Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

Deep Learning-Based Classification of Eggplant Leaf Diseases Using Fine-Tuned CNN Models

Md. Maruful Islam Rafe
Computer Science and Engineering
Netrokona University
Netrokona, Mymensingh, Bangladesh
maruful.rafe.mr@gmail.com

Shanto Babu Sarker
Computer Science and Engineering
Netrokona University
Netrokona, Mymensingh, Bangladesh
shanto.shu.cse@gmail.com

Abdullah Al Shiam
Computer Science and Engineering
Netrokona University
Netrokona, Mymensingh, Bangladesh
shiam.cse@shu.edu.bd

***Abstract*— Eggplant, or aubergine, is an essential crop prized for its nutritional and economic value. However, its growth is frequently obstructed by leaf diseases that greatly impact yield and quality. Timely and precise identification of these diseases is key for efficient management and sustainable farming. This study leverages deep learning techniques to classify eggplant leaf diseases using convolutional neural network (CNN) models. A curated dataset of 3,159 high-resolution images from Mendeley was used, categorized into seven classes: Healthy Leaf, Wilt Disease, Small Leaf Disease, White Mold Disease, Mosaic Virus Disease, Insect Pest Disease and Leaf Spot Disease. Preprocessing techniques, including dataset augmentation and gamma correction, were applied to improve dataset quality and variability. The fine-tuned ResNet50 model achieved high accuracy of 97.01%. Its structure was improved with a Global Average Pooling layer and a Fully Connected layer with 1024 units for better feature extraction and classification. Training optimization involved Early Stopping and Model Checkpoint callbacks to prevent overfitting and improve convergence. The results obtained validate the superiority of the fine-tuned model over the recently developed model.**

***Keywords*—Eggplant leaf diseases, Deep learning, ResNet50, Inception V3, Preprocessing techniques.**

I. INTRODUCTION

This study emphasizes the transformative capabilities of deep learning in agriculture, particularly in classifying eggplant leaf diseases, including Healthy Leaf, Wilt Disease, Small Leaf Disease, White Mold Disease, Mosaic Virus Disease, Insect Pest Disease and Leaf Spot Disease, which significantly impact crop yield and quality. Advanced convolutional neural networks (CNNs) were employed to address these challenges.

Various preprocessing techniques, including data augmentation and gamma correction, were applied to improve dataset quality and variability. The fine-tuned ResNet50 model, which includes a Global Average Pooling layer and a Fully Connected layer with 1024 units, achieved an accuracy of 97.01%, surpassing other models in performance. Training optimization involved the implementation of Early Stopping and Model Checkpoint callbacks to prevent overfitting and ensure efficient convergence.

II. RELATED WORKS

For instance, Haque and Sohel demonstrated the effectiveness of deep networks using score-level integration and transfer learning for plant disease recognition [2, 5]. Similarly, Abisha et al. emphasized the advantages of DenseNet201's dense connectivity for gradient flow and feature extraction [7]. Data enhancement methods, including horizontal flipping, zooming, and rescaling, along with preprocessing steps like gamma correction and contrast stretching, were used to enhance input data quality [4][6]. Measures such as accuracy, precision, recall, and F1-score validated DenseNet201's robust performance compared to other architectures like Inception V3 [7, 9]. García-Fortea et al. highlighted the significance of these metrics in developing automated agricultural systems [9]. Suryavanshi et al. emphasized federated learning's potential in addressing food security and promoting sustainable farming practices [12].

III. RESEARCH METHODOLOGY

This research assesses the effectiveness of fine-tuned ResNet50 and Inception V3 for image categorization. The dataset was resized, normalized, and augmented with techniques like horizontal flipping, zooming, and rotation to enhance diversity and generalization. The dataset was divided into training, validation, and testing sections, and the models were fine-tuned using transfer learning. ResNet50 included Global Average Pooling (GAP) and Fully Connected layers, optimized with the Adam optimizer (learning rate: 0.001), while Inception V3 was enhanced for better feature extraction.

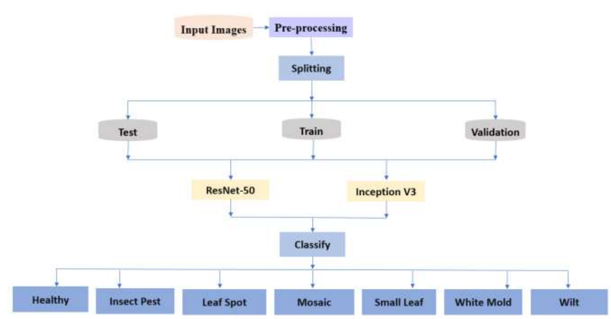

Fig. 1. Workflow Diagram.

Training utilized TensorFlow with GPU acceleration, incorporating batch normalization, dropout, and early stopping to avoid overfitting. Measures like accuracy, precision, recall, and F1-score demonstrated the robustness of both models in advancing precision agriculture and automated disease detection. The following Fig. 1 represents the workflow diagram.

A. Dataset Description

The dataset for this study was collected from Mendeley Data [13]. As outlined in Table I, it consists of 3,159 images distributed across seven categories: Healthy Leaf (536 images), White Mold Disease (64 images), Leaf Spot Leaf (896 images), Wilt Disease (496 images), Small Leaf Disease (112 images), Insect Pest Leaf (767 images) and Mosaic Virus Disease (288 images). The dataset was divided into three portions: 70% (2268 images) for training, 20% (636 images) for testing, and 10% (255 images) for validation. Preprocessing steps, including data augmentation and gamma correction, were implemented to enhance the quality of the dataset and prepare it for training.

TABLE I. DATASET SPLIT FOR TRAINING, TESTING, AND VALIDATION

Training Data	Testing Data	Validation Data
2268	636	255

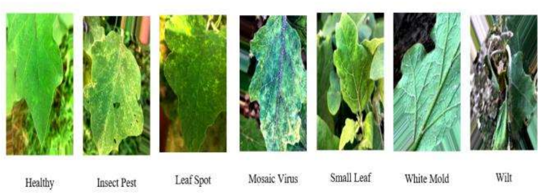

Fig. 2. Sample images in different categories.

Following Table II represents the total number of training images in different classes.

TABLE II. TRAINING DATASET DESCRIPTION

Disease Categories	Sample Data
Healthy	536
Small Leaf	112
Leaf Spot	896
Wilt	496
Insect Pest	767
White Mold	64
Mosaic Virus	288

B. Data Pre-processing

The dataset consists of RGB images that were resized to 224×224 for the ResNet50 model and 256×256 for the Inception V3 model. Pixel values were standardized to the range [0, 1] by rescaling with a factor of 1/255. Data enhancement methods, including horizontal flipping, zooming, and rotation (up to 20°), were applied to improve image quality by adjusting brightness and enhancing contrast. The dataset was partitioned into three sections: 70% for training, 20% for testing, and 10% for validation. This allocation guaranteed a fair and thorough assessment of the model's performance.

C. Feature Extraction

The feature extraction technique in this study organizes and condenses raw data into meaningful representations using advanced image processing and transfer learning. The ResNet50 model was fine-tuned to extract essential features for classifying eggplant leaf diseases. ResNet50's architecture includes residual connections, convolutional layers, batch normalization, ReLU activation functions, Global Average Pooling (GAP), and fully connected layers. Input images, resized to 224×224×3 dimensions, pass through these layers to capture intricate features representing the data. A batch size of 32 was used during batch normalization to stabilize training and improve convergence. Custom Dense layers and a Softmax activation layer were added for categorization into seven categories. The pre-trained ResNet50 facilitated efficient feature extraction, reducing the need for training from scratch and enhancing classification performance.

D. Classification

This study utilized a dataset comprising 3,159 images of eggplant leaf diseases, split into 2,268 images for training, 636 for testing, and 255 for validation. Two deep learning models, ResNet50 and Inception V3, were employed for the classification task. These models were fine-tuned to improve their performance, enabling accurate classification of eggplant leaf diseases. The fine-tuning process was instrumental in enhancing classification accuracy, with ResNet50 achieving the highest accuracy of 97.01%.

a. ResNet-50

The ResNet50 model, a 50-layer Residual Network, was fine-tuned to improve classification accuracy for seven categories of eggplant leaf diseases. It processes 224×224 RGB images using pre-trained ImageNet weights for transfer learning. The architecture was enhanced with Global Average Pooling (GAP), Fully connected layers, and a Softmax activation layer for classification. Data enhancement methods, such as horizontal flipping, zooming (0.2), rotation (20°), and width/height shifting (0.1), improved dataset diversity. Fine-tuning was applied to optimize feature extraction and enhance model performance. During training, a batch size of 32 was employed with the Adam optimizer (learning rate: 0.001) and categorical cross-entropy loss function. A dropout ratio of 0.3 helped prevent overfitting, while L2 weight decay (0.0001) improved generalization. Training ran for 20 epochs, with early stopping (patience: 5 epochs) to optimize efficiency. ReLU activation was applied in hidden layers and Softmax in the output layer. GPU acceleration ensured faster convergence, allowing the fine-tuned ResNet50 to achieve 97.01% accuracy, demonstrating its effectiveness in automated agricultural disease-management.

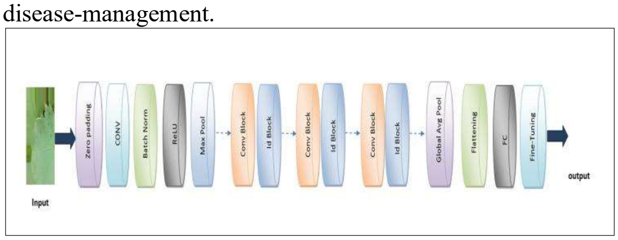

Fig. 3. ResNet-50 model process diagram.

b. Inception V3

The Inception V3 model, a CNN, was fine-tuned to improve classification accuracy for seven categories of eggplant leaf diseases. It processes 256×256×3 RGB images using pre-trained ImageNet weights for transfer learning. The architecture incorporates 1×1, 3×3, and 5×5 convolutions with pooling operations, enabling multi-scale feature learning. Global Average Pooling (GAP) layer, auxiliary classifiers, and a Softmax activation layer enhance classification performance. During training, a batch size of 32 was utilized with the Adam optimizer (learning rate: 0.0005) and categorical cross-entropy loss function. A dropout percentage of 0.4 and L2 weight decay (0.0001) improved generalization, while early stopping (patience: 7 epochs) prevented overfitting. Training ran for 30 epochs, using ReLU activation in hidden layers and Softmax in the output layer. GPU acceleration enabled efficient training, helping the fine-tuned Inception V3 model achieve high accuracy.

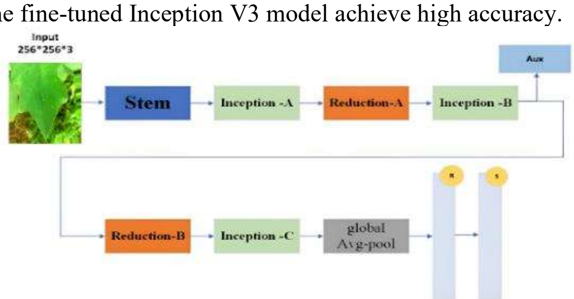

Fig. 4. Architecture of Inception V3 model.

E. Equations

Based on the fine-tuning process typically implemented in ResNet50, here's how the equation can be described:

Let X represent the input image with dimensions 224×224×3 and Y represent the output probabilities for the seven classes of eggplant leaf diseases. The overall function of the fine-tuned ResNet50 can be expressed as:

1. Input Processing: The input image X of size 224×224×3 is passed into the ResNet50 feature extractor. The ResNet50 layers extract high-level feature representations F:

$$F = ResNet50(X, \theta) \quad (1)$$

2. Global Average Pooling (GAP): The extracted feature map F (with dimensions H×W×C, where H and W represent the spatial dimensions, and C denotes the number of channels) is reduced to a vector V using Global Average Pooling:

$$V_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F_{i,j,c} \quad \text{for c=1,2,…,C} \quad (2)$$

Here, V is a 1×C vector.

3. Fully Connected Layer: The pooled feature vector V is passed through a fully connected Dense layer with weights W_2 and biases b_2 to produce the logits Z:

$$Z = W_2 . V + b_2 \quad (3)$$

where W_2 is a matrix of dimensions C×7 (for 7 output classes), and b_2 is a bias vector of size 7.

4. Softmax Activation**:** The logits Z are converted into probabilities Y using the Softmax function:

$$Y_k = \frac{exp(Z_k)}{\sum_{j=1}^{7} exp(Z_j)} \quad \text{for k= 1,2,…,7} \quad (4)$$

where Yk denotes the predicted likelihood for the k-th class.

5. Final Output: The final output Y is a probability vector:

$$Y = [Y_1, Y_2, ..., Y_7] \quad (5)$$

where each Y_k represents the likelihood of the image being assigned to class k, and the sum of all Y_k is 1.

These equations describe the complete forward pass of the fine-tuned ResNet50 model, from input image processing to classification.

IV. Result and Analysis

This study underscores the importance of accuracy and reliability in model evaluation, with conclusions based on rigorous performance metrics. Using early stopping, the models ran for 20 epochs for ResNet50 and 30 epochs for Inception V3 with fine-tuning, demonstrating high classification performance. Fine-tuned ResNet50 attained an accuracy of 97.01%, whereas fine-tuned Inception V3 reached 93.87%. Despite challenges such as dataset biases and algorithmic inefficiencies, ResNet50's residual connections enhanced gradient flow and feature extraction, making it highly effective for classifying eggplant leaf diseases. Similarly, Inception V3's multi-scale feature learning through its parallel convolutional paths contributed to its reliable performance. These results highlight the impact of fine-tuning and advanced architectures in achieving robust classification outcomes. Table III represents the effectiveness of the model with and without optimization.

TABLE II. Performance Comparison Of Fine-Tuned And Without Fine-Tuned Models

Name	Accuracy	Precision	Recall	F1-score	Specificity
ResNet-50 (Fine-Tuned)	97.01	98.28	98.22	98.26	97.08
ResNet-50 (Without Fine-Tuned)	95	96.42	96.40	96.45	95.46
Inception V3 (Fine-Tuned)	94.24	92.33	90.21	90.36	89.22
Inception V3 (Without Fine-Tuned)	93.87	91.41	89.44	90.65	88.23

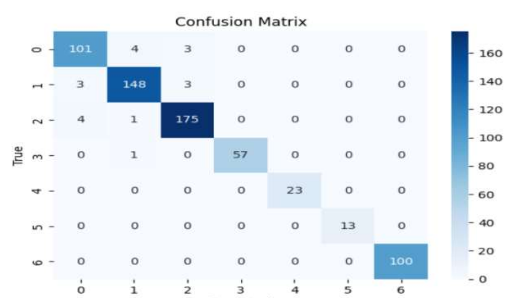

Fig. 5. Confusion Matrix of Fine-Tuned ResNet50.

Fig. 6 demonstrates the training and validation accuracy for the models. The x-axis denotes the number of epochs, while the y-axis represents the accuracy for both training and validation sets. ResNet50 achieved a validation accuracy of 96.86%, followed by Inception V3 at 91.76%. Also Fig. 7 illustrates the training and validation loss for the models. Optimized ResNet50 reached a test accuracy of 97.01% with a loss of 9.22%, while Fine-tuned Inception V3 recorded an accuracy of 93.87% with a loss of 17.93%. Table IV compares these findings with prior studies.

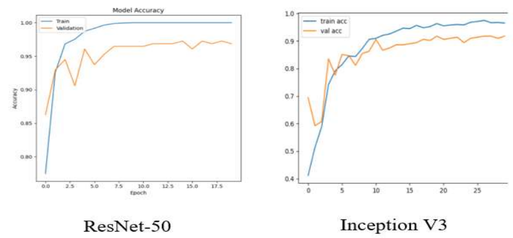

Fig. 6. Training and validation accuracy of all algorithms.

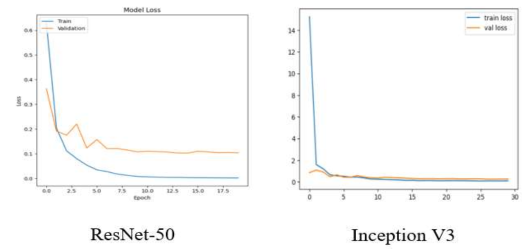

Fig. 7. Training and validation loss of all algorithms.

TABLE IV. COMPARISON WITH PRIOR STUDIES

Author(s)	Architecture used	Accuracy
Krishnaswamy R. Aravind et al. 2019 **[3]**	Deep learning	93.33%
Vikrant Sharma et al. 2023 **[11]**	CNN	94.77%
Nasution, S. W. et al. 2022 **[1]**	YOLO Algorithm	92.85%
Rangarajan, A. K. et al. 2020 **[6]**	Machine learning	94.87%
This study	Deep learning	97.01%

Preprocessing techniques improved accuracy, with this study achieving 97.01% accuracy using a fine-tuned ResNet50 model.

V. CONCLUSIONS

This study showcases the efficacy of optimized deep learning models in precisely identifying eggplant leaf diseases. The ResNet50 model attained an outstanding accuracy of 97.01%, showcasing its robustness in feature extraction and classification. Similarly, Inception V3 delivered reliable performance with an accuracy of 93.87%. The application of advanced preprocessing techniques, including data augmentation and gamma correction, coupled with fine-tuning of the models, significantly enhanced classification accuracy. Future research should concentrate on using larger and more varied datasets to enhance the models' ability to generalize. Moreover, developing a user-friendly application for real-time disease detection can provide practical solutions for farmers, aiding in efficient crop management and reducing the excessive use of pesticides. To conclude, this research emphasizes the promise of ResNet50 and Inception V3 models in enhancing agricultural technology and promoting precision farming practices, contributing to sustainable and efficient disease management in agriculture.

REFERENCES

[1] Nasution, S. W., & Kartika. (2022). Eggplant Disease Detection Using YOLO Algorithm Telegram Notified. International Journal of Engineering, Science & Information Technology, 2(4), 127–132. https://doi.org/10.52088/ijesty.v1i4.383

[2] Haque, M. R., & Sohel, F. (2022). Deep network with score level fusion and inference-based transfer learning to recognize leaf blight and fruit rot diseases of eggplant. Agriculture, 12(8), 1160. https://doi.org/10.3390/agriculture12081160

[3] Aravind, K. R., Raja, P., Ashiwin, R., & Mukesh, K. V. (2019). Disease classification in Solanum melongena using deep learning. Spanish Journal of Agricultural Research, 17(3), e0204. https://doi.org/10.5424/sjar/2019173-14762

[4] Rangarajan, A. K., & Purushothaman, R. (2020). Disease classification in eggplant using pre-trained VGG16 and MSVM. Scientific Reports, 10, 2322. https://doi.org/10.1038/s41598-020-59108-x

[5] Saad, I. H., Islam, M. M., Himel, I. K., & Mia, M. J. (2022). An automated approach for eggplant disease recognition using transfer learning. Bulletin of Electrical Engineering and Informatics, 11(5), 2789–2798. https://doi.org/10.11591/eei.v11i5.3575

[6] Xie, C., & He, Y. (2016). Spectrum and image texture features analysis for early blight disease detection on eggplant leaves. Sensors, 16(5), 676. https://doi.org/10.3390/s16050676

[7] Abisha, S., Mutawa, A. M., Murugappan, M., & Krishnan, S. (2023). Brinjal leaf diseases detection based on discrete Shearlet transform and deep convolutional neural network. PLoS ONE, 18(4), e0284021. https://doi.org/10.1371/journal.pone.0284021

[8] Jayanthi, M. G., Shashikumar, D. R., & Preethi, S. (2022). Eggplant leaf disease detection and segmentation using adaptively regularized multi kernel-based fuzzy C-means and optimal PNN classifier. Indian Journal of Computer Science and Engineering, 13(5), 1542–1558. https://doi.org/10.21817/indjcse/2022/v13i5/221305073

[9] García-Fortea, E., García-Pérez, A., Gimeno-Páez, E., Sánchez-Gimeno, A., Vilanova, S., Prohens, J., & Pastor-Calle, D. (2020). A deep learning-based system (Microscan) for the identification of pollen development stages and its application to obtaining doubled haploid lines in eggplant. Biology, 9(9), 272. https://doi.org/10.3390/biology9090272

[10] Jain, S., & Ali, K. B. (2022). Brinjal Disease classification using deep learning. 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 1–5. https://doi.org/10.1109/icrito56286.2022.9965112

[11] Sharma, V., Kukreja, V., Mehta, S., & Choudhary, A. (2023). Severity Stratification of Brinjal Leaf Diseases: A Federated Learning CNNs Approach. Severity Stratification of Brinjal Leaf Diseases: A Federated Learning CNNs Approach, 1–6. https://doi.org/10.1109/icstcee60504.2023.10584836

[12] Suryavanshi, A., Kukreja, V., Srivastava, P., Mehta, S., & Joshi, K. (2024). Smart Farming: Integrated Federated Learning CNNs for Brinjal Leaf Disease Detection. Smart Farming: Integrated Federated Learning CNNs for Brinjal Leaf Disease Detection, 1–6. https://doi.org/10.1109/iatmsi60426.2024.10503064

[13] Matin, Md Mafiul Hasan, Mst Ava, Arifa Anjum, and Mohammad Shorif Uddin. "A Dataset for Accurately Identifying Eggplant Diseases." Golam Moazzam and Uddin, Mohammad Shorif, A Dataset for Accurately Identifying Eggplant Diseases.