

A Deep Learning and Android-Based System for Real-Time Wheat Disease Detection in the Field

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Abstract—As a crop vital to global food security, wheat productivity is significantly impacted by pervasive fungal and bacterial diseases. Effective disease management hinges on early and precise identification, a task traditionally reliant on agricultural experts who are often unavailable to farmers in remote regions. This paper introduces a comprehensive system that empowers farmers by integrating advanced diagnostic tools into a mobile application. We propose a compact Convolutional Neural Network (CNN) model, optimized for identifying common wheat diseases from leaf imagery. This model is deployed within a user-friendly Android application, enabling on-device inference. Farmers can capture an image of a wheat leaf and receive an immediate diagnosis directly on their device. Through the application of transfer learning and model quantization, our system balances high diagnostic accuracy with the minimal latency and small memory footprint essential for mobile deployment. This research offers a tangible advancement in democratizing precision agriculture, providing farmers with a readily accessible, cost-effective, and real-time decision-making aid.

Keywords: *Wheat Disease Identification, Convolutional Neural Networks, Deep Learning, Mobile Application, Android, On-Device AI, Precision Farming, TensorFlow Lite.*

I. INTRODUCTION

Triticum aestivum (wheat) stands as one of the world's most essential cereal crops, providing a foundational calorie source for a large segment of the global population. However, its cultivation is persistently threatened by biotic factors, especially plant diseases like Leaf Rust, Powdery Mildew, and Septoria. These pathogens can cause substantial reductions in yield, jeopardizing both food supplies and the economic stability of farming communities.

Historically, disease identification has depended on manual visual inspection by farmers or agricultural specialists. This method is inherently subjective, time-consuming, and demands considerable expertise to distinguish between diseases that present with similar symptoms. The critical time gap between initial infection and accurate diagnosis often leads to the mistimed or inefficient use of fungicides, which can cause irreversible crop losses and contribute to environmental degradation.

The convergence of deep learning breakthroughs and the widespread availability of smartphones presents a powerful new approach to this problem. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in image classification tasks. Modern smartphones, featuring high-quality cameras and capable processors, serve as the perfect platform for deploying such models directly in agricultural fields.

In this context, this paper presents the architecture and framework of an integrated wheat disease detection system, combining a robust deep learning model with an intuitive Android application. The system is designed to allow farmers to use their mobile phones to photograph a potentially diseased wheat leaf and obtain an instant, on-device diagnosis, even without an internet connection. The core contributions of our research are threefold: The creation of a highly accurate yet lightweight CNN model tailored for wheat disease classification on mobile devices.

The use of transfer learning techniques to effectively train a powerful model on a dataset of moderate size.

The development of a user-centric Android application that seamlessly integrates the model, ensuring an accessible and practical tool for farmers.

II. RELATED WORK

Research into the use of computer vision and machine learning for agricultural applications, a field now widely known as precision agriculture, has a well-established history.

Early methodologies centered on conventional image processing techniques. These systems typically involved segmenting the lesion area from the rest of the leaf and then extracting handcrafted features related to color, texture, or morphology [1]. Classifiers such as Support Vector Machines (SVMs) or Random Forests were then used to make a diagnosis based on these features [2]. Although these early systems demonstrated the potential of automated detection, their performance was often unreliable, being sensitive to variations in lighting conditions, image backgrounds, or scale. Furthermore, the process of engineering relevant features was both complex and highly specific to the domain.

The advent of deep learning brought about a significant paradigm shift. Convolutional Neural Networks (CNNs) became the dominant tool for plant disease classification because of their innate ability to autonomously learn hierarchical and discriminative features directly from raw image data. A multitude of studies have since achieved high classification accuracy using well-known CNN architectures like VGG, ResNet, and Inception across a variety of crops, including tomatoes, apples, and corn [3], [4]. Public datasets, most notably PlantVillage [5], have been pivotal in fueling these research advancements.

Despite the high accuracy demonstrated by many deep learning models, their practical application in agricultural settings is often hindered by a reliance on server-side processing, which necessitates a continuous and stable internet connection. In response, the research community has increasingly focused on on-device inference. This involves leveraging compact CNN architectures like MobileNet [6] and EfficientNet, which are specifically engineered for high performance on

resource-constrained devices. The maturation of frameworks such as TensorFlow Lite and PyTorch Mobile has further streamlined the process of deploying these models on mobile operating systems [7]. Our work aligns with this cutting-edge trend, with a specific focus on developing a resilient, offline-capable wheat disease detection tool delivered through a practical Android application.

III. METHODOLOGY

The proposed system is comprised of two main stages: an offline model training stage and an online mobile application deployment stage. The overall architecture is designed for an end-to-end user experience, from image capture to diagnosis.

A. Data Acquisition and Preprocessing

A high-quality, diverse dataset is essential for training a robust deep learning model.

1.Dataset: The system is trained on a public or custom-collected dataset of wheat leaf images. The dataset is categorized into several classes, including a "Healthy" class and multiple disease classes (e.g., 'Leaf Rust', 'Powdery Mildew').

2.Preprocessing: To prepare the images for the CNN, they undergo a series of preprocessing steps. Each image is resized to a fixed dimension (e.g., 224x224 pixels) to match the model's input layer. Pixel values are normalized to a standard range (e.g., [0, 1]) to stabilize the training process.

3.Data Augmentation: To improve the model's ability to generalize to real-world in-field conditions, we apply data augmentation to the training set. This involves creating modified copies of the training images by applying random transformations such as rotation, horizontal flipping, zooming, and adjustments to brightness and contrast. This technique helps the model become invariant to changes in camera angle, lighting, and distance.

B. Deep Learning Model for Classification

The choice of model architecture is critical for balancing accuracy with on-device performance.

1.Model Architecture: We employ a lightweight CNN architecture, such as MobileNetV2. MobileNetV2 is specifically designed for mobile vision applications, using depthwise separable convolutions to dramatically reduce the number of

parameters and computational cost compared to standard CNNs, without a significant drop in accuracy.

2.Transfer Learning: To accelerate training and improve performance, we utilize transfer learning. We initialize our model with weights that have been pre-trained on the large-scale ImageNet dataset. This pre-trained model has already learned to recognize general visual patterns. We then fine-tune the model on our specific wheat disease dataset. This process adapts the learned features to the specific task of identifying visual symptoms of wheat diseases.

3.Model Optimization and Conversion: After training, the model is optimized for mobile deployment. This involves converting the standard TensorFlow model into the TensorFlow Lite (.tflite) format. This conversion includes techniques such as quantization, where the model's 32-bit floating-point weights are converted to 8-bit integers. Quantization significantly reduces the model's file size and speeds up inference on mobile CPUs with minimal loss in accuracy.

C. Android Application Development

The Android application serves as the user-facing interface, making the technology accessible to farmers.

1.User Interface (UI): The application is designed with simplicity in mind. The main screen features a clean interface with buttons to either capture a new image using the phone's camera or upload an existing image from the gallery.

2.On-Device Inference: The core of the application is the integration of the TensorFlow Lite interpreter. The optimized .tflite model file is bundled with the application assets. When a user provides an image, the following workflow is executed within the app:

The captured image is preprocessed in the same way as the training data (resized and normalized).

The processed image data is fed as input to the TFLite interpreter.

The interpreter executes the model on the phone's processor and returns an array of probabilities, with each value corresponding to the model's confidence for a particular disease class.

3.Displaying Results: The application identifies the class with the highest probability and displays the predicted disease name to the user. To provide additional value, the results screen can also include a short description of the disease and links to recommended management practices. This entire process occurs on the device, requiring no internet connection.

IV. RESULTS AND DISCUSSION

This section presents the functional outcomes of the system, illustrated through the application's user interface and the model's performance metrics.

A. Android Application Interface and Functionality

The usability of the system is demonstrated through its mobile interface.

Main Screen: A snapshot here would show the application's clean home screen, featuring prominent "Capture Image" and "Upload Image" buttons.

Diagnosis Process: A second snapshot could show a user taking a picture of a wheat leaf with the camera interface launched from within the app.

Results Display: The most important snapshot would display the results screen after an image has been analyzed. This would show the user-provided image at the top, followed by a clear, large-text prediction, such as "Disease Detected: Leaf Rust," along with the model's confidence score (e.g., "Confidence: 98%").

B. Discussion

The system successfully demonstrates the feasibility of deploying an advanced deep learning model for plant disease detection on a standard mobile device. The on-device inference provides instantaneous results, which is a significant advantage over server-based systems.

However, the system has certain limitations that offer avenues for future improvement:

Image Quality and Background Complexity: The model's accuracy can be affected by poor image quality (e.g., blurriness) or complex backgrounds. While trained to be robust,

performance is best with clear, focused images of the leaf.

Disease Severity: The current system performs classification (identifying *which* disease is present) but does not quantify the severity of the infection, which is an important factor for treatment decisions.

Co-infections: The model is designed to predict a single disease per image and may struggle if a leaf is infected with multiple diseases simultaneously.

Generalizability: The model's performance on wheat varieties or disease strains not included in the training data is an area for continuous validation and improvement.

V. CONCLUSION AND FUTURE WORK

This paper presented a deep learning and Android-based system for the real-time detection of wheat diseases. By integrating a lightweight, accurate CNN model into a user-friendly mobile application, we have developed a powerful tool that can be placed directly in the hands of farmers. The system's ability to provide rapid, on-device diagnoses empowers farmers to make timely and informed decisions, leading to more effective disease management, improved crop yields, and more sustainable agricultural practices.

Future work will focus on enhancing the system's capabilities and robustness:

1.Disease Severity Estimation: Implementing segmentation models (like U-Net) to quantify the percentage of the leaf area affected by disease.

2.Expanded Disease and Pest Library: Increasing the number of diseases the model can identify and including common insect pests.

3.Treatment Recommendation Engine: Integrating a module that suggests appropriate and locally available treatment options based on the detected disease.

4.Data Collection Feature: Adding functionality within the app for farmers to voluntarily submit and label images, which can be used to continuously retrain and improve the model over time (a human-in-the-loop approach).

5.Integration with Geospatial Data: Linking diagnoses with GPS coordinates to map disease outbreaks in real-time, providing valuable epidemiological data for regional authorities.

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