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REAL-TIME AGRICULTURAL DISEASE DETECTION AND FERTILIZER RECOMMENDATION USING ADVANCED DEEP LEARNING MODELS

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***Abstract**: This study aims to develop an advanced real-time agricultural disease detection system using deep learning and augmented reality (AR), focusing on cassava leaf diseases. The proposed model leverages multi-scale feature extraction and attention mechanisms to achieve high accuracy in detecting common cassava diseases such as brown spot, cassava mosaic, and green mottle. Integrated with AR technology, the system offers an intuitive mobile interface that allows farmers to scan crops, receive real-time disease diagnosis, and access specific fertilizer recommendations for effective disease management. Optimized using Advanced Harris Hawk Optimization (AHHO), the model if implemented will demonstrate superior performance in terms of accuracy, precision, and computational efficiency. Field testing with smallholder farmers may be able to confirm the system's practicality and effectiveness in real-world environments, with significant improvements in disease management, crop yield, and reduced chemical usage. The study will highlights the potential of combining deep learning with AR for sustainable agriculture, offering scalable solutions adaptable to other crops and agricultural practices.*

Keywords: *Agriculture, Detection, Disease, Fertilizer, Learning, Model, Accuracy, Optimization, Yield, Diagnosis.*

Introduction

Agriculture is the backbone of food security globally, with plant diseases posing a significant threat to crop yields and overall productivity. The unpredictable nature of environmental conditions in recent times, coupled with the increasing prevalence of pests and diseases, has severely impacted agricultural output. For millions of farmers, especially those in developing regions like Sub-Saharan Africa and Southeast Asia, timely detection and management of plant diseases are crucial for preventing large-scale crop losses (Alghamdi *et al.,* 2023). Nevertheless, traditional disease detection methods, which rely on manual inspection and simple image processing techniques, are often slow, inaccurate, and require extensive resources, leaving farmers vulnerable to reduced yields and economic instability.

Cassava, a staple crop for millions, especially in regions such as Africa and Asia, faces multiple challenges from leaf diseases such as brown spot, cassava mosaic, green mottle, and frog skin disease. These diseases not only affect plant health but also significantly diminish crop quality and yield (Yan *et al*., 2022). Furthermore, traditional methods for diagnosing and treating these plant diseases are limited by human error, delayed response times, and the inaccessibility of modern agricultural tools to many farmers.

To address these challenges, advance deep learning technologies have emerged as promising solutions. Advanced deep learning techniques, such as Convolutional Neural Networks (CNNs), attention mechanisms, and optimization algorithms, provide high accuracy in disease identification by automating the detection process and enhancing real-time image analysis. Integrating these models into user-friendly augmented reality interfaces offers farmers the potential to visualize disease identification and treatment recommendations through mobile devices, greatly simplifying the management of plant health (Emmanuel *et al*., 2022).

Prashanth et al., (2024) proposed Modified Pyramidal Convolutional Shuffle Attention Residual Network (MPCSAR-AHH) which incorporate advanced attention mechanisms and Harris Hawk Optimization algorithms, have demonstrated superior performance in classifying plant diseases with remarkable precision and accuracy. The MPCSAR-AHH model combines real-time data from cassava fields with machine learning to classify various disease types and recommend targeted fertilizer treatments. Such systems are vital for creating effective, real-time disease management tools that enable early detection, timely treatment, and improved crop health.

Augmented Reality (AR) technology further enhances these systems by providing an immersive interface where farmers can interact with the detection system in real time. Through AR, farmers can receive intuitive visual feedback on the health of their crops, along with actionable recommendations for disease treatment and fertilizer application. This combination of deep learning with augmented reality creates an interactive, accessible solution for farmers, making disease management more precise and timelier (Alghamdi *et al.,* 2023).

The integration of real-time disease detection and fertilizer recommendation within AR-based systems marks a significant advancement in precision agriculture. By leveraging these technologies, it becomes possible to address the limitations of current approaches, such as labor-intensive manual inspections, delayed diagnoses, and inefficient disease management strategies. Such advancements promise not only to enhance productivity and reduce crop losses but also to make modern agricultural technology more accessible to farmers in resource-limited regions.

This study aims to develop and refine these advanced deep learning models and AR systems to provide a comprehensive, real-time solution for cassava disease detection and management. By focusing on deep feature extraction, optimized model parameters, and immersive visualization techniques, the research seeks to contribute to the growing body of knowledge on precision farming, with the ultimate goal of improving global agricultural sustainability.

Review of related work

The development of advanced deep learning models for real-time agricultural disease detection, integrated with augmented reality (AR), has gained significant attention in recent years. Research efforts have primarily focused on enhancing disease detection accuracy, optimizing computational efficiency, and integrating user-friendly interfaces for real-time applications. This section reviews the latest relevant studies from prominent journals, discussing the methods, contributions, and limitations of each.

Transformer-embedded ResNet (TRNet) for cassava leaf disease classification was introduced by (Zhong et al., 2022), leveraging the transformer architecture to enhance the model's ability to capture long-range dependencies and reduce background noise interference. Although it achieved promising accuracy, its computational complexity posed challenges in training and deployment, particularly in resource-constrained environments.

Lilhore *et al.* (2022) proposed an Enhanced Convolutional Neural Network (ECNN) designed to handle imbalanced datasets in cassava disease detection. This model minimized computational overhead while maintaining accuracy in disease classification. However, data acquisition and annotation for rare diseases remained a significant challenge. Their study emphases on batch normalization rather than combining optimizers; lacks exploration of multistage techniques

This research developed a CNN model using residual and inception connections to improve feature extraction for plant disease classification. It demonstrated a high accuracy of 99.39% on the Plant Village dataset but only 76.59% for cassava leaf disease detection, highlighting the difficulty of cassava-specific disease diagnosis (Hassan *et al*., 2022).

In another study by (Zhang *et al.,* 2022) explored the use of ArsenicNetPlus, a CNN-based model designed to simulate high-frequency residual structures for cassava disease detection. The model achieved an accuracy of 95.93%, demonstrating moderate success but still falling short in comparison to more advanced approaches.

This paper investigated the role of Agriculture 4.0 technologies, including Big Data, IoT, and AR/VR, in improving smart farming. The authors highlighted the benefits of integrating AR for real-time disease detection but noted the high costs associated with deploying these technologies on a large scale (Javaid *et al.* 2022).

However, a real-time localization system using Simultaneous Localization and Mapping (SLAM) algorithms was developed, combined with IMU and visual sensors, to improve the navigation and mapping of agricultural robots in unstructured environments. Though effective in robust mapping, the method was complex and required further optimization for widespread use in agriculture (Yan *et al.,* 2022).

In the same vein, Emmanuel and colleagues presented a Deep Gaussian CNN (DGCNN) that utilized transfer learning to classify cassava leaf diseases. The model achieved notable performance in identifying multiple disease types, but dataset quality and availability were identified as critical factors affecting its generalizability (Emmanuel *et al*., 2022).

Alghamdi & Turki (2023) proposed PDD-Net, a CNN architecture designed to enhance plant disease diagnosis. By capturing multiscale features, the model significantly improved disease detection performance but faced challenges due to the complexity of its multilevel architecture, which led to longer training times.

Lin *et al*., (2023) introduced Graph Pyramid Attention (GPA-Net), which used pyramid neural networks and attention mechanisms for fine-grained disease identification. This model excelled in learning spatial relationships and achieved high precision, but its application was limited to specific crops, requiring further generalization.

Sharma and colleagues developed DLMC-Net, a lightweight CNN model that balanced accuracy and computational efficiency, making it suitable for real-time plant disease detection across various crops. However, it lacked robustness when generalized across diverse plant species and environmental conditions (Sharma *et al.,* 2023).

These studies as examined demonstrated the ongoing advancements in deep learning and AR for agricultural disease detection. While models like MPCSAR-AHH and PDD-Net exhibit high accuracy, challenges remain in terms of computational costs, dataset quality, and generalization to multiple crop types. The integration of real-time disease detection systems with AR provides a promising avenue for improving both the usability and efficiency of these technologies for farmers. However, future work must address the limitations related to high computational demands, dataset diversity, and scalability for broader adoption in global agriculture.

Problem statements

Traditional methods for detecting plant diseases rely heavily on manual inspection or basic image processing techniques, which are often error-prone and inefficient. These methods struggle to deliver high accuracy, especially in distinguishing between visually similar diseases, leading to delayed or incorrect diagnosis that affects crop yield. Advanced deep learning models such as Convolutional Neural Networks (CNNs) and Transformer-based architectures have demonstrated high accuracy in detecting plant diseases. However, these models come with significant computational costs, which make them difficult to implement in resource-constrained environments like small farms or regions with limited technological infrastructure (Prashanth et al., 2024).

While several models have been developed to identify plant diseases, few integrate actionable recommendations, such as the type of fertilizer to apply based on the disease detected. This lack of integration makes it challenging for farmers to respond effectively to specific plant health issues and optimize crop growth conditions (Sharma *et al.,* 2013). Many existing deep learning models are trained on specific crops or datasets, limiting their ability to generalize across various types of plants. As a result, a model effective for cassava disease detection may perform poorly when applied to other crops, necessitating the development of more versatile models that can handle diverse datasets.

The effectiveness of deep learning models for disease detection largely depends on the availability of high-quality, well-annotated datasets. However, collecting and annotating large-scale datasets for different plant diseases is labor-intensive and time-consuming, limiting the scalability of these models to a broader range of agricultural applications. Although Augmented Reality (AR) has great potential to enhance real-time disease detection, integrating AR into existing agricultural systems remains a complex task. Developing intuitive AR systems that provide farmers with real-time disease insights and actionable advice requires significant technical expertise and resources. While cutting-edge technologies like deep learning and AR hold promise, their adoption in real-world agricultural scenarios is limited by the high costs of implementation and the difficulty of scaling these solutions to vast agricultural fields. This creates a gap between technological advancements and practical, cost-effective solutions for smallholder farmers (Alghamdi *et al*., 2023).

Objectives

the following specific objectives will guide the proposed study:

a) To design and develop a real-time disease detection model leveraging advanced deep learning techniques such as Modified Pyramidal Convolutional Shuffle Attention Residual Networks (MPCSAR), optimized for high accuracy in classifying cassava leaf diseases.
b) To integrate Augmented Reality (AR) technology into the disease detection system, providing an intuitive, user-friendly interface that allows farmers to visualize disease diagnoses and receive actionable recommendations in real time through mobile devices.
c) To enhance model efficiency by incorporating Advanced Harris Hawk Optimization (AHHO) for tuning network parameters, ensuring faster convergence and improved performance in disease detection under varying environmental conditions.

d) To provide targeted fertilizer recommendations based on the identified disease types, optimizing the decision-making process for farmers and improving crop management by suggesting specific treatments for each diagnosed disease.
e) To validate the robustness of the proposed model across diverse datasets, environments, and lighting conditions, ensuring its ability to generalize beyond cassava to other crops, thereby increasing its applicability in broader agricultural settings.
f) To analyze and compare the performance of the proposed model with existing state-of-the-art techniques for plant disease detection, assessing improvements in terms of accuracy, precision, recall, and F1-score.

Methodology and Expected Results

This study framework design consists of several interconnected layers, from data acquisition to real-time implementation with augmented reality, ensuring a systematic approach to disease detection and fertilizer recommendation for cassava crops. Below is the structured framework design that outlines the flow of processes and key components involved in achieving the study's aim.

1. Data Acquisition Layer

Input

Cassava leaf images (healthy and diseased) from various sources, including agricultural research centers, public datasets, and real-time field data collection using mobile devices.

Preprocessing

a. Image normalization: Resizing all images to a standard resolution for uniformity (e.g., 256x256 pixels).
b. Data Augmentation: Techniques such as rotation, flipping, and scaling to diversify the dataset and prevent overfitting.
c. Color Space Conversion: Images converted from RGB to LUV color space to reduce sensitivity to lighting conditions and enhance feature extraction for disease detection.

2. Model Development Layer

Deep Learning Model

A deep learning architecture based on the Modified Pyramidal Convolutional Shuffle Attention Residual Network (MPCSAR-AHH) will be used. The key components include:

a. Pyramidal Convolutional Layers: For multi-scale feature extraction at different resolutions.
b. Shuffle Attention Mechanism: To focus on important regions in the images (i.e., diseased areas of leaves), improving classification performance.
c. Modified Residual Blocks (MRB): To capture complex patterns in leaf diseases and avoid vanishing gradients in deeper layers.
d. Optimization: Advanced Harris Hawk Optimization (AHHO) will be implemented to optimize network parameters, ensuring faster convergence, improved accuracy, and reduced computational cost.

3. Augmented Reality (AR) Integration Layer

AR Interface

A user-friendly mobile application will be developed to allow farmers to scan their crops using the phone's camera. The AR system will overlay the disease detection results on the live feed of the cassava plant, displaying affected regions and diagnosed diseases.

Farmers can interact with the AR system for more details, including disease types and recommended fertilizer treatments.

AR Visualization

The diagnosed disease will be displayed in AR along with actionable recommendations. Based on the disease type, the system will recommend appropriate fertilizers in real-time, displayed through AR.

4. Model Training and Validation Layer

a) Training Process

The MPCSAR-AHH model will be trained on labeled cassava leaf images, categorized by disease type (brown spot, cassava mosaic, green mottle, frogskin disease). K-fold cross-validation will be used to ensure the model is robust and not overfitted to the training data.

b) Evaluation Metrics

Accuracy, Precision, Recall, F1-Score: The model's performance will be evaluated using these metrics, with a target of achieving over 95% accuracy in detecting cassava leaf diseases.

c) Dataset Expansion

Incorporating other crops (e.g., tomato, maize) for future scalability of the model.

5. Real-Time Deployment Layer

Field Testing and Feedback

The AR-based system will be tested in real agricultural settings where cassava is grown. The model's performance in real-time will be evaluated, focusing on ease of use and response time. Farmers will provide feedback on the system's usability, including the accuracy of disease detection and ease of following fertilizer recommendations. The system will be tested under different environmental conditions (e.g., lighting, backgrounds) to ensure robustness and real-world applicability.

6. Generalization and Scalability Layer

The model will be expanded to other datasets for different crops, ensuring it can generalize beyond cassava. Ensuring the AR system and deep learning model can be deployed across various regions and scales, from smallholder farms to large agricultural operations. The system can leverage cloud services for real-time processing, or edge computing for low-resource environments, optimizing the model's scalability.

Below is a proposed diagram representation showing the framework design flow:

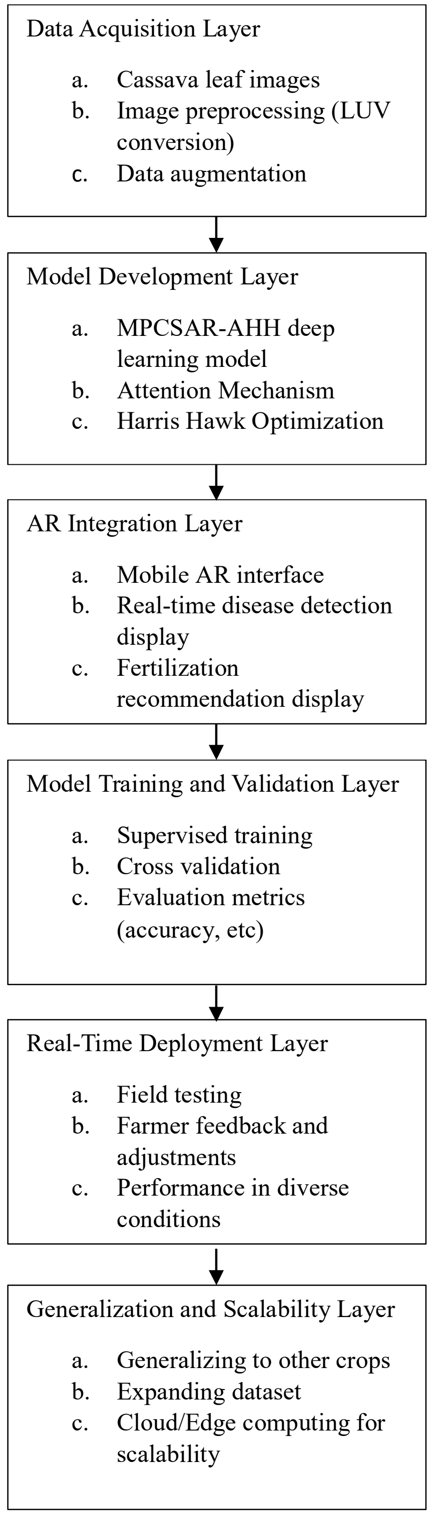

Figure 1: Diagram of the proposed framework

Summary of Framework Design

The framework ensures a comprehensive approach to developing a robust, real-time disease detection system for agriculture. Applying deep learning, augmented reality, and user-friendly mobile interfaces, this study aims to improve the accuracy and accessibility of plant disease management for farmers. The integration of AR technology allows for real-time interaction and actionable insights, making it possible for farmers to manage their crops more effectively. Scalability and generalization to other crops will ensure the system's adaptability in diverse agricultural settings.

Conclusion

The MPCSAR-AHH model is expected to achieve high accuracy (above 95%) in detecting cassava leaf diseases, surpassing existing models like standard CNNs and TRNet due to its multi-scale feature extraction and attention mechanisms. The integration of Advanced Harris Hawk Optimization and AR is anticipated to provide real-time disease detection and fertilizer recommendations, enabling farmers to take immediate action against plant diseases, thus minimizing crop losses.

The AR interface is expected to offer an intuitive, user-friendly experience, making advanced technology accessible to farmers with limited technical expertise. Real-time visual feedback will help farmers easily identify issues and apply recommended treatments. The system will provide precise, disease-specific fertilizer recommendations, optimizing crop treatment and management for improved yield and quality. Farmers will receive tailored advice based on the detected disease, improving both disease management and fertilizer efficiency.

The proposed model is expected to perform well across diverse environmental conditions, including variations in lighting and background. The preprocessing steps and attention mechanisms will help maintain accuracy even in less-than-ideal conditions. While initially developed for cassava, the model is expected to generalize to other crops by training on additional datasets. This will enhance the model's versatility and make it applicable to a broader range of agricultural settings.

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