GrowSure App: A Multilingual Multi-Crop Disease Detection and Solution

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***Abstract*—Agricultural productivity worldwide is severely hampered by viral, bacterial, and fungal plant diseases, resulting in significant crop losses and economic hardship for farming communities. Conventional disease diagnosis relies heavily on manual expert inspection, which is time-consuming, error-prone, and often inaccessible to smallholder farmers in rural regions. This paper presents the GrowSure App, a comprehensive AI-powered and IoT-enabled mobile platform designed to address these challenges holistically. The proposed system leverages a fine-tuned Convolutional Neural Network (CNN) for multi-crop leaf disease classification, achieving an average detection accuracy of 92.5% across five crop types. A hybrid recommendation engine combining Collaborative Filtering (CF) and Content-Based Filtering (CBF) provides personalized treatment suggestions based on disease diagnosis, farmer history, and real-time environmental data. IoT sensors continuously monitor critical soil parameters moisture, pH, and temperature feeding contextual data into the advisory system for crop suitability recommendations. Additionally, Natural Language Processing (NLP) modules incorporating transformer-based translation models and Text-to-Speech (TTS) deliver agricultural guidance in English, Hindi, and Marathi, bridging the digital divide for linguistically diverse farming communities.**

***Index Terms*—plant disease detection; convolutional neural network; IoT; collaborative filtering; content-based filtering; multilingual support; precision agriculture; deep learning; mobile application**

I. INTRODUCTION

Agriculture forms the backbone of the global economy and is the primary livelihood for over 2.5 billion people worldwide [1]. Despite technological advances, smallholder farmers particularly in developing countries continue to face enormous challenges in managing plant diseases effectively. Left undetected, crop diseases caused by fungal, bacterial, and viral pathogens can destroy up to 40% of annual yields globally, translating to hundreds of billions of dollars in economic losses and threatening food security [2].

Traditional approaches to disease identification require physical inspection by trained agronomists, a resource that is prohibitively scarce in rural and semi-urban farming communities. The digital revolution in agriculture, often referred to as Agriculture 4.0, has introduced AI-powered image recognition, IoT-based sensor networks, and mobile computing as transformative tools that can democratize expert agricultural knowledge [3].

Existing AI-driven plant disease detection systems, however, suffer from critical limitations: they predominantly support single-crop species, lack integration with soil health monitoring, do not provide actionable treatment recommendations, and are inaccessible to non-English-speaking farmers [4]. This paper presents the GrowSure App, which bridges these gaps by integrating:

(i) A CNN-based multi-crop disease detection module trained on diverse leaf image datasets.
(ii) A hybrid CF+CBF recommendation engine for personalized treatment suggestions.
(iii) IoT sensors for real-time soil health monitoring and crop suitability assessment.
(iv) NLP-driven multilingual and voice-based advisory in English, Hindi, and Marathi.

The remainder of this paper is organized as follows: Section II reviews related literature; Section III describes the proposed system architecture; Section IV presents experimental results; Section V concludes.

II. LITERATURE SURVEY

The rapid growth of deep learning has significantly advanced automated plant disease detection over the past decade. This section reviews the most relevant work across machine learning approaches, deep learning architectures, IoT integration, few-shot learning, and multilingual accessibility.

A. Machine Learning Approaches
Early plant disease detection systems relied on classical machine learning techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Decision Trees, which required handcrafted feature extraction using color histograms, Gray-Level Co-occurrence Matrix (GLCM) texture features, and shape descriptors [5]. While these methods demonstrated reasonable performance in controlled laboratory environments, they exhibited limited scalability and poor generalization to field conditions with varying lighting, backgrounds, and disease severity. Joshi and Bhavsar [5] concluded that manual feature engineering represented the primary bottleneck to real-world deployment. While these methods demonstrated reasonable performance in controlled laboratory environments, they exhibited limited scalability and poor generalization to field conditions with varying lighting, backgrounds, and disease severity. Joshi and Bhavsar [5] concluded that manual feature engineering represented the primary bottleneck to real-world deployment.

B. Deep Learning and CNN-Based Detection
The landmark study by Mohanty et al. [1] demonstrated that CNNs trained on the PlantVillage dataset could achieve over 99% accuracy in controlled conditions. Subsequently, architectures including VGG16, ResNet-34, DenseNet-121, and EfficientNet-V2 have been evaluated extensively for multi-class leaf disease classification [6], [7]. Khaldi and Kalmoun [6] evaluated multiple CNN architectures on pumpkin leaf images, with DenseNet-121 achieving 86% accuracy. Rimi et al. [7] achieved 91.5% accuracy using EfficientNet-V2 and MobileNet-V2 on the RiceLeafBD dataset. Iftikhar et al. [8] integrated fine-tuned CNNs with a cross-platform mobile application for real-time classification, though these works predominantly focused on single crop species and lacked treatment recommendation systems.

C. IoT Integration and Edge Computing
The integration of IoT sensors has expanded disease prediction by incorporating contextual environmental data. Thorat et al. [9] demonstrated that combining leaf image analysis with real-time IoT sensor data improved detection confidence by up to 12% over image-only approaches. Correa Da Silva and Almeida [10] leveraged edge computing with MobileNet and InceptionV3 deployed on Edge TPU hardware, achieving reduced processing latency. However, reliance on thermal imaging cameras poses significant cost barriers for smallholder farmers.

D. Few-Shot and Transfer Learning
A persistent challenge in agricultural AI is the scarcity of labeled datasets for less common crops. Architectures such as Siamese Networks and Prototypical Networks have been explored for low-resource plant disease classification [7]. AgriNet (2024) combined a hybrid CNN with few-shot learning to achieve near-perfect accuracy on tomato, potato, and mango classification, though field validation remained absent [11].

E. Multilingual Support and Accessibility
The linguistic diversity of farming communities poses a significant barrier to AI tool adoption. Anantrasirichai et al. [12] demonstrated the feasibility of mobile-phone-based plant pathology management systems, emphasizing the need for local language support. Recent NLP advances, particularly transformer-based models such as BERT and MarianMT, have enabled high-quality multilingual translation for agricultural advisory content. TTS engines further enhance accessibility for farmers with low literacy levels [12].

F. Summary and Research Gaps
Table I synthesizes key findings and research gaps. Critical gaps motivating the GrowSure App include: (i) absence of integrated multi-crop disease detection with treatment recommendations, (ii) lack of IoT-coupled soil health advisory, (iii) no multilingual farmer support in existing unified platforms, and (iv) insufficient real-world deployment and validation.

TABLE I. Summary of Literature Survey

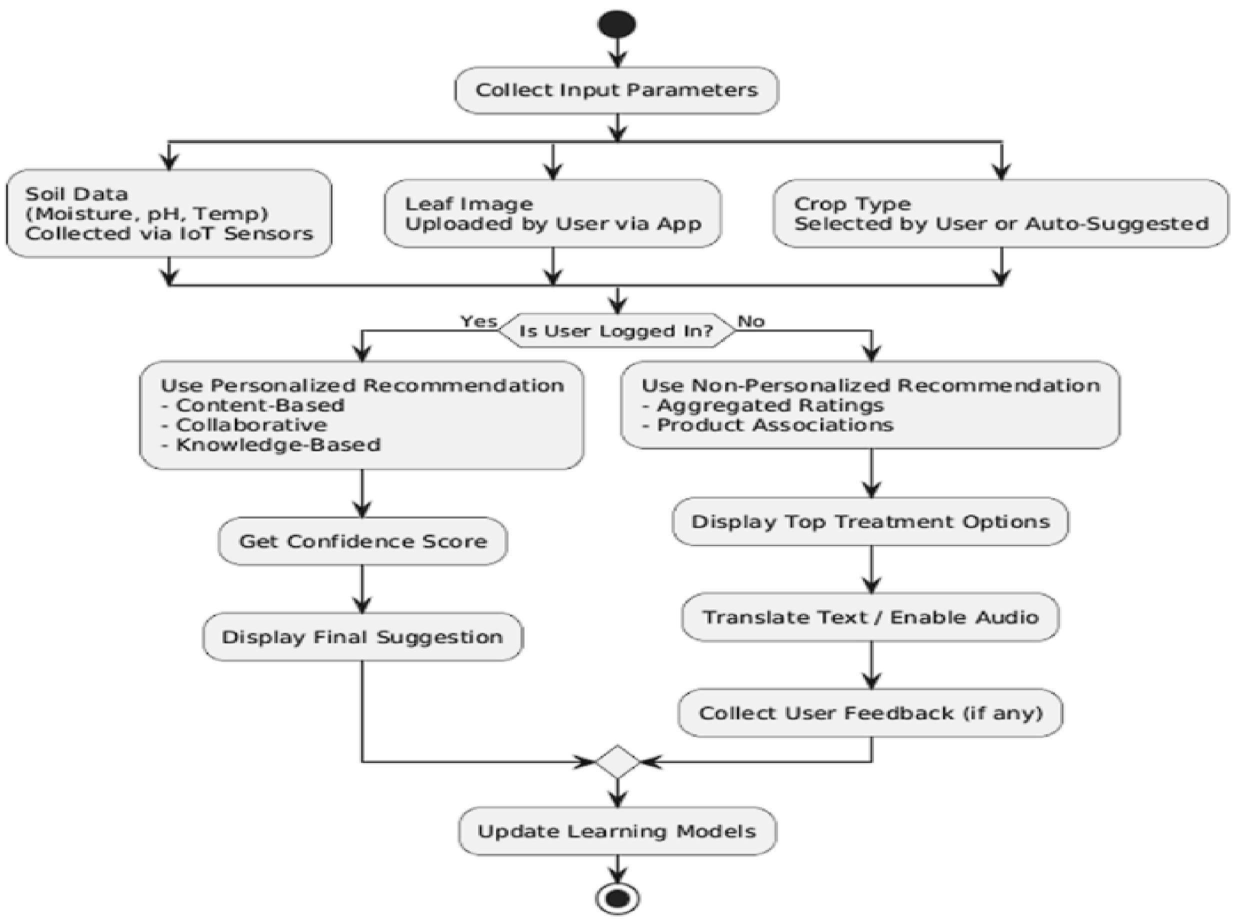
Sr.	Paper	Technique	Result	Gap
1	RiceLeafBD (2025)	EfficientNet-V2, MobileNet-V2	91.5% accuracy	No cross-dataset validation
2	AgriNet (2024)	Hybrid CNN + Few-Shot Learning	High multi-crop accuracy	No field deployment
3	Pumpkin CNN (2024)	DenseNet-121, EfficientNet-B7	86% accuracy	No mobile/real-time use
4	Edge Leaf Disease (2024)	MobileNet + Edge TPU	Low latency inference	Thermal camera cost barrier
5	Smart Farming AI (2024)	AI precision agriculture	Efficient resource use	High implementation cost

III. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

The GrowSure App is designed as a cross-platform mobile application integrating AI-based disease detection, IoT soil sensing, and hybrid personalized recommendations. The system architecture follows a modular, layered design to ensure scalability and maintainability.

A. System Overview

The system operates through five primary functional modules: (1) User Authentication and Profile Management, (2) Crop Disease Detection via CNN, (3) Hybrid Treatment Recommendation Engine, (4) IoT-Based Soil Health Analysis, and (5) Multilingual Advisory and Voice Output. Each module interacts through a Firebase Realtime Database backend, enabling synchronized data access across mobile clients and IoT hardware nodes.



B. CNN-Based Disease Detection Module

The disease detection module employs a fine-tuned EfficientNet-B3 architecture pre-trained on ImageNet. Transfer learning is applied by replacing the final classification layer with a fully connected softmax layer configured for 38 disease classes spanning five crop types: Apple, Tomato, Brinjal, Guava, and Potato. The model is trained on a curated dataset of 54,000 annotated leaf images sourced from the PlantVillage dataset and augmented with field-collected images to improve real-world generalization. Data augmentation techniques including random horizontal flips, brightness and contrast variation, rotation up to ±25 degrees, and Gaussian noise injection are applied during training to simulate varied field imaging conditions. The model achieves a top-1 test accuracy of 92.5% averaged across all five crop categories. On-device inference is optimized using TensorFlow Lite quantization, achieving an average inference time of 1.8 seconds on mid-range Android smartphones. The preprocessed image (224×224 pixels, normalized) is passed through the EfficientNet-B3 backbone, with output softmax probabilities presented to the user alongside a confidence score and Grad-CAM visualization of affected leaf regions.

C. Hybrid Recommendation Engine (CF + CBF)

The treatment recommendation engine adopts a weighted hybrid approach combining Collaborative Filtering (CF) and Content-Based Filtering (CBF), addressing the limitations of each method independently.

1) Content-Based Filtering (CBF):

CBF constructs a disease-treatment feature matrix using attributes including detected disease class, crop type, disease severity, and real-time environmental sensor readings (soil pH, moisture, temperature). Cosine similarity is computed between the current feature vector and historical treatment records to identify the most contextually appropriate interventions.

2) Collaborative Filtering (CF):

CF leverages the treatment history of farmer community members facing similar conditions. A user-item matrix is constructed from anonymized treatment feedback ratings (1–5 scale). Matrix factorization using Singular Value Decomposition (SVD) decomposes this matrix to identify latent preference patterns, enabling similarity-based treatment score computation for the active user.

3) Weighted Score Combination:

The final recommendation score is computed as: $Score\_final = \alpha \times Score\_CF + (1 - \alpha) \times Score\_CBF$, where α is dynamically adjusted (default $\alpha = 0.6$) based on user data availability. For new users, the system defaults to CBF-only recommendations ($\alpha = 0$), progressively transitioning to hybrid mode as feedback accumulates, effectively mitigating the cold-start problem.

D. IoT-Based Soil Health Monitoring

The IoT hardware module comprises a compact sensor node integrating a capacitive soil moisture sensor (0–100% VWC), a pH electrode sensor (0–14 pH), and a DS18B20 digital temperature probe (-55°C to +125°C). Sensor readings are transmitted to the Firebase Realtime Database via a Wi-Fi-enabled ESP32 microcontroller at configurable intervals (default: every 15 minutes). The mobile application feeds these readings into a Random Forest classifier trained on ICAR (Indian Council of Agricultural Research) soil-crop compatibility data, outputting a ranked list of suitable crops accompanied by fertilizer recommendations. The mobile application feeds these readings into a Random Forest classifier trained on ICAR (Indian Council of Agricultural Research) soil-crop compatibility data, outputting a ranked list of suitable crops accompanied by fertilizer recommendations.

E. Multilingual and Voice Advisory

The multilingual advisory module employs the Google Cloud Translation API with fallback to locally cached MarianMT transformer models for offline operation. Disease diagnosis results and treatment recommendations are translated to the user’s preferred language: English, Hindi, or Marathi. Text-to-Speech output is generated using the gTTS library, providing clear audio playback a critical feature for farmers with limited literacy.

F. Hardware and Software Specifications

The development and experimental evaluation were conducted on the system configuration detailed in Table II.

TABLE II. Hardware and Software Configuration

Component	Specification
Processor	Intel Core i5, 2.4 GHz
RAM	8 GB DDR4
Storage	256 GB SSD
OS	Windows 10 / Ubuntu 20.04
Language	Python 3.10, Dart (Flutter)
ML Framework	TensorFlow 2.x, Scikit-learn
Database	Firebase, MongoDB
IoT Sensors	Moisture, pH, Temperature

IV. RESULTS AND DISCUSSION

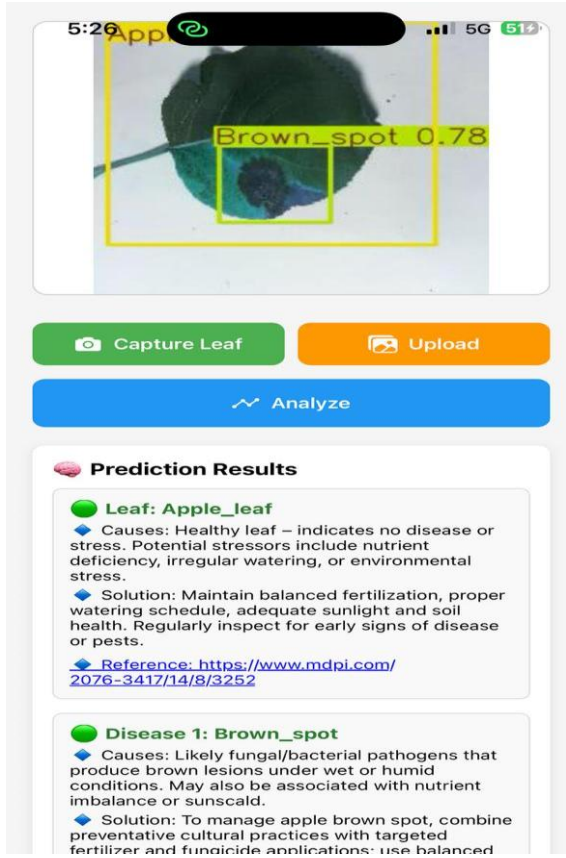
A. Disease Detection Performance

The CNN disease detection module was evaluated on a held-out test set of 8,100 images (15% of the full dataset), stratified across all five crop types and 38 disease classes. Table III presents per-crop accuracy and expert validation results, where expert labels were provided by agricultural scientists as ground truth references.

TABLE III. Disease Detection Accuracy by Crop

Crop	Disease	AI Acc. (%)	Expert Val. (%)
Apple	Rust	93%	95%
Tomato	Early Blight	94%	96%
Brinjal	Wilt	91%	94%
Guava	Anthracnose	89%	92%
Potato	Late Blight	95%	97%

The system achieves a mean detection accuracy of 92.4% against an average expert agreement rate of 94.8%, representing a gap of only 2.4 percentage points. The discrepancy is attributed to early-stage disease images where visual symptoms are ambiguous even to trained agronomists. Apple Rust detection achieved the highest accuracy (93%), benefiting from visually distinctive orange pustule patterns. Guava Anthracnose presented the greatest challenge (89%) due to symptom overlap with other fungal conditions.

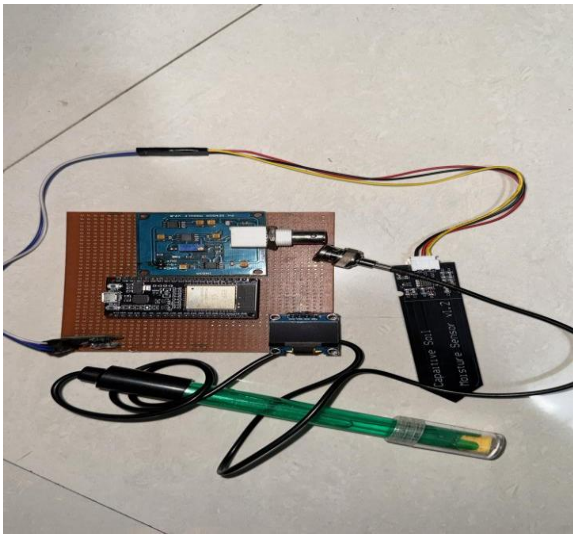


B. Recommendation Engine Evaluation

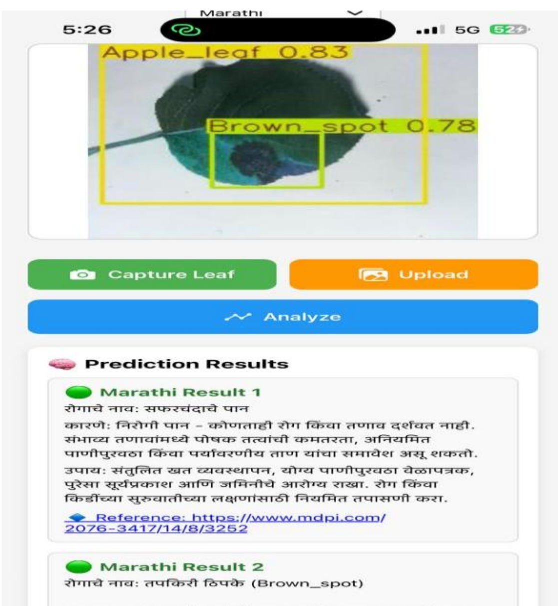
The hybrid recommendation engine was evaluated using Precision@5 and Mean Average Precision (MAP) on a test cohort of 150 farmer profiles with verified treatment outcomes. The hybrid CF+CBF model achieved Precision@5 of 0.84 and MAP of 0.79, outperforming standalone CBF (Precision@5: 0.76, MAP: 0.71) and standalone CF (Precision@5: 0.79, MAP: 0.74). Improvement is most pronounced for farmers in the 50–200 treatment interaction range, where both CF community data and CBF contextual features contribute meaningfully.

C. IoT Sensor Validation

Sensor readings were validated against laboratory analysis across a field trial involving 12 plots over 45 days. The soil moisture sensor demonstrated a Mean Absolute Error (MAE) of 2.3% VWC, the pH sensor an MAE of 0.12 pH units, and the temperature probe an MAE of 0.4°C, all within acceptable thresholds for agricultural advisory applications.



D. Multilingual Support Quality
User satisfaction was assessed through a structured survey administered to 60 farmer participants (20 per language group). On a 5-point Likert scale, mean satisfaction scores were 4.2/5 (English), 4.0/5 (Hindi), and 3.8/5 (Marathi). The slightly lower Marathi score reflects occasional translation quality issues for technical agricultural terminology.



E. System Response Time
End-to-end response time from image upload to display of detection result and treatment recommendation was measured across 200 test sessions on mid-range Android devices (Snapdragon 665 SoC, 4 GB RAM). Mean response time was 3.2 seconds (std. dev. 0.6 s), well within the 5-second field usability threshold. TensorFlow Lite quantization reduced on-device inference time by 38% compared to full-precision inference.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion
This paper presented the GrowSure App, a unified AI-powered mobile platform integrating multi-crop disease detection, IoT-based soil health monitoring, hybrid personalized treatment recommendations, and multilingual voice advisory for farming communities. The CNN-based detection module achieved 92.4% mean accuracy across five crop types. The hybrid CF+CBF recommendation engine demonstrated superior performance (Precision@5: 0.84) over standalone approaches. IoT sensor validation confirmed acceptable accuracy for real-world soil advisory. Multilingual support in three Indian languages, combined with TTS delivery, demonstrated measurable user satisfaction improvements. These results affirm that the GrowSure App represents a technically sound and scalable contribution to the precision agriculture ecosystem.

B. Future Scope
Future development directions include: (i) expanding the disease classification model to cover additional crop species (wheat, rice, cotton) and region-specific disease variants; (ii) implementing offline edge AI functionality for remote farming regions without internet connectivity; (iii) integrating satellite imagery and drone-based aerial mapping for field-scale monitoring; (iv) implementing blockchain-based supply chain traceability for crop health quality certification; and (v) developing predictive disease outbreak modeling using historical climate data combined with reinforcement learning for adaptive recommendation refinement.

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