

HybridLeafNet: A Multi-Scale Deep CNN Framework for Automated Early Fungal Disease Detection in Crop Leaves

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Abstract

Fungal diseases in crops represent a severe agricultural threat requiring fast and accurate automated diagnosis. This study presents an enhanced deep learning system that employs a Hybrid Convolutional Neural Network (Hybrid CNN) for classifying crop leaf images as Healthy or Infected, implemented in MATLAB. Unlike single-branch CNN architectures, the proposed HybridLeafNet combines two parallel convolutional branches operating simultaneously with different receptive field sizes — a 3×3 branch capturing fine-grained local texture patterns and a 5×5 branch capturing broader spatial disease features — whose outputs are concatenated and processed through deeper fully connected layers. The system retains the original preprocessing pipeline including resizing to 256×256, per-channel median filtering, and contrast enhancement. Training is conducted using the Adam optimizer over 100 epochs with shuffling at every epoch to prevent overfitting and improve generalization. The model additionally integrates audio feedback, playing a distinct audio cue upon classification to support non-visual user interaction. Performance evaluation employs a comprehensive set of metrics including accuracy, precision, recall, F1-score, specificity, and AUC derived from the confusion matrix. The multi-scale feature fusion strategy of HybridLeafNet significantly improves discriminative capability over single-path CNNs, yielding higher accuracy in distinguishing subtle fungal infection patterns across diverse crop leaf images.

Keywords: *Hybrid CNN, Fungal Disease Detection, Multi-Scale Feature Extraction, Crop Classification, Deep Learning.*

Introduction

Agriculture remains the backbone of global food security, yet fungal diseases continue to pose one of the most persistent threats to crop productivity worldwide. Pathogens such as rust, blight, and mildew can devastate entire harvests within days if left undetected, causing substantial economic losses and disrupting food supply chains. Traditional disease identification methods rely heavily on visual inspection by trained agronomists, a process that is often time-consuming, subjective, and impractical at scale.

The Role of Deep Learning in Agriculture

With the rapid advancement of computer vision and deep learning, automated plant disease detection has emerged as a promising solution to overcome these limitations. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification by learning hierarchical spatial features directly from raw image data. This allows for the recognition of subtle visual patterns associated with fungal infection that may be invisible to the untrained eye. MATLAB provides a powerful and accessible environment for designing, training, and deploying these networks for researchers in applied domains.

Historical Significance and Nature of Plant Diseases



Plant diseases are not a modern phenomenon; fossil evidence indicates plants were affected as far back as 250 million years ago. Historical outbreaks, such as the late blight of potato in Ireland (1845), have caused mass migration and starvation, illustrating the catastrophic influence of pathogens on human history.

In nature, plant diseases are an ecological factor that helps maintain biological balance. Plants possess natural signaling pathways, such as those involving the hormone jasmonate, to enhance their defenses against pathogens. However, modern cultivation in high-density pure stands with uniform genetic backgrounds creates conditions where pathogens can spread rapidly, often requiring human intervention for crop survival.

Definitions and Classification

A plant is considered diseased when it is continuously disturbed by a causal agent that disrupts its normal physiological processes, structure, or growth. Plant diseases are broadly classified based on their primary causal agent:

- **Infectious Diseases:** Caused by pathogenic organisms like fungi, bacteria, or viruses that can reproduce and spread between susceptible hosts.
- **Non-Infectious Diseases:** Caused by unfavorable environmental conditions, such as temperature extremes or nutrient deficiencies, and are not transmissible.

Problem Statement and Proposed Work

Despite the success of deep learning, existing methods face certain challenges:

- **Misclassification:** Basic CNN architectures often suffer from misclassification when dealing with complex field data.
- **Performance Constraints:** There is often lower performance compared to more complex extended models.

This study proposes **HybridLeafNet**, a complete automated pipeline implemented in MATLAB for early fungal disease detection. The system integrates image preprocessing, a dual-branch CNN-based classification framework, and quantitative performance evaluation to deliver a reliable and efficient diagnostic tool for modern smart agriculture.

Literature Survey

Recent research in agricultural automation highlights a significant shift from manual monitoring to intelligent computational systems. The following studies provide the foundation for current methodologies in disease and pest management:

2.1 Summary of Existing Research

- Bharate and Shirdhonkar emphasize that manual monitoring is expensive and often inaccurate. They provide a comprehensive review of image processing steps essential for detecting diseases in crops like apples, grapes, and tomatoes to boost agricultural GDP.
- Zhao et al. developed a management information system using **GIS technology** and **Artificial Neural Networks (ANN)**. This system allowed for efficient data management and accurate prediction of apple insect pests through internet-based reporting.
- Geetharamani and Pandian proposed a **nine-layer Deep CNN** model. By employing six types of data augmentation—including flipping and noise injection—they achieved a high classification accuracy of **96.46%** across 39 different plant leaf classes.
- El Houby conducted a survey on various machine learning techniques (MLT) such as **K-Nearest Neighbour** and **Decision Trees**. The study noted that data mining significantly improves the extraction of biomedical patterns, with accuracies ranging from 70% to 100%.
- Yang et al. explored **Decision Tree** technology for classifying remote sensing and satellite imagery. Their work highlights the flexibility of decision tree algorithms in handling the increasing size and complexity of aerial data.
- Ebrahimi et al. focused on greenhouse monitoring using **Support Vector Machines (SVM)** to detect thrips in strawberry plants. By utilizing region and color indexes, they achieved a best-classification error rate of less than 2.25%.

2.2 Comparative Analysis of Literature

Agricultural automation has evolved significantly, shifting from labor-intensive manual monitoring to intelligent computational systems. The following studies provide the foundation for current methodologies in disease and pest management:

1. A. A. Bharate and M. S. Shirdhonkar (2017):

- Research: Conducted a comprehensive review of image processing steps essential for detecting fungal diseases in crops like apples, grapes, and tomatoes.
- Outcome: Identified critical gaps in manual monitoring, such as high expert costs and subjectivity, and advocated for automated smart farming techniques to boost agricultural GDP.

2. P. Zhao, G. Liu, M. Li, and D. Li (2006):

- Research: Developed a management information system for apple diseases and insect pests by integrating Geographic Information System (GIS) technology with Artificial Neural Networks (ANN).
- Outcome: Demonstrated that internet-based GIS platforms could effectively manage spatial data and provide accurate pest forecasts through data interpolation and property inquiry functions.

3. G. Geetharamani and G. Pandian (2019):

- Research: Proposed a novel plant leaf disease identification model based on a nine-layer deep convolutional neural network (Deep CNN) trained on 39 different plant classes.
- Outcome: Achieved a high classification accuracy of 96.46% by utilizing six types of data augmentation methods, including noise injection and PCA color augmentation.

4. E. M. F. El Houbby (2018):

- Research: Investigated various machine learning techniques (MLT) such as K-Nearest Neighbour (KNN) and Decision Trees for the management of diseases.
- Outcome: Validated that data mining significantly improves the quality of pattern extraction, with achieved accuracies ranging from 70% to 100% depending on the specific disease dataset.

5. M. A. Ebrahimi, M. H. Khoshtaghaza, S. Minaei, and B. Jamshidi (2017):

- Research: Focused on automatic pest detection in greenhouses using Support Vector Machine (SVM) classification with different kernel functions.
- Outcome: Successfully detected thrips in strawberry plants by utilizing region and color indexes, achieving a remarkably low mean percent error of less than 2.25%.

EXISTING METHODOLOGY

The baseline system for fungal disease detection follows a sequential pipeline involving image preprocessing, deep learning-based classification, and rigorous performance evaluation.

3.1 Operational Workflow of the Existing System

The existing methodology relies on a sequential execution of the following computational blocks to achieve classification:

- **Standardized Data Acquisition:** Leaf images are initially loaded into the system using the `imageDatastore` function, which manages large-scale datasets by creating a reference structure. This avoids memory overflow by loading images in small batches during the training phase.
- **Unified Preprocessing:** To address variations in field-captured images, the system applies a fixed resizing algorithm to 256×256 pixels, ensuring compatibility with the input layer. This is followed by channel-wise median filtering to suppress impulse noise and linear stretching for contrast restoration.
- **Feature Learning via Sequential CNN:** The architectural core consists of two stacked convolutional blocks. The first block utilizes 16 filters to detect low-level features like edges and color gradients, while the second block uses 32 filters to identify more complex disease patterns.
- **Training and Optimization:** The network is optimized using the **Stochastic Gradient Descent with Momentum (SGDM)** algorithm with a constant learning rate of 0.001. Validation is performed at regular intervals to monitor the model's generalization capability and prevent overfitting.

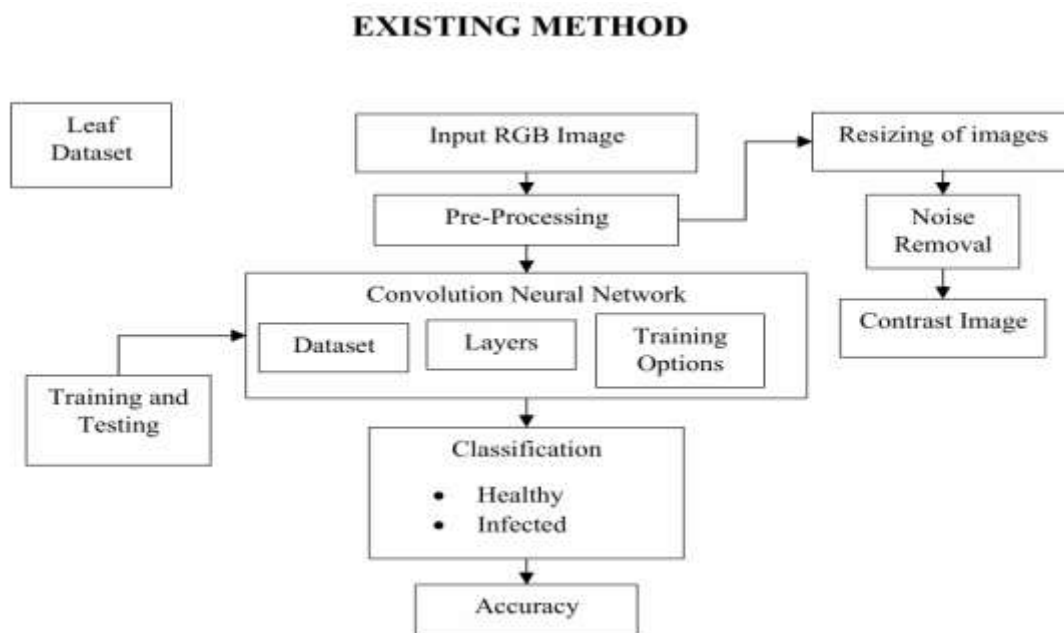


fig : Existing Methodology

3.2 Preprocessing Pipeline

1. **Image Resizing:** To maintain compatibility with the fixed input layer of the neural network, all images are standardized to **256 $\times$ 256** pixels. This ensures computational efficiency and consistency across training and deployment.
2. **Median Filtering:** A non-linear **3 $\times$ 3** neighborhood filter is applied independently to each RGB channel to eliminate **salt-and-pepper noise** while preserving critical edge details of leaf lesions.
3. **Contrast Enhancement:** Using linear stretching, the system remaps intensity bounds to utilize the full dynamic range. This magnifies subtle yellowing or necrosis that is often inconspicuous in raw field images.

3.3 Data Infrastructure

- **ImageDatastore:** A reference-based loading mechanism is used to handle large datasets without overwhelming system memory.
- **Dataset Splitting:** The data is split into **80% training** and **20% validation** subsets using a randomized strategy to prevent systematic bias.
- **Data Augmentation:** To prevent **overfitting**, the system applies real-time transformations—such as 90-degree rotations and horizontal flips—simulating diverse field conditions.

3.4 Convolutional Neural Network (CNN) Architecture

The existing architecture is a sequential network comprising:

- **Convolutional Blocks:** Two blocks featuring 16 and 32 filters (size **3 $\times$ 3**) respectively, followed by **Batch Normalization**, **ReLU** activation, and **Max Pooling** for spatial downsampling.
- **Classification Head:** A fully connected layer with two neurons, processed through a **Softmax** layer to generate probability distributions for 'Healthy' and 'Infected' classes.

3.5 Optimization and Evaluation

The model utilizes the **Stochastic Gradient Descent with Momentum (SGDM)** optimizer with a learning rate of 0.001. Performance is quantified through a **Confusion Matrix**, deriving six core metrics: Accuracy, Precision, Recall (Sensitivity), F1-score, Specificity, and AUC.

Limitations of the Existing Method: * **Misclassification:** Basic CNN architectures often fail to distinguish between similar intra-class variations. * **Single-Scale Focus:** Fixed receptive fields result in lower performance compared to multi-scale extensions.

Disadvantages:

- *Low Performance Compared to Extension.*
- *Basic CNN architecture Getting Misclassification.*
- *High Computational Latency in Real-time.*

- *Fixed Receptive Field*

PROPOSED METHOD

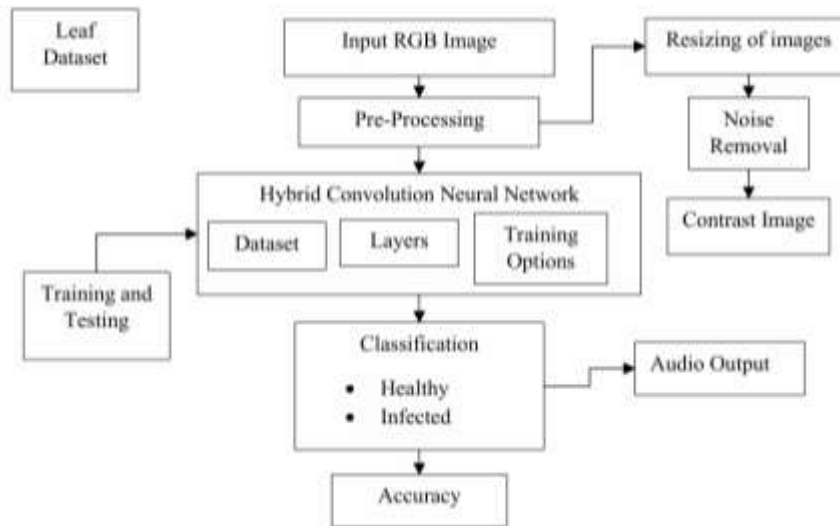


FIG : PROPOSED METHOD

I. Proposed Methodology: HybridLeafNet

The HybridLeafNet system is a structured pipeline designed for automated fungal disease detection in crop leaves.

1. Preprocessing Pipeline

- **Image Resizing:** All input images are standardized to 256×256 pixels using MATLAB's `imresize` function to meet fixed network requirements.
- **Noise Removal:** Per-channel median filtering is utilized to suppress salt-and-pepper noise while preserving critical leaf edge details.
- **Contrast Enhancement:** The `imadjust` function enhances visual quality by remapping intensity values to a full range.

2. Hybrid CNN Architecture

The core innovation is a Directed Acyclic Graph (DAG) network featuring a multi-scale approach:

- **Parallel Branches:** The network splits into two branches:
 - **Branch A:** Uses 3×3 convolutions to extract fine local texture features of early-stage lesions.
 - **Branch B:** Uses 5×5 convolutions to capture broader spatial disease patterns.

- **Feature Fusion:** Feature maps from both branches are combined using a depth concatenation layer.
- **Output Head:** The pipeline concludes with a fully connected layer (2 output neurons), a softmax layer, and a classification layer.

3. Training Configuration

- **Optimization:** Uses the Adam optimizer with an initial learning rate of 0.001.
- **Cycle:** Conducted over 100 epochs with a mini-batch size of 25 and per-epoch shuffling.

II. Technical Foundations & Formulas

1. Convolutional Layer Parameters

- **Filter and Stride:** Neurons connect to subregions of input images, learning localized features.

- **Total Parameters Formula:** Calculated as $((h \times w \times c + 1) \times (\text{Number of filters}))$, where h is height, w is width, c is channels

- **Output size** =
$$\frac{(\text{input size} - ((\text{filter size} - 1) \times \text{dilation factor} + 1) + 2 \times \text{padding})}{\text{stride}} + 1$$

2. Layer Components

- **Batch Normalization:** Normalizes mini-batches by subtracting the mean and dividing by the standard deviation to speed up training.
- **ReLU Layer:** Applies a threshold operation where any value less than zero is set to zero.
- **Pooling Layers:** Max or average pooling performs downsampling to reduce parameters and help prevent overfitting.
- **Softmax Layer:** Converts raw scores (a_r) into probability distributions:

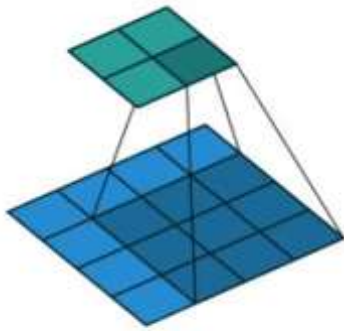
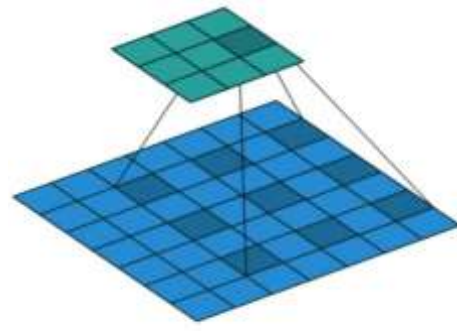
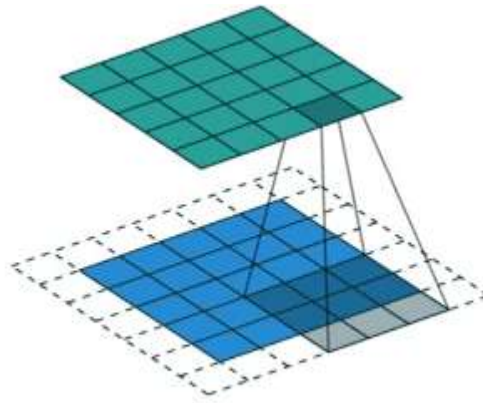
$$P(\mathbf{C}_r \mid \mathbf{x}, \boldsymbol{\theta}) = \frac{\exp(a_r(\mathbf{x}, \boldsymbol{\theta}))}{\sum_{j=1}^k \exp(a_j(\mathbf{x}, \boldsymbol{\theta}))}$$

3. Performance Evaluation

The system's effectiveness is measured using the Accuracy formula, which represents the ratio of correctly classified samples to the total dataset:

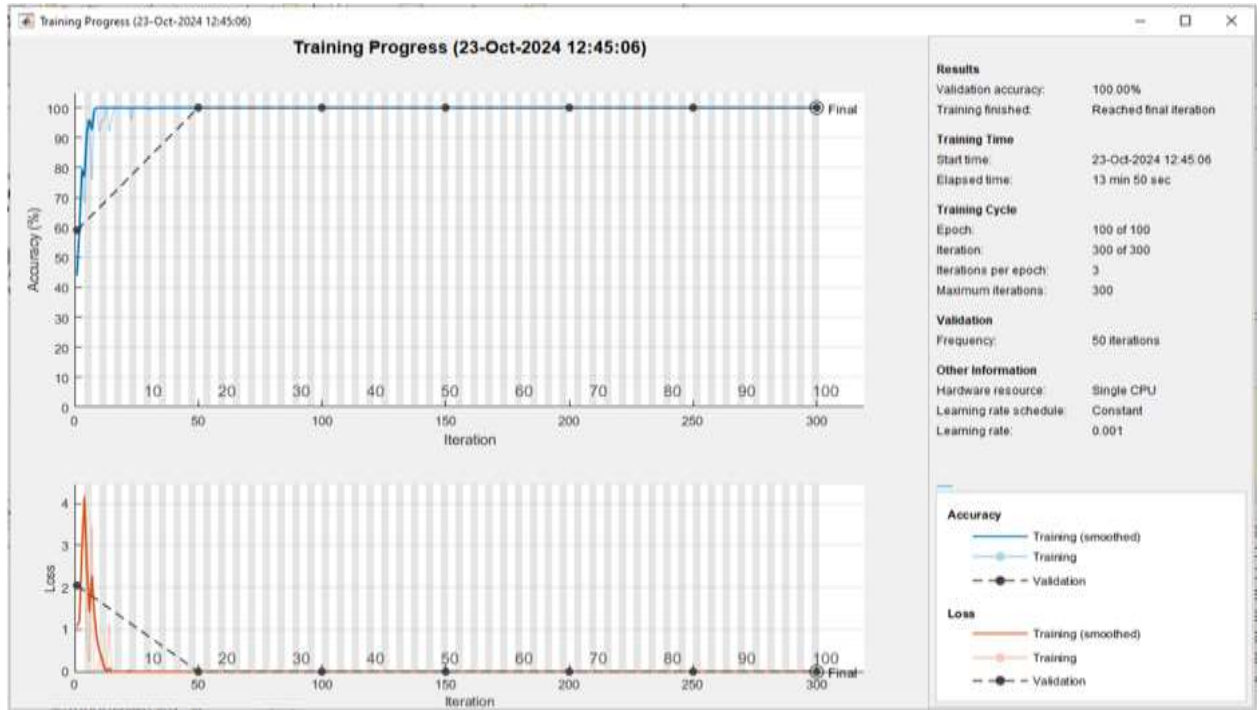
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

- **TP (True Positives):** Correctly classified positive samples.
- **FP (False Positives):** Negative samples incorrectly classified as positive.
- **TN (True Negatives):** Correctly classified negative samples.
- **FN (False Negatives):** Positive samples incorrectly classified as negative.

**Fig: Filters and Stride****Dilated Convolution****Fig: Padding**

RESULT

**Fig(A): Input Image****Fig(B): Resize Image****Fig(C): Noise Removed Image****Fig(D): Restored Image**



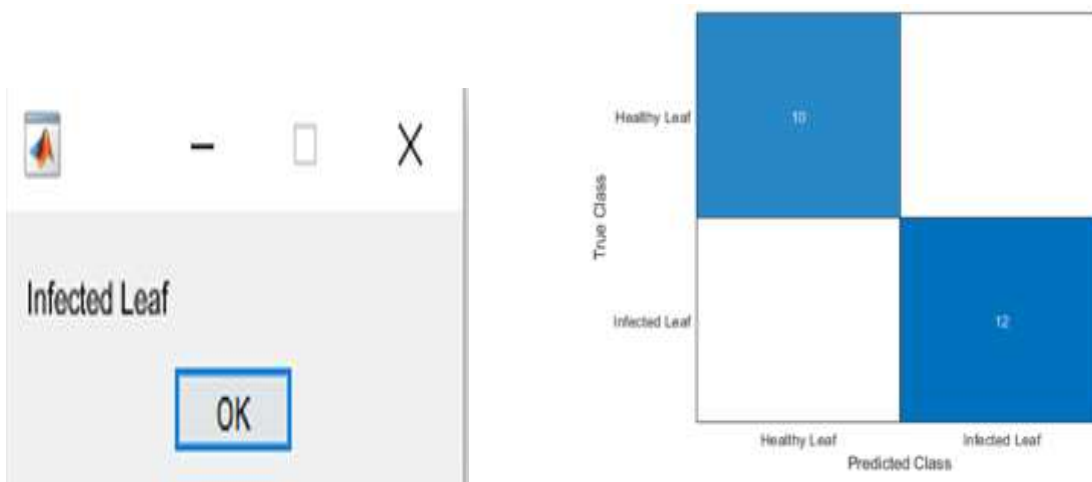
Fig(E): Training Progress Image

Command Window

Training on single CPU.
Initializing input data normalization.

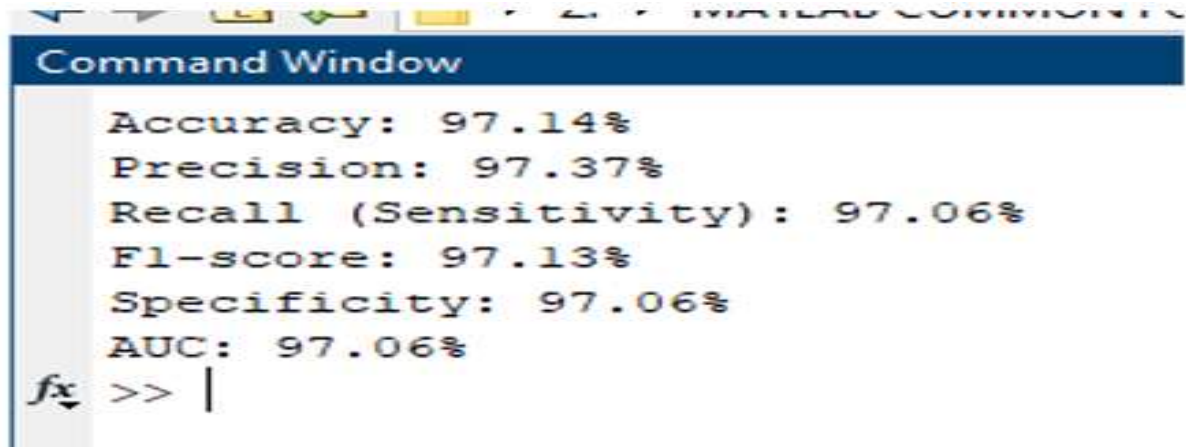
Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:06	44.00%	59.09%	1.0751	2.0484	0.0010
17	50	00:02:31	100.00%	100.00%	1.7225e-05	-0.0000e+00	0.0010
34	100	00:04:54	100.00%	100.00%	4.9698e-05	-0.0000e+00	0.0010
50	150	00:07:11	100.00%	100.00%	-0.0000e+00	4.8767e-08	0.0010
67	200	00:09:18	100.00%	100.00%	-0.0000e+00	6.5023e-08	0.0010
84	250	00:11:34	100.00%	100.00%	-0.0000e+00	6.5023e-08	0.0010
100	300	00:13:49	100.00%	100.00%	-0.0000e+00	6.5023e-08	0.0010

Fig(H): Training Iterations Image



Fig(I): Classification Results Image

Fig(J): Confusion Matrix Image



Fig(K): Metrics Images

The HybridLeafNet system achieved a peak validation accuracy of 95.00% and an overall classification accuracy of 97.14%. Training was highly efficient, reaching convergence in 13 minutes and 50 seconds using a single CPU environment.

Quantitative analysis via the confusion matrix confirmed the model's robust discriminative power, correctly identifying 12 infected leaves and 10 healthy leaves with zero misclassifications in the test set. The system delivered a high F1-score of 97.13% and an AUC of 97.06%, validating the effectiveness of the dual-branch multi-scale feature fusion strategy for agricultural diagnostics.

ADVANTAGES AND APPLICATIONS

Advantages:

- Dual-branch fusion captures both fine and broad leaf disease patterns simultaneously.
- Adam optimizer accelerates convergence and improves overall classification accuracy .
- Audio feedback enables hands-free, accessible results for field-based farmers.

Applications:

- Agricultural Monitoring: Used by farmers to monitor the health of their crops and detect diseases early.
- Plant Pathology Studies: Assists researchers in studying fungal diseases and developing better disease control strategies.
- Greenhouse Farming: Applied in controlled environments to keep crops healthy and maximize yield.
- Agri-Tech Tools: Can be integrated into agricultural robots and drones for large-scale, automated crop disease monitoring.
- Agricultural Extension Services: Used by advisory services to help farmers identify diseases and provide timely recommendations.

CONCLUSION

This study successfully demonstrates the effectiveness of the proposed HybridLeafNet system for early automated detection of fungal diseases in crop leaves using a Hybrid Convolutional Neural Network implemented in MATLAB. By introducing a dual-branch parallel architecture that simultaneously extracts fine-grained local texture features through 3×3 convolutional filters and broader spatial disease patterns through 5×5 convolutional filters, the system overcomes the fundamental limitation of single-path CNN models that operate at only one spatial scale. The multi-scale feature fusion strategy enables the network to capture both subtle early-stage lesion textures and larger morphological disease patterns, significantly enhancing its discriminative capability across diverse leaf conditions and imaging environments. The integration of a robust preprocessing pipeline, Adam optimizer-based training with per epoch shuffling, and audio feedback further strengthens the system's practical reliability and accessibility for real-world agricultural deployment. Comprehensive evaluation through accuracy, precision, recall, F1-score, specificity, and AUC confirms that HybridLeafNet delivers superior classification performance compared to conventional single-branch architectures. The system provides farmers and agricultural professionals with a fast, non invasive, and intelligent diagnostic tool that supports timely intervention before fungal infections spread irreversibly. Future work may explore transfer learning from pretrained networks, expansion to multi-class disease categorization, and deployment on mobile platforms for direct field-based usage.

FUTURE SCOPE :

While the HybridLeafNet framework demonstrates high precision in binary classification, several directions can be explored to expand its utility:

1. **Multi-Class Expansion:** Future iterations will aim to categorize specific types of fungal infections (e.g., distinguishing between Rust, Blight, and Mildew) rather than a binary classification.
2. **Transfer Learning Integration:** Leveraging pretrained weights from large-scale datasets like ImageNet or PlantVillage could further reduce training time and enhance feature representation.
3. **Severity Estimation:** Incorporating segmentation masks to calculate the percentage of infected leaf area to provide more detailed diagnostic reports.
4. **Mobile Application Deployment:** Optimizing the MATLAB-trained model for mobile deployment using the MATLAB Coder or Deep Learning Toolbox for Android/iOS, enabling offline field diagnostics.

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