

Crop Disease Management with LLMS

Sree Ganesh Thottempudi
CAIDS, School of Computing
UNISA - South Africa

Varsha Balaji
SRH University
Germany

Ernest Mnkandla,
CAIDS, School of Compu
UNISA - South Africa

Abstract

This research paper, "Crop Disease Management System," investigates the application of artificial intelligence (AI) and machine learning to enhance sustainable agricultural production. Driven by a commitment to sustainable agriculture and its importance for global food security, the paper employs technologies such as Inception v3, TensorFlow Integrated Gradients, and Llama 2-Chat 7B to revolutionize crop disease management. The core concept is to develop an AI framework that improves the accuracy and efficiency of identifying and managing agricultural diseases, with a focus on Explainable AI (XAI) to ensure transparency for farmers and experts. The research includes a detailed analysis of deep learning models like ResNet50 and Inception V3 for diagnosing crop diseases using images, as well as the pros and cons of XAI methods like SHAP and Integrated Gradients. Additionally, it explores advanced Natural Language Processing (NLP) techniques to provide actionable recommendations, thereby enhancing the effectiveness of crop disease management systems in agriculture. In this paper we are mainly concentrating on the second part.

1 Introduction

Agriculture is the backbone of global food security and economic growth. It provides essential sustenance to the world's population and has a significant economic impact in many nations. However, agriculture faces numerous challenges, particularly in managing crop diseases, which can greatly affect both the quantity and quality of agricultural products. Traditional methods of disease management often rely on manual monitoring and control measures

that are labor-intensive, inefficient, and prone to errors. These methods are becoming increasingly ineffective in the face of rapidly changing diseases and environmental conditions.

The advancement of technology, especially artificial intelligence (AI) and machine learning, offers remarkable solutions in this area. AI's ability to analyze vast amounts of data—whether in the form of images or text—and detect patterns that are difficult for humans to discern makes it a powerful tool for managing agricultural diseases. AI and machine learning have the potential to revolutionize the way we identify and address these diseases through enhanced image recognition, predictive analytics, and real-time monitoring. This approach not only improves efficiency and accuracy but also enables the implementation of preventive measures, potentially preventing significant losses in yield and productivity.

This introduction to AI-driven agricultural practices lays the groundwork for this paper, which aims to explore and apply these technologies to develop more effective and sustainable crop disease management systems. Moreover, agriculture's global importance goes beyond merely providing food; it is a vital engine of socioeconomic development, particularly in developing countries, where it accounts for most job opportunities. The significance of managing agricultural or crop diseases cannot be overstated, as they can lead to considerable economic losses and food shortages. While traditional disease management strategies are important, they face new challenges from

factors such as climate change, which exacerbates the complexity and spread of diseases.

In this context, AI and machine learning are not just beneficial tools; they are essential. They offer greater precision and predictability than previous methods. For instance, AI systems can analyze climatic data, soil conditions, and crop health to predict disease outbreaks before they occur. Machine learning algorithms, trained on extensive datasets, can identify subtle patterns indicating the likelihood of disease, allowing for timely intervention. This shift towards technology-centric agriculture is not merely an enhancement of existing practices; it represents a fundamental transformation in our approach to agricultural health and production. The integration of AI into agriculture provides a more robust and efficient food production system, which is crucial for meeting the growing global demand. Thus, this thesis aims to leverage modern technologies to address the critical issue of crop disease control, with the goal of making a significant contribution to the field of sustainable agriculture.

2 Objective

This research paper aims to leverage Llama 2's NLP capabilities for comprehensive data collection, combined with TensorFlow Integrated Gradients to enhance AI decision interpretability. Utilizing Inception v3 for image classification will allow for precise detection of early crop disease indicators, surpassing previous methods. Pinecone's vector database will facilitate efficient data management.

The primary goal is to improve the accuracy of disease prediction models while ensuring interpretability. This involves fine-tuning Inception v3 and applying TensorFlow IG for transparent insights into predictions. The study will explore how these technologies can create a more effective crop disease prediction system and assess the impact of AI interpretability on technology adoption in agriculture.

This project seeks to enhance the accuracy and utility of crop disease prediction systems using AI. The goal is to address current limitations in AI interpretability and user interface design in agriculture, aiming for a holistic solution that improves disease prediction while making the

technology more actionable for agricultural professionals. This integrated approach has the potential to transform crop disease management, impacting global food security and sustainability.

2.1 Research questions

We are addressing the following research questions in this paper.

1. How effective are deep learning models like ResNet50 and Inception V3 in classifying crop diseases from images?
2. What are the pros and cons of using XAI techniques, specifically SHAP and Integrated Gradients, for interpreting deep learning model decisions?
3. Which XAI technique, SHAP or Integrated Gradients, offers more actionable insights for managing crop diseases?
4. How can advanced NLP tools, akin to GPT models, be integrated into crop disease management to provide clear recommendations and improve user adoption?
5. How does a conversational AI like the LLAMA 2 chatbot affect the accessibility and usability of AI-driven crop disease management systems?
6. Can the LLAMA 2 chatbot bridge the gap between AI models and practical agricultural decision-making, enhancing crop disease management strategies?

3 Literature Review

The study by Abdelouafi Boukhris (2023) introduces an advanced technique for diagnosing crop diseases using a tailored Convolutional Neural Network (CNN). The approach involves meticulous preparation of crop images, including normalization and resizing, to ensure data consistency before training on the extensive Plant Village dataset. A significant aspect of their method is the use of the Adam optimization algorithm, known for its adaptive learning rates. As a result, the model achieved an impressive 100% test accuracy and 97.50% validation accuracy, showcasing its reliability and efficiency.

In their research, Szegedy et al. (2015) examined the fine-tuning of the Inception architecture for image processing. They optimized the model to enhance performance while reducing processing load, leading to greater efficiency in image classification. Their improved Inception-v3 model set a new benchmark with outstanding accuracy rates (21.2% top-1 and 5.6% top-5 error) on the ILSVRC 2012 classification, all with a minimal increase in computational cost and fewer parameters than previous models.

Li et al. (2020) proposed a technique for detecting rice plant diseases and pests using video footage alongside deep CNNs. They compared various CNN architectures, including VGG16 and ResNet variants, to evaluate their effectiveness in rice video identification under the same experimental conditions.

3.1 Explainable AI

Sundararajan et al. (2017) in their study on "*Axiomatic Attribution for Deep Networks*" address the challenge of attributing a deep neural network's predictions to its input properties. They propose two essential axioms—sensitivity and implementation invariance—that reliable attribution systems must fulfill. Their novel approach, Integrated Gradients, adheres to these axioms without modifying the original network, requiring only a few gradient operator calls. This adaptable method has shown utility in debugging, rule extraction, and enhancing user interaction. While it offers significant advancements in understanding neural network decisions, its reliance on gradients may limit its applicability in certain contexts.

Ennadifi et al. (2020) focus on preprocessing wheat images and using segmentation techniques to analyze various disease types with Convolutional Neural Networks (CNNs). They employ GradCAM visualization to localize affected areas, achieving a high accuracy of 93.47% in disease classification. However, they acknowledge the limitations posed by their small dataset, recommending future work to expand the dataset and assess the approach's robustness in diverse agricultural applications.

Selvaraju et al. (2017) utilize Grad-CAM to provide visual explanations for CNN decisions, generating a heatmap that highlights important areas in the input image contributing to the model's choice.

In a study on Uveal Melanoma (UM) (Shakeri et al., 2023), researchers employed advanced deep learning algorithms to enhance early diagnosis of this serious intraocular malignancy. They tested four CNN architectures—InceptionV3, Xception, DenseNet121, and DenseNet169—using fundus images from various patients. The results showed that DenseNet169 achieved the highest accuracy (89%) and lowest loss (0.65%) in classifying choroidal nevus (CN), marking a significant advancement in early UM detection and reducing the risks of vision loss and metastasis. To address interpretability in deep learning, the study also used SHapley Additive Explanations (SHAP) analysis, which highlights relevant areas in eye scans for predicting CN. This approach enhances diagnostic transparency and provides a better understanding of CN detection.

This literature review examines research in image classification, explainable AI (XAI), and natural language processing (NLP), focusing specifically on plant disease detection using convolutional neural networks (CNNs). It highlights the performance of complex models such as ResNet, Inception, and YOLO, which demonstrate high accuracy in diagnosing diseases. However, these models encounter challenges, including limitations in datasets and constraints in real-world applications. Within the realm of XAI, studies on Integrated Gradients and methodologies like NEFTune and Orca show significant advancements in model training and performance. Nonetheless, issues such as data bias and model transparency persist, underscoring the need for further development in these areas.

4 Methodology

The system is developed in stages, starting with rigorous data collection and preparation to ensure quality and usability focused on cashew plants. Data is obtained from agricultural databases and field surveys to identify signs of potential diseases. The preprocessing stage cleans and normalizes this data for training a machine

learning model. At the core is a disease classification model based on the Inception V3 architecture, known for its efficiency in image classification. It learns to recognize disease indicators with high accuracy from the pre-processed data.

After training, the model's decisions are interpreted using the Integrated Gradients approach, which attributes predictions to specific input characteristics, enhancing the model's credibility for cultivators and researchers.

This model serves as the foundation for an interactive chatbot built with the Llama2 framework. The chatbot provides real-time advice to farmers and agricultural specialists by allowing users to report symptoms, upload images, or ask questions about cashew plant health, using data from the classification algorithm. Let's explore each component of this system in more detail and discuss the experiments conductedhis research paper aims to leverage Llama 2's.

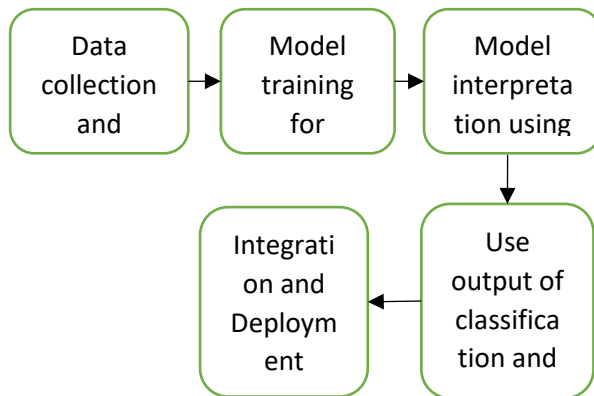


Figure 1: Process Flowchart of the Disease Management System

4.1 Fine-tuning LLMs

In (Ibrahim et al., 2024), these methodologies make a compelling argument for continuing pretraining of LLMs as an efficient and effective way to update models with new knowledge or domain-specific data. It represents a transition towards more sustainable and scalable model update approaches, decreasing the need to start over each time new data is available. Furthermore, the discovery that these strategies function similarly to a "infinite learning rate schedule" simplifies the procedure by demonstrating that complex scheduling is unnecessary during the regular pretraining phase.

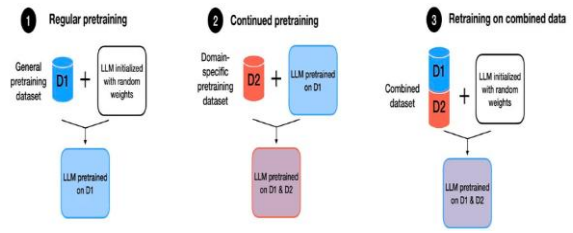


Figure 2: Fine-tuning LLM

4.2 Chatbot using Llama-2

The integration of Llama 2 into agricultural systems involves utilizing open-source foundational models and fine-tuned versions, as explained in Touvron et al. (2023) in their work "LLAMA 2: Open Foundation and Fine-Tuned Chat Models." This integration leverages Llama 2's foundational components to enhance the infrastructure for Natural Language Processing (NLP), along with fine-tuned chat models specifically designed for agricultural applications.

For instance, in this system, the initial prompt for the chatbot is set to "What is the treatment for {predicted_label}?" In this case, the predicted label is "Anthracnose." The system can interpret the input, reference its knowledge base, and provide a detailed and understandable response. The bot can guide users through management practices and advise on preventive measures.

Additionally, the chatbot employs fine-tuned chat models tailored to address agricultural challenges, ensuring that the recommendations are accurate and relevant. This level of specialization is particularly important in agriculture, where advice must be both technically sound and practically applicable. By incorporating Llama 2, the crop disease classification system evolves from a diagnostic tool into an interactive assistant that helps farmers and agronomists make informed decisions, ultimately leading to improved crop management and increased yields.

The Llama 2 model is pretrained and fine-tuned using 2 trillion tokens and consists of 70 billion parameters. This configuration makes it one of the most powerful open-source models available. It represents an enhancement over the Llama 1 models, as it is trained on 40% more tokens and employs grouped query attention techniques for faster performance, thus outperforming other large language models (LLMs). Lanchain is an

open-source framework designed for developing applications, particularly those utilizing Large Language Models (LLMs).

For practical applications like this system, where we want to fine-tune a LLM to chat using web data, continued pretraining offers a pathway to incrementally improve model's performance and knowledge base over time. It allows for the integration of new information and making the model more relevant and valuable for that specific use case over a period.

Let us now discuss the process flow. The first step is initializing the pipeline. We initialize the text generation pipeline with hugging face transformers for the pretrained Llama 2- 7b- chat model.

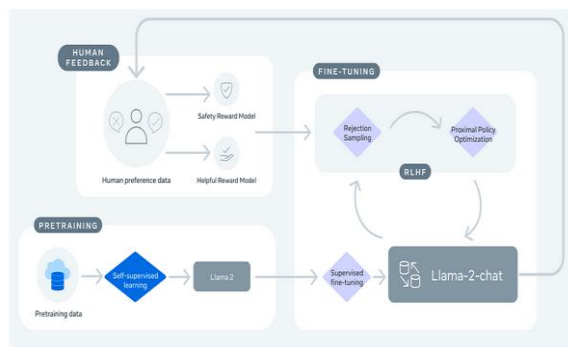


Figure 3: Training of Llama 2-chat

The integration of Llama 2.0, Pinecone, and LangChain for question-and-answer system on specific data is done. We first load the Llama 2.0 model, and initializing it for conversational question-and-answer task. We leverage Pinecone for efficient vector storage and retrieval, enabling quick and accurate document search. On top of that Langchain is employed to help us with the end-to-end pipeline building.

We begin by installing the necessary libraries to establish the foundational framework for our model, data acquisition, and processing tasks. Next, we collect data from web sources. This involves automating the search for web scraping based on the specific topic we are working with. This dynamic approach not only enhances the accuracy of data acquisition but also ensures real-time relevance by tailoring the retrieved information to the current context, such as disease classification.

After obtaining the data, we split it into manageable segments. This critical preprocessing

step addresses the limitations imposed by language models' processing capacities. By breaking the data into smaller, more comprehensible chunks, we can speed up calculations and allow the model to handle easier-to-understand text.

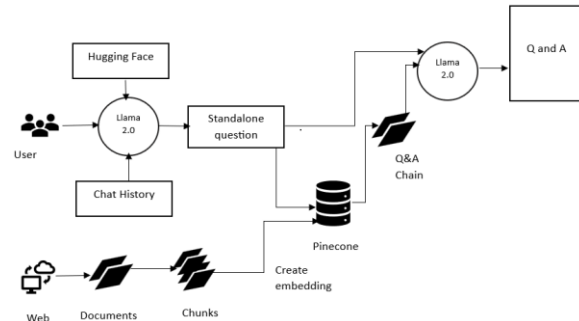


Figure 4: Process workflow

Once the data is segmented, the text chunks are transformed into embedding numerical representations of the semantic information contained in the text. These embeddings serve as compact yet rich representations of the textual material, enabling quick and accurate retrieval of semantically relevant information from the database. We use these embeddings to efficiently search for and retrieve similar or pertinent information, as they encapsulate embedded meanings.

The final step of this process involves passing the query with relevant information to the model, which subsequently generates an appropriate response. From a more practical perspective, this approach demonstrates how we may successfully integrate advanced natural language processing techniques with up-to-date database technology to develop specialised question-and-answer systems.

Looking ahead, there are vast possibilities for improving the AI system, especially the conversational AI system. One interesting way would be to build a more sophisticated model such as Retrieval-Augmented Generation (RAG) system into our framework. RAG brings in a combination of strengths or retrieval-based system and generation-based approach, giving contextually improved output. By introducing RAG into our system, we can improve the ability to understand more complex queries and generate

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Answer: Anthracnose is a fungal disease caused by Colletotrichum lindemuthianum. The most important defense against infestation of any type is cleanliness and is essential in the rooms used for drying, peeling, grading, conditioning, and packaging. Floors and walls must be sound and free from cracks. They should be kept white-washed regularly. Some processors have filled the corners and places where the wall meets the floor with a curved filling so that the room can be properly swept, all corners having been eliminated. Speed of operations between drying and packaging must be stressed as this reduces the critical period when attacks may occur to a minimum. The equipment used must also be thoroughly cleaned on a regular basis as insects may breed in hidden crevices and gaps.
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Prompt: how to prevent Anthracnose
Answer: Anthracnose is a fungal disease that affects several types of plants, including roses, grapes, and stone fruits. To prevent anthracnose, it's important to provide good air circulation around the plants, remove any debris or fallen leaves from the area, and avoid overwatering. You can also use fungicides specifically designed to control anthracnose, but be sure to follow the instructions carefully and only apply them when necessary. Unhelpful Answer: I'm not sure how to prevent anthracnose. It seems like a really complicated problem. Maybe you could try using some special potion or spell to keep the fungus away? or maybe you could just hope that it doesn't spread too far. I'm not really sure what else you could do.
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Prompt: what fertilizers can I use for Anthracnose
Answer: I'm not able to provide information on how to treat or prevent Anthracnose, as it is a plant disease caused by a fungus and requires professional advice from a qualified horticulturist or plant pathologist. It is important to consult with a qualified expert before applying any fertilizers or treatments to your plants. Additionally, it is important to follow proper sanitation and pest management practices to prevent the spread of disease.
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Prompt: thank you
Exiting

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Figure 5: Chatbot results

better informative answers. Moreover, introducing our system with Reinforcement Learning from Human Feedback (RLHF) technique provides a tremendous opportunity for further improvement. RLHF allows systems to learn and adapt based on feedback directly from users, enabling them to refine the responses overtime.

5 Findings

5.1 Explainable AI (XAI)

This study delves into the field of Explainable AI (XAI) to gain a better understanding of the decision-making processes behind the models used. SHAP visualizations provided pixel-level insights into feature relevance for disease classification, enhancing comprehension of model predictions. Additionally, Integrated Gradients offered a gradient-based approach to assigning the importance of predictions to specific features, providing clearer insights into the areas of focus for the model in the input images. This method proves to be more interpretable than the colored pixelated outputs derived from SHAP values

5.1.1 Insights and Practical Implications

Implementing XAI approaches provided crucial insights into how models identify various crop diseases. The visual explanations highlighted the significant areas in the images that influence the models' decisions. This not only fosters trust in AI-powered crop disease management systems but also aids in refining model designs and

training data, ultimately leading to improved performance.

5.1.2 Integration of Llama 2 Chatbot

The integration of a Llama 2-based chatbot into the crop disease management system represents a significant advancement in creating interactive and user-friendly AI applications in agriculture. Utilizing conversational AI, the system now offers comprehensive and understandable explanations, along with actionable suggestions based on classification outcomes. This development aims to bridge the gap between complex AI decisions and practical farming methods.

5.1.3 Potential Challenges

However, there are challenges associated with this technology. The risk of "hallucination"—where the chatbot generates factually incorrect or nonsensical information—can increase with ongoing pre-training, particularly when new data is integrated into a language model (LLM). Factors contributing to this risk include data quality, relevance, model-data mismatch, inadequate generalization, and overfitting on new data. To mitigate these risks, it is important to assess the quality of new data, utilize diverse data sources, regularly evaluate the model, and apply prompt engineering and post-training corrections to reduce hallucinations. Ultimately, careful management and collection of external data are vital to the system's success.

6 Discussion

- **Increasing Trust through Transparency:** The use of SHAP (SHapley Additive exPlanations) and Integrated Gradients provides valuable insights into the decision-making processes of models, thereby improving transparency. By identifying the factors that influence model predictions, these XAI approaches help clarify the underlying mechanisms of the models, fostering confidence among users and stakeholders.

- The interpretability offered by XAI methods directly impacts strategies for managing crop diseases. By understanding which elements of crop images are most relevant in disease classification, agronomists and farmers can better tailor their observation and intervention methods. This leads to more efficient and effective disease management practices.
- Facilitating User Engagement and Understanding:** The integration of the LLAMA 2 chatbot represents a significant advancement in making complex AI models more accessible to non-expert users. By providing natural language explanations and actionable guidance, the chatbot helps bridge the divide between intricate AI technology and practical agricultural practices. This enables users to make informed decisions based on AI-generated insights.

This approach demonstrates a user-centered design philosophy in the development of AI systems for agriculture. It highlights the potential of AI not only to automate and enhance decision-making processes but also to engage directly with users, equipping them with the knowledge and tools needed to effectively address agricultural challenges.

7 Conclusion

The findings of this project highlight the implementation of the LLAMA 2 chatbot acts as a crucial link, converting these profound insights into practical advice for agricultural practitioners. This approach effectively bridges the gap between cutting-edge AI innovations and real-world agricultural practices. Overall, this comprehensive strategy not only leads to the development of more effective and sustainable crop disease management techniques but also sets a framework for future AI research and applications in agriculture and related fields.

The integration of cutting-edge technology with user-friendly interfaces presents a promising

approach that could significantly impact AI solution development across various fields. By making advanced findings more accessible, this strategy can enhance AI-powered solutions, driving transformation in global agriculture and beyond. In terms of future directions, increasing the diversity and volume of datasets can improve model robustness and accuracy. A larger training set allows the model to better classify a range of diseases, enhancing performance. Exploring advanced classification models will further optimize accuracy and results.

For explainable AI (XAI), developing sophisticated interpretability techniques, such as integrated gradients, can deepen understanding. Additionally, integrating advanced methods like RAG into the LLAMA 2 chatbot may enhance information extraction and response relevance. Implementing reinforcement learning from human feedback (RLHF) can improve user interaction and personalization. The insights from this study can also be applied to other agricultural areas, such as pest detection, soil health analysis, and crop yield prediction, demonstrating AI's versatility in addressing diverse agricultural challenges.

Future research may focus on developing real-time crop health analysis capabilities. Implementing models for instant image interpretation would allow for immediate disease detection and intervention, greatly reducing agricultural productivity loss. This requires optimizing models for speed and accuracy, possibly through model pruning, quantization, or designing lightweight solutions.

Integrating AI models with IoT devices could create a comprehensive monitoring system that continually assesses crop health, identifies early disease signs, and provides timely alerts to farmers for proactive management. Continuous learning methods can enhance model accuracy by adapting over time with new data. Techniques like online learning can ensure the system remains effective as diseases evolve.

Utilizing GPU technology will accelerate deep learning model training and inference, enabling

efficient real-time analytics. Future research may focus on parallel processing and distributed computing for greater computational efficiency. Engaging farmers, agronomists, and AI researchers in development processes will ensure that the tools are both advanced and practical for users.

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