Comparative study of deep learning approaches for cucumber disease classification

Supreetha Shivaraj, Manjula Sunkadakatte Haladappa
Departement of Computer Science Engineering, University of Visvesvaraya College of Engineering (UVCE) Bangalore, Bangalore, India

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ABSTRACT

Cucumber leaf diseases, such as downy mildew and leaf miner, pose significant challenges to crop yield and quality. Accurate and timely detection is essential to efficient management. The current research assesses seven convolutional neural network (CNN) models for the classification of diseases of cucumber leaves: DenseNet121, InceptionV3, ResNet50V2, VGG16, Xception, MobileNetV2, and NASNet. The dataset includes images from the cucumber disease recognition dataset (Mendeley) and 500 real-time images captured between December 2022 and February 2023 in Karnataka, covering varied lighting conditions. After augmentation, the dataset is divided into testing, validation, and training sets and includes 804 leaf miner, 807 downy mildew, and 804 healthy images. With an overall test accuracy of 99.37% and nearly flawless precision, recall, and F1-scores in every class, ResNet50V2 showed exceptional performance. InceptionV3 and MobileNetV2 also exhibited strong performance with accuracies of 97.29% and 97.70%, respectively. DenseNet121, VGG16, Xception, and NASNet performed well but were slightly outperformed by the top models. The findings indicate ResNet50V2 as the most reliable model for cucumber leaf disease classification, providing a robust foundation for developing automated disease detection systems. This work demonstrates how precise disease detection using deep learning models can improve agricultural management.

Corresponding Author:

Supreetha Shivaraj
Department of Computer Science Engineering
University of Visvesvaraya College of Engineering (UVCE) Bangalore
Bangalore 560001, Karnataka, India
Email: supreetha.s3191@gmail.com

1. INTRODUCTION

India's agricultural sector is the backbone of its rural economy, making agriculture and its allied sectors a significant source of income. One of the pressing challenges is raising agricultural productivity, which is severely impacted by plant diseases. These diseases reduce crop yield and quality, leading to financial losses. Visual inspection and laboratory testing are labor-intensive and time-consuming traditional disease detection methods. Owing to these methods' limitations, there is a growing need for efficient, automated solutions, especially to meet the world's growing food demand as a result of population growth [1]. Worldwide, cucumbers (Cucumis sativus) are farmed for their nutritional and commercial worth. Unfortunately, diseases like leaf miner and downy mildew pose serious obstacles to cucumber farming because they can negatively affect crop quality as well as yield. Early and accurate disease detection is crucial for the efficient management and control of these diseases, as well as for ensuring healthy crop production and minimizing losses [2]. Automated disease detection using advanced technologies has attracted significant attention as a result of this. Convolutional neural networks (CNNs), in particular, have emerged as the leading technology due to their ability to learn hierarchical image features, making them ideal for detecting subtle differences between healthy and diseased leaves. The application of CNNs in the detection of diseases in plants is the topic of interest of many studies. Ma *et al.* [3] developed a deep convolutional neural network (DCNN) based on its symptoms for cucumber disease detection. Four diseases (anthracnose, downy mildew, powdery mildew, target leaf spots) produced by segmenting the disease symptoms from field-captured leaf images were included in the dataset. The DCNN's performance was compared with AlexNet and traditional classifiers. In balanced and unbalanced data, the DCNN achieved high recognition accuracies of 92.2% and 93.4%. While both models significantly outperformed conventional classifiers, comparative tests revealed that AlexNet performed well in comparison with the DCNN due to its richer feature representations. Zhang *et al.* [4] proposed GPDCNN, a novel deep learning architecture, for classifying cucumber disease. It incorporates global pooling layers to gather multiscale contextual information, boosting recognition rates and speeding convergence, and dilated convolutional layers to extend the receptive field without losing resolution. GPDCNN demonstrated state-of-the-art performance on datasets comprising of images of damaged cucumber leaves. The authors highlighted the use of probabilistic graphical models in the future to further improve the model's ability to identify diseases in crops. Khan *et al.* [5] proposed an advanced segmentation method to accurately detect cucumber leaf disease spots. Using three statistical parameters namely L-Entropy, L-SD, and IQR deep features are extracted before the selection step. In relation to the experimental results, the proposed deep feature selection method operates better than conventional methods and individual features remarkably. In addition, a significant advantage of the proposed method is its lower execution time.

Zhang *et al.* [6] carried out cucumber disease classification, namely powdery mildew, downy mildew, healthy leaves, and their combinations, using EfficientNet-B4 in a complex greenhouse environment. EfficientNet-B4 achieved an accuracy rate of 97% and had the ability to handle complex environmental conditions and distinguish among similar diseases. Li *et al.* [7] employed extended collaborative representation and hyperspectral imaging for classifying brown spot disease and cucumber anthracnose. Results indicate that to precisely and quickly identify diseases of cucumber leaves, the ECR-based classification model is more suitable. Jayanthi *et al.* [8] employed probabilistic neural networks and fuzzy C-means clustering for adaptive disease detection. Strong performance in segmentation and classification tasks especially while dealing with heterogeneous data was demostrated. Liu *et al.* [9] proposed a detection model, namely EFDet with strong robustness to improve the detection effect for cucumber disease leaves in background images with different complexity stages. EFDet has a smaller model size, lower GFLOPs, and a good mAP on the test set. The foundation for new research in real-life scenarios is laid by this work on improving model applicability. Kianat *et al.* [10] proposed a hybrid framework that combines feature fusion and selection methods for cucumber diseases classification. The most discriminant features were classified using multiple classifiers. Feature selection significantly increased accuracy by reducing redundancy while the framework achieved 93.5% accuracy. Future studies on developing a real-time app for infection localization was suggested. Mia *et al.* [11] compared traditional machine learning and transfer learning for classification of cucumber diseases. Before segmentation using k-means clustering and feature extraction, images were preprocessed by resizing, filtering, and contrast enhancement. MobileNetV2 from transfer learning performed superior with an accuracy of 93.23%, demonstrating the superiority of transfer learning for this task, while random forest (RF) achieved the highest accuracy of 89.93% among traditional ML models. The review of recent literature is provided in Table 1.

Table 1. Review of recent literature

Author	Year	Dataset	Technique used	Accuracy
Zhang *et al.* [12]	2021	Self-collected dataset	DICNN	96.11%
Kainat *et al.* [13]	2021	Local dataset with blended features	Fine KNN	94.6%
Wang *et al.* [14]	2021	Selfcollected dataset	DeepLabV3+ and U-Net	92.85%
Agarwal *et al.* [15]	2021	Dataset provided by Zhang *et al.* [16]	CNN	93.75%
Hussain*et al.* [17]	2022	Privately collected dataset	Fine-tuned VGG and Inception V3	96.5%
Liu *et al.* [18]	2022	Self-built dataset	ADDLight	89.1%
Current research	2024	Mendeley's cucumber disease recognition dataset and 500 real-time images	ResNet50V2	99.37%

It is still difficult to identify cucumber diseases in a timely and accurate manner, despite advances in agricultural technology. The process of identification is made more difficult by the variation in disease symptoms and environmental factors. An automated, effective, and dependable system that uses real-time data to classify cucumber diseases especially, downy mildew and leaf miner is desperately needed. Using state-of-the-art deep learning and lightweight models, an automated system is proposed to classify diseases affecting cucumbers. In order to increase generalizability, real-time images and the cucumber disease recognition dataset (Mendeley) were combined to produce a more challenging and varied dataset. In the current research 500 real-time images captured in Karnataka under different lighting conditions is incorporated in comparison to earlier studies that employed carefully picked datasets. It makes the model more robust in real-world situations by filling a gap that previous research failed to address. A single model or limited number of models used to be the focus of prior studies, leaving gaps in the understanding of the relative performance of various architectures.

ResNet50V2 achieved an exceptional 99.37% accuracy in cucumber leaf disease detection setting a new benchmark. This work surpasses previous standards, especially in terms of precision, recall, and F1-scores, and establishes nearly flawless performance across all classes, in comparison to previous studies that achieved high accuracy.

2. METHOD

The method used in the comparative study of cucumber leaf disease detection are divided into discrete stages, each of which is an essential component of the entire process. The phases involved in the comparative study of deep learning approaches for the classification of cucumber diseases is represented by the flowchart in Figure 1.

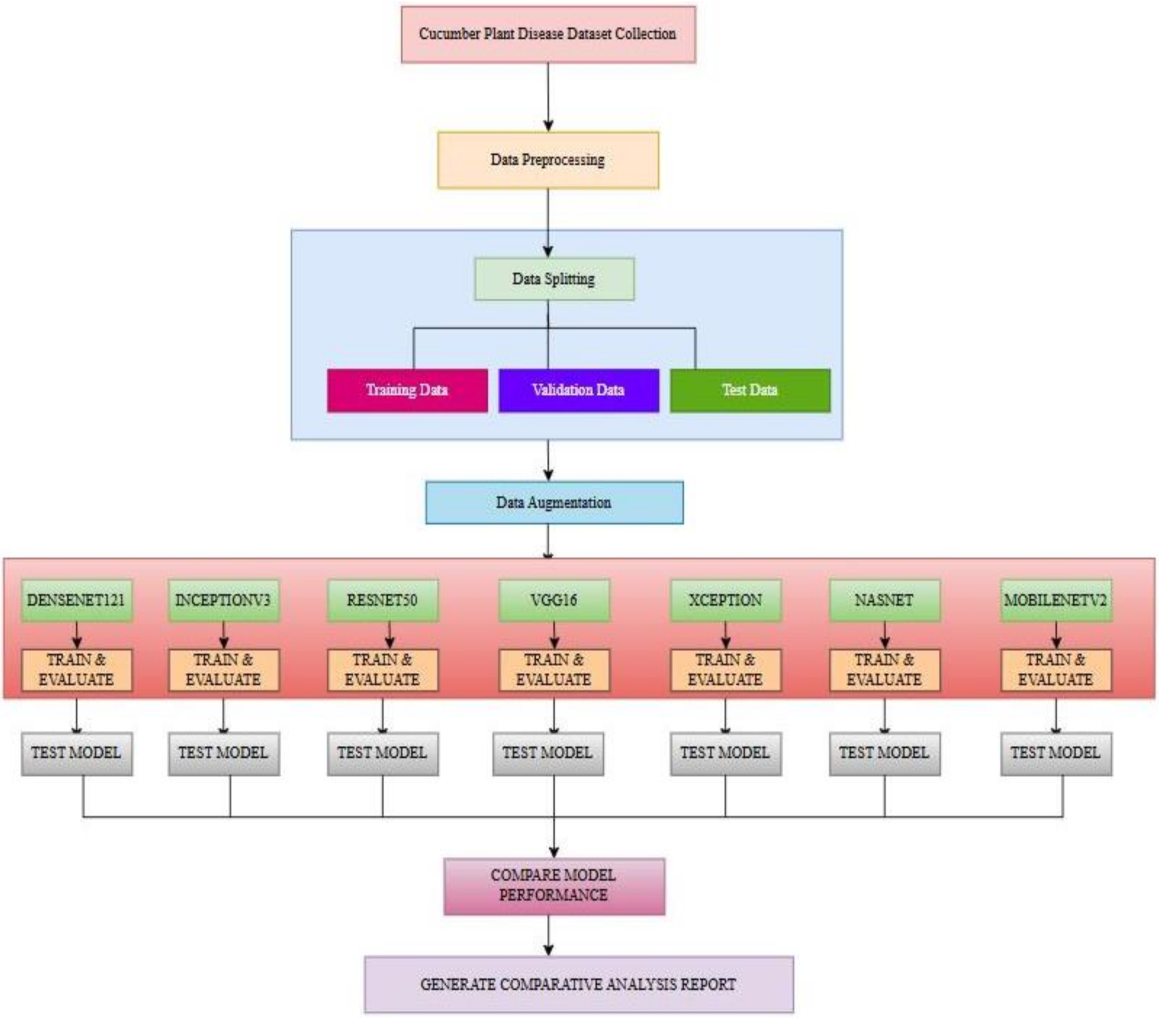

Figure 1. Phases in a comparative analysis of deep learning methods for classifying cucumber diseases

2.1. Cucumber plant disease dataset collection

The first step is data preparation. Gathering images of cucumber disease leaves from primary and secondary sources is the first step in this process, known as data collection. Images of cucumber disease from the cucumber disease recognition dataset (Mendeley) [19] are included in the secondary dataset used in this experiment. About 500 real time images were captured between December 2022 and February 2023 in the farms of Karnataka, taking into account the range of lighting circumstances present in practical applications. The images were categorized into three types: diseased leaves with downy mildew, leaf miner, and healthy cucumber leaves. By incorporating diverse data from secondary sources as well as real-time field images captured under different lighting conditions the model generalizability can be enhanced along with achieving real-world relevance. The Figure 2 represents the sample images of healthy, downy mildew and leaf miner diseases. The dataset consists of 804 leaf miner images, 807 downy mildew images and 804 healthy images after augmentation.

DOWNY MILDEW LEAF MINER HEALTHY

Figure 2. Illustrative images of downy mildew, leaf miner and healthy leaf in cucumber

2.2. Data preprocessing

The next step in preparing the dataset for analysis is called data preprocessing, which includes resizing images, and normalizing pixel values. The pixel values of the images are rescaled by 1./255 to normalize the data to the range [0, 1]. Image resizing and normalization provide consistent gradient flow during training and efficient processing by deep learning models by standardizing input dimensions and scale.

2.3. Data splittin

Data splitting is the process of dividing a dataset into test, validation, and training sets. This is required for training, optimizing hyperparameters, and assessing the model's performance on untested data. A defined function handles the splitting process. It requires the original directory, test directory, train directory, and validation directory as inputs. Using predefined ratios (20% for the test and 20% for validation of the residual data), the data is divided into sets for testing, validation, and training. Table 2 consists of details of the dataset.

Table 2. Details of the dataset

Type of leaf	TRAIN	TEST	VALID
Downy mildew	516	162	129
Healthy	515	161	128
Leaf miner	515	161	128

2.4. Data augmentation

Following the division of the dataset, data augmentation is applied to the training set using ImageDataGenerator. During training, the augmented images are produced in real time and are not saved to disk. Numerous changes are made to the images, such as rescaling, rotation, shearing, zooming, flipping them horizontally, and changing their width and height. Random shifts of up to 20% of the total width and height, as well as random rotations of up to 40 degrees, are applied to the images. Shear transformations are applied with up to a 20% zoom in and out at a shear intensity of 0.2. To fill in newly created pixels following transformations and horizontal flips, the fill mode is set to 'nearest'. The test and validation datasets are just rescaled, not expanded further. The images are resized to (224, 224) after being batched at size 32. The class mode is set to 'categorical' in order to classify more than one class. The augmentation techniques prevent overfitting and improves the robustness of models against unseen data by simulating real-world variability.

2.5. Model selection, training, testing, and validation stage

The fourth step involves selecting and training models. Selecting specific deep learning models for comparison, such as DenseNet121, InceptionV3, ResNet50, VGG16, Xception, NASNet, and MobileNetV2, is the first step in the model selection process [20]. Efficient use of computational resources and fast convergence is assured by the use of pre-trained deep learning architectures like DenseNet121 [21], ResNet50 [22], and InceptionV3 [23]. In the training and evaluation stage, every model undergoes training on the training dataset, and its accuracy is assessed through evaluation using the validation and test datasets.

2.5.1. Deep convolutional neural network model

In the field of cucumber disease detection, a number of DCNN models [24] can be utilized to increase diagnostic efficiency and accuracy. We evaluated the performance of various cutting-edge DCNNs for the identification of downy mildew, leaf miner, and healthy cucumber leaves in the field of cucumber disease detection. Understanding model operations and performance is aided by a number of important equations and diagrams in the analysis of DCNN models for cucumber disease detection. The core DCNN operation, convolution, is described as follows:

$$(IK)(i,j) = \sum_m \sum_n I(i + m, j + n).K(m,n) \tag{1}$$

where K is the kernel and I is the input image. Intricate patterns can be modeled by the network using ReLU, which is represented by (2), and additional activation functions that introduce non-linearity.

$$ReLU\ (x) = max(0, x) \tag{2}$$

Pooling operations highlight key features by reducing spatial dimensions and is presented by (3).

$$P(i,j) = \max_{m,n} I(i + m, j + n) \tag{3}$$

In 4 provides the computation of categorical cross-entropy loss for model evaluation,

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{4}$$

where y_i is the true label and $y\hat{}_i$ is the predicted probability.

Due to their unique architectures and performance characteristics, DenseNet121, InceptionV3, ResNet50, VGG16, Xception, NASNet, and MobileNetV2 were selected for the classification of cucumber diseases.

2.6. Compare model performance and generate comparative analysis report

Reporting and Comparison is the fifth stage. Each model's performance is compared in this phase to ascertain its relative efficacy. This entails combining the evaluation results and contrasting the various models' performance metrics.

2.6.1. Performance metrics

Several significant metrics, including precision, recall, F1-score, and overall test accuracy, are used to assess the effectiveness of the suggested models for detecting cucumber disease [25]. Precision quantifies the degree to which the model's positive predictions are accurate, indicating the proportion of predicted positive cases that are in fact positive, as defined by (5).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{5}$$

Recall evaluates the ability of the model to detect all real positive cases by displaying the percentage of true positives that are correctly detected, as given by (6).

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{6}$$

A single metric that balances precision and recall is provided by the F1-score as given by (7), which is especially helpful when dealing with unbalanced datasets.

$$F1 - Score = \frac{2 * (Precision * Recall)}{Precision + Recall} \tag{7}$$

The percentage of correctly classified instances among the total instances is represented by the overall test accuracy, which is given by (8).

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (8)$$

Creating a comparative analysis report, which summarizes the results and offers insights into which model works best for the task of detecting cucumber leaf disease, is the last step in this phase.

2.7. Experimental setup

2.7.1. Software and hardware requirements

Python 3.8 or later is required. Important Python libraries are scikit-learn for machine learning tasks, Matplotlib for plotting, NumPy for numerical operations, and TensorFlow for deep learning. A machine with a GPU is highly recommended for optimal performance, particularly during model training. GPUs and TPUs are freely accessible through Google Colab, which can greatly accelerate training. All the code execution in this study was carried out in the Google Colab environment.

2.7.2. Details of model training

Data augmentation is applied to the training set using ImageDataGenerator in order to increase the model's resilience. This augmentation includes operations like rotation, horizontal flipping, shearing, zooming, and shifts in width and height. Weights pre-trained on ImageNet are used to instantiate each DCNN model, and include top=False is used to exclude the top classification layers. In this configuration, the models can be used as feature extractors. Three custom layers are then added: a dense layer with 128 units and ReLU activation, a dropout layer to prevent overfitting, and a flatten layer to convert 3D features to 1D. The categories of healthy, leaf miner, and downy mildew are added to the images by applying three units of a dense layer with SoftMax activation. While the new layers are being trained, the pre-trained features of the base model layers are preserved by freezing them. To enhance training convergence, a learning rate scheduler, denoted as lr schedule, dynamically modifies the learning rate. It begins at a given value and drops it exponentially after ten epochs. The models are assembled using the Adam optimizer, which is appropriate for multi-class classification, with an initial learning rate of 1e-3 and a loss function of categorical cross-entropy.

3. RESULTS AND DISCUSSION

The Table 3 provides a comparative analysis with DCNN models and Figure 3 provides accuracy and loss comparison between the different DCNN models. The study provides a thorough study of DCNN models for cucumber leaf disease detection, emphasizing the key pros and cons of the models used for the test. With a remarkable accuracy of 99.37% and high precision, recall, and F1-scores across all disease classes, ResNet50V2 has proved to be the most effective model.

The performance of this model demonstrates how trustworthy and appropriate it is for real agricultural applications where precision is critical. In a similar way, InceptionV3 and MobileNetV2 exhibited competitive results with respective accuracies of 97.29% and 97.70%. MobileNetV2 demonstrated phenomenal recall for leaf miner and healthy leaves, signifying that it could be used for deployment in resource-constrained environment. Although Xception gained 96.45% accuracy, it exhibited a slightly lower recall for downy mildew compared to InceptionV3 and ResNet50V2, highlighting potential for improvement. NASNet proved to be valid but less accurate comparatively than the top models, with an accuracy of 94.37%. DenseNet121 and VGG16 showed lesser recall for specific groups, such as leaf miner and downy mildew, even after achieving acceptable accuracies above 94%. The outcomes of these models indicate that they might yield false negatives.

A significant limitation is the absence of publicly available datasets for leaf miner detection, which directly impedes comparisons with other studies and highlights the need for standardized, publicly shared datasets. This limitation poses an opportunity for future research to focus on dataset development, which could lead in improvements in benchmarking and model improvements. The outcome of these findings are substantial. Crop losses can be reduced by adopting precision agriculture which is directly impacted by high performing models like ResNet50V2, which helps in early and accurate disease detection realizable. MobileNetV2's efficiency improves accessibility to farmers thus making it suitable for adopting in mobile or edge devices. Each model demonstrates convergence patterns, but ResNet50V2 performs superior in terms of accuracy and stability across epochs compared to other models in Figure 3 in Appendix.

Table 3. Comparative analysis with DCNN models

		DM	LM	H	Precision	Recall	F1-score	Support	Accuracy
DenseNet 121	DM	146	16	0	0.95	0.9	0.93	162	
	LM	2	159	0	0.89	0.99	0.94	161	0.9437(0.94)
	H	5	4	152	1	0.94	0.97	161	
InceptionV3	DM	156	6	0	0.97	0.96	0.97	162	
	LM	3	158	0	0.95	0.98	0.96	161	0.9729(0.97)
	H	2	3	156	1	0.97	0.98	161	
ResNet50V2	DM	160	2	0	0.99	0.99	0.99	162	
	LM	0	161	0	0.99	1	0.99	161	0.9937(0.99)
	H	1	0	160	1	0.99	1	161	
VGG16	DM	141	21	0	0.97	0.87	0.92	162	
	LM	0	161	0	0.88	1	0.94	161	0.9458(0.94)
	H	4	1	156	1	0.97	0.98	161	
Xception	DM	149	12	1	0.97	0.92	0.94	162	
	LM	3	158	0	0.93	0.98	0.95	161	0.9645(0.96)
	H	2	0	159	0.99	0.99	0.99	161	
MobileNetV2	DM	154	8	0	0.97	0.95	0.96	162	
	LM	0	161	0	0.95	1	0.98	161	0.9770(0.98)
	H	4	0	157	1	0.98	0.99	161	
NASNet	DM	154	7	1	0.96	0.95	0.95	162	
	LM	1	160	0	0.96	0.99	0.98	161	0.9437(0.94)
	H	6	0	155	0.99	0.96	0.98	161	

4. CONCLUSION

Real-time datasets are scarce in the field of identifying cucumber diseases. Frequently, images will be generated in a lab. Datasets from laboratory environments where individual leaves are isolated and photographed against uniform backgrounds, like white or black, are commonly used in the cucumber disease recognition domain. These datasets, however, frequently lack the complexity and diversity of actual field conditions. Therefore, in order to produce more representative training datasets, we have endeavored to gather and annotate field data and assessed the efficacy of various cutting-edge CNN models in the classification of diseases affecting cucumber leaves, particularly downy mildew, leaf miner, and healthy leaves on the same dataset. DenseNet121, InceptionV3, ResNet50V2, VGG16, Xception, MobileNetV2, and NASNet are among the models evaluated. With an excellent accuracy of 99.37% and good precision, recall, and F1-scores across all classes, ResNet50V2 turned out to be the most reliable among all the models evaluated. With respective accuracies of 97.29% and 97.70%, InceptionV3 and MobileNetV2 demonstrated strong classification capabilities, making them good alternatives, particularly in environments with limited resources. These findings significantly impact the domains of precision farming and agricultural technology. They authenticate that deep learning models, particularly ResNet50V2, have the potential to serve as a foundation for automated disease detection systems that can enable farmers to detect diseases early and take timely action. Improved crop yields, reduced pesticide consumption, and sustainable farming techniques might result from this. Future research should focus on optimizing these models for real-time deployment in diverse field conditions and scalability. Furthermore, sharing of annotated field datasets can encourage innovation and benchmarking in this field, leading in advancements that benefit the global agricultural community.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Supreetha Shivaraj	✓	✓		✓	✓	✓		✓	✓	✓				
Manjula Sunkadakatte Haladappa		✓			✓					✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Supreetha Shivaraj], upon reasonable request.

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APPENDIX

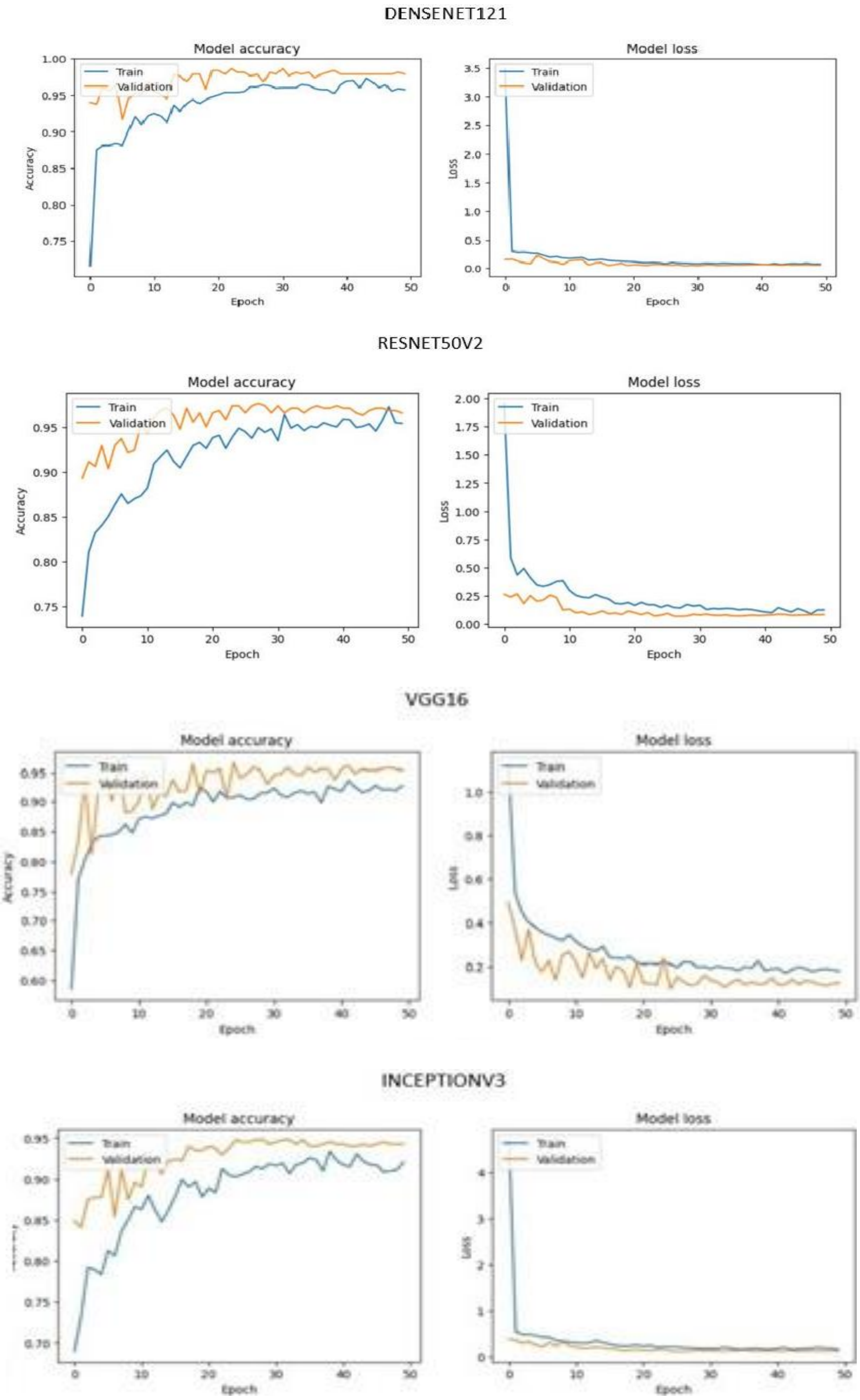

Figure 3. Accuracy and loss comparison between the different DCNN models

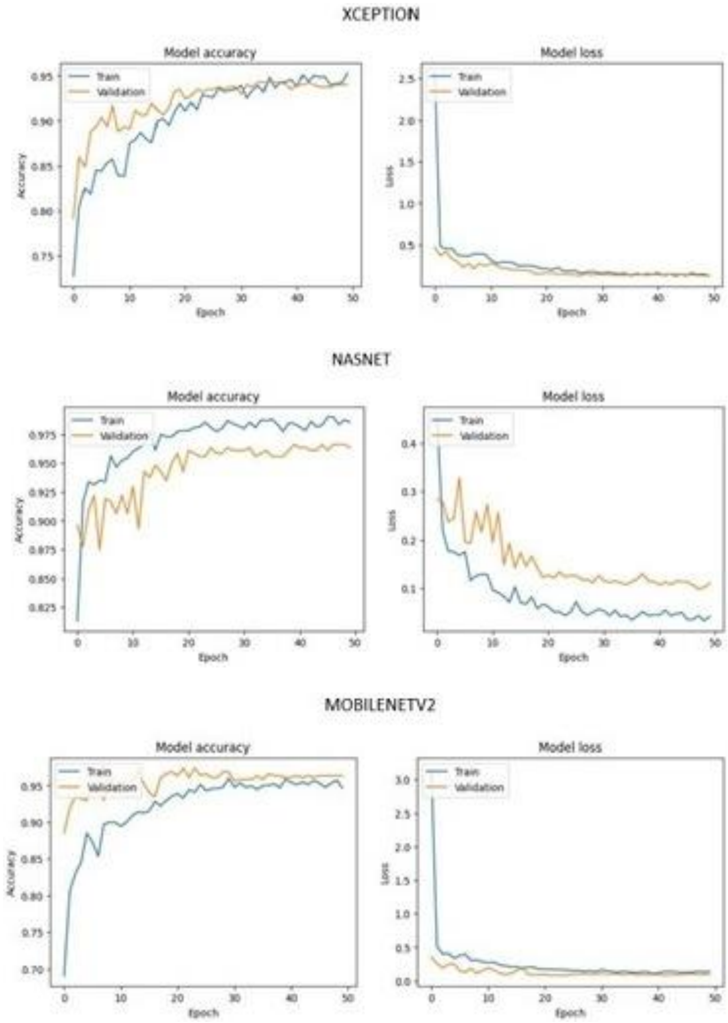

Figure 3. Accuracy and loss comparison between the different DCNN models (*Continued*)

BIOGRAPHIES OF AUTHORS

Supreetha Shivaraj is a research scholar in the Department of Computer Science and Engineering, University of Visveswaraya College of Engineering, Bengaluru, India. She completed her master's in engineering in Computer Network Engineering at the Oxford College of Engineering, Bengaluru, India. Completed her Bachelor's in Computer Science and Engineering from Government Sri Krishna Rajendra Silver Jubilee Tecnological Institute, Bengaluru, India. Currently, she is a part time research scholar pursuing the specialization "Efficient Deep Learning Technique for Plant Leaf Disease Detection". Her subject interests include artificial intelligence, machine learning, deep learning, computer networks and data privacy. She can be contacted at email: supreetha.s3191@gmail.com.

Manjula Sunkadakatte Haladappa currently a professor in the Department of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bangalore University, Bengaluru, has established herself as a prominent figure in the field. Holding a B.E., M.Tech., and Ph.D., in Computer Science and Engineering. She has honed her expertise in computer networks, wireless sensor networks, data mining, cloud computing, artificial intelligence, machine learning, and federated learning. With an impressive track record, she has authored 69 journals, presented 72 conference papers, holds 5 patents, and has contributed 4 book chapters while publishing 4 books, showing her profile and diverse contributions to the academic and technological community. Additionally, Dr. Manjula is currently a respected member of the Executive Council and has served as a former member of the Academic Senate at VTU Belagavi. She can be contacted at email: shmanjula@gmail.com.