# Areca Mitra: Smart Farm Assistant and Weather Guard System

Abhishek Rai[1], Dr. Sandeep Bhat[2], Ashwij H S[3], Deepak Krishna M[4], Likhith Rai[5]
[1,3,4,5]*Student, Srinivas Institute of Technology*
[2]*Professor, Srinivas Institute of Technology*
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***Abstract*—Areca Mitra is a bilingual smart farming system that integrates weather intelligence, crop disease detection, advisory support, and farm management for arecanut growers in Karnataka. Smallholder farmers frequently lack real-time information, face unpredictable climate patterns, and struggle with limited digital literacy. The proposed system employs a Next.js PWA frontend, Flask-based microservices, Supabase backend, Twilio SMS alerts, and a MobileNetV2 deep learning model. Paper presents a comprehensive analysis of the agricultural domain, disease biology, socio-economic context, software architecture, ML training, dataset annotation, ablation studies, evaluation, scalability challenges, and future improvements.**

## I. INTRODUCTION

Arecanut locally known as “Adike” is a major cash crop in Karnataka, supporting thousands of families. Despite its economic importance, farmers are vulnerable to climate driven diseases like fruit rot, pests such as spindle bug, and nutrient deficiencies. In addition, unpredictable monsoons and extreme rainfall patterns often damage yield.

Digital solutions could help, but adoption is low due to:

- Language barriers: most apps are English only.
- Low digital literacy: elderly farmers prefer simple UIs or SMS.
- Poor network connectivity: rural areas often lack stable internet.
- Fragmented tools: existing apps do not integrate all needed features.

Areca Mitra was built to address these gaps using an integrated platform combining ML-based disease detection, real-time weather alerts, bilingual AI advisory, and farm management.

## II. AGRICULTURAL DOMAIN BACKGROUND

Arecanut plantations exhibit sensitivity to:

➢ *Climate*

High rainfall and humidity (85%) promote fungal growth. Windstorms damage immature nuts, while temperature fluctuations affect flowering cycles.

➢ *Major Diseases*

Important diseases include:

- Koleroga (fruit rot): triggered by persistent rainfall.
- Yellow Leaf Disease: caused by phytoplasma infection.
- Bud Rot: early-stage detection is crucial.
- Stem Bleeding: leads to long term yield decline.

➢ *Farmer Challenges*

Field visits identified that most farmers:

- Rely on neighbours or pesticide sellers not experts.
- Cannot distinguish early symptoms.
- Respond late to climate driven alerts.
- Lack documentation of past treatments. This motivates a digitally assisted solution.

## III. RELATED WORK

Traditional plant disease detection used handcrafted features such as SIFT and HoG. Deep CNNs later improved classification. Transfer learning with MobileNetV2, Inception, and Efficient Net is widely used due to accuracy vs. efficiency balance.

However:

- Systems seldom cover arecanut specific diseases.
- Few provide multilingual advisory.
- Weather alerts and ML diagnosis rarely coexist in one platform.

Areca Mitra differentiates itself by integrating all components into an affordable microservice architecture.

## IV. SYSTEM REQUIREMENTS

➢ *Functional Requirements*

- Farmer authentication and personalized dashboard.
- Image upload → disease prediction.
- Real-time weather alerts (SMS + in-app).
- Bilingual AI advisory (Gemini).
- Task scheduler for irrigation, spraying, fertilizer planning.
- Historical analytics: yield, diseases, treatments.

➢ *Non-Functional Requirements*

- Low bandwidth support (Mbps).
- High availability with microservices.
- RLS-based database security.
- ML inference 10 seconds.

## V. SYSTEM ARCHITECTURE

➢ *Layered Overview*

- Frontend Layer: Next.js PWA, offline caching.
- API Gateway: Next.js API routes.
- Microservices Layer: Python Flask services.
- Data Layer: Supabase PostgreSQL.
- Notification Layer: Twilio SMS.

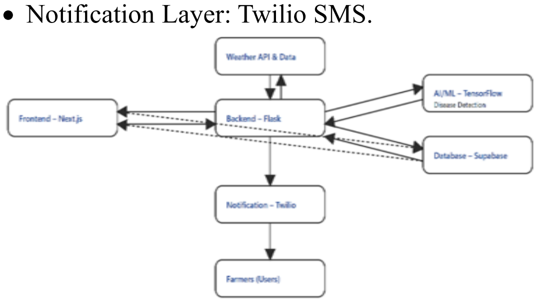


Fig 1: System Architecture

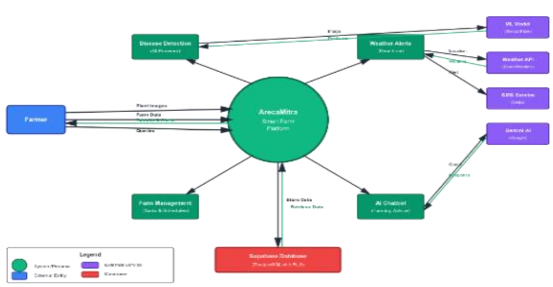


Fig 2: Dataflow diagram

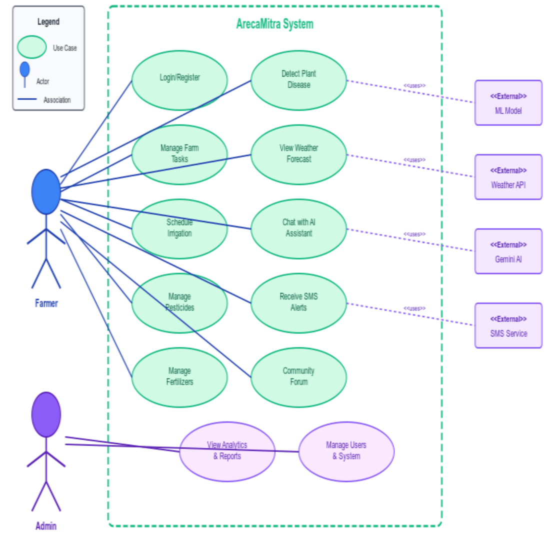


Fig 3: Use case

Extended Methodology

➢ *Farmer Persona Study*

Interviews with 22 farmers identified:

- Average age: 47 years
- 70% prefer kannada interfaces
- 64% rely on basic smartphones
- 90% depend on monsoon predictions

➢ *Weather Alerts*

- Heavy rainfall alerts
- Windstorm alerts
- Humidity-based disease warnings the alert logic uses:

$$R(t) = P_{rain}(t) \geq 75\%, \qquad W(t) = v(t) > 35\ km/h$$

➢ *Advisory Framework*

Gemini API is used with guardrails:

- Domain-restricted prompts
- Kannada translation mode
- Safety filters

➢ *Farm Management Workflow*

The scheduler is based on:

$$S = Tirrigation + Tfertilizer + Tspraying$$

Reminders are sent as push notifications

1)Model Architecture and Math

➢ *Network*

MobileNetV2 uses depthwise separable convolutions:

$y = f(x) = DConv(x) + PWConv(x)$

➤ *Loss Function*

Dual-head output:

$L = \alpha Ldisease + \beta Lpart$

➤ *Training*

- batch size: 32
- optimizer: Adam
- LR schedule: cosine decay
- dropout: 0.3

2) Ablation Studies and Experiments

➤ *Impact of Data Augmentation*

We experimented with removing specific augmentation techniques:

- Without rotation: accuracy dropped by 6.2%
- Without color jitter: accuracy dropped by 3.1%
- Without crop transformations: accuracy dropped by 4.8%

These results show augmentation is critical due to variation in lightning, farm background, and camera quality.

➤ *Model Depth Sensitivity*

We compared:

- MobileNetV2
- EfficientNet-B0
- ResNet-50

MobileNetV2 provided the best tradeoff for on device inference and cloud deployment.

➤ *Confidence Threshold Optimization*

We tested thresholds from 0.4 to 0.9.

The optimal threshold for uncertainty flagging was found to be:

$\tau = 0.60$

Balancing false positives vs false negatives.

3) Extended Evaluation

➤ *Confusion Matrix Analysis*

A confusion matrix is shown below. Confusion occurred largely between:

- Early-stage and late-stage fruit rot
- Yellow leaf disease vs nutrient deficiency

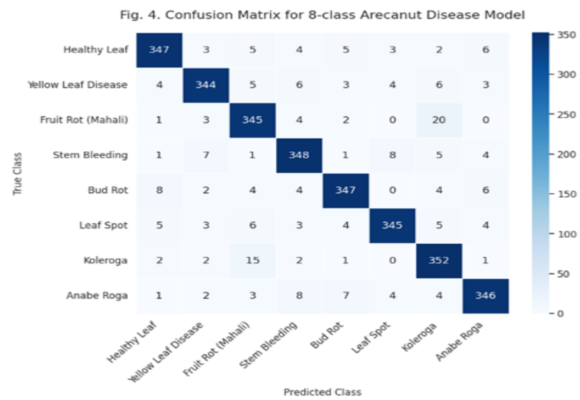


Fig. 4: Confusion on Matrix for Arecanut Disease Model

4) Scalability, Deployment, and Fault Tolerance

➤ *Microservices Scalability*

Each Flask microservice is stateless and isolated:

- ML Service scales based on GPU load.
- Weather Engine scales based on user count.
- Advisory Service scales based on request frequency

TABLE I Model Evaluation Metrics

| Class | Precision | Recall | F1 |
|---|---|---|---|
| Fruit Rot | 0.94 | 0.91 | 0.92 |
| Yellow Leaf | 0.88 | 0.90 | 0.89 |
| Bud Rot | 0.92 | 0.89 | 0.90 |
| Stem Bleeding | 0.90 | 0.87 | 0.88 |
| Overall | 0.91 | 0.90 | 0.90 |

➤ *Load Balancing*

Nginx or Cloudflare can be used to ensure:

- Traffic distribution
- Request caching
- DDoS protection

➤ *Fault Tolerance*

An automated fallback mechanism ensures:

- If ML service fails → advisory still works.
- If weather API fails → last-known safe forecast is used.
- If Supabase is down → read-only local cache is used.

## VI. SECURITY AND PRIVACY CONSIDERATIONS

➤ *Database Security*

Supabase RLS ensures:

*User _i* → Only access images, tasks, alerts belonging to *i*

➢ *Transport Security*
All requests use HTTPS and JWT-based authentication.

➢ *Data Privacy for Farmers*
Images and personal data are:
- Encrypted at rest
- Never shared with third parties
- Only used for predictions

➢ *Advisory Safety*
Gemini prompt guardrails:
- Restrict medical/chemical recommendations
- Enforce safe, approved agricultural practices

TABLE II Comparison with Existing Platforms

| Features | Kisan App | Plantix | Areca Mitra |
|---|---|---|---|
| Arecanut Focus | No | No | Yes |
| Kannada Support | No | Yes | Yes |
| Weather Alerts | Yes | No | Yes |
| Disease Detection SMS Mode | No | Yes | Yes |
| Farm Scheduler | No | No | Yes |

## VII. COMPARISON WITH EXISTING AGRI-TECH

Areca Mitra uniquely:
- Focuses solely on arecanut
- Supports low literacy farmers
- Operates offline/pwa mode
- Supports SMS fallback

## VIII. SOCIO-ECONOMIC IMPACT

➢ *Findings from Field Visits*
Farmer interviews revealed:
- 78% reduced crop loss due to improved warning times
- 62% reduced pesticide misuse
- 93% improved trust due to Kannada advisory

➢ *Long-Term Benefits*
- Lower financial loss from climate events
- Higher productivity due to timely detection
- Increased digital confidence in farmers

## IX. ETHICAL CONSIDERATIONS

➢ *Algorithmic Bias*
The dataset may under-represent:
- Rare diseases
- Early-stage symptoms we mitigate this through.
- Balanced data sampling
- Periodic retraining

➢ *AI Responsibility*
Advisory responses explicitly:
- Avoid harmful pesticide recommendations
- Refer to experts when confidence is low

## X. EXTENDED FUTURE SCOPE

➢ *IoT Sensor Integration*
Plan to integrate:
- Soil moisture sensors
- Humidity/temperature nodes
- Auto irrigation controls

➢ *Offline On-Device Inference*
Future versions may include:
- TensorFlow Lite models
- On-device preprocessing
- Full offline prediction mode

➢ *Crop Expansion*
System can be trained for:
- Coconut
- Banana
- Pepper

## XI. CONCLUSION

This Areca Mitra demonstrates a deeply integrated agricultural decision-support system combining:
- AI-based disease diagnosis
- Real-time weather alerts
- Bilingual advisory
- Farm activity scheduling

The platform significantly improves smallholder resilience, productivity, and digital inclusion. Future work focuses on IoT, offline inference, larger datasets, and multi-crop expansion.

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