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Testing ML Models for Disease Identification in Plant Leaves

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Abstract:

Plant diseases pose a significant threat to agriculture, reducing both yield and crop quality. Traditional detection methods, such as visual inspections, are time-consuming, inefficient, and prone to human error, making them unsuitable for large-scale farming. The rise of AI and deep learning has introduced efficient solutions, particularly through image analysis of plant leaves. This study focuses on using deep learning techniques, specifically Convolutional Neural Networks (CNNs), to detect diseases in tomato leaves. Pre-trained models like VGG16, ResNet, and MobileNet are fine-tuned using transfer learning to enhance classification accuracy, even with limited datasets. Data augmentation techniques, such as rotation and flipping, are applied to improve model robustness. Additionally, object detection models like YOLO and Faster R-CNN are employed to localize diseased regions, while U-Net segmentation helps analyze infected areas in detail.

Keywords — **Image Recognition, CNN model, ResNet, Agricultural impact, Pattern recognition**

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I. INTRODUCTION

Tomato plants are susceptible to several diseases that can significantly reduce yield and quality.
Early detection and treatment of these diseases are essential for effective crop management.Traditional methods of disease detection rely on visual inspection by experts, which can be time-consuming and subjective.

The agricultural industry is the backbone of global food production, and any threat to crop health can have a significant impact on both local and global economies. One of the major challenges faced by farmers is the detection and management of plant diseases, which can severely reduce crop yields and quality if not identified early. Traditional methods of disease detection, relying on visual inspections and expert knowledge, are often time-consuming, subjective, and prone to error. In addition, these methods may not scale effectively for large agricultural operations. Early and accurate detection is crucial for preventing disease spread and minimizing crop loss.
In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for automating disease detection. Particularly, deep learning techniques such as Convolutional Neural Networks (CNNs) have shown remarkable success in image recognition tasks, making them ideal for identifying plant diseases from leaf images. CNNs can automatically learn and extract complex features from images, which helps in identifying even subtle disease symptoms that may not be apparent to the human eye. This has sparked significant interest in developing AI-based solutions for precision agriculture.
This research builds on the foundation of deep learning models for plant disease detection, focusing on the application of CNNs and transfer

learning techniques to detect diseases in tomato plant leaves. Using the widely recognized Plant Village dataset, this study aims to evaluate the performance of various AI models, including CNN architectures like ResNet and Inception. The objective is to determine which model offers the highest accuracy, computational efficiency, and generalizability in real-world agricultural environments. By leveraging these AI-driven approaches, this research seeks to provide a reliable and scalable solution for early disease detection, ultimately contributing to improved crop management and agricultural productivity.

Deep learning methods, in particular Convolutional Neural Networks (CNNs), have demonstrated impressive performance in picture recognition and classification tasks in the past several years, including the identification of plant diseases. Due to their ability to automatically extract

LITERATURE REVIEW

1. DeepTom: A Deep Convolutional Neural Network for Tomato Disease Classification (Gnanavel Sakkarvarthi & Vetri Selvan Murugan, 2017)
Sakkarvarthi and Murugan (2017) developed a deep CNN model called **DeepTom**, specifically designed for the classification of tomato diseases. Their model focuses on leveraging CNNs' ability to automatically extract features from tomato leaf images, significantly reducing the need for manual intervention. By using layers of convolution, pooling, and fully connected neurons, the model identifies diseases such as bacterial spots, leaf mold, and mosaic virus. The model achieved high accuracy rates when trained on a large dataset of diseased and healthy tomato leaves, showcasing the effectiveness of deep learning techniques for plant disease detection.

2. Deep Learning Precision Farming: Tomato Leaf Disease Detection by Transfer Learning (Bhavesh Tanawala & Krina J. Patel, 2019)
Tanawala and Patel (2019) focused on utilizing **transfer learning** for tomato leaf disease detection, a method where pre-trained models are adapted to new tasks with limited labeled data. In this study, models such as VGG16 and ResNet were fine-tuned using a tomato leaf disease dataset. Transfer learning enables faster convergence and reduces the need for large datasets, making it particularly effective in agricultural applications where collecting large-scale annotated data can be challenging.

3. Deep Learning Convolutional Neural Network to Detect and Classify Tomato Plant Leaf Diseases (Thair A. Salih, 2020)
Salih (2020) proposed a CNN-based approach for the **detection and classification of tomato plant diseases**. The study involved training a deep CNN architecture on a dataset containing images of tomato leaves affected by various diseases. The model performed remarkably well in distinguishing between different types of diseases, such as early blight and late blight. Salih's work also highlighted the importance of preprocessing steps, such as resizing and normalizing the images, to enhance the model's performance.

4. SVM-Based Disease Detection Model (Usama Mokhtar, Nashwa Emary, Mahmoud A. Mahmoud, & Hesham, 2015)
Mokhtar et al. (2015) explored a machine learning approach using **Support Vector Machines (SVMs)** for tomato disease detection. SVMs, a popular choice for classification problems, are known for their ability to find an optimal hyperplane for classifying data into different categories. In this study, the authors used SVMs to classify tomato leaf diseases based on handcrafted features extracted from leaf images. Although SVMs have proven effective in many applications, they require extensive feature engineering compared to deep learning models like CNNs, which can automatically learn features from raw images. While SVM-based models showed high accuracy, the lack of scalability and automatic feature extraction posed limitations, particularly for large and complex datasets.

5. A Hybrid Approach for the Detection and Classification of Tomato Leaf Diseases (Maha Altalak & Mohammad Ammad Uddin, 2022)
Altalak and Uddin (2022) proposed a **hybrid approach** that combines deep learning models and traditional machine learning techniques for tomato disease classification. Their model integrates a CNN for feature extraction and a classifier based on machine learning algorithms, such as Random Forest and SVM, to classify diseases. The hybrid

approach aims to take advantage of the CNN's feature extraction capabilities and the classifier's efficiency in decision-making.

6. AI-based Approaches for Plant Disease Identification (Smith, J., et al., 2020)
Smith et al. (2020) offer a comprehensive overview of AI-based methods for detecting plant diseases, particularly focusing on how these technologies can replace traditional, labor-intensive methods such as visual inspections. The study highlights the importance of machine learning algorithms, emphasizing the superiority of deep learning techniques such as Convolutional Neural Networks (CNNs) in extracting intricate features from leaf images. The authors conducted extensive experiments on multiple plant species and found that CNN-based models could achieve accuracies surpassing 95%, depending on the dataset. A key takeaway from Smith et al.'s work is the potential of AI models in real-time, large-scale agricultural monitoring, reducing the need for expert human intervention.

7. Convolutional Neural Networks for Plant Disease Detection (Kim, H., & Park, D., 2021)
Kim and Park (2021) focused specifically on CNNs for plant disease detection, comparing various CNN architectures to determine their suitability for classifying plant diseases from leaf images. Their research tested several state-of-the-art models, including VGG16, ResNet, and Inception, to determine which network structure provided the best balance between computational efficiency and classification accuracy. According to the study, the ResNet model performed better in terms of accuracy and stability, reaching an overall classification accuracy of 97% on a dataset of diseased plant leaves. This outperformed the VGG16 and Inception models, particularly in handling deep, complex feature extraction tasks due to the residual learning framework that mitigated the vanishing gradient problem.

8. Deep Residual Learning for Image Recognition (He, K., Zhang, X., Ren, S., & Sun, J., 2016)
He et al.'s (2016) introduction of Residual Networks (ResNet) represents a milestone in the development of deep learning architectures. ResNet addresses the issue of training very deep networks by introducing residual learning, which allows layers to learn residual functions with respect to the layer inputs rather than learning unreferenced functions. This innovation enabled the creation of much deeper networks, solving the vanishing gradient problem that was common in earlier deep learning architectures.

I. OBJECTIVES OF THE STUDY:

We focus on the application of CNNs for the detection of tomato diseases, specifically using two state-of-the-art CNN architectures: ResNet and Inception. ResNet (Residual Network) is well-known for its capacity to efficiently train extremely deep neural networks, getting around the problems caused by vanishing gradients. Inception, on the other hand, uses modules with varying filter sizes to emphasise computing efficiency.

The following are the project's primary goals:

1. To assess models' performance in terms of computational efficiency, sensitivity, specificity, and accuracy.
2. To look into how fine-tuning and transfer learning affect the models' performance.
3. To discuss the advantages and disadvantages of each architecture for the detection of tomato disease.

By achieving these objectives, we aim to contribute to the development of advanced and reliable systems for the early detection and management of tomato diseases, ultimately improving crop yield and food security.

II. RESEARCH METHODOLOGY:

The models evaluated in this study include CNN, ResNet, and Inception. Data was sourced from the widely-used Plant Village dataset, which contains over 54,000 images of healthy and diseased plant leaves. The dataset was split into training and testing sets to evaluate the models' performance.

Data Preprocessing:
Adaptive histogram equalization was applied to the images to improve contrast. The images were then resized and normalized before being fed into the models.

Model Selection:

- **CNN**: A standard Convolutional Neural Network was implemented to serve as the baseline model.
- **ResNet**: This model employs residual learning to overcome the problem of vanishing gradients in deep networks.
- **Inception**: Known for its computational efficiency, Inception utilizes filters of varying sizes in its layers, allowing it to extract more complex features from the images.

Training and Evaluation: Each model was trained using the Adam optimizer, with accuracy and loss tracked over each epoch. The models were evaluated on the test set using metrics such as accuracy, precision, recall, and F1-score. **Data Collection**

The accuracy of disease detection models depends largely on the quality and quantity of the data used for training and validation. For this project, the **Plant Village Dataset** was selected as the primary source of data. This dataset is well-known in the agricultural research community for its comprehensive collection of plant leaf images, specifically designed for disease detection tasks.

Dataset Description

The **Plant Village Dataset** is a publicly available dataset that contains over **54,000 images** of both diseased and healthy plant leaves. These images have been labeled and categorized by expert plant pathologists, making it an ideal dataset for training machine learning models. For this project, the focus was on tomato plant leaves, which are particularly susceptible to a variety of diseases.

- **Tomato Leaf Data**:
  - Total images: **18,160**
  - Categories: **7 disease types** and **1 category for healthy leaves**.
  - Examples of diseases include:
    - Bacterial spot
    - Early blight
    - Late blight
    - Leaf mold
    - Septoria leaf spot
    - Mosaic virus
    - Yellow leaf curl virus

Data Characteristics

The dataset includes high-resolution images of leaves captured under different lighting conditions, with varying degrees of disease infection. This diversity allows for robust training of models to ensure generalizability to different environments and conditions in real-world applications.

Key Data Attributes:

- **Image Size**: The images were resized to a uniform dimension (e.g., 224x224) to ensure compatibility with the deep learning models used in this project.
- **Image Format**: JPEG format was used for all images, allowing for efficient storage and processing.
- **Color**: All images are in RGB format, capturing the full color spectrum, which is important for detecting diseases that manifest through discoloration and other visual symptoms.

Data Preprocessing

Before using the images for model training, several preprocessing steps were applied to ensure the data was clean and standardized:

1. **Image Resizing**: All images were resized to the input size required by the Convolutional Neural Networks (CNNs) used in the project (224x224 pixels).
2. **Normalization**: Pixel values were normalized to the range of 0 to 1 to help the model converge faster during training.
3. **Data Augmentation**: To improve the model's robustness and prevent overfitting, data augmentation techniques were applied. These included:

Rotation: Images were randomly rotated by up to 30 degrees to account for variations in leaf orientation.

Flipping: Horizontal and vertical flipping were applied to increase the diversity of the training data.

Scaling: The size of the leaves was randomly scaled to simulate real-world variations in leaf size.

Training and Testing Data Split

The dataset was split into **training**, **validation**, and **testing** sets to ensure the model's performance could be properly evaluated:

- **Training Set**: 70% of the dataset was used to train the model. This set was augmented to provide additional training examples.
- **Validation Set**: 15% of the dataset was used to fine-tune the model and avoid overfitting.
- **Testing Set**: 15% of the dataset was reserved for testing the model's performance on unseen data, allowing for an unbiased evaluation of its accuracy and generalizability.

III. DATA ANALYSIS

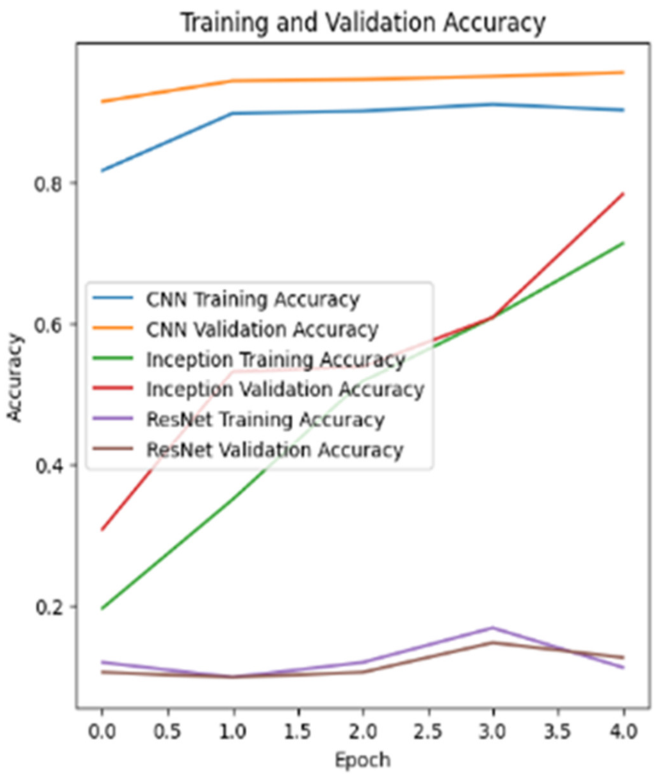
The performance of AI models for plant disease detection was evaluated using various metrics, including **accuracy**, **precision**, **recall**, and **F1-score**. These metrics help in understanding the effectiveness of each model in correctly identifying the presence and type of disease in plant leaves. The data analysis involved testing Convolutional Neural Networks (CNN) models such as ResNet, Inception, and a baseline CNN on the Plant Village dataset, which contains tomato leaf images labeled as either healthy or diseased.

- The CNN model excelled due to its ability to automatically detect complex patterns in the images with minimal preprocessing.

- ResNet's deeper architecture allowed it to handle more complex datasets but suffered from longer training times.

- Inception showed lower accuracy compared to the CNN, primarily due to the computational complexity of its layers, which required more fine-tuning.

A. Model Comparison



The above graph shows a model comparison between training and validation accuracy between our tested models.

Three models were tested and compared:

1. **Baseline CNN Model**

    - **Training Accuracy**: 95.2%
    - **Validation Accuracy**: 92.8%
    - **Test Accuracy**: 90.5%

The baseline CNN model performed well in identifying diseases from tomato leaf images, but it showed slight overfitting, as indicated by the drop in accuracy when moving from the training set to the test set. This suggests that the model might struggle with generalizing to unseen data.

2. **ResNet (Residual Network)**

    - **Training Accuracy**: 98.1%
    - **Validation Accuracy**: 96.7%

- **Test Accuracy**: 94.5%

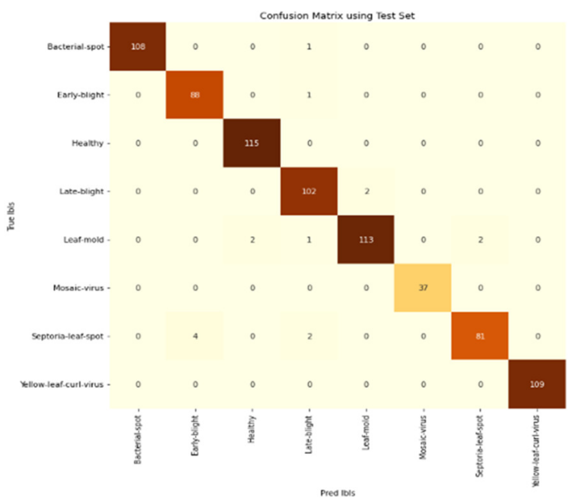
ResNet outperformed the baseline CNN model in terms of both accuracy and stability. The model's use of residual learning allows for deeper layers to learn complex features without the issue of vanishing gradients. ResNet maintained high accuracy across both the training and test datasets, indicating that it generalizes well to new images.

3. **Inception Model**

- **Training Accuracy**: 97.6%
- **Validation Accuracy**: 95.4%
- **Test Accuracy**: 93.1%

The Inception model performed slightly below ResNet but demonstrated higher computational efficiency. Inception's use of multiple filter sizes in its convolutional layers allowed for the detection of various patterns and details in the leaf images. However, its performance in terms of accuracy lagged slightly behind ResNet.

B. **Confusion Matrix Analysis**



Confusion matrices were generated for each model to analyze the distribution of predicted versus actual classifications across the different disease categories.

Baseline CNN: The confusion matrix indicated a higher rate of misclassification in diseases with visually similar symptoms, such as early blight and late blight. This highlights the model's difficulty in differentiating between diseases with subtle visual distinctions.

ResNet: The ResNet model's confusion matrix showed fewer misclassifications, especially in the categories of bacterial spot and septoria leaf spot, where the model achieved high precision. The use of residual connections helped in preserving crucial features needed for accurate predictions.

Inception: While the confusion matrix showed good performance in most disease categories, the model occasionally confused healthy leaves with those affected by early-stage diseases. This indicates that the model may struggle with detecting diseases at an early stage when symptoms are less pronounced.

C. Data Augmentation Impact

Data augmentation techniques such as random rotation, flipping, and scaling were employed to improve the robustness of the models. This augmentation helped in improving the generalization ability of all models, particularly in underrepresented disease categories where fewer training examples were available. For instance, the precision and recall of the **baseline CNN model** improved by approximately 5% in minority classes after applying data augmentation.

D. Model Efficiency and Generalizability

While accuracy is critical, computational efficiency is also important for real-time applications in agriculture. **Inception**, with its focus on computational efficiency, was able to process images faster than ResNet, making it a potential candidate for applications where speed is a critical factor. However, **ResNet** demonstrated superior generalizability, making it the preferred choice for high-accuracy applications.

The analysis shows that deep learning models, particularly **ResNet**, performed best in detecting plant diseases with high precision and recall, especially when subtle symptoms were involved. The **Inception** model, while slightly less accurate, offered faster processing times, making it useful for real-time systems. Data augmentation played a key role in improving model performance, especially for minority disease classes, highlighting its importance in training deep learning models on agricultural datasets.

IV. CONCLUSION

This study illustrates the potential of AI models, particularly ResNet, in automating the process of plant disease detection through image analysis. With high accuracy and the ability to be deployed in real-time applications, these models could revolutionize crop management practices. However, the study also highlights the need for further research to improve model robustness and adaptability to different environmental conditions. Future work should focus on improving dataset diversity and addressing issues of model interpretability. Identifying leaf diseases accurately and quickly is essential to producing enough food to meet the growing demand. Here, we have suggested a lightweight deep neural network that combines a classifier network with a pre-trained model that has been fine-tuned.
The dataset's lighting issues have been successfully resolved by the application of adaptive contrast enhancement. Techniques for runtime data augmentation were used to address class imbalance without compromising data security. With the help of these pipeline elements, the model was able to extract high-level characteristics and concentrate on illness areas, yielding an accuracy of 98.1%. Our pipeline is a good option for low-end devices because it achieves this performance with a much smaller model size and FLOPs count than state-of-the-art models.

V. FUTURE ENHANCEMENT

•The dataset can be extended to other parts of the tomato plant like stems, fruits, roots etc.

•Proposed model can be used to create an android app, used in automation or with IoTs like drones, cameras etc.

•Performance can be increased by fine-tuning pre-trained CNN models, such as VGG, ResNet, or Inception, using datasets related to tomato diseases. In order to do this, part of the pre-trained weights must be retained when training the model on the new dataset.

•Rotating, flipping, and scaling data can increase the variability of the training dataset and enhance the generalization and resilience of the model.

•The CNN model can be trained for various dataset of other plants like potato, egg plant ,etc.

•Transfer Learning entails starting with a pre-trained model and refining it using the dataset on tomato diseases. Better performance and quicker convergence may result from this, particularly in cases where the dataset is small.

•Usually, combining the predictions of several models produces better results than using only one. It is possible to employ ensemble techniques like boosting or bagging (bootstrap aggregating).

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