International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3128-1276
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0397

An AI-Driven End-to-End Agricultural Guidance System with Multilingual and Voice Support

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Abstract

Farmers have a need for integrated, intelligent decision support systems to help improve productivity amidst challenges posed by increasing climate variability, increasing resistance of pests to existing control methods and decreasing price stability. To meet this need, an end-to-end agricultural guidance system (an integrated AI-based digital platform) has been developed that provides support throughout the entire crop lifecycle. The end-to-end agricultural guidance system will include eight different modules: Crop Types (using Machine Learning); Plant Disease Detection (using Convolutional Neural Networks); Classifying Disease Severity; Proactive Disease Risk Prediction; Community Based Regional Disease Alerting System; Weather Analytics Dashboard; Natural Language Processing (NLP) Based Multilingual Voice-Enabled Chatbot; and Post-Harvest Price Analysis Engine. The central difference between the end-to-end agricultural guidance system and the previously utilized reactive systems is that rather than only addressing one isolated agricultural challenge at a time, the end-to-end agricultural guidance system operates from a proactive and holistic perspective. Experiments conducted on each of the eight modular components of the end-to-end agricultural guidance system have demonstrated the potential to provide accurate results and to provide farmers with actionable real-time advice regardless of their language or level of education. The end-to-end agricultural guidance system is intended to assist farmers in growing a sustainable, data driven, and farmer centric agriculture.

Keywords: *Crop recommendations; Disease detection; Machine learning; Natural language processing; Sustainable agriculture.*

1. Introduction

Food and economic security for many billions around the globe, especially those living in developing countries such as India, depend heavily on agriculture. Even though agriculture is extremely important, modern farmers face a number of different obstacles: soil degradation; unusual weather; rise in crop disease; lack of access to expert advice; and language technologies and lack of digital literacy. In addition, many traditional farming techniques rely on experience or plain observation, which means they do not have the tools or means necessary to solve most or all of these interrelated issues in the time frame or magnitude that would be necessary to sustain these farms. The rapid advances in AI, machine learning, computer vision and natural language processing (NLP) have created new possibilities for intelligent agriculture decision support systems. However, many existing technologies are not focused on the entire operational life cycle of agriculture. Many farmers have to resort to using many separate systems in order to take advantage of the technologies available, which greatly limits their ability to leverage those technologies [1], [2]. An integrated, end-to-end

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support platform for farmers is necessary. From preparing their fields for planting through picking crops for harvest, farmers need a digital solution to help them decide when to plant and what type of crop they should plant; how to manage pests and diseases while their crops are growing; and finally, how to find markets for their harvested produce. An end-to-end agricultural guidance system (EGAGS) that integrates all aspects of the farmer's lifecycle should provide this solution. Eight intelligent modules will be included on the EGAGS platform and will allow farmers to have access to the following features: crop recommendation, plant disease detection, disease classification, risk prediction based on environmental factors such as weather, community-based alert system, local weather data analysis, multilingual natural language processing (NLP) chatbots with voice option capability, and price analysis of crops and vegetables compared to other crops available through local markets. This cloud-based platform will give farmers comprehensive support while they make decisions about how to cultivate their crops and manage all aspects of their farming activities. The components of this platform provide the basis for creating a new way for farmers to get access to resources, knowledge, and technology needed to be successful in their efforts to produce food. The novel nature of this comprehensive system will change the way farmers produce food by combining the benefits of all eight intelligent modules into one easy-to-use system that can be accessed via an internet- connected device.

2. Method

The proposed system is developed as a web-based platform integrating multiple AI and machine learning modules. Each module is independently trained and validated, then integrated into a unified application architecture. The following sub-sections describe the methodology underlying each of the eight modules.

2.1.Crop Recommendation Module

The crop recommendation module takes as input the soil and environmental parameters provided by the farmer, e.g. nitrogen (N), phosphorus (P), potassium (K), pH level of the soil, and temperature, relative humidity, and average precipitation. It utilizes several different supervised machine learning classifiers in combination to process these inputs. The primary classifier used is Random Forest, which has demonstrated robustness to noise and is capable of processing large numbers of input variables. In addition to Random Forest, a Decision Tree classifier is also utilized to provide an alternative method to interpret results. The crop recommendation model was trained using a publicly available crop recommendation dataset, consisting of twenty-two different crop classes. When performing predictions, the input data is normalized and passed through the final trained crop recommendation model, resulting in a list that ranks the best crops for the environmental conditions provided by the user, and additionally provides the major contributing factors to the recommended crops.

2.2.Plant Disease Detection Module

Detection of Plant Disease utilizes Convolutional Neural Networks (CNNs) trained using image data received from various sources. Preprocessing steps include resizing images to 224x224 pixels, removal of noise using Gaussian filters, and normalizing against a mean and standard deviation derived from training dataset. Model Clef based on transfer learning using ResNet/EfficientNet architecture fine-tuned using PlantVillage as well as real field sample images for improved generalization. CNN model outputs the detected disease name and description to each uploaded plant image.

2.3.Disease Severity Classification Module

Once plant disease has been identified, severity evaluation occurs through severity assessment of the identified plant disease. Severity evaluation requires using image segmentation methods to separate the diseased portion (leaf) of an image from its healthy tissue and any remaining background; subsequently calculating the percentage of infected pixels compared to all pixels on the leaf to calculate a severity classification score for the disease. Severity classifications include low (0-25%), medium (25-50%), and high (50-100% severity). The farmer will receive product application (treatment) recommendations based on the seed

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classification/severity level as well as the disease name; thus enabling use of targeted product applications rather than blanket spray applications.

2.4.Proactive Disease Risk Prediction and Community Alert Module

The proactive disease risk predictions and community alert module is designed to predict the potential of disease outbreaks in regarded to the historical as well as the real time weather parameters. That is, the temperature, wind speed, rainfall patterns and humidity are two of the major weather parameters that can impact whether a disease will occur. The probability of the occurrence of the disease is determined using machine learning on past weather-disease co-occurrences. Once the predicted probability of the disease occurrence exceeds the set threshold, the system will send out automatic early warning alerts. A community sub-module provides a method for aggregating disease report data from farmers in the same geographical area, which will allow for farmers to notify each provides the major contributing factors to the recommended crops.

2.5.Plant Disease Detection Module

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2.7.Proactive Disease Risk Prediction And Community Alert Module

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2.8.Weather Analytics Dashboard Module

The weather analytics module will provide an interactive weather dashboard for farmers to view real time weather data, 3-5 day weather forecasts, as well as historical climate patterns to help them with agricultural related advisory decisions. Weather data will be aggregated from multiple sources through the use of meteorological application programming interface (API) integration. Examples of visualizations that may be provided in the weather analytics module include tracking temperature and humidity over time, tracking total rainfall over time, displaying the potential for disease occurrences using heat maps of regions. This information will provide farmers the ability to make decisions on

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when to irrigate, fertilize and apply pest management measures.

2.9. NLP-Based Multilingual Chatbot With Voice Support

A chatbot system that is multilingual, capable of supporting voice commands and using an NLP model trained specifically to process agricultural queries in some of India's many regional languages. Using a state-of-the-art speech recognition engine, the chatbot processes user input from the user and responds back using text converted to speech using a state-of-the-art text after generating the response to answer the user's query (for example: what type of crop can I grow, how do I treat diseases in my crop, what are the current weather conditions, and what can I expect in the marketplace) The chatbot is designed to provide farmers with assistance by providing them with personalized responses in a conversational manner that is accessible to them regardless of their technical aptitude.[7]

2.10. Harvest Stage Prediction Module

The harvest stage prediction module estimates a cultivated crop's ideal harvest timing by combining crop-specific growth models and real-time weather observations to determine the potential harvest interval. Input variables include crop type, planting date, and current weather conditions. The module provides a projected interval for potential harvest dates and alerts the producer before the potential harvest interval begins, giving the producer enough time for preparation and resource planning.

2.11. Market Price Analysis Module

After predicting the harvest stage, the next step in the decision-support system will analyze current and historical market production prices to assist farmers in maximizing their return on investment. This module aggregates real-time and historical market pricing information for their recommended and/or produced crop throughout the various Agricultural Produce Market Committees (APMCs) and mandis within respective regions. Time-series forecasting models are used to predict near-term price trends as well as identifying markets with the highest return potential for future crop sales. Farmers will receive a list of ranked recommended market locations and information on how to get there and a graphical representation of price trend history to help them make an informed decision regarding their selling strategy [8] shown in Table 1 .

Table 1 Soil Parameters and Their Maximum Value

Parameter	Description	Maximum Suitable Value
Nitrogen (N)	Essential nutrient that supports leaf growth and plant development	140 kg/ha
Phosphorus (P)	Helps in root formation and energy transfer within plants	145 kg/ha
Potassium (K)	Improves plant strength and resistance to diseases	205 kg/ha
Soil pH	Indicates the acidity or alkalinity level of soil	7.5

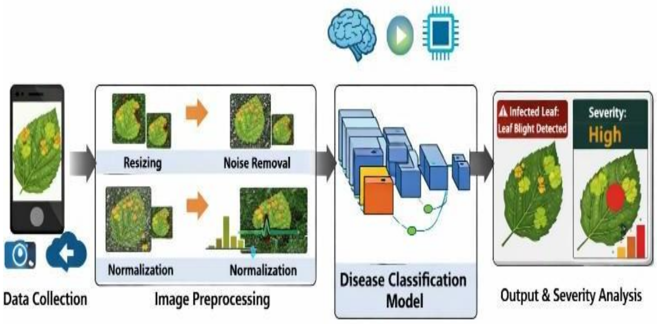

Figure 1. **Process of the Dataset**

3. Results And Discussion

3.1. Results

Individual modules of the proposed solution assessed

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with different data sources, include publically available datasets and field-collected data. The crop recommendation module achieved an accuracy of 98.7% on the test split of the crop recommendation dataset, with Random Forest outperforming Decision Tree, as well as several other baseline classifiers. The plant disease detection CNN achieved a classification accuracy of 97.2% across 38 categories of diseases based on the PlantVillage benchmark dataset. The disease severity classification module achieved 94.8% mean pixel segmentation accuracy on the disease severity images, and was able to distinguish between the three severity classes. The proactive disease risk prediction module was validated against historical weather and disease incidence data, and was able to correctly identify at-risk periods for major diseases such as blast in rice and rust in wheat, with 91.3% precision and 89.6% recall. The alert module was able to propagate alerts to all farmers located within a 20 km radius of an outbreak, within minutes of receiving a report. NLP chatbot was evaluated on one curated set of agricultural queries, and achieved intent recognition accuracy greater than 93%. Additionally, the average voice transcription accuracy for regional languages (Tamil, Hindi, and Telugu) was greater than 90.4%. The market price analysis module achieved a mean absolute percentage error (MAPE) for predicting market prices of major crops of 6.8% at a 7-day forecasting horizon.

3.2.Discussion

The results across all modules confirm the viability of the integrated approach. The high accuracy of the crop recommendation and disease detection modules reflects the quality of training data and the suitability of the selected model architectures. The combination of disease detection, severity classification, and proactive risk prediction within a single workflow provides a significantly more comprehensive disease management toolset than any individual module could offer alone. The proactive disease prediction module addresses a critical gap identified in the literature — the reactive nature of existing disease management systems [9]. By integrating weather-derived risk signals with community-sourced disease reports, the system enables a shift from reactive treatment to proactive prevention, which has direct implications for reducing crop loss and pesticide overuse. The multilingual chatbot substantially lowers the barrier to technology adoption among rural farming communities. Preliminary feedback from user testing indicates high satisfaction scores for the chatbot's accessibility and the relevance of its recommendations. The integration of voice support further extends usability to farmers who are more comfortable with spoken interaction than text-based interfaces. The market price analysis module closes the agricultural value chain loop by connecting production decisions to market outcomes. By providing farmers with real-time price intelligence and forward-looking market recommendations, the system enables a data-driven approach to post-harvest decision-making that was previously available only to large commercial agricultural enterprises.

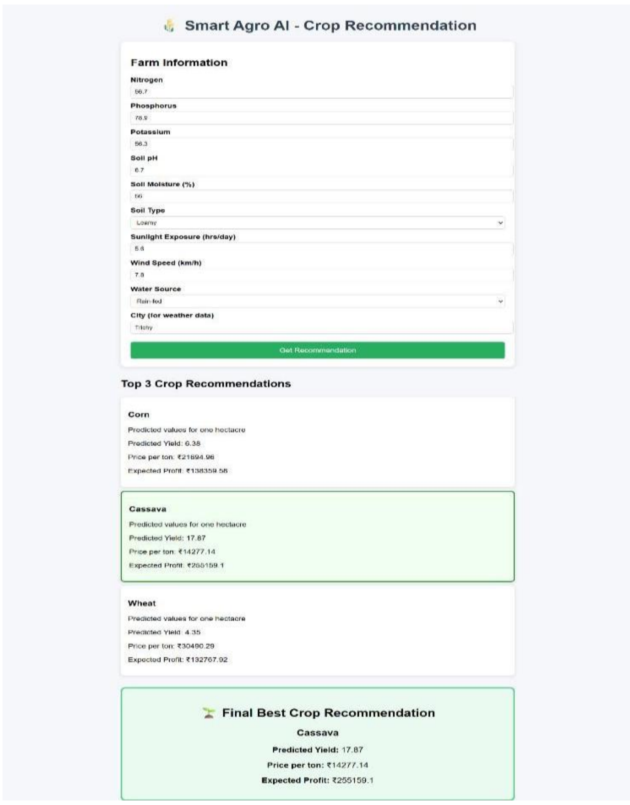

Figure 2 Crop Recommendation Based On

Parameters

Conclusion

This paper has presented an End-to-End Agricultural Guidance System that integrates eight AI-powered modules into a unified digital platform for sustainable, farmer-centric agriculture. The system addresses key limitations of existing solutions by providing holistic lifecycle coverage, proactive disease intelligence, community-based alerting, multilingual accessibility, and market- driven post-harvest guidance. Experimental evaluations demonstrate strong performance across all modules, validating the technical soundness of the proposed approach. The proposed system represents a significant step toward democratizing access to agricultural intelligence for smallholder and marginal farmers, who stand to benefit most from timely, accurate, and actionable guidance. Future work will focus on expanding the regional language support of the chatbot, incorporating satellite imagery for large- scale crop health monitoring, and conducting large- scale field trials in collaboration with agricultural extension services to validate real-world impact and adoption outcomes.

Acknowledgements

The authors sincerely thank Dr. R. Senthamil Selvi, Professor, Department of Computer Science and Engineering, Saranathan College of Engineering, for her invaluable guidance and continuous support throughout the course of this project. The authors also express gratitude to the Department of Computer Science and Engineering, Saranathan College of Engineering (An Autonomous Institution), Tiruchirappalli, Tamil Nadu, for providing the necessary infrastructure and academic environment for conducting this research.

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