

A Novel Deep Learning Design of Plant Disease Recognition and Detection using VGG19, ResNet50, and DenseNet169

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Abstract— The first step in effectively and precisely preventing plant disease in a complex environment is to identify the diseased plants. The identifying of plant diseases becomes digitalized and data-driven only with rapid development of smart farming, enabling better decision support, clever analyses, and planning. In order to increase accuracy, generality, & training effectiveness, a deep learning design of plant disease recognition and detection has been developed using VGG19, ResNet 50, and DenseNet 169. The CLAHE method is first used to identify & localize its leaves in a complex environment. Images that have been segmented using the CLAHE algorithm's findings include the feature of symptoms. Once the leaves have been segmented, they are included in the transfer learning procedure and trained with the data set of sick leaves on a white background. The model is also tested against rust, black rot, and bacterial plaque diseases. Results indicate that DenseNet is more accurate than the conventional method (98.11%), which helps ensure agriculture's long-term viability by reducing the effects of disease on crop yields. Therefore, the deep learning algorithm presented in this paper has important implications for environmental protection, smart farming, and food production.

Index Terms— Plant Disease, VGG19, ResNet 50, DenseNet 169, Deep learning.

I. INTRODUCTION

The prosperity of most countries is crucial to their populations. The expansion for an economy has a major bearing on the rise of a country's gross domestic product. The agricultural sector is highly sensitive to economic conditions. Vegetable and grain yields and quality can be affected by a number of farming techniques. These cereals and vegetables are vulnerable to a wide range of illnesses because they are grown in a wide range of climates and environments [1]. Consequently, farmers everywhere lose a lot of money due to these diseases. Agricultural yield lost to leaf diseases is decreasing over time. The greatest difficulties lie in identifying the cause of the leaf disease plaguing the agricultural field and in increasing production rates to both quality and quantity. The leaves of at least two different crops must be considered when diagnosing a disease. Tomatoes and potatoes are two essential crops that are used in our daily food and also to restore nutrients to the human body. Vegetables and grains are particularly vulnerable to the effects of natural disasters, which can reduce yields and quality. Correct leaf identification and categorization could be essential in the fight against agricultural erosion. Viruses, bacteria, and fungi can infect the leaves and grains of a wide variety of plants. The most common plant diseases are al-ternaria alternata, anthracnose to bacterial blight, cercospora leaf spot, powdery scale, black mold, downy mildew, and

rust. When a plant's leaf becomes infected, the symptoms of that infection can be seen in the leaf's texture, color, shape, and size. Diseases cannot be diagnosed because the majority for symptoms are too small to be seen by the naked eye [2].

Since precision farming techniques' secondary goal is to increase the yield of organically grown crops, it may be worthwhile to take them into consideration in order to meet this goal, particularly given that, at the moment, "organic farming does have the drawback that more property is needed per unit produced." The use of chemical factory protection agents has some drawbacks, which are addressed by precision farming, a method made possible by technological advancement. research on automating several procedures, such as sowing, Precision farming includes practises like weeding and harvesting that aim to have a smaller negative ecological impact, but it still presents a significant technological obstacle that must be overcome gradually. Since over 50% of a aforementioned plant protection chemicals are herbicides, precision weeding is the most important component of precision farming and can be seen as the first step in overcoming the difficulty outlined before. This percentage might be significantly decreased because another objective of precision farming is either to limit its application of chemicals on weeds rather than applying them to the entire field or to completely forego the use of chemicals in favour of automated weed removal tools[3]. Getting rid of weeds is necessary to preserve soil nutrients for crops, although some less dangerous weed species can be kept on the field to increase diversity. Since the elimination task is intended to be carried out by autonomous robots in order to reduce costs, it is imperative that plant detection be implemented quickly and precisely. In order for a robot to completely eradicate weeds, it must be able to distinguish between crops, harmful weeds, or non-harmful weeds in real time. Consequently, analysing images of farm areas is a crucial area of research[4]. Plant diseases inflict annual crop yield losses of about \$40 billion in the United States. Smallholder farmers are crucial to the supply of food in the majority of developing nations, but they are unable to use standard methods of plant disease detection because they are too expensive and time-consuming. So that they may be stopped on their tracks through early detection and management measures, a dependable and cost-effective system for detecting plant diseases is crucial. Recent advances in deep learning technology, combined with the vast amounts of data already available, have shown promise as a means of efficiently and affordably accomplishing this goal [5].

CNNs have been used with impressive success in recent years for disease classification in plants. Researchers have begun favoring multi-layered supervised networks as better results become available. Since the release of LeNet in 1988, there have been many advancements in CNN architecture. Complex features, such as overlapping pooling or ReLu nonlinearity, have become increasingly common in contemporary design. As a result of their developments, both the training time and the error rate have decreased. Above all else, the massive and complex datasets for the twenty-first century have necessitated the development of architecture[6]. also utilized numerous convolutional neural network (CNN) models for classification; examples include DenseNet and ResNet-50. DenseNet and ResNet-50 can classify images for healthy and unhealthy leaves into distinct groups, allowing for the identification of a wide variety of leaf diseases. And while many of today's agricultural technologies can detect diseases in plant leaves, they often don't provide a way to avert those diseases from spreading [7]. As a result, this study proposes a system that employs a GUI for early-stage disorder detection and intervention [8].

II. LITERATURE SURVEY

Falaschetti 2022 et al. In order to classify plant diseases in real time using a convolutional neural network (CNN), an image detector was developed using the Open MV Cam H7 Plus and trained using a minimal set of data. Following its training on the ESCA-dataset or the Plant Village-augmented dataset to plant disease detection, the resultant convolutional neuronal network (CNN) was deployed in a low-power, cheap, Python-configurable neural network webcam for real-time image acquisition or classification. The camera's LCD displays the categorized images and their status to the user immediately after processing. With an accuracy of 98.10%/95.24% at low recalled costs (718.961 KB/735.727 KB) or time to inference (122.969 ms/125.630 ms), the experiments show that Convolution neural network-based detection of images is feasible to deploy on the selected constrained-resource a system and ESCA, with the Plant Village-augmented database of data. This makes it possible to develop a handheld embedded device [1].

Albattah 2022 et al. using an Custom CenterNet architecture and the DenseNet-77 as the base network, a reliable plant disease classification system has been developed. There are three phases to the procedure described. In order to zero in on the region of interest, annotations are created at the outset. The second improvement is the introduction of a new CenterNet and the recommendation of DenseNet-77 for deep keypoint extraction. To wrap things up, the one-stage detection CenterNet is used to diagnose and classify a variety of plant diseases. This performance evaluation made use of the Plant Village Kaggle data set, which is widely recognized as the gold

standard for capturing the full range of plant diseases and problems across a variety of intensity changes, color shifts, and discrepancies in leaf size and shape. Quantitative and qualitative studies show that the presented strategy is superior to other recent methods for recognizing and categorizing plant diseases [9].

Nishant 2022 et al. help develop a technique for identifying diseases by classifying pictures of leaves. Using image processing and convolutional neural networks (CNNs), we can now identify plant diseases. Convolutional neural networks, or CNNs, are commonly used in the image recognition industry to process pixel input [10].

Al-gaashani 2022 et al. Provide a method of classifying tomato leaf diseases that makes use of transfer learning and features concatenation. MobileNetV2 and NASNetMobile's pre-trained kernels (weights) are leveraged to generate features. Then, the dimension of these features is combined and reduced with the help of kernel principal component analysis. After that, it's added to a regular learning process. It is hypothesized that using concatenated features will improve classifier performance, or the experimental results support this idea. Among the many well-known a classic machine learning classifiers, multinomial logistic regression, a support vector machine, or randomized forest were compared in this study. In terms of average accuracy (97%), multinomial logistic regression was the best option [11].

Kathiresan 2021 et al. provides a high accuracy, transferred learning model that can give farmers and agricultural institutions a mobile tool to quickly find rice leaf illnesses. A generative adversarial networks is also used in this study to balance the distribution of illness samples. We also evaluate our model against different transfer learning architectures. The provided model outperforms paradigm classification architectures with an average validation data accuracy of 98.79% when compared to a dataset that has been augmented using a GAN. With out GAN augmentation, the model also is compared on 3 other datasets, establishing benchmark score of 98.38% average accuracy [12].

III. PROPOSED METHODOLOGY

This section will talk about the dataset and the proposed framework. The image collection from PLANT VILLAGE dataset was successfully used in this investigation. Using training datasets & feature extraction, the dataset was further cleaned by deleting duplicate pictures and weeding out pictures that didn't meet the requirements specified for them. After that, I produced graphs to complete the last of the training's data processing processes[13]. The following step is to build a Deep Convolution network. model with ResNet50 & DenseNet169, adjust the model's parameters to match the input, and then train the model. When a model is complete, it should be put through it's paces by being run under a wide range of conditions. Finally, we utilized accuracy, Model effectiveness can be evaluated using recall and F1-Score [14].

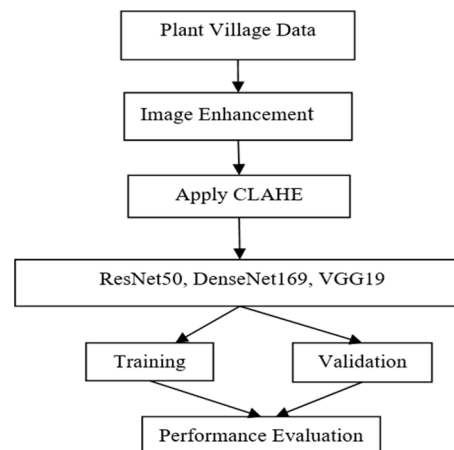


Figure 1. Proposed Methodology Flow Chart

A. Data image collection

There are 54303 images of both healthy and diseased leaves in the Plant the village collection, and these images are split among 38 different categories based on species and ailment [15]. We are unable to access the raw data directly from plantvillage.org, so we obtain the enhanced data from an article that has used and republished the original dataset."enhance" refers to the process of editing a digital image to improve its quality for purposes such

as viewing or research. Decreased noise, increased contrast, and increased brightness are all ways to better make out an image's finer details. Use image-editing and processing methods for this research [16].

- The CLAHE algorithm can be used to process & enhance photographs by boosting contrast. To utilise CLAHE, you first must import each of the pictures, convert it from BGR into LAB format that use the open source computer vision library for Python, and afterwards apply CLAHE on a square grid of size 8x8. This procedure must be reapplied for each distinct classification.
- Lastly, use an image data generator to do image data augmentation, which entails actions like rotation, width & height shifting, zooming, and horizontal and vertical flipping.

B. ResNet50

Paper "Deep Residual Learning for Image Recognition," written by He Kaiming, Zhang was Xiangyu, Ren Shaoqing, and Sun Jian in 2015. ResNet is a type of CNN that is used for image recognition. In computer vision applications, CNNs are frequently used. Res Net-50, a convolutional neural networks with 50 layers, consists of one MaxPool layer, one average pool layer, and 48 convolutional layers [17]. A particular kind of ANN called a residual neural network builds its networks from layering successive residual blocks. ResNet-50 is shorthand for a deep convolutional network of neurons with 50 layers. Numerous imaging applications would not be possible without ResNet (short to Residual Networks), a popular neural network. ResNet's revolutionary feature is that it facilitates the training of networks with a depth of more than 150 layers [18].

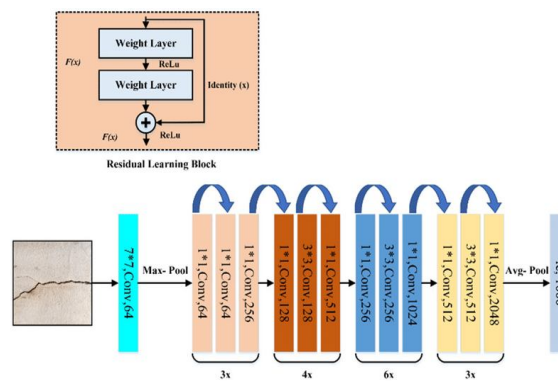


Figure 2. ResNet-50 Architecture

C. DenseNet169

In DL classification problems, the DenseNet-169 topology, which has 169 layers, is frequently used. Its trainable parameter count is significantly lower when compared to other DenseNet Architectures in fewer layers. DenseNet-169 and related DenseNet architectures are a group of highly reliable DL designs that prevent the gradient's vanishing problem, employ a strong feature propagation strategy, require few trainable parameters, and encourage feature reuse. PyTorch or Tensorflow (Keras) both have DenseNet models that can be used [19]. In order to classify images, the DenseNet family for models was created, one of which is the DenseNet-169 model. The DenseNet-121 model differs primarily in terms of its size and its accuracy. When compared to DenseNet-121, which takes up about 31MB, DenseNet-169 takes up just under 55MB. They were rewritten by the authors to be compatible with Caffe* instead of the Torch training they were originally designed for. All of a DenseNet models have been pretrained on the ImageNet image database. For more details on this model family, please peruse the entire repository [20].

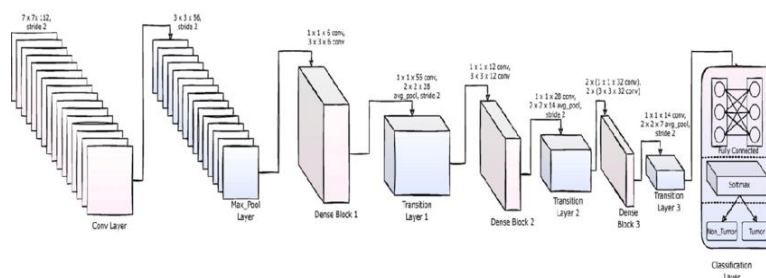


Figure 3. DenseNet-169 Architecture

IV. EXPERIMENTAL ANALYSIS

A. Perform EDA

The first stage (EDA) is exploratory analysis of data. Large datasets can be easily summarized and analyzed with the help for features like class and size distribution. Research findings are often presented visually. Figure 4 shows a plant image illustrating how frequently each Species kind occurs.

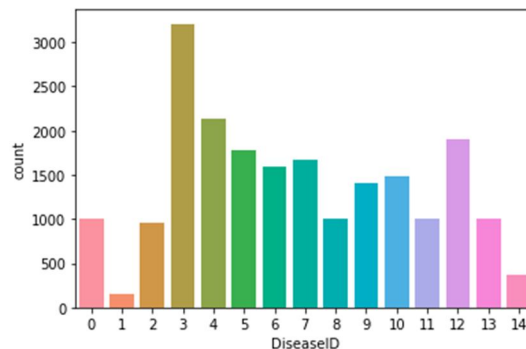


Figure 4. Frequency Histogram of Diseases Classes.

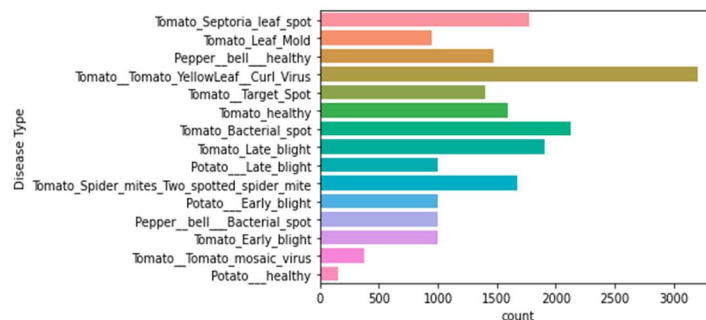


Figure 5. Frequency Histogram of Diseases Type.

B. Data preprocessing

Many tasks benefit from applying pre-processing techniques, such as cleaning up unwanted background noise, highlighting important visual cues for recognition, or even training DL models. Altering the image's height and width will cause a different aspect ratio. The image pre-processing strategy reduces the overall file size of each input image. In order for computers and algorithms to machine learning to be able to understand and evaluate data, a step called "data preprocessing" must be implemented during the data mining or analysis process. Unorganized text, images, and videos are typical of real-world data that has not been processed. It may not be well-designed or consistent, and it may also contain errors and irregularities at times.

C. Data Augmentation

Data Augmentation - The process of assembling groups for image data is referred to as "data augmentation" when discussing data processing. It increases stability and lessens the chance of generalization errors brought on by training. Professionals use this strategy to expand the available data for learning algorithms without the need to introduce new data sources. Next, start converting the tags into organized data. The intensity value for such a pixel is adjusted during image normalization by splicing together two or more pixels. For the most part, it receives images and transforms them into numerical info that depicts the scanned object way it would appear to human vision.

D. Data splitting

Using this technique, the data set is divided in half, with each half receiving half of the data. I divided the data into two after making sure it was clean, leaving 20% to the test data set or 80% to the training set. Models are trained or created using a training set in a simple two-part data split. The use for training sets has significant advantages for both parameter estimation or model evaluation. When the training phases are finished, the test set is used. The

performance of the models is assessed by comparing data collected during the training and testing phases. In machine learning, data is typically classified into at least three categories.

E. Training and Testing

Our Sequential-built models were easily combined with layers from the VGG19, ResNet-50, or DenseNet-169 model for a performance boost via transfer learning. For this experiment, we focused on the VGG19, ResNet50, or DenseNet169 architectures because they proved to be the most effective at classifying images of plant villages. The discovered diseases are initially segmented using a succession of FC (fully associated) layers in order to categories them. An deep neural networks system to image analysis known as Convolutional Neural Network (CNN) is also referred to as "ConvNet." It greatly reduces the amount of time spent pre-processing by employing a multi-perspective structure. The suggested approach entails data collection and pre-processing, which eliminates irrelevant data.

ResNet50, DenseNet 169, and VGG19 Classification and Identification Using Convolutional Neural Networks It is possible to find and predict significant relationships & patterns in the data by using deep learning algorithms. Use 100 epochs to train each neural net while learning the data.

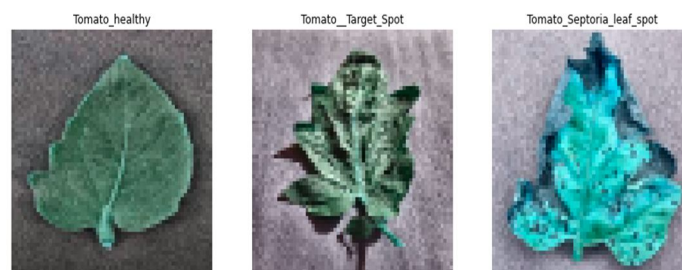


Figure 1. Shows Tomato Healthy & target Spot leaf

Shows below the VGG19 Result Graph and confusion matrix

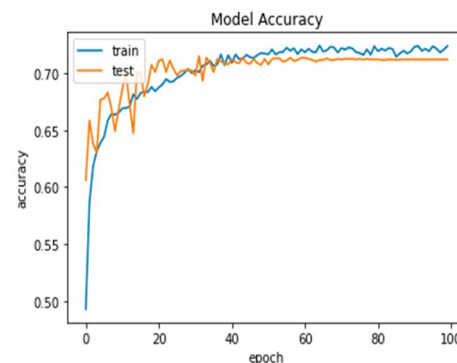


Figure 2. Shows confusion matrix graph of model accuracy of VGG19

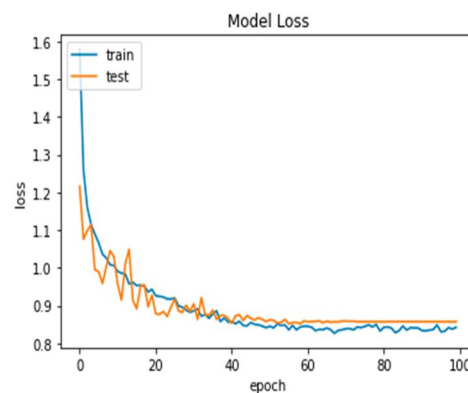


Figure 3. Shows the confusion matrix of model loss of VGG19

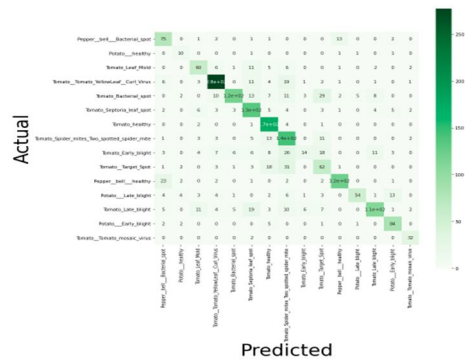


Figure 4. Shows the actual and predicted result of VGG19

Shows below the ResNet50 results Graph and confusion matrix.

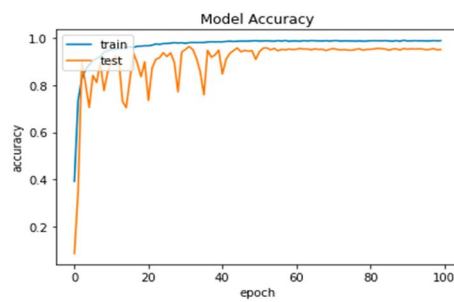


Figure 5. Shows the model accuracy matrix graph of Resnet50

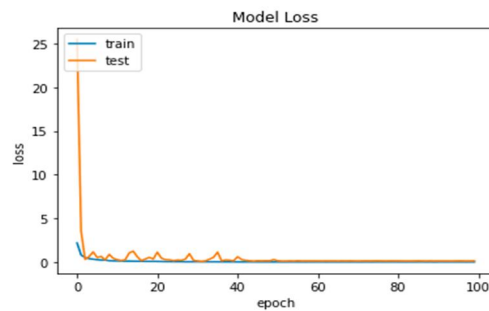


Figure 6. Shows the model loss graph of Resnet50

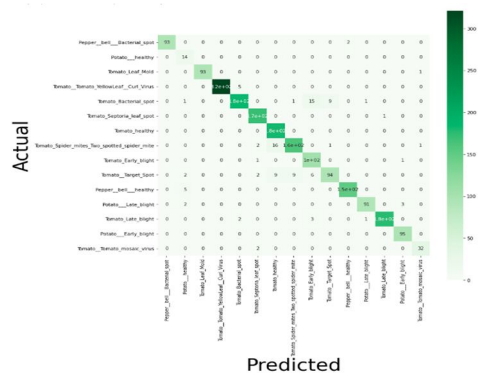


Figure 7. Shows the actual and predicted result of ResNet50

Shows below the DenseNet169 Results Graph and confusion matrix

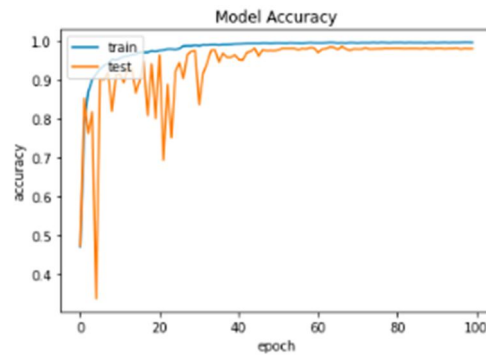


Figure 8. Displays the DenseNet169 Model Accuracy Matrix

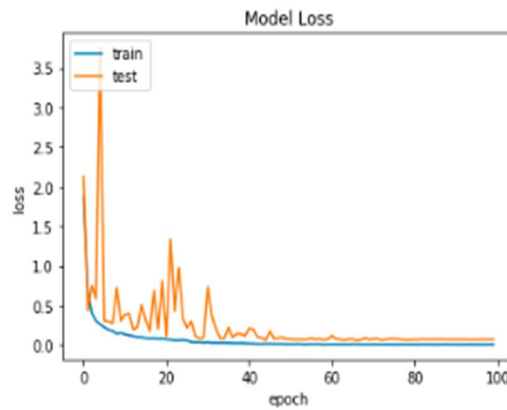


Figure 9. displays the DenseNet169 model loss curve

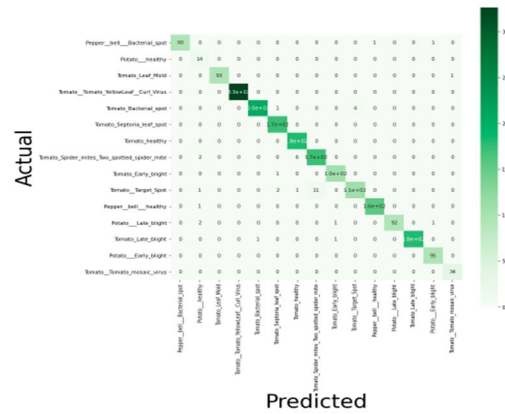


Figure 10. Shows the actual and predicted result of DenseNet169

Table -1 shows the performance evaluation of models such as VGG19, ResNet50 and DenseNet 169. We got the train accuracy and loss of VGG19 are 72.39 and 84.18, Resnet50 got 98.69, 04.31 and DenseNet 169 got 99.67, 1.12 and val accuracy and loss of VGG19 are 71.22 , 85.69, ResNet 50 got 94.96 ,16.86 and DenseNet 169 got 98.11 ,07.30.

Model	Train Acc	Train Loss	Val Acc	Val Loss
VGG19	72.39	84.18	71.22	85.69
ResNet50	98.69	04.31	94.96	16.86
DenseNet169	99.67	01.12	98.11	07.30

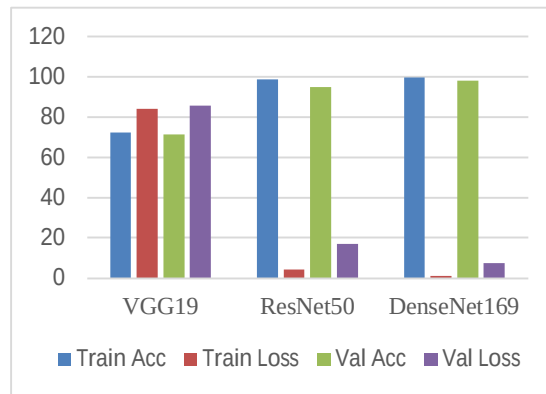


Figure 11. Performance Evaluation of Models

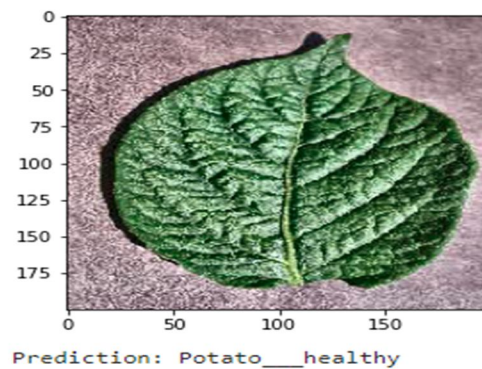


Figure 12. Shows Prediction results of Potato Healthy

V. CONCLUSION

The majority for deep-learning models to fully automated detection of illnesses underperform when applied to real-world, unexplored images. Here, we show that using only part of an image to train the ResNet 50, VGG19, or DenseNet169 models is feasible. Pre-processing images in and before training models in ResNet 50, VGG19, and DenseNet169 can be invaluable as better data sets become more widely available in the future. When a similar model is trained to use the segmented images as opposed to training using full images. In this study, the VGG19 ResNet 50, as well as DenseNet169 models' measuring performance training accuracy & loss were 72.39, 98.69, and 99.67 for accuracy and 84.18, 4.31, and 1.12 for loss

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