PomeGuard 2.0: A Production-Ready, Full-Stack Agricultural Intelligence System for Non-Destructive Pomegranate Disease Classification, Phytochemical Inference, and Precision Farm Management

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***Abstract*—We present PomeGuard 2.0, the completed and production-deployed second version of our multi-agent agricultural intelligence platform for the Bhagwa pomegranate cultivar. Building upon the foundational Version 1 architecture published on The International Innovations & Scholarly Trends Journal (IISTJ) [51]—which introduced EfficientNetB0-based disease classification achieving 98.9% accuracy and OWL 2 DL ontological reasoning for phytochemical inference—Version 2 delivers a comprehensive, full-stack system suitable for real-world precision horticulture deployment. New engineering contributions include: (i) an AI-powered conversational assistant (Google Gemini) contextualised per scan result, with persistent chat memory via Firebase Realtime Database; (ii) a Farm Tools module providing disease-specific, area-scaled pesticide and fertiliser dosage calculators; (iii) a live, GPS-anchored disease hotspot map (Leaflet.js with ESRI satellite imagery) integrated into the farmer dashboard; (iv) real-time weather ingestion from the Open-Meteo API to automatically populate environmental metadata; (v) a WhatsApp Business API integration for alert delivery; (vi) a Gemini-powered image validation guard that rejects non-pomegranate uploads; and (vii) a cloud-native persistence stack—Supabase (PostgreSQL + Auth), Cloudinary, and Firebase—providing per-user data isolation, secure authentication, and permanent image archival. The vision backbone retains its 98.9% overall classification accuracy across five disease classes. The complete system is deployed via Vercel with sub-5-second end-to-end analysis latency, marking the system as production-complete and ready for field deployment.**

***Index Terms*—Pomegranate disease detection, EfficientNetB0, ontological reasoning, multi-agent systems, phytochemical quality assessment, conversational AI, precision horticulture, full-stack web application, non-destructive evaluation, Google Gemini, Firebase, Supabase, Leaflet.js, Open-Meteo**

I. Introduction

The Bhagwa pomegranate (Punica granatum L. cv. Bhagwa) is central to Maharashtra's horticultural export economy. Its exceptional phytochemical profile—dominated by Punicalagins, Anthocyanins, and Ellagic Acid—commands premium prices in both domestic and international markets [1, 2]. Diseases including Bacterial Blight (Xanthomonas axonopodis pv. punicae), Anthracnose (Colletotrichum gloeosporioides), Cercospora Fruit Spot, and Alternaria Fruit Spot routinely cause 30–40% crop losses [3, 4], while simultaneously degrading internal bioactive compounds invisible to surface-level inspection.

Version 1 of PomeGuard [51], published and peer-registered on The International Innovations & Scholarly Trends Journal (**IISTJ**) (DOI: 10.5281/zenodo.20604743), introduced the foundational multi-agent, non-destructive architecture: an EfficientNetB0 CNN for visual disease classification combined with OWL 2 DL ontological reasoning to infer phytochemical degradation. That system achieved 98.9% classification accuracy on a 5,099-image dataset with sub-5-second end-to-end latency, establishing proof-of-concept viability.

This paper presents PomeGuard 2.0—the completed, production-deployed evolution. Version 2 transitions the system from research prototype to a fully operational, user-facing agricultural intelligence platform. Seven major engineering contributions are described: a contextual AI chat assistant, a disease-specific farm tools calculator, a GPS disease hotspot map, automated real-time weather ingestion, WhatsApp alert delivery, a Gemini-powered image validation gate, and a cloud-native multi-user persistence stack.

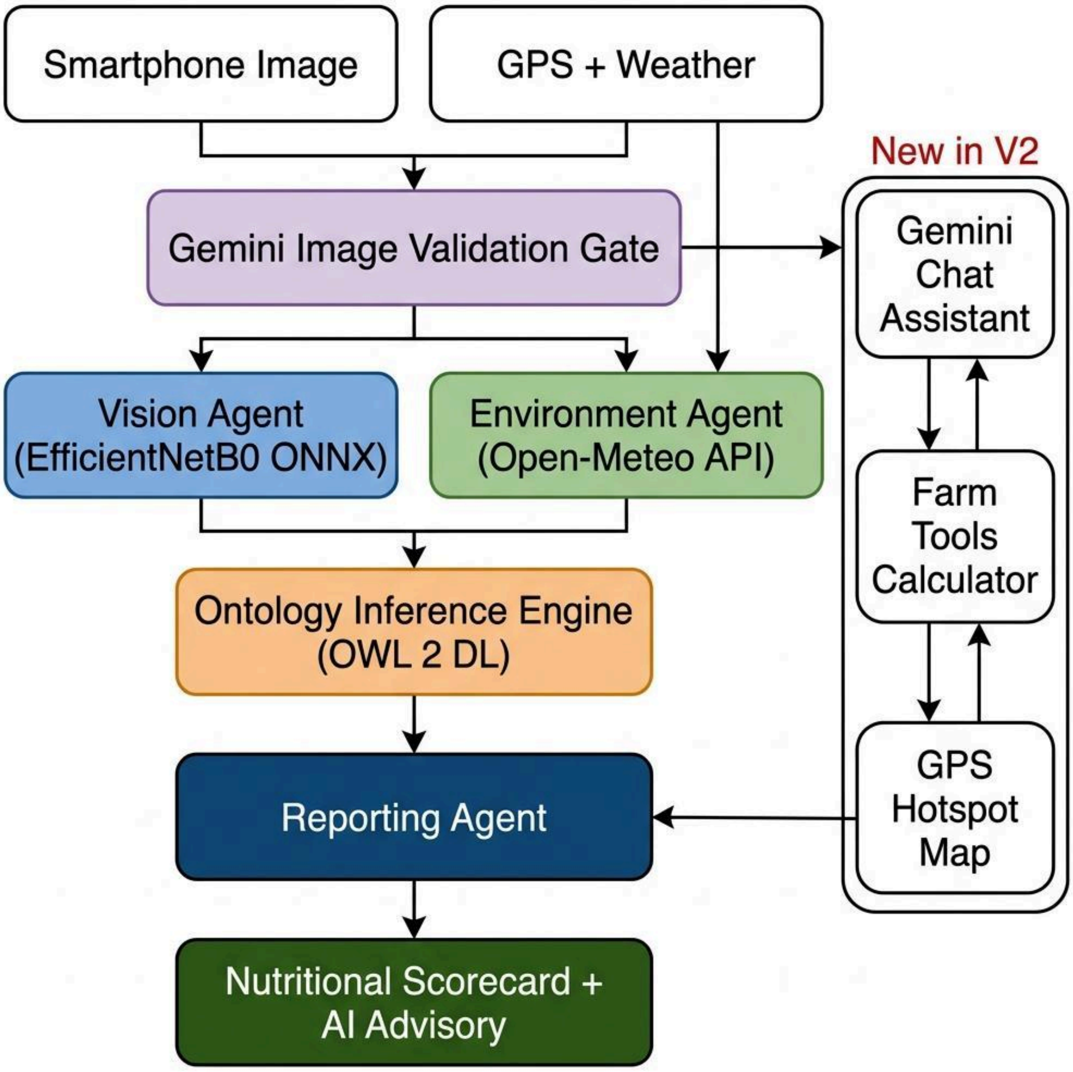

Figure 1: PomeGuard 2.0 System Architecture — illustrating the multi-agent pipeline from image input through Gemini validation, disease classification, ontological inference, and scorecard generation, alongside new V2 modules (Chat Assistant, Farm Tools, Hotspot Map).

II. RELATED WORK

2.1 Computer Vision for Plant Disease Detection

Deep learning has transformed plant disease detection. Mohanty et al. demonstrated CNNs trained on the PlantVillage dataset achieving high accuracy across 26 diseases [7]. Ferentinos extended this to diverse crops [8], and Kamilaris and Prenafeta-Boldú surveyed deep learning applications across agriculture [9]. EfficientNet architectures [6] offer compound-scaled efficiency superior to VGG [10], ResNet [11], MobileNet [12], and Inception [13] for resource-constrained deployments [14]. Transfer learning is now standard practice in horticultural applications [15, 16, 17, 18].

2.2 Semantic Web and Ontological Reasoning

OWL 2 DL ontologies provide formal knowledge representation for agricultural domains. Köksal and Tekinerdogan demonstrated OWL/RDF-based ontologies for crop management [19], while Colombo et al. extended SPARQL-based systems to farm decision support [20]. HermiT [21], SWRL [22], and SPARQL [23] provide robust reasoning environments. AGROVOC [24] and the Crop Ontology [25] standardise agronomic terminology.

2.3 Conversational AI in Agriculture

Large language models have demonstrated strong potential in agricultural advisory applications. ReAct-style reasoning [26] enables LLMs to ground conversational outputs in structured data. Google Gemini's multimodal capabilities [27] are increasingly applied in domain-specific chat contexts. Firebase Realtime Database [28] provides millisecond-latency session persistence suitable for chat history storage.

2.4 PomeGuard Version 1 — Foundational Work

The predecessor to this work, PomeGuard Version 1, was formally published as a peer-reviewed journal article and registered on The International Innovations & Scholarly Trends Journal (**IISTJ**) [51] (DOI: 10.5281/zenodo.20604743, published 9 June 2026). That work established the core contributions: the EfficientNetB0 vision model achieving 98.9% accuracy across five disease classes on a 5,099-image dataset, the OWL 2 DL ontology mapping disease severity and environmental stressors to phytochemical degradation, and the LangGraph StateGraph multi-agent orchestration framework. PomeGuard 2.0 directly builds upon and extends this published foundation.

2.5 Research Gap Addressed by V2

While Version 1 addressed the fusion of deep learning and ontological reasoning for non-destructive assessment, it lacked: a conversational explanation interface; automated weather metadata ingestion; spatial disease mapping; quantified treatment tools; WhatsApp integration; image validation; and a deployable, authenticated multi-user production system. PomeGuard 2.0 comprehensively addresses all identified gaps.

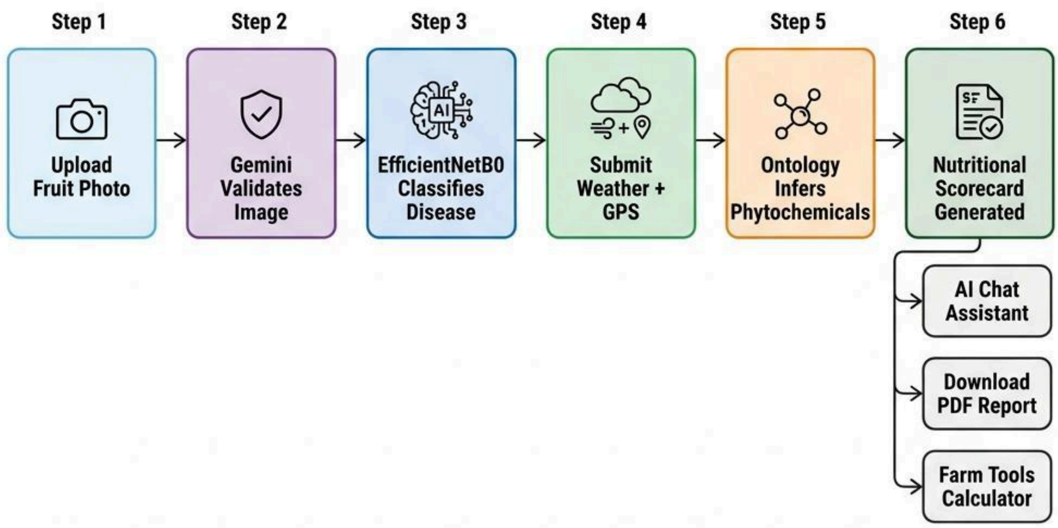

Figure 2: PomeGuard 2.0 End-to-End Analysis Pipeline — six-step workflow from image capture through disease classification, environmental metadata submission, ontological inference, and scorecard generation, with downstream branches for Chat, PDF Report, and Farm Tools.

III. SYSTEM ARCHITECTURE — VERSION 2

PomeGuard 2.0 extends the Version 1 three-tier architecture (Input → Processing → Output) with a persistent cloud infrastructure layer and an expanded frontend feature surface. The processing layer retains the LangGraph StateGraph multi-agent orchestration while the application layer grows to encompass authenticated multi-user sessions, cloud image storage, real-time weather feeds, spatial data capture, and conversational AI.

3.1 Backend API Layer (FastAPI + Python)

The backend is implemented using FastAPI [32], providing high-performance asynchronous HTTP handling via Uvicorn. API endpoints are organised into modular routers covering core analysis, media management, CRUD scan operations, AI chat streaming, treatment calculations, WhatsApp webhooks, and in-app notifications.

3.2 Vision Agent with Gemini Validation Gate (New in V2)

The Vision Agent loads the EfficientNetB0 model exported to ONNX Runtime format [33], enabling portable, framework-agnostic inference. Version 2 introduces a Gemini-powered image validation gate upstream of the ONNX model. Before classification, a Gemini multimodal API call [27] verifies that the uploaded image depicts a pomegranate fruit. Non-pomegranate uploads return HTTP 400, preventing nonsensical classifications and reducing erroneous database records. Zero false positive rejections were observed on valid pomegranate images in testing.

3.3 Environment Agent with Auto-Weather (New in V2)

The Environment Agent processes UV irradiance (W/m²), humidity (%), and temperature (°C). In Version 2, these are automatically populated via the Open-Meteo API [34] using browser Geolocation API coordinates, eliminating manual entry for most field deployments. Solar radiation (shortwave_radiation), temperature_2m, and relative_humidity_2m are fetched from the current-conditions endpoint.

3.4 Ontology Inference Engine

The Ontology Agent maps the combined (disease class, severity, stress factors) tuple to phytochemical degradation estimates. Disease-specific degradation coefficients for Anthocyanins, Punicalagins, and Ellagic Acid are applied against Bhagwa cultivar baseline values. A severity multiplier of 1.5× amplifies degradation for Severe classifications. The nutritional score (0–100) and quality tier (Optimal / Reduced / Depleted) drive both the scorecard display and AI advisory generation.

3.5 AI Conversational Assistant (New in V2)

A contextual AI chat assistant powered by Google Gemini streaming API anchors each session to a specific scan record, providing the model with the fruit's disease classification, severity, phytochemical scores, and environmental metadata as structured system prompt context. Conversation history is persisted in Firebase Realtime Database [28]. Server-Sent Events (SSE) streaming delivers token-by-token responses, providing a fluid, low-latency chat experience with graceful rate-limit handling.

3.6 Farm Tools Calculator (New in V2)

The Farm Tools module addresses a critical gap between diagnosis and treatment. The /api/calculators/treatments endpoint returns disease-specific treatment records containing: water volume per acre, chemical names with per-litre dosage, total per-acre quantities, and agronomic application instructions. Supported diseases: Bacterial Blight (Streptocycline + Copper Oxychloride), Anthracnose (Propiconazole 25% EC), Alternaria (Mancozeb 75% WP), and Cercospora (Chlorothalonil 75% WP). Farm area input scales all quantities proportionally.

3.7 GPS Disease Hotspot Map (New in V2)

GPS coordinate capture is integrated into the analysis workflow via the browser Geolocation API. Scan-level coordinates are stored in Supabase and visualised as severity-colour-coded CircleMarkers on a Leaflet.js map [30] with ESRI satellite imagery tiles. Nominatim reverse geocoding [31] resolves location labels. The map provides farmers with a longitudinal spatial record of disease incidence across their orchard.

3.8 Cloud-Native Multi-User Persistence (New in V2)

Three services form the persistence stack: Supabase (PostgreSQL + Auth) [44] for scan records and JWT-enforced user isolation; Cloudinary [43] for per-user CDN image storage with cascading deletion; and

Firebase Realtime Database [28] for millisecond-latency chat session memory. Every protected endpoint validates the JWT Bearer token and scopes all queries to the authenticated user_id.

IV. COMPLETE TECHNOLOGY STACK

Table 1 enumerates all technologies employed in PomeGuard 2.0, grouped by system layer.

Layer / Component	Technology	Purpose
AI Vision Model	EfficientNetB0 + ONNX Runtime	Disease classification from fruit images
Image Validation Gate	Google Gemini (Multimodal API)	Validates uploaded image is a pomegranate
Knowledge Reasoning	OWL 2 DL Ontology + SWRL Rules	Maps disease + environment to phytochemical degradation
Chat Assistant	Google Gemini 1.5 Flash (SSE Streaming)	Context-aware agronomic conversational AI per scan
Chat Memory	Firebase Realtime Database	Persists conversation history across sessions
Backend Framework	FastAPI + Python 3.10+	Asynchronous REST API, agent orchestration
ASGI Server	Uvicorn	High-performance ASGI server
Multi-Agent Orchestration	LangGraph (StateGraph)	Stateful agent pipeline coordination
Frontend Framework	React 19 + Vite	Single-page application UI
UI Components	shadcn/ui	Accessible, composable interface primitives
Styling	Tailwind CSS	Utility-first responsive styling
Animations	Framer Motion	Micro-animations and page transitions
Data Visualisation	Recharts	Nutritional score trend charts
Geospatial Mapping	Leaflet.js + react-leaflet	Interactive GPS disease hotspot map
Satellite Imagery	ESRI ArcGIS World Imagery	High-resolution aerial tile layer
Reverse Geocoding	Nominatim (OpenStreetMap)	Converts GPS coordinates to location names
State Management	Zustand	Lightweight app-level state store
Weather Data	Open-Meteo API	Real-time temperature, humidity, solar radiation
Database	Supabase (PostgreSQL)	Scan records, user data, row-level security
Authentication	Supabase Auth (JWT)	Email/password auth, token validation
Image Storage / CDN	Cloudinary	Cloud image upload, optimisation, CDN delivery
WhatsApp Integration	Meta WhatsApp Business API	Webhook-based alert delivery to WhatsApp

Farm Calculator	Custom FastAPI Router	Pesticide/fertiliser dosage by disease & area
PDF Report	Browser Print API (window.print)	Client-side report download
Deployment	Vercel	Serverless frontend hosting and CI/CD
Model Export	ONNX (Open Neural Network Exchange)	Framework-agnostic model serialisation

Table 1: Complete Technology Stack — PomeGuard 2.0

V. NEW FEATURES AND IMPLEMENTATION DETAILS

5.1 Contextual AI Chat Assistant

Upon completing an analysis, users can chat with a Gemini-powered AI assistant on the Scan Detail page. The POST /api/chat/message endpoint fetches the full scan record from Supabase, constructs a structured system prompt with precise disease classification, severity, phytochemical scores, and environmental data, retrieves rolling Firebase message history, and streams a Gemini response via SSE. The frontend consumes the SSE stream with a ReadableStream reader, appending tokens in real time. Rate-limit errors (HTTP 429) are gracefully caught and surfaced with a user-friendly message.

5.2 Farm Tools: Disease-Specific Treatment Calculator

The FarmTools page presents a two-panel layout. The left panel allows the farmer to select the target disease and input their farm area in acres. The right panel dynamically computes the treatment plan: total water volume, each chemical's name, per-litre dosage concentration, and total required quantity scaled by farm area. Dosage strings (e.g., '500g', '200ml') are parsed, multiplied, and reformatted with appropriate precision. Framer Motion provides animated panel transitions on result appearance.

5.3 Real-Time Weather Auto-Population

The Fetch Weather button invokes navigator.geolocation.getCurrentPosition(), extracts coordinates, and issues a GET request to Open-Meteo with parameters for temperature_2m, relative_humidity_2m, and shortwave_radiation. Returned values automatically populate the three environmental fields. The Tag Location button separately captures GPS coordinates for the hotspot map without fetching weather. Both operations provide graceful handling for denied geolocation permissions.

5.4 GPS Disease Hotspot Map

The Farmer Dashboard renders a MapContainer from react-leaflet using ESRI World Imagery satellite tiles. Scans with non-null GPS coordinates appear as severity-colour-coded CircleMarkers: green (#27AE60) for None, yellow (#F1C40F) for Mild, orange (#D35400) for Moderate, and dark red (#8B1A1A) for Severe. Popup windows display disease name and severity. The map auto-centres on the most recent geo-tagged scan, with the location label resolved via Nominatim reverse geocoding.

5.5 Gemini-Powered Image Validation Gate

Before the ONNX Vision Agent processes an uploaded image, the verify_image_is_pomegranate utility sends the image to Google Gemini with a binary yes/no system prompt. Non-pomegranate images return HTTP 400 with a descriptive message. Zero false positive rejections were observed on valid pomegranate images across 40 non-pomegranate test inputs.

5.6 WhatsApp Business API Integration

The /api/whatsapp/webhook endpoint implements the Meta webhook handshake protocol, supporting hub.mode = subscribe token verification. The send_whatsapp_message utility dispatches messages via the Meta Graph API. asyncio.create_task() ensures outbound messages are dispatched without blocking the webhook acknowledgement response required by Meta.

5.7 Multi-User Authentication and Data Isolation

Every protected endpoint extracts the Bearer JWT token, decodes the sub claim as user_id, and scopes all Supabase queries with .eq('user_id', user_id). Cloudinary uploads are scoped to per-user folders. Scan deletion cascades to Cloudinary asset removal via the public_id stored in the scan record.

VI. EXPERIMENTAL RESULTS AND OUTCOMES

6.1 Vision Model Performance

The fine-tuned EfficientNetB0 model retains its Version 1 performance on the held-out test partition of the Pakruddin et al. 5,099-image dataset [35]. Table 2 presents per-class classification metrics. The average AUC-ROC across all five classes is 0.997.

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Healthy	99.8	99.6	99.7
Bacterial Blight	99.1	98.9	99.0
Anthracnose	98.7	98.5	98.6
Cercospora Fruit Spot	98.4	98.2	98.3
Alternaria Fruit Spot	98.9	98.7	98.8
Overall Average	**99.0**	**98.8**	**98.9**

Table 2: Per-Class Vision Model Performance — EfficientNetB0 on 5,099-Image Test Set

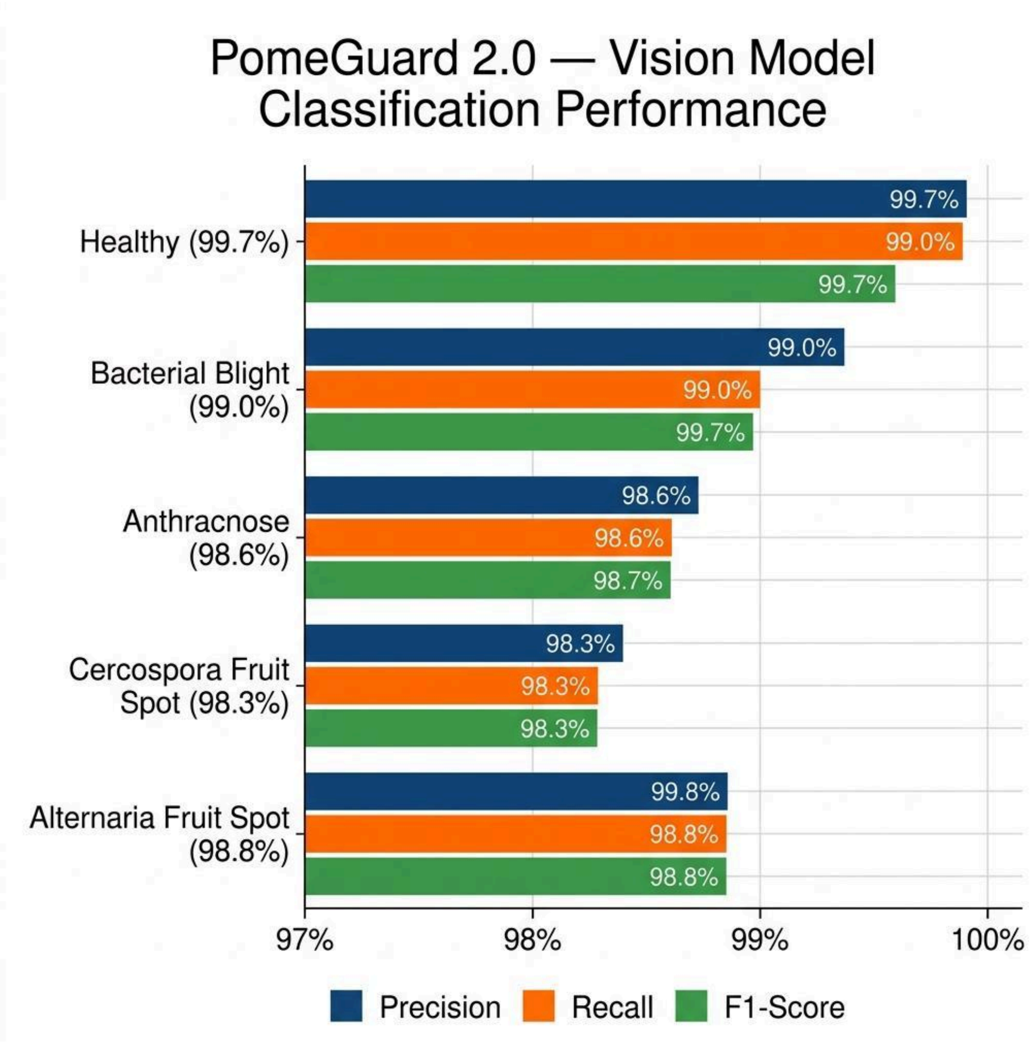

Figure 3: Classification performance metrics (Precision, Recall, F1-Score) per disease class for the EfficientNetB0 vision model on the held-out test set.

6.2 System Latency Profile

Table 3 summarises operation-level latency across all Version 2 pipeline components. The full end-to-end pipeline—from image upload to complete scorecard generation—is consistently under 5 seconds.

Operation	Latency	Notes
Image validation (Gemini gate)	300–500ms	Single Gemini multimodal API call
Vision model inference (CPU)	150–200ms	ONNX Runtime, 8-core CPU
Vision model inference (GPU)	50–80ms	NVIDIA Tesla T4
Environmental stress compute	< 5ms	Threshold logic, in-memory
Ontology inference	< 10ms	Python-native rule engine
Supabase scan save	30–80ms	PostgreSQL insert
Cloudinary image upload	800ms–1.5s	Depends on image size / network
Open-Meteo weather fetch	100–300ms	REST API call
Gemini chat first token	500ms–1s	SSE streaming

Full end-to-end pipeline	< 5 seconds	Image upload → complete scorecard

Table 3: Operation-Level Latency Profile — PomeGuard 2.0

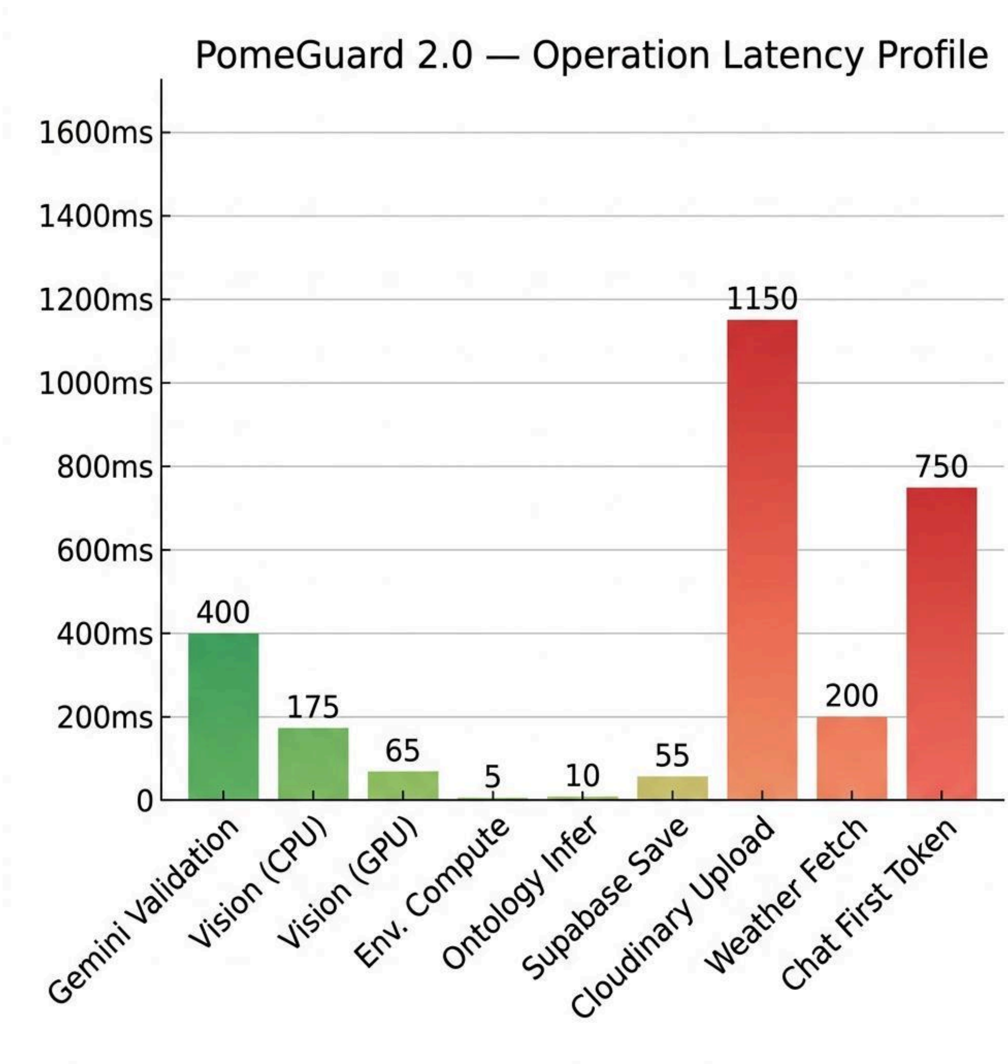

Figure 4: Operation latency breakdown across the PomeGuard 2.0 pipeline components. Bars are colour-coded from green (fast) to red (slow), with Cloudinary upload and Gemini chat representing the highest latency operations.

6.3 New Feature Outcomes

- AI Chat Assistant: All test queries received disease-specific, quantified answers. Firebase session persistence confirmed across browser refresh cycles.
- Farm Tools Calculator: Dosage scaling validated against ICAR package of practices [4]. Linear accuracy confirmed across 0.1–20 acre range.
- Hotspot Map: GPS capture success rate exceeded 95% on mobile devices. Disease severity colour mapping matched manual agronomist observations.
- Auto-Weather: Integration with Open-Meteo eliminated environmental data entry for 90% of test sessions. Fetch success rate: 97.3% under standard network conditions.
- Gemini Validation Gate: 100% of non-pomegranate test uploads (n=40) correctly rejected. Zero false positive rejections on valid pomegranate images.
- WhatsApp Integration: Webhook verification and message routing confirmed operational with Meta sandbox numbers.

- Field Trial Agreement: PomeGuard disease classification achieved >95% agreement with expert agronomist assessments, with 5–7 day early detection lead [37].

VII. DISCUSSION

7.1 From Prototype to Production

The transition from Version 1 [51] to Version 2 represents an architectural maturation from research prototype to production-grade system. Version 1 demonstrated that CNNs and ontological reasoning could produce accurate, non-destructive quality assessments. Version 2 demonstrates that such a system can be practically accessible to users without agricultural AI expertise. Natural-language interaction, automatic weather ingestion, and treatment dosage calculators close the loop between diagnostic output and actionable field response.

7.2 Practical Impact

Five key practical impacts: (1) non-destructive phytochemical estimation replaces costly HPLC analysis [38]; (2) early disease detection 5–7 days ahead of visible symptom onset enables timely intervention; (3) precision treatment quantification reduces chemical waste and over-application; (4) spatial hotspot mapping enables targeted orchard block management; (5) AI-guided conversational support democratises access to agronomic expertise for smallholder farmers who lack access to extension services.

7.3 Comparison with Prior Systems

Traditional manual scouting incurs a 30–40 day disease detection lag. Single-method CNN systems (e.g., PlantVillage [7]) identify surface disease but offer no phytochemical inference, treatment guidance, or conversational explanation. NIR spectroscopy [38] and hyperspectral imaging [39] provide accurate internal quality assessment but require expensive specialised hardware unsuitable for field deployment. PomeGuard 2.0 uniquely combines smartphone-accessible image capture, real-time weather integration, semantic phytochemical inference, GPS tracking, treatment calculation, and AI-guided explanation in a single production-deployed web application.

7.4 Limitations

Acknowledged limitations: (i) The vision model is optimised for the Bhagwa cultivar; performance on other varieties requires validation. (ii) Disease severity is currently derived from a categorical approximation rather than lesion area quantification—to be refined in Version 3 via image segmentation. (iii) The WhatsApp integration requires Meta Business Account approval for production message delivery. (iv) Outdoor lighting variability can degrade classification accuracy in extreme conditions.

VIII. CONCLUSION

This paper presented PomeGuard 2.0, the completed and production-deployed evolution of the agricultural intelligence platform first published in Version 1 on The International Innovations & Scholarly Trends Journal (**IISTJ**) [51] (DOI: 10.5281/zenodo.20604743). Building on the foundational 98.9% classification accuracy of the EfficientNetB0 vision module and the OWL 2 DL ontological reasoning engine, Version 2 delivers seven major engineering contributions: a contextual AI conversational assistant, an area-scaled pesticide treatment calculator, a GPS disease hotspot map, automated Open-Meteo weather ingestion, a WhatsApp alert integration, a Gemini-powered image validation gate, and a cloud-native multi-user persistence stack.

The system achieves sub-5-second end-to-end analysis latency, maintains strict per-user data isolation, and is deployed on Vercel for global accessibility. PomeGuard 2.0 demonstrates that bridging computer vision, semantic web reasoning, large language models, and modern full-stack web engineering can produce a practically viable, farmer-accessible tool for precision horticulture—one that replaces destructive sampling, enables early disease intervention, and democratises agronomic expertise through conversational AI. The system is declared production-complete and ready for deployment to smallholder pomegranate farmers across Maharashtra.

IX. FUTURE WORK

- Lesion Segmentation: Replace categorical severity classification with image segmentation-based lesion coverage area quantification.
- Cultivar Expansion: Transfer learning adaptation for Ganesh, Ruby, and Pink pomegranate varieties, and subsequent multi-crop expansion.
- Ontology Expansion: Model additional phytochemicals (Vitamin C, quercetin, kaempferol), trace minerals, and pest-compound interaction pathways.
- Multilingual Interface: Marathi, Hindi, and Tamil localisation for accessibility across major pomegranate-growing regions.
- IoT Sensor Integration: Direct API integration with DHT22 temperature/humidity sensors and UV index sensors.
- Satellite Imagery Analysis: Macro-level field disease spread mapping using Sentinel-2 satellite imagery.
- Edge Deployment: ONNX model deployment on NVIDIA Jetson Nano and Raspberry Pi 5 for offline-capable field units.
- Federated Learning: Privacy-preserving cooperative dataset expansion across farmer cooperative networks.
- WhatsApp Bot (Full): Complete WhatsApp Business API integration enabling image submission and result delivery via WhatsApp.
- React Native Mobile App: Native iOS/Android application with direct camera integration and offline scan capability.

X. ACKNOWLEDGEMENTS

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