A Project Titled on

Tomato Plant Disease Detection from Leaf Images

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Tomato Plant Disease Detection from Leaf Images

ABSTRACT

Tomato cultivation plays a crucial role in global food security but faces significant challenges from various plant diseases. Small-scale farmers, in particular, struggle with timely and accurate disease management due to resource limitations. To address this issue, our study focuses on developing an AI-powered solution using Convolutional Neural Networks (CNNs) and specifically the ResNet152V2 architecture. The primary goal is to enhance disease detection accuracy and empower farmers with accessible tools to improve crop productivity and health management, thereby contributing to agricultural sustainability.

The current systems for tomato plant disease detection mainly rely on Machine Learning techniques such as Support Vector Machines (SVM) and Random Forest. However, these systems face challenges with multi-class classification and understanding complex features in leaf images. Manual feature engineering is time-consuming, expensive, and prone to human error. Moreover, computational intensity and the need to tune hyperparameters can pose scalability and optimization challenges, especially with large datasets. Existing deep learning CNN models are susceptible to overfitting, particularly when trained on small or imbalanced datasets, leading to poor generalization and inaccurate predictions on unseen data. The complex architectures and large datasets demand significant computational resources, such as high-performance GPUs, which can be costly and require specialized infrastructure. Building these models from scratch also consumes time and may not guarantee high accuracy.

Our proposed system leverages Transfer Learning with the ResNet152V2 architecture for tomato plant disease detection. We also integrate a real-time detection system and develop a user-friendly software interface for easy deployment and usage by farmers and stakeholders. The advantages of this approach include using pre-trained features to accelerate training, reducing the time and computational resources required for training the CNN from scratch, mitigating overfitting, and improving the model's ability to generalize well to unseen disease patterns. These enhancements potentially lead to high accuracy and reliability in disease detection.

The proposed system achieves an accuracy of 0.9110 and a loss of 0.2918 during testing, demonstrating its effectiveness in accurately identifying and classifying tomato plant diseases.

KEYWORDS---Convolutional Neural Networks(CNNs),Transfer Learning,TensorFlow, Keras.

Existing System

Existing systems in tomato plant disease detection employ a range of techniques, including Convolutional Neural Network (CNN) models are pivotal in tomato plant disease detection due to their adeptness in image recognition and feature extraction. However, they encounter several limitations. One significant challenge is the propensity for overfitting, particularly when trained on limited or imbalanced datasets. This can lead to inaccurate predictions and reduced generalization capability when confronted with unseen data, undermining the reliability of disease diagnosis. Additionally, the complex architectures and substantial computational requirements of CNN models necessitate high-performance GPUs and specialized infrastructure, translating to high costs and limited accessibility for smaller-scale agriculture operations.

Moreover, the development and deployment of CNN models entail time-consuming processes, from designing intricate architectures to fine-tuning hyperparameters and optimizing training routines. This time investment delays the implementation of timely disease detection solutions, impacting farmers' ability to mitigate crop losses effectively. Furthermore, CNN models may struggle with adapting to new diseases or integrating additional data sources seamlessly, requiring ongoing updates and retraining efforts to maintain their efficacy. Despite these challenges, advancements in transfer learning, data augmentation, and model optimization hold promise in enhancing the performance and scalability of CNN-based solutions for tomato plant disease detection, paving the way for more accurate and accessible agricultural technology solutions.

Disadvantages of Existing System

Existing systems for tomato plant disease detection using deep learning face the following drawbacks:

- Susceptibility to overfitting, particularly with small or imbalanced datasets
- Complex architectures and large datasets require significant computational resources
- High cost and specialized infrastructure for training (e.g., high-performance GPUs)
- Time-consuming process of building models from scratch, with less guaranteed high accuracy

Proposed System

The proposed system for tomato plant disease detection introduces significant advancements to address these limitations. Integrating transfer learning with ResNet152V2 allows the model to leverage pre-trained features, accelerating training and improving performance. This approach reduces the risk of overfitting, as the model can focus on learning disease-specific patterns while benefiting from the robust feature extraction capabilities of ResNet152V2. The integration of a real-time detection system enhances responsiveness, enabling immediate feedback on disease presence, crucial for timely intervention. Additionally, the user-friendly software interface streamlines deployment and usage for farmers and stakeholders, making disease detection accessible and effective across varying technical expertise levels. These advancements pave the way for more accurate, accessible, and cost-effective agricultural technology solutions, contributing to sustainable crop production and improved yields.

Advantages of Proposed system

- Utilizing pre-trained features accelerates training and improves model performance, leading to faster and more accurate disease detection.
- Transfer learning reduces the computational resources and time required for training, making the system more accessible and cost-effective.
- The use of transfer learning helps mitigate overfitting issues, ensuring better generalization to unseen disease patterns and increasing the reliability of disease diagnosis.
- By leveraging advanced techniques like transfer learning and real-time detection, the proposed system aims to achieve higher levels of accuracy and reliability in tomato plant disease detection, supporting farmers in making informed decisions for crop management.

Requirements

Software Requirements:

Language	:	Python 3.10.7 or above
IDE	:	Google colab / Kaggle Notebook
Management Tools	:	Pandas, NumPy, and Matplot
Deep Learning Libraries	:	TensorFlow, Keras
Frontend Support Frameworks	:	Flask.

Hardware Requirements:

Hard Disk	:	Minimum 256 GB or above
RAM	:	Minimum 4GB or above
Processor	:	Intel i3 or above
Operating System	:	Windows 10 or above

Methodologies (Modules or Algorithms):

- Data Collection
  - Download The Dataset
  - Create Training, Validation and Testing Dataset
- Importing The Libraries
- Configure ImageDataGenerator Class
- Apply ImageDataGenerator Functionality to Train Set, Validation and Test Set
- Pre-Trained CNN Model as A Feature Extractor
- Adding Dense Layer and Average Pooling Layer
- Configure The Learning Process
- Train The Model
- Testing The Model
- Save The Model.
- Integrate with Flaks
- Serve the Application

Comparison between Existing and Proposed Methods (Tables or Graphs to represent better approach)

Existing System	**Proposed System**
Rely on limited datasets	Trained on large, diverse dataset
Standard CNN architecture	Customizes CNN architectures
Need to implement from scratch	Adopt Existing model (ResNet152V2)
Poor Real-time Performance	Better Real-time Performance
Moderate accuracy and Moderate Loss Accuracy-0.7830 Loss- 3.9738	Achieve higher accuracy and Minimal Loss Accuracy- 0.9110 Loss- 0.2918
Time Consuming and More Computation Required	Time Saving and Less Computation Required

Conclusion

Tomato plant disease detection project has leveraged the power of deep learning and AI to develop a robust system for enhancing diagnosis prediction and classification. By utilizing convolutional neural network (CNN) models trained on a diverse range of diseased tomato leaf images and implementing techniques like Transfer Learning, class weighting, and model optimization, we have achieved a solid foundation for accurate disease detection. The integration of a user-friendly Flask-based interface ensures easy image uploads, real-time predictions, and diagnostic recommendations, making our system practical and accessible for farmers and stakeholders.

The project initially achieved moderate accuracy and loss, with accuracy at 0.7830 and loss at 3.9738. However, the focus remains on improving these metrics to a target accuracy of 0.9110 and a target loss of 0.2918. This project demonstrates the potential of AI-powered solutions to revolutionize agricultural practices, paving the way for more efficient and effective disease management strategies in the future.

Signature of Supervisor

Signature of Project Co-ordinator

Signature of HOD