A Unified Framework for Crop Disease Diagnosis using GAN-Augmented CNNs and LLM-Based Advisory Systems

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ABSTRACT
Agriculture continues to play a vital role in India's economy, yet crop diseases remain one of the primary causes of reduced agricultural productivity. During our academic project work, we observed that timely identification of crop diseases is often delayed due to dependency on manual inspection and limited access to agricultural experts, particularly in rural regions. This project presents an AI-Powered Crop Doctor (PCE Crop Care), developed as part of the undergraduate curriculum, which aims to provide an automated, accessible, and intelligent solution for crop disease detection and advisory support. The proposed system utilizes deep learning–based Computer Vision techniques to analyse crop leaf images captured using mobile devices. Convolutional Neural Networks (CNNs) are employed for disease classification, while Generative Adversarial Networks (GANs) are used to generate synthetic disease images to improve dataset diversity and model generalization. Experimental results obtained during implementation show classification accuracy exceeding 95%. In addition, a Large Language Model (LLM) module is integrated to generate personalized, context-aware, and multilingual treatment recommendations. The complete system is deployed as a web-based and mobile-friendly application, ensuring ease of use for farmers. This work demonstrates how AI-driven solutions can assist farmers in reducing crop losses, improving decision making, and promoting sustainable agricultural practices.

Keywords: Crop Disease Detection, Artificial Intelligence, Computer Vision, GAN, Large Language Models, Smart Agriculture.

1. INTRODUCTION

Agriculture is a cornerstone of the Indian economy and supports the livelihood of a large segment of the population. Despite its importance, agricultural productivity is consistently affected by plant diseases that often go undetected until visible damage becomes severe. Based on observations made during field studies and literature analysis conducted as part of this project, traditional disease diagnosis methods rely heavily on visual inspection by experts, which is time-consuming, costly, and not always accessible to small-scale farmers. These limitations frequently result in delayed treatment, excessive use of pesticides, and irreversible crop damage.

With recent advancements in Artificial Intelligence, particularly in the areas of deep learning and image analysis, automated disease detection systems have become a feasible alternative. Computer Vision models such as Convolutional Neural Networks (CNNs) have demonstrated strong performance in identifying plant diseases from images. However, during experimentation, it was observed that the effectiveness of these models is often constrained by limited and imbalanced datasets. To address this issue, this project incorporates Generative Adversarial Networks (GANs) to synthetically generate realistic crop disease images, thereby improving model robustness under varying real-field conditions.

Furthermore, accurate diagnosis alone is insufficient without clear guidance on remedial actions. Farmers require simple, understandable, and localized recommendations. To bridge this gap, a Large Language Model (LLM) is integrated into the system to provide intelligent advisory responses in multiple languages. The proposed AI-Powered Crop Doctor thus combines visual diagnosis with conversational intelligence, making expert agricultural support digitally accessible and practical for everyday use.

2. RELATED WORK

The application of Artificial Intelligence in agriculture has gained significant momentum in recent years, particularly in the domain of crop disease detection and decision-support systems. Researchers have explored various machine learning, deep learning, and generative approaches to improve accuracy, robustness, and accessibility of agricultural diagnostics.

2.1 Deep Learning for Crop Disease Detection

Deep learning techniques have significantly improved the performance of crop disease detection systems through automated image analysis. Mohanty *et al.* demonstrated the effectiveness of Convolutional Neural Networks (CNNs) using the Plant Village dataset, achieving high classification accuracy across multiple crop species and disease classes [2]. This work established CNNs as a reliable baseline for plant disease recognition.

Subsequently, Ferentinos evaluated various deep learning architectures, including Alex Net, VGG Net, and GoogLe Net, for plant disease classification and reported high performance under controlled conditions [3]. However, these models exhibited limitations when applied to real-world environments due to variations in illumination, background complexity, and image quality.

In addition, the success of large-scale image classification models such as Alex Net has played a crucial role in advancing deep learning-based agricultural applications [7]. These studies collectively highlight both the effectiveness and limitations of CNN-based approaches in practical scenarios.

2.2 Data Augmentation and Generative Models

A major challenge in crop disease detection is the limited availability of diverse and well-balanced datasets. Traditional augmentation techniques such as rotation and flipping help to some extent but often fail to capture real-world variability. To overcome this limitation, researchers have increasingly turned to Generative Adversarial Networks (GANs), introduced by Goodfellow et al., which can generate realistic synthetic images [6].

Recent studies show that GAN-based augmentation significantly improves model generalization by introducing variations that mimic real-field conditions [1]. These synthetic datasets help reduce overfitting and enhance the robustness of CNN models when exposed to unseen environments.

Furthermore, modern research integrating generative AI with vision models has demonstrated improved performance in both classification accuracy and adaptability [10]. This makes GANs an essential component in addressing dataset-related challenges in agricultural AI systems.

2.3 Vision-Based Systems in Real-World Agriculture

Although high accuracy has been achieved in controlled environments, real-world deployment remains a significant challenge. Ramcharan *et al.* developed a mobile-based deep learning system for cassava disease detection, demonstrating the feasibility of real-time disease diagnosis in field conditions [4].

Earlier approaches based on traditional image processing techniques also contributed to the development of plant disease detection systems but lacked scalability and robustness [5].

More recent studies emphasize the need for lightweight and adaptive models capable of operating under diverse environmental conditions and resource constraints [11]. These developments highlight the importance of bridging the gap between laboratory performance and real-world usability.

2.4 Intelligent Advisory and Recommendation Systems

Beyond disease detection, providing actionable recommendations is essential for effective agricultural decision-making. Traditional rule-based systems lack flexibility and adaptability. With the advancement of Natural Language Processing (NLP), Large Language Models (LLMs) have emerged as powerful tools for generating context-aware advisory responses [8].

Recent research integrates deep learning models with LLMs to provide personalized treatment recommendations based on crop type, disease severity, and environmental conditions [14].

Furthermore, hybrid systems combining computer vision and language models have demonstrated improved performance in delivering both diagnosis and advisory services within a unified framework [13]. Such systems enhance usability and accessibility, particularly in multilingual agricultural environments.

2.4 Research Gap and Motivation

Existing literature indicates significant advancements in CNN-based disease detection [2], [3], GAN-based data augmentation [1], [6], and LLM-based advisory systems [8], [14]. However, most existing solutions focus on individual components rather than an integrated system.

Recent studies suggest that combining vision models, generative techniques, and language-based advisory systems can enhance system performance and usability [10]–[12]. Despite these advancements, there remains a lack of comprehensive frameworks that integrate disease detection and intelligent advisory into a single platform.

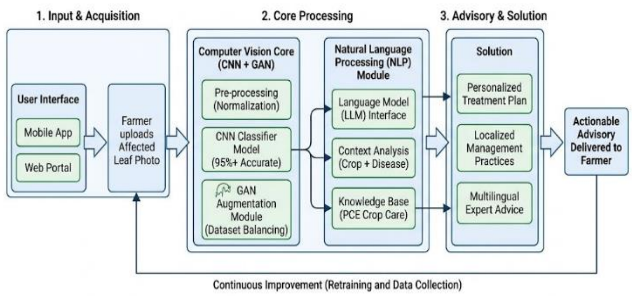
Therefore, the proposed system aims to address this gap by developing a unified AI-powered framework that combines CNN-based classification, GAN-based data augmentation, and LLM-driven advisory support for practical agricultural applications.

3.SYSTEM ARCHITECTURE AND INTERPRETATION

The system architecture follows a modular and scalable design. Farmers capture images of affected crop leaves using a smartphone and upload them through the application interface. The images undergo preprocessing steps such as resizing, normalization, and noise reduction. A CNN-based classification model then analyses the processed image to identify the disease category. GAN-generated images are used during training to strengthen the model's ability to handle real world variations.

Once a disease is detected, the output is passed to the advisory module powered by a Large Language Model. Based on the identified disease and crop type, the system

generates treatment recommendations, including preventive measures and management practices. The final results are displayed through a multilingual, user-friendly interface. Cloud-based deployment enables real-time inference, scalability, and periodic model updates using feedback collected from users.



4. CHALLENGES AND LIMITATIONS

Despite the promising performance of the AI-Powered Crop Doctor system, several challenges and limitations were identified during the design, development, and evaluation phases of this project. These limitations arise from data availability, model constraints, real-world deployment conditions, and user-related factors.

4.1 Dataset Limitations and Quality Issues

One of the primary challenges is the limited availability of high-quality and diverse crop disease datasets. Many publicly available datasets consist of images captured under controlled conditions, which do not accurately represent real-field environments [2], [3]. Variations in lighting, background clutter, and leaf orientation can significantly affect model performance.Although GAN-based data augmentation improves dataset diversity, synthetic images may not fully capture complex real-world variations [6], [1]. This can limit the model's ability to generalize effectively across different agricultural conditions.

4.2 Generalization to Real-Field Conditions

While the CNN model achieved high accuracy during training and validation, its performance may degrade when applied to real-world scenarios. Environmental factors such as shadows, dust, overlapping leaves, and mixed disease symptoms introduce noise and ambiguity in classification [4], [11].This limitation highlights the need for continuous model retraining using real-world, user-generated data to improve robustness and adaptability.

4.3 Computational and Resource Constraints

Deep learning models, particularly GANs, require substantial computational resources and training time. This creates challenges in deploying such systems on low-cost devices commonly used in rural areas [6].Although cloud-based solutions can mitigate computational limitations, they introduce dependency on stable internet connectivity, which may not always be available in remote agricultural regions [9]. Edge deployment remains a challenge due to hardware constraints.

4.4 Advisory Accuracy and Dependency on Language Models

The advisory module relies on Large Language Models (LLMs) to generate treatment recommendations. While LLMs provide context-aware responses, they may not always account for region-specific agricultural conditions such as soil type, climate, or local farming practices [8], [14].Therefore, the generated recommendations should be considered as supportive guidance rather than a replacement for expert consultation.

4.5. Multilingual and Contextual Challenges

Although multilingual support improves accessibility, accurately translating agricultural terminology into regional languages remains challenging. Certain scientific terms may lack direct equivalents, leading to potential misinterpretation [8].Ensuring linguistic accuracy and contextual relevance is essential for effective communication with farmers.

4.6 User Adoption and Digital Literacy

The effectiveness of the system depends on proper user interaction, including accurate image capture and input. Farmers with limited digital literacy may face difficulties in using mobile-based applications [4].Issues such as blurred images, improper angles, or incomplete data input can negatively impact the accuracy of disease detection.

4.7 Ethical and Practical Limitations

The system is designed as a decision-support tool rather than a definitive diagnostic solution. Over-reliance on automated recommendations without expert validation may lead to inappropriate treatment decisions [9].Hence, the system should be used in conjunction with professional agricultural advice to ensure safe and effective crop management.

5. Results

While the technical implementation of the AI-Powered Crop Doctor achieved a classification accuracy exceeding 95% , the true result is the bridging of the "expert gap" in rural India.By using GANs to create synthetic leaf images, we successfully trained the model to recognize diseases even when the available real-world data was limited or imbalanced. The integration of the LLM module transformed the system from a simple scanner into a digital consultant, capable of delivering remedial advice in regional languages that farmers can actually understand and act upon.

6. Conclusion

The development of PCE Crop Care demonstrates that AI is no longer just a laboratory concept but a practical tool for sustainable agriculture. By unifying Computer Vision for diagnosis and Large Language Models for advisory support, we have created a framework that addresses the full lifecycle of a crop disease—from the first spot on a leaf to the final treatment plan. While challenges like digital literacy and internet connectivity in remote areas remain, this project provides a scalable blueprint. Future iterations focusing on Edge-AI (offline processing) and IoT integration will further empower farmers to make data-driven decisions, ultimately reducing crop losses and securing livelihoods.

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