IJVAST | Vol. 1, Issue 9 | September 2026 | Open Access — Peer Reviewed Research Paper

Smart Agriculture & Crop Advisory System

Sneha Patil

Department of Computer Science and Engineering

Shri Guru Gobind Singhji Institute of Engineering and Technology (SGGSIE&T), Nanded, Maharashtra, India

Abstract—Smallholder farmers frequently make sowing, pest-management, and selling decisions with limited access to timely, location-specific guidance, relying instead on generic advice, informal peer knowledge, or a visiting extension officer whose availability cannot keep pace with a crop-disease outbreak or a sudden fall in mandi prices. This paper presents the design, implementation, and evaluation of a Smart Agriculture & Crop Advisory System that unifies soil-and-weather-based crop recommendation, image-based crop disease detection, short-term market price forecasting, and a multilingual advisory chatbot within a single coordinated platform. The system integrates four components — a crop recommendation engine that suggests suitable crops from soil nutrient levels, pH, rainfall, and temperature; a disease detection module that classifies crop leaf images captured on a farmer's phone into disease categories using a fine-tuned convolutional network; a market price advisory module that forecasts short-term mandi prices for major crops; and a multilingual chatbot that answers farmer queries in the farmer's own language and escalates unresolved queries to a human extension officer. A dataset of 18,600 soil-and-weather records, 7,400 historical crop yield records, and 5,200 labelled leaf-image samples across twelve disease categories, collected from state agriculture department archives and partner Krishi Vigyan Kendras over three growing seasons, was used to develop and evaluate the recommendation and detection components. The crop recommendation engine achieved an accuracy of 91.2%, and the disease detection module achieved a classification accuracy of 94.6% and an F1 score of 0.93 on held-out leaf images. A ten-week pilot across six villages and 300 registered farmers found that farmers who followed the system's crop recommendation achieved a 14.2% higher average yield, disease-related crop loss fell from 18.4% to 7.1%, and average query resolution time fell from 3.2 days under the prior extension-officer visit model to 6 minutes through the chatbot. The paper documents the system architecture, module design, evaluation methodology, observed limitations relating to regional data coverage and connectivity, and the future scope of the work.

Index Terms—Precision Agriculture, Crop Recommendation, Plant Disease Detection, Convolutional Neural Networks, Market Price Forecasting, Multilingual Chatbot, Agricultural Informatics, Decision Support System, Smallholder Farming, Krishi Advisory.

I. INTRODUCTION

Smallholder farmers routinely decide what to sow, how to manage an emerging pest or disease outbreak, and when to sell their produce with limited access to timely, location-specific guidance, relying instead on generic package-of-practice advice, informal peer knowledge, or a government extension officer whose visiting schedule cannot match the pace at which a disease outbreak or a price crash unfolds [1], [2].

This gap is particularly costly at two moments: the sowing decision, where a soil-and-climate mismatch with the chosen crop can depress yield for an entire season, and disease onset, where a delay of even a few days in identifying a leaf disease can allow it to spread across a field before treatment begins [3].

Two complementary strands of prior work are relevant here: crop recommendation systems, which use soil and climate parameters to suggest suitable crops but are rarely paired with disease monitoring or market guidance in a single tool, and plant disease detection research, which has shown that convolutional

II. RELATED WORK

A. Crop Recommendation Systems

Rule-based and machine-learning crop recommendation tools that map soil nutrient and climate parameters to suitable crops have been shown to improve on farmers' unaided crop choice, but are typically deployed as isolated advisory tools disconnected from disease monitoring or market information [5].

B. Plant Disease Detection Using Deep Learning

Convolutional neural networks fine-tuned on labelled leaf-image datasets have achieved high classification accuracy for common crop diseases from phone-camera photographs, demonstrating that on-device or cloud-based disease diagnosis is technically feasible at the point of symptom onset [6], [7].

C. Market Price Forecasting

Time-series forecasting approaches applied to mandi price data have shown that short-term price movements for major networks can classify leaf disease from phone-camera images with high accuracy, but is often evaluated only as a standalone classifier rather than as part of an end-to-end farmer advisory pipeline [4].

This paper proposes a Smart Agriculture & Crop Advisory System that combines soil-and-weather-based crop recommendation with image-based disease detection, short-term market price forecasting, and a multilingual chatbot, producing a single advisory pipeline a farmer can use from sowing decision through to sale.

The principal contributions of this work are: (1) a crop recommendation engine combining soil nutrient, pH, rainfall, and temperature parameters; (2) an image-based disease detection module for phone-captured leaf photographs; (3) a market price advisory module forecasting short-term mandi prices; (4) a multilingual chatbot for farmer queries with human escalation; and (5) an empirical evaluation covering recommendation accuracy, detection quality, and a ten-week multi-village pilot.

crops can be predicted with useful accuracy, supporting farmer decisions on when to sell rather than store or transport produce [8].

D. Multilingual Agricultural Advisory Chatbots

Chatbot-based agricultural advisory services in regional languages have been piloted in several states, and have been found to reduce farmer dependence on in-person extension visits for routine queries, while still requiring an escalation path to a human expert for queries outside the chatbot's coverage [9], [10].

Fig. 1 — Layered System Architecture of the Proposed Smart Agriculture & Crop Advisory System

Layer	Principal Components and Responsibilities
Presentation Layer	Mobile advisory app, chatbot interface, extension officer dashboard
Interaction Layer	Multilingual chatbot module, escalation to human expert
Advisory Layer	Crop recommendation engine, disease detection module, price advisory
Data Layer	Soil & weather records, crop yield history, leaf-image repository, mandi prices

TABLE I — Comparative Analysis: Traditional Practice vs. Existing Advisory Tools vs. Proposed System

Feature	Traditional Practice	Existing Advisory Tools	Proposed SACAS	Benefit to Farmer
Crop Guidance	Farmer experience / peer advice	Generic package of practice	Soil-and-climate-based recommendation	Fewer soil-crop mismatches
Disease Diagnosis	Visual inspection, delayed visit	Static disease reference chart	Instant photo-based diagnosis	Faster treatment response
Market Guidance	Informal trader information	Not available	Short-term price trend forecast	Better sell/hold decisions
Query Resolution	Extension officer visit	Toll-free call centre	Multilingual chatbot with escalation	Minutes instead of days
Language Access	Local language, in person	Limited language support	Farmer's own regional language	Wider accessibility
Scale of Coordination	Single village	District call centre	Multi-village advisory network	Consistent regional guidance

TABLE II — Recommendation Accuracy, Disease Detection Quality, and Pilot Study Results

#	Model / Metric	Result	Comparison	Observation
1	Rule-based lookup baseline	68.3%	Baseline	Weak for atypical soils
2	Farmer-self-choice baseline	74.6%	Baseline	No measured soil input
3	Crop recommendation engine (selected)	91.2%	Both baselines	Best top-3 accuracy
4	Disease detection module	94.6% / F1 0.93	Held-out leaf images	Strongest for cotton, soybean
5	Pilot — average yield change	+14.2%	vs. comparison group	Across 10-week pilot
6	Pilot — disease-related crop loss	18.4% → 7.1%	-11.3 pts	6 villages, 300 farmers

III. SYSTEM ARCHITECTURE

A. Architectural Overview

The proposed system follows a four-layer architecture consisting of a data layer, an advisory layer, an interaction layer, and a presentation layer, as summarised in Fig. 1. Layer separation allows the recommendation and detection models to be retrained on new seasonal data independently of the chatbot and the farmer-facing interface.

B. Data Layer

The data layer maintains a soil-and-weather record store segmented by region, a historical crop yield table, a labelled leaf-disease image repository used for model training, and a mandi price history table updated from public market data feeds.

C. Crop Recommendation Engine

The recommendation engine takes a farmer's soil test values, local rainfall, and temperature data as input and applies a trained classifier to rank suitable crops for the coming season, presenting the top recommendations along with the soil parameters that most influenced each suggestion.

D. Disease Detection Module

A farmer photographs an affected leaf using the mobile client, and this module applies a fine-tuned convolutional network to classify the image into one of twelve disease categories or a healthy class, returning a diagnosis with a confidence score and a recommended treatment note.

E. Market Price Advisory Module

This module forecasts short-term mandi price movement for major crops from historical price and seasonal patterns, presenting farmers with a simple upward, stable, or downward trend indicator to inform selling decisions.

F. Multilingual Chatbot Module

The chatbot answers routine farmer queries in the farmer's selected regional language using a retrieval-based response model grounded in verified agricultural advisory content, and escalates queries it cannot answer with sufficient confidence to a human extension officer.

G. Presentation Layer

The presentation layer provides farmers with a mobile-first interface for crop recommendation, disease diagnosis, price trends, and chatbot access, and gives extension officers a dashboard of escalated queries and regional advisory statistics.

IV. METHODOLOGY

A. Dataset Preparation

A dataset of 18,600 soil-and-weather records, 7,400 historical crop yield records, and 5,200 labelled leaf-image samples across twelve disease categories was assembled from state agriculture department archives and partner Krishi Vigyan Kendras over three growing seasons.

B. Experimental Protocol

The crop-yield dataset was partitioned into training, validation, and test subsets in a 70:15:15 ratio using a stratified split by agro-climatic zone, so that recommendation

D. Evaluation Metrics

Crop recommendation quality was measured as top-3 accuracy against the crop farmers actually planted and its recorded yield outcome. Disease detection quality was measured using classification accuracy and macro-averaged F1 score against verified diagnoses. Operational impact was measured as average yield change, crop loss rate, and query resolution time.

E. Implementation Environment

The prototype was implemented in Python 3.11 using scikit-learn for the recommendation and price-forecasting models and a fine-tuned MobileNetV2 network in TensorFlow for disease detection, PostgreSQL for the data layer, and Django for the performance could be assessed separately across regions. The leaf-image dataset was similarly split by disease category, and model parameters were tuned on the validation subsets.

C. Baseline Models

Two baselines were compared for crop recommendation: a rule-based lookup using only dominant soil type, and a farmer-self-choice baseline reflecting the crop farmers reported they would have chosen unaided. For disease detection, a classical colour-and-texture feature classifier was compared against the fine-tuned convolutional network used in the final system.

application layer. The mobile client was built with Flutter, and all experiments were executed on a machine with an Intel Core i5 processor and 8 GB of memory.

F. Pilot Study Design

A ten-week pilot spanning one growing-season window was conducted across six villages and 300 registered farmers. Advisory outcomes were recorded for a comparison group continuing to rely on the prior extension-officer visit model, alongside farmers using the full system over the same period.

V. RESULTS AND DISCUSSION

A. Recommendation and Detection Accuracy

As reported in Table II, the crop recommendation engine achieved a top-3 accuracy of 91.2%, exceeding the farmer-self-choice baseline at 74.6% and the rule-based lookup baseline at 68.3%. The disease detection module achieved a classification accuracy of 94.6% and a macro-averaged F1 score of 0.93 on held-out leaf images, with the strongest performance observed for cotton and soybean diseases, where training image volume was largest.

The improvement over the farmer-self-choice baseline was most pronounced for fields with atypical soil profiles, where the recommendation engine's use of measured soil parameters caught crop-soil mismatches that farmer experience alone would not have flagged.

B. Price Forecasting and Advisory Impact

Across the ten-week pilot, farmers who followed the system's crop recommendation achieved a 14.2% higher average yield than the comparison group, disease-related crop loss fell from 18.4% to 7.1%, and average advisory query resolution time fell from 3.2 days under the prior extension-visit model to 6 minutes through the chatbot, as summarised in Table II.

C. Pilot Study Outcomes

Participating farmers identified the disease-photo diagnosis feature and the regional-language chatbot as the two most valued components, noting that both reduced the delay between noticing a problem and receiving actionable guidance.

D. Discussion

The results indicate that combining soil-based recommendation with fast image-based disease diagnosis and language-accessible advisory addresses a timing gap that neither generic advisory literature nor infrequent extension visits resolve well. The pilot cohort of six villages over one growing season is modest, so the reported yield and loss-reduction figures should be treated as indicative rather than conclusive across all agro-climatic zones.

VI. LIMITATIONS

Several limitations qualify these findings. First, disease detection accuracy is lower for crop-disease combinations underrepresented in the training image set, and the model has not yet been validated on all locally significant crops. Second, the crop recommendation engine depends on a recent soil test, which is not yet available to every farmer in the pilot region. Third, the chatbot's regional-language coverage is currently limited to the languages spoken in the pilot villages. Finally, the ten-week, six-village pilot cannot support strong claims about performance across a full agricultural year or other agro-climatic zones.

VII. FUTURE SCOPE

Future development will proceed along four directions: expanding the disease-image dataset to cover a wider range of crops and regional disease variants; integrating low-cost soil-sensor data to reduce dependence on lab-based soil testing; adding further regional languages to the chatbot; and conducting a full-year, multi-district pilot to validate yield and loss-reduction improvements at larger scale.

VIII. CONCLUSION

This paper presented a Smart Agriculture & Crop Advisory System that integrates soil-based crop recommendation, image-based disease detection, market price advisory, and a multilingual chatbot within a single platform. The recommendation engine achieved a top-3 accuracy of 91.2%,

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and the disease detection module achieved a classification accuracy of 94.6% on held-out leaf images.

A ten-week pilot across six villages and 300 farmers raised average yield by 14.2%, cut disease-related crop loss from 18.4% to 7.1%, and reduced advisory query resolution time from 3.2 days to 6 minutes, indicating that coordinated recommendation, diagnosis, and language-accessible advisory can meaningfully improve smallholder farming outcomes. The limitations relating to regional data coverage, soil-test availability, and pilot scale define a clear agenda for the extensions outlined above.

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