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Tomato Leaf Disease Detection Using Deep Learning

M. Hema[1], P. Jayasree[2], R. Jogendar Reddy[3], B. Yaswanth[4], K. Pavan Kumar[5]
[1]*M. Tech, (Ph. D), Assistant Professor, ECE Department, Annamacharya Institute of Technology And Science, Tirupati*
[2, 3, 4, 5]*B.tech, ECE Department, Annamacharya Institute Of Technology And Science, Tirupati*

Abstract: Tomato leaf diseases cause major losses in crop production and seriously affect agriculture. Identifying these diseases at an early stage is very important for proper treatment and prevention. In this work, we present a new method for tomato leaf disease detection using deep learning with a Counting Sort–based feature extraction technique. Traditional image-based disease detection methods often have problems such as unnecessary features and high computational cost. To solve this, we use Counting Sort to efficiently analyze the distribution of pixel intensity values in different color channels of tomato leaf images. This helps in extracting important color and texture features related to different diseases. These extracted features are then given to a Convolutional Neural Network (CNN) to classify tomato leaves into early blight, late blight, or healthy categories. The model is tested on a publicly available tomato leaf image dataset. Experimental results show that the proposed method achieves better accuracy and faster processing compared to traditional deep learning methods that use raw images.

Overall, this approach provides an effective and automatic way to detect tomato leaf diseases, which can help farmers improve crop management and increase food production.

Keywords: Tomato Leaf Diseases, Deep Learning, CNN, Counting Sort, Feature Extraction, Image Classification.

I. INTRODUCTION

Agriculture plays a crucial role in sustaining the rapidly growing global population, and tomatoes are one of the most widely cultivated and consumed vegetable crops worldwide. However, tomato crops are highly vulnerable to various leaf diseases such as early blight and late blight, which significantly reduce both yield and quality. These diseases spread quickly through leaves and often go unnoticed in the early stages, leading to severe crop losses. Traditionally, farmers depend on manual observation or expert consultation to identify these diseases. This process is time-consuming, labor-intensive, and often inaccurate due to human error and lack of timely diagnosis With the advancement of Artificial Intelligence (AI) and Deep Learning (DL), automated plant disease detection has become a promising solution. Image processing techniques combined with Convolutional Neural Networks (CNNs) can identify subtle patterns in leaf images that are difficult for the human eye to detect. In this project, a novel approach is introduced by integrating Counting Sort–based feature extraction with a CNN classifier. Counting Sort is used to analyze and organize pixel intensity values, effectively highlighting important colour and texture variations in tomato leaves caused by diseases. These extracted features improve the learning capability of the CNN model, leading to more accurate classification.The proposed system classifies tomato leaves into three categories: Healthy, Early Blight, and Late Blight. This automated detection system is fast, reliable, and cost-effective, making it highly useful for farmers and agricultural experts. Early identification of leaf diseases enables timely treatment, reduces pesticide misuse, minimizes crop damage, and ultimately increases productivity. Thus, this project demonstrates how intelligent image analysis and deep learning can support smart agriculture and precision farming practices.

II. LITERATURE SURVEY

Agriculture depends on the timely identification of plant diseases. SSMAN's accuracy in classifying tomato leaf diseases is 98.30%. AlexNet fared better than the original design and conventional techniques[1].

Incorporates data science, botany, and computer science to classify or diseases, detects tomato leaf disease with an accuracy of 98.07%. In tomato leaf categorization, the model performs better than the others [2].

Automatic detection finds early signs of tomato leaf disease. The accuracy of INCVX-Net, which uses ensemble deep learning models, is 99.5%.surpasses the Xception, VGG-16, and Inception V2 models[3].

Makes use of Colour Moments analysis to diagnose tomato leaf diseases. Applies machine learning to the categorization and early identification of diseases. Early and accurate identification of tomato leaf diseases was accomplished. Colour Moments successfully differentiate between diseased and healthy leaves[4].

In tomato leaves, early disease diagnosis is essential. The accuracy of MobileNetV2 with BCCE in identifying diseases is 98.01%. The assessment measures showed that it performed better than other CNN models[5].

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Diseases of tomato leaves must be identified early. Deep learning methods improve the precision of illness detection. Different approaches and categorization strategies assessed for the identification of diseases. Among the performance metrics are specificity, sensitivity. and accuracy [6].

III. EXISTING METHOD

In existing approaches, tomato leaf disease detection initially relied on manual inspection by farmers or plant pathologists, which is time-consuming and subjective. To automate this process, several studies applied deep learning–based object detection models such as YOLO and Faster R-CNN on tomato leaf image datasets consisting of 2403 images, achieving accuracies of 86% and 82%, respectively. To further improve performance, a deep convolutional neural network using a separate, shift, and merge–based AlexNet50 framework (SSMAN) was introduced in earlier research. This approach employed class decomposition to handle image anomalies and better define class boundaries. Among various pre-trained models, AlexNet showed superior performance, with the SSMAN framework achieving an accuracy of 98.30%, outperforming the original AlexNet architecture and other traditional classification methods.

IV. PROPOSED METHOD

The proposed system uses an IoT-based approach for continuous monitoring and disease detection in tomato crops. Leaf images are captured and analyzed using OpenCV to identify the presence of plant diseases. Environmental conditions such as temperature and humidity are monitored using a DHT11 sensor, while soil moisture levels are measured using a soil moisture sensor. A NodeMCUESP8266 module is used to transmit all sensor data and image analysis results to the cloud for real-time monitoring. When disease symptoms or abnormal environmental conditions are detected, the system generates alerts through a buzzer. Additionally, the system automatically controls a water pump using a relay based on soil moisture levels, ensuring proper irrigation. This integrated approach enables timely detection, efficient monitoring, and improved crop management.

V. ALGORITHM: COUNTING SORT–BASED FEATURE EXTRACTION FOR TOMATO LEAF IMAGES

A. Input

- image: A digital RGB image (2D array of pixel values).
- colour_channel: Specific channel to analyze (‘Red’, ‘Green’, ‘Blue’ or index 0,1,2).
- patch_size(optional): Size of image patches for local feature analysis. If not provided, the whole image is processed.

B. Output

- feature_vector: A vector representing extracted colour–texture features from the image.

C. Steps

a) Step 1: Image Preprocessing

1. If patch_size is provided:
    - Divide the image into non-overlapping patches of size patch_size × patch_size.
2. Else:
    - Treat the entire image as a single patch.

b) Step 2: Iterate Through Patches

For each patch in the image (or the whole image if no patches):

c) Step 3: Apply Counting Sort for Each Color Channel

For the selected color_channel in the current patch:
Create a frequency_array[256] initialized to 0
(Assuming pixel intensity range: 0–255).

1. For each pixel in the patch:
    - Extract the intensity value of the pixel for the selected color channel.
    - Increment the corresponding index in the frequency array:
    - frequency_array[intensity_value] += 1

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d) Step 4: Feature Vector Construction for the Patch

1. Initialize an empty patch_feature_vector.
2. For each color channel (R, G, B):
   Append statistical features derived from it such as:
   - Mean
   - Standard Deviation
   - Entropy
3. Store these values in patch_feature_vector.

e) Step 5: Combine Patch Features (if patches are used)

- If patch_size was provided:
  - Concatenate all patch_feature_vectors into a single feature_vector.
- Else:
  - The patch_feature_vector itself becomes the final feature_vector.

f) Step 6: Return

- Return the final feature_vector for CNN classification.

1) DTH11 Temperature Sensor and Humidity Sensor

Fig:1 shows the DHT11 sensor is a low-cost digital sensor used for measuring ambient temperature and relative humidity. Internally, it consists of an NTC thermistor for temperature sensing and a capacitive humidity sensor for moisture detection. The sensor converts the analog signals into digital data using an internal ADC and sends the calibrated output through a single-wire communication protocol.

Specifications:
• Temperature range: 0°C to 50°C
• Humidity range: 20% to 90% RH
• Accuracy: ±2°C (temperature), ±5% RH (humidity)
• Operating voltage: 3.3V to 5V
• Sampling rate: 1 Hz

In the proposed system, the DHT11 sensor is interfaced with the Arduino UNO to continuously monitor environmental conditions. These readings help assess climate suitability for plant growth and support decision-making in disease prediction.

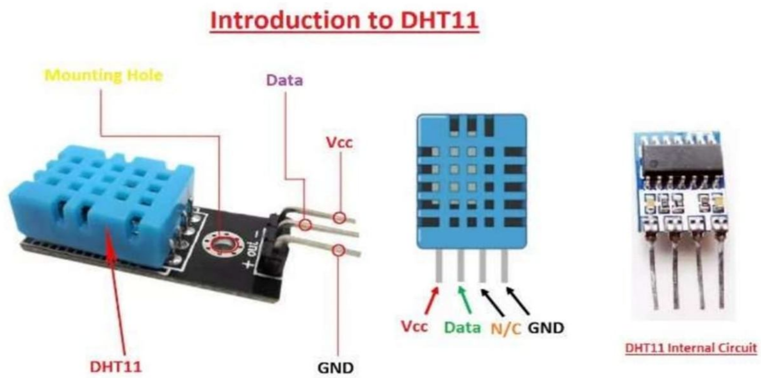

Fig1: DHT11 Sensor

2) Soil Moisture Sensor

Fig:2 shows the soil moisture sensor is used to measure the volumetric water content in soil. It consists of two conductive probes that are inserted into the soil. When moisture content increases, the electrical conductivity between the probes increases, resulting in a lower resistance value. This change is converted into an analog voltage signal.

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Specifications:
- Operating voltage: 3.3V to 5V
- Output type: Analog and Digital
- Response time: < 1 second

The analog output from the soil moisture sensor is read by the Arduino UNO to determine whether the soil is dry, moist, or wet. This information helps in irrigation control and prevents overwatering or underwatering of plants.

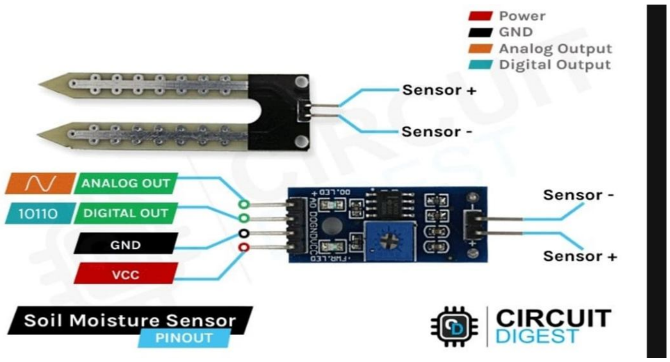

Fig2: Soil Moisture Sensor

3) Camera Sensor (OpenCV-Based Vision System)

The camera functions as a vision-based sensor in the proposed system. It captures real-time images of plant leaves, which serve as input for disease detection. The captured images are processed using OpenCV, where preprocessing techniques such as resizing, noise removal, and segmentation are applied. After preprocessing, relevant features are extracted and sent to machine learning and deep learning models hosted on the cloud platform. These models classify the images to identify healthy or diseased plants. The detection results are sent back to the Arduino system via NodeMCU for alert generation and display.

NodeMCU (ESP8266) NodeMCU is an open-source IoT development platform based on the ESP8266 Wi-Fi SoC, developed by Espressif Systems. It integrates a microcontroller, Wi-Fi module, GPIO pins, and communication interfaces on a single board, making it highly suitable for cloud-connected embedded systems. In the proposed system, NodeMCU acts as a communication bridge between Arduino UNO and the cloud platform.

VI. RESULTS

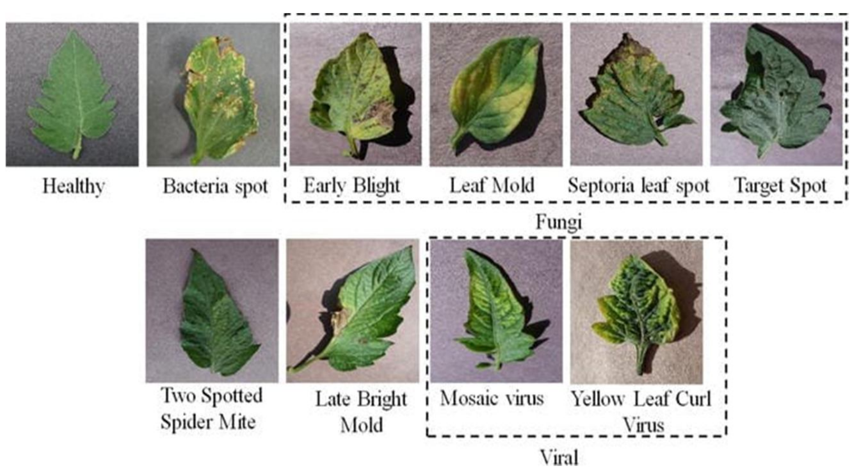

Fig 3: Sample Tomato Leaf Images of Healthy and Diseased Classes

Fig 3 presents the dataset samples used for training and testing the tomato leaf disease detection model, including healthy and multiple diseased leaf categories. Fig 3 illustrates different disease classes such as Bacterial spot, Early blight, Leaf mold, Septoria leaf spot, Target spot, Mosaic virus, Yellow leaf curl virus, and others used for classification.

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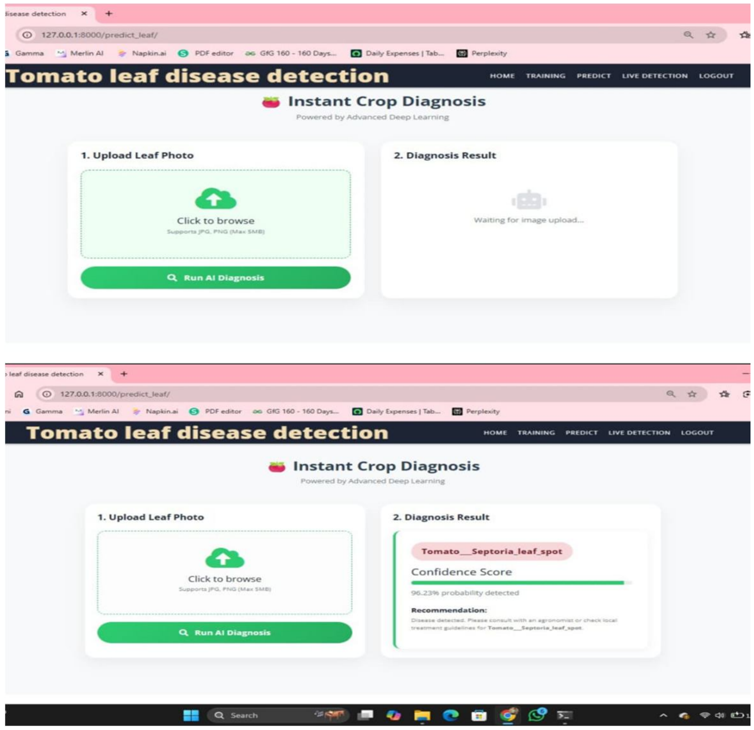

Fig 4: Tomato Leaf Disease Detection – Prediction Interface and Diagnosis Output

Fig 4 shows the prediction module of the proposed Tomato Leaf Disease Detection system, where the user uploads a tomato leaf image for analysis. Fig 4 also displays the detected disease (*Tomato_Septoria_leaf_spot*) along with the confidence score and recommendation generated by the trained deep learning model.

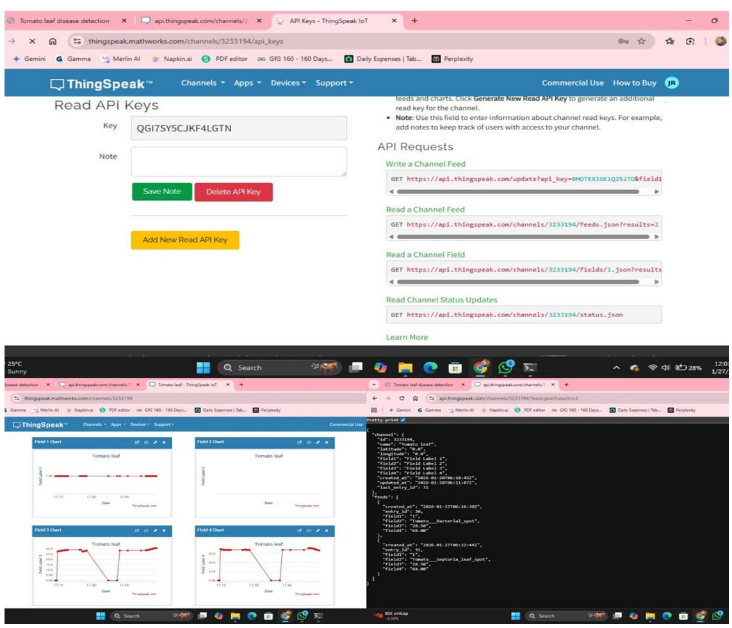

Fig 5: ThingSpeak Cloud Integration and Real-Time Data Monitoring

Fig 5 shows the integration of the proposed system with the ThingSpeak cloud platform, including API key configuration and channel data visualization. Fig 5 also illustrates real-time field charts and JSON data feeds used to store and monitor tomato leaf disease detection results remotely.

Fig 6: LCD Display Output Showing Disease Detection and Soil Status

Fig 6 shows the real-time hardware output displayed on the LCD module, indicating the detected disease as Early_blight. Figure 6 also presents the soil moisture condition as "WET (HIGH)," demonstrating the integration of disease detection with environmental monitoring in the proposed system**.**

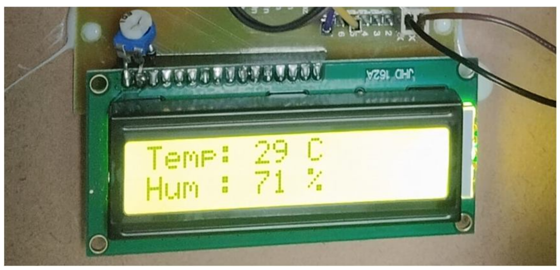

Fig 7: Hardware Setup Displaying Temperature and Humidity Monitoring

Fig 7 shows the hardware implementation of the proposed system integrated with temperature and humidity sensors for environmental monitoring. Figure 7 illustrates how real-time temperature and humidity values are measured and utilized to support accurate tomato leaf disease detection and analysis.

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