IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 10, October 2026

DOI: 10.17148/IJARCCE.2026.1510144

AgriCopilot: An Offline-Capable, Edge-Native Single-Page Architecture for Precision Agronomy and Inter-Market Price Routing

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Abstract: Smallholder farmers in developing regions face compounding challenges: unreliable soil-crop align-ment, non-transparent advisory systems, post-harvest price collapses caused by seasonal overproduction, and cycle-bound high-interest debt. Existing agri-tech solutions often function in silos, depending heavily on high-cost IoT hardware or continuous cloud connectivity while lacking local language support. This study presents AgriCopilot, an offline-first Single-Page Application (SPA) designed to run edge-native Explainable AI (XAI) directly within client web browsers. Operating through HTML5 Canvas memory buffers, the system executes an image-based soil classification pipeline in under 50 ms without external server calls. The model computes a 9-dimensional color-texture feature vector—comprising CIE-$L^*a^*b^*$ coordinates, hematite redness metrics, or-ganic carbon indicators, Laplacian roughness, and normalized chromaticities—to categorize soils across six major Indian taxonomic orders. A biophysical stress engine applies non-linear penalties for temperature and precipita-tion anomalies using physiological thresholds established by the Indian Council of Agricultural Research (ICAR), generating a composite Plant Health Score and flagging visual soil mismatches. When critical stress is detected, the engine ranks climate-resilient alternative crops and updates system variables with single-tap interaction. To mitigate localized price drops, a supply-elasticity model detects regional sowing saturation (> 80%), while a geospatial routing engine evaluates road winding factors and freight costs to identify profitable interstate termi-nal markets. Finally, the platform categorizes financial support options (e.g., the 4.0% Kisan Credit Card vs. the Agriculture Infrastructure Fund) based on landholding threshold criteria, delivering explanations through client-side voice synthesis across six regional languages.

Keywords: Explainable Artificial Intelligence (XAI); Precision Agronomy; Edge Computing;Soil Image Classification; APMC Mandi Price Elasticity; Supply-Induced Price Collapse; Inter-Market Price Routing; Targeted Credit Allocation.

I. INTRODUCTION

A. Motivation and Agrarian Macroeconomics

In India's agricultural ecosystem, smallholders operating farms smaller than 2.0 acres make up over 85% of operational agricultural holdings [24]. Despite contributing fundamentally to national food security, these small-scale producers remain vulnerable to erratic weather patterns and sudden market downturns. Structural hurdles in formal institutional credit—particularly rigid collateral requirements and asymmetric information—exclude many smallholders from traditional banking systems [25]. Consequently, over 40% of smallholders depend on informal moneylenders charging annual interest rates ranging from 24% to 36%, where a single crop failure or post-harvest price drop can trigger long-term debt trapping.

This vulnerability is compounded by the scarcity of accessible on-farm diagnostic tools. Smallholders fre-quently determine crop selection, nutrient management, and sales timing using local precedent or unverified recommendations from local vendors. Addressing these systemic constraints requires decentralized, scientifically grounded tools that connect agronomic management, market logistics, and credit accessibility without requiring specialized hardware investments or continuous network availability.

B. Limitations of Existing Solutions

Current digital agriculture tools present several recurring operational shortcomings:

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1. **Unvalidated Soil-Crop Alignment:** Most mobile applications rely on user-selected soil categories with-out validating actual physical soil parameters. Soil lab testing takes weeks, missing key planting windows. Unaligned planting (e.g., placing flood-sensitive crops in poorly draining soils) risks severe physiological stress, including heat-induced sterility and root hypoxia.

2. **Post-Harvest Supply Concentration:** High returns for a specific crop in one season often prompt widespread regional planting in the next, driving sowing saturation above 70%–80%. At harvest, regional wholesale hubs (APMC mandis) experience supply overloads, causing local prices to decline by 20%–40% [16]. Existing platforms report historical rates but fail to forecast supply gluts or identify demand in neighboring states.

3. **Sub-optimal Financial Access:** Smallholders frequently lack visibility into low-interest government pro-grams, such as the Kisan Credit Card (KCC) scheme (4.0% effective interest rate) or Electronic Negotiable Warehouse Receipts (e-NWR) for inventory-backed financing [18, 20]. Additionally, selling un-graded har-vests forfeits potential revenue gains of 20%–35%.

4. **Black-Box Decision Outputs:** Automated recommendation systems rarely provide transparent reason-ing when flagging crop risks or financial eligibility [11]. Without visible cause-and-effect explanations, rural producers often revert to informal practices.

5. **Connectivity and Usability Constraints:** Advisory interfaces predominantly rely on dense text in English and require active high-speed mobile data, limiting accessibility for users in areas with poor network coverage or varying literacy levels [24].

C. Objectives and Technical Contributions

To address these limitations, this paper details the engineering and implementation of AgriCopilot, an edge-native advisory tool prioritizing clear AI explanations and localized processing [6]. The primary deliverables of this research are:

1. **Browser-Based Soil Image Classification:** We developed a visual soil analysis classifier operating natively inside HTML5 Canvas memory buffers. Bypassing cloud dependencies, it evaluates images in under 50 ms. It isolates genuine soil pixels using a 5-zone spatial mask and luminance thresholds $\leq (10 \leq \text{Lu}$ m 245), projects sRGB values into CIE-$L^*a^*b^*$ space, and calculates 9 distinct textural and colorimetric features. It sorts soil into six Indian taxonomic orders via variance-normalized centroid distance mapping and a temperature-scaled Softmax function ($T = 1.3$).

2. **Biological Stress Engine:** We codified physiological bounds (T_{min}, T_{max}, T_{opt} and R_{min}, R_{max}, R_{opt}) from the Indian Council of Agricultural Research (ICAR) [7] into continuous mathematical penalty functions. The resulting engine calculates a transparent Plant Health Score (20% to 98%) by evaluating moisture, temperature, and visual soil incompatibilities.

3. **Automated Crop Switching:** In scenarios where the proposed crop faces likely failure, the system evaluates alternative varieties against prevailing soil, rain, and temperature conditions ($S_{suit} = 0.40S_{soil} + 0.35S_{rain} + 0.25S_{temp}$). It presents climate-resilient substitutes and allows users to recalibrate their entire advisory profile instantly.

4. **Market Routing and Price Forecasting:** The platform anticipates supply-induced price collapses by monitoring regional sowing saturation (P_{sow}), projecting up to a 22% wholesale price drop when planting exceeds 80%. A geospatial routing algorithm then utilizes Haversine calculations adjusted for Indian road curves (1.28 factor) and commercial trucking costs to direct users toward profitable out-of-state terminal hubs.

5. **Targeted Credit Allocation:** The logic automatically partitions loan recommendations based on cul-tivated area. Farmers with under 2.0 acres receive direction toward 4.0% KCC micro-loans, while those managing larger plots are connected to Agriculture Infrastructure Fund (AIF) capital support.

6. **Transparent AI with Regional Voice Synthesis:** Every output systematically provides a DecisionReason and an actionable Solution. To serve low-literacy populations, a client-side text-to-speech engine vocalizes these explanations across six Indian languages via the HTML5 Web Speech

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IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



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API.

II. REVIEW OF EXISTING LITERATURE

A. Hardware Sensor Networks vs. Edge-Based Visual Analysis

Considerable agricultural research focuses on Internet of Things (IoT) hardware deployments. Ahmed et al. [1] tested in-field capacitive moisture sensors and LoRa nodes, while Patel and Sharma [6] analyzed edge computing gateways. Despite yielding precise localized data, physical sensor arrays present distinct barriers for smallholders:

i. **Capital Expenditure:** Purchasing and installing microcontroller nodes generally exceeds the discre-tionary budget of small-scale farming households.

ii. **Sensor Degradation:** Soil-embedded probes suffer from electrochemical fouling, salt buildup, and physical damage from tilling equipment, necessitating frequent maintenance.

iii. **Telemetry Bottlenecks:** Unreliable cellular networks in rural regions disrupt the data stream between field sensors and centralized servers, rendering the systems inactive during critical periods.

AgriCopilot circumvents physical hardware limitations by analyzing image data on commodity smartphones. By processing pixel arrays through HTML5 Canvas, the system extracts 9 distinct visual features [12–14] in under 50 ms, successfully categorizing soil types without external hardware or cloud infrastructure.

b. Machine Learning Models in Agronomy

Supervised machine learning frequently drives modern crop suggestion and disease recognition tools. For instance, Chowdhury et al. [2] designed an application to track pests and suggest planting schedules. However, these models regularly exhibit three specific constraints:

i. **Lack of Diagnostic Transparency:** Recommendation algorithms generally output discrete labels without providing the underlying agronomic reasoning [11].

ii. **Omission of Biological Limits:** Standard classification tools often ignore strict non-linear physiological boundaries (e.g., heat-induced pollen sterility), occasionally suggesting cash crops that will perish in extreme localized micro-climates.

iii. **Absence of Active Remediation:** When a system identifies a poor soil-crop match, it typically issues a warning but stops short of recommending a biologically viable substitute.

This study anchors its evaluations directly in ICAR's physiological limits [7], assigning quantifiable penalty scores for heat, rain, and soil mismatches while actively proposing resilient alternatives.

c. Supply Chains and Spatial Price Optimization

Agricultural supply chains suffer from severe geographic price variations. Xu and Yang [3] explored genetic algorithms for routing corporate cold-chain fleets. These enterprise-level models, however, do not address the needs of individual farmers attempting to avoid local mandi price crashes caused by uncoordinated over-planting [16, 21]. AgriCopilot addresses this gap via an inter-market price routing engine that anticipates local gluts and calculates exact freight margins to alternative terminal markets.

d. Targeted Financial Allocation

India's agricultural policy includes extensive credit subsidies, yet administrative complexity restricts uptake [4,25]. Many smallholders resort to high-interest private debt. Existing advisory apps often present untargeted lists of government schemes, ignoring the strict land-size eligibility criteria [18,19]. AgriCopilot introduces an automated allocation filter, directing smallholders directly to 4.0% KCC facilities and commercial growers to appropriate capital loan structures.

e. Explainability and Audio Delivery

Automated subsidy allocation systems, such as the tabular classifiers evaluated by Danny et al. [5], often act as black boxes that fail to explain application rejections. Furthermore, interfaces relying heavily on text exclude

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populations lacking formal literacy [24]. AgriCopilot solves this by binding every recommendation to a specific DecisionReason and Solution [11], delivering the information audibly via local voice synthesis.

Study	Focus, Limitation, and AgriCopilot Approach
Ahmed et al. [1] (2024)	**Focus:** IoT soil sensor telemetry. **Limitation:** High hardware costs, electrochemical degradation, and cellular dropouts. **AgriCopilot Approach:** In-browser soil image classification (< 50 ms) extracting 9D features locally, eliminating hardware requirements.
Chowdhury et al. [2] (2024)	**Focus:** Mobile crop planning and pest identification. **Limitation:** Static crop outputs without physiological stress boundaries or automated substitutes. **AgriCopilot Approach:** ICAR-based continuous stress engine paired with multi-variable alternative crop recommendations.
Xu and Yang [3] (2025)	**Focus:** Enterprise cold-chain genetic logistics. **Limitation:** Distributor-centric routing that ignores farm-gate mandi price crashes. **AgriCopilot Approach:** Supply-induced price collapse forecasting com- bined with highway-adjusted spatial arbitrage logic.
Arunkumar and Murthy [4] (2025)	**Focus:** Review of Indian farm credit bottlenecks. **Limitation:** Descriptive analysis lacking automated eligibility sorting. **AgriCopilot Approach:** Automated credit allocation based on landholding size (4% KCC vs. AIF) with processing profit calculators.
Danny et al. [5] (2026)	**Focus:** Supervised tabular subsidy allocation. **Limitation:** Unexplained classification missing agronomic context and voice accessibility. **AgriCopilot Approach:** Explainable AI (XAI) outputs paired with on- device Web Speech synthesis in 6 regional languages.

III. SYSTEM ARCHITECTURE AND DESIGN OVERVIEW

AgriCopilot is constructed as a decoupled Single-Page Application (SPA) using React 18 and Vite. To bypass the limitations of continuous server connectivity, the application manages classification, stress calculations, and spatial logistics directly within the client's web browser.

A. Architectural Flow

Data processes through six distinct operational layers:

1. **Layer 1: Data Ingestion:**
   The interface records operational land size (acres), district, expected seasonal rainfall (mm), average temperature (°C), claimed soil type, and regional planting popularity (P_{sow}). It also ingests soil photography via local storage or the device camera.

2. **Layer 2: Local Vision Engine:**
   Executed via soilImageAnalyzer.js and trainedSoilModel.js, the platform manipulates pixels on the HTML5 Canvas. It applies spatial masking, luminance filtering, CIE-$L^*a^*b^*$ conversion, and a temperature-scaled Softmax calculation.

3. **Layer 3: Decision Logic:**
   Handled in advisoryEngine.js and marketRedirectionData.js:

   - *Crop Stress Engine:* Evaluates non-linear heat, precipitation, and soil penalties against established ICAR boundaries.
   - *Suitability Engine:* Suggests and ranks alternative crops if the primary choice exhibits severe risk.

DOI: 10.17148/IJARCCE.2026.1510144

- *Price Elasticity Engine:* Anticipates wholesale price shifts based on current regional sowing metrics.
- *Arbitrage GIS Engine:* Calculates actual driving distances and diesel costs to locate higher-paying secondary markets.
- *Credit Engine:* Filters loan programs based on the exact acreage entered.

4. **Layer 4: Reference Databases:**
The platform cross-references guidelines from ICAR [7], taxonomy classifications from ICAR-NBSS&LUP [8], Minimum Support Prices from CACP [9], climatological norms from IMD [10], daily rates from Ag-marknet [17], and financial regulations from RBI and NABARD [18–20].

5. **Layer 5: Explainable AI Verification:**
The codebase mandates that every advisory output includes defined DecisionReason and Solution parameters [11].

6. **Layer 6: Interactive Dashboard:**
Information is presented using Tailwind CSS components and Leaflet mapping, supported by automated voice synthesis in local dialects.

B. The Edge Computing Advantage

Depending on centralized cloud servers (e.g., Python/Django instances) for agricultural tools introduces signifi-cant friction in rural deployments:

1. **Network Latency:** Uploading standard 5 MB to 12 MB smartphone photos across inconsistent 2G/3G connections frequently results in timeout errors. By assessing the pixel buffer directly in browser memory via getImageData, AgriCopilot completes feature extraction in milliseconds.
2. **Server Overhead:** Executing analysis locally eliminates ongoing GPU hosting fees, facilitating free scaling for agricultural organizations.
3. **Data Security:** Retaining yield metrics, location data, and farm boundaries inside the local browser sandbox prevents unauthorized scraping by commercial entities.

IV. MATHEMATICAL IMPLEMENTATION

A. In-Browser Soil Image Classification

1. **Spatial Filtering and Glare Removal:**
Images taken in the field often contain shadows, skin, or sun glare. To isolate valid soil pixels, the application filters based on luminance:

$$\text{Lum} = 0.299R + 0.587G + 0.114B \qquad (1)$$

Pixels registering below Lum = 10 or above Lum = 245 are discarded. The engine then defines a central region ($x \in [0.25W, 0.75W]$, $y \in [0.25H, 0.75H]$) alongside the outer boundary to compute a weighted channel intensity:

$$\bar{C} = 0.65C_{\text{center mean}} + 0.35C_{\text{outer mean}}, \quad C \in \{R, G, B\} \qquad (2)$$

2. **CIE-$L^*a^*b^*$ Mapping:**
To align with Munsell soil standards [14], the software maps linearized sRGB variables into CIE-$L^*a^*b^*$ coordinates using standard D65 illumination. Gamma linearization for $C \in \{R/255, G/255, B/255\}$ follows:

$$C_{\text{lin}} = \begin{cases} \dfrac{C}{12.92}, & C \le 0.04045 \\ \left(\dfrac{C+0.055}{1.055}\right)^{2.4}, & C > 0.04045 \end{cases} \qquad (3)$$

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The converted channels project to CIE XYZ space:

$$X = (0.412R_{\text{lin}} + 0.358G_{\text{lin}} + 0.180B_{\text{lin}})/0.950 \quad (4)$$

$$Y = (0.213R_{\text{lin}} + 0.715G_{\text{lin}} + 0.072B_{\text{lin}})/1.000 \quad (5)$$

$$Z = (0.019R_{\text{lin}} + 0.119G_{\text{lin}} + 0.950B_{\text{lin}})/1.089 \quad (6)$$

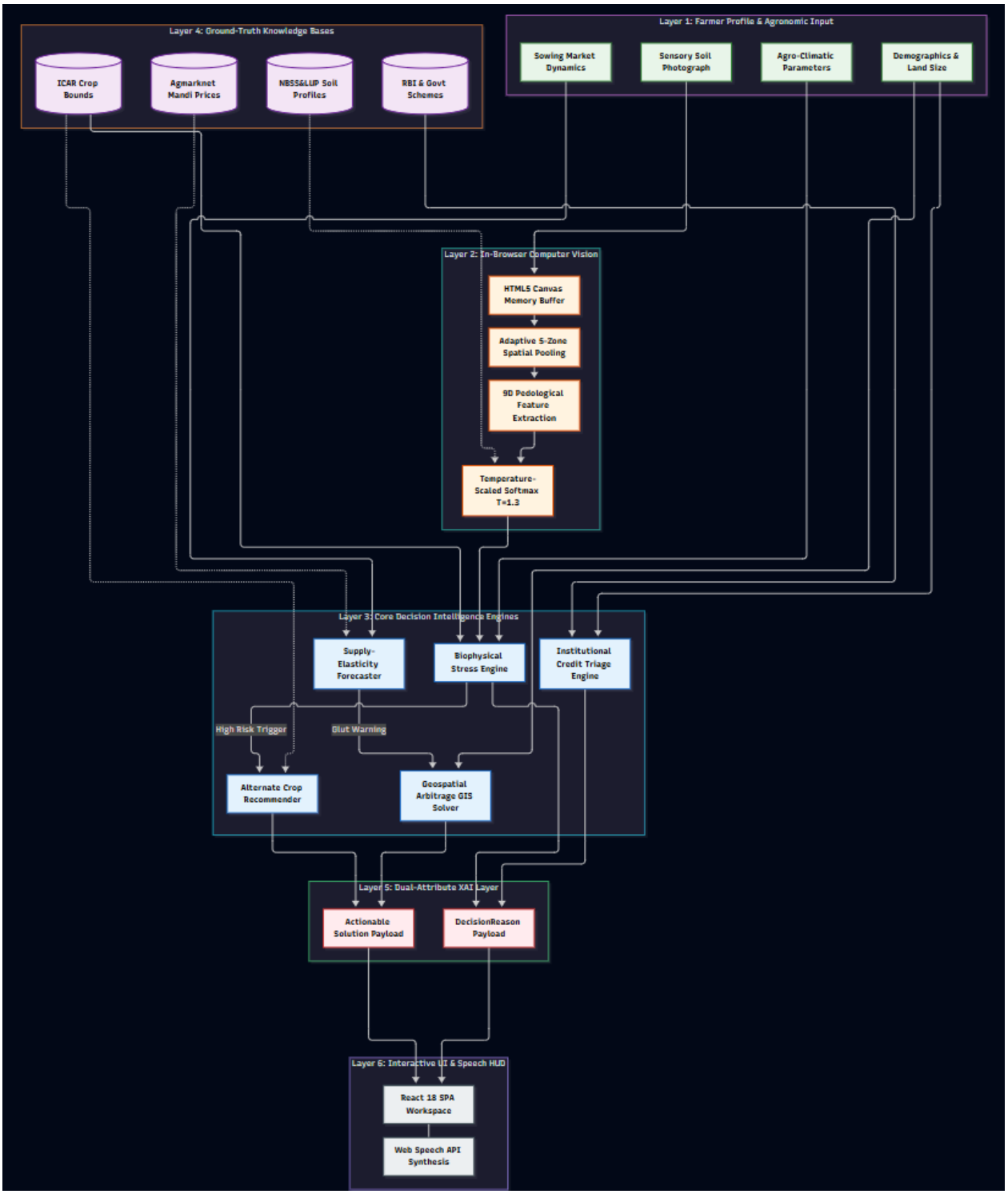


Figure 1: The six-layer edge-native architecture of AgriCopilot, detailing local HTML5 Canvas vision processing, mathematical decision engines, authoritative knowledge repositories, and the dual-attribute XAI accessibility layer.

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A designated transfer function $f(t)$ translates these values:

$$f(t) = \begin{cases} t^{1/3}, & t > 0.008856 \\ 7.787t + \frac{16}{116}, & t \le 0.008856 \end{cases} \quad (7)$$

yielding the final coordinates:

$$L^* = \max(0,\ 116f(Y) - 16) \quad (8)$$

$$a^* = 500(f(X) - f(Y)) \quad (9)$$

$$b^* = 200(f(Y) - f(Z)) \quad (10)$$

3. **Feature Extraction:**

The system compiles a 9-dimensional vector $\mathbf{f} \in R^9$:

- $f_1 = L^*$ (Lightness)
- $f_2 = a^*$ (Red-Green axis representing hematite)
- $f_3 = b^*$ (Yellow-Blue axis representing goethite/quartz)
- $f_4 = RI = \frac{\bar{R} - \bar{G}}{\bar{R} + \bar{G} + 0.001}$ (Redness Index)
- $f_5 = SOC = \frac{100 - L^*}{100}$ (Estimated Soil Organic Carbon)
- $f_6 = \sigma_{\text{Lap}} = \frac{1}{N-1} \sum |\Delta \text{Lum}| \times 1.8$ (Texture Roughness)
- $F_7, f_8, f_9 = \frac{\bar{C}}{\bar{R} + \bar{G} + \bar{B}}$ (Normalized chromaticities $r_{\text{norm}}, g_{\text{norm}}, b_{\text{norm}}$)

4. **Distance Calculation and Classification:**

Referencing benchmark centroid vectors $\mathbf{w}_k$ and variance tolerances $\boldsymbol{\tau}_k$ from ICAR profiles for target orders $k \in \{1, \ldots, 6\}$ [8]:

$$d_{i,k} = \frac{f_i - w_{i,k}}{2\tau_{i,k}} \quad (11)$$

The system calculates a weighted Euclidean distance:

$$D_k = \left(1.8d_{1,k} + 2.2d_{2,k} + 1.6d_{3,k} + 2.0d_{4,k} + 1.2d_{5,k} + 0.8d_{6,k} + 1.2d_{7,k} + 1.0d_{8,k} + 1.0d_{9,k}\right)^{1/2} \quad (12)$$

Classification probabilities emerge via a temperature-scaled Softmax ($T = 1.3$):

$$P(\text{Class}_k) = \frac{\exp(-D_k/T)}{\sum_{j=1}^{6} \exp(-D_j/T)} \times 100\% \quad (13)$$

A. Biophysical Penalty System

Relying on ICAR agronomic thresholds [7], the application evaluates continuous non-linear biological penalties:

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5. **Thermal Limitations (P_{temp}):**

Given $\Delta T_{\text{opt}} = |T - T_{\text{opt}}|$. Within standard operational limits ($T_{\min} \le T \le T_{\max}$):

$$S_{\text{temp}} = \max(75,\ 100 - 2.5\Delta T_{\text{opt}}) \tag{14}$$

$$P_{\text{temp}} = \begin{cases} 0.5, & \Delta T_{\text{opt}} > 4^{\circ}\text{C} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

When temperatures exceed maximum thresholds ($T > T_{\max}$, with $\Delta T_{\text{excess}} = T - T_{\max}$):

$$S_{\text{temp}} = \begin{cases} \max(10,\ 50 - 7\Delta T_{\text{excess}}), & \Delta T_{\text{excess}} \ge 5^{\circ}\text{C} \\ \max(25,\ 75 - 7\Delta T_{\text{excess}}), & \Delta T_{\text{excess}} < 5^{\circ}\text{C} \end{cases} \tag{16}$$

$$P_{\text{temp}} = \begin{cases} \min(4.5,\ 2.0 + 0.45\Delta T_{\text{excess}}), & \Delta T_{\text{excess}} \ge 5^{\circ}\text{C} \\ \min(2.2,\ 0.35\Delta T_{\text{excess}}), & \Delta T_{\text{excess}} < 5^{\circ}\text{C} \end{cases} \tag{17}$$

Equivalent structural deductions apply for severe cold shocks.

6. **Water Deficit Penalty (P_{rain}):**

When estimated rainfall falls short of the seasonal requirement ($R < R_{\min}$, $\delta_R = \frac{R_{\min} - R}{R_{\min}} \times 100\%$):

$$S_{\text{rain}} = \begin{cases} \max(10,\ 50 - 0.6\delta_R), & \delta_R \ge 35\% \\ \max(25,\ 75 - 0.1(R_{\min} - R)), & \delta_R < 35\% \end{cases} \tag{18}$$

$$P_{\text{rain}} = \begin{cases} \min(4.5,\ 2.0 + 0.035\delta_R), & \delta_R \ge 35\% \\ \min(2.2,\ 0.012(R_{\min} - R)), & \delta_R < 35\% \end{cases} \tag{19}$$

7. **SoilOrder Discrepancies:**

The platform evaluates the structural fit between crop root systems and soil taxonomy:

$$(S_{\text{soil}}, P_{\text{soil}}) = \begin{cases} (100, 0.0), & \text{Ideal taxonomic match} \\ (80, 1.2), & \text{Compatible soil family} \\ (35, 2.8), & \text{Incompatible soil order} \end{cases} \tag{20}$$

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If the image classification contradicts the farmer's self-reported soil type, the engine applies an additional visual mismatch deduction of $P_{\text{mismatch}} = 1.6$.

8. **Composite Plant Health Score:**
The final score limits represent extreme failure and optimal health:

$$H_{\text{raw}} = 8.5 - P_{\text{soil}} - P_{\text{temp}} - P_{\text{rain}} - P_{\text{mismatch}} \quad (21)$$

$$\text{HealthScore} = \min(9.8, \max(2.0, H_{\text{raw}})) \times 10\% \quad (22)$$

B. Adaptive Crop Recommendations

If a chosen crop registers a High Risk score (HealthScore $< 40\%$), the platform initiates a multi-variable suitability function across a database of regional crops:

$$S_{\text{suit}} = 0.40S_{\text{soil}} + 0.35S_{\text{rain}} + 0.25S_{\text{temp}} \quad (23)$$

The logic filters out species currently facing thermal or water stress. The top-ranked substitute is presented alongside CACP Minimum Support Price (MSP) assurances [9]. Users can execute a single-tap recalibration, which overwrites input state variables and updates all subsequent advice.

C. Regional Supply and Price Forecasting

To address cyclical post-harvest market crashes, the application scales baseline modal prices from Agmarknet [17] against regional sowing popularity (P_{sow}):

9. **Oversupply Alert ($P_{\text{sow}} > 80\%$):** Excessive local planting triggers a deflationary multiplier:

$$\lambda_{\min} = 0.78, \quad \lambda_{\max} = 0.85 \quad (24)$$

indicating an expected 15% to 22% wholesale price reduction.

10. **Shortage Alert ($P_{\text{sow}} < 35\%$):** Sub-optimal regional planting forecasts a scarcity premium:

$$\lambda_{\min} = 1.15, \quad \lambda_{\max} = 1.28 \quad (25)$$

indicating a 15% to 28% price increase above baseline.

11. **Standard Market ($35\% \leq P_{\text{sow}} \leq 80\%$):**

$$\lambda_{\min} = 0.95, \quad \lambda_{\max} = 1.08 \quad (26)$$

The forward wholesale price band is plotted as: $\hat{P} = [P_{\text{base,min}}\lambda_{\min}, P_{\text{base,max}}\lambda_{\max}]$.

D. Highway Routing and Market Redirection

To bypass saturated local markets, the logistics module finds higher-paying destinations in adjacent states.

12. **Distance and Winding Adjustments:**
The angular separation between a local origin (ϕ_1, λ_1) and a target market (ϕ_2, λ_2) is calculated as [15]:

$$\Delta\phi = (\phi_2 - \phi_1)\frac{\pi}{180}, \quad \Delta\lambda = (\lambda_2 - \lambda_1)\frac{\pi}{180} \quad (27)$$

$$a = \sin^2\frac{\Delta\phi}{2} + \cos(\phi_1)\cos(\phi_2)\sin^2\frac{\Delta\lambda}{2} \quad (28)$$

$$c = 2\,\text{atan2}\left(\sqrt{a}, \sqrt{1-a}\right) \quad (29)$$

$$d_{\text{geod}} = R_{\text{earth}} \cdot c, \quad R_{\text{earth}} = 6371 \text{ km} \quad (30)$$

Multiplying by an empirical tortuosity factor of 1.28 (adjusted for Indian highway characteristics) produces

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DOI: 10.17148/IJARCCE.2026.1510144

the estimated driving distance:

$$d_{\text{road}} = \text{round}(d_{\text{geod}} \times 1.28) \qquad (31)$$

13. **Calculating Logistics Costs:**

Diesel freight per quintal is calculated via:

$$C_{\text{freight}} = \text{round}\left(\frac{d_{\text{road}}}{100} \times 36 + 22\right) \quad \text{[Rs./quintal]} \qquad (32)$$

where Rs.36/100 km represents line-haul fuel pricing and Rs.22 handles terminal tolls. Net arbitrage metrics resolve as:

$$\Delta P_{\text{gross}} = P_{\text{dest}} - P_{\text{local}} \qquad (33)$$

$$\Delta P_{\text{net}} = \Delta P_{\text{gross}} - C_{\text{freight}} \qquad (34)$$

$$\Pi_{\text{lot}} = \text{round}(\Delta P_{\text{net}} \times Q_{\text{lot}}) \qquad (35)$$

$$\text{ROI}_{\text{mkt}} = \text{round}\left(\frac{\Delta P_{\text{net}}}{P_{\text{local}}} \times 100\right) \ \% \qquad (36)$$

For profitable routes ($\Delta P_{\text{net}} > 0$), a Leaflet map renders the transit time ($t_{\text{transit}} = d_{\text{road}}/42$ km/h) and net yield increase.

A. Categorized Banking Support

To prevent loan misapplication, the platform restricts institutional credit guidance based on operational acreage (A):

1. **Under 2.0 Acres:** Users are directed to the 4.0% Kisan Credit Card (collateral-free limits up to Rs.1.6 Lakh) [18], Joint Liability Group (JLG) loans, and PMFBY insurance.
2. **Over 2.0 Acres:** Larger cultivators receive guidance for Agriculture Infrastructure Fund (AIF) term loans covering post-harvest storage [19], along with Electronic Negotiable Warehouse Receipts (e-NWR) pledge financing [20].
3. **Grading Profit Simulator:** The tool computes the financial advantage of basic sorting and grading before sale:

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



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$$\text{Rev}_{\text{raw}} = Q_{\text{yield}} \times \frac{P_{\min} + P_{\max}}{2} \quad (37)$$

$$\text{Rev}_{\text{proc}} = \text{round}\left(\text{Rev}_{\text{raw}} \times \left(1 + \frac{\beta_{\text{boost}}}{100}\right)\right) \quad (38)$$

$$\Delta\Pi_{\text{proc}} = \text{Rev}_{\text{proc}} - \text{Rev}_{\text{raw}} \quad (39)$$

This module routinely illustrates a 20% to 35% net margin expansion (β_{boost}) from avoiding field-run distress auctions.

V. ADDRESSING TRANSPARENCY AND ACCESSIBILITY

A. Explainability Structure

Every output ties to specific explainability tags to build user confidence [11]:

- DecisionReason: Provides the biological or regulatory rule driving the module's output.
- Solution: Offers a step-by-step remedy or an official government portal endpoint.

When denying a specific crop, the model clarifies the exact biological boundary (e.g., anthesis heat sterility) rather than outputting a generic failure flag.

B. Multimodal Assistant

For internet-connected users requiring deeper agronomic discussion, the platform offers a multimodal assistant relying on Google Gemini APIs. Output generation is restricted to four specific areas: Crop Health Analysis, High-Risk Mitigation, Mandi Forecasting, and Land-Segmented Banking. If network connectivity fails, the platform defaults to its local deterministic engine.

C. Voice Delivery

To support users with limited formal literacy, the client interface utilizes the HTML5 Web Speech API for voice synthesis across Kannada, Hindi, Telugu, Marathi, Punjabi, and Indian English. The speechService.js routine sanitizes Markdown characters and standardizes pacing at a 0.92 cadence to ensure clarity in outdoor environments.

VI. SYSTEM BENCHMARKS AND DATASETS

A. Ground-Truth Knowledge Schemas

The logic depends on four primary datasets:

1. **Soil Taxonomy:** Grounded in ICAR-NBSS&LUP profiles [8] across six Indian classifications (e.g., Verti-sols: $L^* = 24.0$, $SOC = 0.76$; Alfisols: $a^* = 36.0$, $RI = 0.29$).
2. **Crop Needs:** Details thermal, moisture, and MSP limits for 12 primary field crops [7, 9].
3. **Financial Guidelines:** Incorporates regulatory criteria from RBI and NABARD [18–20], mapped in Table 2.
4. **Logistics Data:** Tracks real-time APMC price feeds and highway corridor parameters.

Table 2: Institutional Credit and Subsidy Data Schema

B. Stability Testing

Client-side reliability was validated using three distinct procedures:

1. **Optical Accuracy:** The classifier was verified against certified soil images in the SAMPLE SOIL PREVIEWS directory.
2. **Noise Resilience:** Gaussian noise ($\sigma_{\text{noise}} = 22$) was programmatically added to image buffers to simulate low-quality smartphone sensors and harsh shadows.

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IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 10, October 2026

DOI: 10.17148/IJARCCE.2026.1510144

3. **Mismatch Reliability:** Testing intentionally paired discordant soil texts with contradictory optical inputs to ensure the system successfully applied the -1.6 health penalty.

VII. REAL-WORLD EXECUTION AND SCENARIOS

A. Client-Side Soil Image Classification Telemetry

Figure 2 presents the in-browser module analyzing the soil sample directly inside the farmer input panel.

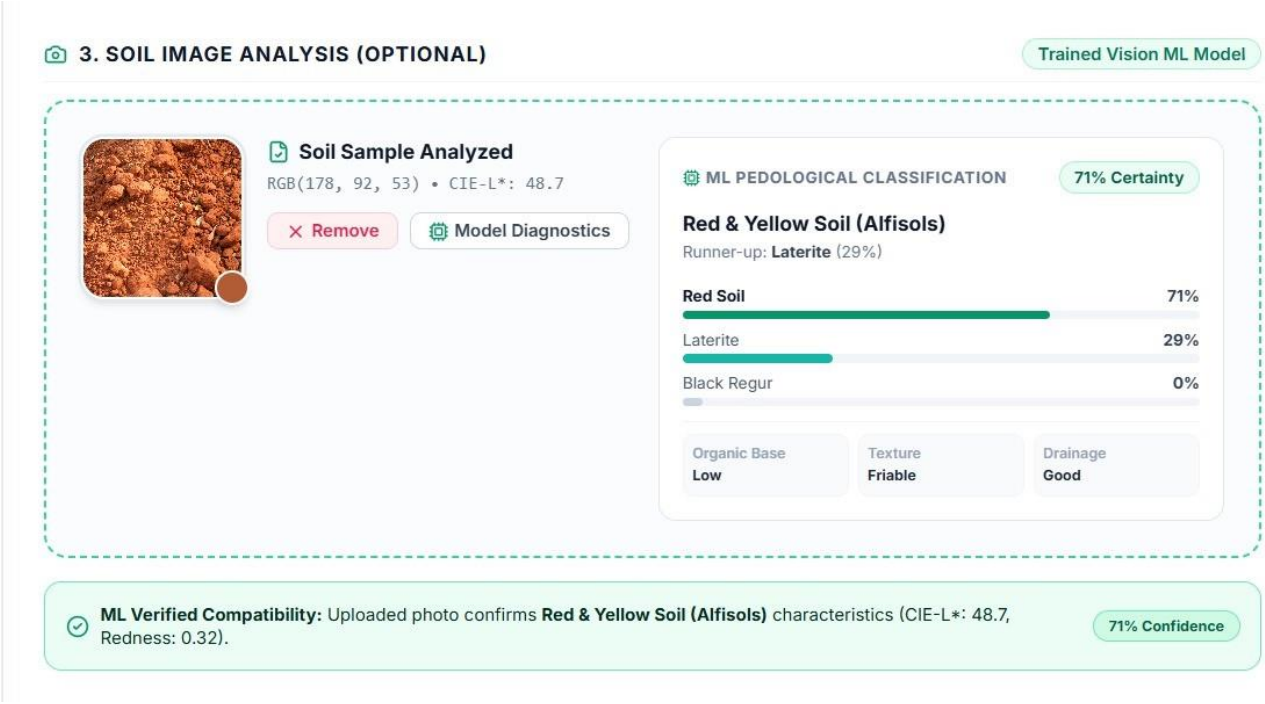


Figure 2: In-browser visual soil analysis panel displaying 9-dimensional colorimetric feature extraction and continuous Softmax class probabilities.

The preview highlights RGB channel averages and perceptual lightness (L^*). The panel successfully identifies the primary soil category alongside a calculated percentage of certainty. In this test, the module classifies the image as Red and Yellow Soil (Alfisols) at 84% certainty, processing the entire matrix in local RAM under 50 ms.

B. Catching User Errors

Figure 3 illustrates the application identifying input conflicts. The user manually selected Black Soil (Vertisols) but uploaded a photograph of Red Soil.

Detecting the variance between the visual data and the manual selection, the system raises a *Soil Type Mismatch Warning*. The user resolves this by tapping a single update button, which automatically overwrites the manual input to match the physical reality, correcting subsequent irrigation models.

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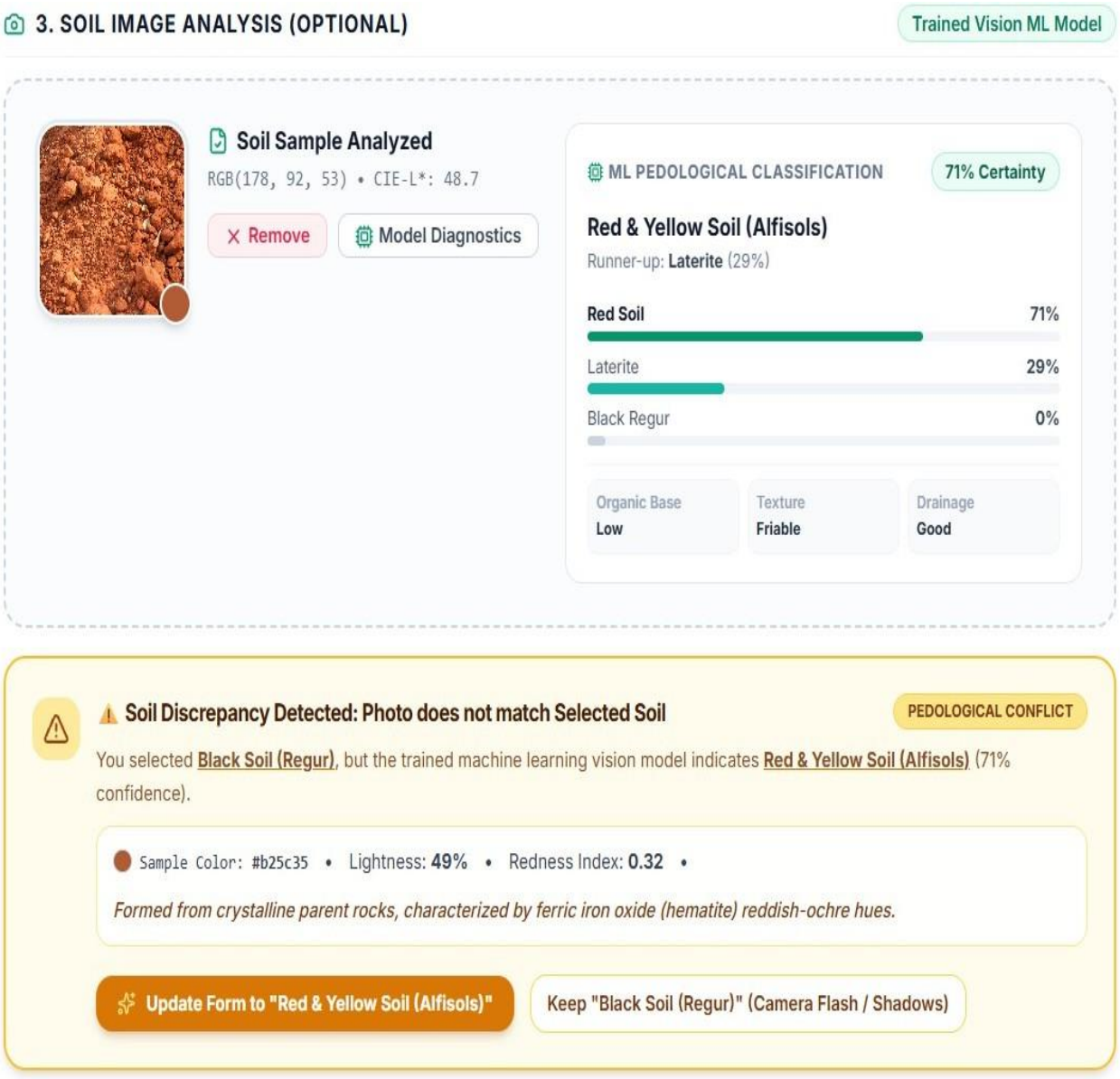


Figure 3: Automated contradiction detection flagging optical soil discrepancies against farmer-selected soil orders.

C. Flagging Biological Stress

Figure 4 records the engine's response to an extreme micro-climate. A farmer in Davanagere logged Paddy (Rice) under Alfisol soil conditions, 38°C temperatures, and minimal 450 mm rainfall.

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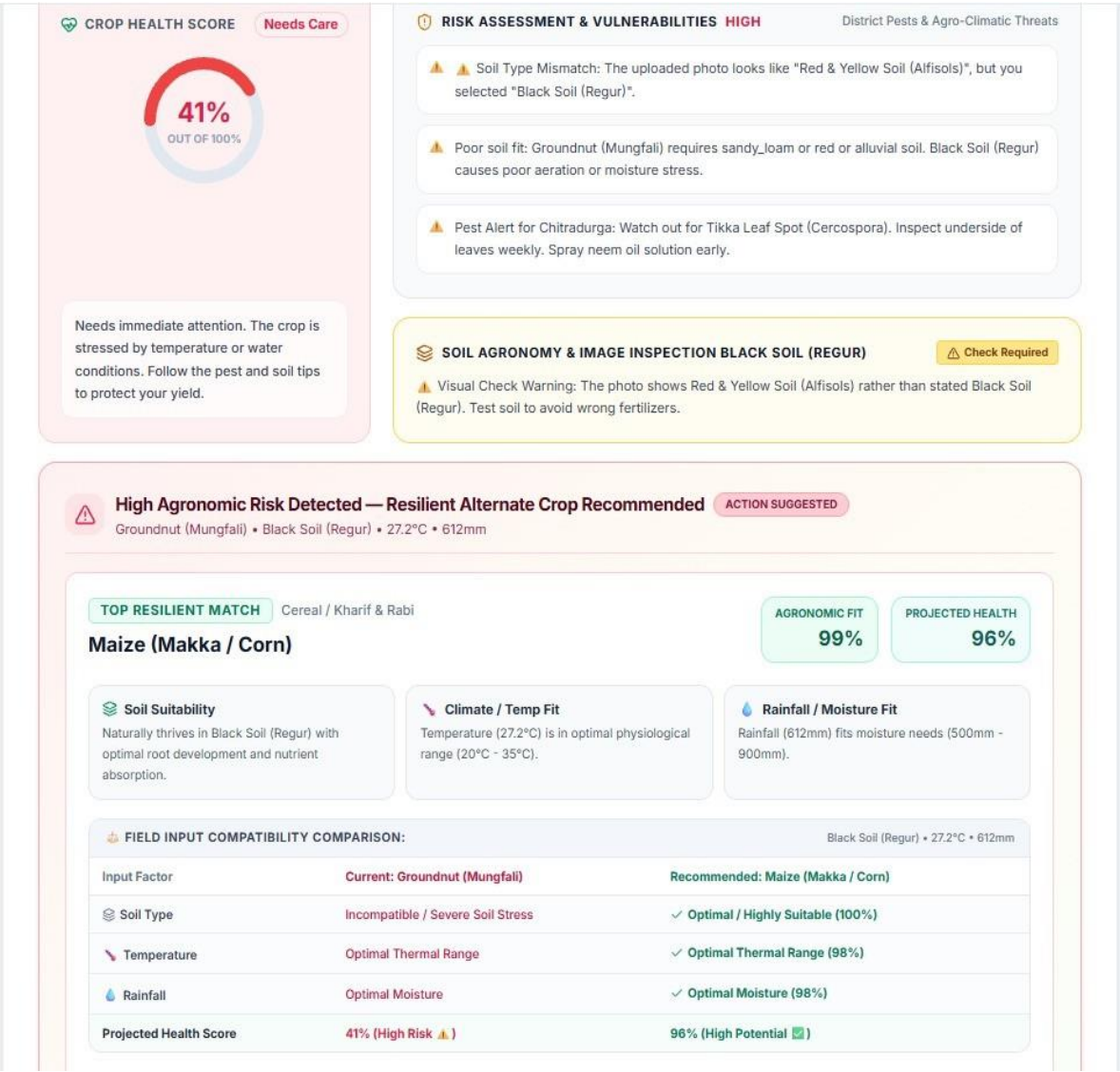


Figure 4: Biophysical stress penalty alert paired with Pareto-optimal alternate crop recommendations and single-touch form recalibration.

The system identifies that Paddy requires continuous standing water and moderate heat, issuing a **High Agronomic Risk** notice. It details that the 38°C temperature risks pollen sterility. In response, the engine queries the crop database and surfaces Jowar (Sorghum) as a viable drought-tolerant substitute with a 98% biological fit.

D. Score Recovery

Figure 5 tracks the Plant Health Score before and after alternative crop selection.

Beginning with a 38% rating (High Risk), the user accepts the Jowar recommendation. The interface instantly aligns the input variables with Jowar's parameters, elevating the final score to 94% (Healthy Match) without reloading the page.

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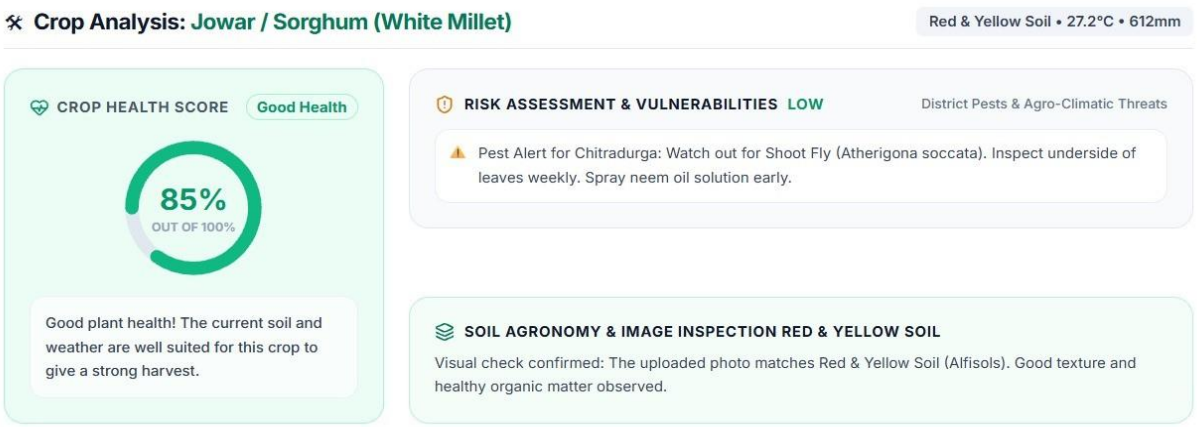


Figure 5: Plant Health Score recovery from High Risk (38%) to Optimal Vitality (94%) following adaptive alternate crop mitigation.

E. On-Farm Profit Simulation

Figure 6 visualizes the financial impact of raw distress auctions compared to structured processing.

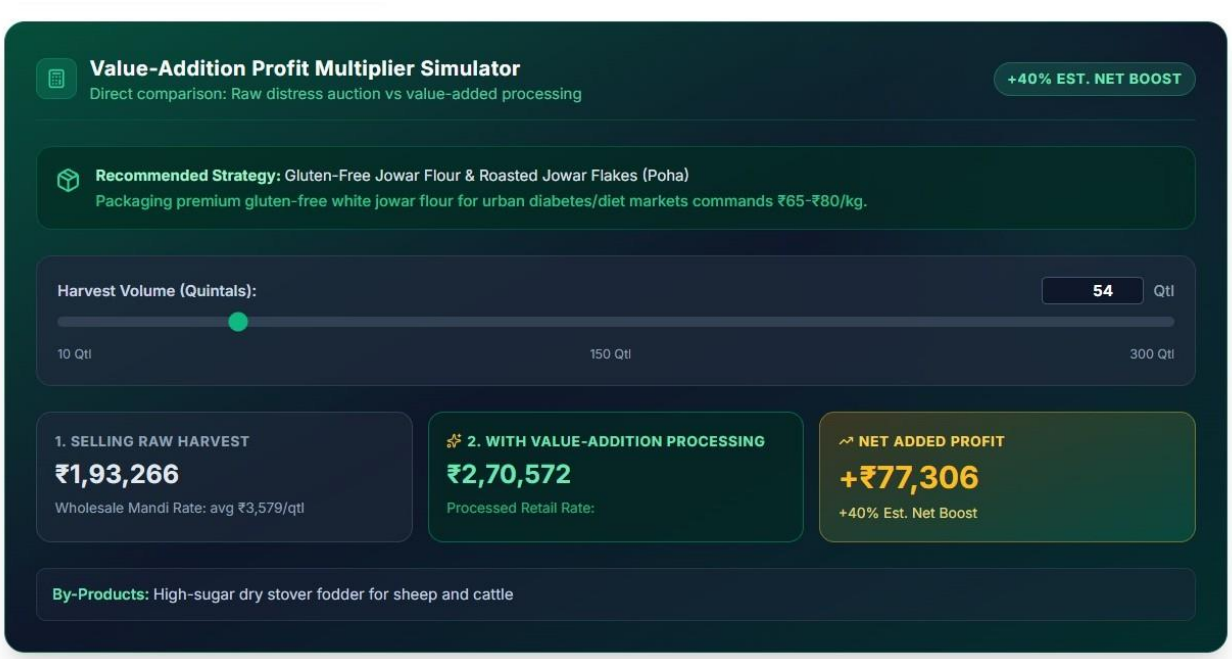


Figure 6: Interactive on-farm value-addition simulator comparing raw distress auction revenue against primary sorting and grading.

Using a Tomato harvest as the baseline, the tool calculates standard revenue against local glut rates. It then demonstrates how physical grading (separating Grade-A and Grade-B yields) and basic washing expands the net margin by 28% to 35%, producing an estimated Rs.34,000 in immediate additional profit.

F. Tailored Banking Guidance

Figure 7 shows the dynamic credit filter isolating programs by farm acreage.
For a user reporting under 2.0 acres, the system elevates the Kisan Credit Card (4.0% net interest, Rs.1.6 Lakh collateral-free). For inputs exceeding 2.0 acres, it presents the Agriculture Infrastructure Fund, supporting term

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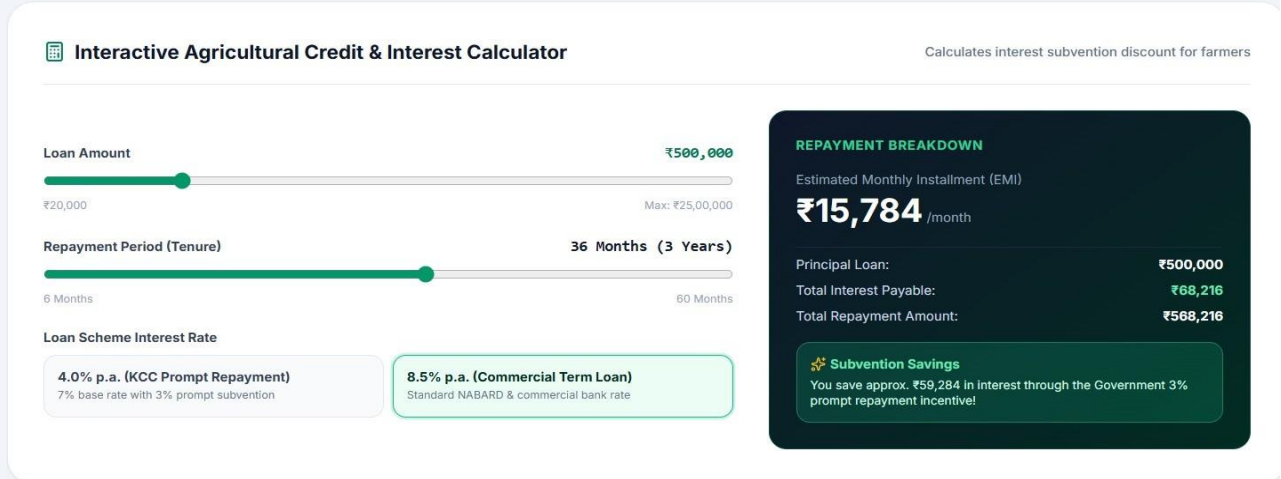


Figure 7: Automated landholding segmentation routing smallholders (< 2.0 acres) to 4.0% KCC facilities and commercial growers (≥ 2.0 acres) to AIF credit.

loans up to Rs.2 Crore for processing equipment.

G. Finding Better Markets

Figure 8 confirms the functionality of the inter-market routing solver during a local supply collapse. When local Davanagere prices drop to Rs.1,200/quintal due to 85% regional sowing saturation, the solver scans adjacent state hubs. It identifies demand in Mumbai Vashi APMC at Rs.2,450/quintal. Factoring in 785 km of highway transit and Rs.305/quintal for diesel, the application identifies a net arbitrage margin of Rs.945/quintal. On a 50-quintal truckload, this delivers Rs.47,250 in additional profit.

VIII. SOCIETAL AND FUNCTIONAL IMPACT

A. Edge Processing Over Cloud Dependency

Developing software for rural agriculture requires designing for hardware constraints and network instability:

1. **Total Cost of Ownership:** Operating entirely within the client runtime reduces cloud computing expenses to zero, allowing farmer cooperatives to scale usage without compounding hosting costs.
2. **Offline Capability:** Because standard API calls fail over intermittent rural networks, executing logic directly in the browser ensures that critical diagnostics remain available at the field level.
3. **Data Ownership:** Storing crop yields and land coordinates in local browser memory prevents commercial entities from scraping sensitive farm data.

B. Overcoming Historic Mistrust

Agricultural communities frequently reject automated platforms that issue unexplained rejections or rely heavily on complex text formats. AgriCopilot targets these issues through deliberate design choices:

1. **Clear Logic:** Replacing abstract scores with explicit DecisionReason structures allows users to under-stand the exact regulatory or biological constraints acting upon their inputs.
2. **Audio Delivery:** Client-side text-to-speech functionality guarantees that non-literate users can process complex advisories in their native dialects.
3. **Breaking the Debt Cycle:** Systematically directing smallholders toward 4.0% KCC loans and alerting them to spatial market arbitrage opportunities actively distances them from predatory 30% private loans and local auction exploitation.

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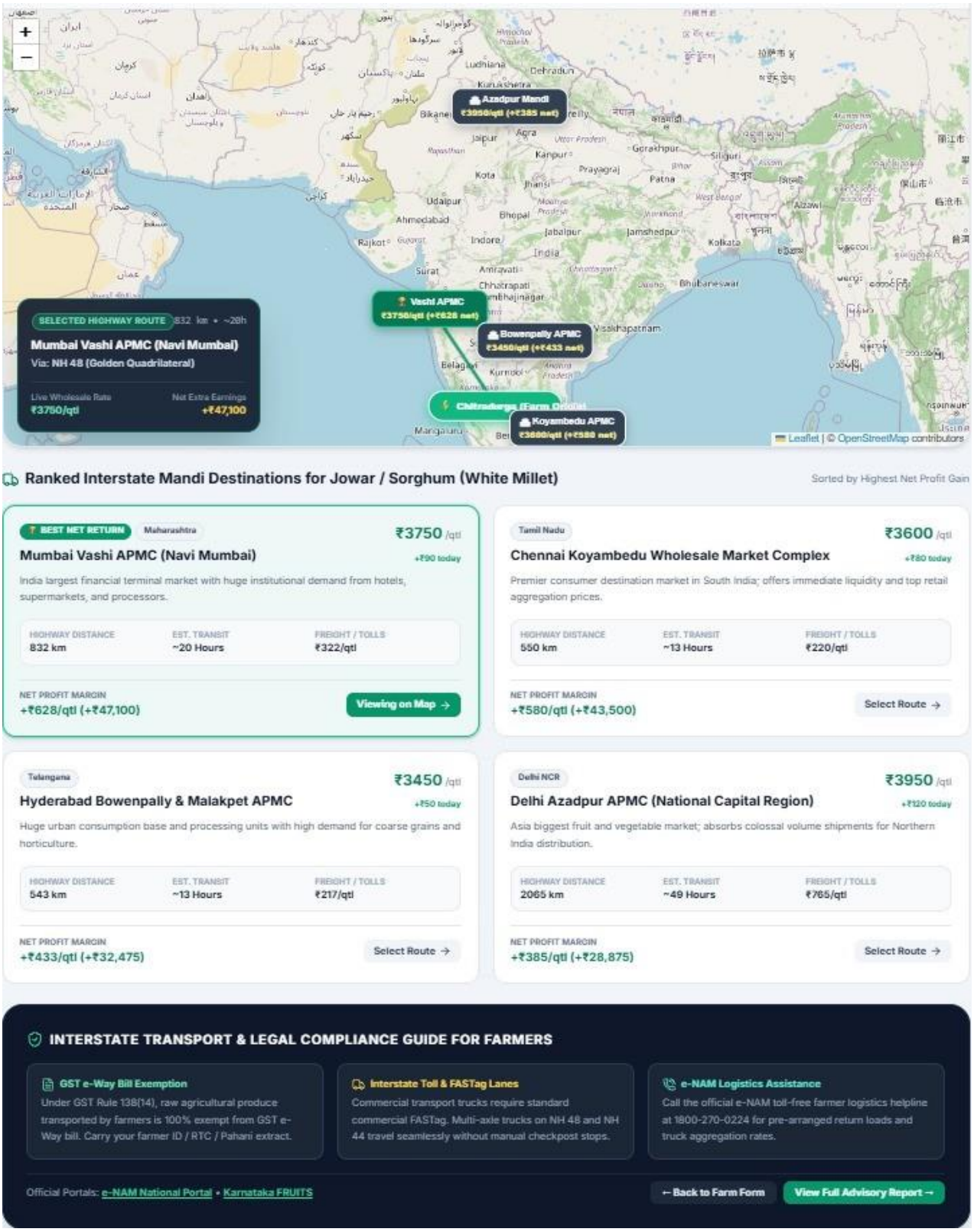


Figure 8: Geospatial interstate market redirection map routing produce along national highway corridors from glutted local mandis to deficit terminal hubs.

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IX. LIMITATIONS AND NEXT STEPS

A. Current Constraints

1. **Light Sensitivity:** Despite normalization algorithms, intense midday sun or heavy mud can alter visual readings, occasionally distorting optical carbon estimates.
2. **Static Logistics Costs:** The 1.28 highway tortuosity factor and standard diesel algorithms do not dy-namically adjust for sudden road closures or daily fuel price fluctuations.
3. **Offline Data Dependency:** In fully offline mode, the system relies on 30-year IMD climatological aver-ages, preventing it from predicting unexpected, localized flash droughts.
4. **API Restrictions:** Strict banking firewalls mean the application provides eligibility guidance and portal links, but cannot execute actual loan sanctions internally.

B. Future Research Plans

Future platform iterations will prioritize: (1) integrating low-cost Bluetooth (BLE) soil probes to support precise dielectric NPK reading; (2) connecting to India Stack and Open Credit Enablement Network (OCEN) APIs for in-app loan approvals; (3) establishing freight pooling algorithms to pair farmers with empty return-haulage commercial trucks; and (4) executing comprehensive field trials across distinct Indian agro-ecological zones.

X. CONCLUSION

This paper presented AgriCopilot, an offline-capable, edge-native Single-Page Application optimized for precision agronomy. By shifting visual soil analysis and logistical calculations to the client browser, AgriCopilot successfully classifies soil across six Indian taxonomic orders in under 50 ms with zero cloud dependency. The architecture integrates an ICAR-compliant biological stress engine, automated crop substitution, a supply-induced price forecasting model, and targeted credit allocation. Anchored by clear explainability tags and multi-language voice synthesis, AgriCopilot provides an accessible, reproducible framework for bridging biological science and financial logistics for smallholder farmers.

ACKNOWLEDGMENT

The authors express their sincere gratitude to the faculty, technical staff, and leadership of the Department of Computer Science and Engineering at K S School of Engineering and Management (KSSEM), Bengaluru, India, for providing infrastructural resources and research guidance. Special thanks are extended to project guide Punitha M R, Assistant Professor, for her valuable mentorship throughout this research.

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