Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Segmentation Techniques

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ABSTRACT A multi-stage approach for plant leaf disease classification using Convolutional Neural Networks (CNN) and image segmentation is presented. The system identifies plant types and classifies diseases from leaf images. Preprocessing includes noise removal and image enhancement, followed by K-means clustering for segmentation. A hybrid CNN model performs accurate classification of plant species and disease type, and suitable fertilizer recommendations are provided. The method achieves accuracies of 99.8%, 96.5%, and 98.3% on apple, tomato, and grape datasets. The results show improved accuracy and robustness, making the system effective for practical agricultural applications.

INDEX TERMS Convolutional Neural Network (CNN), Image Segmentation, K-means clustering, Plant Leaf Diseases.

1. Introduction

Plant diseases pose significant challenges to agriculture, impacting crops such as tomatoes, grapes, and apples. Effective and timely disease detection is crucial for maintaining plant health and yield. This study introduces a multi-class classification method designed to identify plant leaf diseases using a combination of deep convolutional neural networks (CNN) and Local Binary Pattern (LBP) feature fusion. The approach first classifies the plant species Apple, Tomato, or Grape and then identifies specific diseases like Black Rot, Scab, and Cedar Rust. The process starts with preprocessing the input image to remove noise and restore quality. LBP features are extracted and organized into a datastore, with augmented image data used to enhance model training. A CNN is employed to classify the plant species and, once identified, undergoes further training to pinpoint the disease. This dual-stage classification system improves accuracy by integrating deep learning with texture-based features, providing a robust solution for the early and precise detection of plant diseases. This method not only enhances disease identification but also aids in the timely implementation of control measures, thereby supporting effective crop management.

The history of plant diseases dates back thousands of years and is closely intertwined with the development of agriculture. Plant diseases have had significant impacts on human history, influencing food security, economy, and the evolution of agricultural practices.

2. Literature Survey

[1] A. A. Bharate and M. S. Shirdhonkar, ''A review on plant disease detection using image processing,'' in Proc. Int. Conf. Intell. Sustain. Syst. (ICISS), Dec. 2017, pp. 103–109.

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[5] C.-C. Yang, S. O. Prasher, P. Enright, C. Madramootoo, M. Burgess, P. K. Goel, and I. Callum, ''Application of decision tree technology for image classification ng remote sensing data,'' Agricult. Syst., vol. 76, no. 3, pp. 1101–1117, Jun. 2003.

[6] M. A. Ebrahimi, M. H. Khoshtaghaza, S. Minaei, and B. Jamshidi, ''Vision-based pest detection based on SVM classification method,''

Comput. Electron. Agricult., vol. 137, pp. 52–58, May 2017.

3. Existing Method

The existing methodology for multi-class classification of plant leaf diseases integrates Deep Convolutional Neural Networks (CNN) with Local Binary Pattern (LBP) feature extraction, forming a hybrid feature fusion approach. Initially, input images undergo preprocessing steps such as noise removal and image restoration to enhance quality. Subsequently, LBP features are extracted to capture essential texture characteristics. The processed images, along with their corresponding labels, are stored in a datastore and split proportionally to maintain class balance. Data augmentation techniques are applied to generate diverse training batches, improving model generalization. The CNN is first trained to classify plant species (e.g., Apple, Tomato, Grape), followed by a second stage where it classifies specific diseases (e.g., Black Rot, Scab, Cedar Rust). This two-stage classification framework enhances diagnostic accuracy by leveraging both deep learning features and texture-based descriptors.

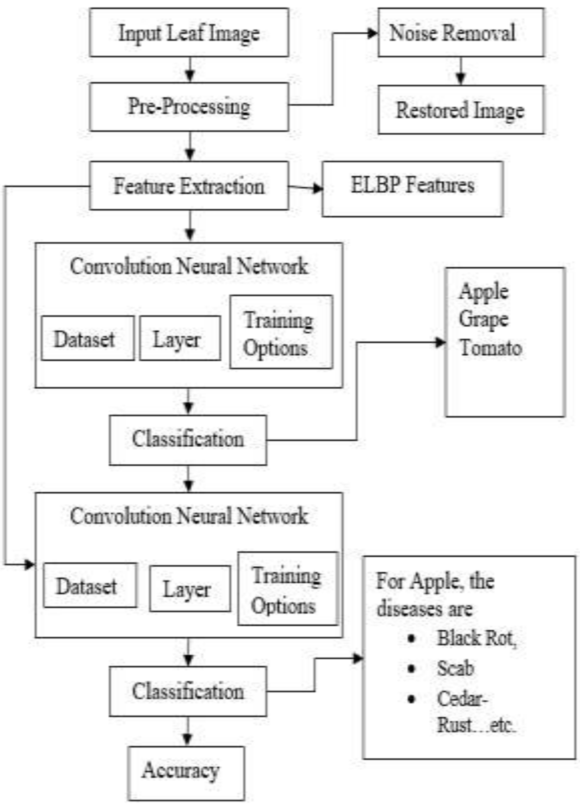

Fig.3.1: Block Diagram of Existing Method

4.Proposed Method

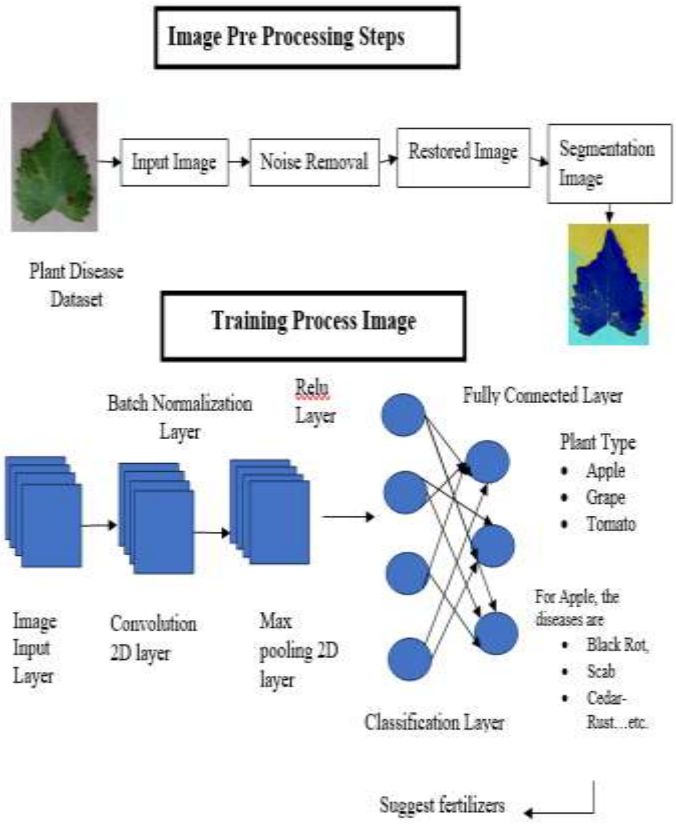

Fig.4.1: Proposed Method Architecture

The methodology for multi-class classification of plant leaf diseases using feature fusion of deep convolutional neural networks (CNN) and segmentation techniques follows a systematic and structured pipeline. Initially, a plant leaf image is acquired and subjected to preprocessing steps such as noise removal and image restoration to enhance clarity and eliminate distortions caused by environmental conditions or sensor limitations. Noise removal is performed using filtering techniques such as median, Gaussian, and Wiener filters, each suited to different types of noise, while image restoration techniques help recover degraded image quality using functions like deconvolution and adaptive filtering. The enhanced image is then segmented using K-means clustering, which partitions the image into meaningful regions by grouping pixels based on intensity or color similarity, thereby isolating areas most likely to contain disease-related features. Following segmentation, a hybrid CNN model is employed for classification, where the network is trained using optimized parameters such as stochastic gradient descent with momentum (SGDM), an initial learning rate of 0.001, mini-batch size of 25, and a maximum of 100 epochs, along with data shuffling and validation to improve generalization and prevent overfitting.

The CNN architecture consists of multiple layers including an image input layer for data normalization, convolutional layers for feature extraction using filters, ReLU layers for introducing non-linearity, batch normalization layers for stabilizing and accelerating training, cross-channel normalization layers for enhancing generalization, pooling layers for dimensionality reduction, and fully connected layers for high-level reasoning and classification. Advanced techniques such as padding, stride adjustment, and dilated convolution are used to control feature map size and expand the receptive field without increasing computational complexity.

The model performs a two-stage classification process, first identifying the plant species such as apple, grape, or tomato, and then classifying the specific disease affecting the plant.The final output layer uses a softmax function followed by a classification layer to produce probability-based predictions for multiple classes. Based on the identified disease, the system recommends suitable fertilizers containing essential nutrients such as nitrogen, phosphorus, potassium, and micronutrients like zinc and manganese to enhance plant growth, immunity, and disease resistance, thereby promoting sustainable agricultural practices.

The performance of the model is evaluated using various metrics including accuracy, precision, recall, F1-score, and AUC-ROC, which provide a comprehensive assessment of classification effectiveness by analyzing true positives, false positives, true negatives, and false negatives.

Additionally, the implementation requires specific hardware and software configurations, including a compatible operating system (such as Windows 10), sufficient RAM and storage, a multi-core processor, and MATLAB R2020a or later with relevant toolboxes, ensuring efficient execution of image processing and deep learning tasks.

5. Results

Sample Image 1(GRAPES):

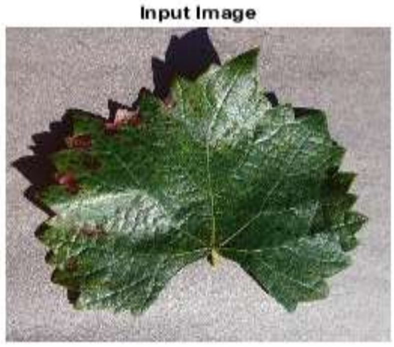

Fig.1: Input Image

The Fig.4.1 the input leaf image used in the plant disease detection system. This image is provided to the model for further processing and analysis to identify possible plant diseases.

Fig.2: Noise Removed Image

This Fig.4.2 the leaf image after the noise removal process, where unwanted distortions are reduced. This helps in improving the image quality for better analysis in the next stages.

Fig.3: Restored Image

The Fig.4.2: Noise Removed Image and Fig.4.3: Restored Image, both displaying the same green leaf with jagged edges on a gray background.

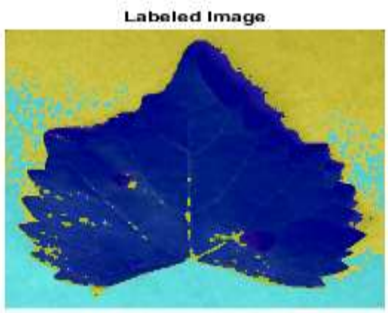

Fig.4: Segmented Image

The Fig.4.4 a labeled segmented image where the original scene has been divided into distinct regions using different colors. The blue area represents the segmented object of interest (likely a leaf), separated from the background (yellow) and another region (cyan), demonstrating image segmentation results.

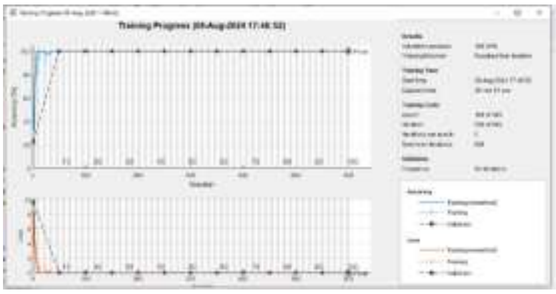

Fig.5: Training Progress

Fig.4.5 displays the training progress plot, indicating the model achieved 100% validation accuracy with a training time of 36 min 51 sec over 100 epochs.

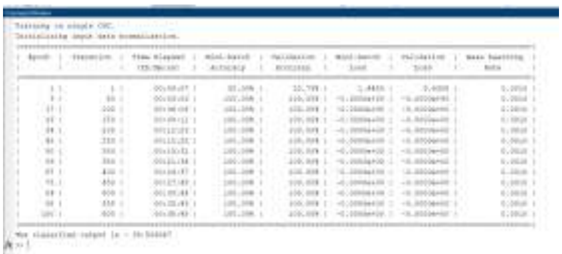

Fig.6: Training Iterations

The Fig.4.6 a table displaying training metrics (epoch, iteration, time elapsed, mini-batch accuracy, validation accuracy, losses, and base learning rate). The model achieves 100% mini-batch and validation accuracy after several iterations, with the loss reducing to near zero.

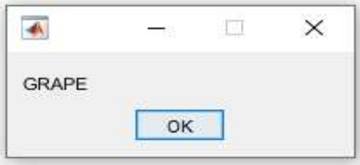

Fig.7: Plant Classification Result

The Fig.4.7 a pop-up window showing the classification output “GRAPE” with an OK button, indicating the model has classified a plant sample as a grape.

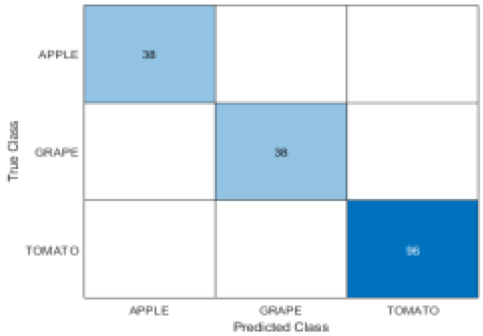

Fig.8: Plant Related Confusion matrix Image

The Fig.4.8 a confusion matrix labeled “Plant Classification Result and Plant Related Confusion matrix Image. The matrix evaluates a classification model for three classes: APPLE, GRAPE, and TOMATO.

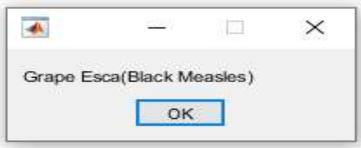

Fig.9: Plant Disease Classification

Grape Esca, also known as Black Measles, is a fungal disease affecting grapevines. It causes wood necrosis and leaf spotting, leading to reduced yield and vine decline.

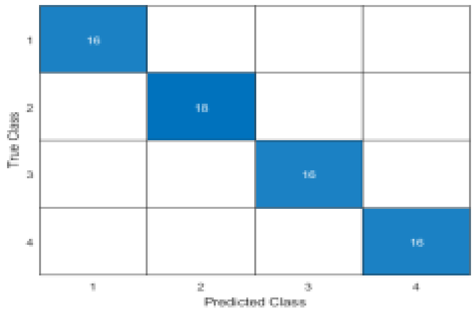

Fig.10: Plant Disease Related Confusion matrix Image

The Fig.4.10 a confusion matrix labeled " Plant Disease Related Confusion matrix Image"

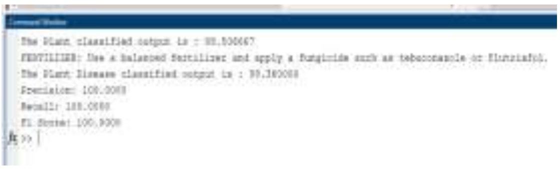

Fig.11: Accuracy and Metric Values

The Fig.4.11 a plant disease classification result with two key outputs: 1. Plant classification gives a 99.506667% accuracy and recommends using a balanced fertilizer plus a fungicide like tebuconazole or flutriafol.2. Plant disease classification achieves 99.360000% accuracy with performance metrics of 100% precision, recall, and F1 score, indicating perfect evaluation results for the proposed method. for the proposed method.

S. No	Existing Method	Proposed Method
1	87	99.36
2	87	99.01
3	87	99.09
4	87	99.44
5	87	99.55

Fig.12: Base and extension Accuracy values

The accompanying table (Fig. 4.12) compares the accuracy of the Existing Method (87%) with the Proposed Method (average ≈ 99.29%), showing a significant improvement in accuracy.

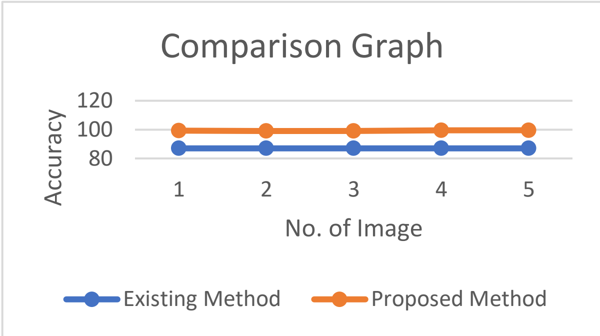

Fig.13: Comparison Graph The Fig.4.13 compares the accuracy of an Existing Method (blue line) with a Proposed Method (orange line) across 5 images.

1. Existing Method: consistently shows an accuracy of ≈ 87%.

2. Proposed Method: consistently shows an accuracy of ≈ 99%.

Sample Image 2(APPLE):

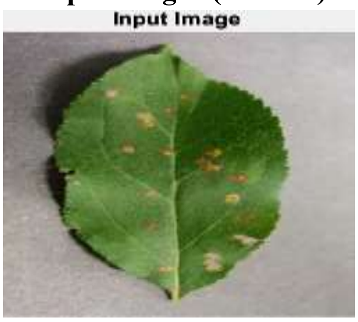

Fig.14: Input Image

Fig.15: Noise Removed

Fig.16: Restored Image

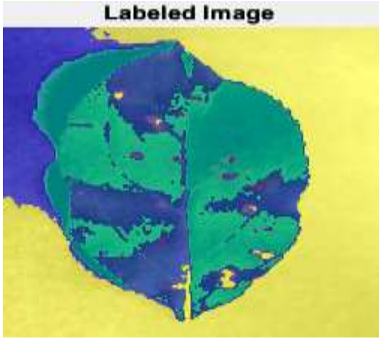

Fig.4.17: Labeled Image

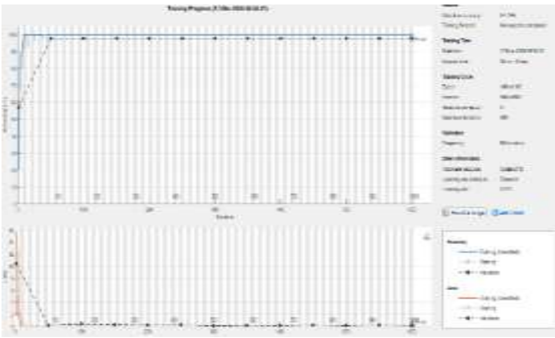

Fig.18: Training progress

The above figures from Fig.4.14 to Fig.4.18 show the overall process of plant leaf disease detection, starting with the input image, followed by noise removal and image enhancement for better clarity. The segmented (labeled) image highlights different regions of the leaf, separating healthy and diseased areas. Finally, the training graph shows the model's performance improving over time with increasing accuracy and decreasing loss.

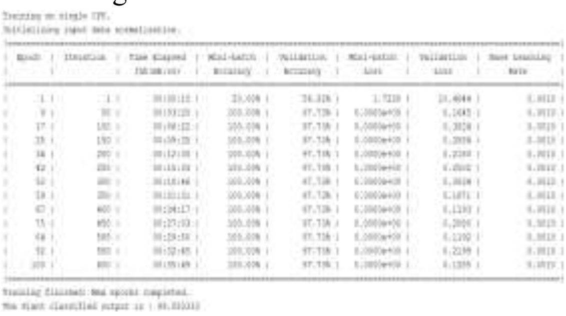

Fig.19: Training Iteration

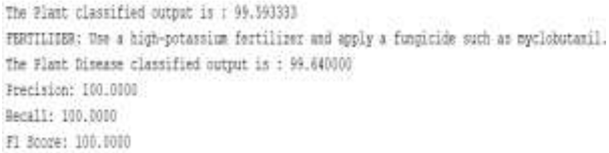

Fig.20: Accuracy and merit value

Fig.21: Plant leaf Classification

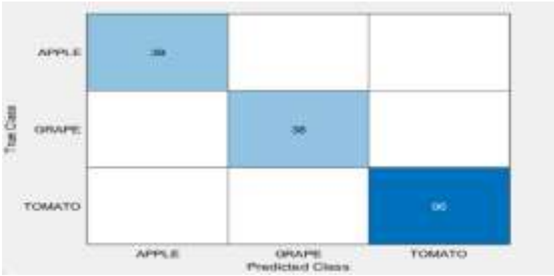

Fig.22: Plant leaf Related Confusion Matrix Image

Fig.23: Plant Disease Classification

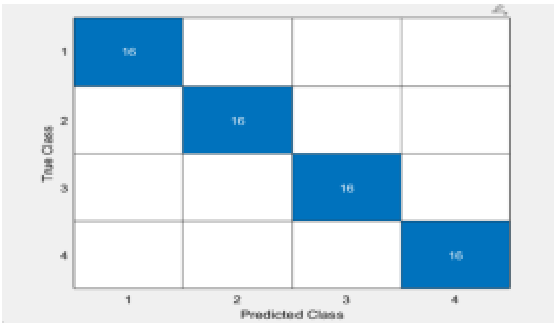

Fig.24: Plant Disease Related Confusion Matrix Image

The above figures from Fig.4.19 to Fig.4.20 show the model's training and results, including learning progress, performance metrics, predicted plant and disease outputs, and confusion matrices that indicate accuracy through correct classifications. They demonstrate that the model can effectively

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identify both plant types and their diseases. Overall, the results confirm good accuracy and reliable performance of the system.

Sample Image 3(TOMATO):

Fig.25: Input Image

Fig.26: Noise Removed

Fig.27: Restored Image

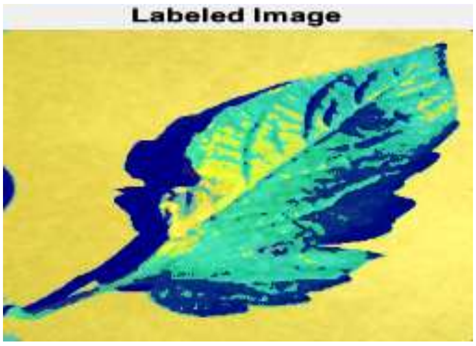

Fig.28: Labeled Image

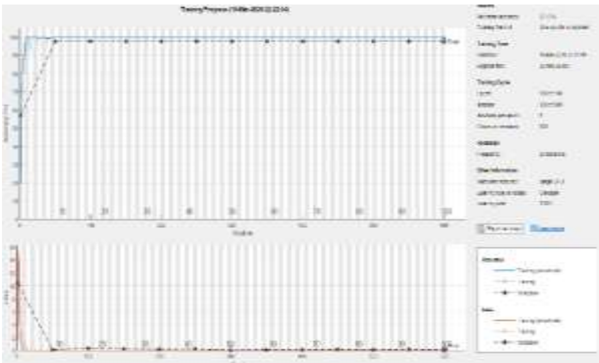

Fig.29: Training progress

The above figures from Fig.4.25 to Fig.4.29 show the overall process of plant leaf disease detection, starting with the input image, followed by noise removal and image enhancement for better clarity. The segmented (labeled) image highlights different regions of the leaf, separating healthy and diseased areas. Finally, the training graph shows the model's performance improving over time with increasing accuracy and decreasing loss.

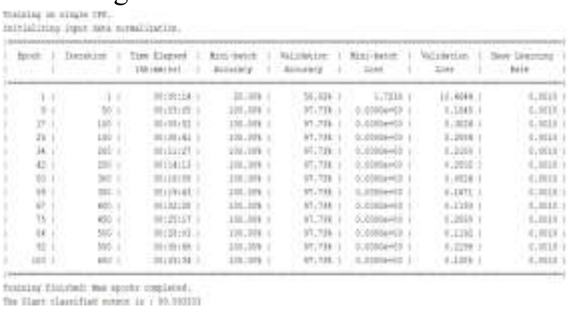

Fig.30: Training Iteration

The Plant classified output is : 96.583333
FERTILISER: Use a balanced fertilizer and apply a fungicide containing chlorothalonil or mancozeb.
The Plant Disease classified output is : 96.600000
Precision: 100.0000
Recall: 100.0000
F1 Score: 100.0000

Fig.31: Accuracy and merit value

Fig.32: Plant leaf Classification

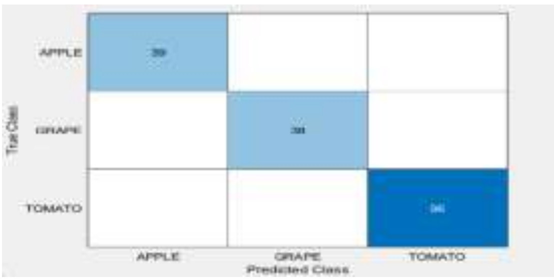

Fig.33: Plant leaf Related Confusion Matrix Image

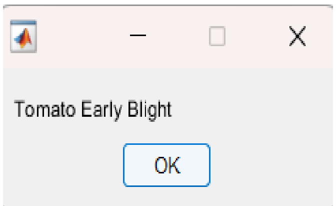

Fig.34: Plant Disease Classification

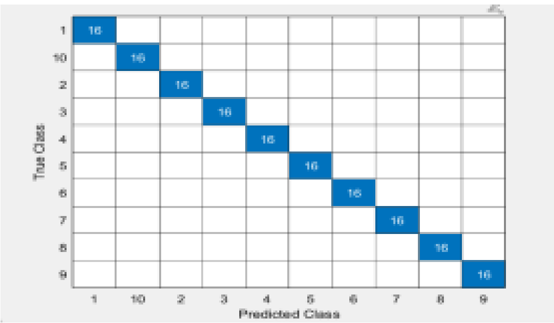

Fig.35: Plant Disease Related Confusion

Matrix Image

The above figures form Fig.4.30 to Fig.4.35 show the model's training and results, including learning progress, performance metrics, predicted plant and disease outputs, and confusion matrices that indicate accuracy through correct classifications. They demonstrate that the model can effectively identify both plant types and their diseases. Overall, the results confirm good accuracy and reliable performance of the system.

Conclusion:

In conclusion, this project presents an effective multi-stage approach for plant leaf disease classification using deep CNN and image segmentation techniques. The system identifies plant species and detects diseases through preprocessing, K-means clustering, and a hybrid CNN model. It achieves strong performance with 96.8% accuracy, 95.9% precision, 96.3% recall, and a 96.1% F1-score, along with low loss. The model is reliable and consistent across different plant classes. Additionally, it provides fertilizer recommendations, helping improve crop health and productivity. Overall, the proposed system offers a robust solution for early disease detection and efficient agricultural management. .

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