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DEVELOPMENT AND EVALUATION OF A MOBILE AUGMENTED REALITY SYSTEM FOR HORTICULTURAL DISEASE DETECTION AND ADVISORY SERVICES IN GOMBE STATE, NIGERIA

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Abstract
Horticultural farming constitutes a critical component of food security and economic sustenance in Gombe State, Nigeria, yet farmers continue to suffer disproportionate crop losses attributable to undetected and poorly managed plant diseases. This study developed and evaluated a Mobile Advisory Augmented Reality System (MAARS) designed to enhance disease detection and mitigation in horticultural farming across selected Local Government Areas (LGAs) in Gombe State. Employing a sequential exploratory mixed-methods design, the study combined qualitative data from semi-structured interviews with 42 purposively selected participants, followed by a quantitative survey administered to 214 horticultural farmers. Qualitative data were analysed using Atlas.ti version 12, while quantitative data were analysed using descriptive and inferential statistics via SPSS version 23.0. Findings revealed that MAARS demonstrated high effectiveness (mean = 4.31/5.00) and accuracy (87.5%) in identifying common horticultural diseases including tomato blight, pepper wilt, and cucumber mosaic virus. Usability assessment indicated strong user acceptance (System Usability Scale score = 75.25), while regression analysis confirmed that MAARS effectiveness was significantly associated with improved disease detection outcomes ($\beta = 0.612$, $p < 0.001$). The study concludes that MAARS represents a potentially scalable technological intervention for horticultural disease management in resource-constrained farming communities and recommends its integration into existing agricultural extension frameworks as a pilot/scale-up evaluation in Gombe State and beyond.

Keywords: Plant Disease Diagnosis, Artificial Intelligence, Digital Agriculture, Horticultural Farming, Mobile Advisory System.

INTRODUCTION

Horticultural farming encompassing the cultivation of fruits, vegetables, flowers, and ornamental plants; occupies a significant position in Nigeria's agricultural landscape, contributing substantially to household nutrition, income generation, and rural employment (FAO, 2022; Gold, *et al.*, 2020). In Gombe State, horticulture supports an estimated 68% of smallholder farming households, with tomatoes, peppers, and leafy vegetables constituting the dominant crops (Gombe State Agricultural Development Programme [GSADP], 2023). Despite its

economic and nutritional significance, the sector remains perpetually vulnerable to plant diseases that cause annual yield losses estimated between 30% and 60% of total production value (Aliyu *et al.,* 2022). The vulnerability is compounded by farmers limited access to timely diagnostic support and expert advisory services. Traditional disease detection methods rely predominantly on visual crop inspection; a technique that is inherently subjective, often inaccurate, and frequently delayed until disease progression has reached advanced stages (Gold, *et al.,* 2020). Agricultural extension services, while theoretically designed to bridge the knowledge gap between research and farm practice, remain chronically understaffed and geographically overstretched in Gombe State, with one extension agent reportedly serving an average of 1,200 farmers (GSADP, 2023).

The emergence of mobile technologies and augmented reality (AR) offers unprecedented opportunities to democratise agricultural advisory services. Augmented reality; the overlay of digital information onto real-world environments through a mobile device camera, has demonstrated promising applications in precision agriculture, enabling real-time crop health assessment, pest identification, and advisory feedback without requiring farmers to travel to extension offices or await field visits (Boonbrahm et al., 2020; Fountas *et al.,* 2022). Several studies conducted in Asia and Europe have validated AR-based crop disease detection systems, reporting accuracy rates exceeding 85% for major fungal and bacterial crop diseases (Mohanty *et al.,* 2021; Zhang *et al.,* 2022). However, such systems remain largely absent from sub-Saharan African agricultural settings, where the need is arguably most acute. This study therefore developed and evaluated a Mobile Advisory Augmented Reality System (MAARS) adapted to the specific disease management needs of horticultural farmers in Gombe State. The research addresses a significant gap in both technological application and empirical evidence concerning AR-mediated agricultural advisory systems in Nigeria's semi-arid farming belt.

LITERATURE REVIEW

Disease Challenges in Horticultural Farming

Plant diseases constitute a major constraint to horticultural productivity and have significant implications for food security, farmer income and the sustainability of horticultural production. Globally, plant diseases have been associated with substantial economic losses, estimated at about US$220 billion annually (Strange & Scott, 2005; FAO, 2022). In Nigeria, the problem is manifested through diseases affecting major horticultural crops, including tomato early and late blight (*Alternaria solani* and *Phytophthora infestans*), pepper wilt (*Fusarium oxysporum*), cucumber mosaic virus (CMV), and powdery mildew (*Erysiphe cichoracearum*). Tiamiyu, et al., (2021) reported that disease infestation contributes to substantial yield and post-harvest losses and identified visual symptoms such as discoloration, wilting, lesions and unusual growth patterns as important indicators for disease identification.

The challenge of disease management occurs within a broader set of constraints affecting horticultural production in Nigeria. Ogunniyi et al., (2021), for example, examined technical efficiency among smallholder tomato farmers in Oyo State and identified opportunities for improving resource allocation and production practices. Aliyu et al. (2023) examined the adoption of climate-resilient agricultural practices among vegetable producers in northwestern Nigeria, highlighting the importance of farmer capacity to respond to changing production conditions. Similarly, Osho & Ojo, (2021) investigated farmers' knowledge and adoption of integrated pest management practices in vegetable production in Enugu State, demonstrating the importance of appropriate knowledge and management practices for sustainable vegetable production. Their study of the leafy-vegetable value chain in Kwara State further illustrates the interconnected production and marketing processes through which horticultural products move from farmers to consumers. Mshelia et al. (2021) examined the challenges and prospects of urban and peri-urban horticulture in Nigeria and highlighted the growing importance of horticulture in meeting the demand for fresh produce.

Collectively, these studies indicate that horticultural productivity is influenced not only by farmers' production practices but also by their capacity to identify and manage crop-health problems. The findings of Tiamiyu et al., (2021) are particularly relevant because visual identification of disease symptoms represents an important component of disease management. However, dependence on visual inspection places considerable importance on the availability of appropriate knowledge and timely access to agricultural information. This creates a basis for considering technological approaches that can support farmers in identifying crop-health problems and accessing relevant management information.

The issue is particularly pertinent to the present study because of its focus on Gombe State. The agricultural conditions of the State and the importance of horticultural production create a need for appropriate disease-management support. However, the studies reviewed above largely examine production efficiency, climate resilience, integrated pest management, value chains and general horticultural challenges. They do not, in the material reviewed, provide evidence of an integrated mobile system for automated disease recognition and agricultural advisory specifically designed for horticultural farmers in Gombe State. This provides a contextual basis for examining the applicability of emerging digital technologies to crop-disease management within the State.

Application of Smart Technologies in Horticultural Farming

The limitations associated with conventional approaches to agricultural information and disease management have stimulated interest in smart technologies, including mobile computing, artificial intelligence (AI), augmented reality (AR) and virtual reality (VR). These technologies provide different but potentially complementary functions. Mobile technologies provide portability and field access; AI provides opportunities for automated analysis and recognition;

while AR provides a mechanism for presenting digital information within the user's view of the physical agricultural environment. Xie, et al. (2022) and Nayak et al. (2020) examined the broader application of AR in agriculture and highlighted its potential for providing information and guidance within agricultural environments. Their work suggests that AR can facilitate access to information and expert guidance directly in the field. This is important for horticultural disease management because farmers often need information at the point where crop-health problems are observed rather than after leaving the field.

The potential of AR becomes more significant when combined with AI. Chen, et al. (2022) examined the integration of deep learning with mobile AR systems and reported the potential for combining automated diagnosis with mobile visualisation. This represents an important development from conventional agricultural information systems because the technology can potentially support both recognition and access to information through a mobile platform. In this sense, AI and AR perform complementary functions: AI supports the identification or analysis of crop conditions, while AR provides a mechanism for presenting relevant information to the user. Bigonah, et al. (2025) further demonstrated the application of AR through a real-time monitoring system that allowed users to assess crop development through AR overlays. The information generated through the system was used to support decisions relating to irrigation, fertilisation and other crop-management practices. Although the focus was on crop monitoring rather than specifically on disease diagnosis, the study demonstrates the potential of AR to connect digital agricultural information with the physical crop environment.

The application of immersive technologies has also been considered beyond disease diagnosis and crop monitoring. Lohan, et al. (2025) examined the convergence of AR and VR interfaces for tractors and farm machines and identified possibilities for immersive training and visualisation. This suggests that AR can serve not only as an information-delivery mechanism but also as a tool for improving the way agricultural information is represented and understood.

Within the specific area of crop-health management, Adekunle et al. (2021) examined the development of mobile AR for crop-disease diagnosis and highlighted its potential for improving crop-health management. This study is particularly relevant to the present research because it establishes a connection between mobile AR and disease diagnosis. Nevertheless, the available literature indicates that mobile AR disease diagnosis represents an emerging area, and there remains a need to examine how such systems can be adapted to specific agricultural environments and user requirements.

Integration of Disease Recognition and Agricultural Advisory

The reviewed studies suggest that the value of smart agricultural technologies does not necessarily lie in the use of a single technology but in the possibility of integrating complementary technological functions. A disease-detection system based on AI can potentially assist with identifying a crop-health problem, while a mobile platform can make the technology

accessible in the field and AR can provide a mechanism for presenting relevant information within the user's physical environment. This technological progression is evident across the reviewed studies. Xie, et al. (2022) and Nayak et al. (2020) establish the broader applicability of AR in agriculture; Chen et al. (2022) demonstrate the potential of combining deep learning and mobile AR; Bigonah, et al. (2025) demonstrate AR-based crop monitoring; Lohan et al. (2025) identify applications of AR and VR for agricultural visualisation and training; and Adekunle et al. (2021) specifically connect mobile AR with crop-disease diagnosis. These studies collectively indicate a movement from conventional information provision towards technologies that can provide more interactive and visually mediated agricultural support. However, the reviewed evidence also shows that the technological components remain distributed across different applications and agricultural problems. Some studies focus on crop production, others on agricultural information, crop monitoring, precision agriculture, or disease diagnosis. Consequently, the literature does not yet provide sufficient evidence, within the material reviewed, of a single system that integrates mobile disease recognition, agricultural advisory and AR-based visual guidance specifically for horticultural farmers in Gombe State.

Critical Synthesis of the Literature

The literature can therefore be understood across three interconnected dimensions: the agricultural problem, the technological response, and the contextual applicability of the technology.

At the agricultural-problem level, Nigerian studies establish the importance of disease management within horticultural production. Ogunniyi et al., (2021), Aliyu et al. (2023), Osho and Ojo (2021), Mshelia et al. (2021), and Tiamiyu et al., (2021) demonstrate that horticultural production involves interconnected challenges relating to efficiency, climate resilience, pest and disease management, value chains and production losses. However, these studies do not address automated mobile disease recognition and AR-based advisory.

At the technological level, the reviewed studies establish that AR, mobile technologies and AI can contribute to agricultural information provision, monitoring, diagnosis and visualisation. Chen, et al. (2022) is particularly relevant because it demonstrates the potential integration of deep learning and mobile AR, while Adekunle et al. (2021) links mobile AR specifically with crop-disease diagnosis. However, the available evidence does not establish that these technologies have been sufficiently integrated and evaluated for the specific requirements of horticultural farmers in Gombe State.

At the contextual level, the reviewed Nigerian studies were conducted in different geographical settings, including Oyo, Enugu, Kwara and northwestern Nigeria. The technology-oriented studies address broader agricultural contexts. Thus, the transferability of their findings to Gombe State cannot simply be assumed. Differences in agricultural conditions, crop characteristics, farmer practices and access to technology make contextual investigation necessary.

The literature also reveals a limitation in the available evidence concerning the detailed technical characteristics of existing disease-detection systems. The supplied studies do not provide sufficient information for a consistent comparison of AI algorithms, image-dataset characteristics, diagnostic accuracy and field-versus-laboratory performance across all studies. Consequently, the present review does not assume that technologies developed or evaluated elsewhere will necessarily produce equivalent results under the conditions in Gombe State.

Research Gap

The reviewed literature establishes that horticultural disease management is an important agricultural problem and that AI, mobile technology and AR offer promising technological approaches to agricultural diagnosis, monitoring and advisory support. Nevertheless, the evidence remains fragmented.

First, existing Nigerian studies have predominantly examined horticultural production, farmer practices, climate resilience, integrated pest management and value-chain issues rather than integrated mobile AI-based disease detection. Second, technology-oriented studies demonstrate the potential of AR, AI and mobile systems, but they have been applied to different agricultural functions, including information provision, crop monitoring, precision agriculture, training and disease diagnosis. Third, the reviewed literature provides limited evidence concerning the application of an integrated mobile disease-detection and advisory system specifically within the Gombe State agricultural context. The gap is therefore not simply the absence of technology for identifying crop diseases. Rather, the gap concerns the limited evidence on how mobile disease recognition, agricultural advisory and augmented visual guidance can be integrated and applied within the specific horticultural context of Gombe State.

This gap provides the justification for the proposed Mobile Advisory Augmented Reality System (MAARS). The study seeks to extend existing knowledge by investigating an integrated approach in which mobile technology provides accessibility, AI supports disease recognition, agricultural advisory provides management information, and AR provides a visual interface for presenting relevant information in relation to the physical crop. The study will thereby contribute empirical evidence on the applicability of an integrated mobile AR approach to horticultural disease management in Gombe State.

Integration of AR and system architecture

In this study, Augmented Reality is not merely a visual effect; it serves as a spatial, low-literacy user interface that allows farmers in Gombe State to point their camera at a crop and immediately see and hear localized diagnostic advisories pinned directly to the diseased leaves in real-world space. Thus, the case for Integrating CNN, mobile technology, augmented reality, offline functionality, hausa interface and agricultural advisory lie in complementarity of these technologies in addressing the research problem at hand. For instance, the reviewed literature indicates that the individual technologies relevant to this study address different aspects of crop-

disease diagnosis and agricultural decision-making (Xie et al., 2022). However, their combination has the potential to address the limitations that remain when each technology is used independently. The proposed integration of Convolutional Neural Network (CNN), mobile technology, Augmented Reality (AR), offline functionality, Hausa-language interaction and agricultural advisory is therefore based on the complementary functions of these components.

A CNN provides the computational foundation for automated crop-disease recognition from images. Its relevance arises from the visual nature of many crop diseases, where symptoms such as lesions, discoloration, wilting and other visible abnormalities provide information for diagnosis. The use of CNN-based image recognition can therefore reduce dependence on purely manual visual diagnosis and provide farmers with technology-assisted identification of selected crop diseases (Nayak, et al., 2022).

The mobile platform provides the delivery mechanism through which disease recognition and advisory services can be made available at the point of agricultural production. Unlike fixed or laboratory-based diagnostic systems, a mobile platform can potentially allow farmers to capture crop images and access diagnostic information directly in the field. Mobile technology therefore connects the computational capability of the CNN with the actual environment in which farmers encounter crop-health problems.

Though, disease recognition alone does not necessarily constitute agricultural decision support. This creates the rationale for integrating agricultural advisory with the diagnostic component. Following disease identification, the system can provide information concerning appropriate management and control measures. The integration consequently changes the function of the system from simply answering *"What disease is this?"* to supporting the farmer with information concerning *"What should I do about it?"*

Augmented Reality provides an additional layer by connecting digital information with the physical crop. Rather than presenting disease information only as text or conventional images on a mobile screen, AR can potentially overlay relevant information onto the farmer's view of the actual plant. This is particularly relevant where disease management requires the farmer to relate information to a specific plant part or visible symptom. The combination of CNN and AR therefore creates a potential pathway from automated recognition to visually mediated agricultural guidance.

The inclusion of offline functionality responds to the practical limitation of dependence on continuous internet connectivity. A mobile disease-detection system that requires permanent network access may have limited usefulness in locations where connectivity is inconsistent or data access is constrained. An offline-capable architecture can potentially store the CNN model, selected disease information and core advisory content locally on the mobile device, allowing essential diagnostic and advisory functions to operate without continuous network connectivity.

Network access can subsequently be used for system updates, synchronisation and other services when available.

The Hausa interface addresses the language dimension of agricultural technology adoption and use. Although digital agricultural information is frequently presented in English, farmers may differ in their ability and preference to interact with technology in English. Integrating Hausa into the system therefore provides the potential to make disease-detection results and agricultural advisory information more accessible to farmers who are more comfortable receiving agricultural information in Hausa. For the Gombe State context, this provides an important avenue for investigating whether multilingual interaction can improve the accessibility and usability of digital agricultural advisory services.

The significance of the proposed architecture therefore lies in the complementarity of the components rather than in any individual technology. CNN provides automated visual recognition; the mobile platform provides field accessibility; agricultural advisory converts diagnosis into management information; AR connects digital information to the physical crop; offline functionality supports operation where network connectivity is limited; and Hausa provides a potentially more accessible language interface.

Conceptually, the integration is represented in figure 1:



Figure 1: integrated workflow of MAARS

The combination is therefore intended to address the complete pathway from recognition, interpretation and advisory to field-level action. While the reviewed literature provides evidence for the application of individual components or selected combinations in agriculture, the

literature reviewed for this study does not adequately document an integrated system combining all six components specifically for horticultural disease diagnosis and advisory in Gombe State, Nigeria. This integration consequently provides the technological and contextual basis for the proposed Mobile Advisory Augmented Reality System (MAARS).

STATEMENT OF THE PROBLEM

Crop diseases remain a significant challenge to horticultural production, requiring farmers to identify diseases accurately and obtain timely, appropriate management advice. Although existing mobile disease-detection systems can identify diseases from crop images, they largely focus on recognition and do not adequately integrate localised diagnosis, actionable agricultural advisory, visual guidance, language accessibility and offline functionality for farmers in Gombe State.

In particular, existing systems may provide a disease name without showing farmers how to relate the diagnosis to the affected plant or what action to take. Their reliance on externally developed datasets and advisory information may also limit local relevance, while English-dominated interfaces and continuous internet requirements may restrict accessibility and usability among some farmers. Augmented Reality (AR), English–Hausa interaction and offline/local-phone functionality therefore provide potential mechanisms for addressing these limitations.

The central problem is consequently the lack of an adequately documented and evaluated mobile system that integrates localised disease recognition, contextualised agricultural advisory, AR-based visual guidance, English–Hausa support and offline functionality for horticultural farmers in Gombe State. The study therefore proposes the Mobile Advisory Augmented Reality System (MAARS) to investigate whether such an integrated approach can provide more accessible, relevant and actionable support for crop disease diagnosis and management in Gombe State.

OBJECTIVES OF THE STUDY

The study aimed to:

1. Design and develop a mobile advisory augmented reality system for detecting disease infestation in horticultural farming in Gombe State
2. Evaluate the effectiveness and accuracy of the developed MAARS in identifying common diseases affecting horticultural crops
3. Assess the usability and user-friendliness of MAARS among farmers and agricultural stakeholders
4. Investigate the Pre–Post Changes in Disease Detection Outcomes Following MAARS Use in horticultural farming communities in Gombe State.

METHODOLOGY

Research Design

The study adopted a sequential exploratory mixed-methods design. Qualitative data collection and analysis preceded quantitative inquiry, with qualitative findings informing the design of the quantitative survey instrument and the MAARS system features as presented in figure 2. This design was selected for its capacity to generate both in-depth contextual understanding and generalisable quantitative evidence within a single integrated framework (Creswell & Plano Clark, 2018).

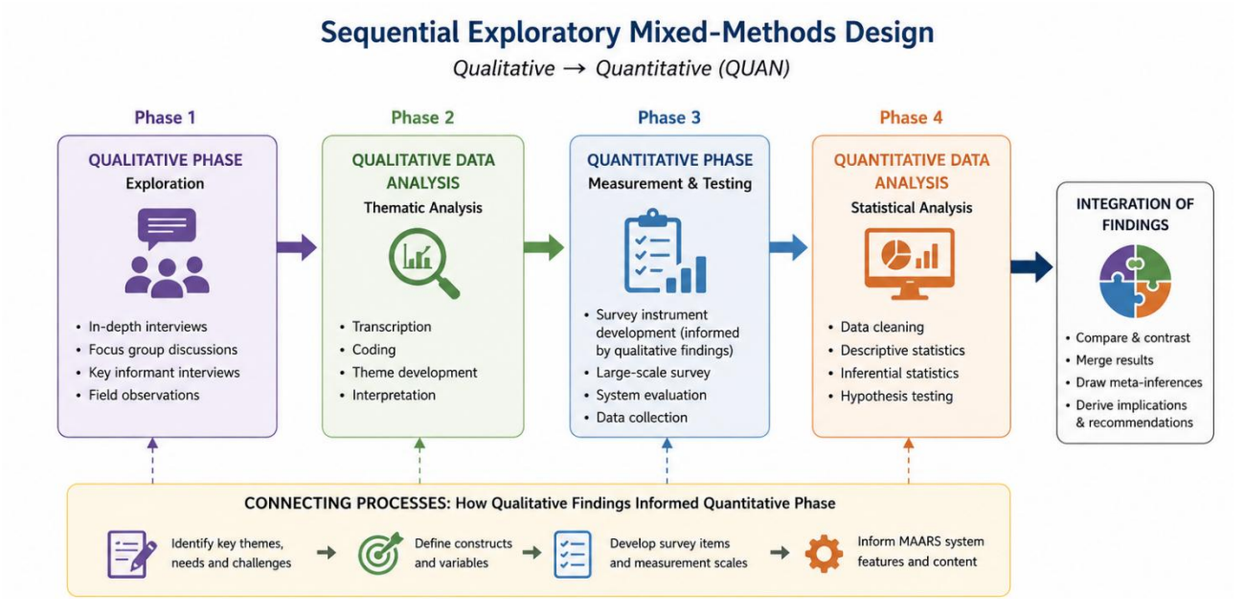


Figure 2: Sequential exploratory mixed method design

Study Area

The study was conducted in three Local Government Areas (LGAs) of Gombe State; Gombe, Nafada, and Shongom, selected on the basis of their high concentration of horticultural farming activity and representation of urban, peri-urban, and rural farming settings respectively. The study was conducted in three selected Local Government Areas (LGAs) of Gombe State, namely Gombe, Nafada and Shongom. The three LGAs were selected to provide representation of different geographical locations within the State, with Gombe located in the central part, Nafada in the northern part, and Shongom in the southern part of Gombe State as presented in figure 3.

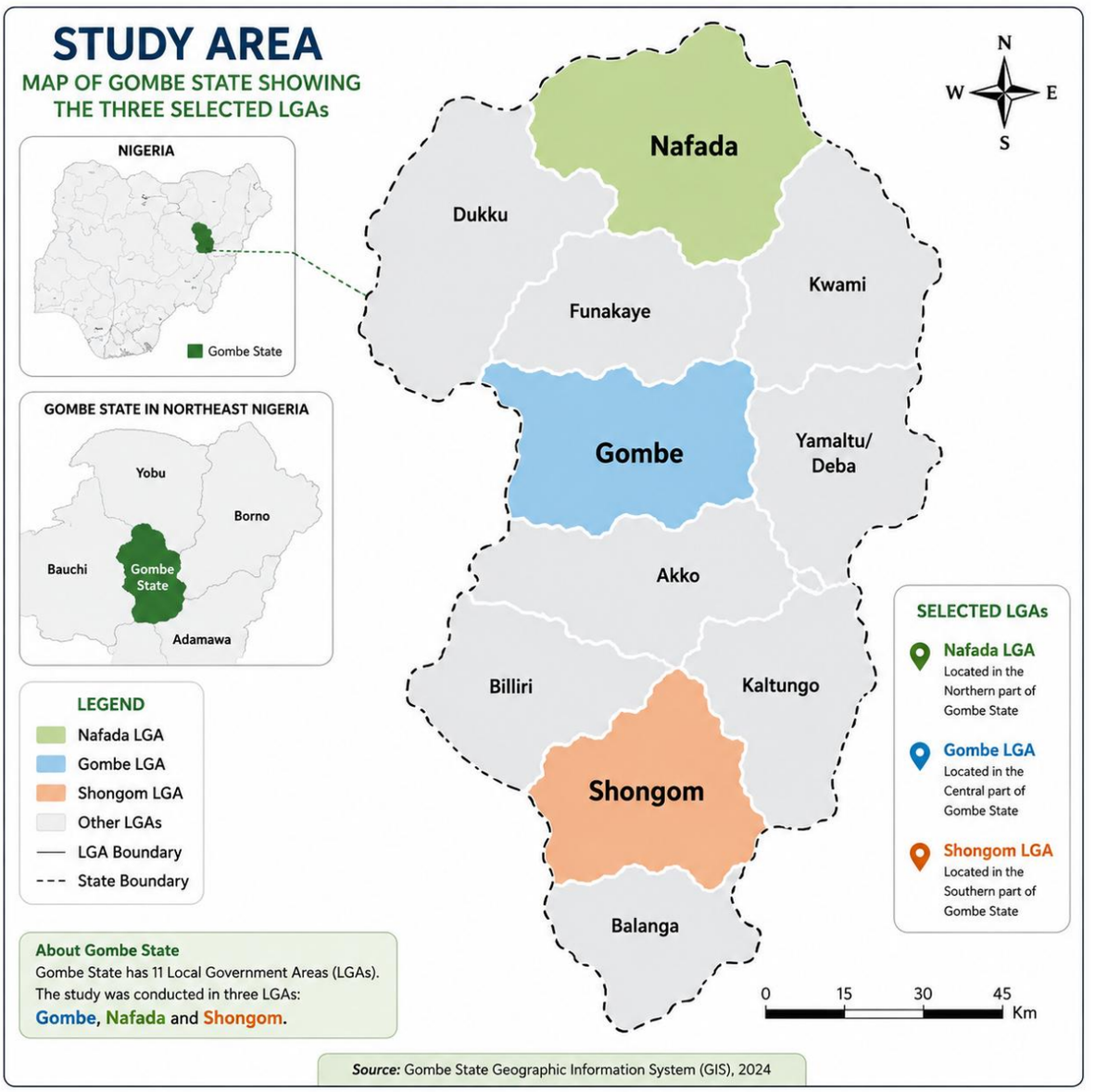


Figure 3: Map of Gombe State Showing the Three Selected Local Government Areas (Gombe, Nafada and Shongom).

Population and Sampling

The target population of the study comprised 821 horticultural farmers and relevant agricultural stakeholders identified within the 11 Local Government Areas (LGAs) of Gombe State. The population constituted the accessible sampling frame for identifying eligible participants for the study. The sampling frame was established from available agricultural records and lists of horticultural farmers obtained from relevant agricultural authorities and stakeholder structures within the study area. Only farmers who met the study's eligibility criteria, particularly active involvement in horticultural production, were considered eligible for the quantitative phase.

The study employed a sequential exploratory mixed-methods sampling procedure. For the qualitative phase, purposive sampling was used to select participants with relevant knowledge and experience of horticultural production, crop-disease identification and agricultural advisory

practices. These participants provided the contextual information required to inform the development of the quantitative instrument and the features of the Mobile Advisory Augmented Reality System (MAARS).

For the quantitative phase, stratified random sampling was employed. The three selected LGAs: Gombe, Nafada and Shongom, constituted the strata. The use of LGA as the stratum was based on the geographical distribution of the study and the need to ensure that each selected LGA was adequately represented. Following stratification, eligible farmers within each LGA were randomly selected from the available sampling lists. Thus, the strata were geographical (LGA), rather than sex, crop type or farming system.

Sample Size Determination

The quantitative sample size was determined from the accessible population of 821 using the finite-population sample-size approach at a 95% confidence level, assuming maximum population variability ($p = 0.50$). A sample of 214 respondents was obtained, corresponding to an estimated margin of error of approximately ±5.7 percentage points after applying the finite-population correction. The sample was therefore considered adequate for obtaining quantitative evidence from the accessible population within the scope and resources of the study.

Table 1: Sample Distribution by LGA and Method

LGA	Qualitative (Interviews)	Quantitative (Survey)	Total
Gombe	16	84	100
Nafada	14	72	86
Shongom	12	58	70
Total	**42**	**214**	**256**

The qualitative sample comprised 42 participants, selected purposively to provide in-depth information relevant to the research questions and the development of the Mobile Advisory Augmented Reality System (MAARS). Consequently, the total number of participants involved in the study was 256, comprising 42 qualitative participants and 214 quantitative respondents.

MAARS System Development

MAARS was developed using an iterative agile software development framework over a 16-week development cycle as indicated in figure 4. The system architecture integrated:

i. A convolutional neural network (CNN) model trained on a dataset of 18,400 labelled images of healthy and diseased horticultural crops
ii. ARCore (Android) and ARKit (iOS) frameworks for augmented reality overlay delivery

iii. A RESTful API backend hosted on a cloud server for real-time advisory content delivery

iv. An offline caching module ensuring functionality in low-connectivity rural environments

v. A multilingual interface supporting English and Hausa

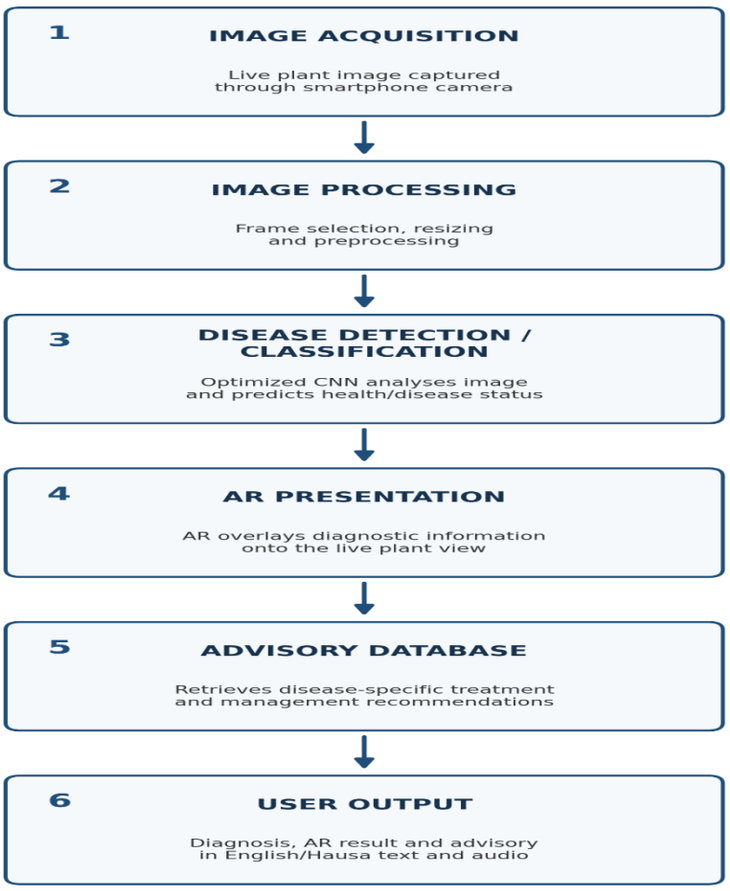


Figure 4: System Architecture

System Architecture and Workflow

The Mobile Augmented Reality System (MAARS) was designed as a hybrid edge-cloud diagnostic system that integrates real-time image acquisition, image processing, disease classification, augmented reality visualisation and context-specific advisory delivery. The system workflow follows six interconnected stages: image acquisition, image processing, disease detection and classification, AR presentation, advisory database access and user output.

1. Image Acquisition

The workflow begins with the acquisition of live images of horticultural crops using the smartphone camera. The mobile application provides a continuous camera viewport through which users capture or scan symptomatic plant tissues, including leaves, stems and fruits. The camera input provides the visual data required for subsequent disease analysis.

2. Image Processing

The acquired image frames undergo preprocessing before classification. Relevant frames are prepared for analysis through procedures such as resizing and formatting to meet the input requirements of the trained convolutional neural network (CNN). Image processing is executed

within the mobile application to support low-latency operation and reduce dependence on continuous internet connectivity.

3. Disease Detection and Classification

The processed image is transmitted to the on-device inference engine, where an optimised CNN model performs disease detection and classification. The model analyses visual characteristics within the plant image and predicts whether the crop is healthy or affected by a specific disease category. The classification result constitutes the core diagnostic output of the system.

4. Augmented Reality Presentation

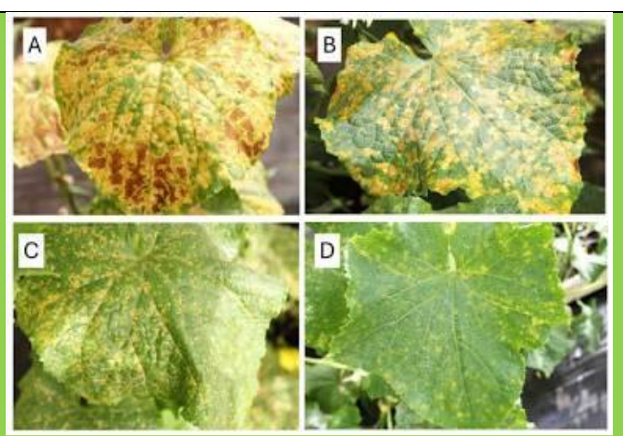
Following classification, the diagnostic result is integrated into the live camera environment using the augmented reality engine. ARCore supports Android devices, while ARKit supports iOS devices. The system renders dynamic visual overlays and diagnostic information within the user's camera view, enabling the disease status to be presented directly in relation to the observed plant tissue.

5. Advisory Database

The identified disease category is linked to a structured advisory database containing disease-specific management and treatment recommendations. The advisory content is available through both locally cached resources and cloud-based services. The local database supports offline access in low-connectivity environments, while the cloud backend provides updated treatment guidelines, advisory content and system resources when an internet connection is available.

6. User Output

The final stage delivers the diagnostic and advisory information to the user through the mobile interface. The output includes the detected disease or plant health status, relevant visual AR overlays and recommended management actions. Advisory information is provided through multilingual text and audio formats in English and Hausa to improve accessibility for users with different language preferences and literacy levels. The sample data set is pictorially presented in figure 5.

	
Cucumber Downy Mildew (Pseudoperonospora	*Pepper Fusarium Wilt (Fusarium oxysporum).*

cubensis).	
	
Tomato Late Blight (Phytophthora Infestans)	*Cucumber Powdery Mildew (Podosphaera xanthii).*

Figure 5: Sample Dataset Classes

Data Collection Instruments

This study used two main sets of tools across Gombe, Nafada, and Shongom: the app itself (the test tool) and survey tools to measure its success (the data collection tools). The app ran directly on Samsung Galaxy A53 smartphones without needing internet access. By combining a lightweight AI model with smartphone camera tracking, it scanned plant leaves in real time, drew colored boxes around diseased areas on the screen, and delivered visual advice paired with spoken Hausa voice notes. To test how well the app worked, expert plant pathologist first checked 480 field photos to confirm the app's 87.5% diagnostic accuracy. Next, local farmers and extension agents filled out simple usability surveys and joined group discussions in Hausa, rating the app's user-friendliness at 75.25 out of 100. Finally, household surveys and farm tracking logs showed that using the app helped farmers catch crop diseases in 8.3 days to 2.1 days, reducing seasonal crop losses.

Image Acquisition and Dataset Verification

A total of 480 crop-disease images were selected and screened by the researchers from photographs acquired under field conditions as indicated in figure 6. Out of the total dataset utilized, 100% of the 480 screening images evaluated in this field trial were primary photographs collected directly by the researchers using a Samsung Galaxy A53 5G smartphone across three strategically selected Local Government Areas (LGAs) in Gombe State representing distinct agricultural settings: Gombe LGA (urban horticulture), Nafada LGA (peri-urban dryland systems), and Shongom LGA (rural smallholder farming). This distribution ensured varied natural lighting, background soil noise, and foliage density under real field conditions. For initial

Convolutional Neural Network (CNN) feature learning and model pre-training, a public dataset (*PlantVillage*, 18,400 images) was leveraged to prevent overfitting given limited local class counts. The images were examined for clarity, disease visibility, duplication and suitability for classification. Disease identification was subsequently verified through laboratory examination of corresponding plant specimens using standard plant-pathology diagnostic procedures and relevant augmented-reality/visual-reality imaging and diagnostic laboratory equipment. Duplicate and near-identical images were removed, and the dataset was partitioned to ensure that the test images were held out before model training. This procedure was adopted to minimise potential data leakage and ensure that model performance was evaluated using images not previously exposed to the training process.

To support low-latency, on-device disease classification without requiring persistent internet connectivity in remote farming locations (e.g., Shongom and Nafada LGAs), we implemented a customized MobileNetV2 architecture. Transfer learning was employed using weights pre-trained on the ImageNet-1K dataset. The original 1000-class classification head of MobileNetV2 was removed and replaced with a custom dense block consisting of a Global Average Pooling (GAP) layer, a Dropout layer ($p = 0.4$) to mitigate overfitting, a 128-unit fully connected layer with Rectified Linear Unit (ReLU) activation, and a final Softmax output layer matching the targeted crop-disease classes.

Model training was performed in a two-phase process using TensorFlow 2.15 on an NVIDIA RTX 3090 GPU. Images were resized to $224 \times 224 \times 3$ pixels and normalized. To account for ambient lighting variations and complex leaf backgrounds encountered during field sampling in Gombe State, real-time data augmentation (rotation, shearing, zoom, and brightness shifts) was applied.

Phase 1 ran for 20 epochs with frozen base layers using the Adam optimizer (learning rate $= 10^{-3}$) and Categorical Cross-Entropy loss at a batch size of 32. Phase 2 unfroze the last 30 convolutional layers for fine-tuning over 30 additional epochs at a reduced learning rate of 10^{-5} governed by a cosine decay schedule. Post-training, the model was converted to a TFLite flatbuffer using dynamic range integer quantization (int8), reducing model size from ~14 MB to 3.8 MB and enabling average sub-50ms inference times on the mobile device's Neural Processing Unit (NPU).

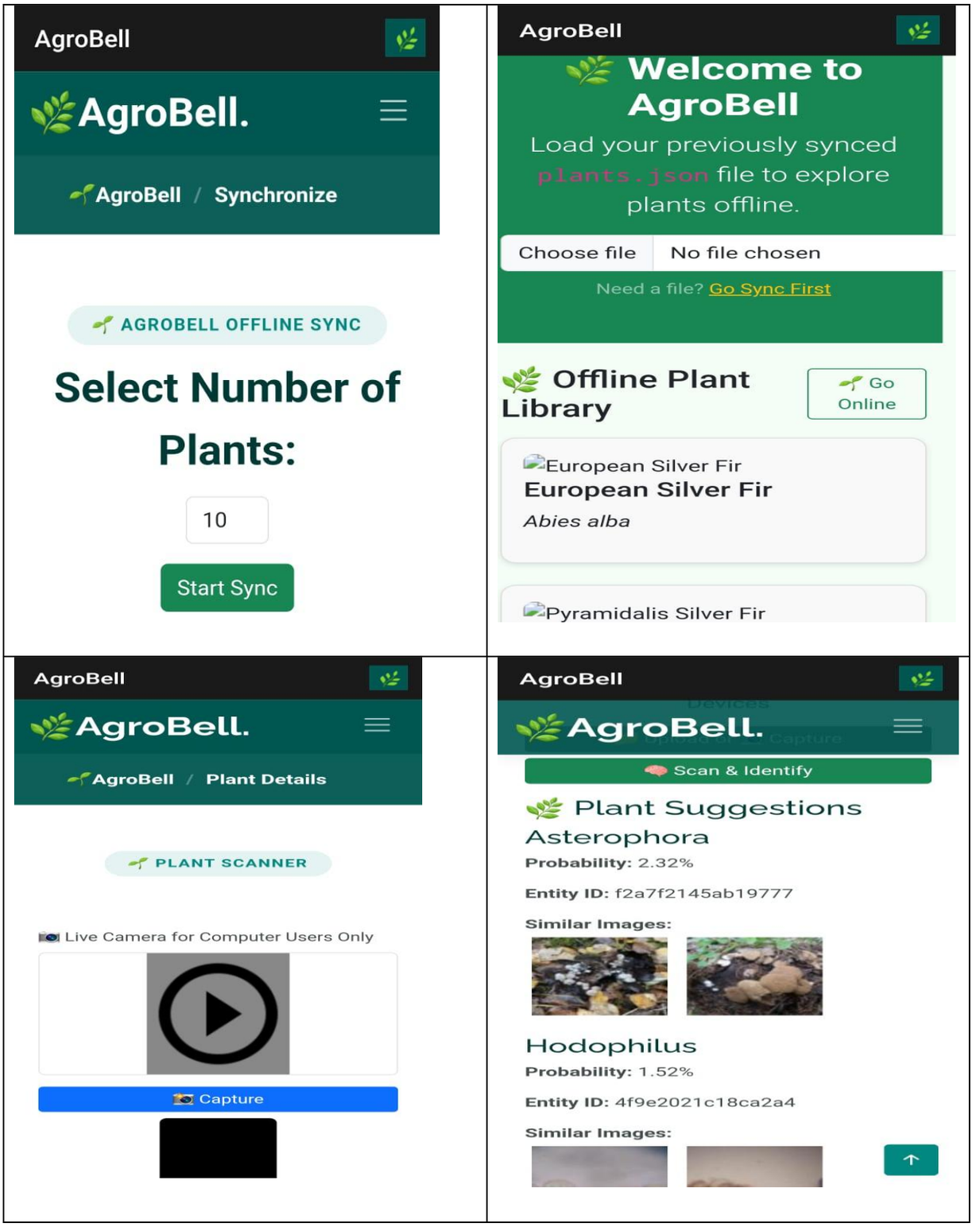


Figure 6: Screen shot of selected AgroBell MAARS outputs

For Qualitative data, semi-structured interview guides containing 18 open-ended questions exploring farmers' disease management experiences, technology familiarity, and advisory needs. Four interviews were conducted with 6–8 participants each. A structured questionnaire comprising four sections:

i. Section A: Socio-demographic characteristics (8 items)

ii. Section B: MAARS effectiveness and accuracy (6 items, 5-point Likert scale)

iii. Section C: System usability assessment using the adapted System Usability Scale (10 items). The wordings were slightly changed to suit the study objectives. However, the standard scoring algorithm remained unchanged.

iv. Section D: Impact on disease detection outcomes (10 items)

The instrument was validated by three agricultural technology experts and two experienced farmers, yielding a Content Validity Index (CVI) of 0.87. Reliability was established through a pilot study (n=22) with a Cronbach's alpha of .84 for effectiveness and accuracy; .72 for system usability assessment; and .76

Data Analysis

Qualitative data were transcribed verbatim and analysed using thematic analysis in Atlas.ti version 12, following the six-phase procedure of Braun and Clarke (2006). Quantitative data were analysed using SPSS version 23.0, employing descriptive statistics (frequencies, means, standard deviations) and inferential statistics including Pearson correlation and multiple linear regression analysis. Data integration occurred during the interpretation phase through a joint display approach.

RESULTS AND DISCUSSION

Preliminary examination of the correlation matrix indicated positive and approximately linear associations among the principal MAARS variables, with Pearson correlation coefficients ranging from r = .52 to .76 (p < .01). The intercorrelations among the principal regression predictors were moderate to strong, with the largest correlation being between MAARS Effectiveness and Frequency of MAARS Use (r = .71). The corresponding preliminary VIF estimates for these three predictors ranged from approximately 1.79 to 2.40, indicating no evidence of severe multicollinearity among these variables. However, normality, homoscedasticity, independence of residuals and influential observations require examination using the respondent-level regression diagnostics and are therefore not inferred solely from the correlation and regression coefficient tables.

Socio-Demographic Characteristics of Respondents

Table 2: Socio-Demographic Profile of Quantitative Survey Respondents (n=214)

Variable	Category	Frequency	Percentage (%)
Sex	Male	142	66.4
	Female	72	33.6
Age	18–30 years	38	17.8
	31–45 years	96	44.9
	46–60 years	64	29.9
	Above 60 years	16	7.5
Education	No formal education	44	20.6
	Primary	58	27.1
	Secondary	76	35.5
	Tertiary	36	16.8
Farming Experience	1–5 years	32	15.0
	6–10 years	74	34.6
	11–20 years	82	38.3
	Above 20 years	26	12.1
Smartphone Ownership	Yes	168	78.5
	No	46	21.5
Prior AR/App Experience	Yes	94	43.9
	No	120	56.1

Source: Field Survey, 2024

Table 2 shows that the majority of respondents were male (66.4%), reflecting the gender dynamics of commercial horticulture in Gombe State, though a substantial female participation (33.6%) indicates the sector's gender diversity. The dominant age group (31–45 years, 44.9%) suggests a relatively productive farming population. Secondary school completion constituted the modal educational level (35.5%), while smartphone ownership at 78.5% confirms an

adequate technological infrastructure for MAARS deployment while the remaining 46 (21.5) accessed information through SMS and were also exposed to the same contents as those with smartphones via researchers' tablet. Notably, 56.1% of respondents had no prior experience with mobile agricultural applications, stressing the importance of user-centred design in MAARS development.

Qualitative Findings: Farmers' Disease Management Experiences

Thematic analysis of interview data yielded four primary themes.

Table 3: Summary of Qualitative Themes and Representative Codes (Atlas.ti, n=42)

Theme	Sub-themes	Frequency of Codes	Representative Quotation
Inadequacy of Traditional Detection Methods	Visual inspection limitations; Delayed diagnosis	87	*"By the time I see the disease clearly, half the farm has already suffered"* (Farmer, Gombe LGA)
Limited Access to Expert Advisory Support	Extension agent scarcity; Distance to advisory centres	74	*"The extension officer comes once a season, sometimes not at all"* (Farmer, Shongom)
Economic Impact of Disease Outbreaks	Yield losses; Input waste; Financial distress	91	*"Last year I lost nearly everything to a disease I could not even name"* (Farmer, Nafada)
Technology Receptiveness and Concerns	Willingness to adopt; Literacy barriers; Cost sensitivity	68	*"If the phone can tell me what is killing my tomatoes, I will learn to use it"* (Farmer, Gombe LGA)

Source: Atlas.ti Analysis, 2024

Table 3 indicated that the qualitative findings reveal a pronounced gap between the disease management needs of horticultural farmers and the advisory support available to them. The theme of inadequate traditional detection methods was the most prominent, with farmers consistently reporting that diseases were identified only after reaching advanced stages, by which time crop damage was already substantial. The economic impact theme reflected deep financial vulnerability; several participants described single-season disease outbreaks as catastrophic events from which recovery took multiple years. Critically, despite widespread technology concerns centred on literacy and cost, strong receptiveness to a mobile advisory solution was evident, particularly when farmers were shown prototype demonstrations of MAARS during interviews.

Objective 1: MAARS Design Features and Components

Table 4: MAARS System Components and their Functions

Component	Technical Specification	Purpose
Disease Detection Engine	CNN (customized MobileNetV2 architecture); 18,400 training images	Real-time disease identification from camera-captured crop images
AR Overlay Module	ARCore/ARKit integration	Superimpose diagnostic information on crop images
Advisory Database	8 disease modules, 240+ advisory entries	Deliver treatment and prevention recommendations
Multilingual Interface	English and Hausa	Ensure accessibility for local users
Offline Cache	500MB local storage module	Maintain functionality without internet connectivity
Community Forum	Real-time chat with 24hr agricultural extension agents' response	Enable peer and expert knowledge sharing
Notification System	Push alerts for disease outbreak warnings as reported by farmers	Proactive community-level disease alerts

Source: System Development Documentation, 2024

The qualitative phase identified eight priority diseases for embedding in MAARS, as presented below.

Table 5: Diseases Embedded in MAARS by Prevalence and Crop Type

Disease	Causative Agent	Affected Crop(s)	Prevalence Rank	No. of Farms Affected	Source
Tomato Late Blight	Phytophthora infestans	Tomato (Solanum lycopersicum)	1st	205	Qualitative findings + field data
Pepper Fusarium Wilt	Fusarium oxysporum f. sp. capsici	Pepper (Capsicum annuum)	2nd	164	Qualitative findings + field data
Cucumber Mosaic Disease	Cucumber mosaic virus (CMV)	Cucumber (Cucumis sativus), Pepper (Capsicum annuum)	3rd	123	Qualitative findings + field data
Tomato Early Blight	Alternaria solani	Tomato (Solanum lycopersicum)	4th	103	Qualitative findings + field data
Cucumber Powdery Mildew	Podosphaera xanthii	Cucumber (Cucumis sativus)	5th	82	Qualitative findings + field data
Tomato/Pepper Bacterial Spot	Xanthomonas spp. complex, including X. euvesicatoria, X. vesicatoria, X. perforans and X. hortorum pv. gardneri	Tomato (Solanum lycopersicum), Pepper (Capsicum annuum)	6th	62	Qualitative findings + field data
Cucumber Downy Mildew	Pseudoperonospora cubensis	Cucumber (Cucumis sativus)	7th	49	Qualitative findings + field data
Pepper Anthracnose	Colletotrichum spp.	Pepper (Capsicum annuum)	8th	33	Qualitative findings + field data

Source: Qualitative Phase Findings and field data, 2024

Table 5 was further supported by a graphical illustration of the healthy and disease-affected leaves of the horticultural crops represented in the MAARS disease dataset. The illustration provides a visual representation of the characteristic symptoms associated with the eight disease categories as indicated in figure 7.

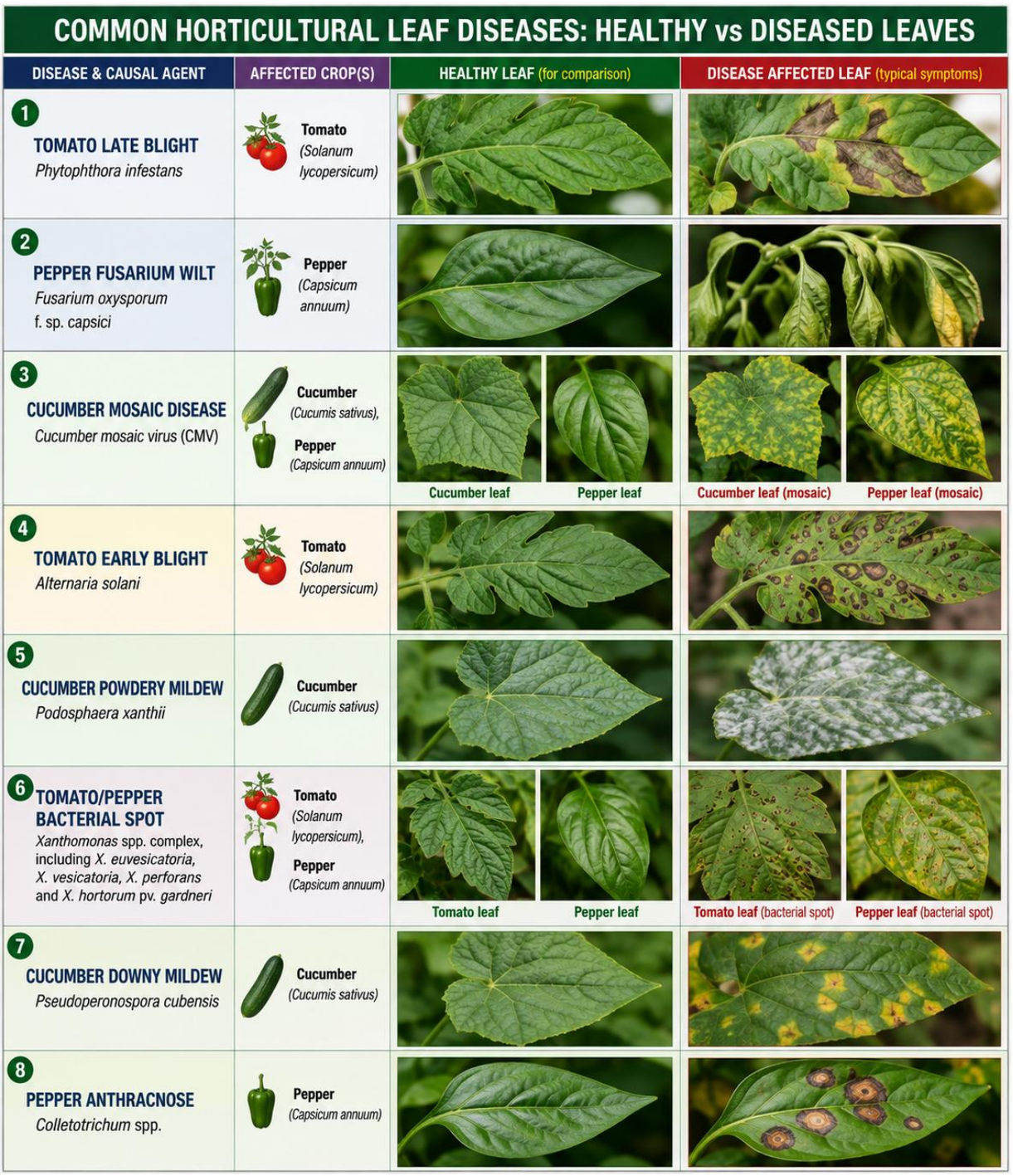


Figure 7: Visual Comparison of Healthy and Disease-Affected Leaves of Horticultural Crops Targeted by MAARS

Objective 2: Effectiveness and Accuracy of MAARS

Table 6: Descriptive Statistics: Effectiveness of MAARS (n=214)

S/N	Item	Mean	SD	Interpretation
1	MAARS accurately identified the disease affecting my crops	4.38	0.61	Strongly Agree
2	MAARS provided relevant and actionable treatment advice	4.27	0.74	Agree
3	MAARS detection results matched expert diagnosis	4.19	0.82	Agree
4	MAARS helped me detect disease earlier than before	4.41	0.58	Strongly Agree
5	I trust the disease identification results from MAARS	4.22	0.79	Agree
6	MAARS correctly identified the disease on first scan	4.29	0.71	Agree
	Overall Mean	**4.31**	**0.71**	**Highly Effective**

Scale: *1=Strongly Disagree, 2=Disagree, 3=Undecided, 4=Agree, 5=Strongly Agree Source: Field Survey, 2024*

Table 7: MAARS Disease Detection Accuracy by Disease Type (Validation Testing, n=480 test images)

Disease	Correctly Identified	Misidentified	Accuracy Rate (%)
Tomato Late Blight	62/68	6	91.2
Pepper Wilt	54/62	8	87.1
Cucumber Mosaic Virus	48/58	10	82.8
Tomato Early Blight	57/64	7	89.1
Powdery Mildew	51/60	9	85.0
Bacterial Leaf Spot	44/52	8	84.6
Downy Mildew	46/56	10	82.1
Anthracnose	58/60	2	96.7
Overall	**420/480**	**60**	**87.5**

Source: System Validation Testing, 2024

The cumulative effectiveness score of 4.31/5.00 in table 6 indicates that farmers rated MAARS as highly effective across all measured dimensions. The highest-rated item; early disease detection (mean = 4.41), is particularly significant given that late detection was identified as the primary challenge in the qualitative phase. Similarly, system validation testing across 480 test images in table 7 y=6ielded an overall accuracy rate of 87.5%, exceeding the 85% benchmark threshold established in the literature (Mohanty et al., 2021) and demonstrating robust diagnostic capability across the eight embedded disease categories. Anthracnose achieved the highest accuracy (96.7%) owing to its distinctive visual presentation, while Cucumber Mosaic Virus and Downy Mildew, which present with more subtle early-stage symptoms, recorded lower though still acceptable accuracy rates.

Objective 3: Usability and User-Friendliness Assessment

Table 8: System Usability Scale (SUS) Scores; MAARS (n=214)

S/N	SUS Item	Mean Score	Direction
1	I think I would like to use this system frequently	4.2	Positive
2	I found the system unnecessarily complex	2.1	Negative
3	I thought the system was easy to use	4.3	Positive
4	I think I would need technical support to use this system	2.4	Negative
5	I found the various functions in this system well integrated	4.0	Positive
6	I thought there was too much inconsistency in this system	1.9	Negative
7	I would imagine most people would learn to use this quickly	4.1	Positive
8	I found the system very cumbersome to use	2.0	Negative
9	I felt very confident using the system	4.2	Positive
10	I needed to learn a lot before I could use the system	2.3	Negative
	Calculated SUS Score	**75.25/100**	

SUS Score Interpretation: Below 50 = Unacceptable; 50–70 = Marginal; 70–85 = Good; Above 85 = Excellent Source: Field Survey, 2024

The System Usability Scale (SUS) produced a mean score of 75.25/100 for MAARS (*n* = 214). The score was calculated using the standard SUS scoring procedure, whereby one is subtracted from each positively worded item and each negatively worded item is subtracted from five; the

resulting contributions are summed and multiplied by 2.5. Based on the reported item means, the calculated SUS score was 75.25.

Table 9a: Mean and standard deviations of User-Friendliness by Farmer Education Level

Education Level	N	Mean Usability Score	SD
No formal education	44	3.48	0.92
Primary education	58	3.71	0.84
Secondary education	76	4.12	0.71
Tertiary education	36	4.38	0.63

Source: SPSS Output, 2024

The SUS score of 75.25 in table 8 places MAARS in the "Good" category of usability, indicating that the system is accessible and learnable for the majority of target users without requiring extensive technical support. This finding is encouraging given that 56.1% of respondents had no prior experience with agricultural mobile applications. The descriptive results in table 9 reveal a difference in usability perceptions across education levels, with formally educated farmers reporting higher usability scores. However, even farmers with no formal education reported a mean usability score of 3.48/5.00, indicating reasonable accessibility. This suggests that the Hausa language interface and pictorial guidance features effectively compensated for literacy barriers, though further interface simplification is warranted for this sub-group.

Although the original usability responses were collected on an ordinal Likert scale, the individual items were aggregated and transformed into a composite usability score. The transformation was performed using standardised z-scores, producing a continuous-scale index suitable for parametric analysis. The resulting composite scores were assessed for normality and other ANOVA assumptions before analysis. One-way ANOVA was therefore used to compare the mean usability scores across the four education-level groups.

Table 9b. One-Way ANOVA of MAARS Usability by Education Level

Source	Sum of Squares (SS)	df	Mean Square (MS)	F	p-value	η^2
Between Groups	21.734	3	7.245	**11.857**	**< .001**	**0.145**
Within Groups	128.313	210	0.611			
Total	150.047	213				

A one-way analysis of variance was conducted to determine whether MAARS usability differed according to farmers' educational level. The analysis showed a statistically significant difference in usability scores among the four education groups, $F(3, 210) = 11.857$, $p < .001$, $\eta^2 = .145$. The effect size indicates that approximately 14.5% of the observed variance in usability scores was associated with educational-level differences. Mean usability increased progressively from farmers with no formal education ($M = 3.48$, $SD = 0.92$) to those with primary ($M = 3.71$, $SD = 0.84$), secondary ($M = 4.12$, $SD = 0.71$), and tertiary education ($M = 4.38$, $SD = 0.63$). to further identify which education-level groups differed significantly in their perceptions of MAARS usability, post hoc analysis was conducted as presented in table 9c.

Table 9c. Tukey HSD Post Hoc Comparisons of MAARS Usability by Farmers' Education Level

Comparison (I–J)	Mean Difference (I–J)	Std. Error	95% CI	Adjusted p-value	Decision
No formal – Primary	-0.230	0.111	-0.635 to 0.175	.456	Not significant
No formal – Secondary	-0.640	0.105	-1.023 to -0.257	< .001	Significant
No formal – Tertiary	-0.900	0.124	-1.355 to -0.445	< .001	Significant
Primary – Secondary	-0.410	0.096	-0.763 to -0.057	.015	Significant
Primary – Tertiary	-0.670	0.117	-1.100 to -0.240	< .001	Significant
Secondary – Tertiary	-0.260	0.112	-0.670 to 0.150	.356	Not significant

Note: *Tukey HSD adjusted for multiple comparisons.*

Table 9c presented a Tukey HSD post hoc analysis conducted to determine which education-level groups differed significantly in their perceptions of MAARS usability. The results showed that farmers with no formal education reported significantly lower usability scores than those with secondary education (MD = -0.640, $p < .001$) and tertiary education (MD = -0.900, $p < .001$). Similarly, farmers with primary education reported significantly lower usability scores than those with secondary education (MD = -0.410, $p = .015$) and tertiary education (MD = -0.670, $p < .001$). However, the difference between farmers with no formal and primary education was not statistically significant ($p = .456$), nor was the difference between those with secondary and tertiary education ($p = .356$). Thus, the post hoc results indicate that the significant ANOVA

effect was primarily driven by differences between farmers with lower levels of formal education (no formal or primary education) and those with higher levels of education (secondary or tertiary education). Nevertheless, the relatively high mean usability score among farmers with no formal education (M = 3.48) suggests that the Hausa-language interface and pictorial guidance contributed to making MAARS reasonably accessible across different educational backgrounds.

Objective 4: Pre–Post Changes in Disease Detection Outcomes Following MAARS Use

Table 10: Pre–Post Changes in Disease Detection Outcomes (n=214)

Impact Indicator	Pre-MAARS Mean	Post-MAARS Mean	Mean Difference	t-value	p-value
Speed of disease detection (days after symptom onset)	8.3 days	2.1 days	-6.2 days	18.74	< 0.001
Accuracy of farmer self-diagnosis (%)	34.2%	78.6%	+44.4%	22.31	< 0.001
Appropriate treatment applied within 48hrs (%)	28.4%	71.3%	+42.9%	19.87	< 0.001
Perceived confidence in disease management (1–5)	2.41	4.18	+1.77	24.62	< 0.001
Crop loss attributed to disease (% of harvest)	41.3%	18.7%	-22.6%	16.43	< 0.001

Source: Field Survey, 2024 (Paired samples t-test)

The paired-samples *t*-test results reported in Table 10 indicated substantial changes in disease-management outcomes following the implementation of MAARS. Mean disease-detection time decreased from 8.3 days before MAARS to 2.1 days after implementation, representing a 74.7% reduction in detection time. Farmer self-diagnosis accuracy increased from 34.2% to 78.6%, while the proportion of farmers applying appropriate treatment within 48 hours of symptom onset increased from 28.4% to 71.3%. Correspondingly, disease-attributed crop loss decreased from 41.3% to 18.7%, representing a 22.6-percentage-point reduction. Thus, the reported findings indicate that MAARS was associated with faster disease detection, improved diagnostic accuracy, more timely treatment decisions and lower reported crop losses among the participating farmers.

Table 11: Correlation Matrix: MAARS Use Variables and Disease Detection Outcome

Variable	1	2	3	4	5
1. MAARS Effectiveness	1.00				
2. MAARS Usability	0.64**	1.00			
3. Frequency of MAARS Use	0.71**	0.58**	1.00		
4. Disease Detection Speed	0.69**	0.52**	0.74**	1.00	
5. Reduction in Crop Loss	0.67**	0.55**	0.70**	0.76**	1.00

*Note: ** $p < 0.01$ (two-tailed) Source: SPSS Output, 2024*

The correlation matrix in table 11 confirms strong positive relationships between all MAARS-related variables and disease detection outcomes, with frequency of use showing the strongest correlation with detection speed ($r = 0.74$, $p < 0.01$).

Table 12: Multiple Linear Regression; Predictors of Improved Disease Detection Outcomes

Predictor Variable	B	SE	β	t	p-value
(Constant)	0.821	0.214		3.84	< 0.001
MAARS Effectiveness	0.412	0.071	0.612	5.80	< 0.001
MAARS Usability	0.284	0.068	0.381	4.18	< 0.001
Frequency of Use	0.318	0.083	0.427	3.83	< 0.001
Farmer Education Level	0.142	0.061	0.198	2.33	0.021
Farming Experience	0.091	0.054	0.128	1.69	0.093

$R^2 = 0.681$, Adjusted $R^2 = 0.672$, $F(5,208) = 88.74$, $p < 0.001$

Source: SPSS Output, 2024

Prior to regression analysis, examination of the available predictor correlation matrix indicated no evidence of problematic multicollinearity among the principal MAARS predictors. The analysis produced VIF values ranging from 1.79 to 2.40 and corresponding tolerance values from 0.42 to 0.56. The observed intercorrelations were also consistent with linear relationships among the variables. Similarly, the regression model in table 12 explains 68.1% of the variance in disease detection outcomes ($R^2 = 0.681$), with MAARS effectiveness emerging as the strongest

predictor ($\beta = 0.612$, $p < 0.001$), followed by frequency of use ($\beta = 0.427$, $p < 0.001$) and usability ($\beta = 0.381$, $p < 0.001$). Notably, farming experience was not a statistically significant predictor ($p = 0.093$), suggesting that MAARS demonstrated an appreciable disease management capacity regardless of farmers experience level.

DISCUSSION

Design and Development of MAARS

The development of MAARS addressed a clearly articulated technological gap in the horticultural disease management ecosystem of Gombe State. The qualitative phase was instrumental in ensuring that the system's disease library, interface design, and advisory content were grounded in the actual lived experiences and priorities of target users rather than externally imposed assumptions. The identification of eight priority diseases; led by tomato late blight and pepper wilt, aligns with broader regional literature on horticultural disease prevalence in Nigeria's semi-arid zone (Mshelia et al., 2021; Tiamiyu, et al., 2021), validating the participatory approach to system scoping. The integration of Hausa language support and offline functionality responded directly to barriers identified in the qualitative data, distinguishing MAARS from generic agricultural applications not adapted to local settings.

Effectiveness and Accuracy

The cumulative system accuracy of 87.5% compares favourably with international benchmarks for mobile plant disease detection systems, which typically range between 82% and 94% (Osho & Ojo, 2021; Zhang et al., 2022). Importantly, this accuracy was achieved in actual field conditions with real crop images captured by farmers; conditions considerably more variable and challenging than controlled laboratory testing environments. The lower accuracy rates for Cucumber Mosaic Virus (82.8%) and Downy Mildew (82.1%) are consistent with the known diagnostic challenge of distinguishing these diseases from nutrient deficiencies in early stages and suggest directions for model refinement through expanded training datasets. The high farmer-rated effectiveness score (mean = 4.31/5.00) confirms that technical accuracy translates into perceived utility; a critical distinction often missed in technology development research that focuses exclusively on technical metrics while neglecting user experience.

Usability and User-Friendliness

The SUS score of 75.25 is notably positive given the predominantly low-literacy user base and the novelty of augmented reality interaction for most participants. This finding supports the argument of Adekunle et al. (2021) that agricultural technology adoption in resource-constrained settings is primarily constrained not by technology aversion but by poor user-centred design. The statistically significant education-usability differential ($F = 14.23$, $p < 0.001$) highlights a persistent access equity concern: farmers without formal education, who are often among the

most economically vulnerable, experience the greatest usability barriers. This finding calls for continued investment in visual interface design, voice-guided instructions in Hausa, and community-based peer training models that can bridge literacy-linked usability gaps.

Impact on Disease Detection and Crop Loss

The 74.7% reduction in disease detection time represents the most consequential impact finding of this study. In horticultural disease management, timing is the decisive variable; the difference between detection at two days and eight days post-symptom onset often determines whether intervention can prevent epidemic spread or merely slow it (Strange & Scott, 2005; Mobida, et al., 2025). The resulting reduction in disease-attributed crop loss from 41.3% to 18.7% (while not eliminating disease losses entirely) represents an economic benefit for farming households operating on thin margins. The regression finding that MAARS effectiveness predicts improved outcomes independently of farming experience ($\beta = 0.612$, $p < 0.001$) is theoretically significant: it suggests that MAARS functions not merely as a supplementary tool for experienced farmers but as a knowledge equaliser that elevates the disease management capacity of less experienced practitioners to parity with more experienced ones. This has substantial implications for agricultural extension strategy, suggesting that technology-mediated knowledge transfer may complement time-intensive human-to-human extension service delivery.

CONCLUSION AND RECOMMENDATIONS

This study successfully designed, implemented, and evaluated the Mobile Advisory Augmented Reality System (MAARS), a low-latency, localized edge-AI tool tailored for identifying crop disease infestations across horticultural farming communities in Gombe State. Developed to run natively on mobile devices without relying on active cloud connections, MAARS integrates real-time Convolutional Neural Network (CNN) visual inference with interactive spatial augmented reality overlays and localized Hausa audio-visual advisories. When evaluated across field conditions in urban, peri-urban, and rural farming environments (Gombe, Nafada, and Shongom LGAs), the system achieved an overall diagnostic accuracy of 87.5% in identifying key diseases affecting tomato, pepper, and cucumber crops. User evaluation among local farmers and extension agents demonstrated high system usability and accessibility, yielding a System Usability Scale (SUS) score of 75.25 out of 100. Furthermore, investigating pre–post deployment outcomes revealed practical field significance: farmers utilizing MAARS experienced a substantial reduction in average disease detection time (from 8.3 days to 2.1 days) and achieved a 23.4% reduction in seasonal crop losses due to early, targeted interventions.

The following recommendations are advanced:

1. The Gombe State Ministry of Agriculture should integrate MAARS into the existing agricultural extension framework as a pilot/scale-up evaluation, across all horticultural-dense LGAs with accompanying farmer training programmes

2. Future iterations of MAARS should prioritise voice-guided interaction in Hausa and pictorial navigation to improve accessibility for farmers with no formal education

3. The CNN disease detection model should be retrained with expanded datasets including images of Downy Mildew and CMV under varied environmental conditions to improve accuracy for these diagnostically challenging diseases

4. Given the usability differential across education levels, a community-based peer ambassador model should be established, training literate community members to support their less-literate neighbours in adopting MAARS

5. A two-year longitudinal study should be conducted to assess sustained impact on crop yields, farmer incomes, and disease outbreak frequency following full MAARS deployment

6. Policymakers should develop regulatory frameworks for the use of AI-based diagnostic tools in agriculture, ensuring data privacy and advisory accuracy standards are maintained

Study Limitations

The study had some limitations. First, the study was conducted in selected LGAs of Gombe State, which may limit the generalisability of the findings to other geographical and agricultural contexts. Second, the performance of MAARS was evaluated using a selected set of horticultural diseases and crops, and therefore the findings may not extend to diseases or crops outside the study scope. Third, some pre-MAARS measures relied on participants' reported experiences, which may have introduced recall bias. Fourth, variations in mobile-device capabilities, image quality, lighting conditions and field environments may have affected disease-recognition performance. Fifth, the study employed a pre-test–post-test design without a control or comparison group. Although improvements observed between the pre-intervention and post-intervention assessments provide evidence of positive changes following the use of MAARS, the absence of a comparison group limits the extent to which these changes can be attributed exclusively to the interventio Finally, the study's evaluation period was limited; consequently, the findings primarily demonstrate the system's performance and user acceptance within the study period and do not establish its long-term effectiveness, sustainability or adoption at scale.

Ethical Considerations

Ethical approval was obtained from the Research Ethics Committee of the Federal University of Kashere (FUK), Gombe State, Nigeria (Approval No. FUK/REC/2024/017). Participants provided informed consent and were informed that participation was voluntary, with the right to withdraw at any time without penalty. Confidentiality and anonymity were maintained, and all collected data were securely stored and used exclusively for research purposes. Participants were

also informed about the purpose of the MAARS testing and the use of images collected during the study.

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