

## NOVEL HYBRID MODEL USING DEEP LEARNING FOR LEAF DISEASE CLASSIFICATION :A COMPARATIVE STUDY

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### ABSTRACT

The implementation of appropriate control measures for leaf diseases depends on the early and accurate diagnosis of these diseases. Recent years have witnessed encouraging progress in using deep-learning models to classify leaf diseases from images. This study presents a comparison of many deep learning models for the categorization of leaf diseases. This research work was carried out at Khalsa College, Amritsar, Punjab in December 2023, using the Plant Village dataset, five commonly used deep learning models, including VGG16, VGG19, ResNet 50, InceptionV3 and Novel Hybrid model, were trained and assessed. Findings from this study suggest that a novel hybrid model outperformed the other deep learning models for leaf disease classification. The findings revealed potential of deep learning in early disease detection and classification, which can help farmers to apply timely disease control methods. Farmers can benefit from this research because it enables them to spot diseased leaves quickly and take measures to stop the disease from spreading. The models VGG16, VGG19, ResNet50 and InceptionV3 achieved 0.958, 0.978, 0.943, 0.946 accuracy respectively and novel hybrid exhibited the utmost accuracy of 0.986. Among the current models for detecting leaf diseases, the findings show that the Novel hybrid model outperformed the others with a 98.60% accuracy rate, according to the training assessment and model testing.

(Key words: Deep Learning (DL), Rectified Linear Unit (ReLU), Residual Neural Network (ResNet), VGG16, VGG19)

### INTRODUCTION

A positive step toward agricultural advancements is the development of artificial intelligence and machine learning. It is possible to estimate crop yield, fertilizer needs, and disease detection more accurately by analyzing massive geospatial data and extracting useful patterns (Sajan *et al.*, 2023). Among the most rapidly expanding technologies of the past decade, deep learning (DL) has sparked a revolution in several fields of approaches to data analysis and pattern detection. With deep learning, the key to success is learning the hierarchical properties of objects by stacking layers on top of each other (Mohanty *et al.*, 2016). The precise identification of leaf diseases has the potential to boost output and guarantee product quality in the agricultural sector. Most leaf diseases are too minute for farmers to notice, but properly trained machine models can identify them with a far higher degree of accuracy in less time than humans. Consequently, this study aimed to compare the accuracy of many deep learning models in order to determine the best model for disease prediction (Sladojevic *et al.*, 2016). With a high diagnostic ratio, the suggested innovative hybrid model attempts to classify the dataset by finding a significant feature in leaf images. To identify leaf diseases, experts mostly employ image processing techniques, which

include applying several processes to an image to improve its quality, draw attention to its characteristics, and ultimately aid in disease diagnosis (Turkoglu and Hanbay, 2019) variety of variables, such as poor soil quality, unfavorable crop choices, pest weeds, inadequate manure, and several plant diseases, can result in a range of plant infections and diseases. Contaminated plants can suffer anything from a little damage to their leaves or fruits to complete plant death due to infectious diseases caused by bacteria, fungi, and viruses (Kamilaris and Prenafeta-Boldu, 2018). To ensure that distinct classes were not oversaturated, the dataset was additionally augmented. In addition to enhancing models generalizability and anti-overfitting capabilities, data augmentation also yielded better outcomes in imbalanced classification problems (Ferentinos, 2018). The most popular deep learning models (Google Net and Alex Net) were applied in this research to classify leaf (Brahimi *et al.*, 2017).

The authors extracted almost 2000 images with a focus on cotton leaf disease diagnosis using deep learning. Several different kinds of classifiers were utilized in an effort to identify leaf diseases and classifying the numerous diseases that might affect cotton leaves (Memon and Iqbal, 2022). While implementing the model that was built, an accuracy of 98% was achieved. In order to differentiate between healthy and infected plant pictures, (Maniyath *et*

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*al.*, 2018) used feature extraction and random forest algorithms for plant disease diagnosis. The optimal results for data classification were achieved through the training of the classified data using machine learning. Analogously, Madiwalar and Wyawahare (2017) utilized image processing to address the issue of plant disorders in a similar manner. The extraction was carried out to diagnose plant disease based on leaf color and texture. An SVM classifier was used, and with the use of over a 100 images, an accuracy of 83% was achieved.

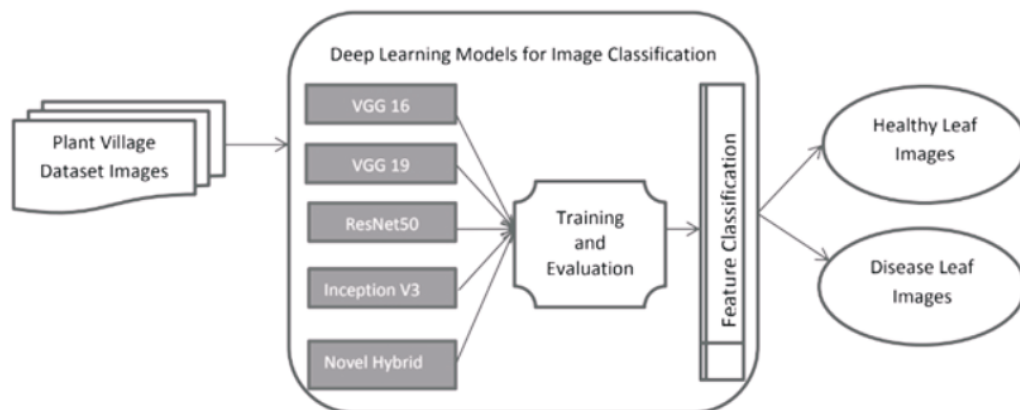
Thopate *et al.* (2023) created plant prediction system using Java by taking values for moisture, pH, temperature and humidity. The program generated a plant name that matches the input values and standard values of plants in a csv file by comparing the input values of soil taken and soil condition.

An image-segmentation-based CNN model for apple leaf disease diagnosis was proffered in a study by Nachtigall *et al.* (2016). The CNN model, trained using over 2000 images from an internet source, accurately differentiates between five different apple leaf diseases with a 78% success rate. 93% accuracy was achieved in disease identification using the KNN method, which was applied to 1200 photos for object categorization. In order to identify grape plant diseases, Santos *et al.* (2020) built a CNN model using instance segmentation and feature extraction. With

an 81% success rate, the investigators used a variety of designs, including a neural network and three-dimensional connections, to identify diseases in grape plants.

## MATERIALS AND METHODS

Models VGG-16, VGG-19, ResNet50, Inception V3 were selected due to their balanced combination of accuracy, computational efficiency and ease of implementation. All the models that trained in the commencement stage were given to the Plant Village dataset of images, which differentiates between healthy and diseased leaves as shown in Figure 1. Among competing models, the VGG 16/19 model has the fastest training time. Although VGG's simplicity commonly expedites training, it appeared to impede its capacity to learn particular pathology features in the images (Chen *et al.*, 2020). So, it's essential to either increase the model's depth or consider using a different set of pre-trained weights. Ideal for adding more dense layers, the ResNet 50 model's strength is in its deep network training capabilities. Nevertheless, Dropout regularization proves to be an advantageous component when training the ResNet50 model. Inception V3 model supports multi-scale feature capturing capability that is valuable for detecting various leaf diseases across different fragments of an image by fine-tuning the learning rate and intensifying layer in width or depth (Kurmi *et al.* 2020).



**Figure 1.** Various deep learning models for classifying leaf diseases

The role of deep learning was implemented for the proposed novel hybrid model which works on accurate as well as on amorphous images and transfigures into labels for different leaf disease detection (Massi *et al.*, 2020). The role of convolutional layer is basically feature extraction having 5\*5 filter size initially. The size of filters rapidly increased as the data images switch from one block to another (Nevavuori *et al.*, 2019). This will additionally benefits for the reduction of feature maps to retain the actual size of an image. The role of pooling layer is reducing feature maps, training speed and less varied hybrid model. To avoid overfitting the training set, dropout regularization technique was also used in the novel proposed model. The role of fully connected layer is to mesh all the data directly with each other and further apply activation function to compute the accuracy of the hybrid model.

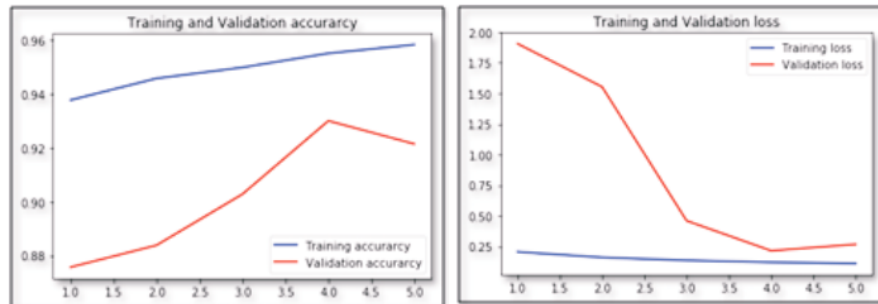
## RESULTS AND DISCUSSION

Several models (VGG-16, VGG-19, ResNet50, Inception V3 and Novel Hybrid) had implemented via Scikit-learn, a machine learning toolkit that integrates with NumPy, a scientific library. In order to compute the performance of hybrid model using mathematical notations, the Tensorflow library is required to depict the layout graphically. Keras is also used for neural network implementation in Python with multiple optimizers, different activation functions and additional tools which can be easily imported in any programming environment. The entire implementation is on Jupyter notebook which is an open source application for running modules that includes modeling, machine learning, visualization etc.

### VGG16 Model

VGG (Visual Geometry Group) model is a deep CNN model consists of various hyper parameters by applying layers with combinations of convolutional and Relu (Rectified Linear Unit) filters with max pooling (Simonyan and Zisserman, 2015). At the end of VGG model, the structure was fully connected neural network approach with softmax output function to produce the classification of leaf disease. It contained 16 layers with a combination of convolutional, pooling layers with dense layers at the end

of structure (Yan *et al.*, 2020). The valuable approach was to apply multiple small combinations of layers due to non-linear activation layers by enhancing classification during leaf disease detection. It also reduced over fitting in the network while training the model. The input images forwarded the data to convolutional layers in fragments with receptive field of 3\*3. It also had a convolutional stride to retain the spatial resolution after convolution. 5 Epochs were applied to identify the accuracy and loss in the VGG 16 model on Plant Village dataset of leaf images.



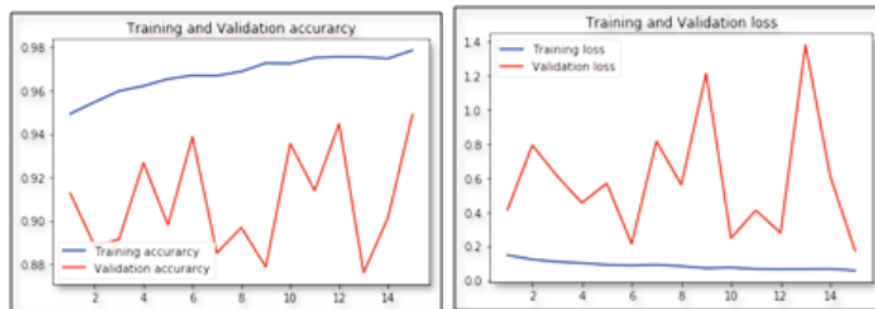
**Figure 2. Representation of VGG16 training accuracy and training loss**

VGG 16 model achieved 95.82% training accuracy and 92.14% validation accuracy while classifying leaf diseases as depicted in Figure 2. 0.111, 0.2677 were the training and validation loss respectively while implementing the VGG 16 model.

### VGG 19 Model

The 19-layer deep CNN model VGG-19 has an unvarying architecture of 16 convolutional layers and 3

fully connected layers and 5 pooling layers. To diminish memory requirements and time, VGG model does not support local response normalization which is beneficial to produce results in limited time. The convolutional step was fixed to 1 pixel size to maintain the equal resolution among images. Due to VGG19's depth and small filter size, the performance of this model produced optimum results in comparison with other deep CNN models.

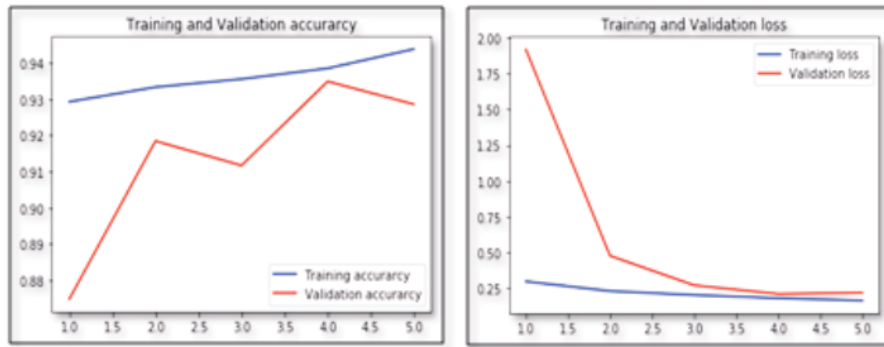


**Figure 3. Representation of VGG19 training accuracy and training loss**

15 Epochs were applied to identify the accuracy and loss in the VGG 19 model. VGG 19 model attained 97.86% training accuracy and 94.9 % validation accuracy with training loss of 0.0576 and validation loss of 0.172 while classifying leaf diseases.

### ResNet50 Model

ResNets (Residual Networks) are convolutional neural networks (CNNs) that stack residual blocks of 48 convolutional layers, one MaxPool layer, and one average pool layer. All the weights in the model specify kernel constraint to normalize the data input with batch normalization layer.



**Figure 4. Representation of ResNet50 training accuracy and training loss**

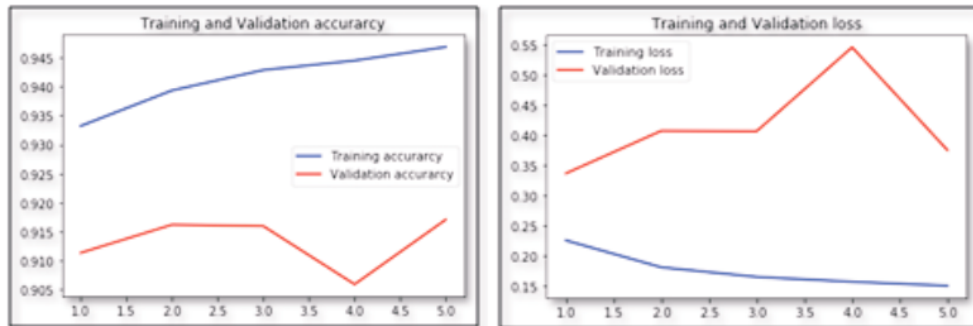
ResNet 50 model attained 94.38% training accuracy and 92.86% validation accuracy with training loss of 0.1616 and validation loss of 0.2166 as shown in Figure 4.

**Inception V3 Model**

Inception model represented more computationally proficient while creating the total number of parameters and reduced memory size in the network. For better model, multiple techniques were applied for efficient network with supreme accuracy among other deep learning models. Convolutional factorizations, dimensional reduction, regularization with parallel evaluations are the common techniques applied in this Inception model which also eludes overfitting.

The layers were symmetric as well as non-symmetric in the model which consisted of convolutional, dropouts, and pooling layers. In contrast with VGG 16/19 model, Convolution filters with selected pooling were functional to the input in the inception module and the output was integrated.

This model was basically known for its accuracy among other deep learning models with its best computational approach and accomplished remarkable results for image recognition (Nevavuori *et al.*, 2019). Such type of architectures helped to improve the speed of the network by changing its layout according to the given problem as shown in the output Figure 5.

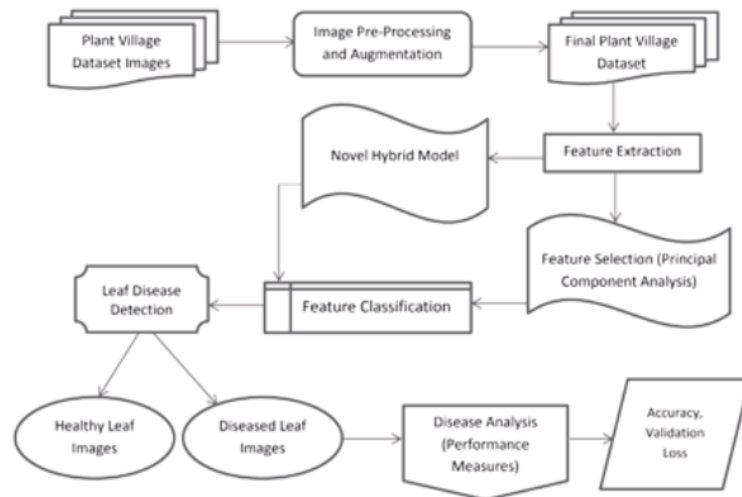


**Figure 5. Representation of Inception V3 training accuracy and training loss**

Inception V3 model achieved 94.68% training accuracy and 91.71% validation accuracy. 0.1511, 0.3754 were the training and validation loss respectively while classifying the Inception V3 model.

**Novel Hybrid Model**

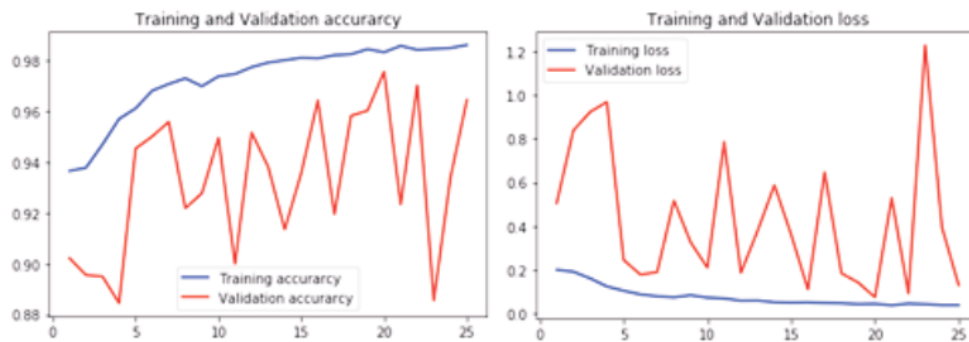
After preprocessing on dataset images, the proposed novel hybrid model attained the maximum accuracy among the dataset which contains multiple pairs of convolutional and pooling layers represented in Figure 6 (Kaur and Sharma , 2024).



**Figure 6. Novel hybrid model for leaf disease classification**

Dense layer was also used to flatten feature maps with activation function to produce the multiple class representation of the leaf disease. The suggested hybrid model has several layers, such as a convolutional layer that transforms input data into an output tensor and a pooling layer that maximizes the use of the pool size divided by the window size. The convolutional layer, which takes in two-dimensional convolutional inputs activated by the Rectified Linear Unit (ReLU) function, was used to normalize the images.

The images were normalized using the convolutional layer, which received convolutional two-dimensional inputs with the ReLU activation function, after the image dataset was adjusted. Data from the convolutional layer passed on to the pooling layer in a chain fashion until the dropout stage reached with values of 0.25. The role of dense layer is to provide all the classes in fully connected format with an output function. The distribution of images was implemented using Adam Optimizer which reflects the validation loss and value accuracy with 25 Epochs.



**Figure 7. Representation of hybrid model training accuracy and training loss**

The training accuracy attained by the system while detecting leaf disease was 98.604675012 and test accuracy was 96.446702232 as shown in Figure 7. The training loss reduced to 0.0394 whereas validation loss minimized to 0.1300.

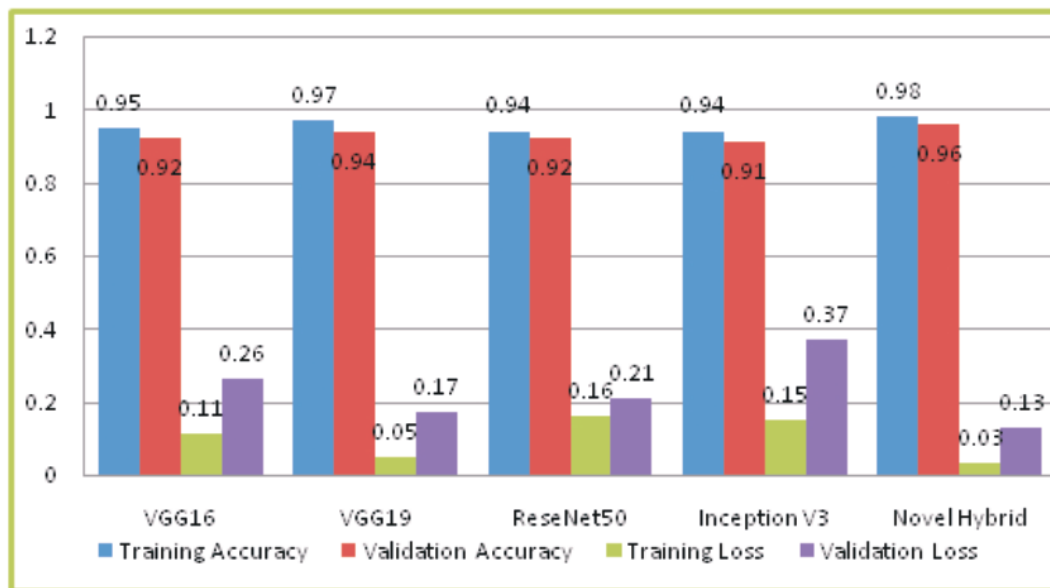
This study aimed to examine the efficacy of five different deep learning models for image-based leaf disease classification: VGG-16, VGG-19, ResNet50, Inception V3, and Novel Hybrid model. We presented a hybrid deep learning model for the classification of leaf diseases in this study. Finding the optimal feature and improved accuracy were

the primary goals of our suggested approach. The primary aim of our proposed strategy was to identify the best possible feature and guarantee higher accuracy. We compared the outcomes of several deep learning models before moving on to assessing the suggested approach. It was shown that the hybrid deep learning models outperformed other deep learning models, such as VGG-16/19, ResNet 50, and Inception V3, in terms of accuracy rate. The Hybrid model outperformed all of the others models with a success rate of 98.60%.

**Table 1. Summary of deep learning models with findings**

Models	Training Accuracy (%)	Validation Accuracy (%)	Training loss	Validation loss
VGG16	95.82	92.14	0.1110	0.2677
VGG19	97.86	94.90	0.0576	0.1720
ResNet50	94.38	92.86	0.1616	0.2166
Inception V3	94.68	91.71	0.1511	0.3754
Novel Hybrid	98.60	96.44	0.0390	0.1300

Table 1 shows that the VGG 19 model achieved 97.86%. Moreover, the Inception V3 classifier model had a validation accuracy of 91.71%, which was the lowest overall validation accuracy among other applied models.

**Figure 8. Comparative analysis of deep learning models with findings**

It should be noted that among all the classification models tested, the innovative hybrid model achieved the best overall accuracy, with a training accuracy rate of 98.60%. This research investigates the use of existing deep learning models to enhance training speed while aiming for superior classification performance through Novel Hybrid model.

The advent of deep learning models drastically reduced the time it takes to resolve seemingly complicated issues, such as leaf disease classifications. With the goal of achieving high accuracy in leaf disease identification using Plant Village dataset images, this study examined five deep learning models: VGG-16, VGG-19, ResNet50, Inception V3, and Novel Hybrid model. The initial obstacles encountered by the models, specifically ResNet, were mitigated through the implementation of Dropout regularization, which resulted in a substantial enhancement of categorical accuracy. Overfitting was still an issue, though, even if the

training accuracy was 94.38%. On the other hand, Inception V3 displayed remarkable development throughout training, obtaining an astonishing 94.68% accuracy rate. The results obtained with VGG16/19 were statistically significant up to a training accuracy rate of 97%. Among the current models for detecting leaf diseases, the findings showed that the Novel hybrid model outperforms the others with a 98.60% accuracy rate, according to the training assessment and model testing. We can improve growth by accurately identifying diseases and classifying them, which has led to the creation of various cutting-edge agricultural practices.

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**Rec. on 25.03.2024 & Acc. on 08.04.2024**