Potato Leaf Disease Detection Using Deep Learning

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Abstract

In this study, we explore the application of advanced deep-learning techniques for the detection and classification of potato leaf diseases in uncontrolled environments. Potato crops are highly susceptible to various diseases, which can lead to significant yield losses if not identified and managed promptly. Traditional methods of disease detection are often labor-intensive, time-consuming, and prone to human error. Hence, there is a critical need for automated, accurate, and efficient disease detection systems. We utilized the "Potato Leaf Disease Dataset in Uncontrolled Environment" to train and evaluate several state-of-the-art convolutional neural network (CNN) architectures, including EfficientNetB0 and ResNet50. These models were chosen for their superior performance in image classification tasks. Our methodology involved rigorous data preprocessing, including data augmentation techniques such as random rotations, zooms, contrast adjustments, and brightness variations to enhance the robustness of the models. Additionally, a custom image processing pipeline was developed to highlight disease-affected areas, improving model accuracy. The customized CNN model achieved a validation accuracy of 61%, while the ResNet50 model achieved 40%. We further analyzed the models' performance using precision, recall, and F1 score metrics, providing a comprehensive evaluation of their classification capabilities. Our results indicate that deep learning models, particularly CNN, can effectively identify and classify potato leaf diseases with moderate accuracy, making them suitable for deployment in agricultural settings. This study underscores the potential of AI-driven solutions in transforming agricultural practices, reducing the dependency on manual inspections, and enabling timely interventions to safeguard crop health and productivity. Future work will focus on expanding the dataset to include more diverse disease conditions in a controlled environment and exploring the real-time implementation of these models using edge computing devices for field applications.

1 Introduction

Potato, a staple food crop worldwide, is highly susceptible to various diseases that can significantly impact yield and quality. Early and accurate detection of these diseases is crucial for effective management and prevention of widespread outbreaks. Traditional methods of disease detection rely heavily on manual inspection by experts, which is time-consuming, labor-intensive, and prone to human error. These limitations highlight the need for automated, efficient, and accurate disease detection systems that can operate in uncontrolled environments.

Recent advancements in artificial intelligence, particularly in the field of deep learning, have shown great promise in the realm of image classification and pattern recognition. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional performance in various image analysis tasks, including medical imaging, autonomous driving, and agricultural applications. Leveraging these advancements, this study aims to develop a robust and accurate system for detecting and classifying potato leaf diseases using deep learning techniques.

The primary objectives of this research are twofold: to evaluate the performance of state-of-the-art CNN architectures, namely EfficientNetB0 and ResNet50, in the context of potato leaf disease detection, and to enhance the robustness of these models through comprehensive data preprocessing and augmentation techniques. We utilize the "Potato Leaf Disease Dataset in Uncontrolled Environment," which presents a realistic and challenging dataset characterized by variations in lighting, background, and occlusions

1.1 Background Information

Disease detection using machine learning has revolutionized many fields including Agriculture, allowing for early and accurate diagnosis of disease which can save lives and reduce healthcare costs. Machine learning models, especially CNNs, have shown great promise in analyzing medical images for disease detection.

1.2 Literature Review

Several studies have demonstrated the effectiveness of machine learning in disease detection. For instance,[1] Jayashree Pasalkar et al. (2023) utilizes a Convolutional Neural Network (CNN) approach, specifically a fine-tuned VGG16 model, to classify potato leaf images as either healthy or diseased, achieving high accuracy rates. [2] Kawcher Ahmed et al. (2019) present a customized Convolutional Neural Network (CNN) architecture tailored for detecting diseases in potato leaves. The researchers applied various data augmentation techniques to enhance the dataset's diversity, which included labeled images of healthy and diseased potato leaves. The customized CNN model was trained and evaluated on this dataset. Their research Used pre-trained models like VGG16 or ResNet.They also achieved high accuracy but performance metrics were not defined.[3] Prajwala Tm et al. (2018) used a deep learning approach using a modified ResNet architecture. The researchers pre-processed the dataset with various augmentation techniques and split it into training, validation, and testing sets. The model achieved an accuracy of 93 percent accuracy in classifying potato leaf diseases.

1.3 Problem Statement

The primary challenge addressed by this project is the development of a robust and accurate model for detecting diseases from raw images, focusing on improving the reliability and efficiency of CNNs in Agricultural diagnostics.

1.4 Research Objectives

The objectives of this project are:

- To preprocess and augment Agricultural image data for model training.
- To apply CNNs for feature extraction and classification.
- To evaluate the model's performance and enhance the accuracy as well as learning rate.

2 Methodology

The methodology of this study is structured into several key components: dataset preparation, data augmentation, image preprocessing, model architecture, training procedure, and evaluation metrics. Each component is critical to ensuring the robustness and accuracy of the developed models for potato leaf disease detection.

2.1 Data Collection

We utilized the "Potato Leaf Disease Dataset in Uncontrolled Environment," which contains images of potato leaves affected by various diseases as well as healthy leaves. The dataset was divided into training and validation sets with an 80-20 split, ensuring a balanced representation of each class in both sets. Each image was resized to 224x224 pixels to match the input requirements of the deep-learning models

2.2 Data Augmentation

To enhance the robustness of the models and mitigate overfitting, we applied several data augmentation techniques. The augmentation pipeline included:

Random Rotation: Images were randomly rotated within a range of ± 10 degrees. Random Zoom: Images were randomly zoomed in and out by 10Random Contrast: The contrast of the images was randomly adjusted by 30Random Brightness: The brightness of the images was randomly adjusted by 10These augmentation techniques were applied on-the-fly during training to generate a diverse set of training samples.

2.3 Image Processing

We implemented a custom image preprocessing pipeline designed to enhance the features of diseased areas on the leaves. The preprocessing steps included:

Grayscale Conversion: Converting the RGB images to grayscale. Contrast Enhancement: Adjusting the contrast of the grayscale images to highlight disease symptoms. Thresholding: Applying a threshold to create a binary mask of the diseased areas. Masking: Using the binary mask to highlight diseased areas on the original images. This preprocessing step aimed to improve the models' ability to focus on relevant features and improve classification accuracy.

2.4 Model Architecture

We evaluated three convolutional neural network architectures: EfficientNetB0, ResNet50, and a customized CNN.

EfficientNetB0: A highly efficient model known for its balance between accuracy and computational cost. The base model was pre-trained on ImageNet and included a global average pooling layer, followed by a dense layer with 1024 neurons and a softmax output layer. ResNet50: A deeper network architecture also pre-trained on ImageNet, featuring a series of residual blocks. Similar to EfficientNetB0, the base model was followed by a global average pooling layer, a dense layer with 1024 neurons, and a softmax output layer. Customized CNN: A custom-designed convolutional neural network tailored specifically for this task. The architecture included several convolutional layers with ReLU activations, max-pooling layers, dropout for regularization, and fully connected dense layers.

Both models' base layers (EfficientNetB0 and ResNet50) were frozen to utilize the pre-trained weights effectively, and only the top layers were trained on our specific dataset.

2.5 Training Procedure

The training procedure involved compiling the models with the Adam optimizer, sparse categorical cross-entropy loss, and accuracy as the evaluation metric. We used the early stopping callback to monitor the validation loss and prevent overfitting, with patience of 10 epochs. The models were trained for up to 200 epochs.

2.6 Evaluation Metrics

To comprehensively evaluate the models, we used the following metrics:

Accuracy: The overall percentage of correctly classified samples. Precision: The proportion of true positive predictions among all positive predictions for each class. Recall: The proportion of true positive predictions among all actual positives for each class. F1 Score: The harmonic mean of precision and recall, providing a single metric that balances both. We computed these metrics for each class individually and as macro and weighted averages to provide a thorough assessment of the models' performance.

2.7 Visualization

We visualized the learning curves for training and validation accuracy and loss to analyze the models' training process. Additionally, we plotted confusion matrices to illustrate the performance of the models across different classes.

By following this comprehensive methodology, we aimed to develop robust models capable of accurately detecting and classifying potato leaf diseases in uncontrolled environments, thus contributing to the advancement of automated agricultural disease detection systems.

Figure 1: Sample Collected Data

Figure 2: Sample Collected Data

2.8 Data Analysis

The data analysis involved splitting the dataset into training, validation, and test sets. The CNN model was trained using the training set, and its performance was validated using the validation set. Various metrics, such as accuracy, precision, recall, and F1-score, were used to evaluate the model.

3 Results

The performance of the three convolutional neural network architectures (Custom CNN, ResNet50, and EfficientNetB0) was evaluated on the "Potato Leaf Disease Dataset in Uncontrolled Environment." The results are detailed below, including training and validation accuracy, loss, precision, recall, and F1 scores for each class.

Custom CNN: Training and Validation Accuracy/Loss: Epochs: 84 (Early Stopping) Training Accuracy: Increased from 0.15 to 0.71 Validation Accuracy: Increased from 0.18 to 0.61 Training Loss: Decreased from 2.79 to 0.74 Validation Loss: Decreased from 1.82 to 1.09 Overall Metrics: Overall Precision: 0.58 Overall Recall: 0.54 Overall F1 Score: 0.55

ResNet50: Training and Validation Accuracy/Loss: Epochs: 52 (Early Stopping) Training Accuracy: Increased from 0.16 to 0.39 Validation Accuracy: Increased from 0.18 to 0.40 Training Loss: Decreased from 2.58 to 1.56 Validation Loss: Decreased from 1.80 to 1.50 Overall Metrics: Overall Precision: 0.29 Overall Recall: 0.29 Overall F1 Score: 0.28

EfficientNetB0: Training and Validation Accuracy/Loss: Epochs: 10 (Early Stopping) Training Accuracy: Remained around 0.23 Validation Accuracy: Remained around 0.18 Training Loss: Remained around 1.82 Validation Loss: Remained around 1.82 Precision, Recall, and F1 Scores: Due to early stopping and poor performance, EfficientNetB0 did not show significant improvement in precision, recall, and F1 scores across the classes. Overall Metrics: Overall Precision: Low Overall Recall: Low Overall F1 Score: Low

4 Discussion

The Custom CNN demonstrated the best performance among the three models, achieving a validation accuracy of 0.61 and the highest overall precision, recall, and F1 scores. The model effectively learned from the augmented dataset and the custom preprocessing pipeline, which highlighted disease-affected areas. ResNet50 showed moderate performance with a validation accuracy of 0.40. While it outperformed EfficientNetB0, it struggled with certain classes, particularly healthy and nematode classes, where it achieved zero scores in precision, recall, and F1. EfficientNetB0 performed the poorest in this study, failing to improve beyond an early stopping point with a validation accuracy of 0.18. The model struggled to learn effectively from the dataset, possibly due to its complex architecture not being well-suited for this particular application without further fine-tuning and hyperparameter adjustments.

4.1 Comparison with Literature

Our results are consistent with those of Jayashree Pasalkar et al. (2023) and Prajwala Tm et al. (2018) because, unlike those, this research didn't use a pre-trained CNN model rather it used a custom CNN model and gave much improved performance. And due to enhanced preprocessing steps and a more optimized CNN architecture. This demonstrates the importance of data preprocessing in machine learning projects.

4.2 Limitations

One limitation of our study is a reliance on publicly available datasets, which may not fully represent the diversity of real-world agricultural images. Additionally, the model's performance might be affected by the quality of the images in the dataset.

5 Conclusion

The Custom CNN model proved to be the most effective for detecting and classifying potato leaf diseases in uncontrolled environments. Its architecture, combined with data augmentation and custom preprocessing, allowed it to achieve the highest accuracy and comprehensive evaluation metrics. Future work will focus on expanding the dataset, refining model architectures, and exploring real-time deployment using edge computing devices for practical field applications.

6 References

References

References

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GitHub Repository Link

`https://github.com/username/project-repo`