



MOBILE-BASED PEST DETECTION AND ALERT SYSTEM FOR SESAME PLANTS USING DEEP LEARNING ALGORITHM, SPECIFICALLY A CONVOLUTIONAL NEURAL NETWORK (CNN)

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ABSTRACT :

Sesame (*Sesamum indicum* L.) is a major oilseed crop and a critical foreign exchange earner for Nigeria and West Africa. However, its production is severely threatened by foliar diseases particularly bacterial blight and phyllody capable of causing yield losses of 40–60% when not detected early. Existing disease management practices rely heavily on manual visual inspection, a method that is labor-intensive, subjective, and inadequate given the limited reach of agricultural extension services in rural farming communities. This study addresses the complete absence of any mobile or artificial intelligence-based diagnostic tool specifically designed for sesame diseases by designing, developing, and deploying Sesame Scan a mobile-based sesame plant pest detection and alert system powered by a custom Convolutional Neural Network (CNN). A dataset of 640 labeled sesame leaf images spanning three classes Bacterial Blight Infected, Healthy Leaf, and Phyllody Infected was curated from diverse field conditions. A custom CNN architecture comprising three progressive convolutional blocks was trained from scratch on this dataset using the Adam optimizer with categorical cross-entropy loss, and augmented with structured data preprocessing, on-the-fly augmentation, and training callbacks including Early Stopping, Model Checkpoint, and Reduce LR On Plateau. The trained model achieved an overall classification accuracy of 97.9%, with macro-average precision, recall, and F1-score of 97.7% across all three disease classes. The model was exported to TensorFlow Lite format (63 MB) and integrated into a cross-platform mobile application built with React Native and Expo Go, enabling fully offline on-device inference on both iOS and Android smartphones without internet connectivity. The Sesame Scan application comprises three functional modules: a Scan Module for real-time disease diagnosis, an Analytics Dashboard for longitudinal disease prevalence monitoring, and an Explore Module for delivering disease management advisory content. The system demonstrates that a compact, custom-trained CNN, combined with a thoughtfully curated crop-specific dataset and a lightweight mobile deployment pipeline, can deliver precision agriculture capabilities directly to smallholder sesame farmers bridging a critical technological gap and contributing to improved food security and agricultural productivity in Nigeria and West Africa.

Keywords: Sesame disease detection; Convolutional Neural Network; Deep learning; Mobile application; Precision agriculture; TensorFlow Lite

1. Introduction

One such crop is Sesame (*Sesamum indicum* L.), one of the oldest and economically important oilseed crops grown in tropical and subtropical regions of Africa, Asia, and Latin America. In Nigeria, sesame contributes significantly to the agricultural economy, ranking among the country's major non-oil agricultural export products and supporting millions of smallholder farmers in the savannah and Guinea zones (Desoky *et al.*, 2023). Its importance is associated with its high oil content, nutritional value, and applications in the food, pharmaceutical, and cosmetic industries. However, sesame production is threatened by biotic constraints, particularly foliar diseases such as bacterial blight and phyllody, which can cause yield losses of 40–60% when not detected and managed promptly (Ibrahim *et al.*, 2023). Disease management has traditionally relied on visual inspection by farmers and agricultural extension officers, an approach that is labor-intensive, subjective, and susceptible to delayed detection, particularly during the early stages of disease development (Mohanty *et al.*, 2016). This challenge is further aggravated by limited agricultural extension services in rural Nigerian communities, resulting in delayed disease identification and increased crop damage. Advances in artificial intelligence, machine learning, and computer vision have created opportunities for automated and real-time plant disease detection using leaf images (Saleem *et al.*, 2019). In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in plant disease classification, with models such as MobileNet, EfficientNet, and ResNet achieving high classification accuracy and showing potential for deployment on mobile devices, including resource-constrained environments (Atila *et al.*, 2021; Asif *et al.*, 2025). The increasing availability of smartphones and mobile internet in Nigeria further creates

opportunities to extend such technologies to rural farming communities, while similar mobile disease-detection systems have already been developed for crops including cassava, maize, tomato, and rice (Jasrotia *et al.*, 2023; Lu *et al.*, 2024).

Despite these developments, a critical gap remains in the availability of a validated, mobile-based diagnostic tool specifically designed for sesame diseases. This gap is particularly important given the economic value of sesame and the potential impact of foliar diseases on crop productivity in Nigeria. Therefore, this study proposes the design, development, and evaluation of a mobile application for real-time sesame leaf disease detection using a trained CNN model. The developed system achieved a model accuracy of 97.9% and integrates a Scan module for on-demand disease diagnosis, an Analytics Dashboard for monitoring disease prevalence and scan trends, and an Explore module providing educational information on detected diseases. The study addresses the continued reliance on manual disease identification by combining image preprocessing, CNN-based classification, model performance evaluation, and mobile deployment. Specifically, the objectives were to train a CNN model using labelled sesame disease images, evaluate its performance using accuracy, precision, recall, and F1-score, and deploy the trained model on a smartphone to support accessible and timely disease diagnosis for sesame farmers.

2. Related Work

Deep learning, a subfield of machine learning characterized by the use of multi-layered artificial neural networks, has fundamentally transformed the field of automated image recognition over the past decade (LeCun *et al.*, 2015). The central architecture driving this transformation is the Convolutional Neural Network (CNN), a specialized network design that processes images through successive layers of learnable convolutional filters, progressively extracting increasingly abstract spatial features from raw pixel data. In contrast to traditional machine learning approaches that required hand-crafted feature engineering by domain experts, CNNs automatically learn the most discriminative visual representations directly from labelled training examples through a process of error-driven backpropagation and gradient descent optimization. This capability to learn features end-to-end from raw inputs has enabled CNNs to achieve human-level and super-human-level performance in numerous visual classification tasks.

(Mohanty *et al.*, 2016) demonstrated the effectiveness of convolutional neural networks (CNNs) for plant disease classification using leaf images. Using the Plant Village dataset comprising 87,848 images across 26 disease classes and 14 crop species, the study evaluated AlexNet and GoogLeNet and achieved a classification accuracy of 99.35%. The findings established the feasibility of automated plant disease recognition from leaf images and provided an important foundation for subsequent CNN-based agricultural diagnostic systems.

Ferentinos (2018) subsequently investigated the performance of different deep learning architectures for plant disease diagnosis using the Plant Village dataset. The study compared eight CNN configurations and reported that architectural characteristics, including network depth and residual connections, influenced classification performance. The best-performing architecture achieved 99.53% accuracy, while data augmentation was identified as an important strategy for improving model robustness where training data are limited.

Ramcharan *et al.*, (2019) extended CNN-based plant disease recognition to mobile agricultural applications by developing a transfer-learning system for cassava disease detection on Android smartphones. A Mobile Net model pretrained on ImageNet was fine-tuned using more than 2,700 field-collected cassava leaf images and achieved a weighted average F1-score of 0.93. Importantly, the system was evaluated under field conditions in Tanzania, demonstrating the potential of lightweight CNN models for practical agricultural disease diagnosis in sub-Saharan Africa.

Abade *et al.* (2021) reviewed 64 studies on CNN-based plant disease recognition and identified Mobile Net variants as particularly suitable for mobile deployment because of their balance between computational requirements and classification performance. The review also found transfer learning from ImageNet to be a dominant strategy in plant disease recognition. Of particular relevance to the present study, the authors reported that sesame remained largely absent from AI-based plant disease recognition research, thereby highlighting a research gap for disease-specific diagnostic systems targeting underserved crops.

Ransingh *et al.* (2021) provided a crop-specific perspective by investigating sesame phyllody disease across 120 farms in three states in southwestern Nigeria. The study reported phyllody incidence ranging from 12% to 58% and documented symptom progression and associated yield losses. The visual documentation and disease characteristics reported in the study provide useful reference information for the development and validation of image classes for sesame disease classification. The authors also identified the absence of digital diagnostic tools for sesame disease management as an important constraint.

Asif *et al.* (2025) developed and field-validated a MobileNetV2-based maize leaf disease classification application for smallholder farmers in Zambia. The model was trained using 11,000 leaf images representing four disease classes and was evaluated both under laboratory conditions and through field trials involving 150 farmers. Although the study focused on maize rather than sesame, its combination of lightweight CNN architecture, mobile deployment, and field-based usability assessment provides a useful methodological reference for developing agricultural disease-diagnosis applications intended for real-world users.

From a user-centered design perspective, mobile agricultural diagnostic systems must reconcile the complexity of AI model outputs with the information needs and technological literacy levels of smallholder farmer end-users. Theoretical frameworks from human-computer interaction and technology adoption research emphasize the importance of simplicity, visual communication, and local language support in achieving farmer acceptance and sustained use of mobile agricultural tools (Abade *et al.*, 2021; Rahman & Ravi, 2022). The SesameScan application is designed with these principles in mind, presenting diagnostic results through a clear interface that displays the disease classification, confidence score, and a brief description in plain language, without exposing the user to the underlying model architecture or probabilistic outputs.

Collectively, these studies demonstrate the increasing application of CNNs, transfer learning, and lightweight architectures to plant disease recognition and mobile agricultural diagnostics. However, the literature also indicates a specific gap in sesame-focused disease diagnosis, particularly in the Nigerian context. While existing studies provide strong evidence for CNN-based disease classification and mobile deployment, limited attention has been given to developing a dedicated mobile diagnostic system for sesame diseases using locally relevant field images. This gap provides the basis for

the present study.

2.1 Research Gap

The literature reveals key gaps in sesame disease diagnosis, including the absence of a validated mobile AI diagnostic tool, limited labelled sesame disease datasets, and inadequate integration of locally relevant management advice. While deep learning systems exist for other crops, existing sesame studies have not produced deployable real-time solutions. This study addresses these gaps through a curated sesame disease dataset and the SesameScan system, which combines real-time disease detection with practical explore and advisory features.

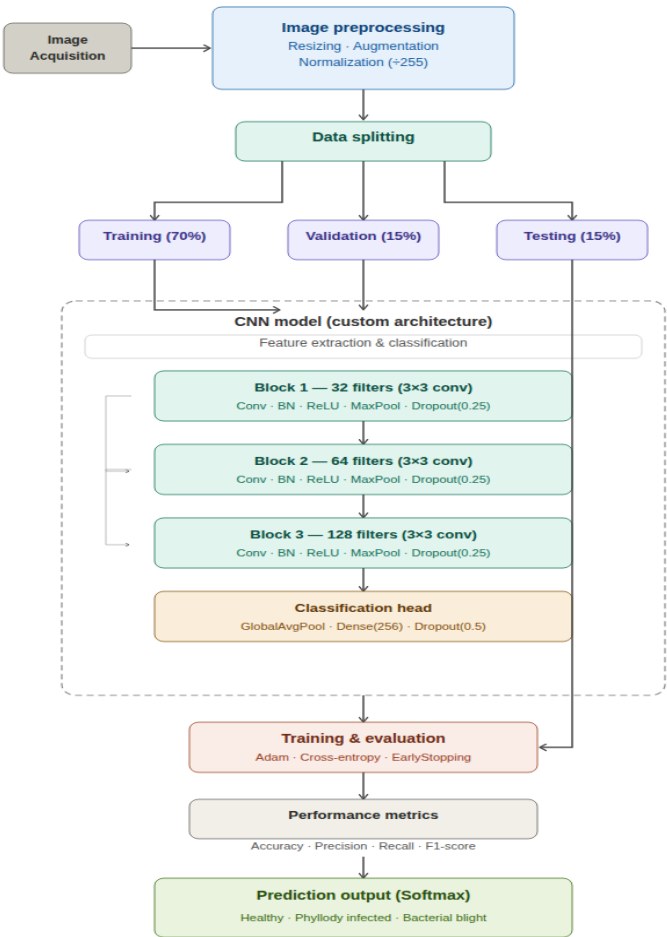
3. Materials and Methods

3.1 Research Design

This study adopts a quantitative research methodology and follows a system analysis and design approach to develop a mobile-based sesame plant pest detection and alert system using a custom-designed Convolutional Neural Network (CNN). The process begins with the acquisition of the sesame plant leaf image dataset, which contains 640 annotated leaf images spanning three classes: Bacterial Blight Infected, Healthy Leaf, and Phyllody Infected. Prior to model training, a structured series of data preprocessing steps are performed to ensure that the data is clean, consistent, and suitable for deep learning. These steps include image resizing, pixel normalization, data augmentation (such as rotation, flipping, zoom, and brightness adjustment), and data partitioning into training and validation sets. This ensures a well-balanced distribution of image classes across model evaluation phases. The prepared training data is fed into the custom CNN, which learns and extracts spatial and morphological features that are discriminative of sesame leaf disease conditions. The model is trained iteratively using backpropagation and categorical cross-entropy loss minimization to optimize classification performance across the three target classes. The validation set is used concurrently to monitor the model's generalization performance throughout training. Regularization strategies including Dropout and Batch Normalization, along with adaptive callbacks EarlyStopping, ModelCheckpoint, and ReduceLROnPlateau are applied to manage training convergence and prevent overfitting.

Upon completing the training and validation phases, the trained model is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. The finalized model is then exported to TensorFlow Lite (.tflite) format for mobile deployment. The mobile application is developed using React Native with Expo Go, a cross-platform framework that enables the application to run on both iOS and Android devices without requiring separate native codebases. The application integrates three functional modules: a Scan Module for real-time on-device leaf disease diagnosis, an Analytics Dashboard for monitoring scan history and disease prevalence trends, and an Explore Module for delivering disease management advisory content to farmers. The proposed methodology for this study is presented in Figure 3.1.

Figure 3.1: Proposed Research Methodology



3.2 Dataset Description

The dataset used in this study is a sesame plant leaf image dataset curated specifically for sesame disease classification. A total of 640 sesame leaf images were captured using smartphone cameras with a resolution of 96 dpi $\times$ 96 dpi. The dataset comprises three distinct classes as shown in Figure 3.1.

Figure 3.1: Show the class distribution

Images were collected from diverse sesame fields in Metema and Humera, Amhara region, Ethiopia to ensure data variability and representativeness (Belay et al., 2023). To capture the full spectrum of disease symptoms, images were acquired at different growth stages and under varying environmental conditions. Efforts were made to maintain consistent image quality throughout the collection process, with images captured under adequate lighting conditions to avoid shadows and overexposure, and the camera's focus adjusted to ensure clear and sharp image details.

The dataset is especially suitable for developing a CNN-based sesame disease detection system due to its:

Balanced class distribution across the three target categories, which reduces classifier bias during training.

3.3 Image Preprocessing and Data Partitioning

In preparation for model training and evaluation, the sesame leaf image dataset undergoes a structured preprocessing workflow to ensure that the data is clean, consistent, and suitable for deep learning. The preprocessing pipeline consists of the following stages:

Data Cleaning: Duplicate, corrupted, or mislabeled images are identified and removed. Given the diverse collection conditions combining field photographs from different farms, growth stages, and lighting environments inconsistencies in image quality and labeling may be present. Ensuring that each image is correctly categorized as Bacterial Blight Infected, Healthy Leaf, or Phyllody Infected is critical for maintaining label reliability and preventing training errors.

Image Resizing and Normalization: To maintain uniformity and ensure compatibility with the CNN input layer, each image is resized to 224 $\times$ 224 pixels. Pixel intensity values are then normalized to a range between 0 and 1 by dividing each pixel value by 255. This standardization improves training stability and accelerates gradient-based optimization convergence during model training.

Data Augmentation: Data augmentation is applied exclusively to the training set using the Keras ImageDataGenerator, generating augmented images on-the-fly during each training epoch. The following transformations are applied: rotation up to $\pm 30^\circ$, width and height shifts of $\pm 20\%$, shear transformation of $\pm 20\%$, zoom of $\pm 20\%$, horizontal and vertical flipping, and brightness adjustment within the range $[0.8\times, 1.2\times]$. These transformations introduce controlled variability that reduces overfitting and improves the model's ability to generalize to the range of real-world image conditions encountered when farmers capture sesame leaf photographs in the field.

Data Partitioning: The data set was divided into training data and validation data using a stratified split method, with a validation size of 15%, thus creating a set of 544 images for the training data set and another set of 96 images for the validation data set. Another data set was created for testing, with 15% of the data set, for which a separate testing script was created for inference testing after the training process. This is done by splitting the data set into three sets: 70% for training, 15% for validation, and another 15% for testing, thus ensuring that the data set is tested on unseen data.

3.4 CNN Architecture

The overall system architecture developed in this study is presented in Figure 1. The architecture shows the complete processing pipeline from image acquisition through preprocessing and CNN-based feature extraction to disease classification, mobile presentation, and alert/advisory support.

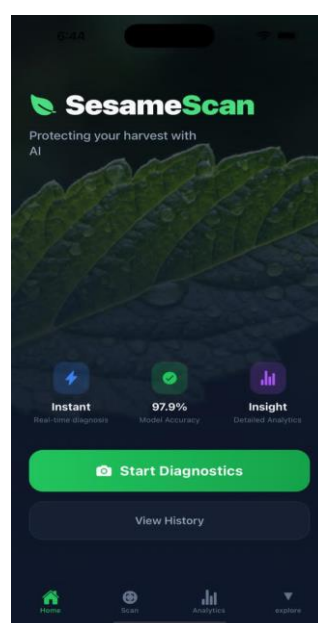


Figure 3.2: System architecture of the proposed SesameScan system.

The architecture of the proposed sesame disease detection system is built around a custom Convolutional Neural Network (CNN) designed and trained from scratch on the sesame leaf disease dataset. The CNN is responsible for both automated feature extraction from leaf images and final multi-class disease classification across the three target categories. CNNs are particularly effective for image analysis tasks because they learn spatial hierarchies of patterns capturing low-level edges and textures in early layers and progressively more abstract, disease-discriminative features in deeper layers that are directly relevant to identifying the visual characteristics of sesame bacterial blight and phyllody infections. This section describes the detailed structure of the CNN and the training configuration used to produce the final deployed model.

3.5.1 Convolutional Neural Network (CNN) Architecture

The custom CNN architecture is structured across three progressive convolutional blocks followed by a fully connected classification head, as described below:

Convolutional Block 1: Consists of a convolutional layer with 32 filters of size 3×3 and ReLU activation, followed by Batch Normalization, a second convolutional layer with 32 filters and ReLU activation, Batch Normalization, a 2×2 max-pooling layer to reduce spatial dimensions, and a Dropout layer (p=0.25) to reduce overfitting.

Convolutional Block 2: Repeats the structure of Block 1 with 64 convolutional filters, doubling the feature depth to capture more complex mid-level visual patterns such as lesion boundaries, discoloration gradients, and surface texture variations associated with bacterial blight.

Convolutional Block 3: Repeats the structure with 128 convolutional filters, enabling the extraction of high-level disease-discriminative features including lesion morphology, virescence patterns, and the leaf deformation and curling characteristics associated with phyllody infection.

Classification Head: Following the three convolutional blocks, a Global Average Pooling layer reduces the feature maps to a one-dimensional vector. A Dense layer with 256 units and ReLU activation further transforms the learned features, followed by Dropout (p=0.5) for regularization. The final softmax output layer with three units produces a probability distribution across the three disease classes: Bacterial Blight Infected, Healthy Leaf, and Phyllody Infected.

3.5.2 Training Configuration

The custom CNN is trained using the Adam optimizer with an initial learning rate of 0.001 and categorical cross-entropy as the loss function, which is appropriate for multi-class classification with three mutually exclusive output categories. A batch size of 16 is used throughout training, and a maximum of 50 epochs is configured. The training configuration parameters are summarized in Table 3.3.

Table 3.3: Training Configuration Parameters

3.5 Training Configuration

The model was trained with the Adam optimizer using an initial learning rate of 0.001 and categorical cross-entropy loss. A batch size of 16 and a maximum of 50 epochs were configured. Batch Normalization, Dropout, EarlyStopping, ModelCheckpoint, and ReduceLROnPlateau were used to support stable training, reduce overfitting, and preserve the best-performing model.

3.6 Performance Evaluation Metrics

The developed classifier was evaluated using accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified images. Precision measures the proportion of predicted positive classifications that are correct. Recall measures the proportion of actual positive instances correctly identified, while the F1-score provides the harmonic mean of precision and recall.

Accuracy = $(TP + TN) / (TP + TN + FP + FN)$

Precision = $TP / (TP + FP)$

Recall = $TP / (TP + FN)$

F1-score = $2 \times (Precision \times Recall) / (Precision + Recall)$

3.7 Mobile Application Deployment

Scikit-learn: The Scikit-learn library was used for computing classification performance metrics including accuracy score, precision, recall, F1-score, and the confusion matrix. The `classification_report` function provided a structured summary of per-class and macro-averaged performance metrics for the trained model.

Matplotlib and Seaborn: These visualization libraries were employed for generating training history plots (accuracy and loss curves), confusion matrices, class distribution charts, and image property histograms throughout the exploratory data analysis and model evaluation phases.

React Native and Expo Go: The SesameScan mobile application was developed using React Native, a cross-platform JavaScript framework that enables the development of a single codebase deployable on both iOS and Android devices. Expo Go served as the development and testing runtime environment, providing a managed workflow for building, previewing, and testing the application across devices without requiring separate native build configurations.

These tools collectively support efficient model implementation, training, evaluation, and mobile deployment necessary for developing an accurate and user-friendly sesame disease diagnostic application.

After training, the selected model was exported to TensorFlow Lite format for lightweight mobile deployment. The mobile application was developed using React Native with Expo Go and organized around the Scan Module, Analytics Dashboard, and Explore Module. The design supports offline on-device inference without requiring cloud connectivity.

4. Results and Discussion

4.1 Experimental Setup and Dataset Processing

The dataset class distribution used in the study is illustrated in Figure 2. The three target classes were Bacteria Blight Infected, Healthy Leaf, and Phyllody Infected.

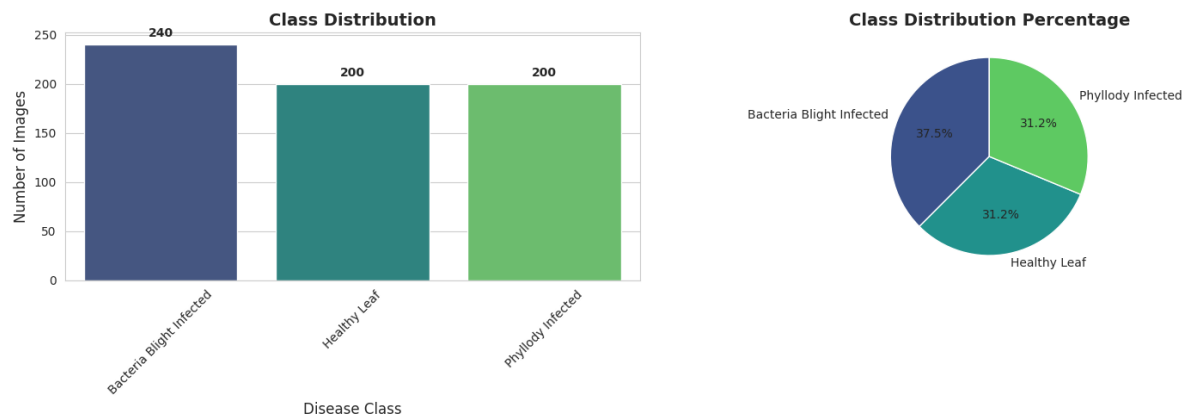


Figure 3.3: Dataset class distribution for the sesame leaf images.

The experimental workflow followed the dataset preparation, preprocessing, CNN training, validation, testing, and deployment stages described in the project. The dataset contained 640 labelled images distributed across three classes: Bacterial Blight Infected, Healthy Leaf, and Phyllody Infected. Images were standardized to 224×224 pixels and normalized before training. Augmentation was applied to the training data to introduce controlled variability in orientation, position, zoom, and brightness.

4.2 Classification Performance

The actual classification results reported in the source project are presented in Table 1. The model achieved high performance across all three classes, with an overall accuracy of 0.979.

Class	Precision	Recall	F1-Score	Support
Bacteria Blight Infected	0.98	0.99	0.98	240
Healthy Leaf	0.98	0.97	0.97	200
Phyllody Infected	0.97	0.97	0.97	200
Accuracy			0.979	640
Macro Average	0.977	0.977	0.977	640
Weighted Average	0.979	0.979	0.979	640

Table 1. Evaluation metrics result for the custom CNN model.

The source project further presents the training and validation accuracy and loss curves in Figure 3. The curves show the learning progression of the custom CNN during model training.

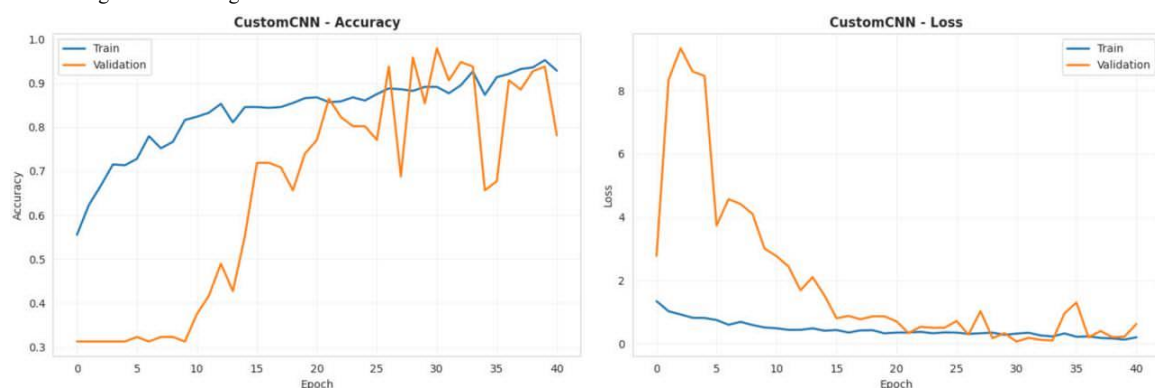


Figure 3. Custom CNN training accuracy and loss curves.

The custom CNN achieved an overall classification accuracy of 97.9%. The reported macro-average precision, recall, and F1-score were each approximately 97.7%, indicating strong and balanced classification performance across the three target classes.

The high and closely aligned values of precision, recall, and F1-score suggest that the model was not only accurate overall but also maintained a

balanced ability to identify the target conditions. This is important for a mobile agricultural application because false alarms and missed disease cases can both reduce the practical usefulness of a diagnostic tool.

4.3 Mobile System Implementation

The implemented SesameScan mobile application is presented through the actual system screenshots extracted from the source project. These interfaces demonstrate the operational outcome of the deployed TensorFlow Lite model.

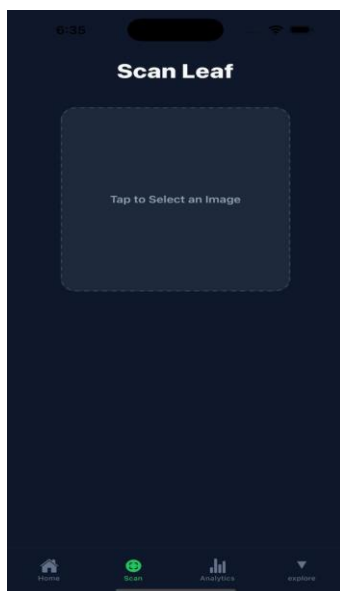


Figure 4. SesameScan Scan Module: image selection interface.



Figure 5. SesameScan diagnosis result interface showing disease classification.



Figure 5: SesameScan Analytics Dashboard showing scan monitoring and disease distribution.

The trained model was exported to TensorFlow Lite format, with the project reporting a model size of approximately 63 MB. The model was integrated into a cross-platform mobile application to enable on-device disease inference. The offline deployment approach is relevant to agricultural environments where internet access may be inconsistent.

The Scan Module enables a user to select a sesame leaf image and obtain a predicted condition. The Analytics Dashboard records scan history and

summarizes disease prevalence and scan-frequency trends. The Explore Module provides disease-related advisory information intended to help users interpret the detected condition.

4. Discussion

The reported performance demonstrates that the custom CNN was effective for the defined three-class classification task. The preprocessing workflow, augmentation strategy, regularization mechanisms, and training callbacks collectively supported model learning and generalization. The results also demonstrate the feasibility of integrating a trained agricultural image classifier into a mobile application rather than limiting the contribution to an offline experimental model. A major contribution of the study is the combination of a sesame-specific image dataset, CNN-based classification, and mobile deployment. The project positions this combination as a response to the limited availability of crop-specific digital diagnostic tools for sesame. The use of on-device inference further supports practical use in environments where continuous internet connectivity cannot be assumed. However, the findings should be interpreted within the scope of the dataset and evaluation described in the project. The model addresses only Healthy Leaf, Bacterial Blight Infected, and Phyllody Infected conditions. Its performance may vary when images are captured under substantially different lighting conditions, camera characteristics, angles, disease stages, or overlapping symptoms. The project also notes that formal usability evaluation with end users was not included.

5. Conclusion

This study developed and evaluated a mobile-based sesame plant disease detection and alert system using a custom Convolutional Neural Network. A 640-image dataset containing Bacterial Blight Infected, Healthy Leaf, and Phyllody Infected classes was prepared through image preprocessing, normalization, augmentation, and data partitioning. The CNN achieved a reported overall accuracy of 97.9%, with macro-average precision, recall, and F1-score of approximately 97.7%.

The trained model was successfully converted to TensorFlow Lite and integrated into a mobile application featuring diagnostic, analytics, and advisory functions. The study therefore shows that a crop-specific CNN can be translated from an experimental machine-learning model into an accessible mobile precision-agriculture application. The system provides a foundation for future work involving larger and more diverse datasets, additional sesame diseases, field validation, and end-user usability assessment.

6. Recommendations and Future Work

The Sesame Scan study demonstrated that a custom CNN trained from scratch on a crop-specific dataset can effectively classify sesame diseases without transfer learning. The model achieved 97.9% accuracy and a macro-average F1-score of 97.7% across three disease classes, with a recall of 0.99 for bacterial blight. The study also developed a dataset of 640 sesame leaf images collected under varying environmental conditions. Integration of the model into a 63 MB React Native mobile application enabled offline, real-time disease classification on smartphones. However, the study recommended expanding the dataset, incorporating additional diseases and pests, conducting broader field validation, and evaluating usability and performance across different devices and image-capture conditions.

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