Image Classification for Maize Disease Detection Using Transfer Learning

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ABSTRACT

Maize, a staple crop globally, is highly susceptible to various diseases that significantly impact agricultural yield. This study addresses the critical need for efficient disease detection by developing and evaluating deep learning models for accurate classification of maize leaf diseases. Leveraging the power of transfer learning, we fine-tuned state-of-the-art convolutional neural networks, including EfficientNetB0, B2, B3, and ResNet50, on a comprehensive Kaggle dataset. Each model was trained for 10 epochs using both Stochastic Gradient Descent (SGD) and Adam optimizers. Our findings indicate that the **ResNet50 model with the Adam optimizer** exhibited superior generalization capabilities, achieving a **test accuracy of 93.98% at epoch 10**. This model was subsequently deployed as an interactive web application using Streamlit, further enhanced by the integration of a **Gemini-powered AI recommendation system** to provide practical insights for disease management, demonstrating a holistic solution for real-time disease diagnosis to aid farmers in mitigating crop losses.

Keywords: Image Classification, Deep Learning, Maize Disease, Transfer Learning, ResNet50, Adam Optimizer, Generative AI, Gemini

1 INTRODUCTION

Maize (corn) is a foundational global crop, vital for food security, livestock feed, and industrial applications. However, its productivity is frequently undermined by various plant diseases, leading to substantial economic losses for farmers. Early and accurate identification of these diseases is paramount for effective disease management and ensuring sustainable agricultural practices. Traditional diagnostic methods are often labor-intensive, time-consuming, and require expert knowledge, limiting their scalability.

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image classification tasks, offering automated and highly accurate solutions across diverse domains. This paper presents a robust approach to maize leaf disease detection by applying transfer learning techniques with pre-trained CNN architectures. We aim to identify prevalent maize diseases—Common Rust, Gray Leaf Spot, and Blight—alongside healthy leaves. Furthermore, the developed diagnostic tool is augmented with **AI-powered treatment recommendations**, providing a comprehensive solution for farmers. The objective is to develop an effective diagnostic tool to support farmers in rapidly identifying and managing maize plant health.

2 RELATED WORK

The application of deep learning in agricultural disease detection has seen significant advancements in recent years, proving instrumental in safeguarding global food security [Haque et al., 2023; Kaur et al., 2020]. Prior studies have demonstrated the efficacy of various CNN architectures in classifying plant diseases from leaf images [Soto-Gómez & Pérez-Rodríguez, 2022]. Specifically, for maize leaf disease classification, researchers have explored deep learning models, often leveraging transfer learning to adapt pre-trained weights from large-scale datasets like ImageNet to specific agricultural contexts [Subramanian et al., 2022]. Works such as that by Ubaidillah et al. (2022) have also investigated various machine learning methods for corn disease classification, highlighting the diverse approaches within the field. Our work builds upon these foundational successes, focusing on a comparative analysis of modern CNN architectures (EfficientNet, ResNet50) and optimizers for robust maize-specific disease identification.

3 DATASET AND PREPROCESSING

The dataset utilized for this study is sourced from Kaggle and is specifically curated for the classification of corn or maize plant leaf diseases. This dataset is a composite derived from the popular PlantVillage and PlantDoc datasets [Singh et al., 2020; J, ARUN PANDIAN; GOPAL, GEETHARAMANI, 2019]. It comprises images across four distinct classes:

- Common Rust: 1306 images
- Gray Leaf Spot: 574 images
- Blight: 1146 images
- Healthy: 1162 images

For model training and evaluation, the dataset was subjected to a **70-30 train-test split**, ensuring a clear separation of data used for learning and for performance assessment.

Preprocessing steps involved resizing all images to a uniform dimension and converting them into tensor format. The default transforms associated with the ResNet50 weights from torchvision were applied to ensure consistency with the pre-trained model's expected input format, including normalization.

4. METHODOLOGY

Our approach employs transfer learning, a powerful technique that leverages knowledge gained from training on a large dataset (e.g., ImageNet) and applies it to a new, related task. This significantly reduces training time and improves performance, especially with limited domain-specific data. The specific transfer learning technique applied was freezing the feature extraction layers of the pre-trained models, allowing only the final classification layers to be trained on our maize disease dataset.

We evaluated four prominent pre-trained Convolutional Neural Network architectures:

- **EfficientNetB0**
- **EfficientNetB2**
- **EfficientNetB3**
- **ResNet50**

Each model was trained for **10 epochs**. To assess the impact of different optimization algorithms on model performance and generalization, two distinct optimizers were used:

- **Stochastic Gradient Descent (SGD)** with a learning rate (lr) of 0.1.
- **Adam optimizer** with a learning rate (lr) of 0.001.

The training objective was to minimize the categorical cross-entropy loss. Model performance was evaluated based on training accuracy, training loss, test accuracy, and test loss across all epochs. The final model selection was based on its generalization capability, primarily indicated by its performance on the unseen test set at the final epoch.

5 EXPERIMENTAL RESULTS

A comparative analysis was conducted across all trained models and optimizers. While EfficientNetB0, B2, and B3 also showed promising results, the ResNet50 architecture consistently demonstrated superior performance. The detailed results for ResNet50 using both SGD and Adam optimizers are presented in the tables below.

The graphs below show the training logs of ResNet50 models with both optimizers.

Figure 1: *ResNet50 with SGD Loss/Accuracy Curves*

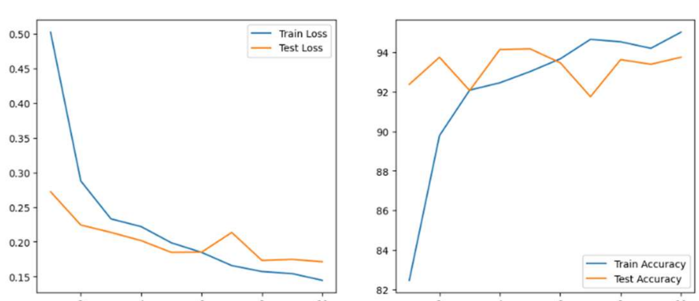
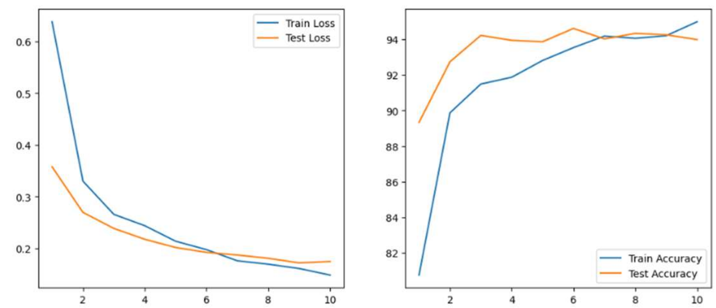


Figure 2: *ResNet50 with Adam Loss/Accuracy Curves*



6 DISCUSSION

Upon detailed analysis of the experimental results, the ResNet50 model optimized with Adam demonstrated slightly superior generalization capabilities compared to its SGD counterpart. Specifically, at epoch 10, the Adam-optimized ResNet50 achieved a test accuracy of 93.98%, marginally outperforming the SGD-optimized ResNet50's 93.75% test accuracy. This slight edge in test accuracy was the deciding factor for its selection, as it directly reflects the model's ability to classify unseen maize leaf images accurately.

The selected ResNet50 with Adam model has been successfully deployed as a web application using Streamlit. https://maizediseasepredictorv1.streamlit.app/

7 CONCLUSION AND FUTURE WORK

This study successfully developed and deployed a deep learning-based solution for maize leaf disease detection, leveraging transfer learning with various CNN architectures. Our comparative analysis highlighted the **ResNet50 model with the Adam optimizer** as the most effective, achieving a remarkable **93.98% accuracy on the test set**. The successful deployment on Streamlit, augmented by the **AI-powered treatment recommendations from Gemini**, underscores the potential of AI in revolutionizing agricultural practices by providing accessible, rapid, and actionable diagnostic tools.

For future work, expanding the diversity and size of the dataset could further enhance the model's robustness and generalization, potentially mitigating any minor overfitting observed. Exploring ensemble methods or more advanced fine-tuning strategies could also yield incremental improvements. Additionally, integrating environmental data or geographic information systems could lead to more comprehensive disease management systems, further enhancing the utility of AI in smart agriculture.

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