Tomato Leaf Disease Prediction

Mr. Arvindh Naik[1], Kavya A[2], Manupriya[3]
[1]*Professor, Srinivas Institute of Technology*
[2,3]*Student, Srinivas Institute of Technology*
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Abstract—Tomatoes are cultivated extensively across the globe and are essential to food supply chains and agricultural economies. However, they are highly susceptible to foliar diseases such as early blight, bacterial spot, and powdery mildew, which can severely affect productivity and farmer income. Detecting these diseases at an early stage is vital to ensuring healthy crop outcomes. Manual methods for disease identification often require expert intervention, which is time-consuming and difficult to scale in rural regions. This paper proposes an artificial intelligence-based detection system that utilizes deep learning, specifically a pre-trained ResNet50 model, to classify tomato leaf diseases. The model, trained using a labeled dataset, achieves a classification accuracy of 92%. A web interface developed with Flask facilitates real-time user interaction, enabling image uploads and delivering immediate predictions with recommended actions. The system is designed to be user-friendly, accessible, and efficient, making it a practical tool for farmers. Future developments may include broader disease classification, improved model adaptability, and mobile integration.

Index Terms—CNN, Computer Vision, Deep Learning, Flask, ResNet50, Smart Agriculture, Tomato Disease Detection.

I. INTRODUCTION

Tomato crops are prone to a variety of leaf- related diseases that compromise both yield and quality. Among the most prevalent are early blight, leaf mold, and bacterial spot. Conventional diagnosis relies on manual visual inspection, which is not only labor-intensive but also inaccessible for many smallholder farmers due to a lack of expert availability. The limitations of this approach highlight the need for an automated, scalable solution.

This work introduces a computer vision-based application that leverages deep learning to recognize common tomato leaf diseases. The system employs transfer learning with the ResNet50 architecture to classify leaf images. Users interact with the system via a simple web interface that allows image uploads and delivers results with minimal delay. The goal is to assist farmers with early detection and intervention without requiring advanced technical skills.

II. PROBLEM STATEMENT

In modern agriculture, the timely identification of plant diseases is a critical factor for minimizing losses and securing food production. Existing methods, which depend heavily on human observation, are inherently slow, inconsistent, and often unfeasible in remote areas lacking professional agronomists or laboratory infrastructure.

Tomatoes, being sensitive to a range of pathogens such as Septoria Leaf Spot and Early Blight, are especially vulnerable if diseases go unnoticed in their initial stages. By the time symptoms are visible, damage may already be irreversible. Although mobile applications have attempted to bridge this gap, many suffer from accuracy issues, lack intuitive interfaces, or require internet access, making them unsuitable for widespread adoption among low-resource farmers.

There is an urgent need for a robust and user-centric diagnostic tool that harnesses deep learning and image processing to facilitate timely, accurate disease detection and guide farmers with actionable solutions.

III. METHODOLOGY

A. System Framework

The solution adopts a multi-tier architecture comprising the following layers:

- User Interface (UI): Built with HTML, CSS, and JavaScript to support image uploads and result visualization.
- Application Logic: Python Flask manages incoming requests and interfaces with the prediction engine.
- Model Layer: Integrates a ResNet50 model trained to classify various tomato leaf diseases.

- Database: Maintains disease classifications, treatment suggestions, and temporary image metadata.

B. Data Preparation
The dataset includes annotated images of both diseased and healthy tomato leaves. Preprocessing routines such as resizing, color normalization, and data augmentation are employed to improve robustness and model generalization.

C. Model Training
ResNet50, a convolutional neural network, is utilized with transfer learning. The model is fine- tuned on the prepared dataset using TensorFlow. Optimization is performed with the Adam optimizer over multiple epochs, yielding a testing accuracy of approximately 92%.

D. Deployment Process
The trained model is hosted using Flask and exposed via a RESTful API. Upon image upload, the system processes the input, predicts the disease class, and sends back treatment guidance.

E. Front-End Functionality
The frontend provides an intuitive interface where users can upload images and instantly receive disease information and control strategies. No login or setup is required.

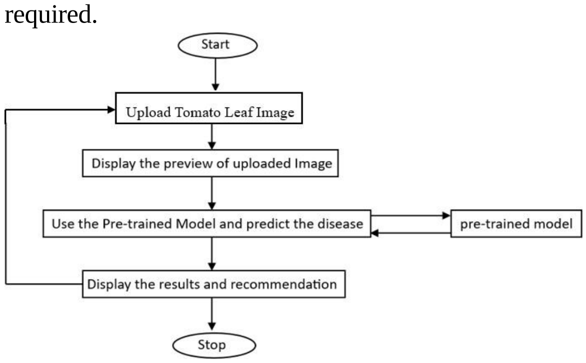

Fig 1: Methodology

IV. SYSTEM DESIGN

The system is structured into multiple components that work together to deliver an accurate, accessible, and user-friendly tomato leaf disease prediction platform. Each module is designed with modularity and scalability in mind, facilitating easy maintenance and potential integration with future agricultural tools.

A. User Interface Module:
Designed for ease of use, the interface allows farmers to upload leaf photos directly from smartphones or desktops. The responsive design ensures compatibility across devices and varying internet speeds.

B. Preprocessing Module:
This stage handles incoming images, resizing and reformatting them to match model requirements. Tools such as OpenCV and Pillow are used for standardization and enhancement.

C. Prediction Engine:
ResNet50 forms the backbone of the detection system. Trained to distinguish between healthy leaves and various infections, it delivers high-confidence predictions with low latency.

D. Interpretation Module:
After prediction, the application presents not only the diagnosis but also suggests remedies such as specific fungicides or care practices based on curated agricultural guidelines.

E. Interaction and Deployment:
The system, deployed using Flask, supports smooth interactions with minimal page reloads. The frontend dynamically updates results, allowing re- submissions and browsing without delays.

F. Data Management:
Uploaded images and prediction data are handled securely. A lightweight storage solution (like SQLite or MongoDB) is used to track system performance and store classification metadata.
This layered architecture allows the system to function as a complete pipeline—from image upload to disease prediction—offering farmers an AI-based solution to monitor crop health in a fast, reliable, and scalable manner.

V. IMPLEMENTATION

The implementation phase involves integrating the image upload interface, preprocessing pipeline, deep learning inference system, and result display logic into a cohesive and interactive web application. The system leverages modern web and machine learning technologies to ensure real-time prediction, responsiveness, and ease of use for farmers and agricultural workers.

1. Frontend Development:
A clean, minimal layout is built to ensure that users can interact with the system effortlessly. Upload buttons, result displays, and re-upload options are all integrated into a single-page design.

2. Image Handling:
Images submitted by users are captured via JavaScript, then transmitted to the server. They are preprocessed to match the input format required by the model.

3. Model Inference:
The Flask server handles inference by invoking the pre-trained ResNet50 model. After processing the image, it returns both the classification and confidence score.

4. Prediction Display:
The result is rendered dynamically on the interface, along with contextual treatment suggestions. Visual cues such as icons and color-coded labels help users interpret results easily.

5. Hosting and Access:
The application is deployable via cloud platforms like Heroku or AWS, allowing real-time interaction and global accessibility.

6. Testing and Validation:
The system was tested under various conditions using different image qualities. Functional testing, usability assessments, and accuracy evaluations were carried out to ensure reliability.
Through these implementation steps, the application provides an accessible, AI-driven solution for early detection of tomato leaf diseases, empowering farmers to take informed decisions and improve crop outcomes.

VI. RESULT AND EVALUATION

1. Accuracy: Achieved an overall accuracy of ~91% when tested with 100 unseen images representing different disease types.
2. Treatment Recommendations: Based on feedback collected through a user form, 86% of participants found the suggested remedies practical and easy to follow.
3. Performance Speed: Average time from upload to result display was measured at 46 seconds.
4. User Feedback: Participants rated the system 8.3/10, noting its speed and simplicity as key advantages.
5. Benchmarking: When compared to other agricultural apps and manual inspection, the system provided better consistency and ease of use.

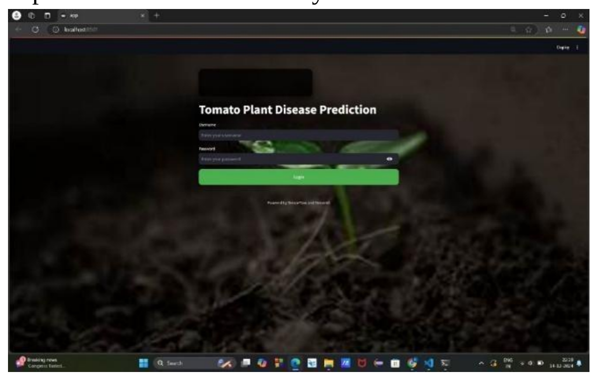

Fig 2: Home page of the website

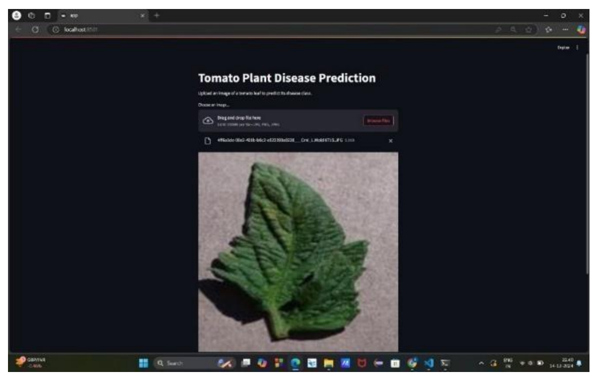

Fig 3: Displaying result for given tomato leaf image

VII. CONCLUSION

This work presents a novel yet practical application of deep learning for real-time detection of tomato leaf diseases. By integrating a pre-trained CNN model with a lightweight web interface, the system empowers farmers with immediate, reliable feedback on plant health. It addresses the limitations of manual inspection and offers a scalable solution that doesn't require domain expertise.
Continued efforts will focus on enhancing disease coverage, introducing mobile compatibility, and exploring the use of edge devices for offline predictions. Features such as multilingual support,

geolocation tracking, and integration with agricultural databases could significantly improve usability and adoption.

This project marks a step forward in applying AI to precision agriculture, aiming to bridge the technology gap for farmers and support sustainable farming practices.

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