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A Study on the Performance of Deep Learning Models for Leaf Disease Detection

G. Sucharitha[1,*], M. Sirisha[2], K. Pravalika[3] and K. Navya Gayathri[3]

[1]Department of Data Science, Institute of Aeronautical Engineering College, Hyderabad, Telangana
[2,3,4]Department of Computer Science and Engineering, Institute of Aeronautical Engineering College, Hyderabad, Telangana

Abstract

The backbone of our Indian economy is agriculture. Plant diseases are a key contributor to substantial reductions in crop quality and quantity. Finding leaf diseases is a crucial job in the study of plant pathology. So, Deep learning models are essential for classification objectives with positive outcomes. Many different methods have been employed in recent years to classify plant diseases. This work has aided in identifying and categorizing a plant leaf disease. Images of Tomato, Potato, and Pepper plant leaves from the PlantVillage Database, which includes fifteen disease classifications, were used in this study. The pre-trained Deep learning models like InceptionV3, MobileNet, DenseNet121, Inception-ResNetV2, and ResNet152V2 are utilized to diagnose leaf diseases. The classification of both healthy and various sorts of leaf illnesses is taught to deep learning models.

Keywords: InceptionV3, MobileNet, DenseNet121, Inception-ResNetV2, leaf Disease, Pretrained models, ResNet152V2, Classification

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1. Introduction

Over two-thirds of the population in emerging countries rely on agriculture as their main source of income, making it one of a nation most important economic driver. The economy is crucially influenced by the weather other environmental conditions that affect the quality of agricultural goods. Therefore, the first step in ensuring higher food quality is safeguarding the plants that produce it against disease. It is very typical for the plant to have a condition that could be viral or fungal. Plant disease is one of the most recognized symptoms of loss of product quality. The plant's yield could suffer significantly from the sickness, both in terms of quantity and quality. Early activities rely on time- and money-consuming traditional approaches. When plant illnesses are discovered, farmers frequently use chemical fertilizers to stop the disease's spread. Alternatives include using organic fertilizers, which are safe for both crops and people who come in contact with them. A lot of machine learning and image processing techniques have recently been applied for classification. Deep learning approaches have increased the classification's performance.

Deep learning networks can automatically classify a plant leaf. Time is saved, and less manual labour is required. It all depends on how many leaves from the crop have the disease in them. The diseases of the tomato, potato, and pepper plants as well as the health category and diseases in Indian states were chosen for the study in this article from the PlantVillage database. In total, fifteen classes of tomato, potato, and pepper are considered in this work. Algorithms like segmentation and feature extraction are utilized in the methods for diagnosing plant diseases from photos of its leaves. [1]. The four main steps of the proposed processing approach are: creating a colour transformation structure for the input RGB image; segmenting; computing the texture statistics for the user segments; masking and removing the

*Corresponding author. Email: sucharithasu@gmail.com

green pixels using a specific threshold value; and finally sending the extracted features through the classifier. [2]. The physical characteristics and traits of plant leaves, such as their color, intensity, and size, are analysed for categorization [3].

Plant leaf diseases were classified using the fundamental Convolutional Neural Network (CNN), including which diseases were discovered to achieve outstanding accuracy during assessment and training [4]. Alex Net, VGG16, Google Net, MobileNetv2, and Squeeze Net are pre-trained deep learning models that categorize plant leaves as healthy or ill and assign them to a specific disease class [5]. The affected area is initially found, photographed, and image processing is done. Once the segments have been acquired and the area of interest has been found, the feature extraction process is finished. SVM classifiers are then employed to receive the data collected and produce the results. [6]. K-means clustering, an unsupervised approach, and a Support Vector Machine (SVM) are used to address the problem of the most prevalent diseases that afflict salad cucumbers. [7]. VGG 16, Inception V4, ResNet with 50, 101, and 152 levels, as well as Dense Nets with 121 layers, were some of the designs that were tested. 38 different types of data were collected during the experiment, including images of healthy and injured leaves from 14 different plants from Plant Village. [8]. There were 20,639 images of both unhealthy and healthy plants. The sequential convolutional neural network developed by Keras was trained to recognise twelve diseases and three different crops. [9]. Like a virus or wilt, pepper-related diseases will obliterate your entire yard. The best course of action when there are problems with the pepper crop is to remove the infected plant before it spreads to the rest of the yard. [10]. Three algorithms for regression, multilabel classification, and focus loss function were developed using the DenseNet-121 deep convolution network. [11]. The Deep Convolutional Neural Network, based on LeNet, provides illness detection and classification for soybean leaf spots by using diseased portions of disease spots. The fuzzy clustering technique was used to produce segments of the sick leaf areas. [12].

The section 2 outlines significant research, followed by Sections 3 through 5, which present the methods, results, and conclusions.

2. Related Works

To advance effectively, it is imperative to understand earlier research in this area. Plant leaf disease has shown to be difficult to diagnose. In this crucial area of research, deep learning algorithms are frequently utilized to alter images for proper categorization. The techniques that are most often utilized in the relevant literature are reviewed in this article. Manually keeping track of an important agricultural area is laborious. Reducing the amount of human labor required for plant oversight is necessary. Because of this, the study is well-known. Many researchers are drawn to this field of inquiry. Many articles about plant diseases may be found in the literature.

Mohanty et al. [13], utilized a public dataset of 54,306 photographs of healthy and sick plant leaves collected under controlled conditions. They identified 26 diseases and 14 different types of crops (or lack thereof) using a deep convolutional neural network. This strategy works well, as seen by the trained model's accuracy of 99.35% on a held-out test set. The author claims that the application of transfer learning and data augmentation may further improve the model's performance. In order to improve the precision and efficacy of disease diagnosis, the author also emphasizes the necessity for greater study. Utilising photographs of apple black rot from the PlantVillage dataset with four botanist-labelled severity levels labelled by botanists, Guan Wang et al. [14], created a series of deep convolutional neural networks to gauge the disease's severity. Their research offers a complete evaluation of the capabilities of deep models modified by transfer learning and external networks created from scratch. With a score of 90.4% on the hold-out test set, the deep VGG16 model with transfer learning training has the highest overall accuracy. The study's results show that by accurately determining sickness severity from photos, deep learning surpasses traditional procedures like human inspection and grading. In their research, Erika et al. [15], proposed a novel beneficial plant-disease detection technology. They used 7,520 images of cucumber leaves, many of them whole, and they had practically every viral disease when they left. The classification system utilised by the researchers, which makes use of convolutional neural networks, achieved an average accuracy of 82.3% using a 4-fold cross-validation procedure, despite the fact that half of the images used in the experiment were taken in low light. The various parts of the suggested diagnostic system, such as picture taking, image segmentation, feature extraction, and classification, were then discussed by the authors. According to Sladojevic et al. [16], the proposed model can distinguish between healthy and plant leaves with 13 distinct plant illnesses. The researchers conducted in-depth CNN training using Caffe, which is a deep learning platform created by Berkley Vision and Learning Centre. The accuracy of the experiments using the developed model ranged from 91% to 98% for testing on different classes, with an average accuracy of 96.3%. The use of deep neural networks for leaf image-based disease detection and classification in plants is thoroughly explained in the publication.

Muhammad Sufyan Arshada et al. suggested using ResNet50 with Transfer Learning in this work to identify potato, tomato, and maize difficulties. Plant disease diagnosis accuracy for ResNet50 is 98.7%. It may be possible to create more reliable and accurate models for plant disease detection using pre-trained models and transfer learning approaches. Plant diseases can be categorized by the model into 16 separate classes. [17]. Abhinav Sagar et al. used the Plant Village dataset, which contains 38 different disease classes. They built their research using five different architectures, including VGG16, ResNet50, InceptionV3, Inception ResNet, and DenseNet169. On the test set, they discovered that ResNet50 produces the best results. We examined metrics including recall, F1 score, accuracy, precision, and class-level confusion metric for assessment. Their model uses ResNet50, which yields the best results. [18]. Including Ananda S. Paymode. It was mentioned that their main objective is to foresee the sickness that will affect tomato and grape leaves first. Utilising Convolutional Neural Network (CNN) techniques, Multi-Crops Leaf Disease (MCLD) is diagnosed. For better performance measures, the Visual Geometry Group (VGG) model, which is based on CNN, is used. In the test, the study's tomato accuracy rate was 95.71% and its grape accuracy rate was 98.40%. [19]. In order to detect and diagnose several leaf diseases of the potato, tomato, and pepper, Md. Tarikul Islam et al. created a multi-plant leaf disease detection (MLDD) model employing three pre-trained models: MobileNet-V2, Inception-V3, and ResNet-50. They compared and evaluated the effectiveness of the transfer learning strategy in identifying and classifying crop leaf diseases. Inception-V3, MobileNet-V2, and ResNet50 each had an average accuracy for diagnosing leaf diseases of 97.54%, 94.01%, and 99.01%, respectively. This study will improve agricultural methods for growing food and reduce early-season crop loss. [20]. Sumalatha et al. [21], demonstrated the application of deep neural networks for plant disease detection using picture categorization. This paper uses simple leaf images of healthy and diseased plants from the Plant Village dataset to demonstrate a transfer learning-based method for identifying various ailments in various plant species. Two crop species and eight diseases were among the 11333 images from 10 different classes that were utilised to train, validate, and test the models. Multi-class categorization was used to solve a problem. There are comparisons between the six CNN architectures: VGG16, InceptionV3, Xception, Resnet50, MobileNet, and DenseNet121. Comparing the model developed by Gugan Karthiresan et al. with several transfer learning models, they discovered that DenseNet121 achieves the highest accuracy of 95.48 on test data. The presented model outperformed paradigm classification models with an average cross-validation accuracy of 98.79% when tested on a GAN-augmented dataset. Without the GAN augmentation, the model is tested on three different datasets, yielding a benchmark result of 98.38% average accuracy. [22]. In order to reduce the computation time and parameter count, Mahmudul Hassan et al. claim that SK Standard CNN models moved from regular convolution to depth separable convolution. The application models were trained using an open dataset consisting of 14 different plant species, 38 different categorical illness classes, and healthy plant leaves. To evaluate the performance of the models, various parameters, including batch size, dropout, and different numbers of epochs, were used. The implemented models produced disease-classification accuracy rates of 98.42% and 99.11%, respectively 97.02% and 99.56%, which were greater than those of traditional handmade feature-based methods. InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0 were employed. In comparison to other deep-learning models, the implemented model performed more accurately and required less training time. When the option is changed, the MobileNetV2 architecture also functions with mobile devices. The deep CNN model has great potential and can have a big impact on how well diseases are identified. Accurate findings in the identification of diseases suggest that it may have the capacity to identify diseases in real-time agricultural systems. [23]. Suk Winder Kaur et al. proposed the VGGNet-19 model, which is pre-trained using the weights of the "Image Net" dataset. They added a few layers by freezing the top layers and utilising transfer learning in an effort to improve the model's performance and accuracy. This results in accuracy for apple leaves of 97.52 percent and grape leaves of 95.75 percent after 20 iterations of the algorithm. [24]. Ghosh et al. (2023) embarked on a comprehensive study to assess water quality through predictive machine learning. Their research underscored the potential of machine learning models in effectively assessing and classifying water quality. The dataset used for this purpose included parameters like pH, dissolved oxygen, BOD, and TDS. Among the various models they employed, the Random Forest model emerged as the most accurate, achieving a commendable accuracy rate of 78.96%. In contrast, the SVM model lagged behind, registering the lowest accuracy of 68.29% [25]. Sharma et al. (2020) presented a comprehensive study on the impact of COVID-19 on global financial indicators, emphasizing its swift and significant disruption. The research highlighted the massive economic downturn, with global markets losing over US $6 trillion in a week in February 2020. Their multivariate analysis provided insights into the influence of containment policies on various financial metrics. The study underscores the profound effects of the pandemic on economic activities and the potential of using advanced algorithms for detection and analysis.[26]. Alenezi et al. (2021) developed a novel Convolutional Neural Network (CNN) integrated with a block-greedy algorithm to enhance underwater image dehazing. The method addresses color channel attenuation and optimizes local and global pixel values. By employing a unique Markov random field, the approach refines image edges. Performance evaluations, using metrics like UCIQE and UIQM, demonstrated the superiority of this method over existing techniques, resulting in sharper, clearer, and more colorful underwater images [27].

3. Framework of Deep Learning Models for Leaf Disease Detection

Transfer learning is a machine learning technique that involves utilizing the knowledge acquired by a model while performing one task and applying it to another task that may be unrelated but equally significant. In other words, transfer learning enables us to apply the information we have gained from one difficulty to another. The main concept is to avoid starting from scratch by using the information gained from solving one issue to tackle another similar but distinct. As the model may be trained more quickly and using less data than when starting from scratch, this can save significant time and money. For a specific job, like as image classification or natural language processing, we frequently use pre-trained models that have been trained on large datasets for transfer learning. These pre-trained models have mastered the ability to identify patterns and characteristics beneficial for a particular activity, and they may apply this understanding to complete similar tasks. Transfer learning has several advantages, such as quicker training, fewer data, better performance, and adaptability.

3.1. Experimental Models

• INCEPTIONV3

In the year 2015, the Google Researchers created the Deep Convolutional Neural Network architecture InceptionV3. The InceptionV3 architecture comprises several modules called Inception blocks that are optimized for effectively capturing multi-scale and multi-level representations of the input picture. Convolutional layers, pooling layers, and bottleneck layers make up these blocks, which are intended to lessen the computational complexity of the model while keeping it accurate.

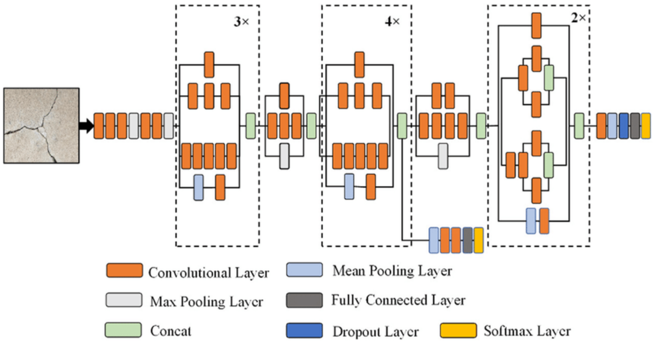

Figure1: Architecture of InceptionV3

• INCEPTION-RESNETV2

The Inception-ResNetV2 architecture is a deep convolutional neural network introduced in 2016 by Szegedy et al. It combines the Inception module and residual connections to enhance performance. The Inception module enables multi-scale feature learning with filters of varying sizes, capturing fine-grained and coarse-grained features. Residual connections facilitate deeper and more complex representation learning by allowing information flow within the network.

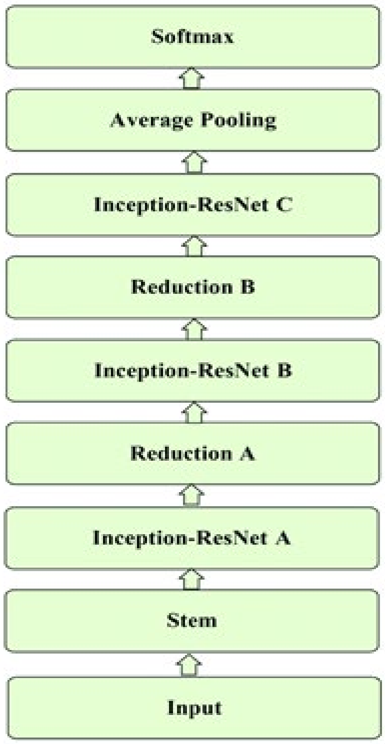

Figure 2: Architecture of Inception-ResNetV2

• MOBILENET

MobileNet is a convolutional neural network structure created with a specific focus on effective implementation on mobile and embedded devices. Its primary characteristic is the utilization of depth-wise separable convolutions, which consist of two types of convolutions: depth-wise and pointwise. The depth-wise convolution applies filters individually to each input channel, resulting in a reduction of parameters and computations. The output from the depth-wise convolution is then merged with the output from the point-wise convolution using a 1x1 convolution, allowing the network to generate significant and robust representations.

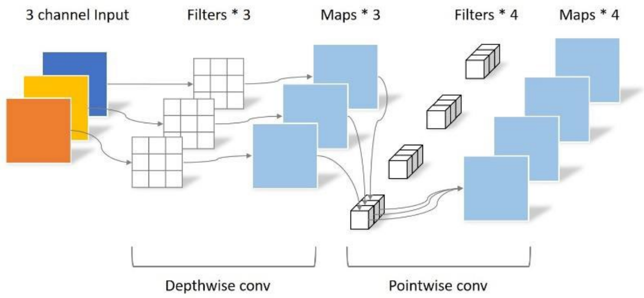

Figure 3: Architecture of MobileNet

• DENSENET121

DenseNet121 is a deep convolutional neural network architecture that uses dense blocks instead of residual connections to enable feature reuse across layers and increase parameter efficiency. DenseNet121's architecture comprises four dense blocks, each with many convolutional layers and a transition block that shrinks the output feature maps' spatial dimensions. Information may move more quickly across layers because each dense block includes numerous levels that are densely linked to all other layers inside the block. Each dense block's output is combined with the input of the one after it to produce a dense feature map that includes data from all prior layers. As a result, a model that can learn intricate feature representations is constructed that is highly expressive and parameter efficient.

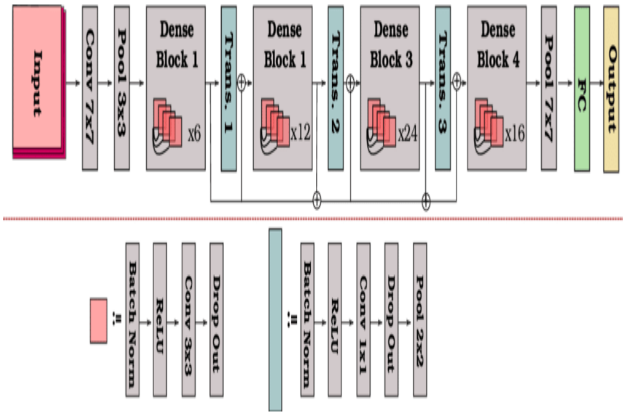

Figure 4: Architecture of DenceNet121

• RESNET152 V2

ResNet152V2 is an enhanced version of ResNet152 architecture, focusing on improved accuracy and stability. It incorporates batch normalization layers and rectified linear unit (ReLU) activation functions. This architecture consists of multiple residual blocks, each containing multiple convolutional layers. These residual blocks enable information to propagate through the network without degradation, facilitating the learning of deeper and more complex feature representations. The inclusion of batch normalization and ReLU activation further enhances the model's stability and precision.

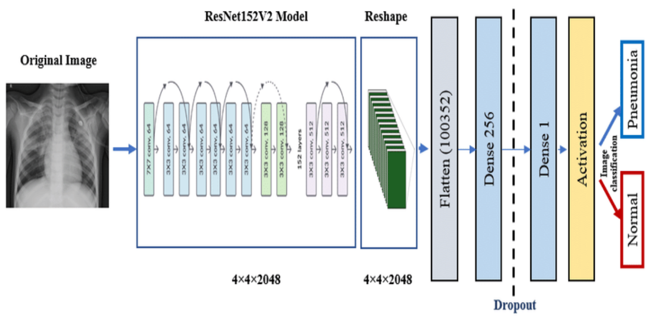

Figure 5: Architecture of ResNet152 V2

3.1. Fine-Tuning Pre-Trained Models

We used transfer learning to classify different plant categories from the plant village dataset by fine-tuning pre-trained models- InceptionV3, Inception ResnetV2, MobileNet, DenseNet121, and Resnet152V2.

Specifically, we replaced the original classification layer of models with a flatten layer and a dense layer with 15 output nodes, representing 15 different disease categories. The flatten layer was used to convert the output of the Inception V3 model from a 3D tensor to a 1D tensor, which was then passed through the dense layer to obtain a probability distribution over 15 disease categories.

We froze the top layers of these models and trained only recently added flat and dense layers in order to fine-tune the pre-trained model. We used Adam optimizer and a categorical cross-entropy loss function to train these models. To keep an eye on the model's progress during training, we used a validation set, and we used early stopping to avoid over-fitting. In this case, we employed the categorical-cross entropy loss function, which is frequently used in multi-class classification problems in machine learning. It has a number of benefits over utilizing categorical cross-entropy. When dealing with many classes, it is frequently utilized in classification jobs. Here are several justifications for choosing categorical cross-entropy.

Suitability for Multi-Class Classification: Categorical cross-entropy is specifically designed to handle multi-class classification problems, where each input sample belongs to one of several mutually exclusive classes.

Differentiable and Easy to Optimize: Categorical cross-entropy is a differentiable function, which means it can be optimized using gradient-based methods such as back propagation. The gradient of the loss concerning the model parameters can be efficiently computed, allowing for effective training using gradient descent-based optimization algorithms.

Encourages Probabilistic Predictions: Categorical cross-entropy encourages the model to produce probabilistic predictions by modeling the predicted class probabilities using a softmax activation function. The loss penalizes large deviations from the true class probabilities, promoting more accurate and confident predictions.

Handle Class Imbalance: Categorical cross-entropy can handle a class imbalance in the dataset. It assigns higher penalties to incorrect predictions on the minority classes, which helps address the challenge of imbalanced class distributions and encourages the model to learn equally from all classes.

Widely supported and Interpretable: Categorical cross-entropy is a well-established and widely supported loss function implemented in various deep learning frameworks. Its popularity makes it easier to find resources, libraries, and pre-trained models that utilize this loss function. Additionally, the cross-entropy loss has clear interpretabilitylower values indicate better model performance, while higher values imply higher dissimilarity between predicted and true class probabilities.

Advantages of using categorical cross-entropy:

Gradient-based optimization: Categorical cross-entropy is a differentiable function, which means it has a well-defined gradient. The gradient provides direction for updating the weights, allowing the model to learn from the data and improve its performance.

Handles class imbalance: In real-world datasets, it is common to encounter class imbalance, where some classes have significantly more or fewer samples than others. Categorical cross-entropy can effectively handle class imbalance by assigning higher weights to underrepresented classes during optimization. This helps prevent the model from being biased towards the majority class and promotes better learning across all classes.

Multiple class support: Categorical cross-entropy naturally extends to scenarios with multiple classes. It can handle classification problems where the number of classes is greater than two, making it suitable for multi-class classification tasks.

Efficient implementation: Categorical cross-entropy has a simple and efficient implementation, which makes it computationally tractable for large-scale datasets. Many deep learning frameworks provide built-in support for categorical cross-entropy, making it easy to use and integrate into various neural network architectures.

We have used an optimization function called the Adam optimization which is a popular choice in deep learning due to its efficiency and effectiveness in training neural networks. Adam is often preferred for the following reasons:

Adaptive Learning Rate: Adam combines the benefits of two other optimization algorithms, namely AdaGrad and RMSProp, by adapting the learning rate for each parameter individually. It automatically adjusts the learning rate based on the estimated first and second moments of the gradients. This adaptivity allows for faster convergence and better handling of sparse gradients.

Momentum: Adam incorporates the concept of momentum, which helps accelerate the optimization process. By utilizing the exponentially decaying average of past gradients, Adam effectively adds inertia to the optimization process, enabling faster convergence and reduced oscillation around the minima.

Robustness to Different Hyper parameters: Adam is relatively less sensitive to the choice of hyper parameters compared to other optimization methods. It works well with default parameter settings and often does not require extensive tuning, making it convenient for practical applications.

Efficient Memory Usage: Unlike some other optimization algorithms that require storing the entire history of gradients, Adam only keeps a fixed size moving average of past gradients. This memory efficiency is particularly beneficial when dealing with large-scale datasets or complex models that consume significant memory resources.

Wide Applicability: Adam has shown excellent performance and has become a widely adopted optimizer in the field, supported by most deep-learning frameworks.

3.2. Dataflow Diagram

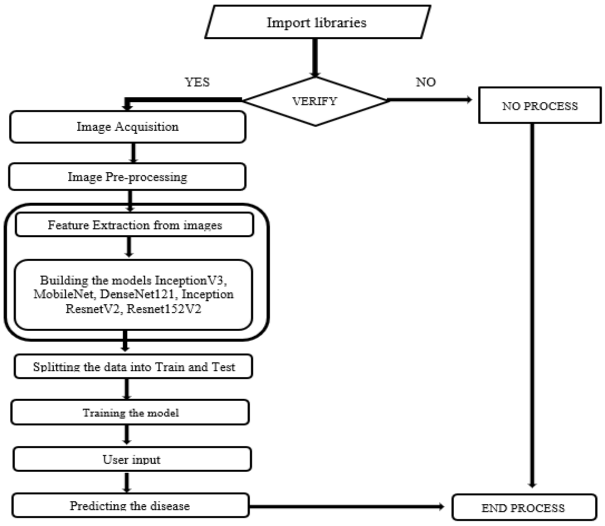

Figure 6: General Execution Framework of Deep Learning Models

The suggested deep-learning model for categorizing tomato, potato, and pepper plant illnesses is shown in Figure 6 above. The suggested model classifies the data using InceptionV3, Mobile Net, DenseNet121, Inception ResnetV2, and Resenet152V2. The classification of plant diseases and the validation of predictive models using the PlantVillage dataset are the main foci of this project. There are a total of fifteen groups that need to be categorized in this case, hence transfer learning is applied.

3.3. Dataset

In this work, we used pre-trained, weight-based Image Net models and retrieved detailed characteristics from them. In order to categorize and identify sickness on images that the model had never seen before, deep learning models were trained and tested using plant leaf images. The images for the dataset were gathered from the Plant Village collection. The gathered dataset has 20638 photos that have been divided into 15 groups. Images of healthy and sick leaves from three distinct plant types are included in the collection (tomato, potato, and pepper).

The graphics were initially colored images of varying sizes. Below figure 7 displays sample images from the PlantVillage dataset. Images for each model included in this research are first downsized to 128x128. To normalize the data and make it consistent with the network's starting values, the division operation divides every pixel value by 255. First, two sections of the data are separated. With a percentage ratio of 80% to 20%, the training data arrive first, followed by the validation data. The validation set had 2070 samples, whereas the training set had 18568 samples. For model assessment and prediction, the test set is used.

Figure 7: Sample images from PlantVillage Database

4. Results and Discussion

Almost 18568 images of healthy and sick plant leaves are included in the widely known Plant Village dataset, which is used to identify plant diseases. Many studies have assessed the effectiveness of various transfer learning models for detecting plant diseases. Some of the models InceptionV3, MobileNet, DenseNet121, InceptionResnetV2, and ResNet152V2's findings are listed below.

A cutting-edge deep learning model that has been extensively employed for image classification applications is the inceptionV3 model. Therefore, the InceptionV3 model may have been used to classify the images in the Plant Village dataset and evaluate its performance in identifying diseased plants. As a result, we were able to categorize the photos with this model's accuracy up to 83.7%. The accuracy and validation loss charts for the InceptionV3 model are displayed in Figure 8.

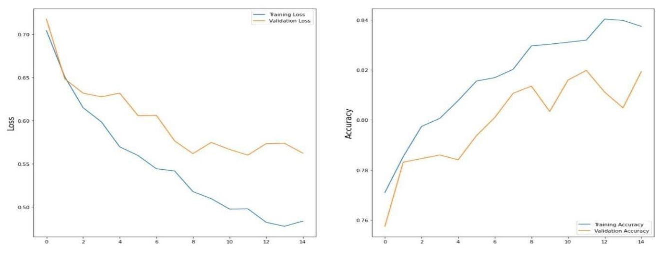

Figure 8: The aforementioned graphs display the accuracy and loss of the Inception V3 model for a specified number of epochs.

MobileNet is a model that can be pre-trained in transfer learning to extract useable features from photos, then tweaked for a new classification issue. Even when fine-tuned with a little data, it has demonstrated outstanding accuracy and efficiency. Also, owing to its lightweight architecture, it can be implemented on devices with minimal resources. So, we achieved an accuracy of our model in categorizing the photos up to 99.4%. The accuracy and validation loss graphs for the MobileNet model are displayed in Figure 9**.**

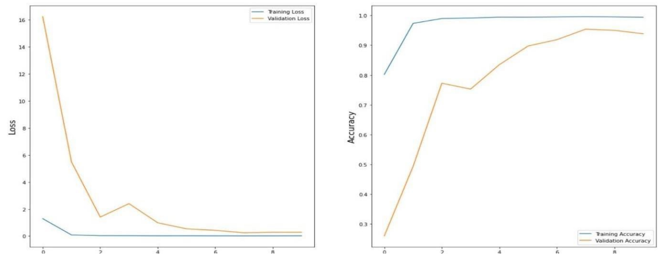

Figure 9: The aforementioned graphs display the MobileNet model's loss and accuracy for a specified number of epochs

DenseNet121 may not be as efficient as other designs, however, for tasks like object detection that call for the capture of spatial information. Furthermore, if not properly regularized, its dense block architecture may render it susceptible to over-fitting. Therefore, we got the accuracy of this model in classifying the images up to 99.4%. The accuracy and validation loss charts for the DenseNet121 model are displayed in Figure 10.

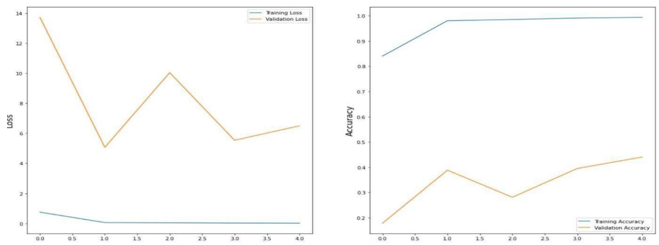

Figure 10: The aforementioned graphs demonstrate the accuracy and loss of the DenseNet121 model for a specific number of epochs

Inception-ResNetV2 has demonstrated its effectiveness in transfer learning for a variety of image classification tasks based on numerous experiments and assessments. It is well suited for tasks that require capturing complex patterns in images because of its inception module design, which enables it to capture both spatial and channel-wise features.

However, it's crucial to keep in mind that Inception ResNet V2 has a sizable number of parameters, making computation costly and necessitating a sizable quantity of data for fine-tuning. Furthermore, if not correctly regularized, its deep architecture can make it susceptible to over-fitting. Therefore, we got the accuracy of this model in classifying the images up to 98.5%. Figure 11 shows the accuracy and validation loss plots for the Inception-ResNetV2 model.

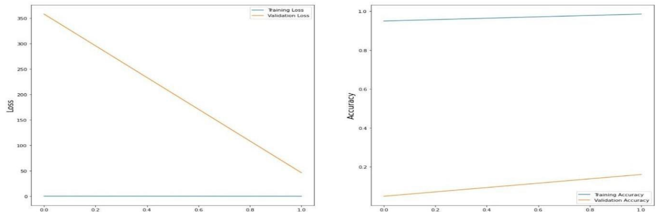

Figure 11: The aforementioned graphs display the Inception ResNetV2 model's loss and accuracy for a given number of epochs

ResNet152V2 has demonstrated its effectiveness in transfer learning for a variety of image classification tasks based on numerous experiments and assessments. It is well adapted for jobs that call for high accuracy due to its deep architecture and residual connections, enabling it to capture complex image patterns. ResNet152V2 has a significant number of parameters, which makes computation costly and necessitates a substantial quantity of data for fine-tuning.

Furthermore, if not correctly regularized, its deep architecture can make it susceptible to over-fitting. Therefore, we got the accuracy of this model in classifying the images up to 64.3%. The accuracy and validation loss charts for the Resnet152V2 model are displayed in Figure 12.

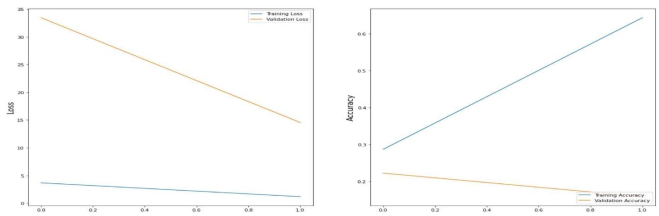

Figure 12: The aforementioned graphs display the accuracy and loss of the ResNet 152V2 model over a specified number of epochs

Table 1: Accuracy of Deep Learning models on the PlantVillage dataset

S.No	Transfer learning models	Accuracy (in %)	Loss (in %)
1	InceptionV3	83.7	0.48
2	MobileNet	99.4	0.18
3	DenseNet121	99.4	0.17
4	InceptionResnetV2	98.5	0.59
5	Resnet152V2	64.3	1.18

Overall, the findings imply that the PlantVillage dataset may be used to accurately diagnose plant diseases using transfer learning models. While other models, including InceptionV3, and Resnet152V2 have shown promising results, the models MobileNet, DenseNet121, and Inception-ResnetV2 have been proven to perform exceptionally well. It is crucial to remember that the model performance may be further enhanced by applying data augmentation approaches or fine-tuning smaller plant disease datasets.

5. Conclusion

By utilizing pre-trained models on sizable datasets, transfer learning models have demonstrated considerable potential in the detection of plant diseases. They lessen the need for large amounts of labelled data, which can be costly and time-consuming to collect. ResNet, Inception, and similar models have demonstrated high accuracy in detecting plant diseases. By adjusting these models and using data augmentation techniques, their performance can be further improved on smaller plant disease datasets. These transfer learning models offer a potential solution for identifying plant diseases, enabling early detection and treatment, leading to higher crop yields and sustainable agriculture. The proposed method focuses on identifying diseased leaf areas that are closely associated with existing disease diagnostic tools. It acknowledges the possibility of surrounding leaves being affected and aims to assist in early disease identification, even if some false negatives occur.

To ensure reliability, the system only transmits partially correct regions to the subsequent classifier when it is deemed unreliable. Accuracy is important, and a balance between false positives and false negatives must be maintained. Initial tests with real on-site photos have shown promising detection performance, although most leaves in these wide-angle photographs were healthy. Further research is planned to evaluate the approaches in various realistic settings with a higher number of contaminated leaves, with the goal of developing a practical plant diagnostic system.

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