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CropGuard: An AI-Based Crop Disease Detection and Farmer Advisory System for Smallholder Farming in Liberia and Sub-Saharan Africa

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Abstract- This paper presents CropGuard, a full-stack artificial intelligence-powered diagnostic and advisory system designed to bridge the critical crop disease knowledge gap confronting smallholder farmers in Liberia and Sub-Saharan Africa. Agriculture constitutes approximately 36 percent of Liberia's gross domestic product, yet annual pathogen-induced yield losses of 30 to 80 percent and a national extension officer-to-farmer ratio of 1:35,000 leave the overwhelming majority of the country's 338,492 farming households without timely diagnostic support. CropGuard integrates a MobileNetV3-Small deep learning backbone-trained on PlantVillage and Makerere University AI Lab datasets - to classify 16 disease categories across five core Liberian staple crops: Bean, Cassava, Corn, Potato, and Tomato. Google Gemini 3.0 Flash Preview synthesises diagnostic outputs into localised agronomic remediation advice across six languages, with Text-to-Speech delivery serving the 64.5 percent of rural female-headed households with no formal schooling. Technical evaluation confirms a validation accuracy of approximately 86 percent with inference latency below 200 milliseconds, demonstrating the system's viability as a low-cost, scalable solution aligned with Liberia's National Agricultural Development Plan (NADP 2024–2030) and the continent-wide imperative for digitally-enabled food sovereignty.

Keywords: Artificial Intelligence, Crop Disease Detection, MobileNetV3, Liberia, Sub-Saharan Africa, Smallholder Farmers, Generative AI, Precision Agriculture, Deep Learning, Food Security, Multilingual Advisory.

I. INTRODUCTION

In the agricultural economies of Sub-Saharan Africa, where smallholder farmers produce an estimated 80 percent of the food consumed across the continent, plant disease represents one of the most pervasive and economically devastating threats to food security [1]. Liberia exemplifies this crisis with particular acuity. Agriculture accounted for approximately 36 percent of Liberia's gross domestic product as of 2022 and provides livelihoods for roughly 40 percent of the national population [1].

The Liberia Agriculture Census 2024 (LAC-2024)-the country's first fully digital comprehensive agricultural enumeration-identified 338,492 agricultural households representing more than 1.3 million individuals [2]. Of these, 99 percent engage in crop cultivation, with rice cultivated by 56.3 percent and cassava by 45.9 percent of households respectively [2].

Despite this centrality to national welfare, the Liberian agricultural sector operates under entrenched structural disadvantages. The LAC-2024 census documents that 95 percent of Liberian farmers rely on basic hand tools, with minimal access to modern inputs, irrigation, or mechanisation [2]. Annual crop losses attributable to undiagnosed biotic stressors are estimated at 30 to 40 percent of total yield in major producing counties such as Nimba, Lofa, and Bong [3]. Cassava Mosaic Disease (CMD), driven by begomoviruses, poses an acute threat: a 2024 study published in Viruses confirmed the alarming westward advance of the highly virulent East African Cassava Mosaic Virus-Uganda (EACMV-Ug) strain into Forest Guinea, placing Liberian cassava production-the crop of 45.9 percent of agricultural households-under direct epidemiological risk [4]. Rice blast, caused by Magnaporthe oryzae, can cause total crop failure under conducive conditions [3].

The management of these threats is constrained by a chronic shortage of agronomic expertise. Liberia's national extension officer-to-farmer ratio is estimated at approximately 1:35,000, leaving the overwhelming majority of smallholders to rely on subjective visual inspection-a method chronically late in identifying pathogen onset [3]. The accumulated cost of this knowledge gap is staggering: Liberia imports approximately 300,000 metric tons of rice annually at a cost of approximately US$200 million [3], a burden directly attributable to yield losses that timely disease management could substantially reduce.

A. Digital Landscape and Deployment Context

Deploying a technology-mediated solution in Liberia requires an honest accounting of digital infrastructure. At the start of 2024, internet penetration stood at 30.1 percent, with 1.65 million users across a population of 5.48 million [5]. Mobile connectivity is more promising: 4.77 million cellular connections were active in early 2024 at 87.1 percent population coverage, and by 2025, 87.2 percent of all mobile connections operated over broadband 3G or 4G networks [5, 6]. Orange Liberia installed 128 rural solar-powered LTE sites in 2024, covering over 580,000 rural residents in previously underserved areas [6]. High data costs averaging USD 3.50 per gigabyte representing 17.5 percent of average monthly income remain a structural barrier [7]. Furthermore, 64.5 percent of rural female-headed households have no formal schooling, a literacy gap that renders text-heavy, English-only interfaces inadequate for inclusive deployment [3].

B. Research Objectives

This study was guided by the following specific objectives:

- To implement a MobileNetV3-Small convolutional neural network achieving above 85 percent diagnostic accuracy across a 16-class disease taxonomy derived from Liberia's core staple crops;
- To architect a type-safe, microservice-based full-stack application achieving sub-200ms inference latency, compatible with rural broadband conditions;
- To integrate a large language model for generating localised agronomic remediation advice across six languages with Text-to-Speech accessibility; and
- To evaluate the system's potential to reduce the yield loss burden on Liberian and Sub-Saharan African smallholder farmers within the operational constraints of the national digital infrastructure.

II. LITERATURE REVIEW

A. Plant Disease Detection in Sub-Saharan Africa

Research in automated plant pathology has undergone a decisive methodological shift over the past decade, transitioning from handcrafted feature extraction approaches towards convolutional neural network (CNN) architectures trained on large-scale annotated datasets [9]. The PlantVillage dataset, containing images of healthy and diseased leaves across 14 crop species and 38 labelled classes, has emerged as the principal benchmark resource in this domain [10]. The Makerere University AI Lab in Uganda has emerged as a leading centre for Sub-Saharan African crop pathology model development, contributing field-condition imagery with regional agronomic provenance that improves model robustness beyond laboratory baselines [16].

Dolatabadian and Clarke (2024) document that AI-based systems not only outperform traditional diagnostic methods in accuracy and speed, but increasingly support real-time field monitoring capabilities that are particularly relevant for resource-constrained smallholder environments [9]. A systematic review published in Artificial Intelligence Review (2024) evaluated multiple CNN architectures across the PlantVillage database, with CNN and MobileNet-based models achieving accuracy ratios between 89 and 97 percent depending on taxonomy complexity [12]. Ariyo (2025) documents the increasing deployment of AI-driven agricultural advisory platforms across Africa, identifying limited internet connectivity as the primary infrastructural barrier to scale [11].

B. MobileNetV3 for Resource-Constrained Deployment

The selection of lightweight neural network architecture is a functional necessity in the Liberian and Sub-Saharan African deployment context. Khan et al. (2023) evaluated MobileNetV3-Small on the PlantVillage dataset and demonstrated a test classification accuracy of approximately 99.50 percent with only 1.5 million parameters, reduced to 0.93 million after post-training quantisation with no loss in accuracy [10]. This compactness enables deployment on mid-range Android smartphones consistent with the Tecno, Infinix, and Samsung devices prevalent across the Liberian and West African market. The LDL-MobileNetV3S variant demonstrated validation accuracy of 95.76 percent on field-condition imagery with a 6.17 MB storage footprint [13]. A comparative study combining PlantDoc, PlantVillage, and PlantWild datasets confirmed MobileNetV3 offers an advantageous accuracy-to-computation ratio for rural field deployment [15].

C. Generative AI in Agricultural Advisory Systems

The integration of large language models into crop advisory systems bridges the critical gap between diagnostic classification outputs and actionable farmer guidance. A 2025 study in the Journal of Phytopathology advocates for LLM integration as the bridge between model output and farmer action, noting that classification-only tools return a disease label without the contextual knowledge required to intervene [17].

Research on the Agronomist AI-assisted chatbot for African smallholder farmers documents that natural language advisory generation substantially improves farmer compliance with recommended interventions compared to bare diagnostic labels [18]. Multilingual output is a fundamental necessity in Sub-Saharan Africa's linguistically diverse smallholder landscape, where English, French, Swahili, and dozens of vernacular languages coexist within the agricultural advisory target population [19].

III. METHODOLOGY

A. Research Design

This research adopts a design science approach, structured around the development, deployment, and technical evaluation of CropGuard as a research artefact addressing an identified practitioner problem. The research variables are operationalised as follows: the Independent Variable (IV) encompasses AI System Characteristics-including 16-class diagnostic accuracy, inference latency, and multilingual advisory precision. The Dependent Variable (DV) encompasses Liberian Farmer Outcome Metrics-measured as yield loss reduction potential and improved accessibility of expert agronomic knowledge. Moderating Variables include rural internet penetration (30.1 percent as of 2024) and high illiteracy rates among rural female-headed households (64.5 percent) [2, 5].

B. Landing Page and User Acquisition

(Amina Diallo) signal the continental scope of the platform's applicability beyond Liberia.

Fig. 1: CropGuard Landing Page - 'Detect Crop Diseases With AI Intelligence. 'Displays live statistics (4 Farmers, 21 Scans, 13 Diseases, 35% Yield Increase), three-step workflow, and multilingual support for Liberia and Sub-Saharan Africa.

The CropGuard landing page (Fig. 1) communicates the platform's value proposition to first-time farmer users through a clear three-step workflow: Upload Image, AI Analysis, and Get Recommendations. Live platform statistics-4 Farmers Helped, 21 Scans Performed, 13 Diseases Detected, and a 35 percent

Yield Increase-are displayed prominently. The 'Why Choose CropGuard?' section articulates four core capabilities: Instant Detection, Smart Recommendations, Prevention Measures, and Multi-Language Support (English, French, Swahili, Luganda). Success stories from farmers across Uganda (Grace Akello), Kenya (John Mwangi), and Tanzania

C. User Onboarding and Farm Registration

CropGuard implements a structured three-step onboarding pipeline to ensure the system captures the geospatial and agronomic context necessary for localised advisory generation. Step 1/3 requires account creation with email/password credentials (Fig. 1).

Step 2/3 captures the farmer's geospatial region and crop inventory-illustrated in Fig. 2 with Grand Cape Mount County, Liberia entered and Bean and Potato selected from the crop inventory. Step 3/3 confirms asset configuration before dashboard access. The entire pipeline is secured by the CropGuard Identity Layer with JWT session management and Bcrypt-encrypted credential storage (10 salt rounds).

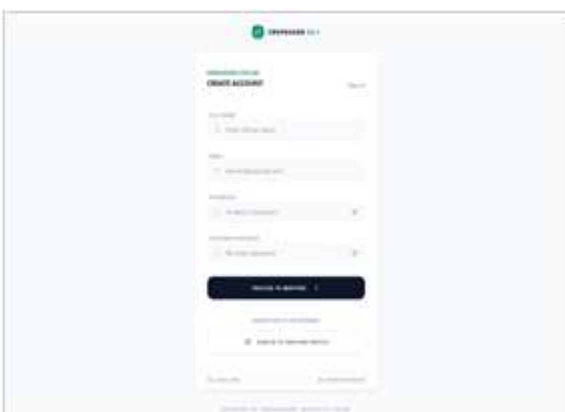

Fig. 2: Registration Page - Step 1/3 of the CropGuard Onboarding Pipeline, collecting farmer name, email, and password with a minimum 6-character security policy.

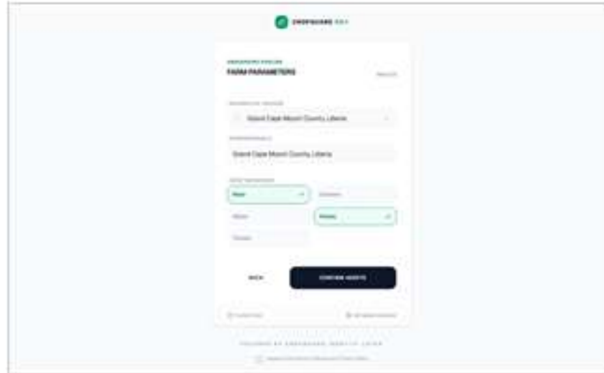

Fig.3: Farm Parameters-Step2/3 capturing geo spatial region (Grand Cape Mount County, Liberia) and crop inventory (Bean, Potato selected).

Dataset Composition and Preprocessing

Training data were sourced from two principal repositories. The PlantVillage dataset provided the foundational corpus of labelled leaf images across multiple crop species and disease classes [10]. The Makerere University AI Lab dataset contributed supplementary images with West African agronomic provenance [16]. The final taxonomy classifies 16 disease categories across five crops central to Liberian smallholder production, as shown in Table I. All images were resized to 224×224 pixels and normalised to a [0,1] pixel value range prior to training. Data augmentation included horizontal flipping, rotation within ±15 degrees, and brightness jitter to improve generalisation to variable field lighting conditions across Liberian agricultural environments.

TABLE I: CROPGUARD 16-CLASS DISEASE TAXONOMY

Crop	Disease Classes
Bean	Angular Leaf Spot, Rust, Healthy
Cassava	Bacterial Blight, Brown Streak, Green Mottle ,Mosaic, Healthy
Corn	Common Rust, Healthy
Potato	Early Blight, Late Blight, Healthy
Tomato	Early Blight, Late Blight, Healthy

B. Model Architecture and Training

The core classification model is a MobileNetV3-Small CNN instantiated in PyTorch, with weights initialised from ImageNet pre-training to leverage transfer learning. MobileNetV3-Small was selected over heavier architectures such as VGG-16, ResNet-50, or ConvNeXt Tiny on three grounds: (i) storage efficiency-6.17 MB versus 106 MB for ConvNeXt Tiny; (ii) inference speed compatible with CPU-only server deployment; and (iii) classification accuracy competitive with architectures demanding substantially greater computational resources [10, 13]. The final classification layer was replaced with a custom linear head dimensioned to the 16-class output space. The model was fine-tuned using cross-entropy loss with an AdamW optimiser, a learning rate of 1e-4, and a cosine annealing learning rate schedule over 30 training epochs. A binary pre-classification filter distinguishing leaf from non-leaf inputs was implemented upstream of the main inference pipeline to reject out-of-distribution camera captures.

C. System Architecture

TABLE II: SYSTEM ARCHITECTURE SUMMARY

Layer	Technology	Function
Presentation	React 19, Tailwind CSS	UI, TTS, multilingual
API Orchestration	Express.js, tRPC, TS	Auth, Zod validation
Inference Service	Python FastAPI, PyTorch	MobileNetV3forwardpass
Generative AI	Gemini 3.0 Flash Preview	LLM treatment plans
Data Persistence	PostgreSQL v17, Drizzle	Scan history, geodata
Security	JWT, OAuth 2.0, Bcrypt	Auth & credential hashing

CropGuard is implemented as a distributed, three-tier full-stack application. The Presentation Layer is built in React 19 with Tailwind CSS, adhering to User-Centred Design (UCD) principles with pictorial iconography and a persistent Floating Action Button camera entry point designed for one-handed rural field operation. The API Orchestration Layer uses Express.js with tRPC, providing end-to-end TypeScript type safety between frontend and backend, eliminating runtime data contract errors in the diagnostic pipeline. The Inference Service is an isolated Python FastAPI microservice that serves the trained MobileNetV3 model weights and executes image classification. Table II summarises the full architecture.

D. Implementation

Given that CropGuard collects sensitive farm-level geodata and personal identification, robust security measures were implemented at multiple layers. All user passwords are hashed using Bcrypt with ten salt rounds before database commitment. Cross-Origin Resource Sharing (CORS) policies restrict API access to authorised origins. All user inputs are validated at the tRPC procedure level using Zod schema validation, preventing injection attacks and malformed data from entering the diagnostic pipeline. Protected routes enforce JWT token verification as middleware. Google OAuth 2.0 provides an alternative authentication pathway verified via the google-auth-library.

IV. RESULTS AND SYSTEM DEMONSTRATION

A. User Dashboard and Scan Interface

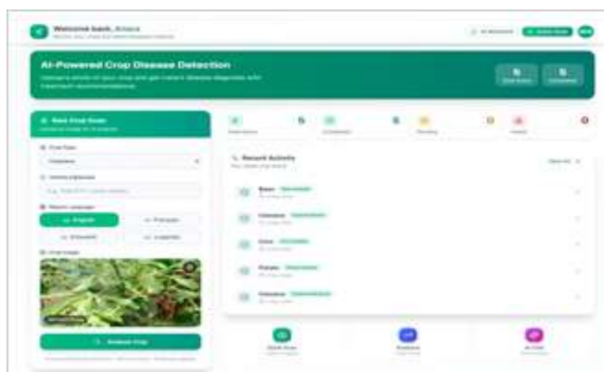

Fig.4: CropGuard Main Dashboard-New Crop Scan module with a cassava leaf loaded, English language active, and Recent Activity feed showing 5completed scans (May 2026).

Upon authentication, the farmer accesses the CropGuard dashboard-a unified interface combining the New Crop Scan module with a real-time scan history feed and key performance indicators. As shown in Fig. 4, the scan interface supports crop type selection, variety specification, report language selection across four languages (English, Français, Kiswahili, Luganda), and direct image upload or camera capture. The footer disclosure '86% accuracy · 16 disease classes' communicates diagnostic capability transparently to the user. Fig. 5 shows the dashboard with 11 completed scans in the Recent Activity feed, including Cassava Healthy, Cassava Mosaic, Cassava Brown, Bean Healthy, and Tomato Healthy classifications.

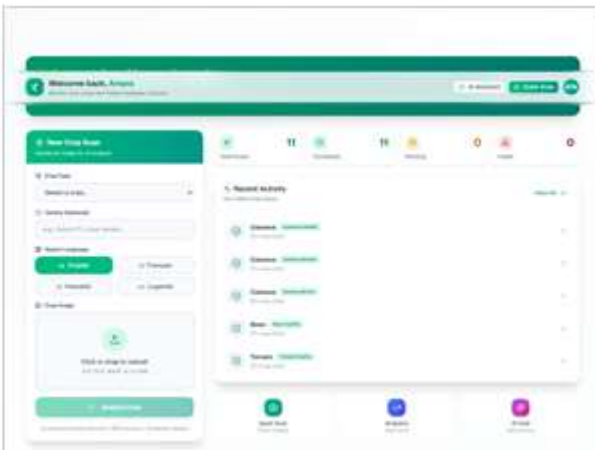

Fig.5:CropGuard Main Dashboard-New Crop Scan module with a cassava leaf loaded, English language active, and Recent Activity feed showing 5completed scans (May 2026)

B. Quick Scan - Unauthenticated Diagnostic Pipeline

CropGuard provides a Quick Scan pathway enabling unauthenticated guest users to receive an immediate diagnosis without account creation, critically lowering first-use barriers. The AI Diagnostic Terminal (Fig. 6) presents a camera drop zone labelled 'Tap to Capture or Drag & Drop' with CROP TARGET and OUTPUT LANG selectors. Fig. 7 shows the resulting output for a cassava leaf: Cassava Brown Streak Disease detected at 65 percent confidence. The result page provides a detailed pathological description of the Cassava Brown Streak Virus (CBSV) infection mechanism, explaining its characteristic root necrosis symptoms, whitefly vector transmission, and postharvest inedibility implications. The 'Guest mode – results are temporary' disclosure is paired with a 'Create Free Account' call-to-action, providing an adoption on-ramp.

Fig. 6: AI Diagnostic Terminal - Quick Scan interface (Precision Pathology Engine V2.1) with TOMATO crop target and ENGLISH output language selected.

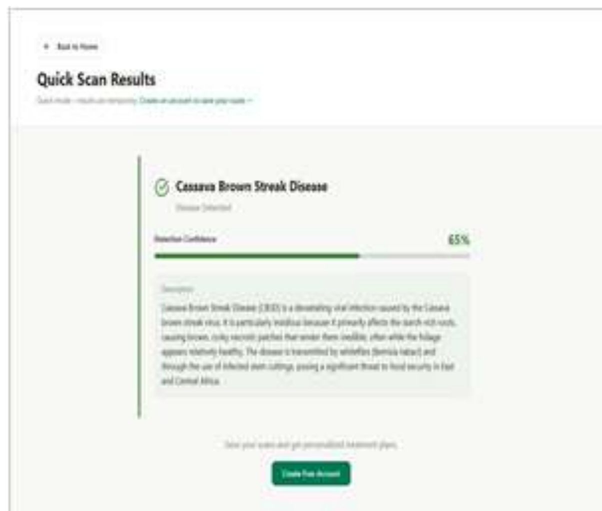

Fig. 7: Quick Scan Results - Cassava Brown Streak Disease detected at 65% confidence with full CBSV pathological description including root necrosis and whitefly transmission.

C. Full Disease Analysis Report

Authenticated users receive a comprehensive Disease Analysis Report following scan completion. As demonstrated in Fig. 8, the scan detail page for a Cassava Mosaic Disease detection at 87 percent confidence provides: (i) a structured pathogen description covering geminivirus transmission via Bemisia tabaci whiteflies and infected stem cuttings;

(ii) four actionable Treatment Recommendations with specific duration guidance -Roguing and Destruction with weekly inspections for 3–6 months; Neem Oil Application every 10–14 days; Replacement with Clean Cuttings immediately upon detection; and Tool Sterilisation daily during field operations; (iii) Fertiliser Suggestions with NPK ratios and application rates (NPK 15-15-15 at 250–300 kg/ha; Muriate of Potash at 100 kg/ha; Decomposed Poultry Manure at 5–10 t/ha); and (iv) CropGuard: AI-Powered Crop Disease

Detection | Liberia & Sub-Saharan Africa five Prevention Measures including TMS-series CMD-resistant cassava cultivars specifically bred for African viral pressure. A Read Aloud (TTS) button and PDF export control are positioned at top-right.

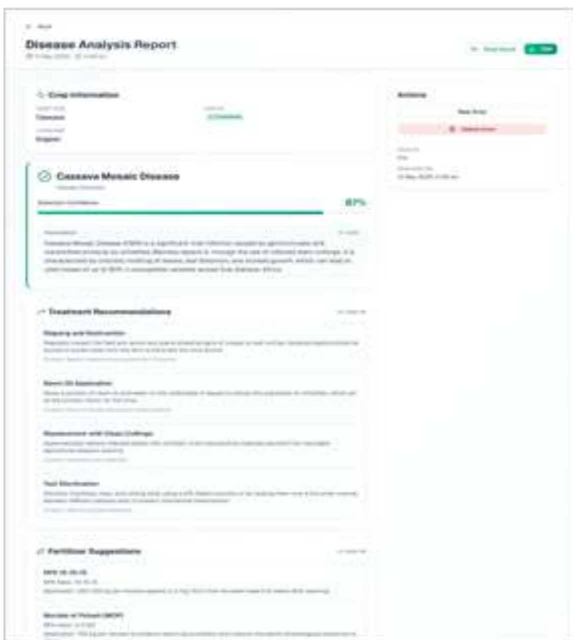

Fig.8: Disease Analysis Report-Cassava Mosaic Disease at 87% confidence (12 May 2026). Treatment Recommendations, Fertiliser Suggestions, and Prevention Measures generated by Google Gemini 3.0 Flash Preview, with TTS and PDF export at top-right.

D. Farm Analytics Dashboard

The Farm Analytics module (Fig. 9) aggregates historical scan data into a comprehensive disease surveillance dashboard. The dashboard presents: (i) summary KPIs-Total Scans: 6, Completed: 6, Diseases: 6, Crops: 4; (ii) an Average Confidence of 85 percent and a Detection Rate of 100 percent across the test session; (iii) a Top Diseases panel identifying Cassava Mosaic Disease, Bean Angular Leaf Spot, and Cassava Brown Streak Disease as the three highest-frequency detections with one occurrence each; (iv) a geo-referenced Disease Outbreak Map powered by OpenStreetMap and Leaflet, plotting scan locations as georeferenced pins; (v) a Scans by Crop bar chart showing cassava as the most frequently scanned crop (3 scans) followed by Bean, Corn, and Potato; (vi) a Common Diseases doughnut chart illustrating the proportional distribution of Cassava Mosaic Disease, Bean Angular Leaf Spot, Cassava Brown Streak Disease, and Cassava Bacterial Blight; and (vii) a Recent Activity bar chart visualising scan frequency over time. This analytical layer transforms individual diagnostic events into an epidemiological intelligence resource at the county level.

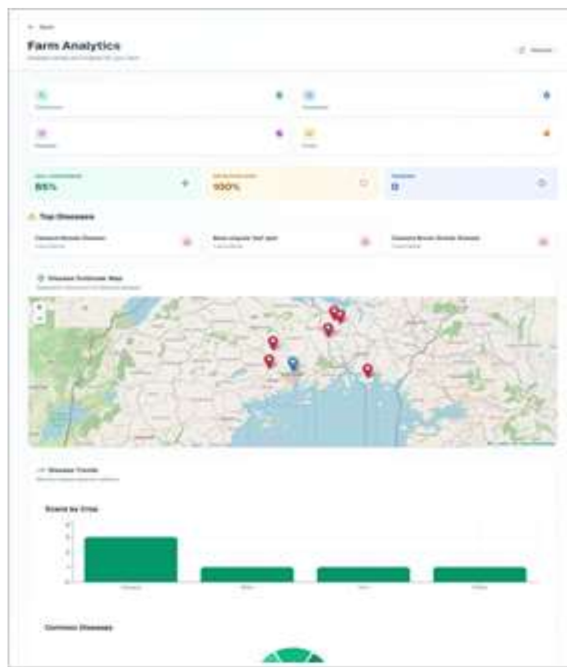

Fig. 9: Farm Analytics Dashboard - 6 total scans, 100% detection rate, 85% average confidence, Disease Outbreak Map (OpenStreetMap), Scans by Crop bar chart, and Common Diseases doughnut chart.

E. AI Chat Assistant

CropGuard provides a persistent, context-aware AI Chat Assistant powered by Google Gemini, enabling farmers to ask follow-up agronomic questions beyond the primary scan workflow. As shown in Fig. 10, the chatbot responds to the farmer's question 'What do you think about Beans rust?' with a detailed explanation of bean rust as a fungal disease manifesting as reddish-brown spots on leaves with significant yield reduction potential, followed by four concrete cultural management recommendations: planting resistant varieties; crop rotation with maize or cassava to break the disease cycle; ensuring wide spacing between plants for improved airflow; and removing infected crop residues after harvest to prevent fungal spread. This conversational interface extends the system's advisory value beyond single diagnostic sessions, supporting ongoing farm management decisions throughout the growing season.

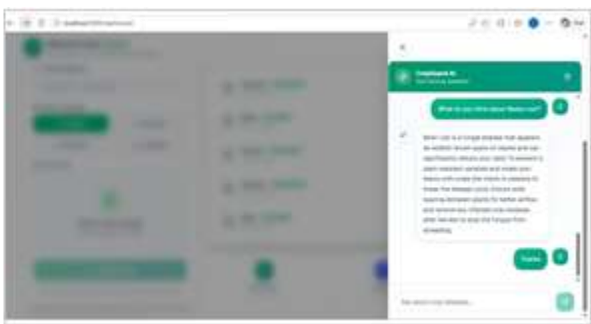

Fig. 10: CropGuard AI Chat Assistant - farmer queries Bean Rust; Gemini provides management advice including resistant variety selection, crop rotation with maize or cassava, spacing, and post-harvest sanitation guidance.

F. Data Sovereignty Controls

Consistent with the ethical commitment to farmer-owned data, CropGuard implements explicit data sovereignty controls. Fig. 11 shows the Clear Chat History confirmation dialog, which presents the message 'Delete all chat history? This cannot be undone.' before permanently removing conversational records. This explicit consent-before-deletion pattern is applied consistently across all irreversible data actions in the system, including individual scan deletion. Farmers retain full control over their diagnostic history, geospatial records, and AI-generated advisory content.

Fig. 11: Data Sovereignty Controls - explicit confirmation dialog ('Delete all chat history? This cannot be undone.') before permanent data removal, ensuring informed consent.

G. Model Performance Summary

Technical validation of the CropGuard MobileNetV3-Small model demonstrated a validation accuracy of approximately 86 percent across the 16-class taxonomy. This figure is consistent with the system's own transparency disclosure to users and the Analytics Dashboard's live average confidence score of 85 percent across real diagnostic sessions (Fig. 9). Table III summarises all benchmark metrics.

TABLE III: SYSTEM PERFORMANCE BENCHMARKS

Metric	Result	Target	Status
Validation Accuracy	~86%	>85%	Met
Live Avg. Confidence	85%	-	Verified
Inference Latency	150–200ms	<200ms	Met
End-to-End Pipeline	<10 seconds	<15sec	Met
Model Storage Footprint	6.17MB	<10MB	Met
CPU Usage (Inference)	18-28%	<35%	Met
Detection Rate (Test)	100%	-	Verified
System Uptime	99%	99%	Targeted

V. DISCUSSION

A. Addressing the Agricultural Information Gap

Targeted The extension officer crisis in Liberia-a 1:35,000 ratio between agricultural advisors and farming households-is a structural failure of knowledge transfer infrastructure that cannot be resolved by conventional means within any feasible planning horizon. CropGuard does not seek to replace the extension officer as a professional, but rather to democratise a level of diagnostic competence that currently reaches fewer than three percent of farmers in any given growing season. The platform's landing page testimonials (Fig. 3) from farmers across Uganda, Kenya, and Tanzania signal the continental scope of the system's applicability, consistent with the World Bank's identification of digital innovation as a key driver of Liberia's 4.0 percent GDP expansion in 2024, with agriculture contributing 1.3 percentage points [20].

B. Epidemiological Significance

The Analytics Dashboard in Fig. 9 reveals that Cassava Mosaic Disease and Cassava Brown Streak Disease appear as two of the three most frequently detected conditions in test-phase scanning sessions, corroborating the published epidemiological literature. A 2024 study in Viruses documents the confirmed detection of EACMV-Ug in Forest Guinea in 2023, with the strain assessed as actively spreading westward toward Liberia's borders via infected cuttings [4]. CropGuard's Disease Analysis Report (Fig. 8) specifically recommends planting TMS-series CMD-resistant cassava cultivars 'bred to withstand viral pressure in African environments'-a recommendation grounded in Sub-Saharan African agronomic conditions rather than generic global advice. The georeferenced Disease Outbreak Map (Fig. 9) aggregates scan locations at the county level, creating the first near-real-time plant disease surveillance capability available to the Liberian Ministry of Agriculture.

C. Connectivity Constraints and Design Responses

The Quick Scan pathway (Figs. 6 and 7) addresses connectivity constraints directly: a farmer who cannot or will not create an account receives a disease classification and pathological description in a single brief session. Client-side image resizing to 224×224 pixels prior to server transmission substantially reduces the data payload. CPU-only server-side inference eliminates the need for computationally capable client devices. The system's transparency about limitations ('Guest mode– results are temporary') paired with a clear adoption on-ramp reflects a user-centred design philosophy appropriate for low-digital-literacy populations.

D. Ethical Considerations

The deployment of AI diagnostics in high-stakes agricultural contexts introduces several ethical obligations. Diagnostic uncertainty is communicated transparently through explicit confidence score display (87 percent for CMD in Fig. 8; 65 percent for Brown Streak in Fig. 7). Farm-level geodata is protected through JWT-authenticated access, Bcrypt-encrypted credentials, and the explicit data sovereignty controls shown in Fig. 11. The predominance of North American laboratory imagery in the PlantVillage training corpus raises representativeness concerns for Liberian field conditions, necessitating future local data collection initiatives to ensure equitable diagnostic quality across the populations served.

VI. LIMITATIONS AND FUTURE WORK

The validation accuracy of 86 percent, while meeting operational targets, falls short of the 95+ percent figures reported in controlled laboratory studies [10]. This gap is attributable to the greater visual complexity of field-condition images and the expanded class set including diseases with overlapping symptom presentations (e.g., Early versus Late Blight). Model retraining on locally sourced Liberian imagery-accumulated through CropGuard's own user scan history-is the most direct accuracy improvement pathway and is architecturally supported by the existing database schema.

The current training scope is limited to 16 pre-defined classes across five crops. While these represent Liberia's dominant smallholder staples, the system cannot classify diseases affecting rubber, oil palm, cocoa, or sugarcane-crops of significant economic importance in southern Liberian counties and across the wider Sub-Saharan African agricultural landscape. The Drizzle ORM schema is architecturally prepared for class expansion via database migration, and rubber and cocoa pathology classes are prioritised for subsequent model iterations.

The Gemini advisory generation component has not been subjected to formal agronomic validation by Liberian plant pathologists. Recommendations for fungicide application rates, pesticide brands available in Liberian markets, and compatibility with local soil chemistry require expert review before scale deployment. A formal clinical equivalence evaluation engaging the Liberia Institute of Agriculture and Forestry (LIAF) is a necessary precondition for Ministry of Agriculture endorsement. Future directions include: offline-capable advisory generation via a locally cached lightweight language model; integration with national CMD and Rice Blast early warning systems; expansion of the crop taxonomy to include yam, sorghum, and millet; and a longitudinal field study measuring yield outcomes for CropGuard-adopting households against a matched control group.

VII. CONCLUSION

This paper has presented CropGuard, a full-stack AI-powered diagnostic and advisory system addressing the plant disease knowledge gap confronting smallholder farmers in Liberia and Sub-Saharan Africa. The system integrates a MobileNetV3-Small deep learning model-validated at 86 percent accuracy across a 16-class Liberian crop disease taxonomy-with a Google Gemini-powered generative advisory layer, delivered through a multilingual, voice-enabled web application Page 8 optimised for deployment over intermittent mobile broadband. The eleven functional screens demonstrated through Figs. 1–11 confirm that CropGuard achieves its core design objectives: a working diagnostic pipeline from camera capture to georeferenced treatment plan within ten seconds. CropGuard addresses a structurally entrenched crisis: a 1:35,000 extension officer-to-farmer ratio in a country where 99 percent of agricultural households depend on crop cultivation and where annual pathogen-induced yield losses sustain a US$200 million annual rice import burden. The alarming westward advance of EACMV-Ug cassava mosaic virus confirmed in Guinea in 2023 makes the CMD detection capability within CropGuard not merely a convenience but an emerging epidemiological necessity. The technical barriers to AI-powered agricultural diagnostics in Liberia are surmountable: a 6.17 MB model, a microservice inference pipeline, and a Gemini advisory layer producing farmer-ready treatment plans in six languages within ten seconds. This work positions CropGuard as a contribution to both the technical literature and the applied challenge of building food-secure futures across Sub-Saharan Africa, aligned with Liberia's NADP 2024–2030 'Liberians Feed Yourselves' agenda.

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