Deep Learning-Based Agricultural Image-Based Leaf Disease Detection in Crops

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Abstract - One area of artificial intelligence is deep learning. The benefits of feature extraction and autonomous learning have made it a hot issue in academia and business in recent years. Natural language processing, audio processing, and picture and video processing have all made extensive use of it. It has also developed into a hub for agricultural plant protection research, which involves diagnosing plant diseases and evaluating the range of pests. Deep learning may be used to detect plant diseases without the drawbacks of artificial selection of disease spot features, as well as increasing the objectivity of plant disease feature extraction and accelerating technological development and research efficiency. An overview of the state of research on deep learning technology is given in this report. in the area of deep learning using agricultural images. Agriculture, which contributes most to expanding economies and populations, is essential to the availability of high-quality food. Plant diseases have the ability to wipe out species variety and result in large losses in food production. Using precise or automated detection methods for early plant disease diagnosis could improve food production quality and lower losses. Deep learning has significantly increased the recognition accuracy of object detection and picture classification systems in recent years. Therefore, we employed convolutional neural network (CNN)-based pre-trained models in our work to efficiently identify plant illnesses. We concentrated on fine-tuning the hyperparameters of many popular pre-trained models, including Inception V4, DenseNet-121, ResNet-50, and VGG-16.

Key Words: CNN, deep learning, transfer learning, leaf disease, and patholog

1.INTRODUCTION

Agriculture, being a substantial contributor to the world's economy, is the key source of food, income, and employment. In India, as in other low- and middle-income countries, where an enormous number of farmers exist, agriculture contributes 18% of the nation's income and boosts the employment rate to 53% [1]. For the past 3 years, the gross value added (GVA) by agriculture to the country's total economy has increased from 17.6% to 20.2% [2,3]. This sector provides the highest share of economic growth. Hence, the impact of plant disease and infections from pests on agriculture may affect the world's economy by reducing the production quality of food. Prophylactic treatments are not effective for the prevention of epidemics and endemics. Early monitoring and proper diagnosis of crop Infected plants typically have noticeable marks or spots on their stems, fruits, leaves, or flowers; more specifically, each infection and pest condition leaves distinct patterns that can be used to diagnose abnormalities; identifying a plant disease requires expertise and manpower; additionally, manual examination when identifying the type of infection of plants is subjective and time-consuming; and, occasionally, the disease identified by farmers or experts may be misleading [4]. Determining the types of plant diseases is a critical issue that requires careful attention to detail.

Plant Village is a plant disease dataset released by Pennsylvania State University [17]. There are 38 plant disease classes and 54,305 RGB photos in Plant Village. It includes pictures of fourteen distinct plants. Every plant has a minimum of two 256 × 256 picture classes that depict both healthy and damaged leaves. Figure 1 displays a selection of the dataset's pictures. Numerous studies on plant disease identification have been conducted after the dataset's publication [18–21].

CNN deep learning models are widely used in image-based research. They are effective at extracting simple, low-level features from pictures. Unfortunately, training deep CNN layers is challenging due to the high computational cost. Several researchers have suggested transfer learning-based models to address these problems [22–26]. The VGG-16, ResNet, DenseNet, and Inception models are well-liked transfer learning models [27]. The ImageNet dataset, which comprises several classes, is used to train these models. Because image characteristics like edges and contours are shared by all datasets, these models can be trained on any dataset. Thus, the most appropriate and reliable model for image classification has been determined to be the transfer learning approach[28].

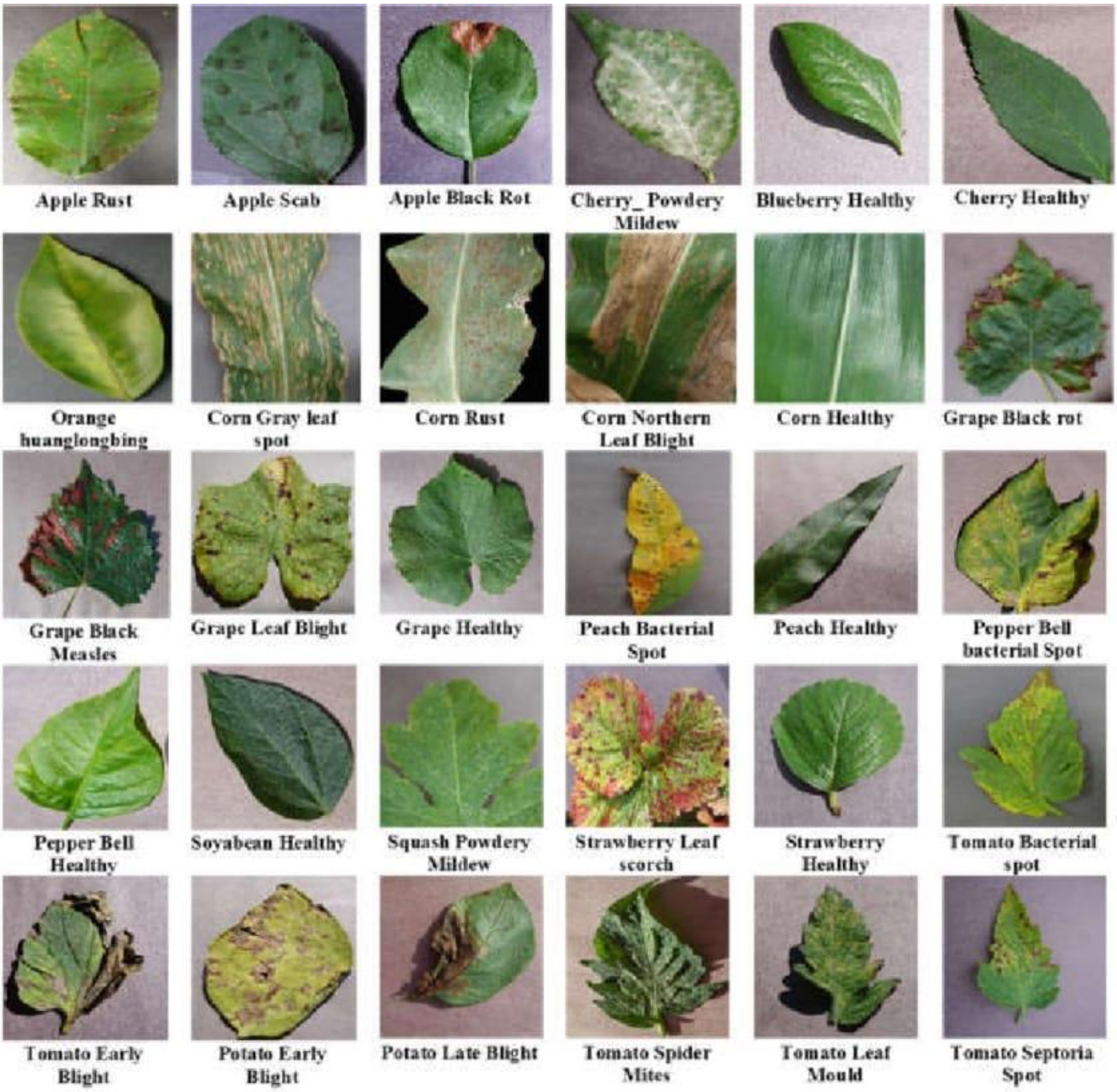

Fig – 1: shows sample photos for 38 different kinds of leaf diseases from the Plant Village collection.

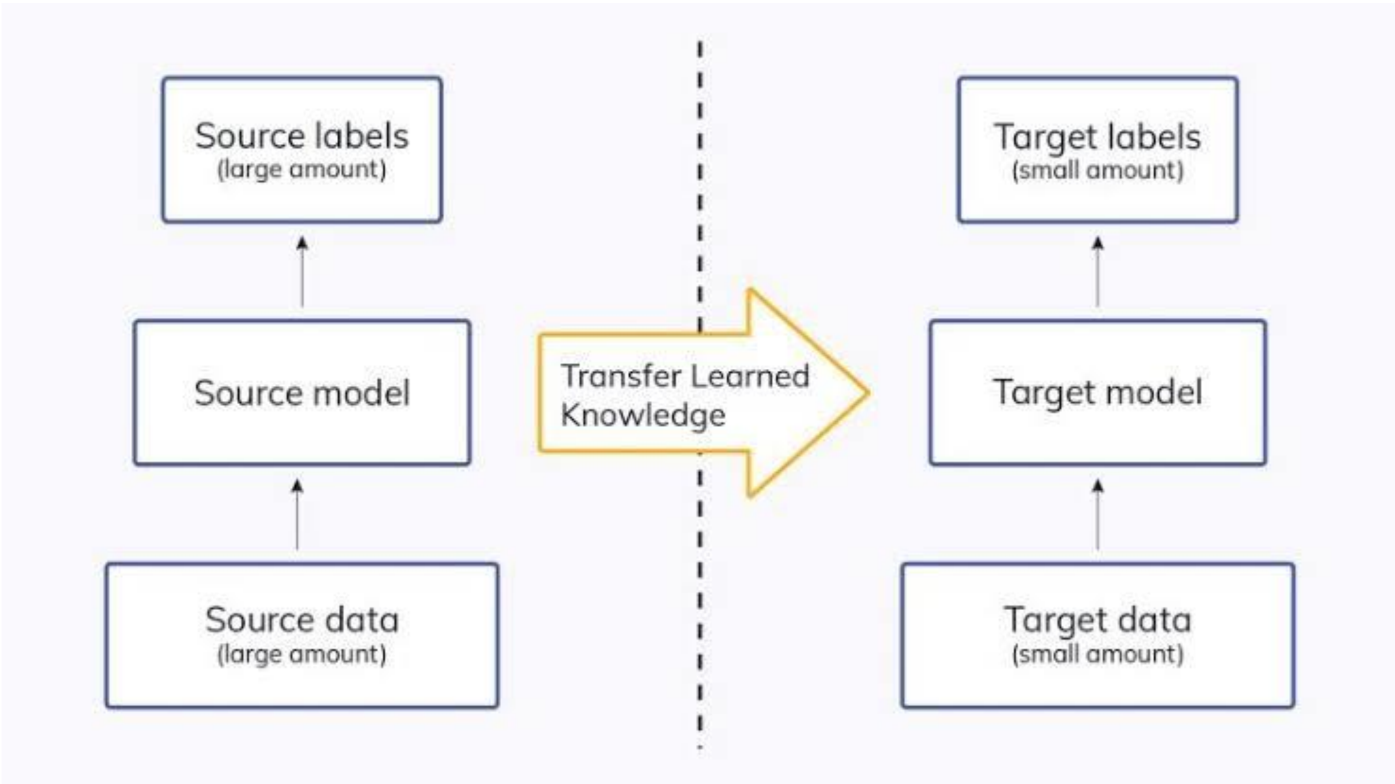

Fig – 2: Basic idea behind transfer learning.

Tasks are more accurate with transfer learning [22], since the model can be taught by freezing either the initial or last layers. The model parameters can therefore be maintained and adjusted for feature extraction and classification by freezing the layers [29]. In order to improve recognition and classification accuracy and reduce time complexity, we conducted a comparative performance analysis of various transfer learning models using deep CNNs. Figure 3 shows our workflow architecture. The Plant Village dataset and pre-trained CNN models, including VGG-16, DenseNet-121, ResNet-50, and Inception V4, were used in the tests.

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The following succinctly describes the main contributions of this manuscript:

• Creating a deep learning model to diagnose different plant diseases; identifying the best transfer learning method to achieve the highest classification and recognition accuracy for multi-class plant diseases; resolving different labeling and class problems in plant disease recognition by suggesting a CNN model based on multi-class, multi-label transfer learning; resolving the overfitting issue using data augmentation techniques.

• A multi-class, multi-label transfer learning-based CNN model was proposed to address the separate labeling and class concerns in plant disease recognition; data augmentation techniques were used to address the overfitting issue.

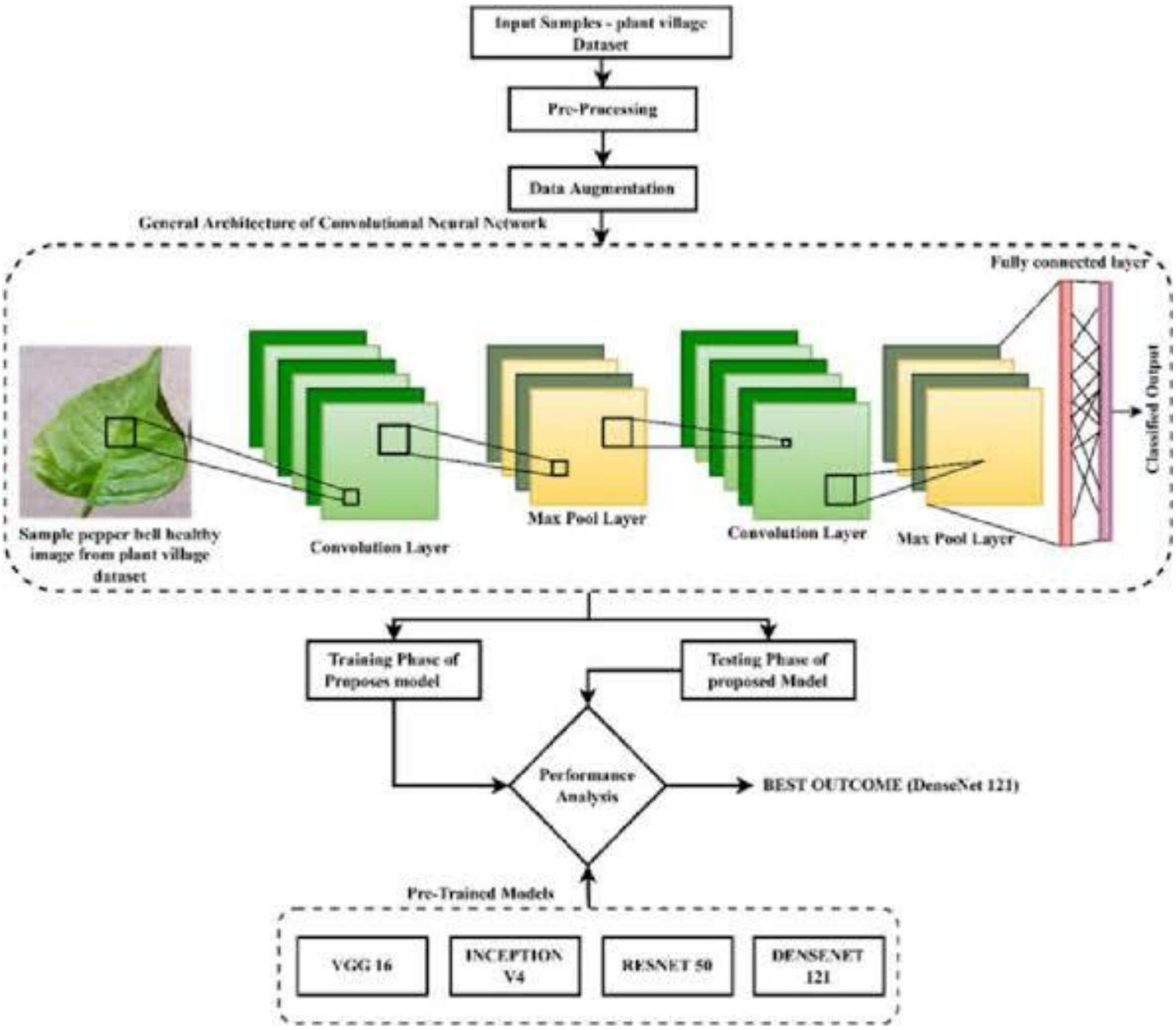

Fig – 3: Overall workflow diagram.

2. Related Work:

If the early warning indications of plant disease are ignored in the sphere of agricultural production, food crop losses could potentially devastate the global economy [30].

In order to accurately classify plant diseases, a CNN-based deep learning model was presented in [31]. A publicly accessible dataset consisting of 87,000 RGB images was used to train the model. First, preprocessing was done, and then segmentation.

CNN was utilized to classify the data. Despite achieving a 93.5% identification accuracy, this model was unable to categorize certain classes, which caused confusion with the classes in later stages. Furthermore, the model's performance declined as a result of the data's limited availability. However, Narayanan et al. [32] suggested a hybrid convolutional neural network to categorize banana plant disease in order to increase recognition accuracy. Their method used a median filter to preserve the conventional image dimensions while preprocessing the raw input image without changing any default information.

Reference	Crop Focus	Disease Addressed	Dataset	Classes	Model	Model Performance
[41]	Tomato plant	Various diseases and pests in tomato plant	Self-generated database	9	Faster Region-based CNN with SSD 1 and Region-based Fully Convolutional Network	Precision: 85.98%
[29]	Several	Citrus canker, black Mould, bacterial blight, etc.	Plant disease symptoms database	12 56 diseases under 12 classes	CNN Google Net with tenfold cross-validation	Accuracy: 84%
[45]	Tomato	ToMV, leaf mould fungus, powdery mildew, blight	AI-Challenger plant disease recognition	4	Faster regional CNN	Accuracy: 98.54%
[42]	Several	Powdery mildew, early and late blights, cucumber mosaic, downy mildew, etc	Open dataset	58	CNN with pre-trained VGG network	Accuracy: 99.53%
[43]	Several	Pepper bell bacterial spot, tomato early and late blight	PlantVillage	38	ImageNet, GoogLeNet, and VGG-16 models	Accuracy: 99.09%

Table 1. Detailed summary of the CNN models used in the recognition and classification of plant disease.

3. Methodology:

CNN models work best with picture databases for object recognition and classification. CNNs have many benefits, but there are still drawbacks, like the lengthy training period and the need for big datasets.The training of deep CNN models becomes more difficult in order to extract the low-level and complex characteristics from the images. The difficulties listed above can be overcome by using transfer learning strategies. Model parameters gained on a specific dataset can be applied to different issues through the use of pre-trained networks in transfer learning. The methods employed in this work are covered in this section.

3.1. Classification by Multiple Classes:

Each plant sample is assigned to a specific class, and plant disease datasets contain several photos of both healthy and afflicted plant samples. Images of both healthy and diseased banana plant samples, for example, will be mapped to the appropriate class if we think of the banana plant as a whole. At this point, just the features taken from the source image are used to classify the target image. Black sigatoka, bunchy top virus, fusarium wilt, and xanthomonas wilt are the four disease groups that affect the banana class, using the same example as the banana plant [32]. Once all four sets of illness samples from the banana class have been used for training, the testing phase output will categorize when a sample of a certain disease is downloaded as input.

3.2. The Approach to Transfer Learning:

Most state-of-the-art models require days or weeks to train and fine-tune, even when they are trained on powerful GPU computers. It takes time to train and create a model from the ground up. In 200 epochs, a CNN model constructed from scratch using a publicly available plant disease dataset appeared to achieve 25% accuracy, but a pretrained CNN model employing a transfer learning technique achieved 63% accuracy in nearly half the iterations (more than 100 epochs). There are a number of transfer learning techniques; which one is used will rely on the specifics of the dataset and the pre-trained network model selected for classification.

3.3. VGG-16:

The VGG-16 [50] network model, also known as the Very Deep Convolutional Network for Large-Scale Image Recognition, was built by the Visual Geometry Group from Oxford University. The depth is pushed to 16–19 weight layers and 138 M trainable parameters. The depth of the model is also expanded by reducing the convolution filter size to 3 × 3. This model requires more training time and occupies more disk space.

4.Experiments:

Our studies were evaluated using a GPU NVIDIA GeForce GTX workstation as the baseline system. The system specifications were Core i5 9th generation, GDDR5 graphics memory, Windows 10, and 8 GB of random-access memory. Utilizing the Anaconda3, Keras, OpenCV, Numpy CuDNN, and Theano libraries, software implementation was carried out. Simple libraries called CUDNN and CUMeM were created specifically to execute deep learning implementations more quickly and with reduced memory usage. NVIDIA created both of these libraries to function in the Theano backend. With support for Linux, Windows, Mac OS, iOS, Python, Java, and Android interfaces, OpenCV facilitates the development of both commercial and academic projects. Both the testing and training accuracy were assessed for every experiment in this study.We computed the losses for each model during the training and testing stages. The PlantVillage dataset was used to train the models in order to increase the CNN's learning speed utilizing transfer learning techniques. For our investigation, we selected pre-trained models such as ResNet-50, Inception V4, VGG-16, and DenseNet-121. These models were previously trained using the ImageNet dataset, which contained 1.2 million images and 1000 image categories.

4.1 Dataset Description:

A publicly accessible dataset with several plant disease categories is PlantVillage [17]. There are 54,305 photos in 38 classes in this dataset. We divided the dataset into training, testing, and validation samples for our experimental study.Eighty percent of the PlantVillage dataset was utilized to train the pre-trained models, with the remaining twenty percent being used for testing and validation. Additionally, of the 54,305 samples that were available for the plant classes, 43,955 were used for training, 4902 for validation, and 5488 for testing. All 38 classes of the various plant diseases are included in these train, test, and validation sets.

Table 2. Details of PlantVillage dataset split for training, validation, and testing.

Plant Type	Diseases Classes	Total Samples	Training Samples	Test Samples	Validation Samples
Apple	Apple_scab Apple_black_rot Apple_cedar_apple_rust Apple_healthy	573 565 250 1497	510 502 222 1332	63 63 28 165	*57* *56* *25* *148*
Blueberry	Blueberry_healthy	1366	1215	151	*136*
Cherry	Cherry_powdery_mildew Cherry_healthy	957 777	851 691	106 86	*95* *77*
Corn	Corn_gray_leaf_spot Corn_common_rust Corn_northern_leaf_blight Corn_healthy	466 1084 896	414 964 797	52 120 99	*47* *108* *89*

		1057	940	117	*105*
Grape	Grape_black_rot Grape_black_measles Grape_leaf_blight Grape_healthy	1073 1258 979 385	955 1119 871 342	118 139 108 43	*107* *125* *97* *38*
Orange	Orange_haunglongbing	5011	4460	551	*496*
Peach	Peach_bacterial_spot Peach_healthy	2090 327	1860 291	230 36	*107* *33*
Pepper	Pepper bell_bacterial_spot Pepper Bell_healthy	997 1478	807 1197	100 148	*90* *133*
Potato	Potato_early_blight Potato_healthy Potato_late_blight	1000 1000 152	810 810 122	100 100 16	*90* *90* *14*
Raspberry	Raspberry_healthy	664	299	38	*34*
Soybean	Soybean_healthy	5295	4122	509	*459*
Squash	Squash_powdery_mildew	1669	1485	184	*166*
Strawberry	Strawberry_healthy Strawberry_leaf_scorch	1009 415	898 369	111 46	*100* *41*
Tomato	Tomato_bacterial_spot Tomato_early_blight Tomato_healthy Tomato_late_blight Tomato_leaf_mold Tomato_septoria_leaf_spot Tomato_spider_mites_twospotted_spider_mite Tomato_target_spot Tomato_mosaic_virus Tomato_yellow_leaf_curl_virus	2127 1000 1591 1909 952 1771 1676 1404 373 3209	1722 810 1546 770 1433 1357 1136 4338 301 1287	213 100 191 96 178 168 141 536 38 160	*192* *90* *172* *86* *160* *151* *127* *483* *34* *144*
Total		54,305	43,955	5448	*4902*

4.2. Data Augmentation and Preprocessing:

There were 38 classes, 26 illnesses, and 14 crop species in the dataset. Since the color photos from the PlantVillage dataset work well with the transfer learning models, we used them for our experiment. Since we employed various pre-trained network models that require varying input sizes, the images were downscaled to 256 × 256 pixels as a standard format. While the input shape of pictures for Inception V4 is 299 × 299 × 3 (height, width, and channel width), the input size for VGG-16, DenseNet-121, and ResNet-50 is 224 × 224 × 3 (height, width, and channel width). Despite the size of the dataset—roughly 54,000 photos of various crop diseases—the photos correspond to actual photos taken by farmers using various image collecting methods.smartphones, Kinect sensors, and HD cameras, for example. Furthermore, overfitting is a common problem with datasets of size. Thus, overfitting regularization methods were developed to get around this, like data augmentation following pretreatment. Zoom intensity, rescaling, flipping horizontally and vertically, and clockwise and anticlockwise rotation were among the augmentation techniques applied to the preprocessed photos. Compared to models created from scratch, the transfer learning model has the advantage of learning more quickly and allowing for the freezing of model layers so that the final layers can be trained for more precise categorization. First, some hyperparameter standardizations for various pre-trained models were carried out.

To optimize the models, stochastic gradient descent was used. For DenseNet-121, ResNet-50, VGG-16, and Inception V4, the initial learning rates were set to 0.001. Every model ran for 30 epochs, with a fixed dropout value of 0.5. After a few iterations (i.e., the output graph began to converge after 30 epochs), our experiment was able to overcome the problems of overfitting and degradation.

Table 3. Hyperparameter specifications.

Hyperparameters	Epochs
Dropout	0.5
Epochs	30
Activation	ReLu
Regularization	Batch normalization
Optimizer	Stochastic gradient descent (SGD)
Learning rate	0.001
Output classes	38

4.4. Model of Network Architecture:

The selection of pre-trained network models was based on how well they applied to the objective of classifying plant diseases. Table 4 provides information on the model architecture.Different filter sizes are used by each network to extract particular characteristics from feature maps.When it comes to feature extraction, filters are essential. Additionally, each filter will extract distinct features from the input when convolved with it; the particular feature extraction from the feature maps is contingent upon the filter values. We employed real pre-trained network models in our studies, utilizing the precise convolution layer combinations and filter sizes for every network model.

5. Findings and Conversation:

In order to diagnose plant illnesses, this section of the study used cutting-edge deep learning models with the transfer learning methodology. The deep CNN networks that had already been trained using the ImageNet dataset were further trained using PlantVillage, a publically accessible dataset. Each model was standardized for our experiment with 38 output classes, a dropout of 0.5, and a learning rate of 0.01.Training, test, and validation samples were taken from the dataset. The pre-trained Inception V4, VGG-16, ResNet, and DenseNet-121 models were trained using 80% of the PlantVillage samples. After 30 epochs of operation for each model, it was discovered that our model began to converge with excellent accuracy after 10 epochs.High yields in agricultural production depend on early crop disease identification.The newest technology should be used in the early diagnosis of plant diseases in order to maintain a high output rate. The literature review revealed that transfer learning-based models are effective in removing training complexity and the need for large datasets, while deep learning models are effective at classifying images. In order to identify the model that was most effective in classifying different plant illnesses, we assessed four pre-trained models in this study: VGG-16, ResNet-50, Inception V4, and DensNet-121. Evaluation criteria like specificity, sensitivity, and F1 score values were used to assess the pre-trained models' performance. The F1 score was used to calculate the validation accuracy, and a graphical depiction of the validation.Displays a statistical depiction of the pre-trained network models according to the evaluation metrics. Regularization techniques like batch normalization were used to remove the vanishing gradient problems caused by skip connections. Deeper models presented a number of difficulties, including covariant shifts, overfitting, and the complexity of training time. We adjusted the hyperparameters in our experiments to get around these obstacles. In order to forecast the percentage of genuinely healthy plants classified as healthy (true positive) and genuinely healthy plants classified as unwell (false negative), the tests employed sensitivity. ResNet-50 and DenseNet-121 outperformed the VGG-16 and Inception V4 models, according to the evaluation.An evaluation of the various pre-trained models' performance based on their sensitivity and specificity.

6. CONCLUSIONS:

In this work, we were able to examine the different transfer learning models that are suitable for accurately identifying 38 different plant disease classes.The performance analysis of the various pre-trained architectures revealed that DenseNet-121 outperformed ResNet-50, VGG-16, and Inception V4.Training the DenseNet-121 model seems straightforward due to its lower computational complexity and smaller number of trainable parameters. When a novel plant disease needs to be included in the model, DenseNet-121 is more suited for plant disease detection due to its lower training complexity. The classification accuracy of the proposed model was 99.81%.In future studies, we will address the difficulties related to multi-object deep learning algorithm that can even detect plant diseases from a collection of leaves rather than a single leaf using real-time data collection. The trained model from this study will also be used to develop a mobile application. The capacity to detect leaf diseases in real time will be helpful to farmers and the agriculture sector.

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