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Advancing Agriculture with CNN for Timely Leaf Disease Detection and Enhance Crop Production

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Abstract

The Indian economy relies heavily on the agricultural sector. Improving crop and plant yields is crucial because 60% of India's labour force is involved in this industry. It took until recently for Indian farmers to see increases in both production and selling prices due to a variety of crop-related ailments. The current revolution in smartphone penetration and computer vision models has opened up new opportunities for agricultural picture classification. Modern picture identification systems, such as Convolutional Neural Networks, are able to make precise and rapid diagnoses. In order to correctly detect plant diseases, this article utilizes pre-trained models that are built on convolutional neural networks (CNNs). Tuned-hyper-parameters for ResNet50, DenseNet121, VGG16, and Inception V4 in particular. The Plant-Village dataset, which includes several image examples of various plant diseases, was utilized in the experiments. F1, sensitivity, specificity, and classification accuracy were the parameters used to estimate the model's efficacy. We also compared our results to those of other, similar, state-of-the-art investigations. We can see that DenseNet-121 gets a success rate of 99.81% from the validation data.

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This paves the way for artificial intelligence solutions for small holder farmers and shows that convolutional neural networks (CNNs) can classify plant illnesses.

Keywords: Agriculture, Crop production, Disease Detection, Deep Learning, Convolution Neural Network, Modified Deer Hunting Algorithm.

I. Introduction

Agriculture is the primary sector that contributes significantly to India's economy. Because of the progressive rise in the population, there has been an accompanying rise in the need for food; nevertheless, the productivity and quality of the crop have suffered as a result of the widespread use of pesticides on the crop. A number of factors, including the presence of a range of plant diseases, the use of excessive amounts of pesticides, which can have a negative influence on product quality, and other factors, such as a lack of available water, can have a negative impact on the crop's productivity and quality. These factors can all contribute to the decrease in crop quality and productivity [1]. These are just some of the factors that can have this effect. Out of all of these reasons, the various sorts of illnesses that are occurring for the crops are generating the most significant impact in lowering the quality of the food and not gaining better prices at the market. Because they constitute the only source of nutrition for all land-dwelling organisms, plants are indispensable to the existence of terrestrial life. Additionally, they shield Earth from the sun's destructive UV rays by preserving the ozone layer. Diseases may impede plant growth, despite the fact that they are essential to life itself. Even though diseases are essential, this is nevertheless the case. Timely identification and diagnosis of diseases is a critical component in mitigating the risk of ecological damage. The absence of a methodical approach to the detection of illnesses has a negative impact, not only on the amount of products but also on the quality of those items. There are additional repercussions that this has for the economy of a country [2]. In order to meet the demands for food on a global scale, the International Food and Agricultural Organization of the United Nations recommends that crop production should increase by a factor of seventy by the decade 2050 [3]. This is done with the intention of fulfilling the demand for food from around the world [3].

Through the process of inspecting the plant in issue and generating assumptions based on their existing knowledge, farmers are able to ascertain the nature of the illness [4]. There is a potential that the farmers will incorrectly identify a disease, which could result in the plant having improper treatment and more harm being inflicted upon it. In a similar vein, it is an expensive endeavour to send domain experts out into the field to do their activities. Consequently, a system that can simplify the tasks of disease diagnosis and classification using images while simultaneously functioning as a domain expert is essential.

In this study, our focus is on the efficacy of convolutional neural network-based structures for determining and categorizing leaf diseases using photographs. Due to the fact that the learning model [5] can be taught by freezing either the topmost or bottom layers, it is possible to carry out tasks with greater precision. As a result of this, freezing the layers makes it possible to maintain the model parameters and fine-tune them for the purpose of feature extraction and categorization [6]. Several deep CNN-based transfer learning models were compared to determine their respective merits, as shown in Figure 1. The goal that we set for ourselves was to enhance the precision of the recognition and classification processes while also reducing the amount of time that was required for these activities. In order to carry out the research, the PlantVillage dataset was utilized in conjunction with pre-trained CNN prototypes. The conclusions are arrived at by analyzing a wide range of performance parameters, including accuracy, recall, precision, and F1-score, among others. Therefore, our evaluation methods are more dependable and precisely portray a condition that could conceivably happen in the actual world.

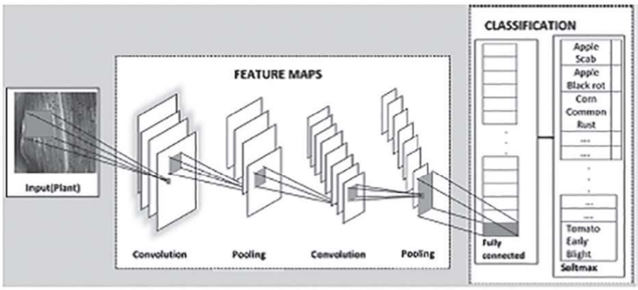


Figure1 General Framework of CNN

The following is a condensed summary of the most important contributions made by this manuscript:

- To create a framework that uses deep learning and is capable of precisely recognizing various plant diseases.
- To regulate the optimal transfer learning practice for the identification and categorization of plant diseases across many classes.
- In order to resolve the various labeling and class challenges that arise in plant disease recognition, a CNN model that is based on transfer learning and incorporates several classes and labels has been proposed.
- The problem of overfitting is resolved by employing strategies that incorporate data augmentation;

The following is the structure that has been designed for the organization of the present paper: The literature review is presented in Section II, along with the characteristics and difficulties of the various leaf disease detection methods that are currently in use. This includes a description of the datasets, an explanation of how the CNN models function, and parameters for judging how well they perform. The proposed CNN pre-trained model for effective diagnosis is also detailed in Section III of the report. There is a discussion of the methods that were utilized in order to do early leaf disease observation. The results of the feature extraction and parameter-tuning performance evaluation measures are detailed in Section IV. These results are presented in the section. After all has been said and done, the conclusion of the entire article is discussed in Section V.

II. Literature Review

A. *Related Works*

In 2020, Singh, A., and Srivastava, R. [7] discuss the application of deep learning strategies to identify leaf diseases in crop plants at an early stage. The researchers explore the utilization of convolutional neural networks (CNNs) in order to analyze leaf images and identify the initial signs of sickness. In the study, the necessity of early detection in preventing crop yield loss is emphasized, and a CNN-based strategy is proposed as a means of achieving accurate and efficient disease detection. In addition to providing insights into the implementation of deep learning algorithms, the paper also examines the issues that are related to this topic as well as the future paths that it will take.

The article by Panchal, A.V. et al. [8] revealed theproper categorization of plant diseases in 2021 using a CNN-based deep learning network. We trained the model using the 87,000 RGB pictures that were part of the open-source dataset. The data underwent pre-processing prior to being divided into segments. The data was classified using a convolutional neural network (CNN). The model confused later stages due to incorrect classifications, even though it had 93.5% identification accuracy. Also, because there wasn't enough data, the model's performance dropped.

The purpose of using a hybrid convolutional neural network to recover recognition accuracy was pursued by Narayanan et al. [9] in their 2022 study on banana plant sickness classification. The authors employed a pre-processing approach to verify that the default information stayed unchanged before processing the raw input image. Additionally, in order to preserve the initial image dimensions, a median filter was employed. The study employed a hybrid approach, combining a CNN with an SVM. The testing steps involved the use of a multiclass Vector Machine to categorize the precise kind of disease present in the sick banana leaves. The initial step, on the other hand, was to use the SVM to check for disease or health in the banana leaves. An impressive 99% success rate was achieved by a support vector network that was trained using the categorized CNN's output. Previous research indicated that Convolutional Neural Networks (CNNs) were more accurate than conventional approaches. It should be mentioned that this specific method was deemed lacking in diversity.

Jadhav et al. [10] suggested using CNN as a diagnostic tool for plant diseases at one point in their research. The disease that affects soybeans was identified by the utilization of pre-trained convolutional neural network models in this manner.

During the studies, pre-trained transfer learning techniques were utilized, which resulted in superior outcomes; nonetheless, the model was not as successful in terms of categorization variety as it could have been. Rather than developing a model that can classify all plant diseases, the majority of the models that are now in use focus on identifying specific kinds of plant diseases exclusively. For the most part, this is because there is a limited amount of data that can be acquired from an extensive selection of plant genera for the objective of constructing models that utilize deep learning.

A conditional generative adversarial network was proposed by Abbas et al. [11] in the year 2021 with the purpose of producing a library of synthetic images of tomato plant leaves. As a response to Olusola et al., this work was carried out. Because of the development of procreative networks, it is now possible to collect data in real-time and gather data in real-time. Historically, these procedures were not just laborious but also prohibitively expensive, time-consuming, and difficult.

During the training segment of a data-hungry learning model, the method that they developed involved the creation of synthetic images through the modification of color value distributions. This was done in order to address the problem of a lack of data that the technique encountered. As a consequence, this made it possible to achieve better results.

Dutta and Das [12] in 2019 propose a CNN-based approach for detecting crop diseases at an early stage. They utilize leaf images as input data and design a CNN model to categorize the images into healthy or diseased categories. The methodology likely involves pre-processing steps, such as image normalization or augmentation, to enhance the accuracy of disease detection. The paper may present experimental results, including accuracy, sensitivity, specificity, and F1-score, to estimate the performance of their CNN-based approach. These results are likely compared with existing methods to highlight the effectiveness and potential advantages of their proposed method.

The authors Jiang H *et al.* [13] conducted a comprehensive analysis of all CNN forms for the sorting of plant diseases in 2021. They also provided an overview of all of the deep learning principles that were utilized for the identification and categorization of leaf diseases. The authors concentrated their attention primarily on the most recent CNN models and analyzed how well they performed. The authors provide a brief overview of CNN variants here, including VGG16, VGG19, and ResNet. This study explores the benefits, drawbacks, and potential applications of several different CNN variations.

The fundamental purpose of this endeavour is to determine which method is the most efficient for the identification of illnesses that damage the leaves of plants. In 2020, Sharma.P *et al.* [14] suggests that a segmentation-based CNN is the optimal approach to taking in order to deliver the best answer to the problem that has been described. In contrast to other models those are developed using the entire image, the model that is being trained in this paper uses segmented images. Additionally, the model achieved a classification accuracy of 98.6%, which was far higher than what was anticipated. The model was trained and verified with the help of data obtained from sources that were acquired independently. These sources comprised ten different types of illnesses.

B. Review

Despite significant advancements over the last decade, there are still challenges with plant disease detection that must be addressed in order to make it more efficient. The use of CNN for disease diagnosis in plants was suggested by Jadhav et al. An improved method for detecting soybean disease was to employ pre-trained CNN models. The model, on the other hand, did not have diverse classifications. Due to data limitations, current algorithms are trained to detect specific plant diseases. A generative adversarial network was employed by Abbas et al. to generate digital representations of tomato plants leaves. Generative networks made it possible to collect data in real-time. When real-world data was insufficient for deep-learning models, the solution was to generate synthetic images. In order to identify agricultural illnesses early on, Dutta and Das suggested using a CNN-based method. Evaluation of performance metrics and pre-processing processes were part of the strategy. In order to achieve the best results for illness diagnosis, Sharma.P et al. recommended using a CNN that is based on segmentation. Therefore, in order to successfully apply for early diagnosis of plant disease detection in the future, it is necessary to overcome the problems mentioned above.

III. Materials and Methods

A. Convolutional Neural Network

Many researchers in computer vision and image classification are presently concentrating on deep learning. Many hidden layers, an input/output or classification layer, and comparable components are common in deep CNNs [23]. The hidden layers of a CNN can be either convolutional or pooling, completely connected or, on rare occasions, Softmax. Most CNN designs adhere to the architectural pattern of the Lenet-5 architecture, which was established by LeCun *et al.,* (1998). Multiple examples of popular CNN architectures are shown in Figure 2. It has been a long time since many other kinds of architectures were created. Here, we put the cutting-edge convolutional neural network through its paces using PlantVillage images to identify and categorise plant diseases. Open and freely available at PlantsVillage is a dataset with 54,306 photos illustrating 26 illnesses affecting 14 different grain plants. Among the architectures that were included in the evaluation were DenseNets (121 layers), ResNet (50, 101, and 152 layers), and VGG 16. We need models that can identify plant diseases quickly and accurately so that we can take the right actions when they spread. Effective leaf disease detection methodology is built on top of deep learning models.

In order to extract regions of interest, a Deep Convolutional Neural Network (CNN) model is configured with an algorithm. The reality of the plan leaf disease prediction model is brought about as a consequence of this. The recycling of knowledge models in leaf disease detection is made easier with the assistance of pre-trained deep learning models. It is possible to optimize the framework during the training and testing phases by applying transfer learning. The dataset from Plant Village is utilized in order to evaluate the model that has been proposed.

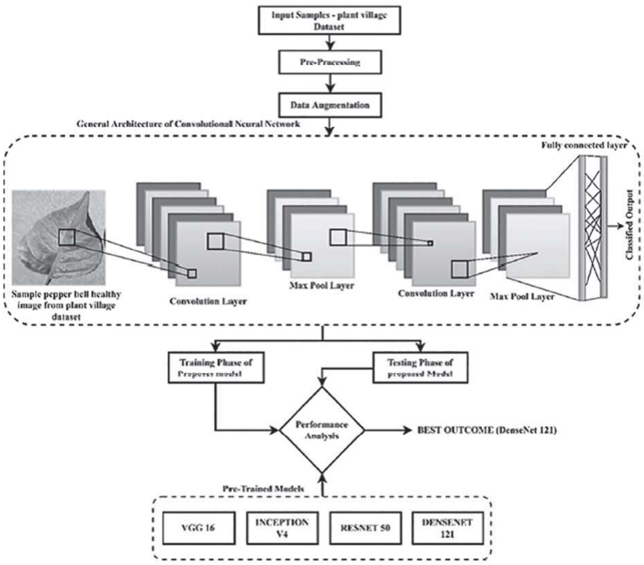


Figure 2 Overview of Proposed Methodology with CNN

The interest in CNNs has lately increased, and deep learning is the architecture that has gained the greatest popularity. For the same reason that the human brain is able to learn important features from input images at various convolutional levels, deep learning models can do the same. Applying DL to complicated circumstances has several advantages, including improved classification accuracy and reduced error rate [14]. Some of the individual parts that compose the deep learning model include activation functions, pooling layers, convolutional layers, and fully connected layers.

B. Dataset

The PlantVillage dataset on a typical open-access basis [53] was employed by us in order to accomplish the goals of training and testing. There are 54,305 statistics of good wellness and diseased or sick plant foliage included in this collection. The common and scientific names of the virus that causes disease are included in the information accessible in dataset. Additionally, the number of classes and images that are contained inside each class are also included in this table. Thirty-eight distinct classes of fourteen distinct plant species are included in the database, along with photographs of healthy and disease-affected leaf tissue. Three distinct types of Plant Village datasets are utilised in our experiment. Initially, carry out the experiment using coloured leaf photos, followed by conducting the experiment using segmented leaf images from the same dataset. In order to improve the valuable information and make analysis easier, the backdrop of the segmented photographs was smoothed down. Last but not least, grayscale photographs taken from the same dataset were employed in order to evaluate the effectiveness of the traditional methods. In order to facilitate the learning process, the leaf imageries were separated into two unique arrangements: a training set and a validating set. The leaf photos were separated into three independent sets so that we could evaluate their performance. In the first batch, testing accounted for 20% while training constituted for 80%, the second set consisted of 70% for training and 30% for testing, and the third set consisted of 60%.

C. Pre-Trained Deep Learning Classifiers

- **ResNet-50**

  ResNet-50 is a neural network consisting of 50 stratums with significant depth. Each of the five phases of the model has its own set of identity and convolution blocks. In computer vision, these residual networks serve as the framework. The concept of vertically stacked convolution layer structures was first proposed by ResNet [49]. In addition to arranging the convolution layers in a stacked manner, the convolutional neural network also has many skip connections. These skip connections allow the original input to avoid certain levels and directly influence the result of the network. It is also possible to solve the issue of fading gradients by placing the connection used for skips before the function for activation. Consequently, more complex models result in a higher number of errors. Incorporating skip connections into the resulting neural network helped with this issue. All of these quick links came from identity mapping. Let us contemplate 'i' as the input image, F(i) as the nonlinear layers appropriate mappings, and H(i) as the residual mapping. Thus, the function for residual mapping turns out to be:

  $$H(i) = F(i) + I$$

  The ResNet-50 architecture utilises convolution as an identification chunk. Every identity block consists of three CNN layers and more than 23 million trainable metrics. The matrices "Input x" and "shortcut x" must have the same output dimension from the convolution layer and batch normalisation in order to be joined together. Alternatively, the shortcut x needs to pass through a convolutional layer and undergo batch normalisation in order to align with the desired dimension

- **VGG Net**

  The Oxford University Visual Geometric Group (VGG) introduced the pre-trained model [17]. More layers with smaller filters are the VGG Net's main idea. The VGG architecture input layer supports a 244 × 244 image size. Pre-processing subtracts the average RGB value from each input pixel. Five convolutional layers and a MaxPool layer follow pre-processing. In other words, MaxPool follows each layer group. The last MaxPool layer is trailed by three FC layers. The top two fully connected (FC) levels have 64 x 64 channels, while the last layer has 1000 channels. A softmax activation function follows. The VGG-16 and VGG-19 models have the identical structure but diverse layers. VGG-19 has 19 layers, while VGG-16 has 16. Differentiating the third, fourth, and fifth stacks is the number of convolutional layers they contain.

- **Inception V4**

  Images can range in size and provide a wealth of information. It is difficult to choose an appropriate filter size for feature extraction due to these size discrepancies. It is recommended to choose a larger kernel size for extracting global information and a smaller one for extracting local information. There is a risk of overfitting and disappearing gradients when convolution layers are stacked. This is addressed by the Inception modules by making the network model larger rather than deeper by incorporating varied kernel sizes in each block [18]. The naïve Inception module, for example, can employ 3x3, 1x1, or 5x5 filter sizes following three distinct convolutional stages. Shortly after max-pooling, the final result is transmitted to the subsequent layer. Prior to executing the Inception module, the Inception layer's stem is responsible for establishing a baseline set of processes. In addition, you can change the grid's height and breadth with the reduction blocks in Inception V4.

- **DenseNet-121**

  For image classification, DenseNet-121 [17] use a deep CNN model that makes advantage of dense layers with minimal connections. As it receives input from lower layers, each node in this network builds a feature map and feeds it up the network. By using this method, the data from all the layers below it is "concatenated" into the layer below it. Also, the network is small and slender because subsequent layers reuse the feature mappings from earlier ones. This reduces the numeral of channels in a condensed block, where k is the channel development rate. Figure 3 depicts the idea of a DenseNet dense block. With respect to every layer of the composition, we process the k-channel output feature maps using regularisation, activation, and convolution techniques. We use batch convolution, pool, and ReLu to alter the output of the following layers:

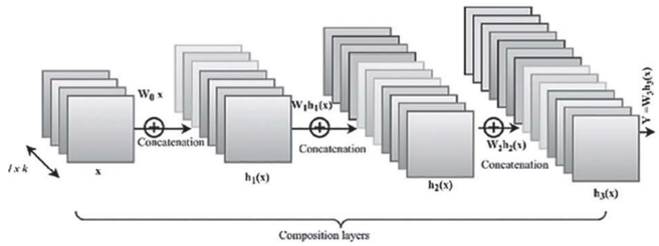


Figure 3 Principle of Dense Block

Layers are more diverse and have a strong gradient flow. In contrast to ResNet, DenseNet is quite little. And while the classifiers in the default ConvNet prototypical handle complicated features, DenseNet makes use of all features—no matter how complicated—and offers seamless decision boundaries.

The suitability of the previously trained neural systems for the plant disease classification challenge was the deciding factor in their selection. You may find all the information about the model's architecture in Table 1. For the purpose of feature map extraction, each network employs a unique set of filter sizes.

Table. 1 Layered Descriptions of Different Architectures

Layer Description	VGG-16	Inception V4	ResNet – 50	DenseNet – 121
Aggregate Layers	16	22	50	121
Optimal Pool Layering	5	5	1	4
Stack of Dense	3	-	3	4
Drop-out layers	2	-	2	-
Flattened layers	1	-	1	-
Filter Dimension	3x3	1x1, 3x3, 5x5	3x3	3x3, 1x1
Stride	2x2	2x2	2x2	2x2
Trained Parameters	41.2 M	119.6 M	23.6 M	7.05 M

The feature extraction procedure relies heavily on filters. In addition, the input will retain its unique characteristics after each filter has been applied using convolution; the definite features to be mined from the feature maps be contingent on the exact standards of the filters. Authentic pre-trained network models were used in our investigations, with each model retaining its original configuration of layers and filter dimensions.

D. Optimize the various Models

Transfer learning encompasses the idea of fine-tuning. Machine learning's transfer learning approach involves applying what's learned to new problems in a comparable domain or activity. The first steps in deep learning involve training the lower layers to ascertain aspects of the chore at hand. For additional training with extra layers for the desired work, you might discard the final few segments of the trained model via transfer learning. Although fine-tuned learning trials do take some time to master, they outpace starting from square one when it comes to speed (Mohanty et al., 2016). On top of that, they outperform models that are trained from the ground up in terms of accuracy.

Faster learning was achieved by using pre-trained CNN approaches on the ImageNet dataset to detect and categorise 38 types of plant diseases. Roughly 1.2 million photos covering 1000 different classes make up the ImageNet collection. In contrast, the PlantVillage collection has 54,306 photos from 38 different classifications. This leads us to employ the ImageNet pre-trained weights since the PlantVillage dataset is inadequate for deep network training. The PlantVillage dataset was used to fine-tune CNN Inception v4, VGG16, Res Network, and dense networks architectures, un-augmented data was not used. Once the models were constructed, the pre-trained weights from ImageNet were fed into them. We defined an additional fully-connected softmax layer on top of the current one to further shrink the top layer. Stochastic gradient descent (SGD) was also employed to refine the model, beginning with a learning rate of 0.001.

IV. Results and Discussion

This specific area of the study employed state-of-the-art deep learning algorithms for plant disease diagnosis; these algorithms were developed using the transfer learning technique. After having been previously trained with the ImageNet dataset, the deep convolutional neural nets underwent further training with the PlantVillage the information set, which is available to the general public in a broad variety of forms. One rate of learning of 0.01, a rate of dropping out of 0.5, and 38 categories of output were all specified for the various models that was employed in our experiment. In addition, we used 38 output classes.

A. Performance Evaluation Metrics

An F1-score, recall, accuracy, and precision were the performance measurements that were utilised. It should be noted that the basic confusion matrix has the potential to be deceiving; thus, the performance evaluation criteria indicated earlier were utilised.

- **Accuracy**

The following is the formula for calculating accuracy (A), which is the percentage of forecasts that are currently classified:

$$A = (TP + TN) / (TP + TN + FP + FN)$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

- ***Precision***

Here is how to measure precision (P), which is the fraction of correct positive outcomes:

$$P = TP / (TP + FP)$$

- ***Recall***

To find the percentage of true positives that were accurately detected, employ the following formula:

$$R = TP / (TP + FN)$$

- ***F1-Score***

F1-score is well-defined as the harmonic mean ofprecision and recall and calculated as follows:

$$F1 = 2(PR/P + R)$$

B. Measuring Effectiveness of Various Learning Models

Training, test, and validation samples were created from the dataset. After 30 iterations of running each model, we saw that ours began to converge with near-perfect accuracy after only 10 iterations. Figure 4a is a graph showing the reliability of the Inception V4 prototype's recognition. Figure 4b displays the Inception V4 representation's log loss, and the training accuracy it attained was 99.78. Refer to Table 2 for the experiments involving the pre-trained network models.

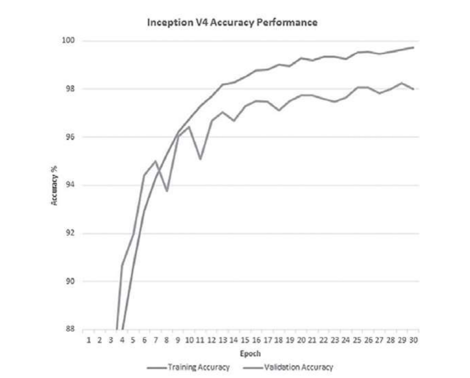
Table 2 Assessment Exploration of various Learning Models

Various Models	Learning Phase		Validation Phase	
	Accurateness	Loss	Accurateness	Loss
Inception V4	99.76	0.01	97.55	0.0586
VGG 16	84.23	0.52	82.67	0.64
ResNet 50	99.81	6.12	98.70	0.027
DenseNet – 12	99.89	0.016	99.79	0.0154

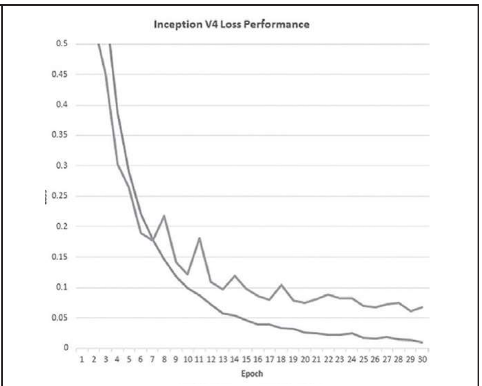
By utilising the identical dataset, the subsequent experiment also tested the VGG-16 prototype. The model was trained using 80% of the original dataset following hyper-parameter standardisation. We used 10% of the dataset for testing, and we used 10% of the image samples for validation and testing. Looking at Figure 4b, we can see that in the first 10 epochs, the prototypical accomplished a recognition accurateness of about 78%. Then, the recognition accuracy kept going up until it hit 84.27%, which was still lower than the Inception V4 model. Figure 4c shows that the validation model had a loss of 0.64% while the training loss was 0.52%.

Using the ResNet-50 model, the third experiment was conducted. Recognition accuracy, validation, and training loss graphs are shown in Figures 4e and 4f, respectively, and the same methodology was used to assess model loss and recognition accuracy. The model's accuracy was 99.83 with a loss of only 0.027. Comparatively, it fared enhanced than VGG-16 and Inception V4.

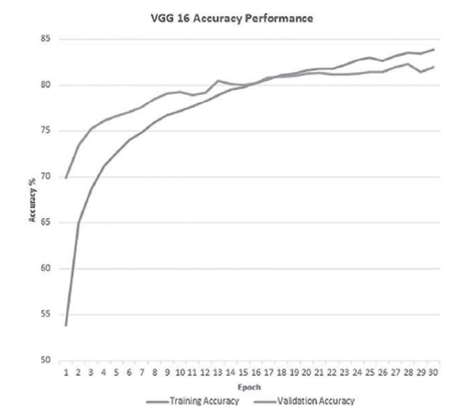
Standardizing the hyper-parameters allowed us to run the last experiment with DenseNet-121, a 121-layer network with four dense blocks and a transition layer between them. For a period of thirty epochs, the graphs depicted in Figure 4g and Figure h illustrate the training and validation accuracy and loss. A maximum accuracy of 99.81% was reached during the testing phase that followed the training phase, and the greatest validation loss that was estimated was 0.0154%. On display in Figure 4 is a comparative performance analysis.



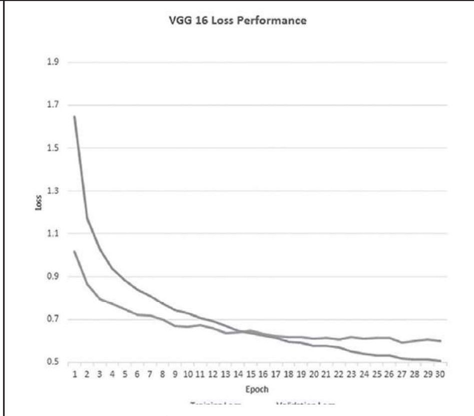
(a) Inception V4: Accuracy



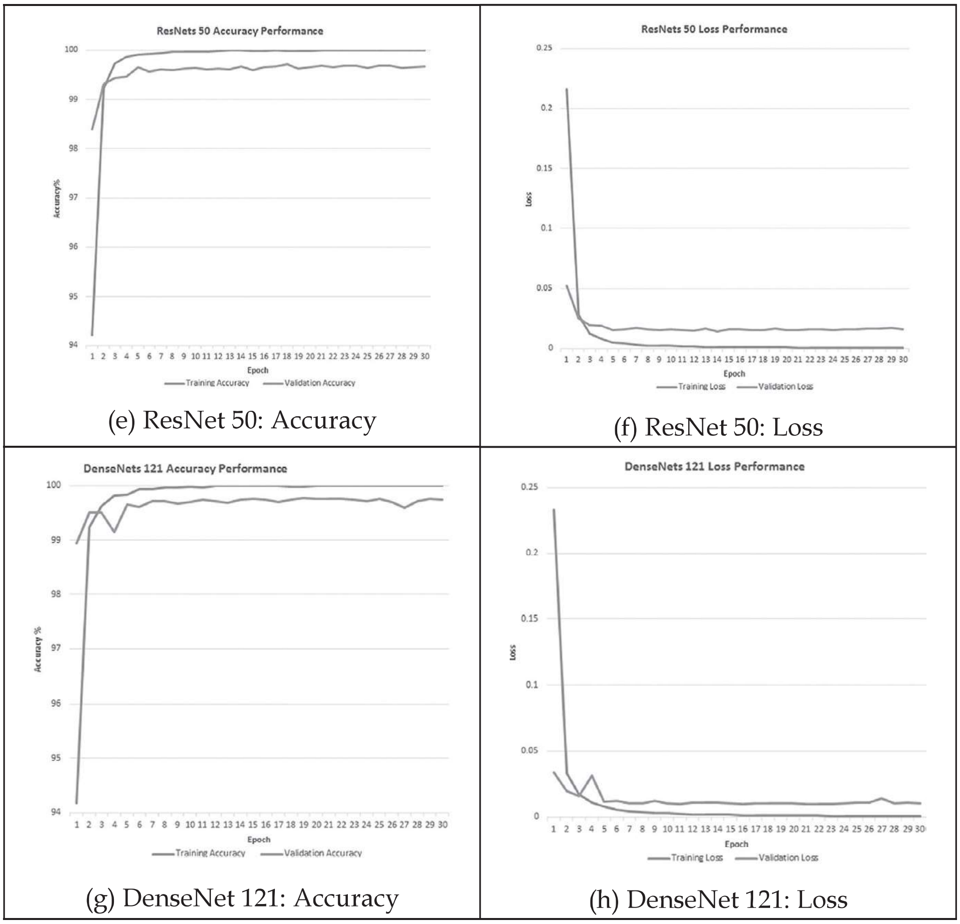
(b) Inception V4: Loss



(c) VGG 16: Accuracy



(d) VGG 16: Loss



(e) ResNet 50: Accuracy

(f) ResNet 50: Loss

(g) DenseNet 121: Accuracy

(h) DenseNet 121: Loss

Figure 4 Performance Analysis of Inception V4, VGG 16, DenseNet1 21 and ResNet-50

V. Conclusion

The agriculture industry is crucial because crops provide the most fundamental requirement for human sustenance. The agriculture sector cannot function without the prompt identification and diagnosis of these diseases. Diseased plant leaves can be used in a variety of ways for disease diagnosis and classification. Nevertheless, no commercially available technology has yet proven to be both efficient and effective in illness identification. We compared the efficiency of four distinct models on the PlantVillage datasets: VGG-16, ResNet 50, Inception V3, and DenseNet 121. The purpose of this article was to use convolutional neural networks to identify and distinguish between various plant kinds and illnesses. Testing the trained model on real-time photos for disease detection and recognition in plants is possible. Through the use of many pre-trained convolutional neural networks, we were able to automate the task of plant disease detection and classification in this study. With a precision of 99.89%, the proposed model can help farmers identify and detect plant conditions. To enhance the trained models, future study can involve adding more plant kinds and more plant diseases to the current dataset.

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