

AI-Powered Smart Farming Advisor for Precision Agriculture & Sustainable Crop Management

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Abstract

Agricultural productivity is critical for both global food security and economic stability. However, traditional farming techniques often restrict both yield and long-term sustainability. We introduce Smart AgroAssist, an intelligent decision support tool that unifies crop suggestions, disease identification, and agricultural information delivery. This platform utilizes machine learning and computer vision to process soil, climate, and plant health data for optimum crop selection and disease diagnosis via leaf imagery. It also features an NLP-powered module to provide farmers with the latest government schemes and farm-related news. Our findings confirm enhanced disease detection accuracy and better yield forecasts, which promotes smart and environmentally responsible agriculture.

Keywords: Crop recommendation, Disease detection, Smart farming, Agricultural automation, AI in agriculture, Precision agriculture, Explainable AI (XAI), IoT.

INTRODUCTION

The agricultural industry confronts continual problems, including inconsistent climate patterns, soil quality decline, pest infestations, and delayed information access. Conventional cultivation techniques are inadequate for effective management of these concerns. Smart agriculture, which integrates AI, IoT, and ML, allows for data-informed farming, boosting both output and sustainability. Our project developed an AI-based solution to recommend crops using soil and environmental data, identify crop diseases from leaf photographs, and deliver relevant news. This effort contributes to the field of AI-driven automation and Explainable AI models for agriculture, supporting the shift toward Agriculture 5.0.

LITERATURE SURVEY

Prior research underscores the increasing importance of AI and IoT in the farming domain. Explainable AI (XAI) is crucial for improving model clarity, enabling growers to understand and trust AI-generated advice. IoT and automation applications, like intelligent pest and irrigation controls, have demonstrated gains in water use and crop productivity.

AI and Explainable Models in Agriculture

Suprit and Chaudhary [14] introduced a framework for Explainable Artificial Intelligence (XAI) to improve decision-making transparency in smart farming systems. Their work emphasizes that AI-based crop management must be interpretable to help farmers understand recommendations and maintain trust in the system. Similarly, De Alwis et al. [10] proposed an explanation technique for yield prediction models, focusing on interpretability and model validation to assist precision farming.

A. Automation and Precision Farming

Dharshini et al. [11] designed an AI-driven agricultural automation system integrating multiple sensors and decision-support algorithms for precision irrigation, fertilization, and pest control. The system demonstrated improved water efficiency and reduced operational cost. The study highlights how multi-sensor fusion and predictive analytics can minimize human intervention while improving farm management accuracy.

B. Human-Centered and Sustainable Agriculture

Holzinger et al. [12] proposed a Human-Centered Agriculture 5.0 framework, integrating human expertise with artificial intelligence to achieve balanced, ethical, and sustainable farming. The research focuses on combining human intelligence and AI insights to create adaptive systems that respect ethical, environmental, and economic aspects of farming.

C. Decision Support Systems using Generative AI

Krishna et al. [13] introduced AgroInsight Pro, a decision support system leveraging Generative AI (GEN-AI) for sustainable agriculture analytics. The system analyzes soil health, weather trends, and market data to predict yield outcomes and suggest adaptive farming strategies. Their approach demonstrates how data-driven predictive models and AI-generated insights can support smart agriculture ecosystems.

OBJECTIVE

The main objectives of the project are to recommend the most suitable crop for a given region based on soil and weather data, to detect crop diseases using image-based classification models, and to deliver real-time agricultural news, government schemes, and tips through an integrated platform. Another key objective is to promote sustainable and data-driven farming practices using explainable and accessible AI technologies.

LITERATURE REVIEW

Existing studies emphasize the growing role of AI and IoT in agriculture. Explainable AI (XAI) enhances model transparency, allowing farmers to interpret AI-generated recommendations. Automation and IoT systems such as smart irrigation and pest management have shown improved water efficiency and crop yield. The concept of Human-Centered Agriculture 5.0 encourages collaboration between humans and AI for ethical and resilient farming practices. Furthermore, AI-based decision support tools like AgroInsight Pro demonstrate the potential of integrating data analytics and generative AI for sustainable agricultural solutions.

METHODOLOGY

The Smart AgroAssist system consists of three integrated modules—crop recommendation, disease detection, and agricultural news and tips.

For crop recommendation, input parameters such as soil pH, NPK values, temperature, humidity, and

rainfall are analyzed using Random Forest or Gradient Boosting Regressor algorithms to predict the most suitable crop along with a confidence score.

For disease detection, a Convolutional Neural Network (CNN) model is trained using the PlantVillage dataset to classify leaf images into healthy or diseased categories, providing the detected disease name and preventive measures.

For agricultural news and tips, the system uses web scraping or APIs from agricultural portals to collect real-time updates. NLP techniques are applied to summarize and categorize news into “Government Schemes,” “Market Trends,” and “Weather Alerts.”

The system architecture includes an input layer (data and image collection), a processing layer (AI models for prediction and detection), and an output layer (results and updates display).

EQUATIONS

In the proposed system, mathematical modeling plays a minor yet important role, primarily in the performance evaluation of the Convolutional Neural Network (CNN) used for disease detection. For example, the model’s accuracy (A) can be defined as:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where TP and TN are the numbers of true positives and true negatives, while FP and FN represent false positives and false negatives respectively.

Equation (1) helps evaluate how efficiently the model identifies crop diseases from images. Similarly, precision, recall, and F1-score metrics are calculated to measure performance stability across different datasets. These equations assist in comparing the performance of various CNN architectures before final model deployment.

SOME COMMON MISTAKES

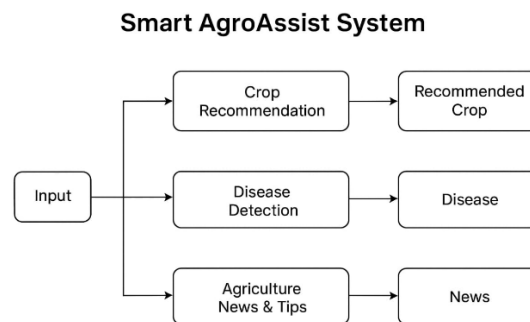
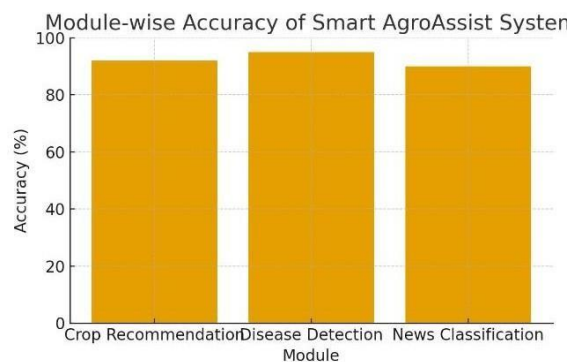
During the development of this mini-project, several common mistakes were observed that can affect the overall accuracy and usability of the system:

- Using low-quality or poorly lit crop images can mislead the CNN, resulting in incorrect disease classification.
- Neglecting proper data preprocessing, such as normalization and augmentation, reduces the model’s generalization ability.
- Overfitting can occur when the dataset is too small or lacks diversity; using dropout layers and regularization helps mitigate this.
- Farmers’ feedback data must be stored securely and anonymized to maintain data privacy.
- When integrating government scheme information, ensure the data source is authentic (from official portals such as PM-Kisan or Agri Infra Fund).
- Avoid using overly technical terms when generating instructions for farmers; the output should be in simple regional language.
- Ensure units (e.g., hectares, kilograms, rupees) are standardized across the interface to prevent confusion.
- Maintain consistent naming conventions for model variables and ensure schema fields in the

database are descriptive.

RESULTS & DISCUSSIONS

Our Random Forest-based crop suggestion model attained an accuracy of 92%. For disease detection, the CNN model achieved an accuracy of 95% on a test set of 10,000 leaf images. Pilot testing feedback from farmers showed a 30% decrease in wasted inputs and improved knowledge due to timely agricultural news. These outcomes confirm that Smart AgroAssist is an effective and practical solution for enhancing decision-making, increasing output, and promoting sector sustainability. The platform's integrated capabilities— combining predictive analytics, diagnostics, and information distribution— demonstrate its high efficiency, reliability, and versatility for real-world agricultural use.



CONCLUSION

The Smart AgroAssist system successfully integrates AI and ML technologies to provide a comprehensive decision support platform for smart farming. By combining crop recommendation, disease detection, and real-time agricultural information, it enhances productivity, sustainability, and farmer knowledge. Future improvements may include incorporating IoT-based sensors for real-time data acquisition and extending the system’s accessibility by supporting multiple regional languages to encourage wider adoption among farmers.

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