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Krushimate-Smart Farming

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ABSTRACT

Agriculture remains a critical sector for economic stability and food security, yet crop diseases continue to cause significant yield losses worldwide. Early detection and timely advisory support are essential for mitigating these losses, particularly for small-scale farmers with limited access to agricultural experts. This paper presents a web-based smart farming application integrated with a large language model (LLM)–powered intelligent agent for crop disease analysis and decision support. The proposed system enables farmers to upload crop images for AI-assisted disease interpretation and interact with an intelligent agent to obtain practical guidance on disease severity, treatment, and prevention. The application is implemented using a lightweight Flask-based architecture and cloud-hosted AI inference, ensuring scalability and accessibility. Experimental validation demonstrates that the system provides real-time, farmer-friendly advisory responses, making it a cost-effective and deployable solution for precision agriculture.

KEYWORDS: *Smart Farming, Crop Disease Detection, Intelligent Agent, Large Language Models, Precision Agriculture, Web Application*

INTRODUCTION

Agriculture plays a fundamental role in sustaining human life and supporting national economies, especially in developing countries. However, crop diseases remain a persistent challenge, causing severe reductions in agricultural productivity and economic losses.

Traditional crop disease diagnosis relies heavily on expert knowledge, manual field inspections, and laboratory testing, which are often time-consuming, expensive, and inaccessible to rural farmers. These limitations not only delay timely interventions but also exacerbate the risk of disease spread, leading to cascading effects on food security and farmer livelihoods.

Recent advancements in artificial intelligence (AI) and smart farming technologies have introduced automated approaches for crop disease detection, primarily through image-based analysis and machine learning techniques. Computer vision models, trained on large datasets of diseased and healthy crop images, have demonstrated high accuracy in classifying multiple crop diseases. Despite this progress, many existing systems are constrained by several factors: they often operate as standalone tools with limited user interaction, lack interpretability of their predictions, and do not provide actionable guidance beyond classification results. Consequently, farmers, particularly those with limited technical knowledge, may struggle to translate disease predictions into effective on-field management strategies.

To address these limitations, this paper proposes a web-based smart farming system integrated with an intelligent agent powered by a large language model (LLM). The system provides AI-assisted crop disease analysis and interactive advisory services through a simple web interface, eliminating the need for specialized hardware. Farmers can upload images of affected crops, receive automated disease detection results, and interact with the intelligent agent to obtain tailored recommendations on treatment, preventive measures, and resource management. By combining image-based disease interpretation with conversational decision support, the proposed solution fosters a more intuitive and accessible user experience.

Moreover, the integration of a web-based platform ensures scalability, allowing multiple users across different regions to access real-time guidance without relying on physical visits from agricultural experts. The intelligent agent also supports continuous learning and contextual advice, adapting recommendations based on seasonal variations, crop type, and local environmental conditions. By enhancing early disease awareness and reducing dependency on human experts, the system contributes to sustainable farming practices, optimized resource utilization, and improved crop yield. Ultimately, this approach demonstrates how web-based agentic AI solutions can bridge the gap between advanced digital technologies and practical agricultural applications, promoting resilience and efficiency in modern farming ecosystems.

RELATED WORK

Numerous studies have explored the application of machine learning and deep learning techniques for crop disease detection. Convolutional neural networks (CNNs) have been widely adopted to classify plant diseases using leaf images, demonstrating high accuracy under controlled experimental conditions. For example, models trained on publicly available datasets such as PlantVillage have achieved classification accuracies exceeding 95% for certain crops. Other approaches have employed ensemble learning, support vector machines, and hybrid deep learning architectures to improve robustness across diverse plant species and environmental conditions.

Beyond image-based techniques, some studies have integrated Internet of Things (IoT) sensors with smart agriculture platforms to monitor environmental parameters, soil moisture, and crop health indicators. These systems combine sensor data with predictive models to alert farmers of disease risks or suboptimal growth conditions. While effective, such approaches are heavily dependent on hardware deployment, which can increase costs and limit accessibility for smallholder farmers in resource-constrained regions.

Despite these advancements, existing crop disease detection systems exhibit several limitations. First, accessibility is often constrained by hardware requirements or mobile application dependencies, restricting widespread adoption. Second, many models provide classification outputs without explanations, making it difficult for farmers to understand the reasoning behind disease diagnoses. Third, interactive decision support—guidance on remedial actions, preventive measures, or adaptive farm management—is minimal or absent in most systems. Finally, computational and deployment costs for deep learning models or IoT-integrated platforms can be prohibitive, particularly for web-scale applications.

Recently, research has begun exploring the use of large language models (LLMs) in agriculture, primarily for knowledge dissemination, advisory services, and natural language-based query answering. LLMs offer the potential for contextual, conversational interactions with users, enabling more interpretable and actionable recommendations. However, the integration of LLM-based intelligent agents with web-based crop disease analysis remains largely underexplored. Few systems combine automated image-based disease detection with interactive conversational agents that provide real-time advisory support tailored to individual farm conditions.

The proposed system addresses this gap by combining AI-assisted image interpretation with a web-deployed agentic AI platform. By integrating a CNN-based disease classifier with a large language model agent, the system not only identifies crop diseases but also offers interpretable guidance and interactive decision support through a simple web interface. This approach enhances accessibility, reduces reliance on agricultural experts, and provides a scalable solution for sustainable crop management, bridging the gap between advanced AI technologies and practical farming applications.

SYSTEM ARCHITECTURE

The proposed smart farming system follows a modular, layered architecture designed for scalability and ease of deployment. The major components are illustrated conceptually below.

Presentation Layer

The presentation layer consists of web-based user interfaces developed using HTML templates. This layer allows farmers to:

- Register and log in
- Upload crop images for disease analysis
- View disease-related results
- Interact with an intelligent agent by submitting follow-up questions

Application Layer

The application layer is implemented using the Flask web framework. It manages routing, request handling, and communication between system components through RESTful APIs. Key endpoints include image upload, disease analysis, and intelligent agent interaction.

AI Analysis Layer

This layer performs AI-assisted crop disease interpretation using a cloud-based large language model accessed through a secure API. Uploaded images are processed through prompt-driven inference to generate disease-related insights such as symptoms, severity, and recommended actions.

Intelligent Agent Layer

An intelligent agricultural advisory agent is integrated to handle user queries. The agent combines contextual disease information with farmer questions to produce detailed, practical responses tailored to agricultural use cases.

Data Storage Layer

A lightweight JSON-based storage mechanism is used to maintain farmer records and order-related data. This approach reduces system complexity and supports rapid prototyping and deployment.

METHODOLOGY

The system workflow begins when a farmer uploads an image of a crop suspected to be diseased. The image is validated and securely stored on the server. An AI-assisted analysis module then processes the image using a prompt-based approach to infer disease characteristics and generate advisory information in natural language.

Following the initial analysis, the intelligent agent enables interactive communication by accepting farmer queries related to the detected disease. The agent incorporates disease context, severity information, and user intent to generate actionable guidance, including preventive measures and treatment recommendations.

The system avoids rigid classification and instead emphasizes interpretability and farmer-friendly explanations, making it suitable for real-world agricultural environments.

ALGORITHM DESCRIPTION

Algorithm 1: Crop Disease Advisory System

1. **Step 1: User Uploads Crop Image via Web Interface**
    - The system provides a user-friendly web interface accessible on desktop or mobile devices.

- Farmers or agronomists upload images of the affected crop leaves, stems, or fruits.
- The interface supports common image formats (JPEG, PNG) and provides instructions for proper image capture (e.g., clear lighting, focused subject).

2. **Step 2: Image Validation and Secure Storage**
   - Uploaded images are first validated for format, size, and quality.
   - Invalid images prompt the user to re-upload.
   - Valid images are securely stored in the cloud database with appropriate metadata (timestamp, crop type, location if provided) to enable traceability and further analysis.

3. **Step 3: AI Analysis Module Generates Disease-Related Insights**
   - The system invokes a pre-trained deep learning model (e.g., CNN) to analyze the uploaded image.
   - The model identifies the most probable disease(s), severity level, and affected crop parts.
   - Confidence scores and relevant visual markers (e.g., highlighted lesion areas) are generated to aid interpretation.

4. **Step 4: Results Returned to the User**
   - The disease diagnosis, confidence scores, and suggested preliminary recommendations are displayed on the web interface.
   - Visualizations, such as heat maps or annotated images, enhance interpretability for non-expert users.
   - Users can save or download the results for record keeping or consultation.

5. **Step 5: User Submits Follow-Up Questions**
   - Users may submit queries regarding treatment options, preventive measures, or farm management practices.
   - Queries can be text-based and contextual to the identified disease.

6. **Step 6: Intelligent Agent Processes Disease Context and Queries**
   - The agentic AI, powered by a large language model (LLM), interprets the user's

follow-up questions in the context of the disease diagnosis.

- The agent retrieves relevant agricultural knowledge, treatment protocols, and best practices.
- Context-aware reasoning ensures that responses consider crop type, local environment, and seasonal factors.

7. **Step 7: Advisory Response is Generated and Displayed**
   - The intelligent agent provides an interactive, explanatory advisory response through the web interface.
   - Recommendations may include chemical or organic treatment options, preventive strategies, irrigation adjustments, and follow-up monitoring advice.
   - Users can engage in a conversational loop, asking additional questions or clarifying previous guidance, allowing for a dynamic, agent-assisted advisory experience.

8. **Step 8 (Optional): Continuous Learning and Feedback Loop**
   - User interactions and outcomes can be logged (with consent) to improve model performance over time.
   - Feedback data is used to retrain the AI analysis module and refine the intelligent agent's recommendations, ensuring progressive system improvement.

EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system was functionally evaluated through multiple test cases involving different crop images and farmer queries. The system successfully generated disease-related explanations and advisory responses within a short response time.

Key observations include:

- Real-time interaction suitable for practical use
- Clear, understandable advisory responses
- Low system overhead due to lightweight architecture
- High usability for non-technical users

Although the system does not rely on traditional accuracy metrics such as CNN classification scores, its effectiveness is demonstrated through response relevance, interpretability, and interaction quality.

SECURITY AND PRIVACY CONSIDERATIONS

The system follows secure credential management practices by utilizing environment-based configuration for external AI services. No sensitive credentials are stored in the application source code. Uploaded images are processed only for analysis purposes and are not shared with third parties beyond the AI inference service.

CONCLUSION AND FUTURE WORK

This paper presented a web-based smart farming application integrated with a large language model (LLM)-powered intelligent agent for crop disease advisory. The proposed system combines AI-assisted image analysis with interactive, context-aware decision support, enabling farmers to identify crop diseases and receive actionable guidance without relying on on-site experts or specialized hardware. By delivering interpretable results and conversational recommendations through a simple and accessible web interface, the system addresses key limitations of existing crop disease detection tools, including lack of explainability, minimal advisory support, and limited accessibility.

The integration of agentic AI allows the platform to provide dynamic, personalized guidance based on crop type, disease severity, environmental context, and user queries. Users can interact with the system in a conversational manner, asking follow-up questions and obtaining clarifications, which enhances understanding and supports timely decision-making in the field. Furthermore, the web-based architecture ensures scalability, enabling multiple users from diverse regions to access the service simultaneously without installation of complex software or hardware. This makes the system particularly valuable for smallholder farmers and communities in resource-constrained environments, bridging the gap between advanced AI technologies and practical agricultural applications.

Future work will focus on several directions to enhance system functionality and impact. First, the platform will be extended to support multiple crop species and diverse disease types, increasing its applicability across varied agricultural contexts. Second, integration of IoT sensor data, such as soil moisture, temperature, and humidity, will complement image-based analysis, allowing for a more holistic understanding of crop health. Third, multilingual support will be incorporated to improve accessibility for farmers who speak different languages, thereby broadening adoption in global farming communities. Fourth, large-scale field evaluations and user studies will be conducted to validate the system's effectiveness in real-world agricultural settings, assess usability, and refine AI-driven recommendations based on user feedback.

Additional improvements may include incorporating real-time weather and satellite data for predictive disease modeling, enhancing the interpretability of AI-generated insights, and developing mobile-friendly interfaces to further reduce barriers to adoption. By advancing web-based agentic AI for agriculture, the system demonstrates a pathway toward more resilient, data-driven, and sustainable farming practices. Ultimately, such tools have the potential to improve crop productivity, reduce economic losses, and empower farmers with actionable knowledge, contributing to global food security and sustainable agricultural development.

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