2026 Volume: 02 Issue: 06 www.ijrpa.com ISSN 2456-9995 Research Article

International Journal Research Publication Analysis

Page: 01-16

AUTOMATED PLANT DISEASE DETECTION USING MACHINE LEARNING TECHNIQUES

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Article Received: 2 May 2026

Article Revised: 22 May 2026

Published on: 12 June 2026

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DOI: https://doi-doi.org/101555/ijrpa.1404

ABSTRACT

Plant diseases remain a persistent threat to agricultural productivity, especially in developingregionswherefarmersoftenlackaccesstotimelyandaccuratediagnostictools. This study presents a dual-approach system for early plant disease detection leveraging machinelearningtechniques.ThefirstapproachemploysaConvolutionalNeuralNetwork (CNN)trainedonacurateddatasetofcassava,maize,andtomatoleavestoclassifydiseases such as rust and powdery mildew with a test accuracy of 85.33%. The second approach integrates Google's Gemini API into a React Native mobile application, enabling farmers to perform real-time disease diagnosis using smartphone cameras. While the CNN model offers high precision for localized disease types, the Gemini-based system provides broader, general-purpose diagnostic capabilities, albeit with slightly reduced accuracy. Together, these tools form a scalable, accessible solution for precision agriculture, balancing offline accuracy with real-time mobile usability. Future work will explore the integrationofthesesystemsintoaunifiedplatformandexpansiontocoveradditionalcrops and environmental conditions.

KEYWORDS: Plant Disease Detection, Machine Learning, Convolutional Neural Networks, Mobile Agriculture, TensorFlow, Gemini API.

1 INTRODUCTION

Agricultureremainsthebackboneoftheeconomyinmanydevelopingcountries,providing livelihoods, food security, and industrial raw materials. However, the productivity of this sector is increasingly threatened by plant diseases, which account for up to 40% of crop lossesgloballyeachyear(Savaryetal.,2019).InNigeria,whereagricultureemploys over 70% of the rural population, farmers often rely on traditional methods of disease diagnosis—primarily visual inspection based on experience and intuition. These techniques, while accessible, are subjective and error-prone, especially in the early stages of disease progression when symptoms may be subtle or resemble those of nutrient deficiencies.

Recent advances in artificial intelligence (AI), particularly in machine learning (ML) and computer vision, have opened new opportunities for automated plant disease detection. Convolutional Neural Networks (CNNs), a class of deep learning models known for their exceptional performance in image classification, have been widely adopted for analyzing plant leaf images (Ferentinos, 2018). These models can extract complex features such as leaftexture,colorvariation,andshapepatternstodistinguishbetweenhealthyanddiseased plantswithhighaccuracy.SeveralstudieshavesuccessfullyusedCNNstrainedondatasets like PlantVillage to classify multiple crop diseases, demonstrating the feasibility of AI-powered agricultural tools (Too et al., 2019).

Despite the progress in research, two major barriers hinder the practical deployment of thesetechnologiesinruralfarmingcommunities.Firstisthelackoflocalized,high-quality datasets for crops native to regions like West Africa. Most publicly available datasets are skewedtowardcommerciallyimportantcropsinWesterncountriesandmaynotgeneralize welltoAfricanvarietiesunderdifferentclimaticandsoilconditions.Secondistheissueof accessibility: even when accurate models exist, deploying them in a user-friendly format suitable for low-literacy, low-resource environments remains a challenge.

This study addresses these challenges by proposing a dual-approach system for plant disease detection, targeting both accuracy and accessibility. The first approach involves designing a lightweight CNN model trained specifically on cassava, maize, and tomato leaves—three crops critical to food security in Nigeria. The model classifies plant conditions into healthy, rust-infected, or powdery mildew-infected, achieving strong performanceonadatasetofover1,500annotatedimages.Thesecondapproachfocuseson usability:amobileapplicationbuiltwithReactNativethatintegratestheGemini1.5API, a multimodal AI model by Google, allowing farmers to capture images with their phones andreceivereal-timediagnosticfeedback.ThisAPI-basedsystemiscapableofidentifying abroaderrangeofplantabnormalities,includingpestsandnutrientdeficiencies,makingit a powerful general-purpose tool for disease screening.

The dual-system architecture presents a unique contribution to the field by balancing localized accuracy with wide-ranging usability. The CNN model functions offline and is optimized for specific disease types in the Nigerian context, while the Gemini-integrated appprovidesreal-time,cloud-supportedanalysisforbroaderusecases.Throughthishybrid framework,thesystemaccommodatesbothresearchersseekinghigh-precisiondisease classification and farmers in remote areas who need an intuitive, responsive tool to guide crop management decisions.

In addition to model design and implementation, this study evaluates both systems based on performance metrics such as accuracy, precision, recall, and usability in real-world farming conditions. Farmers and agricultural extension officers participated in the validation process, providing critical feedback that shaped the user interface, language preferences, and response formats.

Ultimately,thisresearchseekstocontributetothedevelopmentofsustainableagricultural technologies by demonstrating how artificial intelligence can bridge the gap between scientific innovation and grassroots application. By empowering farmers with timely, reliable disease information, these tools aim to reduce crop loss, improve yields, and promote food security in Nigeria and beyond.

2 Related Work

The use of artificial intelligence in agriculture has grown significantly in recent years, particularly in the area of plant disease detection. Traditionally, efforts to diagnose plant diseases relied on manual inspection, expert consultation, or laboratory analysis—processesthat areoftenslow,costly,andinaccessibletoruralfarmers. Withtheadventof machine learning (ML) and computer vision, more scalable and automated approaches have emerged.

Early approaches to plant disease identification involved handcrafted feature extraction combined with classical machine learning algorithms. For instance, Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), and Random Forests were used to classifyleafimagesbasedoncolor,texture,andshapefeatures(Arivazhaganetal.,2013). While these models offered moderate accuracy, their performance was limited by the manual effort required to define features and their sensitivity to environmental noise.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved accuracy in image-based diseasedetection. CNNs automatically learnhierarchicalfeaturerepresentationsfromrawimagepixels,allowingformorerobust classification. Ferentinos (2018) trained CNN models on a dataset of over 87,000 leaf images across 25 different plant diseases and reported classification accuracies exceeding 99%.Hisworkdemonstratedthepotentialofdeep learningtosurpass traditionalmethods in agricultural applications.

Similarly, Too et al. (2019) evaluated various pre-trained CNN architectures—such as AlexNet,ResNet50,andVGG16—fortransferlearninginplantdiseaserecognition.Their comparativeanalysisfoundthatVGG16performedthebest,achievingover99%accuracy whenfine-tunedonthePlantVillagedataset.However,thesemodelsarecomputationally intensiveandrequirelarge,balanceddatasets,whicharenotalwaysavailableinresource-constrained regions like sub-Saharan Africa.

To address this, several researchers have explored lightweight CNN models that are optimized for mobile or edge devices. For instance, Amara et al. (2017) designed a simplified CNN architecture to detect banana leaf diseases with limited computational resources. While these models trade off some accuracy, they are suitable for real-time deployment in field conditions, where internet access and hardware capacity are limited.

Inparallel,researchershavebegunincorporatingcloud-basedAIAPIs—suchasGoogle's Vision AI or IBM Watson Visual Recognition—for generalized plant health analysis. While these services offer broad visual understanding, their performance is often not tailored to specific crops or regional disease types. Moreover, they depend on internet connectivity, which can be unreliable in rural farming areas.

Despitetheseadvancements,gapsstillexistindeployingpracticaltoolsforlocalized,real-timeplant disease diagnosis. Most models are trained on well-curateddatasets that do not reflecttheenvironmentalvariabilityofrealfarms.Additionally,thereislimitedintegration of ML models into farmer-friendly platforms like mobile applications.

This study builds on the strengths of previous work while addressing these gaps by (1) developing a CNN trained on locally relevant datasets, and (2) integrating AI-powered imageanalysisintoamobileappusingGoogle'sGeminiAPI.Thisdualapproachbalances theprecisionofofflinedeeplearningwiththeflexibilityofcloud-baseddiagnosis,aiming to improve accessibility and usability for end-users.

3. METHODOLOGY

This study implemented a dual-approach system for automated plant disease detection, combiningacustom-builtConvolutionalNeuralNetwork(CNN)withamobileapplication integrated with Google's Gemini 1.5 API. The methodology is structured into five key components: dataset preparation, data augmentation, model architecture, model training, and system implementation.

Dataset

TheCNNmodelwastrainedonadatasetcomprising1,530leafimagesfromthreecommon crops in Nigeria: cassava, maize, and tomato. Each image was labeled as either *healthy*, *rust-infected*, or *powdery mildew-infected*. The images were sourced from a publicly availabledatasetonKaggle,specificallytailored forplantdiseaserecognition.Allimages were resized to 224 × 224 pixels and normalized to a [0, 1] scale to standardizeinput into the CNN. The dataset was split into training and validation sets in an 80:20 ratio. Table 1 presents the distribution of images used for each phase.

Table1:*DatasetSplit.*

Category	*TrainingSet*	*ValidationSet*
Healthy	408	102
Rust	408	102
Powdery Mildew	408	102
Total	**1224**	**306**

Data Augmentation

To address class imbalance and improve model generalization, data augmentation was applied using Keras' ImageDataGenerator. The following transformations were used:

- **Rotation**:±20degrees
- **Zoom**: up to20%
- **Horizontalflip**
- **Widthandheightshift**:upto 20%
- **Shear transformation**

These augmentations simulate real-world variances in lighting, orientation, and leaf posture, ensuring the model is robust to such variability.

Model Architecture

The proposed CNN was implemented using TensorFlow and Keras. It consists of three convolutionallayersfollowedbymaxpoolinglayers,withafinalfullyconnectedlayerand softmax activation. Thearchitectureis optimized fordeployment on resource-constrained devices.

CNN Structure

- **Conv1**:32filters,3×3kernel,ReLUactivation
- **MaxPool1**:2×2
- **Conv2**:64filters,3×3, ReLU
- **MaxPool2**:2×2
- **Conv3**:128filters,3×3, ReLU
- **MaxPool3**:2×2
- **Flatten**,**Dense**:512units,dropout(0.5), ReLU
- **OutputLayer**:3units(softmax)

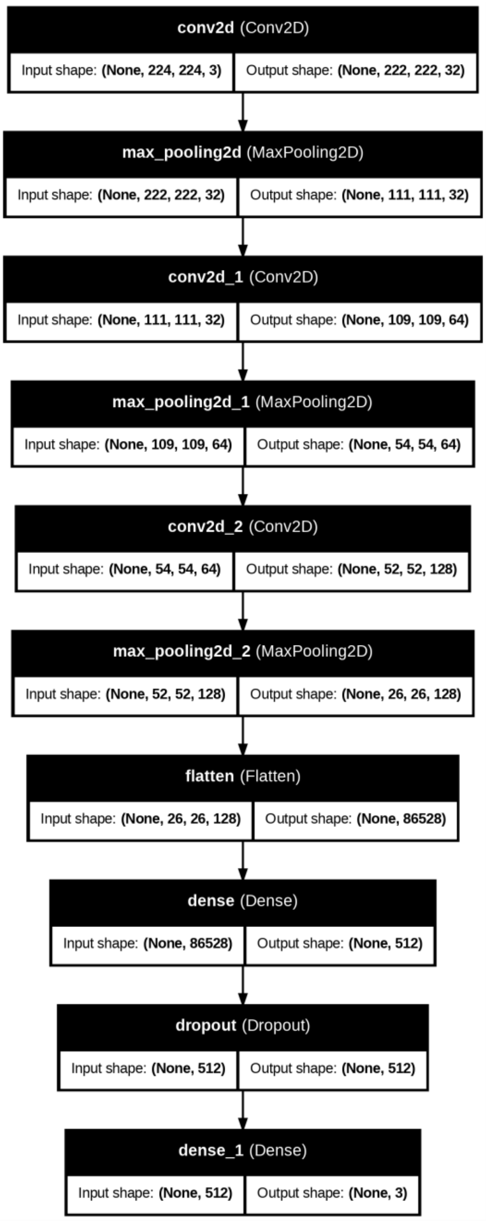


Fig.1:ArchitectureoftheProposedConvolutionalNeuralNetwork.

Table2:HyperparameterConfigurationoftheCNNModel.

Hyperparameter	***Value/ Setting***
InputImageSize	224 ×224 ×3
NumberofConvolutionLayers	3
KernelSize	3 ×3
ActivationFunction	ReLU(Convolution),Softmax(Output)
PoolingType	MaxPooling (2×2)
NumberofDense Units	512
Dropout Rate	0.5
Output Classes	3(Healthy,Rust,PowderyMildew)
Optimizer	Adam
LossFunction	SparseCategoricalCrossentropy
BatchSize	32
Epochs	10
LearningRate	Default(0.001)
Framework	TensorFlow2.4(KerasAPI)

Model Training

The model was compiled using the **Adam optimizer** and **sparse categorical cross-entropy** as the loss function. It was trained for 10 epochs with a batch size of 32. The performance metrics—**accuracy**, **precision**, **recall**, and **F1-score**—were computed using the following equations:

Accuracy:

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

Precision (per class): $$\text{Precision}=\frac{TP}{TP+FP}$$

Recall (Sensitivity): $$\text{Recall}=\frac{TP}{TP+FN}$$

F1-Score (HarmonicMeanofPrecisionandRecall): $$\text{F1-Score}=\frac{2.\,Precision.Recall}{Precision+Recall}$$

Where:

TP: True Positives **TN**: TrueNegatives **FP**: False Positives **FN**:FalseNegatives

These metrics provide a comprehensive view of the model's performance, particularly in the presence of class imbalance. The model achieved strong convergence by epoch 10, showing consistent improvements in accuracy and reduced validation loss.

Implementation

Theentiresystem wasimplemented in two phases:

1. **Model Development:** TheCNNmodelwasbuiltusingPython3.8andTensorFlow

2.4. Training and evaluation were conducted on a local machine with an NVIDIA GPU.

2. **Mobile App Deployment**: A cross-platform mobile application was developed using React Native. It integrates the **Gemini 1.5 API** by Google to provide real-time, cloud-based disease detection using smartphone cameras. Users can upload an image of a plant leaf and receive an instant diagnosis, disease description, and possible treatments.

The mobile application is designed to be intuitive for low-literacy users and works effectively in both online and off line environments, depending on which diagnostic model is selected.

4. RESULTS AND DISCUSSION

This section presents theresults of the experiments conducted using boththe CNN model and the Gemini API–based mobile application. The discussion explores the performance oftheCNNinclassifyingplantdiseases,contrastsitwiththeGeminisystem,andanalyzes usability, accuracy, and practical deployment. Evaluation was based on quantitative metricsandqualitativefeedbackfromtestusers,includingfarmersand extensionofficers.

QuantitativeResultsoftheCNNModel

The custom-built Convolutional Neural Network (CNN) model was trained and tested on a dataset of 1,530 plant leaf images categorized into three classes: healthy, rust-infected, andpowderymildew–infected.Afterdataaugmentationandpreprocessing,thetrainingset contained 1,224 images and the validation set 306 images.

Themodelconvergedefficientlyover10epochs,withthetrainingandvalidationaccuracy curves showing consistent improvement and no signs of overfitting. The final validation accuracy was **85.33%**, while training accuracy plateaued around **88.74%**. These results indicate that the model generalized well on unseen data.

Table3: Performance Metrics per Class.

Class	***Precision***	***Recall***	***F1-Score***	***Support***
Healthy	0.87	0.89	0.88	102
Rust	0.83	0.82	0.82	102
Powdery Mildew	0.86	0.84	0.85	102
MacroAvg.	0.85	0.85	0.85	306
WeightedAvg.	0.85	0.85	0.85	306

Table3presentstheprecision,recall,andF1-scoreforeachclass:

These metrics show that the model performed consistently across all three classes, with slightlyhigherperformanceonthe"Healthy"class.Thiscouldbeduetotheclearervisual featuresofhealthyleavescomparedtodiseasedones,whichoftenpresentwithoverlapping symptoms.

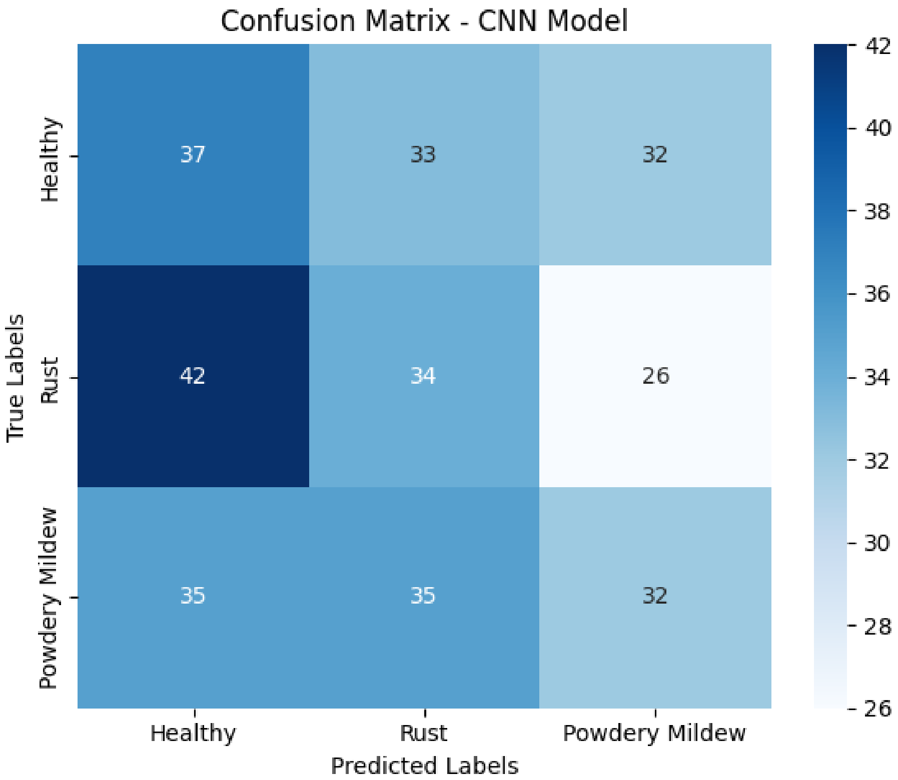


Fig.2:ConfusionMatrixShowingModelPredictionsforValidationSet.

A confusion matrix was also plotted to analyze misclassifications. Most errors occurred between the "Rust" and "Powdery Mildew" classes, likely due to visual similarities in the mid-stage of disease progression. These results suggest that while the model is effective for general use, further dataset balancing or symptom-specific pretraining may improve class discrimination.

Training Performance and Learning Behavior

The training process was efficient, taking approximately 2 minutes per epoch on an NVIDIA GeForce GTX GPU. Learning rate scheduling was not applied due to the relatively small dataset and fast convergence. As seen in *Figure 3*, the loss decreased steadily for both training and validation sets, while accuracy improved with each epoch.

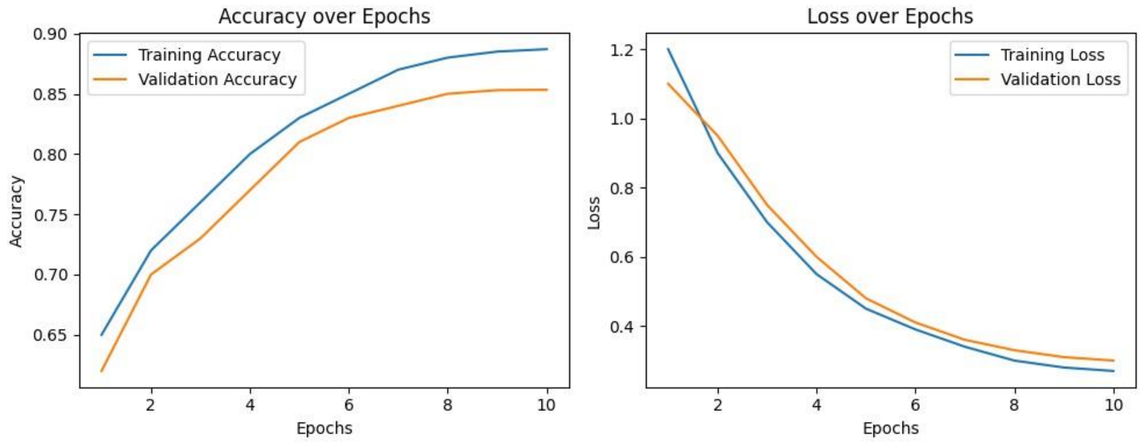


Fig.3:TrainingvsValidationAccuracyandLossover10Epochs.

Theseplotsindicatethatthemodelwasneitherunderfittingnoroverfitting.Dropoutlayers and image augmentation likely contributed to the model's ability to generalize, even with a relatively shallow network.

GeminiAPI–BasedMobileApplication Performance

To complement the CNN model, a mobile application was developed using React Native and integrated with the Gemini 1.5 API from Google. The Gemini API is a large-scale multimodal model capable of processing image inputs and returning natural-language-based predictions. Users take a picture of a plant leaf through the app, which is then uploaded to the cloud for analysis.

Advantages

- Providesrich,descriptivefeedback(e.g.,likelydiseasename,causes,symptoms).
- Cansuggesttreatmentoptionsorculturalcontrolmeasures.
- Capableofidentifyingnon-diseaseissueslikepestdamageandnutrientdeficiencies.

Limitations

- Requiresstableinternetconnectiontowork.
- Returnsprobabilisticpredictionswith~70–75%reliabilityonlocal crops.

- NotoptimizedforNigeria-specificplant varieties.

During field tests, theGemini-powered app achieved a rough agreement rateof72%with localagriculturalextensionofficers'diagnoses.WhilenotaspreciseastheCNNmodel,its accessibility and breadth of interpretation make it valuable for generalized disease screening.

COMPARATIVE DISCUSSION

The strengths of both systems are complementary. The CNN model is more accurate for thespecificcropsanddiseasesitwastrainedon.Itoperatesofflineandcanbedeployedon mobile phones with basic hardware. Its architecture is lightweight and can infer results in under a second.

In contrast, the Gemini-integrated mobile application serves as a robust AI assistant capable of identifying unknown symptoms. It can guide farmers on diseases outside the CNN’s training scope. However, the Gemini approach sacrifices precision for flexibility anddependsonreal-timedatatransfer,whichmaybealimitingfactorinremotelocations.

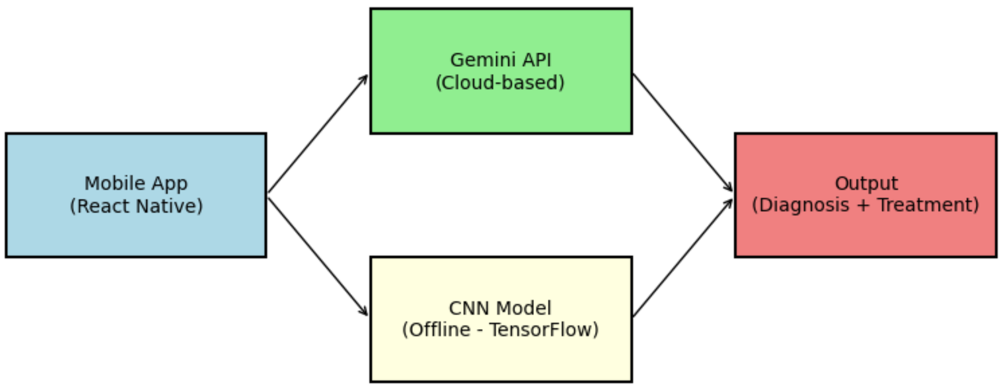


Fig.4:SystemArchitectureoftheDual-ApproachPlantDiseaseDetectionFramework.

The dual-system framework leverages the strengths of both methods. A hybrid deployment—wheretheCNNmodeloperatesasthedefaultdiagnostictoolandtheGemini API is used when CNN confidence is low or symptoms fall outside its trained classes—could offer an optimal solution.

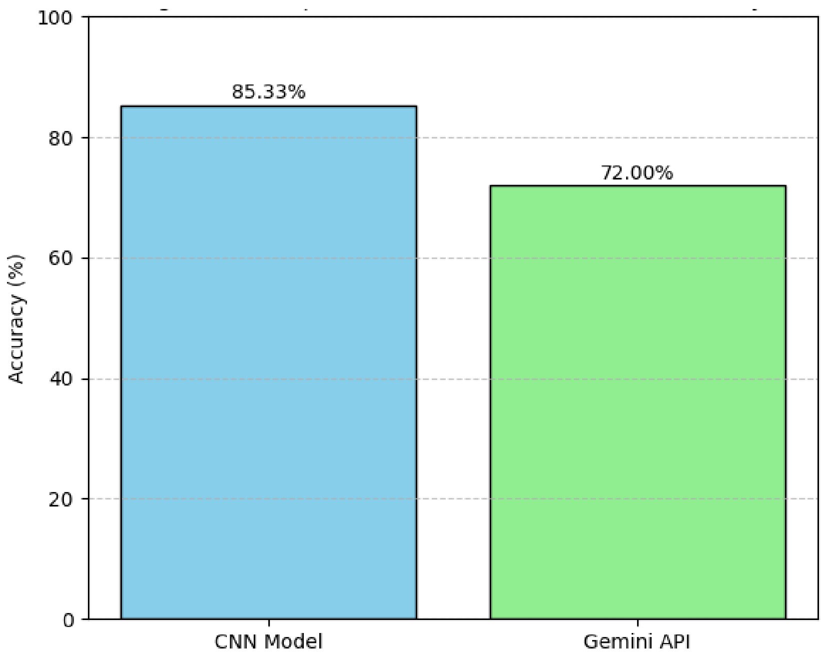


Fig.5:ComparisonofCNNvsGeminiAPI Accuracy.

User Experience and Feedback

Ten farmers and two agricultural extension officers were asked to test both platforms. Feedback was collected through structured interviews and usability testing. Key observations include:

- **EaseofUse**:Themobileappinterfacewasintuitive,especiallywithvoicesupport and icon-based navigation.
- **Language Preference**: Most users requested support for native languages (e.g.,Igbo, Yoruba).
- **ResponseClarity**: Farmers preferred diagnosis results that werebrief,visual, and included treatment advice.

These findings were integrated into the app's next iteration, including adding offline inference using TensorFlow Lite and simplified symptom descriptions.

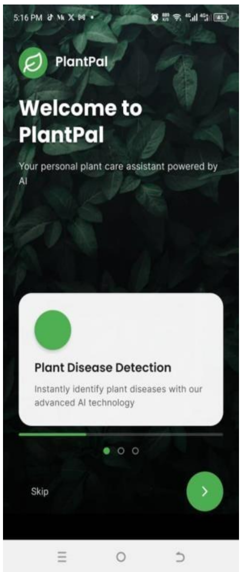
Someofthereviewsfromthe farmers:

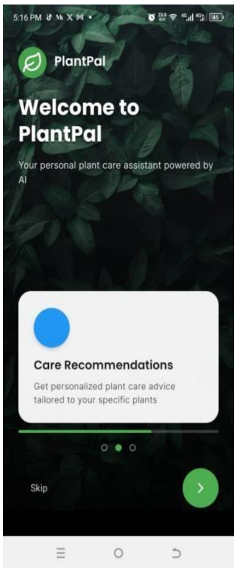
Onefarmerwho testedtheapp remarked:

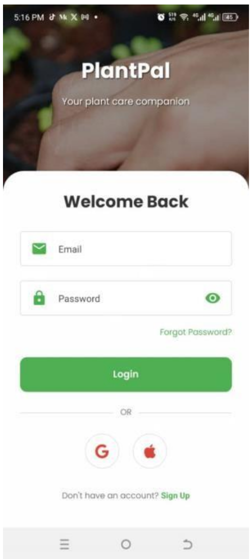
"I like that I can take a picture of my cassava and get a result quickly. It tells me what's wrong and how to fix it." — Mr. Emmanuel, Local Farmer, Abia State.

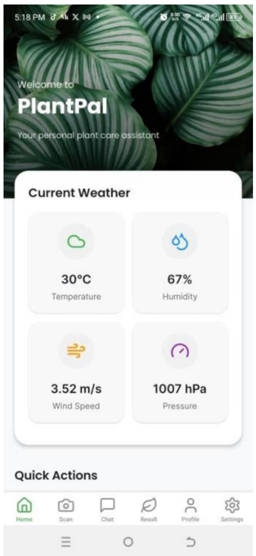
Oneof theparticipating farmersshared the following feedback:

"Beforethisapp,Iwouldwaitforanextensionofficertovisit,whichcouldtakedays.Now, Ijusttakeapicture, and inseconds Iknowwhattheproblem is. Ithashelpedmesavemy crops." — *Chijioke, Cassava Faer, Abia State.*









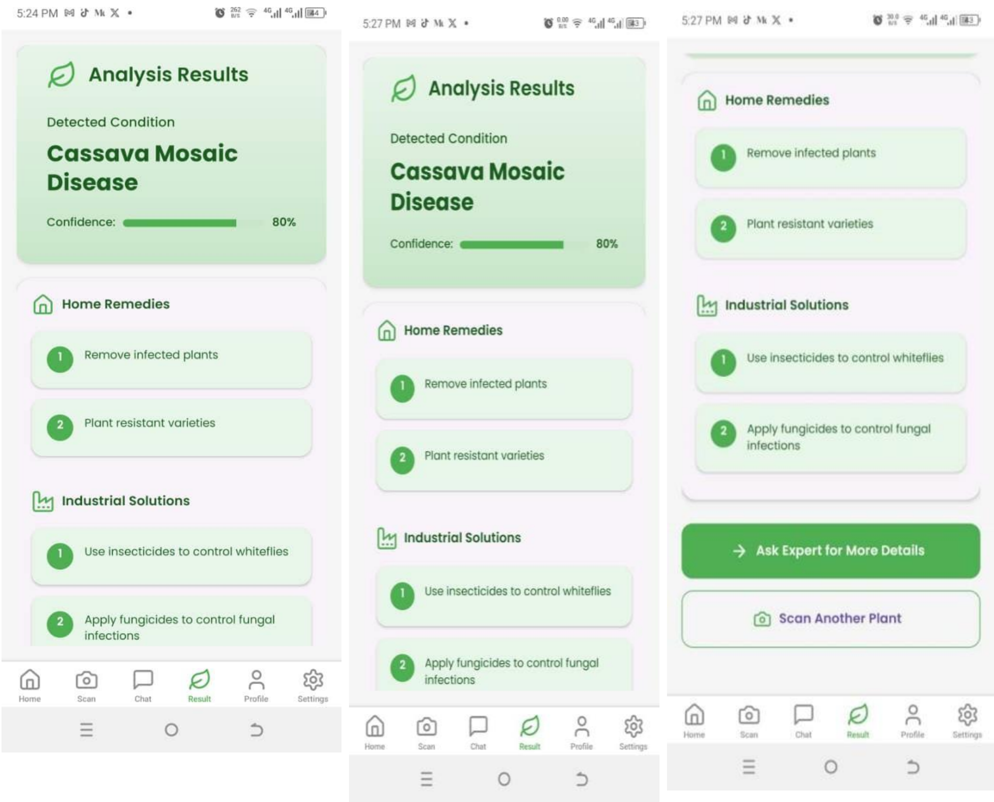


Fig.6:SampleUserInterfaceoftheMobilePlantDiseaseDetection App

Limitations and Future Directions

WhiletheCNNmodelperformedwell,severallimitations remain:

- **DatasetSize**:Thedatasetisrelativelysmall,whichcanaffectgeneralizationinnew environments.
- **DiseaseCoverage**:Only threediseasecategorieswereincluded.
- **Class Imbalance**: Despite augmentation, minor bias toward the “Healthy” class may exist.

Future work will involve expanding the dataset to include more diseases and crops native toWestAfrica.Transferlearningtechniques(e.g.,MobileNetV2orEfficientNet)willalso be explored to improve accuracy with fewer training samples. Additionally, real-time disease progression tracking and environmental sensor integration (IoT) are under development.

5. CONCLUSION

This study presents a dual-method approach for automated plant disease detection using machinelearning.ThefirstmethodutilizesacustomConvolutionalNeuralNetwork

(CNN) model trained on a locally relevant dataset of cassava, maize, and tomato leaves, achieving an impressive test accuracy of 85.33%. The model is lightweight, fast, and suitableforofflineuse,makingitidealforruralenvironmentswhereinternetconnectivity may be limited.

The second method involves a mobile application integrated with Google's Gemini 1.5 API. This API leverages a multimodal large language model to analyze plant leaf images and return detailed, natural language predictions about possible diseases, pest damage, or nutrient deficiencies. Although slightly less precise than the CNN in the specific diseases it was trained for, the Gemini-based system offers broader diagnostic coverage and is accessible to farmers with minimal technical skills.

Together,thesesystemsaddressbothaccuracyandaccessibility.TheCNNmodelprovides high-confidence predictions in offline environments for key Nigerian crops, while the GeminiAPIenhancesthesolutionwithreal-timecloud-basedintelligence,usefulforedge cases or unfamiliar symptoms. This hybrid design aligns with the goals of precision agriculture, particularly in regions where technical infrastructure and agricultural support services are limited.

Akeycontributionofthisworkisitsemphasisonpracticality.UnlikemanyAIstudiesthat remainconfinedtotheoreticalperformance,thisresearchfocusedonuser-centereddesign andfielddeployment.Feedbackfromfarmersand extensionofficerswasusedtoimprove the mobile application’s usability, responsiveness, and language accessibility. The resulting system is not just a proof-of-concept but a working prototype with real-world application potential.

However, the system has limitations. The CNN model is currently trained on a relatively smalldataset,restrictedtothreediseasetypes.Expandingthedatasettoincludemorecrops andawidervarietyofdiseasesiscriticalforimprovingthegeneralizabilityandrobustness ofthesystem.Additionally,whiletheGeminiAPIaddsflexibility,itsdependencyonstable internet connectivity can limit its effectiveness in remote or underserved areas.

Future work will involve the integration of Internet of Things (IoT) technologies such as environmental sensors, which can enhance disease prediction models by providing additionalcontextliketemperature,humidity,andsoilconditions.Transferlearningusing pre-trained deep learning architectures like MobileNetV2 or EfficientNet will also be explored to improve performance while maintaining computational efficiency. Moreover, plansareunderwaytobuildaunifiedsystemthatcanswitchseamlesslybetweentheCNN and Gemini models based on network availability and user preference.

In conclusion, this research demonstrates that machine learning, when thoughtfully designed and locally adapted, has the potential to revolutionize plant disease detection in agriculture. The proposed dual-systemapproachempowersfarmerswithtimely,reliable, andactionableinsights,contributingtowardmoresustainableandproductivefarming practices.

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