KrishiMitra AI: An AI-Powered Smart Farming and Agricultural Advisory System

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ABSTRACT

Agriculture increasingly depends on timely information about crop health, suitable farming inputs, market prices, and public support programmes. However, these services are often distributed across different websites, local providers, and government resources, making it difficult for farmers to obtain a unified view. This survey reviews artificial-intelligence approaches relevant to an integrated agricultural advisory system named KrishiMitra AI. The proposed concept combines five modules: crop disease detection from leaf images, agricultural shop demand or sales prediction, crop price forecasting, a recommendation system for crops and agricultural inputs, and a multilingual chatbot for government schemes. Recent studies indicate that computer vision, machine learning, time-series forecasting, recommendation methods, and multilingual natural-language processing can support parts of this workflow. The survey compares these approaches, identifies practical limitations such as data quality, local adaptation, explainability, and language accessibility, and outlines a modular methodology for integrating them. KrishiMitra AI is presented as a proposed system; its performance must be established through implementation and evaluation using suitable datasets and user testing.

KEYWORDS

Smart agriculture, artificial intelligence, crop disease detection, sales prediction, crop price forecasting, recommendation system, multilingual chatbot.

I. INTRODUCTION

Farming decisions are influenced by crop health, soil and weather conditions, availability of agricultural inputs, market prices, and access to public support programmes. Farmers may need to consult several separate sources to answer these questions. This fragmented process can increase the difficult to compare recommendations.

Artificial intelligence (AI) offers methods for analysing images, learning patterns from historical data, generating forecasts, and processing natural-language questions. Computer-vision models can classify visible crop symptoms, supervised learning can estimate demand or recommend crops, and time-series models can learn trends in market prices. A multilingual chatbot can provide a conversational interface for information that is otherwise difficult to navigate.

This paper surveys relevant approaches and proposes KrishiMitra AI, a unified smart-farming and agricultural advisory concept. Its goal is to bring five functions into one accessible platform. The paper does not claim that the proposed modules have already been implemented or validated; rather, it describes the research background, system design, and evaluation plan.

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II. SURVEY OF RELATED WORK

A. Crop disease detection: Image-based plant disease identification commonly uses convolutional neural networks (CNNs) and transfer learning. These methods learn visual features from leaf images and classify them into disease categories. A recent agricultural assistant study, AgroBot, combines CNN-based disease recognition with multilingual, knowledge-based advisory support [1]. Such results are promising, but performance in field conditions may differ from performance on clean, well-lit images. Background clutter, changing light, overlapping symptoms, and diseases not represented in the training set can reduce reliability.

B. Integrated agricultural advisory: Recent work increasingly combines multiple agricultural functions rather than providing a single prediction. The IntelliFarm+ study describes a modular platform for crop recommendation, image-based disease detection, and crop-price forecasting [2]. A multilingual conversational-agent study also integrates farmer queries, disease detection, market-price access, and agricultural advisories [3]. These projects show the value of integration, while also highlighting the need to keep each module's data source, model, and evaluation method clearly defined.

C. Crop price forecasting: Crop prices are time-dependent and can be affected by seasonality, arrivals, demand, weather, transport, policy, and regional market conditions. Statistical time-series methods and machine-learning models can be used to forecast prices from historical observations. A study on an AI-powered smart agriculture advisor describes the use of XGBoost and ensemble approaches for price prediction alongside crop recommendation and disease detection [4]. Forecasts should be treated as estimates, not guaranteed future prices, and should report uncertainty where possible.

D. Recommendation and multilingual support: Crop recommendation models commonly use features such as soil nutrients, pH, temperature, humidity, and rainfall. However, agronomic suitability alone does not necessarily indicate economic suitability; expected price, input cost, water availability, and local constraints can also matter. Research on multilingual agricultural advisory systems identifies language and fragmented information access as important barriers for farmers [5]. A useful chatbot should therefore present concise answers in the user's language and distinguish verified scheme information from general generated text.

E. Research gap: Existing work demonstrates useful individual models and several integrated prototypes.

Nevertheless, an agricultural decision-support platform must also address the less commonly connected workflow of agricultural shop demand prediction, alongside crop health, market prices, recommendations, and government-scheme guidance. KrishiMitra AI proposes to connect these five functions through a modular architecture. This is a design objective, not a claim that no other system has similar capabilities.

III. EXISTING SYSTEM AND LIMITATIONS

In many existing agricultural workflows, farmers obtain crop-disease advice, market prices, shop information, recommendations, and government scheme details from separate sources. These may include local experts, agricultural shops, market websites, printed notices, or government portals. Information can be difficult to compare, may require repeated visits or searches, and may not always be available in the farmer's preferred language.

Individual digital tools may address only one task, such as classifying a leaf image or displaying a market price. Their output may not be connected to the farmer's next decision. For example, disease detection alone may not explain what verified guidance to consult next, while a price forecast alone may not account for the farmer's crop choice or local market context.

Common limitations include uneven dataset quality, regional variation, delayed or incomplete market data, limited explainability, connectivity constraints, and the risk of presenting uncertain predictions as facts. Scheme information may also become outdated when eligibility rules or deadlines change. A practical system should therefore show data dates and sources, communicate uncertainty, and provide a route to authoritative information or human assistance.

IV. PROPOSED SYSTEM: KRISHIMITRA AI

KrishiMitra AI is proposed as a modular web or mobile-accessible platform that connects five agricultural support functions through a common interface. A user can select a module, provide the required input, and receive a result with a short explanation. The modules may share relevant information where appropriate, but each should remain independently testable and maintain its own data-processing pipeline.

The system can be organised into four layers: (1) user interface, including language selection and image or form input; (2) application layer, which validates requests and routes them to the correct module; (3) AI and data layer, containing trained models, historical datasets, and a curated scheme knowledge base; and (4) output and monitoring layer, which displays predictions, source dates, confidence or uncertainty indicators, and feedback options. A backend API can connect the interface to the prediction models.

The proposed platform should not replace agricultural officers, plant pathologists, financial judgement, or official scheme authorities. Its role is to provide accessible decision support and help users identify the next useful step. Any advice involving pesticide use, dosage, or scheme eligibility should be based on trusted and current sources and should be phrased with suitable safeguards.

V. SYSTEM MODULES

A. Crop disease detection: The farmer uploads a crop-leaf image. Image preprocessing resizes and normalises the image before a CNN or transfer-learning model predicts a supported disease class. The result should include the predicted class, confidence score where calibrated, and a recommended next step based on a verified advisory dataset. If image quality is poor or the model is uncertain, the system should request another image or recommend expert confirmation. Suitable evaluation measures include precision, recall, F1-score, confusion matrix, and performance on images collected outside the training dataset.

B. Shop prediction: This module estimates demand or sales for agricultural shops using historical transaction records. Potential features include product category, date, season, price, stock level, local crop calendar, and past sales. Depending on data availability, baseline moving averages or regression models can be compared with tree-based methods and time-series forecasting. Evaluation should use chronological train-test splits and measures such as MAE, RMSE, and MAPE when appropriate. Predictions can help shop owners plan inventory, but they should not be treated as exact sales guarantees.

C. Crop price prediction: This module estimates a future price or price range for a selected crop and market using historical market-price observations and relevant factors. Candidate methods include statistical forecasting, regression, gradient-boosting models, and recurrent neural networks such as LSTM when the dataset supports them. The system should record market name, unit, date, and source. Performance should be measured against simple baselines using MAE, RMSE, or MAPE. A range or uncertainty interval is preferable to a single unsupported value.

D. Advanced recommendation system: This module recommends suitable crops, fertilizers, or other agricultural inputs based on available information. Crop recommendations may use soil pH, nitrogen, phosphorus, potassium, temperature, rainfall, and humidity. Input recommendations may additionally require crop stage, soil-test results, local guidelines, and product information. Rule-based agronomic constraints can be combined with machine-learning ranking. The system should explain the main factors behind a recommendation and avoid suggesting fertiliser quantities without sufficient soil and crop information.

E. Multilingual government scheme chatbot: The chatbot answers questions about agricultural schemes in Marathi, Hindi, and other supported languages. A safer design is to retrieve relevant information from a curated collection of official scheme documents before generating a concise response. Each answer should show the source and last-checked date where possible, explain eligibility in simple language, and direct users to the official portal for applications or confirmation. The chatbot should acknowledge when it cannot find reliable information instead of inventing deadlines, benefits, or eligibility rules.

VI. PROPOSED METHODOLOGY

1) Data collection: Obtain appropriately licensed crop-leaf images, historical shop sales records, market-price time series, soil and weather data, and official scheme documents. Data should be relevant to the intended region and use case. Personal or commercially sensitive records should be

protected, and permission should be obtained where required.

2) Data preparation: Remove duplicates, check missing values, standardise units and dates, label disease images, and document the origin of each dataset. Use separate training, validation, and test sets. For time-dependent sales and price data, split by time rather than randomly to reduce data leakage.

3) Model development: Establish a simple baseline for every predictive module before testing more complex models. Compare image classifiers for disease detection; regression or time-series methods for sales and price forecasting; and classification, ranking, or rule-based methods for recommendations. Build the chatbot around retrieval from verified scheme content and test answers in each supported language.

4) Integration: Expose module functions through a backend API and connect them to a responsive interface. Include input validation, error handling, access controls, logging, and model-version information. Where connectivity is unreliable, the interface should communicate service limitations clearly.

5) Evaluation: Evaluate each module independently and then assess the complete user journey. Technical measures should include classification precision/recall/F1, forecasting MAE/RMSE/MAPE, response latency, and chatbot retrieval relevance. User testing should examine readability, language quality, task completion, and whether users understand prediction uncertainty. No performance score should be reported until it has been measured on a documented test set.

VII. EXPECTED ADVANTAGES AND APPLICATIONS

KrishiMitra AI is expected to reduce the need to search across multiple disconnected sources by presenting several functions in one interface. Image-based disease screening may help users identify a possible crop-health issue earlier; sales forecasts may support agricultural retailers in planning stock; price estimates may help farmers compare market information; and recommendations may help organise available soil and crop data.

The multilingual chatbot may make scheme information easier to understand for users who prefer Marathi or Hindi. The modular design also allows individual models and datasets to be updated without rebuilding the entire platform. Potential users include farmers, agricultural-input retailers, farmer-producer organisations, extension workers, and educational or research institutions. These benefits are expected outcomes and require evaluation through real use.

VIII. CHALLENGES AND FUTURE SCOPE

Key challenges include collecting representative local data, obtaining reliable shop sales records, handling price volatility, maintaining current government-scheme information, and supporting low-connectivity environments. Image models may fail on unfamiliar crops or symptoms, while forecasts can deteriorate when market conditions change. Language translation alone is not enough: agricultural terms, local names, and regional context must also be tested.

Future work can add weather forecasts, crop-yield estimation, voice input and text-to-speech, offline support for selected functions, local-market comparisons, and feedback from agricultural experts. Explainable AI methods can help users understand which inputs influenced a prediction. A pilot deployment in selected villages or agricultural shops should be conducted before wider release. The project should measure not only model accuracy but also usability, reliability, accessibility, and the quality of decisions supported.

IX. CONCLUSION

This survey reviewed AI approaches relevant to crop disease detection, agricultural shop demand prediction, crop price forecasting, crop and input recommendations, and multilingual government-scheme assistance. Related research shows that computer vision, machine learning, time-series forecasting, and multilingual natural-language processing can contribute to agricultural decision support. KrishiMitra AI proposes to combine these capabilities in a single modular platform. Its usefulness will depend on trustworthy data, transparent predictions, current official information, local-language usability, and careful testing. Implementation and empirical evaluation remain necessary before claims about accuracy or real-world impact can be made.

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