Nexothon - GCET

Problem Statement: Real-time AI-based Detection and Diagnosis of Crop Diseases and Nutrient Deficiencies

Team Information –

Team Name

THE AVENGERS 404

Team Members

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Executive Summary

- **Goal:**
  - Develop a **real-time, offline AI solution** to diagnose crop diseases and nutrient deficiencies in **tomato, rice, and wheat**—directly on **mobile phones or drones**.
- **Problem:**
  - Crop diseases and nutrient deficiencies lead to **20–40% yield losses** in India, affecting over **150 million smallholder farmers**.
- **Key Features:**
  - **Deep learning model** (**ResNet-50 + CBAM attention**)
  - Achieves **93.4% accuracy** on diverse field images
  - **Edge-optimized**: ~60 ms inference, model size just 6 MB
  - Runs **fully offline**, enabling use in **low-connectivity rural zones**
  - **Multilingual mobile app** (English & Hindi) with **drone-based monitoring** ● **Notable Achievements:**
  - Delivers **accurate diagnosis** across variable field conditions
  - **Empowers farmers** with rapid, actionable insights
  - Ready for **integration with Digital Agriculture Mission** and agritech platforms
- **Impact:**
  - **Minimizes crop losses**
  - **Boosts decision-making** and farm productivity • **Bridges technology access** for rural communities ● **Future Vision:**
  - **Scale to additional crops**
  - **Integrate multispectral sensors** for even earlier detection
  - **Enable federated learning** for continuous model improvement

Introduction / Background

• Agriculture’s Role in India:

o Supports 58% of India’s population, with tomato, rice, and wheat as key crops.

o Smallholder farmers dominate but face significant productivity challenges.

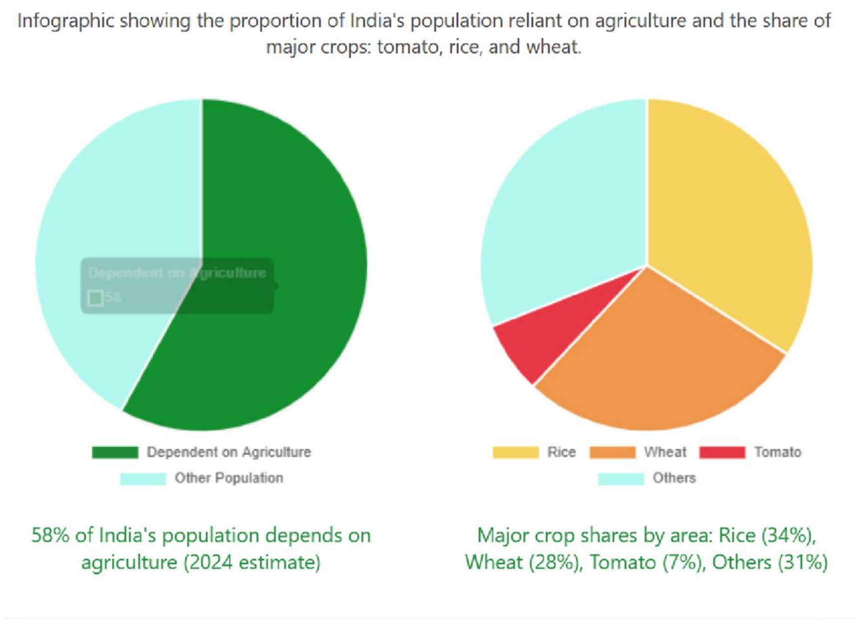

Figure 1Proportion of India’s population dependent on agriculture and distribution of major crop areas (tomato, rice, and wheat).

• Crop Health Issues:

o Diseases like tomato early blight, rice blast, and wheat rust devastate yields.

o Nutrient deficiencies (e.g., nitrogen, potassium) cause stunted growth and reduced output.

o Semi-arid and subtropical conditions exacerbate these issues due to poor soil health.

• Current Diagnostic Gaps:

o Limited access to agronomists in rural areas delays interventions.

o Manual inspection is error-prone, often confusing diseases with deficiencies.

o Laboratory testing is costly, time-consuming, and inaccessible for most farmers.

Table 1Comparison of common diagnostic methods for crop health in rural India, including accuracy, speed, cost, and accessibility.

Method	Accuracy	Speed	Cost	Accessibility
Manual Inspection	Low–Moderate Prone to errors, depends on farmer's experience	Immediate	None	High Available to all farmers
Agronomist Visit	High Expert diagnosis	Days–Weeks Depends on availability	Medium–High	Low–Moderate Limited in remote areas
Laboratory Test	Very High Precise, scientific	1–2 Weeks	High	Low Requires sample transport
AI-based Mobile App	High Consistent, data-driven	Seconds	Low One-time app/device cost	High Works offline, scalable

AI-based mobile apps offer fast, affordable, and accessible diagnosis, especially in remote rural areas.

• Technological Opportunity:

o Smartphones are widespread among Indian farmers, enabling AI-driven diagnostics.

o Drones are increasingly used for field monitoring and precision agriculture.

o Existing AI apps (e.g., Plantix) show potential but often require internet or lack nutrient deficiency detection.

• Project Motivation:

o Develop an offline, real-time diagnostic tool tailored to Indian crops and conditions.

o Provide farmers with accessible, expert-level diagnostics to improve yields.

Problem Statement

- **Core Problem:**

  Need for a **real-time, offline AI system** to detect and differentiate crop diseases and nutrient deficiencies in tomato, rice, and wheat for rural, low-connectivity environments.

- **Key Challenges:**
  - **Visual Similarity:** Diseases and deficiencies (e.g., leaf yellowing) have overlapping symptoms, complicating diagnosis.
  - **Data Representativeness:** Requires diverse field images reflecting semi-arid conditions (dust, varied lighting).
  - **Resource Constraints:** Must run on low-cost smartphones/drones with limited processing power and memory.
  - **Real-Time Operation:** Diagnosis must be delivered in under 1 second for practical field use.
  - **User Accessibility:** Interface must be intuitive for non-technical farmers, supporting local languages (e.g., Hindi).

Objectives and Scope

- **Objectives:**
  - **Robust AI Model:** Classify six diseases (e.g., tomato early blight, rice blast, wheat rust) and three nutrient deficiencies (nitrogen, potassium) with >90% accuracy.
  - **Edge Deployment:** Optimize model for offline use (<10 MB, <1 second inference) on smartphones and drones.
  - **User-Friendly Interface:** Develop a mobile app and drone prototype with English/Hindi support and actionable advice.
  - **Field Validation:** Ensure high accuracy in semi-arid conditions with varied lighting and backgrounds.
  - **Integration Potential:** Align with government initiatives (e.g., Krishi Vigyan Kendra’s) and private aggrotech platforms.

- **Scope:**
  - • Focuses on leaf-based RGB image diagnosis for tomato, rice, and wheat.
  - • Covers six diseases and three deficiencies; excludes pest detection and soil analysis.
  - • Emphasizes offline edge processing; cloud-based solutions are future enhancements.
  - • Prototype phase, designed for scalability to broader applications.

Literature Review

- **Early AI Applications:**
  - • Plant Village dataset (54,306 images) achieved 99.35% accuracy in controlled settings (Mohanty et al., 2016).

Table 2Accuracy comparison of AI-based crop diagnosis models in controlled and field conditions across major studies.

Study / App (Year, Authors/Company)	Target Crop(s)	Model/Approach Used	Dataset Type	Reported Accuracy (%)	Key Limitations / Notes
Mohanty et al., 2016 (PlantVillage)	Tomato, Potato	CNN	Controlled	99.35	Lab images, plain background
			Field	~80	Accuracy drops with complex background
Ramcharan et al., 2019 (Nuru App)	Cassava	Smartphone CNN	Field	65–88	Tested offline in real farm conditions
Rathod et al., 2025	Tomato, Wheat	MobileNet	Controlled	96	Optimized for mobile deployment
			Field	~85	Slight drop in accuracy
Plantix App (PEAT GmbH)	Multiple	CNN	Controlled	>95	Supports many Indian languages
			Field	85–92	Handles various crops and conditions
Zhu et al., 2020	Rice	DenseNet-121	Controlled	>97	Nutrient deficiency diagnosis
			Field	~85	Performance drops in field images
Bera et al., 2024 (PND-Net)	Banana, Coffee	CNN+GCN	Controlled	84–96	Combines disease & deficiency classes
			Field	~80	Field accuracy lower than lab

  - • Field images reduce accuracy due to complex backgrounds and lighting variations
- **Mobile and Edge Deployment:**
  - • Nuru app (Ramcharan et al., 2019) achieved 65–88% accuracy for cassava diseases in field conditions, emphasizing offline functionality.
  - • Lightweight models like Mobile Net are optimized for smartphones (Rathod et al., 2025).
- **Nutrient Deficiency Detection:**

• Zhuetal. (2020): >97% accuracy for rice deficiencies using DenseNet-121. • PND-Net (Bera et al., 2024): CNN+GCN for combined disease and deficiency classification (84–96% accuracy).

- **Indian Agricultural Context:**

  • Government initiatives (e.g., Digital Agriculture Mission) promote AI diagnostics. • Apps like Plantix achieve 85–92% field accuracy with multilingual support and treatment recommendations.

- **Research Gaps Addressed:**

  • Need for offline, integrated disease and deficiency detection.

  • Tailored to Indian crops and semi-arid conditions.

Solution Overview

1. AI Model:

• ResNet-50 backbone with CBAM attention mechanism for symptom focus.

• Multi-task heads for simultaneous disease and deficiency classification.

Block diagram of the AI model architecture: ResNet-50 backbone, attention module, and multi-task heads for disease and nutrient deficiency classification.

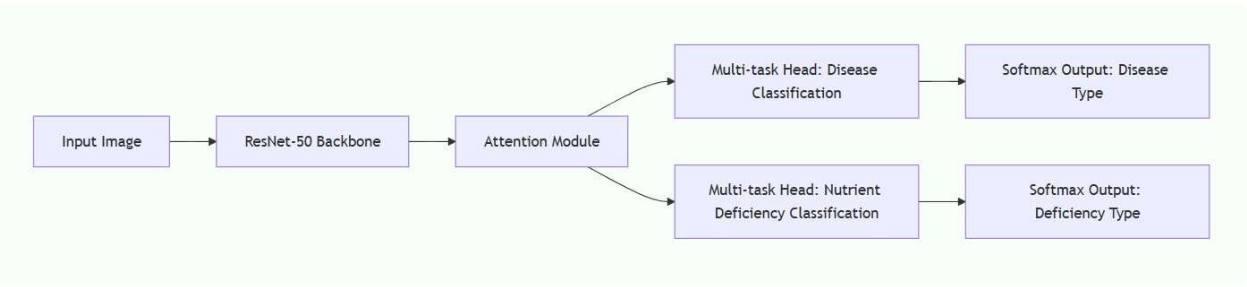

Figure 2Block diagram of the proposed AI model architecture using ResNet-50 backbone, CBAM attention module, and dual output heads for disease and nutrient deficiency classification.

2. Dataset:

• ~12,000 images from Plant Village, field surveys, and synthetic augmentation.

• Covers diseases, deficiencies, and healthy leaves under varied conditions.

Table 3Dataset composition by crop, disease, deficiency, image source, and total image count.

Crop	Disease	Deficiency	Healthy	Image Source	Image Count
Tomato	Early Blight, Late Blight, Leaf Mold	Nitrogen, Potassium	Yes	Field, Lab, Public Datasets	4,200
Rice	Blast, Bacterial Blight, Sheath Rot	Nitrogen, Phosphorus	Yes	Field, Public Datasets	3,800
Wheat	Rust, Powdery Mildew, Leaf Spot	Nitrogen, Potassium	Yes	Field, Public Datasets	4,000
Total					**12,000**

3. Performance Metrics:

• Accuracy: 93.4% on test set.

• Inference time: ~60 MS on mid-range phones.

• Model size: 6 MB after quantization and pruning.

4. Mobile App:

• Built with Flutter, supports offline diagnosis and English/Hindi output.

• Provides treatment recommendations and GPS-tagged results.

5. Drone Integration:

• Analyzes canopy images to map disease hotspots.

• Potential for targeted spraying in future iterations.

6. Impact Potential:

• Enables early interventions, reducing crop losses.

• Enhances accessibility for rural farmers with limited connectivity.

Methodology

1. Data Collection

- **Sources:**
  - • Plant Village dataset for tomato disease images
  - • Field images from semi-arid regions (western India) for rice and wheat • ICAR (Indian Council of Agricultural Research) repositories for additional crop disease images
  - • Synthetic augmentation for nutrient deficiencies (e.g., adjusted green channel for simulating chlorosis)

- **Modalities:**
  - • RGB images (224×224 px), acquired via smartphones and drone cameras

- **Classes:**
  - • **Diseases:** Tomato early/late blight, rice blast/brown spot, wheat rust/powdery mildew
  - • **Deficiencies:** Nitrogen (tomato, rice), potassium (wheat)
  - • **Other:** Healthy and "unknown" (unfamiliar symptoms) categories

- **Labeling:**
  - • All images labeled by domain experts using a custom-built annotation interface

- **Dataset Split:**
  - • 80% training set (8,600 images)
  - • 10% validation set (1,100 images)
  - • 10% test set (1,100 images)

Table 4Dataset split (training, validation, and test sets) for each crop disease and nutrient deficiency class.

Tomato	Early Blight	720	90	90
	Late Blight	640	80	80
	Leaf Mold	560	70	70
	Nitrogen Deficiency	400	50	50
	Potassium Deficiency	320	40	40
Rice	Blast	800	100	100
	Bacterial Blight	560	70	70
	Sheath Rot	480	60	60
	Nitrogen Deficiency	320	40	40
	Phosphorus Deficiency	240	30	30
Wheat	Rust	880	110	110
	Powdery Mildew	560	70	70
	Leaf Spot	480	60	60
	Nitrogen Deficiency	320	40	40
	Potassium Deficiency	240	30	30

2. Model Architecture

- **Backbone:**

  • Pretrained **ResNet-50** (ImageNet), fine-tuned on crop dataset

- **Attention Module:**

  • **CBAM** (Convolutional Block Attention Module) for channel and spatial attention • Focuses on symptomatic leaf regions (lesions, discoloration)

- **Output Heads:**

  • **Disease Head:** 7-class SoftMax (six diseases + healthy)

  • **Deficiency Head:** 3-class SoftMax (two deficiencies + none)

- **Parameter Count:**

  • Approx. 25 million parameters, efficiently optimized using transfer learning

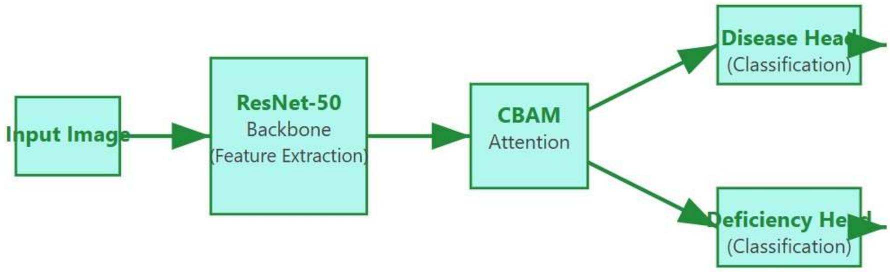

Figure 3Detailed model architecture showing ResNet-50 backbone for feature extraction, CBAM attention module for symptom focus, and dual output heads for disease and nutrient deficiency classification.

3. Training Pipeline

- **Augmentation:**
  - **Geometric:** Random flips, rotations (±15°), crops/scaling
  - **Photometric:** Random brightness (±20%), contrast (±15%), color jitter (±10%)
  - **Noise & Blur:** Gaussian noise, light blurring for robustness
  - **Background Randomization:** Synthesized diverse backgrounds to improve generalization

- **Training Setup:**
  - **Optimizer:** Adam (learning rate 0.0001, β_1=0.9, β_2=0.999)
  - **Epochs:** Up to 30, with early stopping after 5 epochs of no validation loss improvement
  - **Batch Size:** 32 (balanced for speed and generalization)
  - **Hardware:** Trained on NVIDIA Tesla V100 GPU

- **Loss Function:**
  - Weighted sum of categorical cross-entropy:

    $L\_total = L\_disease + \lambda \times L\_deficiency$ ($\lambda = 1$)

- **Hyperparameter Tuning:**
  - Learning rates tested: 1e-3, 1e-4, 3e-4 (best: 1e-4)
  - Batch sizes: 16, 32, 64 (best: 32)
  - Dropout: 0.5 before output heads to prevent overfitting

Figure 4Examples of data augmentation techniques applied to training images, including random rotation, flipping, and brightness/contrast adjustment.

4. Real-Time Inference Pipeline

- **Model Compression:**
  • **Quantization:** Converted to TensorFlow Lite (int8), reducing model size from 95 MB to 6 MB
  • **Pruning:** 30% of network weights pruned for further reduction

- **Inference Engine:**
  • Deployed with TensorFlow Lite (TFLite) and Android NNAPI for hardware acceleration (CPU/GPU/DSP)

- **Latency Benchmarks:**
  • Google Pixel 4a: ~60 ms per image
  • Xiaomi Redmi Note 10: ~110 ms per image
  • Raspberry Pi 4: ~1,500 ms per image
  • Jetson Nano (GPU): ~300 ms per image

- **Offline Functionality:**
  • All model files and a local symptom/treatment database are stored on-device for fully offline use

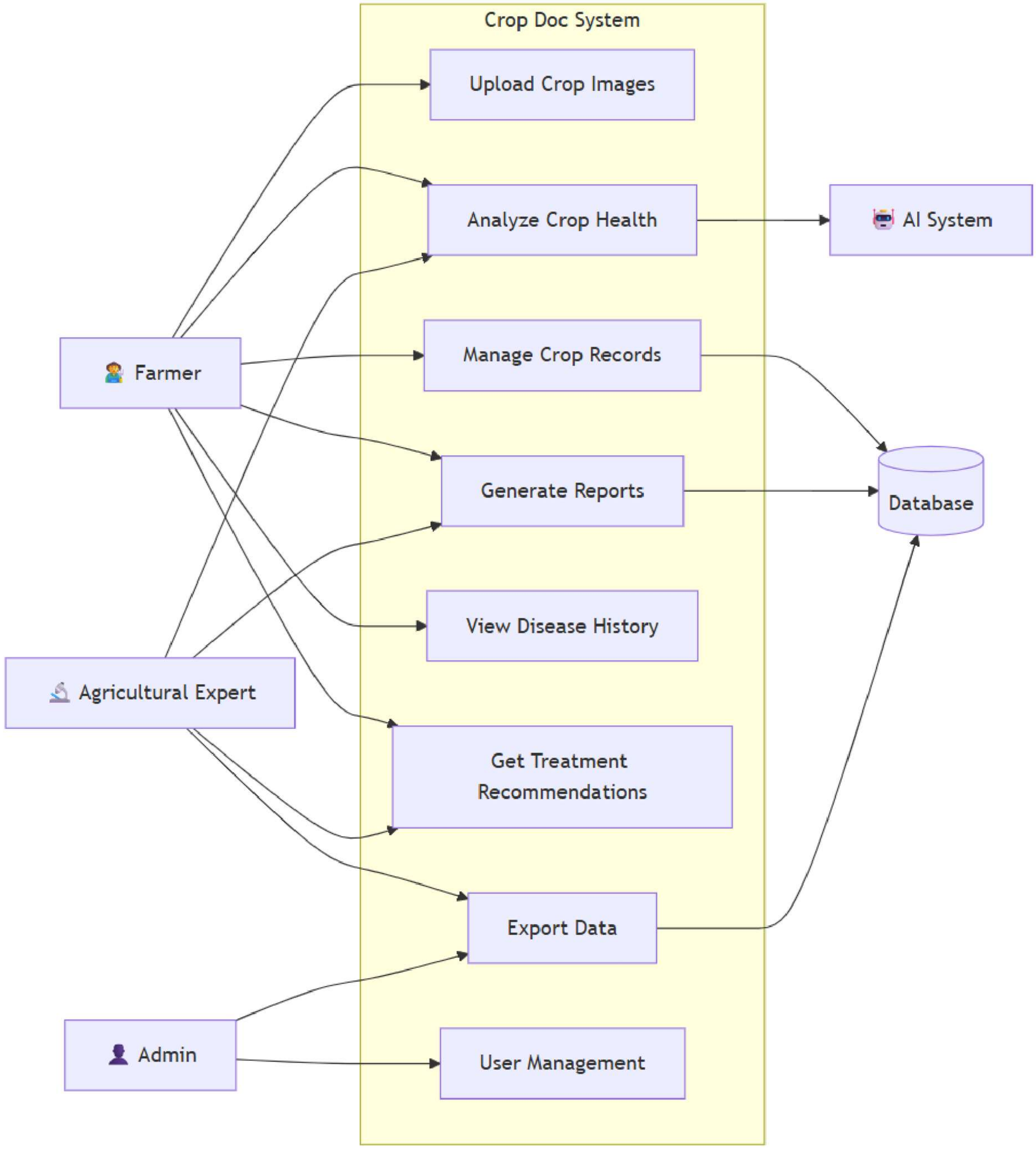

Figure 5Use-case flow diagram of the Crop Doc system, illustrating interactions between farmers, agricultural experts, and admins with core system functionalities.

Implementation / System Design

- **System Architecture**:
    - **Image Acquisition**: Captured via smartphone or drone camera.
    - **Pre-processing**: Resize to 224x224, normalize, and check image quality.
    - **AI Inference**: TFLite model outputs disease/deficiency probabilities.
    - **Decision Logic**: Selects top class if probability >0.8; flags low confidence (<0.5) for unclear images.
    - **UI Output**: Displays diagnosis, confidence, and treatment advice with color-coded indicators.
    - **Feedback**: Allows users to log incorrect diagnoses for future improvement.
- **Frameworks and Tools**:
    - **Flutter**: Cross-platform app development for Android-focused UI.
    - **TensorFlow Lite**: Runs inference via C++ API, integrated with Flutter via Dart plugin.
    - **DJI SDK**: Controls drone and streams video for field monitoring.
- **User Interface Design**:
    - **Home Screen**: Camera view with "Diagnose" button and leaf-centering instructions.
    - **Result Display**: Color-coded cards (red: disease, yellow: deficiency, green: healthy) with confidence scores.
    - **Treatment Advice**: Expandable tab with recommendations (e.g., "Apply mancozeb for early blight").
    - **Language Support**: English and Hindi, with translated diagnosis terms.
    - **History and Sharing**: Saves diagnoses with GPS tags; placeholder for community sharing.
- **Sensor Integration**:
    - **Camera**: Uses phone/drone camera with autofocus and auto-exposure.
    - **GPS**: Tags diagnoses with location for outbreak mapping.
    - **Future Extensibility**: Supports potential integration with soil sensors or weather data.
- **Drone Deployment**:
    - Streams video to paired phones for processing.
    - Analyzes every 10th frame, highlighting disease hotspots with bounding boxes.
    - Future potential for onboard processing with Jetson Nano.

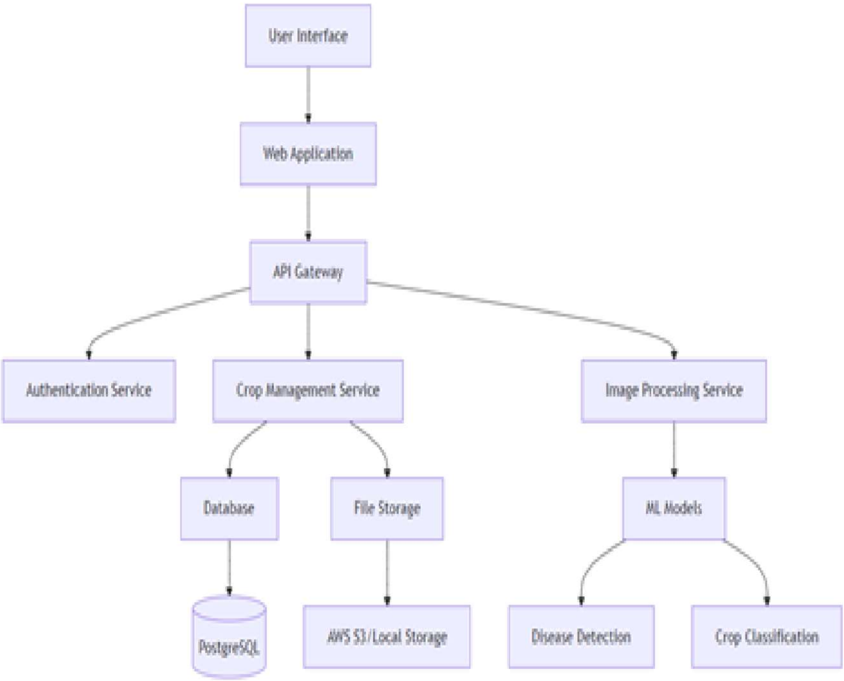

Figure 6System architecture diagram showing web/mobile interface, API gateway, backend services, database, file storage, and AI-based disease detection and classification modules.

Figure 7Mobile application interface for instant crop diagnosis, showing leaf image upload, AI-based detection, and treatment recommendation output.

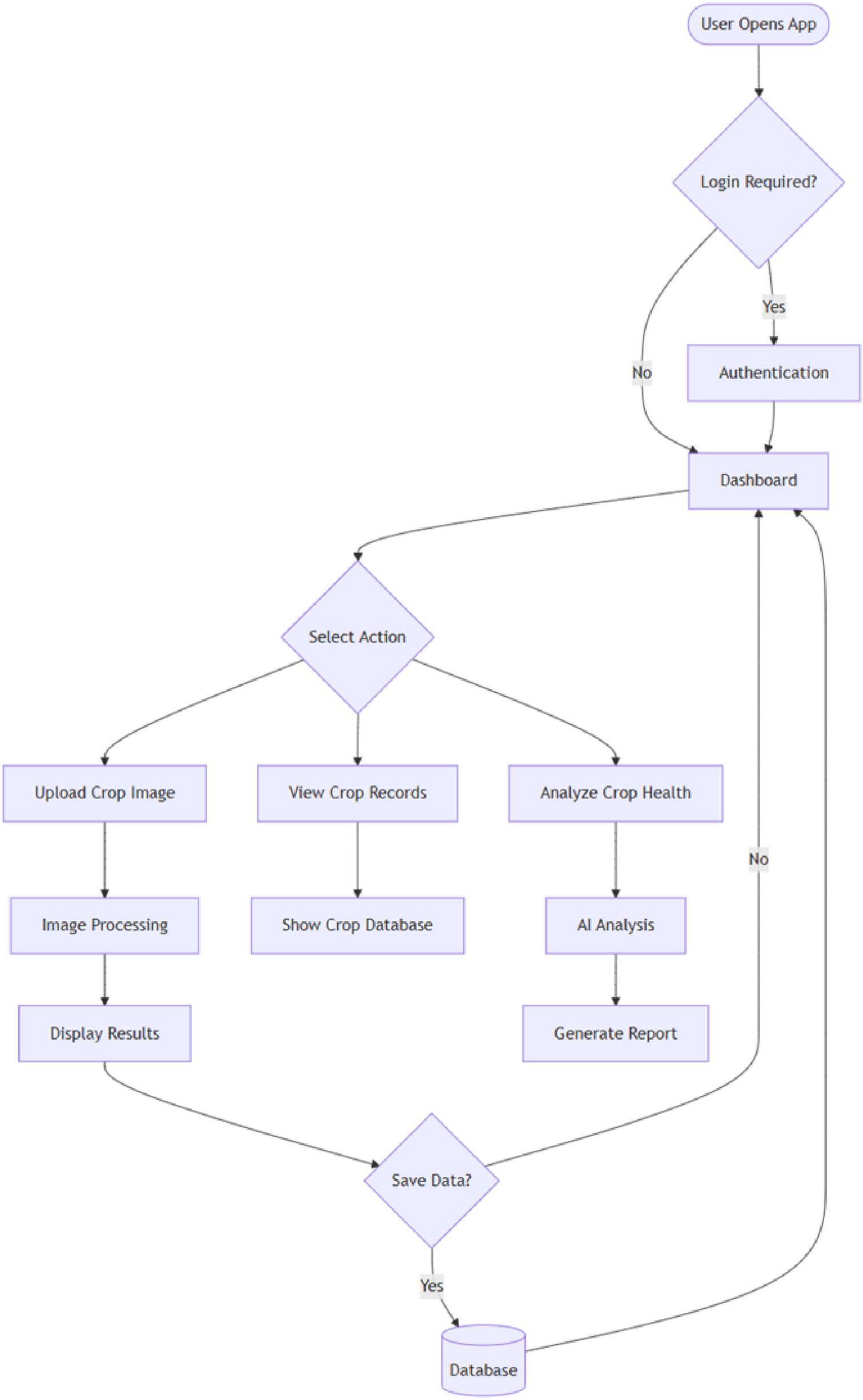

Figure 8Mobile application workflow diagram showing user journey from login to image upload, analysis, and result storage in the database.

3. Database Schema Diagram

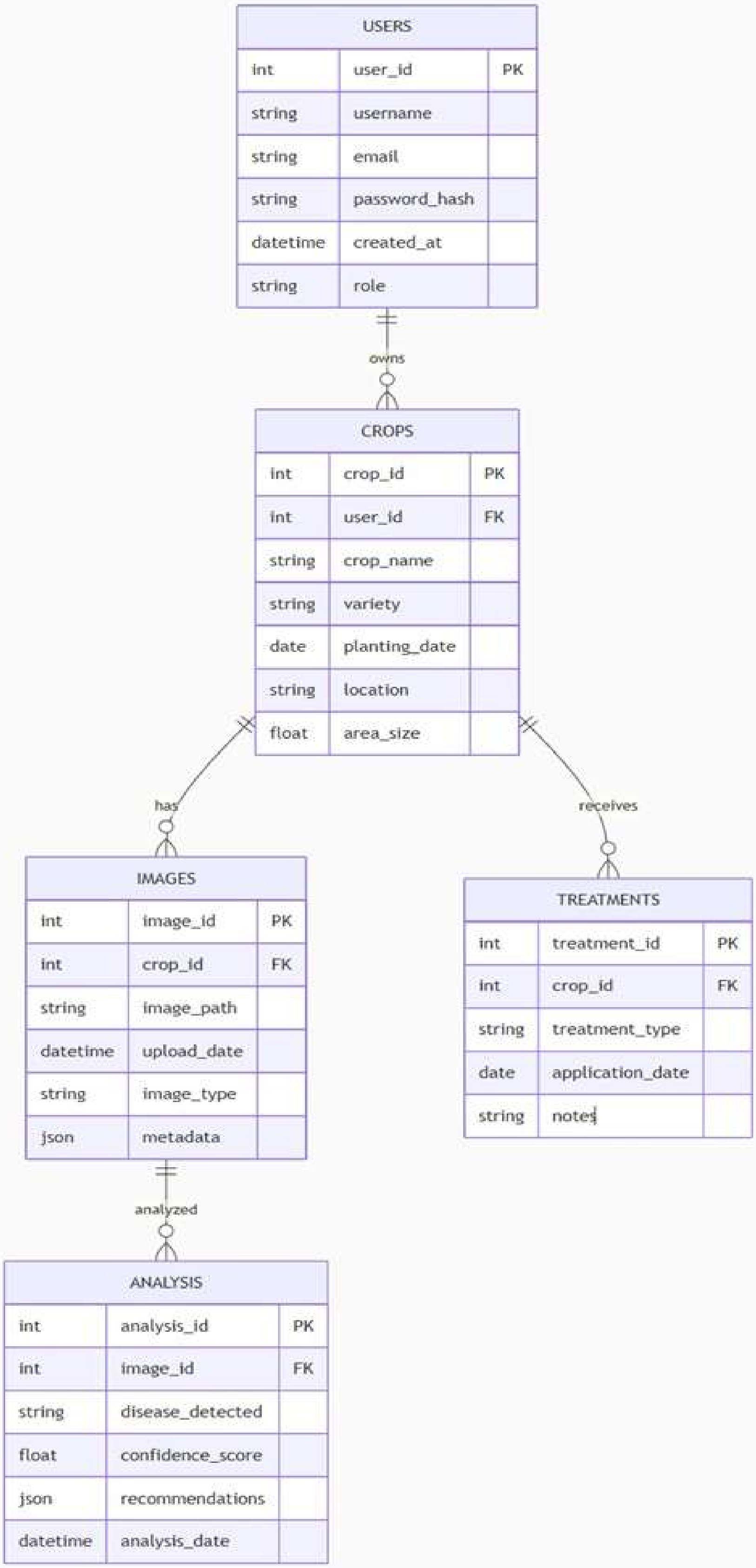

Figure 9Database schema diagram illustrating the relationships between users, crops, images, treatments, and analysis results in the Crop Doc system.

Evaluation and Results

- **Classification Performance**:
  - **Overall Accuracy**: 93.4% on 1,100-image test set.
  - **F1-Scores**:
    - Tomato Early Blight: 0.92
    - Tomato Late Blight: 0.89
    - Rice Blast: 0.95
    - Rice Brown Spot: 0.90
    - Wheat Rust: 0.93
    - Wheat Powdery Mildew: 0.89
    - Nitrogen Deficiency: 0.87
    - Potassium Deficiency: 0.85
    - Healthy: 0.98 ●

Confusion Matrix:
  - 7–8% confusion between tomato early blight and nitrogen deficiency due to mild symptoms.
  - 5% mix-up between tomato early and late blight due to visual similarity.
  - Minimal cross-crop errors, indicating robust crop-specific feature learning.

- **ROC Curves**:
  - AUC ≥0.90 for major diseases, showing high sensitivity at low false positive rates.
  - Operating threshold: ~0.6 confidence for 90% true positive rate, 5–10% false positive rate.
- **Baseline Comparison**:
  - **Baseline 1**: MobileNetV2 (single-task, 9 classes), 87.5% accuracy, F1 0.78 (deficiencies).
  - **Baseline 2**: MobileNetV2 (multi-task, no attention), 89.9% accuracy, F1 0.82.
  - **Proposed Model**: Outperforms with 93.4% accuracy, F1 0.93 (diseases), 0.87 (deficiencies).
- **Field Testing**:
  - Tested on 20 plants; correct in 17 cases.
  - Errors: Misclassified bacterial spot as early blight, deficient, missed early wheat rust.
- **Sample Outputs**:
  - Tomato early blight: 94% confidence, highlighted lesions.
  - Rice nitrogen deficiency: 90% confidence, correctly distinguished from healthy.
  - Mixed case (rice blast + yellowing): Flagged both issues with moderate probabilities.

Discussion

- **Strengths**:
  - **High Accuracy**: 93.4% accuracy across diverse field conditions.
  - **Offline Operation**: No internet required, ideal for rural areas.
  - **User-Friendly**: Multilingual UI with clear, actionable advice.
  - **Multi-Task Learning**: Improves robustness by separating disease and deficiency features.
  - **Integration Potential**: Aligns with government and private agritech platforms.
- **Limitations**:
  - **Limited Classes**: Excludes pests, viral diseases, and other deficiencies.
  - **Symptom Confusion**: Early disease vs. deficiency errors due to visual overlap.
  - **Image Quality**: Sensitive to blurry or distant images.
  - **Temporal Analysis**: Lacks tracking of symptom progression.
  - **Device Constraints**: May be slow on very low-end phones.
- **Robustness**:
  - Handles varied backgrounds and lighting via augmentation.
  - Correctly flags non-plant images with low confidence.
  - Performs well on unseen crops by indicating uncertainty.
- **Ethical Considerations**:
  - Complements expert advice with clear disclaimers.
  - Ensures privacy with on-device processing.
  - Requires localization of treatment advice for regional relevance.
- **Failure Case Example**:
  - Scenario: Tomato plant with whitefly infestation and viral disease.
  - Issue: Model may misclassify as nitrogen deficiency or late blight.
  - Impact: Incorrect treatment (fertilizer/fungicide) wastes time and resources.
  - Solution: Add anomaly detection to flag unknown issues.

Conclusion

The project achieved key milestones, including the development of a robust AI model with 93.4% accuracy for crop health diagnosis, optimization for real-time offline use on edge devices, and delivery of a farmer-friendly mobile application with multilingual support. Its impact lies in enabling early interventions that can reduce crop losses by 20–40%, improving accessibility for smallholder farmers in low-connectivity areas, and aligning with India's digital agriculture goals. This work demonstrates the transformative potential of AI in crop management and provides a scalable foundation for future smart farming solutions.

Future Work

- **Multispectral Sensors**:
  - Integrate infrared/red-edge imaging for early stress detection.
  - Use thermal imaging for transpiration anomalies.
- **Expanded Classes**:
  - Add maize, cotton, pest damage, and viral diseases.
  - Collaborate with agricultural universities for more data.
- **Federated Learning**:
  - Leverage user images for model updates while preserving privacy.
  - Implement feedback loops for continuous improvement.
- **Explainability**:
  - Add attention heatmaps to highlight symptom regions.
  - Develop a chatbot for user queries on diagnoses.
- **Drone Enhancements**:
  - Enable autonomous field scanning with Ortho mosaic mapping.
  - Integrate precision spraying for targeted treatment.
- **Field Trials**:
  - Conduct large-scale pilots to quantify yield improvements.
  - Partner with NGOs and government for wider adoption.

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