Multiple Crop Diseases Detection and Diagnosis Using AI

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Abstract - This project presents a mobile application leveraging artificial intelligence (AI) for efficient crop disease detection and diagnosis. Traditional methods for identifying crop diseases are often slow, require specialized knowledge, and may not be accessible to all farmers. This application provides a fast, user-friendly solution, enabling farmers to diagnose diseases with high accuracy. By analyzing image data, the app employs advanced AI algorithms to compare results with a comprehensive disease database, identifying potential diseases and offering tailored management recommendations. This tool empowers farmers to make informed decisions, adopt sustainable practices, and optimize crop productivity. Collaboration with agricultural and AI experts is integral to refining the AI model and ensuring its accuracy across diverse farming environments. The mobile application aims to enhance food security and promote sustainable agricultural development, addressing critical challenges in modern agriculture..

Keywords: Artificial Intelligence, Crop Disease Detection, Mobile Application, Machine Learning, Sustainable Agriculture, Disease Diagnosis, Farming Technology, Image Analysis.

I. INTRODUCTION

Agriculture is a cornerstone of Zambia's economy, with staple crops such as maize, cassava, and sorghum serving as primary food sources for a significant portion of the population. These crops, however, are highly susceptible to diseases, leading to significant yield losses that threaten food security. The complexities of disease management are further compounded by the impact of climate change on pathogen behavior and crop resilience [1].

Traditional disease detection and diagnosis methods are insufficient for addressing the scale and urgency of these challenges [2]. While breeding for resistance and genetic modification offer partial solutions, their widespread Brian Halubanza

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adoption is constrained by time, cost, and genetic variability. Moreover, the misuse of pesticides has led to resistant pathogen strains, exacerbating the problem [3].

The need for timely, accurate disease diagnosis is paramount to optimizing resource use and enhancing crop productivity. Artificial intelligence (AI) offers transformative potential in this domain. Leveraging advancements in machine learning, AI systems can analyze large datasets, detect disease patterns, and provide actionable insights with remarkable accuracy [5]. This research focuses on developing an AI-based mobile application tailored to the detection and diagnosis of diseases affecting Zambia's staple crops. By integrating image analysis and machine learning, the system can provide early disease detection, personalized treatment recommendations, and sustainable management strategies.

II. LITERATURE REVIEW

Recent studies highlight the potential of AI in revolutionizing crop disease detection. Dai and Fan [7] developed an automated system for crop disease detection in San Francisco using convolutional neural networks (CNNs), achieving notable accuracy. Similarly, Singh V. et al. [8] introduced an image segmentation algorithm adaptable to various crop species, showcasing its effectiveness in diverse agricultural settings.

Singh T. [9] reviewed a range of machine learning algorithms, including Artificial Neural Networks (ANNs), for plant disease detection. These studies emphasize the adaptability of AI models to different crop diseases. Vashisht et al. [10] and Islam et al. [11] explored advanced techniques like multiclass support vector machines (SVMs) and deep learning models, while Liu and Wang [12] underlined the importance of high-quality datasets in achieving robust model performance. These findings underscore the feasibility of AI in improving disease detection and management.

III. PROPOSED SYSTEM

The proposed system features a mobile application designed for user-friendly interaction. The app enables farmers to upload or capture images of crop leaves, which are then analyzed by an AI-powered classifier. Based on the analysis, the system identifies diseases or confirms the crop's health and provides tailored recommendations or professional advice. The app also stores anonymized user data to improve the AI's performance over time through continuous learning.

A. System Architecture

The system incorporates object-oriented design methodologies to ensure a robust and coherent architecture. The design includes a seamless user interface, a secure data storage mechanism, and an efficient AI engine for real-time analysis.

B. Key Features

- User Interaction: Simple navigation allowing farmers to select crops and upload images for analysis.

- Disease Diagnosis: AI-based predictions with detailed disease descriptions.

- Recommendations: Personalized management strategies tailored to the detected disease.



Fig. 1 General Overview of The System

Figure 1 shows the general overview of the system, illustrating the user interface and workflow of the application from image capture to disease diagnosis and recommendations.

IV. METHODOLOGY

A. Research Design

This study employed an experimental design to evaluate the effectiveness of machine learning models, with a focus on CNNs, for crop disease detection. Targeted crops included cassava, tomatoes, and maize due to their economic significance and susceptibility to diseases [14].

B. Data Collection and Preprocessing

High-resolution images of diseased crops were collected from agricultural research institutions and online databases such as Kaggle. The dataset was preprocessed using techniques such as resizing, rescaling, and data augmentation to ensure uniformity and enhance model robustness as shown in figure 3. The data was split into training (80%), testing (20%), and validation sets.



Fig. 2 Image Split into Train and Test and Validation

Figure 2 illustrates the dataset splitting process, showing how high-resolution images are divided into training, testing, and validation sets.





C. Model Training and Evaluation

The AI model, built using TensorFlow, was trained on the processed dataset. Key metrics, including accuracy, precision, and recall, were calculated to evaluate performance. The model achieved an impressive training accuracy of 0.995 and a validation accuracy of 0.8617, indicating its reliability across different crop species.



Fig. 4 Training and Validation Graph

Figure 4 presents the training and validation graph, showing the progression of accuracy and loss over multiple epochs.

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Fig. 5 Model training

Figure 5 summarizes the model training results in tabular format, showcasing key metrics such as training accuracy (99.5%), training loss (0.021), validation accuracy (86.17%), and validation loss (0.5132). These metrics demonstrate the model's robustness and effectiveness in handling diverse data inputs.

V. RESULTS

The trained model demonstrated exceptional accuracy in detecting diseases across multiple crop types. Key results include:

- Tomato Late Blight: 100% accuracy.
- Healthy Tomato Plants: 91% accuracy.
- Cassava Brown Streak Disease: 100% accuracy.

Testing results validate the model's potential to provide reliable disease diagnoses, as illustrated in the figures below:







Figure 7: Detection of Late Blight in tomatoes.





Figure 8: Healthy tomato leaf diagnosis.



Figure 9: Cassava Brown Streak Disease detection.

VI. ETHICAL CONSIDERATIONS

Data used in this study was sourced from publicly available datasets, ensuring compliance with ethical guidelines. No personal or sensitive data was involved, and all sources were appropriately credited [17].

VII. CONCLUSION

This study demonstrates the efficacy of custom AI models, particularly CNNs, in enhancing crop disease detection. By analyzing high-resolution images, the proposed system delivers accurate diagnoses and actionable recommendations. This innovation holds significant promise for mitigating yield losses, promoting sustainable agriculture, and bolstering food security. Future work will focus on expanding the dataset and refining models to encompass a broader range of crops and diseases, further advancing AI-driven agricultural technologies.

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