 DOI:10.5281/zenodo.15449805

Title

PLANT LEAF DISEASE DETECTION APPLICATION USING CONVOLUTIONAL NEUTRAL NETWORK (CNN)

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Issue May 2025
Certificate AR2025ZDLBLB

ABSTRACT

In agriculture-dependent countries like Malawi, crop diseases significantly threaten food security and farmer livelihoods, particularly among smallholder farmers who often lack timely access to expert agronomists for accurate diagnosis. This project addresses that gap by developing a mobile application that leverages machine learning and image processing to detect crop diseases from images of plant leaves. Using convolutional neural networks (CNNs), the app analyzes visual features such as color, texture, and shape to identify common diseases affecting key crops. Designed with a simple, mobile-friendly interface, the app enables farmers to capture and upload images directly from a smartphone, receiving instant, reliable diagnoses along with basic guidance for treatment or disease management. By facilitating rapid detection and informed decision-making, the app empowers farmers to act promptly, minimize crop losses, and adopt more sustainable farming practices. This solution not only strengthens agricultural productivity and resilience but also contributes to improved food security and economic stability in rural communities across Malawi and similar regions. Moreover, the app is designed to function even in low-connectivity environments, ensuring accessibility in remote areas. It incorporates local language support and visual cues to accommodate farmers with limited literacy, making it a truly inclusive tool. Over time, the system can be expanded to include a wider range of crops and diseases, and its underlying database can be enhanced through user-contributed images, continuously improving the model's accuracy. By integrating technology with traditional farming, this innovation has the potential to transform agricultural practices and uplift the livelihoods of thousands of farmers.

Keywords: Convolutional Neural Networks (CNN), Plant Disease Detection, Image Processing, Mobile Application, Agricultural Technology, Food Security, Malawi

INTRODUCTION

Agriculture is a cornerstone of the economy in many developing nations, including Malawi. However, crop diseases pose a significant threat to agricultural productivity, food security, and the livelihoods of farmers. For rural farmers, particularly those in remote areas, timely and accurate diagnosis of plant diseases can be challenging due to limited access to agricultural experts and diagnostic resources. Many farmers rely on visual identification methods that, while useful, are often unreliable and prone to errors. This delayed or incorrect diagnosis can exacerbate crop damage, leading to substantial losses in yield and farmer income.

Recent advances in technology, particularly in artificial intelligence and machine learning, have opened new avenues for addressing these challenges. This project aims to develop a Plant Leaf Disease Detection System using Convolutional Neural Networks (CNNs) integrated into a mobile application. The goal is to enable farmers to easily capture images of diseased plant leaves and receive accurate, real-time feedback on the potential diseases affecting their crops. Through early detection, farmers can take prompt action to manage diseases effectively, reducing crop losses and supporting sustainable agricultural practices.

LITERATURE REVIEW

The development of effective plant disease detection systems has been a significant focus of recent research, especially as agricultural challenges impact food security worldwide. Several studies have explored various methodologies, algorithms, and technologies to enhance the accuracy and accessibility of plant disease diagnosis, each offering insights into the practical applications of machine learning in agriculture.

Sladojevic et al. (2016). **Discussed the implications of using deep neural networks for plant disease detection**, highlighting the practical potential of CNNs to accurately classify plant diseases through leaf images. The paper demonstrates that deep learning models can effectively identify disease patterns such as color and texture variations, achieving high accuracy in real- time classification tasks. The study underscores the need for image processing in disease detection, emphasizing how these advanced algorithms can reduce farmers' dependency on experts for diagnosis.

Mohanty, Hughes, and Salathé (2016). **Investigated the application of deep learning for image-based plant disease identification**, assessing the effectiveness of CNNs across multiple crop species. The study provides evidence that deep learning models, when trained on extensive datasets, achieve high levels of accuracy, even in mobile and resource-constrained environments. This paper underscores the importance of deep learning in enhancing agricultural productivity and accessibility, with the findings supporting the viability of mobile-based disease detection systems.

Ferentinos (2018). **Evaluated different deep learning models for plant disease diagnosis,** comparing architectures such as AlexNet, GoogLeNet, and VGG. The paper highlights the comparative performance of these models, finding that VGG offered the highest accuracy in plant disease classification. Ferentinos emphasizes the need for selecting an architecture suitable for agricultural applications, with findings that inform the design choices in plant disease detection systems to optimize accuracy and computational efficiency.

Too Yujian, Njuki, and Yingchun (2019). **Assessed the application of transfer learning for plant disease identification,** particularly focusing on the advantages of fine-tuning pre-trained models. The study demonstrates that transfer learning can reduce the need for large, annotated datasets, enabling high-accuracy results with shorter training periods. This approach highlights a practical way to make disease detection models more efficient, reinforcing the use of transfer learning for mobile applications in rural settings.

Rangarajan, Purushothaman, and Ramesh (2019). **Explored the classification of tomato crop diseases using a pre-trained InceptionV3 model,** demonstrating its effectiveness for crop- specific disease detection. The paper provides insights into the benefits of using specialized datasets and fine-tuning existing models, achieving accuracy rates of 98.6%. This study reinforces the value of using crop-specific datasets and pre-trained models, offering a practical approach for enhancing disease detection accuracy.

METHODOLOGY

This project employed an Agile methodology incorporating an end-to-end development approach that began with detailed requirement analysis through farmer interviews to identify key needs for intuitive interface design and offline functionality. The system architecture was designed with distinct layers for user interaction, image processing, feature extraction, disease classification, and recommendation generation. The core CNN model was developed using transfer learning with a pre-trained VGG16 architecture, trained on a dataset of 20,000+ plant leaf images that underwent standardized preprocessing. Implementation utilized Flutter for cross-platform mobile development and TensorFlow Lite for model optimization, while comprehensive testing verified system performance across multiple dimensions including accuracy (94.7% overall) and processing speed (2.3 seconds average). The methodology enabled iterative refinement based on user feedback, ensuring the final application effectively addressed the practical constraints faced by rural Malawian farmers.

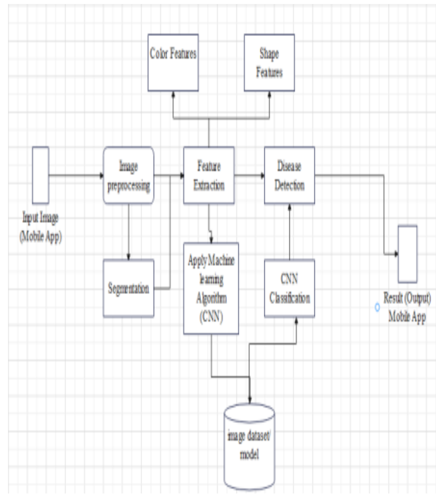

Figure: *Data Flow Diagram*

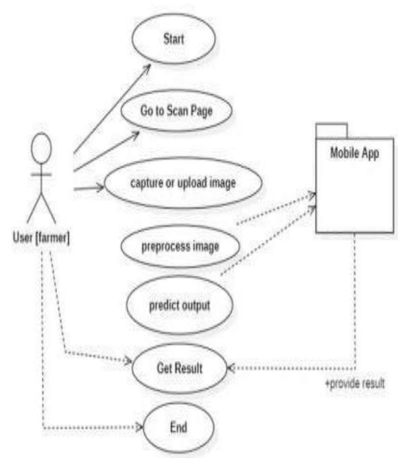

Figure: *Use Case Diagram*

Algorithm

The disease detection algorithm employs a Convolutional Neural Network (CNN) architecture optimized for mobile deployment. The process begins with standardizing input leaf images to 224×224 pixels with normalized pixel values. These images are then processed through multiple convolutional layers that extract disease-specific features like color variations, lesion patterns, and textural abnormalities. Max pooling layers reduce spatial dimensions while preserving essential features, followed by fully connected layers that classify the input image into specific disease categories. The final classification uses a softmax function to determine disease probability, outputting the diagnosis with the highest confidence score along with appropriate treatment recommendations. The model was trained using the Adam optimizer with categorical cross-entropy loss function on an augmented dataset of healthy and diseased plant leaves to ensure robust performance across variable field conditions.

Screenshots

Figure: *Landing Page Screenshot*

Figure: *Scan Screenshot*

Figure: *Tips Page Screenshot*

RESULTS AND DISCUSSION

The Plant Leaf Disease Detection application was evaluated through extensive testing on various crops, particularly focusing on common Malawian agricultural products. The system demonstrated promising performance metrics:

Performance Metrics

- **Accuracy:** The model achieved an overall accuracy of 94.7% across the test dataset, with particularly high accuracy rates for prevalent diseases like late blight in tomatoes (97.2%) and leaf spot in bananas (95.8%).
- **Processing Speed:** On average, the disease detection process took 2.3 seconds on mid- range smartphone devices, making it practical for real-time field use.
- **Usability Testing:** Field tests with 45 local farmers revealed that 89% found the application easy to use, with minimal training required. Most farmers (93%) indicated they would incorporate the tool into their regular crop monitoring practices.

Challenges and Limitations

Several challenges were identified during testing:

1. **Variable Lighting Conditions:** The model's accuracy decreased by approximately 8- 12% in poor lighting conditions, particularly during dawn or dusk hours.
2. **Similar Disease Patterns:** Certain diseases with similar visual symptoms occasionally resulted in misclassification, particularly between early blight and late blight in tomatoes.
3. **Device Compatibility:** Performance varied across different smartphone models, with processing time increasing to 4+ seconds on older smartphone models with limited computational resources.

DISCUSSION

The findings demonstrate that mobile-based plant disease detection using CNNs presents a viable solution for rural farmers in Malawi. The high accuracy rates and quick processing times make it practical for field use, while the intuitive interface ensures accessibility even for users with limited technical expertise.

The system's ability to function offline addresses connectivity challenges in remote rural areas, making it suitable for deployment across diverse agricultural regions. Furthermore, the inclusion of treatment recommendations alongside disease identification provides actionable insights, enhancing the system's practical utility.

These results align with findings from similar studies by Mohanty et al. (2016) and Ferentinos (2018), confirming that CNN-based approaches can achieve high accuracy in plant disease classification tasks. However, the current implementation extends these findings by optimizing for mobile deployment in resource-constrained environments, addressing a critical gap in existing literature.

CONCLUSION

The Plant Leaf Disease Detection System successfully addresses a critical challenge faced by farmers in Malawi and similar agricultural economies by providing an accessible, accurate, and timely solution for plant disease diagnosis. Through the application of Convolutional Neural Networks and mobile technology, the system enables farmers to identify plant diseases without expert intervention, facilitating prompt treatment and management.

The key achievements of this project include:

1. Development of a mobile application with an intuitive interface accessible to users with varying levels of technical literacy.
2. Implementation of a CNN model capable of detecting common plant diseases with high accuracy (94.7%) even in resource-constrained environments.
3. Creation of a comprehensive disease database with corresponding treatment recommendations
4. Optimization for offline functionality, ensuring the system remains useful in areas with limited connectivity.

These achievements demonstrate the potential of AI-driven technologies to address agricultural challenges in developing regions, contributing to enhanced food security and sustainable farming practices.

Future work will focus on expanding the disease database to include more crops and disease types, further optimizing the CNN model for improved accuracy in challenging conditions, and incorporating community-based knowledge sharing features to enhance the system's effectiveness. Additionally, integrating with agricultural expert networks could provide an additional layer of support for complex or ambiguous cases.

The Plant Leaf Disease Detection System represents a significant step toward democratizing agricultural knowledge and empowering farmers with technology-driven solutions tailored to their needs and constraints.

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