Plant Health Monitoring Using Convolutional Neural Networks with Automated Leaf Classification and Counting

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Abstract: This Research paper develops an automated Plant Health Monitoring system that leverages Convolutional Neural Networks (CNNs) to perform simultaneous leaf- level disease classification and leaf counting from plant images. The proposed pipeline uses a CNN-based feature extractor feeding two task-specific branches: a classification head that identifies healthy versus diseased leaves (and the disease type) and a counting head that estimates leaf number via a regression/segmentation approach. Input images are preprocessed with augmentation and normalization to improve robustness to lighting, occlusion, and background variation. The model is trained on a curated set of annotated plant images and adapted for efficient inference using transfer learning and lightweight architectures suitable for edge deployment. Results show the approach provides reliable disease detection and accurate leaf counts, enabling timely alerts and actionable insights for precision agriculture. The system aims to reduce manual inspection effort, speed up diagnosis, and support better crop-management decisions.

Keywords: *Leaf Segmentation, Deep Learning, Convolutional Neural Networks, Precision Agriculture, Smart Farming.*

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I. INTRODUCTION

Plants form the backbone of agriculture, providing food, fiber, and energy, and their health directly impacts crop yield, quality, and economic returns. Plant diseases, caused by pathogens such as fungi, bacteria, and viruses, are a major threat to agriculture, often resulting in significant losses if not detected and managed promptly. Early detection of diseases and monitoring of plant growth are therefore critical for sustainable agriculture. Traditional methods of assessing plant health rely on manual inspection by experts, which is labor- intensive, time-consuming, and prone to human error due to fatigue, visual limitations, or adverse environmental conditions such as poor lighting or extreme temperatures. On large- scale farms, maintaining consistent monitoring through manual observation is impractical and costly.

Recent advancements in computer vision and deep learning offer automated, efficient, and accurate alternatives for plant health monitoring. Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in image-based tasks, including object detection, classification, and segmentation. In the context of agriculture, CNNs can automatically extract features from plant images to identify healthy versus diseased leaves, classify the type of infection, and estimate growth parameters such as leaf count. By combining disease detection with leaf counting, these systems enable comprehensive plant monitoring that can inform timely interventions, optimize crop management, and reduce losses.

This automated approach minimizes manual inspection efforts, provides actionable insights, and supports precision agriculture practices, contributing to increased productivity, better crop quality, and sustainable farming. Furthermore, the system can be adapted to monitor multiple plant species and varied environmental conditions, making it scalable and versatile for modern agriculture practices.

- *Objective*

The primary objective of this project is to design and implement an automated Plant Health Monitoring system using Convolutional Neural Networks (CNNs) that can simultaneously perform leaf-level disease classification and leaf counting from plant images. The system aims to accurately identify healthy and diseased leaves, determine the type of disease, and estimate the number of leaves per plant, providing precise and actionable information for crop management. By leveraging image preprocessing techniques

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such as augmentation, normalization, and noise reduction, the model is made robust to variations in lighting, occlusion, and background. The proposed framework is designed to be lightweight and efficient, enabling deployment on edge devices for real-time monitoring in smart farming applications. Ultimately, the system seeks to reduce the dependence on manual inspection, accelerate disease diagnosis, and support informed decision-making in precision agriculture, thereby improving crop yield and sustainability.

II. LITERATURE REVIEW

Artificial intelligence (AI) and image processing have recently emerged as transformative technologies in health issues has been visual inspection by farmers or agricultural experts. Symptoms such as leaf spots, color changes, and wilting were observed with the naked eye to diagnose diseases. While this approach is inexpensive and requires no equipment, it is highly subjective and inconsistent, as accuracy depends on the experience, attention, and physical condition of the observer. Furthermore, manual inspection is time- consuming and labor-intensive, making it unsuitable for large farms agriculture, offering new possibilities for automation and precision farming. Tanha Talaviya et al. discussed the role of AI-driven systems in agricultural practices such as irrigation, weeding, and spraying with the help of robots and drones equipped with sensors. Their study highlighted how intelligent automation reduces the overuse of water and pesticides, preserves soil fertility, optimizes labor, and enhances both productivity and crop quality, demonstrating the potential of AI to increase farming efficiency.

Neha Tete and Sushma Kamlu applied image processing techniques for plant disease identification using K-means clustering and a feed- forward backpropagation neural network. While their approach showed promise in disease classification, its effectiveness was constrained due to the limited size of the dataset, affecting scalability across diverse crop species and varied disease conditions.

An IoT-based approach was presented by Dr. S. Balaji, R. Saravanan, L. Suvetha, R. Anandhi, and M. Jeevadharshini, where sensor nodes were deployed to monitor soil moisture, pH, temperature, and air quality. The collected values were processed using microcontrollers and compared against stored thresholds for decision-making. This system enabled continuous environmental monitoring but lacked visual analysis of plant leaves, which is essential for detecting early-stage infections.

Vignesh Dhandapani, S. Remya, T. Shanthi, and R. Vidhy explored disease detection using K-means clustering integrated with Support Vector Machine (SVM) classifiers. Their studydemonstrated that these algorithms, widely used in medical imaging applications, can be effectively applied to agriculture for identifying disease symptoms from plant images. However, the reliance on handcrafted features limits the adaptability of such methods to complex visual datasets.

AI, IoT, and image processing have advanced agricultural monitoring, but many approaches remain limited by reliance on environmental parameters or conventional machine learning, which struggle with accuracy and scalability. Convolutional Neural Networks (CNNs) address these challenges by automatically learning hierarchical features from images. They enable simultaneous disease classification and leaf counting, offering a reliable, scalable, and interpretable framework for automated plant health monitoring that supports timely interventions and precision agriculture.

III. TRADITIONAL PRACTICES

Monitoring plant health has always been a vital component of agriculture, as it directly affects crop yield, food quality, and farmer income. Traditionally, plant disease detection and leaf health assessment were carried out using manual or semi-automated methods. While these techniques provided valuable insights at the time, they often lacked accuracy, scalability, and robustness, particularly in large-scale farming scenarios. The following sections outline some of the commonly used practices and their limitations.

- *Manual Inspection*

The most widely practiced method for detecting plant health issues has been visual inspection by farmers or agricultural experts. Symptoms such as leaf spots, color changes, and wilting were observed with the naked eye to diagnose diseases. While this approach is inexpensive and requires no equipment, it is highly subjective and inconsistent, as accuracy depends on the experience, attention, and physical condition of the observer. Furthermore, manual inspection is time-consuming and labor-intensive, making it unsuitable for large farms.

- *Sensor Based Monitoring*

With the advancement of agricultural technologies, sensor-based systems were introduced to monitor environmental factors like soil moisture, pH levels, temperature, and humidity. These parameters indirectly indicate plant health and stress conditions. Although effective in identifying environmental imbalances, sensor-based monitoring fails to detect visible symptoms on leaves, which often provide the first and most reliable indicators of disease. Thus, while sensors improved environmental monitoring, they could not replace the need for direct disease identification.

- *Leaf Counting Methods*

In addition to disease identification, leaf counting was traditionally carried out manually by farmers to estimate plant growth and productivity. Some semi- automated systems used simple image segmentation or contour-detection methods for counting. While these provided partial automation, they often failed in cases of occluded, overlapping, or clustered leaves, leading to inaccurate counts. As a result, manual counting remained the dominant method, limiting efficiency in large-scale farms.

➢ *Drones*

Drones, both autonomous and remotely controlled, are increasingly being used in agriculture to capture high-resolution images of crops. In the context of plant health monitoring, drones can collect detailed leaf- level imagery over large fields, enabling efficient disease detection and growth assessment. The images captured by drones can be fed into Convolutional Neural Networks (CNNs) for automated leaf classification and counting, reducing the need for labor-intensive manual inspection. Additionally, drones provide rapid coverage of difficult-to- access areas, allowing for timely detection of stressed or diseased plants.

➢ *AI & IOT Integration*

Artificial Intelligence (AI) and Internet of Things (IoT) technologies complement visual monitoring by providing real-time environmental and plant data. Sensors such as temperature, humidity, light intensity, and soil moisture can collect field-level parameters, which are then analyzed using AI algorithms to enhance the accuracy of disease detection and growth estimation. When combined with CNN-based image analysis, AI and IoT enable predictive insights, helping farmers take proactive measures to manage crop health. This integration of imaging, AI, and IoT supports precision agriculture, reduces manual effort, and ensures timely interventions to improve yield and quality.

IV. PROPOSED METHODOLOGY

This section addresses the detection of plant leaf diseases through Python-based image processing and deep learning techniques. The objective is to provide a reliable, automated tool that assists farmers in early identification of leaf diseases, thereby minimizing agricultural losses and improving crop management.

The approach utilizes a Convolutional Neural Network (CNN), which is well-suited for image-based classification due to its capability to automatically learn hierarchical features from visual data. The CNN serves as the primary model for differentiating between healthy and diseased leaves, ensuring accurate and efficient detection.

Implementation is carried out using Python within Jupyter Notebook, leveraging the Keras library for constructing and training the CNN, and Matplotlib for visualization of results. Prior to training, the dataset undergoes preprocessing and extensive augmentation to enhance model robustness. Augmentation techniques include rescaling, rotation, zooming, width and height shifts, and horizontal flipping, which collectively increase the diversity of training samples and improve generalization under varying lighting, angles, and backgrounds.

Through the combination of image preprocessing, data augmentation, and CNN-based feature extraction, the system can effectively classify leaves as healthy or diseased. This methodology establishes a scalable, reliable, and automated framework for plant health monitoring, contributing to precision agriculture and informed decision-making for farmers.

Initially, the necessary libraries were imported to build the CNN model for plant disease detection. The primary libraries used include Keras, for constructing and training the deep learning model, and Matplotlib, for visualizing results and performance metrics. One crucial step in the workflow is data augmentation, which improves model accuracy and generalization. Augmentation involves generating additional training samples by applying transformations such as rescaling, rotation, width and height shifts, zooming, and horizontal flipping. These techniques help the model to better handle variations in lighting, orientation, and background during classification.

Python: Python is a high-level, interpreted programming language widely used for general-purpose development. Its rich ecosystem of libraries and tools makes it particularly suitable for image processing and machine learning applications. For this project, Python facilitates the implementation of Convolutional Neural Networks (CNNs) for leaf disease detection and classification.

OpenCV: OpenCV (Open Source Computer Vision Library) is a powerful library for image processing and computer vision tasks. It provides functionalities for image manipulation, feature extraction, and object detection across multiple platforms, including Windows, Linux, macOS, and Android, with interfaces for C++, C, and Python. In this project, OpenCV is utilized for preprocessing leaf images, such as resizing, normalization, and basic transformations, which help in accurate leaf identification and disease detection within the CNN framework.

A. System Architecture

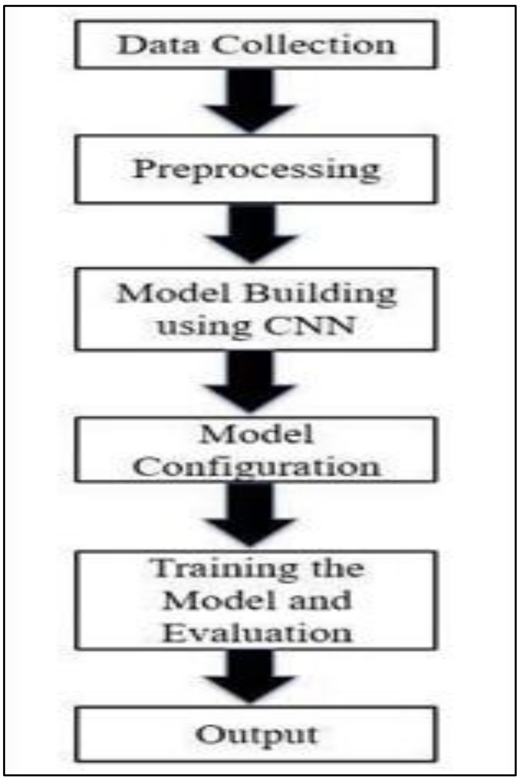

Fig 1 Flowchart of the Proposed Methodology for CNN-Based Model Development

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➢ *Keras*

Keras is a user-friendly deep learning framework built on top of TensorFlow, designed to make the development of neural networks fast and efficient. In the context of this project, Keras is employed to design and train the Convolutional Neural Network (CNN) model used for plant leaf disease detection. Its high-level API allows rapid prototyping, making it easier to build and fine-tune deep learning architectures.

- *Key Features of Keras that Benefit this Project Include:*

✓ Consistent and flexible API that simplifies model building.
✓ Straightforward structure enabling easy experimentation without unnecessary complexity.
✓ Cross-platform compatibility, supporting various backends.
✓ Support for both CPU and GPU execution, improving training efficiency.
✓ Scalability, which allows handling larger datasets and complex models effectively.

By leveraging these advantages, Keras ensures that the CNN model used in this work is both robust and computationally efficient for accurate classification of healthy and diseased plant leaves.

➢ *Matplotlib*

Matplotlib is a widely used Python library for data visualization, particularly for generating two- dimensional plots and charts. It is built on top of NumPy arrays and integrates seamlessly with the broader SciPy ecosystem. In this project, Matplotlib is used to visualize the performance of the CNN model, such as plotting training vs. validation accuracy and loss curves.

One of the key advantages of Matplotlib is its ability to transform large amounts of numerical data into clear and interpretable visual representations. It supports a wide range of plot types, including line graphs, bar charts, scatter plots, and histograms, making it a versatile tool for analyzing model behavior and performance trends.

Through these visualizations, the progression of the training process can be monitored, helping to ensure that the plant disease detection model is well-optimized and not overfitting.

➢ *TensorFlow*

TensorFlow is an open-source library designed for large-scale numerical computation, machine learning, and deep learning applications. It provides multiple levels of abstraction, giving developers the flexibility to choose between simple high-level APIs or more advanced configurations based on project requirements.

In this work, TensorFlow serves as the core framework for building and training the CNN model used in plant disease detection. Through its integration with Keras, it allows the creation of both simple and complex deep learning architectures with ease. TensorFlow also offers a rich ecosystem of supporting tools and pre-built models, enabling efficient experimentation and optimization.

One of the powerful features of TensorFlow is its use of dataflow graphs, which represent the flow of data through interconnected processing nodes. These graphs can be distributed across multiple CPUs, GPUs, or even specialized hardware such as Tensor Processing Units (TPUs), making the library highly scalable for large datasets and intensive training processes. In this research paper, TensorFlow plays a crucial role in accelerating model training, ensuring efficient computation, and supporting real- time prediction tasks in detecting healthy and unhealthy plant leaves.

➢ *Proposed Model*

Convolutional Neural Networks (CNNs) are a class of deep learning models that have become highly influential in computer vision applications. Unlike traditional neural networks, CNNs are capable of automatically learning spatial features from images, making them particularly effective for tasks such as plant disease detection. These networks are composed of specialized layers, including convolutional layers, pooling layers, and fully connected layers, which work together to extract and classify hierarchical patterns from input images.

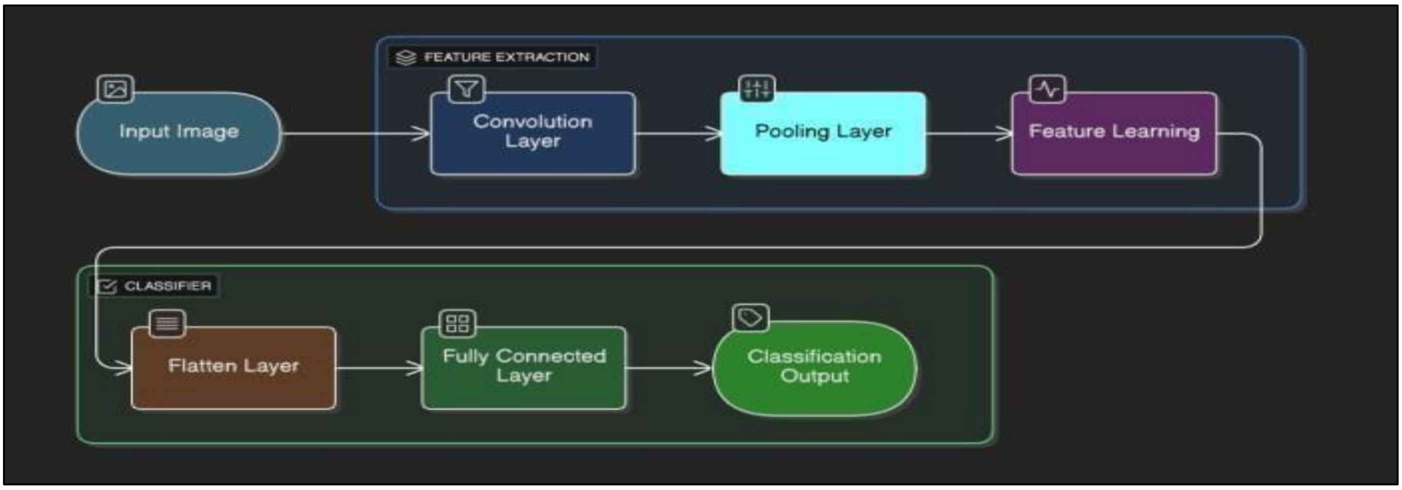

Fig 2 Architecture of a Convolutional Neural Network (CNN)

In CNNs, two-dimensional filters are applied along with non-linear activation functions and pooling operations, enabling the model to capture spatial dependencies and reduce computational complexity. Key features such as local receptive fields, translation invariance, and weight sharing make CNNs both efficient and accurate, while significantly reducing the number of trainable parameters.

For this research paper, CNNs are utilized to distinguish between healthy and unhealthy plant leaves. Their ability to automatically learn discriminative features without manual intervention allows for robust classification and real-time prediction, thereby enhancing the reliability and scalability of automated plant health monitoring systems.

In the context of this research, CNNs are employed to classify plant leaves as either healthy or unhealthy. By automatically learning discriminative features from the input images, the network eliminates the need for manual feature extraction, which can be time-consuming and prone to error. This capability allows the model to generalize effectively to unseen images, ensuring robust classification even under varying lighting conditions, leaf orientations, or background noise. Furthermore, the automated feature learning and classification capabilities of CNNs facilitate real-time prediction, making the system practical for continuous plant health monitoring. Overall, leveraging CNNs in this project enhances both the accuracy and scalability of automated plant health monitoring, supporting timely intervention and better crop management decisions.

B. Proposed Model Functions

```
# 2. Simplified CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(img_height, img_width, 3)),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.3),

    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(0.001)),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.4),

    # Replacing Flatten with GlobalAveragePooling
    GlobalAveragePooling2D(),

    Dense(64, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
```

Fig 3 Detailed Layers of the Simplified CNN Model

The proposed model employs a simplified Convolutional Neural Network (CNN) architecture to classify plant leaves as healthy or unhealthy. The model is constructed using the Sequential API in TensorFlow and Keras. It begins with a Conv2D layer containing 32 filters of size 3×3 and uses the ReLU activation function to introduce non-linearity. A Batch Normalization layer is then applied to stabilize and accelerate training, followed by a MaxPooling2D layer with a pool size of 2×2 to reduce spatial dimensions and computational complexity. A Dropout layer (0.3) is used to prevent overfitting by randomly deactivating certain neurons during training. The second convolution block consists of 64 filters with L2 regularization (0.001) to reduce overfitting further. Similar to the first block, this layer is followed by batch normalization, max pooling, and a dropout of 0.4.

Instead of flattening the feature maps, a Global Average Pooling (GAP) layer is used, which reduces the feature space by averaging each feature map, leading to a more compact and generalized representation. This is followed by a Dense layer with 64 units and ReLU

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activation, incorporating L2 regularization to enhance generalization. Another Dropout layer (0.5) is added for regularization.

Finally, a single Dense output layer with a sigmoid activation function produces a binary output that distinguishes between healthy and unhealthy leaves. This architecture efficiently balances performance and computational cost, making it ideal for real-time plant health monitoring applications.

- *Conv2D:* The Conv2D layer performs a two-dimensional convolution operation, generating feature maps by sliding a convolutional kernel across the input image. In the context of plant leaf analysis, this layer helps extract essential visual features such as color variations, texture patterns, and disease spots. The convolution kernel (or filter) acts as a feature detector, enhancing specific characteristics like edges, contours, or infected regions within the leaf image, which are crucial for accurate disease identification and classification.
- *MaxPooling2D:* The MaxPooling2D layer is employed to downsample the feature maps by selecting the maximum value within a defined region of the input matrix. This process reduces the spatial dimensions while preserving the most significant features, such as disease patterns or leaf texture variations. In this research paper, MaxPooling2D helps the model focus on the most dominant visual cues of healthy and unhealthy leaves, improving computational efficiency and minimizing redundant information for better disease detection accuracy.
- *GlobalAveragePooling2D:* The Global Average Pooling 2D layer replaces the traditional Flatten operation by computing the average of each feature map from the convolutional layers. Instead of converting all pixel values into a single long vector, it summarizes each feature map into a single value, reducing the number of parameters and preventing overfitting. In this project, this layer efficiently extracts the essential spatial information from leaf images, enabling the CNN model to classify healthy and unhealthy plants with improved generalization and stability.
- *Dense:* The Dense layer represents a fully connected neural network layer where each neuron receives input from all neurons of the preceding layer. It is one of the most widely used layers in deep learning models, serving as the decision-making component of the network. In this study, the Dense layers transform the extracted spatial features from plant leaf images into class scores, enabling the model to accurately distinguish between healthy and diseased leaves.
- *Dropout:* The Dropout layer is a regularization technique applied during training to minimize overfitting in deep learning models. It works by randomly deactivating a fraction of neurons in the network during each training iteration, forcing the model to learn more robust and generalized feature representations. In this paper, Dropout is used to ensure that the CNN does not become overly dependent on specific neurons, therebyimproving its ability to accurately classify plant leaves as healthy or Unhealthy when tested on unseen data.
- *Image Data Generator:* The ImageDataGenerator is a preprocessing utility that enhances the training dataset by applying real-time data augmentation. It performs operations such as rescaling, zooming, shifting, rotating, and horizontal flipping of plant leaf images, ensuring the model is exposed to diverse variations. This helps the CNN learn more generalized features, improving accuracy and robustness while reducing the chances of overfitting.
- *Training Process:* For model training, the dataset is prepared using the train_datagen.flow_from_directory() function, which loads images from the training directory and resizes them to a defined target size suitable for the CNN. Similarly, validation data is generated using the same approach with a separate subset of images. The training is carried out using the fit() function, where parameters such as the number of epochs and steps per epoch are defined. These parameters control how many iterations the model performs during training, ensuring that the network progressively learns to differentiate between healthy and unhealthy leaves.
- *Epochs:* Epochs represent the number of complete training cycles the model undergoes, where each cycle includes both forward and backward propagation. They determine how many times the learning algorithm processes the entire dataset to refine the model's accuracy.
- *Validation Process:* The validation process involves supplying the model with unseen validation and test data to evaluate its performance during training. It provides an estimate of how well the model generalizes beyond the training set by reporting validation accuracy and loss across the specified dataset samples.

C. Training & Testing Model

The dataset undergoes preprocessing operations such as reshaping, resizing, and converting images into array format. The same steps are applied to the test images to ensure uniformity. The dataset contains images of both healthy and unhealthy plant leaves, which are used to train and test the proposed model. The Convolutional Neural Network (CNN) is trained using layers like Convolution2D, MaxPooling2D, Dense, Dropout, and Activation to identify and classify plant diseases. Once training is completed, the model can accurately predict the condition of a plant leaf by comparing the input test image with the features learned during training.

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D. Implementation and Analysis

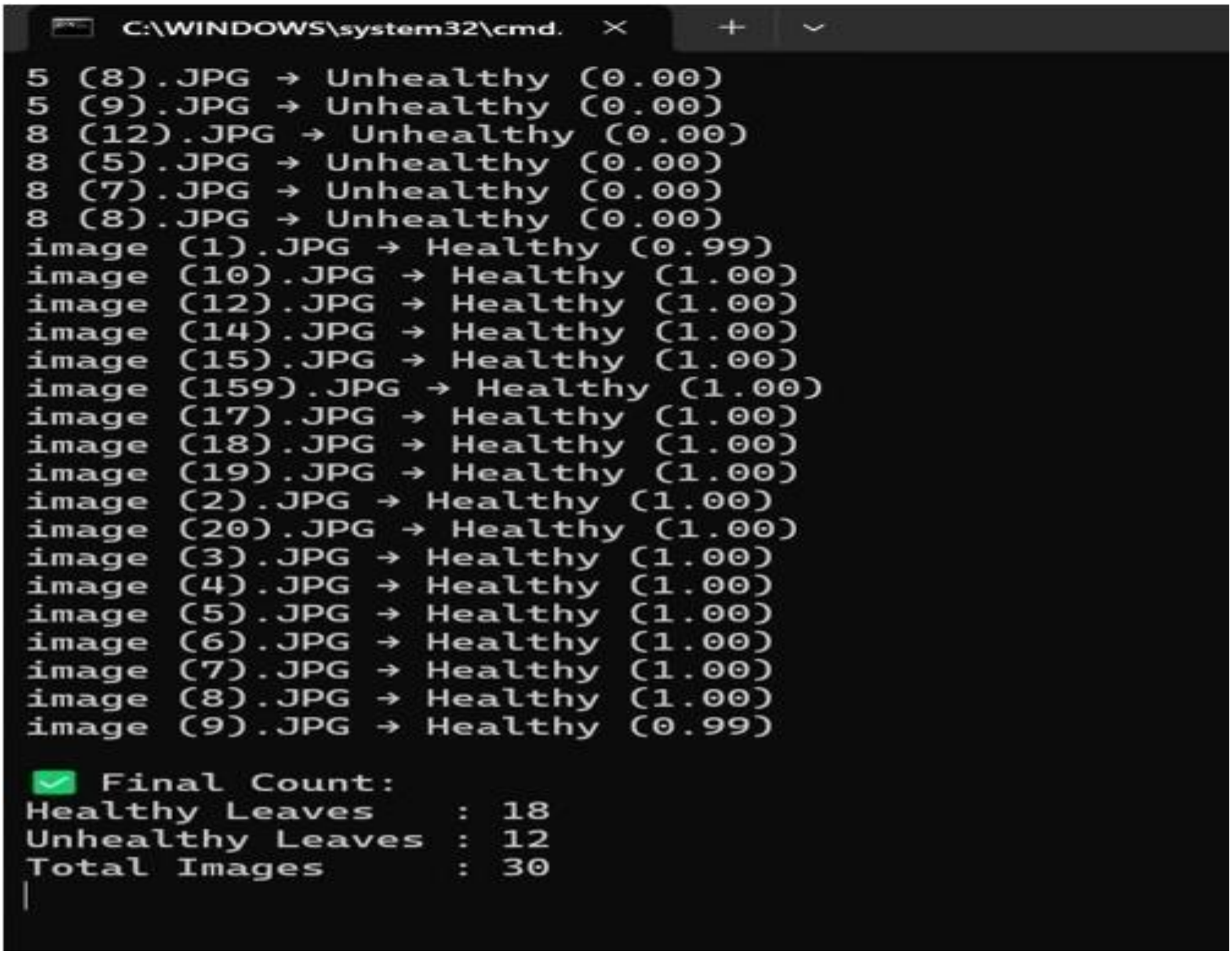

Fig 4 Classification Output Showing Healthy and Unhealthy Image Counts

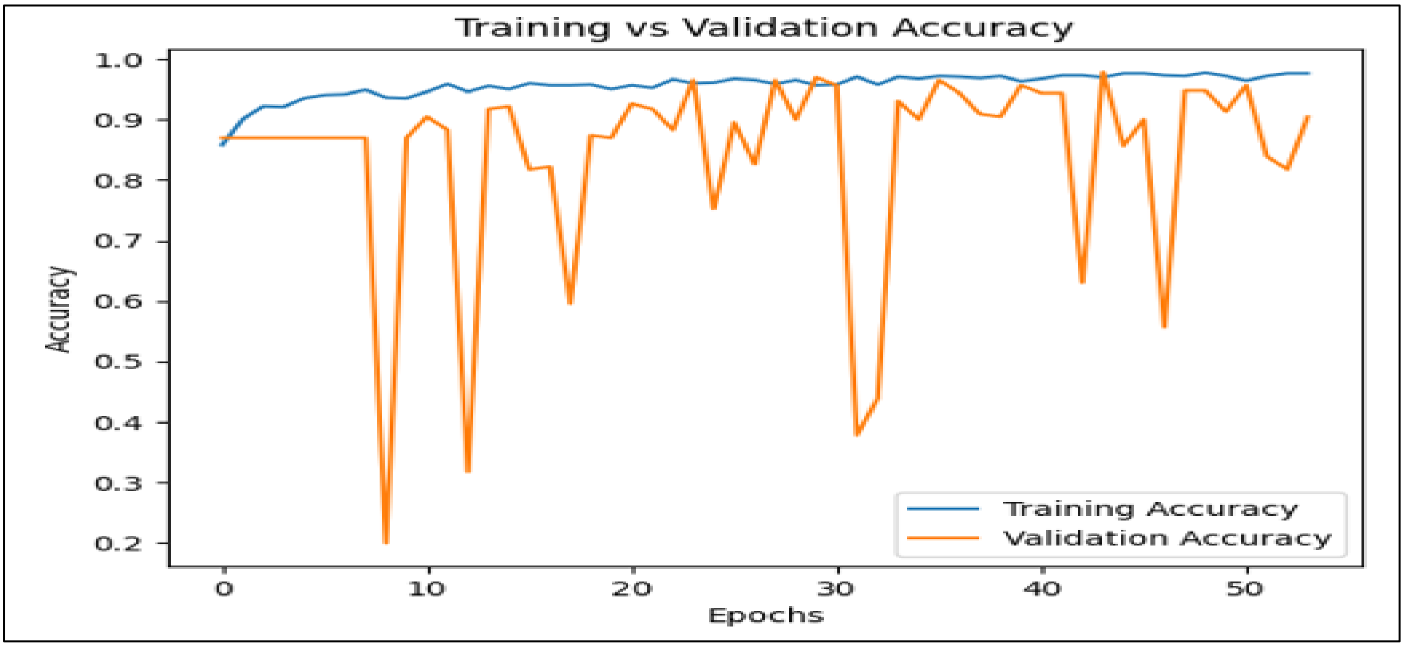

Fig 5 Accuracy Curve for Training and Validation

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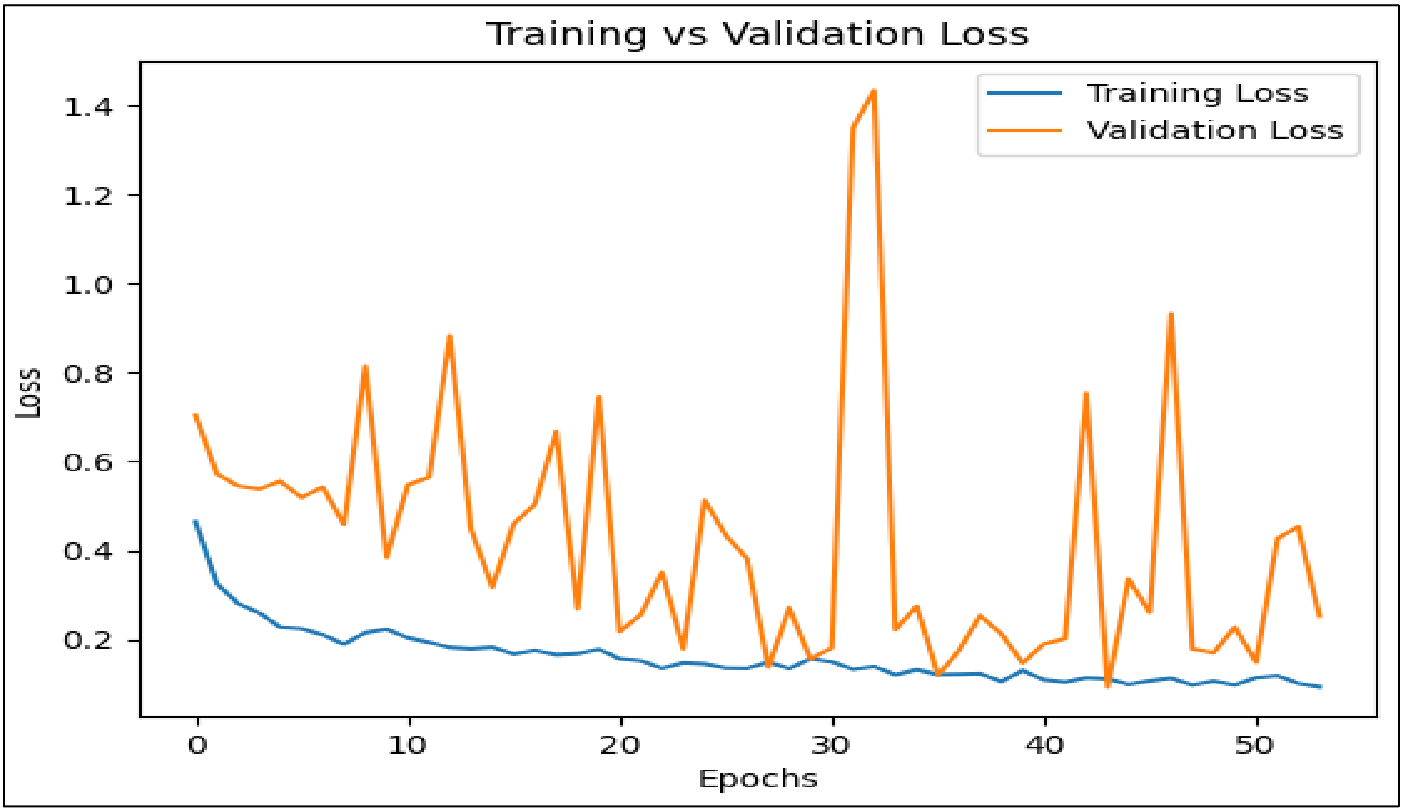

Fig 6 Loss Curve for Training and Validation

The above figure illustrates the performance of our CNN model in terms of accuracy and loss during training. It can be observed that the model achieves over 90% training accuracy, indicating strong learning capability. As the number of epochs increases, the accuracy steadily improves while the loss decreases, showing effective convergence. When a new leaf image is provided as input, the model can accurately predict whether the leaf is healthy or unhealthy, based solely on the visual features extracted from the image.

E. Model Execution and Results Display

In this Research work, the trained CNN model for leaf health classification is executed using Visual Studio on a computer. Unlike mobile deployment, the program runs directly on the system, and the results are displayed on the monitor in real-time. The system is designed to provide a clear visual interface, allowing users to easily understand the health status of plant leaves.

➢ *Step 1. Load the Trained Model*

The CNN model, trained to distinguish between healthy and unhealthy leaves, is first loaded into the program using Python with the TensorFlow/Keras framework. The model architecture and learned weights are initialized to prepare it for predictions on new images.

➢ *Step 2. Input Leaf Images*

Leaf images, either captured from real plants or selected from the prepared dataset, are fed into the model. The program accepts images in common formats (such as .jpg or .png) and performs necessary preprocessing, such as resizing, normalization, and conversion to arrays compatible with the model input.

➢ *Step 3. Model Prediction*

The loaded model processes each leaf image and extracts relevant features to determine its health status. Using the learned patterns from the training phase, the CNN classifies each leaf as either healthy or unhealthy. This step ensures that the prediction is based on visual characteristics such as color, texture, and any visible signs of disease.

➢ *Step 4. Display Results and Validation*

The predicted results are displayed on the monitor along with the corresponding leaf image. Multiple images are tested to validate accuracy and ensure reliable performance, demonstrating the model's practical applicability in plant health monitoring.

Fig 7 Image Classification Output

V. CONCLUSION

In this research work, a Convolutional Neural Network (CNN) was successfully developed and implemented for automated plant leaf health monitoring. The project focused on a binary classification problem, where leaves were classified as either healthy or unhealthy. The dataset of leaf images was preprocessed to ensure uniformity, including resizing, reshaping, and conversion into a standardized format compatible with the model.

The CNN model was trained to recognize visual patterns and features indicative of leaf health, using a combination of Convolutional, MaxPooling, Flatten, Dense, Dropout, and Activation layers. The trained model effectively extracted critical features from input images, enabling accurate classification. During testing, the system demonstrated reliable performance in predicting the health status of new leaf images, with results displayed clearly for user interpretation.

This study highlights the potential of CNN-based approaches for automated plant health assessment. The system provides a fast, accurate, and non-invasive method for monitoring plant conditions, which can support timely interventions and contribute to better crop management and yield optimization. The proposed model can serve as a foundation for future enhancements, including real-time monitoring and integration with larger agricultural management systems.

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