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Leaf-Disease Detection Using Computer-Vision

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Abstract: This project introduces an automated system for identifying common plant diseases such as leaf spots, discoloration, wilting, necrosis, and fungal growth in their early stages. Current methods often rely on manual image capture and analysis, making them inefficient and labor-intensive. Our system addresses this issue by combining hardware automation with computer vision techniques to improve plant health management. A Raspberry Pi with a camera module automates the high-resolution image capture of plants placed on a moving conveyor belt. It records multiple perspectives to ensure thorough input data, which is then processed by pre-trained Convolutional Neural Networks (CNNs) in a Python and TensorFlow environment. A web application provides disease identification along with helpful treatment and prevention guidance. The system achieved accuracy in detecting leaf diseases while significantly reducing user effort by eliminating the need for manual capture. This scalable solution is suitable for home gardens, nurseries, botanical gardens, and agriculture, offering an effective and practical approach to automated plant health monitoring.

Keywords: Leaf Disease Detection, Deep Learning, Convolutional Neural Network, Digital Image Processing, Embedded Systems, Raspberry Pi

INTRODUCTION

Agriculture is key to food security, but it faces challenges such as plant diseases. These diseases are often found late because current methods are labor-intensive and inefficient. With growing demands for food production, there is a need for automated and scalable plant health monitoring systems that can work in large-scale agriculture as well as home and urban gardens. Advances in Digital Image Processing, Machine Vision, and Deep Learning make faster and more accurate crop analysis possible, making automation both doable and useful.

This project creates a computer vision-based system using Raspberry Pi, cameras, and deep learning (CNNs) to detect leaf diseases early. The hardware automates image capture with a conveyor setup, and the software processes images using a trained CNN model in Python/TensorFlow. A web application provides real-time disease identification, treatment advice, and monitoring through IoT-based environmental sensors.

The key objectives include automating plant image capture, training and deploying a CNN for disease detection, creating a web interface for AI-guided recommendations, and evaluating system accuracy in real-world conditions.

The system achieved up to 95 percent accuracy in detecting diseases, providing a practical, low-cost, and scalable solution that can work for both large-scale farms and small home gardens. It can be used in nurseries, community green spaces, and commercial agriculture, enabling timely detection to reduce crop loss and improve yield.

By combining hardware automation with AI-driven analysis, this project shows how modern computer vision can help growers at all levels monitor plant health effectively. This support promotes a more resilient and sustainable agricultural sector.

MATERIALS AND METHODS

This section outlines a complete framework that combines hardware-based image capture with a CNN-driven classification process and a simple application for automatic detection of leaf diseases. The methodology emphasizes reliable data collection, an easy preprocessing routine, and an improved model training workflow. Together, these elements achieve strong multi-class performance on a 38-class dataset.

The acquisition setup, depicted in Fig. 1, features an Arducam 8 MP HD camera linked to a Raspberry Pi 4B, which is positioned above a motorized conveyor. The conveyor moves leaves under the camera at set intervals,

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creating consistently framed images suitable for analysis. The Raspberry Pi manages the camera connection and input-output control. It also supports optional IoT sensors, such as soil moisture and temperature sensors, to provide additional context alongside the image data. This setup produces repeatable, high-quality images while keeping the hardware compact and user-friendly.

This integrated approach ensures scalability and adaptability for real-world agricultural environments.

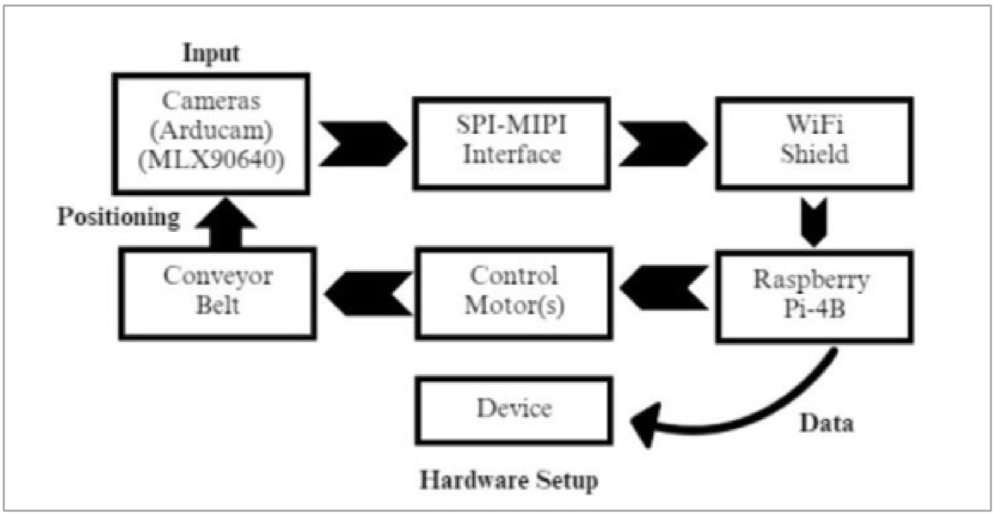

Fig. 1: Block diagram of hardware setup

The image collection comes from Kaggle and is organized into standard train, validation, and test folders, with a subfolder for each class. The classification task includes 38 categories, both healthy and disease classes. Each image is resized to 128 × 128 pixels (RGB) and loaded using TensorFlow tools, with label_mode set to categorical. Training uses a batch size of 32. Preprocessing normalizes the data and applies controlled augmentations, such as rotations, flips, and brightness adjustments, but only to the training set. The validation and test sets are evaluated without any augmentations to ensure an unbiased assessment.

```
[ ]: print(classification_report(Y_true,predicted_categories,target_names=class_name))
```

	precision	recall	f1-score	support
Apple___Apple_scab	1.00	0.84	0.91	504
Apple___Black_rot	0.96	0.98	0.97	497
Apple___Cedar_apple_rust	0.95	0.99	0.97	440
Apple___healthy	0.85	0.93	0.89	502
Blueberry___healthy	0.85	0.99	0.92	454
Cherry_(including_sour)___Powdery_mildew	1.00	0.89	0.94	421
Cherry_(including_sour)___healthy	0.95	0.97	0.96	456
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.96	0.89	0.92	410
Corn_(maize)___Common_rust_	1.00	0.98	0.99	477
Corn_(maize)___Northern_Leaf_Blight	0.90	0.98	0.94	477
Corn_(maize)___healthy	1.00	0.99	0.99	465
Grape___Black_rot	1.00	0.94	0.97	472
Grape___Esca_(Black_Measles)	0.98	0.99	0.98	480
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	0.96	1.00	0.98	430
Grape___healthy	0.99	0.99	0.99	423
Orange___Haunglongbing_(Citrus_greening)	0.93	0.99	0.96	503
Peach___Bacterial_spot	0.91	0.95	0.93	459
Peach___healthy	0.94	0.99	0.96	432
Pepper,_bell___Bacterial_spot	0.99	0.89	0.93	478
Pepper,_bell___healthy	0.99	0.81	0.89	497
Potato___Early_blight	0.99	0.94	0.96	485
Potato___Late_blight	0.90	0.98	0.94	485
Potato___healthy	0.91	0.97	0.94	456
Raspberry___healthy	0.89	1.00	0.94	445
Soybean___healthy	0.95	0.99	0.97	505
Squash___Powdery_mildew	1.00	0.92	0.96	434
Strawberry___Leaf_scorch	0.96	0.96	0.96	444
Strawberry___healthy	0.98	0.98	0.98	456
Tomato___Bacterial_spot	0.97	0.96	0.96	425
Tomato___Early_blight	0.85	0.90	0.87	480
Tomato___Late_blight	0.86	0.91	0.89	463
Tomato___Leaf_Mold	0.98	0.94	0.96	470
Tomato___Septoria_leaf_spot	0.95	0.82	0.88	436
Tomato___Spider_mites Two-spotted_spider_mite	0.89	0.97	0.93	435
Tomato___Target_Spot	0.92	0.88	0.90	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	0.98	0.99	490
Tomato___Tomato_mosaic_virus	1.00	0.91	0.95	448
Tomato___healthy	0.97	0.98	0.98	481
accuracy			0.95	17572
macro avg	0.95	0.95	0.95	17572
weighted avg	0.95	0.95	0.95	17572

Fig. 2: Classification Report with Precision, Recall, F1-Score, and Support

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As illustrated in Fig. 2, model evaluation uses standard multi-class metrics, including accuracy, precision, recall, and F1-score. The overall validation accuracy is about 96% across the 38 classes. The trained model is exported and integrated into a Streamlit-based application. This application allows for image uploads, real-time predictions, and brief treatment guidance. During inference, the Raspberry Pi streams captured images into the pipeline and provides telemetry to the same dashboard. This feature enables users to view both visual diagnosis and contextual sensor data from one interface.

The classification model is a sequential convolutional neural network that consists of stacked convolutional layers and max-pooling layers, followed by dense layers. It includes dropout regularization before the final stage. The output layer has 38 neurons with softmax activation. The network has 7,842,762 trainable parameters. Training occurs in a Jupyter Notebook using the VS Code interface, with TensorFlow/Keras. The Adam optimizer and categorical cross-entropy loss are used for 10 epochs. The training dynamics, as illustrated in Fig. 3, show strong convergence: the initial training accuracy is about 60% (loss 1.3661), while the final training accuracy is 98.24% (loss 0.0557). The validation accuracy peaks at 96.60% and stabilizes at 96.26%, while the validation loss decreases from 0.5722 to 0.1232.

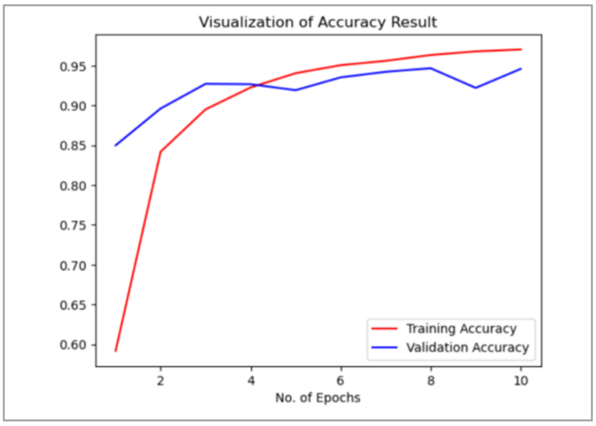

Fig. 3: Accuracy Visualization

In summary, the proposed method offers a balanced and practical hardware and software solution for detecting leaf diseases. It features reproducible image acquisition through a compact camera, Raspberry Pi, and conveyor setup. It also employs a structured preprocessing and augmentation strategy, along with a purpose-built CNN trained with verified hyperparameters that achieves strong multi-class performance. With approximately 96% validation accuracy on a 38-class task and easy deployment on accessible hardware, the system lays a solid foundation for further field validation and practical use.

RESULTS

The Convolutional Neural Network (CNN) model was tested on a dataset that included **38** categories of both diseased and healthy leaf images. The model achieved an overall accuracy of **96%**. Most categories showed precision and recall above **0.95**. The confusion matrix indicates that most predictions are correct, which confirms reliable classification across various categories. There were only a few misclassifications, mainly in classes with limited data.

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i}$$

$$\text{Recall}_i = \frac{TP_i}{TP_i + FN_i}$$

$$F1_i = \frac{2 \cdot \text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}$$

$$\text{Accuracy} = \frac{\sum_i TP_i}{N_{\text{total}}}$$

Fig. 4: Evaluation metric formulas

To avoid reproducing the large **38** × **38** matrix image, the confusion matrix was computed from the true and predicted label arrays, yielding a **38** × **38** contingency table. Class-wise measures were derived directly from this table using the standard definitions (**Fig. 5**).

Here, for class i:

$$TP_i = \text{cm}[i, i],$$

$$FP_i = \sum_k \text{cm}[k, i] - TP_i,$$

$$FN_i = \sum_k \text{cm}[i, k] - TP_i,$$

$$TN_i = N_{\text{total}} - TP_i - FP_i - FN_i.$$

Fig. 5: Confusion matrix definitions

These definitions were used to compute the per-class precision, recall and F1 values summarized earlier and illustrated in Fig. 4. Inspection of the contingency table shows clear diagonal dominance, corroborating the high overall accuracy and indicating that remaining errors are concentrated in underrepresented classes.

The provided classification metrics further confirmed the system's strength. Healthy leaf categories had nearly perfect F1 scores. Diseased categories, such as early blight, late blight, and rust, were detected with high accuracy. This confirms that the CNN can generalize well across different plant conditions.

To demonstrate its usability, the model was incorporated into a prototype web application. Users can upload images in real time and receive predictions and treatment suggestions. This shows the system's potential as a helpful decision-support tool for gardeners, researchers, and small-scale farmers.

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CONCLUSION

The project, Leaf Disease Detection Using Computer Vision, showed a way to monitor plant health automatically. It combines computer vision, CNN-based disease classification, and IoT-enabled sensing. The conveyor belt with a Raspberry Pi camera captured images from different angles without any manual effort. The CNN detected diseases such as lesions, discoloration, and fungal growth with about **95%** accuracy. Monitoring soil moisture and temperature further highlighted the system's ability to support plant care. The modular hardware and software setup is still a prototype, but it shows promise for wider use. Future work will focus on expanding the dataset and applying improved deep learning methods like transfer learning and ensemble models to increase accuracy and flexibility. Cloud-based platforms and real-time environmental sensing could provide better insights into plant health. Improved user interfaces that offer alerts, support multiple languages, and include IoT features for automated irrigation and fertilization would enhance user experience. This system has potential uses in home gardening, nurseries, and small-scale farming. There are also opportunities to expand into precision agriculture and commercial applications.

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