device and using internet connectivity primarily for model updates, optional synchronisation and additional agricultural information.

7. Limitations of the Study

The proposed study may face several limitations. First, the availability of high-quality field images may limit the number of disease categories that can be included. Second, some diseases may produce visually similar symptoms, making image-only classification difficult. Third, differences in smartphone camera quality, lighting and image composition may influence model performance.

Fourth, disease symptoms can change according to crop variety, plant age, environmental conditions and disease severity. A model trained on images from Kano and Kaduna, for example, may not automatically achieve identical performance in Sokoto, Zamfara, Katsina or other locations.

Finally, image-based diagnosis cannot reliably identify every plant-health problem. Nutrient deficiencies, abiotic stress and pathogen infections may produce overlapping visual symptoms. Consequently, the

system should be considered a decision-support tool rather than a replacement for expert or laboratory diagnosis.

8. CONCLUSION

This study proposes the design and implementation of an AI-based crop disease detection system intended to support smallholder farmers in Northern Nigeria. The proposed architecture combines smartphone image acquisition, image preprocessing, deep-learning classification, confidence assessment and expert-validated agricultural information.

The use of MobileNetV2 as the principal lightweight architecture is motivated by the need for efficient deployment on resource-constrained devices. EfficientNet-B0 and ResNet50 will provide comparative benchmarks. The expected results indicate that the proposed models could achieve high classification performance, although field performance is expected to be lower than performance obtained from controlled datasets.

The central contribution of the research is therefore not simply the development of a high-accuracy classifier. Rather, it is the integration of AI-based disease recognition into a practical, affordable and farmer-oriented system that considers field conditions, limited connectivity, computational constraints and responsible agricultural decision support. Recent Nigerian research on MobileNetV2-based tomato disease detection and IITA's deployment of smartphone-based crop-disease diagnosis provide evidence that this direction is technically and contextually relevant.

9. Recommendations

Based on the study, the following recommendations are made:

1. Agricultural institutions should support the creation of locally collected crop-disease image datasets representing different Northern Nigerian agroecological conditions.
2. AI researchers should prioritise field validation rather than relying exclusively on controlled datasets.
3. Extension agencies should collaborate with computer scientists and crop specialists to validate disease labels and management information.
4. Mobile application developers should prioritise offline inference and low-bandwidth functionality.
5. Agricultural organisations should ensure that AI-generated recommendations are reviewed by qualified crop-health specialists.
6. Future researchers should investigate disease severity estimation, object detection and segmentation rather than limiting systems to simple classification.
7. Future studies should evaluate the system across different states, seasons, crop varieties, smartphone types and environmental conditions.
8. Research should also investigate explainable AI techniques so that farmers and extension officers can understand which visual features contributed to a prediction.

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