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Classification of Potato Leaf Diseases using Convolutional Neural Networks and Transfer Learning

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***Abstract*—One of the most popular crops in the world, potatoes have seen a sharp rise in demand, especially during the global coronavirus pandemic. Potato diseases, on the other hand, present a significant problem since they can negatively affect plant health by reducing both quantity and quality as well as delaying the identification and categorization of disease kinds. Notably, leaf conditions can be used to identify certain potato plant illnesses. In order to tackle this problem, a strong classification system is suggested that combines transfer learning models like VGG19, Xception, EfficientNetV2S, and DenseNet201 with deep learning methods, particularly convolutional neural networks. Based on leaf conditions, these models are used to categorize two different kinds of potato plant diseases. By reaching higher classification accuracy, the experiment shows that these models are both feasible and effective.**

***Index Terms*— Potato leaf diseases, Deep learning algorithms, Transfer learning, Classification.**

I. INTRODUCTION

In nations like India, where the economy is largely dependent on agricultural activity, agriculture is an essential sector. Achieving desired yields requires that crops be properly cared for from the seedling stage until harvest. Throughout their lives, crops must contend with a variety of issues, such as weather, animal protection, and disease prevention. Although proper field protection can protect crops from animals, farmers must still hope for favourable weather conditions because they are beyond their control. Fighting diseases brought on by infections, fungi, bacteria, germs, and viruses—which can have a negative impact on crop growth and yield—is the most important task, though. By enabling the application of the right nutrients, early detection and prompt intervention can greatly lessen the burden of various disorders. By decreasing the time needed for detection and increasing the accuracy of illness identification, digitizing the disease diagnosis and classification process could be extremely advantageous to farmers [1][2].

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The potato is one of the most important crops in India, and more than three-quarters of the population eats it every day, making it one of the most consumed vegetables. However, diseases like late blight and early blight, which are brought on by Alternaria solani and Phytophthora infestans, respectively, can affect potato crops [11]. To avoid yield losses and financial setbacks, these diseases must be identified and classified promptly. Disease detection has always depended on skilled visual inspection, a laborious process that is constrained by the lack of specialists in rural areas. An efficient method for tracking and identifying plant diseases is image analysis. Certain disease-related patterns can be found and compared with the available data for precise categorization by examining visible patterns on leaves using a variety of image processing techniques. Early detection of potato leaf diseases is essential for increasing crop yield and reducing losses. In addition to improving accuracy, using image-based disease detection techniques helps farmers manage crop health more effectively[10].

II. Literature Review

Several methods for categorizing potato leaf diseases have been proposed by numerous studies in the field of leaf disease detection. An overview of those classification techniques is given in this section. To categorize plant diseases, Betirhanu et al. [1] employed a CNN architecture called the Inception V3 model. When they used transfer learning on plant leaves, they discovered that Inception V3 outperformed alternative CNN architectures in terms of training accuracy and duration. They trained 2,152 photos and divided them into three classes for their study: early-stage infected leaves, late-stage infected leaves, and healthy plant leaves. Other CNN frameworks like AlexNet and GoogLeNet were also put to the test. With an accuracy of 93.75%, the AlexNet model outperformed the GoogLeNet model by a small margin, with 96.63%. But Inception V3 did better than both, with 98.3% accuracy. According to their research's findings, the best model for transfer learning in the classification of plant diseases is Inception V3.

An overview of deep learning algorithms for feature extraction from photos is given by Ananda S. Paymode and Vandana B. Malode [2]. To improve performance metrics, they use the Convolutional Neural Network (CNN) model based on VGG. Facilitating continual improvements and increasing the effectiveness of performance evaluation are the main objectives of their work. The pooling layer, dropout layer, flattening layer, and fully connected layer are among the CNN layers that are covered in the study. They classified crop photos using the VGG16 model, which is a pre-trained model. For classification tasks, they also took into account grapes and tomatoes in addition to potatoes. A machine learning technique for identifying illnesses in potato plant leaves was presented by Xudong Li and associates in 2022 [10].

They collected a dataset of potato plant leaves from Hebi Agriculture's experimental location. Their accuracy, using the Mask R-CNN model, was 95.2%. The Support Vector Machine (SVM) algorithm, a kind of machine learning technique utilized for both classification and regression issues in real-world applications, was covered by R. Gowtham and Dr. R. Jebakumar [14]. The SVM algorithm is used in their suggested approach, "Disease Detection with Auto-Spraying Mechanism," to identify plant diseases. An automatic spraying system is then triggered to administer the proper medication for each disease that has been found. They used the SVM approach to categorize illnesses in different kinds of plant leaves in addition to potato leaves. A study comparing deep learning architectures for identifying late blight and early blight illnesses in potatoes was carried out by Soumo Emmanuel Arnaud and associates [15]. Using the SGD optimizer, they assessed five CNN models and obtained an accuracy of 73.21% and an F1-score of 50.86%. Using transfer learning, Birhanu Gardie and associates [16] investigated the identification of leaf diseases in potato plants. For this, they created an Inception-V3 transfer learning model, which trained with 96.8% accuracy.

III. Data Description

The publicly accessible PlantVillage image database, which includes over 54,306 photos of 14 tamed plant species in both healthy and ailing conditions, is where we got our data. The suggested algorithms made use of the potato species data from this collection. 2,152 photos of potato leaves in three classes are included in the dataset:

A robust leaf

Leaf of late blight

Blight leaf in its early stages

The potato leaf collection includes 1,999 photos of diseased leaves and 152 photos of healthy leaves, as indicated in Table 1. Thirty percent (430 images) of the dataset is utilized for testing, while eighty percent (1,721 images) is used for training. Each image has a resolution of 128x128 pixels.

TABLE I: CLASS NAMES WITH NO. OF IMAGES

Dataset Images	
Healthy leaf	152
Early blight leaf	999
Late blight leaf	1000

IV. PROPOSED MODEL

In this study, we suggest two methods for classifying the illnesses (diseases) found in potato leaves.

A. Learning Transfer

Adapting a previously trained Keras model to address a novel issue is known as transfer learning. Because it can efficiently train deep neural networks using very minimal datasets, this method has become very popular. We use four transfer learning frameworks in this study, all of which have been pre-trained on the sizable ImageNet dataset, which has about 1,000 classes. In order to prevent the pre-trained model from being further trained, we set include_top=False for these models, which excludes the top layers of the imported model. Rather, the model is customized for our particular goal by adding unique layers, such as activation function layers, dropout layers, and thick layers. The four transfer learning models that were applied in this study are listed below:

B. VGG19

There are 19 layers in all in the VGG19 transfer learning network. We used a pre-trained version of VGG19 for this investigation, which was created using more than a million photos from the ImageNet dataset. A variety of animals and things, such as pencils, mice, and keyboards, can be classified into 1,000 categories by this pre-trained model. Consequently, the network has acquired rich feature representations that may be applied to a variety of images. We categorized potato leaf diseases using this approach. This network requires an input image with a size of 224 x 224 pixels.

TABLE II: VGG 19 MODEL

Layer (type)	Output Shape
VGG19 (Functional)	(None, 4, 4, 512)
Flatten_1(Flatten)	(None, 8192)
Dense_2(Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_3 (Dense)	(None, 3)
Total params: 21,073,475 Trainable params: 1,049,091 Non TrainableParams:20,024,384	

An overview of all the parameters in the VGG19 classification model is given in Table 2. There are 1,049,091 trainable parameters and 20,024,384 non-trainable parameters that come from the VGG19 model. To improve the VGG19 model's output, additional custom top layers were added. It took about 22.45 minutes for a CPU to train this model.

C. Xception

One of the most comprehensive classifiers is Xception, a deep neural network with 81 layers. It makes use of separable convolutional layers, which are more cost-effective and memory-efficient than conventional convolutional layers. The needed input image size for the model is 299×299×3.

TABLE III: XCEPTION MODEL ARCHITECTURE

Layer (type)	Output Shape
xception (Functional)	(None, 4, 4, 2048)
flatten (Flatten)	(None, 32768)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 3)
Total params: 25,056,299 Trainable params: 4,194,819 Non TrainableParams:20,861,480	

D. EfficientNetV2S

EfficientNet-V2S, a streamlined version of EfficientNet-V2, was used for classification with ImageNet-1k and ImageNet-21k datasets, offering faster training and better parameter efficiency. Our model, with 26,21,955 trainable and 2,03,31,360 non-trainable parameters (from EfficientNet-V2S), includes custom top layers for enhanced performance. Despite taking 19.20 minutes on a CPU, it outperformed other models significantly.

TABLE IV: EFFICIENT V2S MODEL

Layer (type)	Output Shape
Efficientnetv2-s(Functional)	(None, 4, 4, 1280)
flatten (Flatten)	(None, 20480)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 3)
Total params: 22,953,315 Trainable params: 2,621,955 Non TrainableParams:20,331,360	

E. Densenet201

The 201-layer transfer-learning network DenseNet-201 helps to alleviate gradient problems and reaps the benefits of feature reuse. For better performance, our model incorporates custom top layers with 39,32,675 trainable and 1,83,21,984 non-trainable parameters (from DenseNet-201). It took a CPU 38.28 minutes to train.

TABLE V: DENSE NET MODEL

Layer (type)	Output Shape
densenet201 (Functional)	(None, 4, 4, 1920)
flatten (Flatten)	(None, 30720)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 3)
Total params: 22,254,659 Trainable params: 3,932,675 Non TrainableParams:18,321,984	

We employed a CNN with convolutional, pooling, fully connected, dropout, and activation functions to classify leaf diseases. Max-pooling shrinks the size of the feature map, while the convolutional layer extracts features from the image. The completely linked layers, which carry out categorization, are prepared for the image by a flatten layer. During training, 50% of nodes are randomly disabled using dropout to avoid overfitting. SoftMax and ReLU are used as activation functions. There are 16,29,731 trainable parameters in the model.

TABLE VI: CNN MODELS LAYERS

Layer	Output Shape
rescaling(Rescaling)	(None, 128, 128, 3)
cov2d(Conv2D)	(None, 126, 126, 16)
max_pooling2d(MaxPooling2D)	(None, 63, 63, 16)
conv2d_1(Conv2D)	(None, 61, 61, 32)
max_pooling2d_1(MaxPooling2D)	(None, 30, 30, 32)
conv2d_2(Conv2D)	(None, 28, 28, 64)
max_pooling2d_2(MaxPooling2D)	(None, 14, 14, 64)
flatten(Flatten)	(None,12544)
dense(Dense)	(None, 128)
dropout(Dropout)	(None, 128)
dense_1(Dense)	(None, 3)
Total params: 1, 629, 731 Trainable params: 1, 629, 731 NonTrainableParams:0	

V. RESULT

By controlling biotic variables, deep learning and transfer learning approaches efficiently identify plant leaf diseases, increasing agricultural output. The model's training and validation accuracy in the first epoch were 68.94% and 84.94%, respectively. Both accuracies rose over 20 epochs while validation loss decreased. Training the model took a total of 4.05 minutes on a CPU.

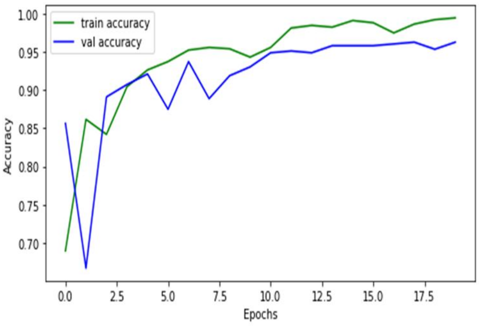

Figure 1. Training and Testing accuracy

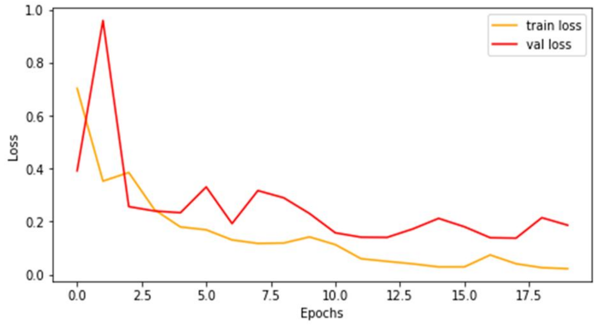

Figure 2. Training and Testing loss A.CNN

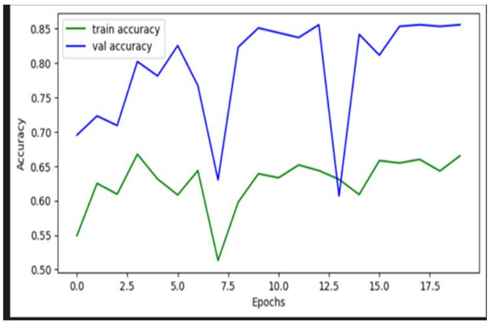

Figure 3. Training and Testing accuracy

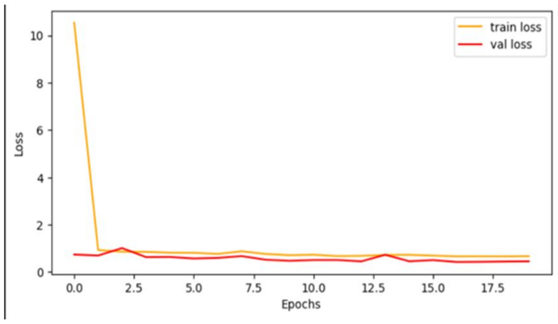

Figure 4. Training and Testing loss B. Xception

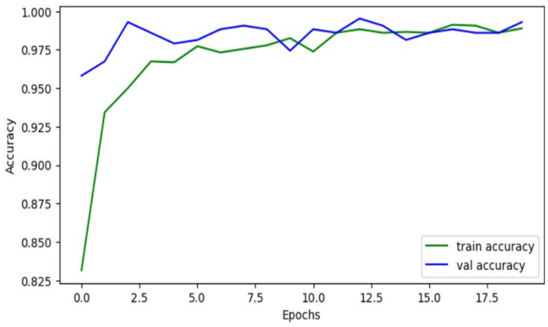

Figure 5. Training and Testing accuracy

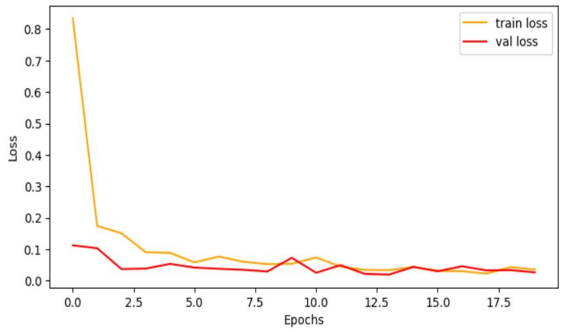

Figure 6. Training and Testing loss C. efficientnetV2S

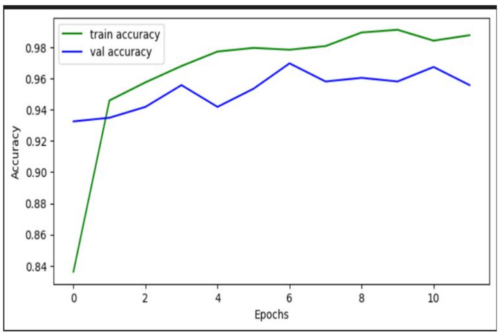

Figure 7. Training and Testing accuracy

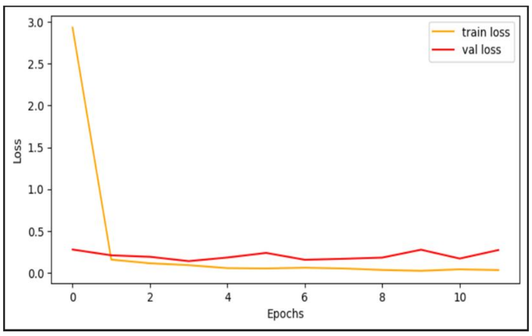

Figure 8. Training and Testing loss D. VGG19

VI. Conclusion

After reviewing several studies on the categorization of potato plant diseases, we developed a model utilizing transfer learning and deep learning (CNN) (DenseNet, VGG19, EfficientNetV2S, Xception). DenseNet and EfficientNetV2S were the most accurate of them. Therefore, EfficientNetV2S achieved the highest classification accuracy of 99% in transfer learning, whereas CNN offers the best performance for deep learning.

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