# A Novel Deep Learning Design of Plant Disease Recognition and Detection Using VGG19, and DenseNet121

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**Abstract- Plant diseases pose a significant threat to global agriculture, leading to substantial yield losses and economic impact. Addressing this issue, deep learning models have emerged as powerful tools for automated plant disease detection, aiding in early and accurate diagnosis. In this study, we investigate the efficacy of two popular convolutional neural network architectures, VGG19 and DenseNet121, for plant disease detection. We propose a comparative analysis of these models, evaluating their performance in terms of accuracy, sensitivity, specificity, and computational efficiency.The examination reveals significant performance differences between plant disease detection models, particularly VGG19 and DenseNet121. VGG19 achieves a commendable validation accuracy of 88.06%, but at the cost of a significantly higher validation loss of 31.44 and a training accuracy of 85.06% with a loss of 41.20. In contrast, DenseNet121 showcases superior performance, maintaining an exceptional training loss of 6.21 while achieving a high training accuracy of 97.57%, surpassing VGG19. DenseNet121 also excels in validation, boasting a validation accuracy of 97% and a validation loss of just 2.24. These results underscore DenseNet121's accuracy and effectiveness, positioning it as an attractive choice for tasks related to plant disease identification. Its potential to substantially contribute to plant health assessment and agricultural disease management is underscored by its remarkable accuracy in identifying disease patterns.**

***Keywords- Plant Disease, VGG19, DenseNet 169, Deep learning.***

## I. INTRODUCTION

The vast majority of the world's population relies on their robust economies. Growth of the economy also has a significant impact on a nation's GDP development. Agriculture is wholly dependent on the effects of this economy. However, various farming practises have an impact on the quantity and quality of vegetables and grains. Due to varying climatic conditions and environmental factors in various locations, these grains & vegetables are exposed to a variety of diseases[1]. Therefore, cultivators in any nation suffer significant losses as a result of these diseases. The amount of agricultural yield affected by leaf disease is steadily declining. Finding the agricultural field's leaf disease and boosting output rates for both quality and quantity are the key challenges. To determine disease, it is first required to take into account the leaves of two crops. Two crucial crops that are utilized in our food daily and to restore nutrients in the human body are tomatoes and potatoes. Any illness that occurs naturally can have detrimental impacts on vegetables and grains as well as ultimately lower production, product quality, and output. In order to reduce agricultural erosion, appropriate classification & identification of leaf may be crucial. Different grains & vegetable leaves have various illnesses, including bacterial, fungal, and viral ones. Al-ternaria Alternata, Anthracnose, Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, Black mould, Downy Mildew, and Rust are the most prevalent plant diseases. When an illness affects a plant's leaf, the texture, colour, shape, and size of the plant leaf reveal the infection's symptoms. Since the majority of symptoms are tiny, disease identification is impossible due to the limitations of human vision[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. This classification of a vegetation into crops, weeds, and non-harmful weeds must be done in real-time so that the robot can carry out the total devastation of the weeds. 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. Therefore, it is essential to have a reliable and economical system for diagnosing plant diseases so that they can be stopped in their tracks by early detection and control measures. A potential strategy for achieving this objective effectively and economically was demonstrated by the recent advancements in deep learning technology and the considerable amount of data that had been collected[5].

In recent years, using CNNs to classify plant diseases has produced remarkable results. The multi-layered supervised networks has gained favour among researchers as better findings continue to emerge. LeNet was released in 1988, and CNN architecture have undergone a significant development since then. Modern design has increasingly included complex functionalities like overlapping pooling and ReLu nonlinearity. Training time and mistake rate have both decreased as a result of these advancements. Above all, the development of architecture has indeed been required by the massive and complicated datasets of the twenty-first century[6]. further used a variety of convolutional neural (CNN) models for classification, including DenseNet and ResNet-50. Images of healthy and ill leaves are categorised, and different leaf diseases are identified, using DenseNet and ResNet-50. In addition, many of the technologies already in use in agriculture can identify some plant leaves diseases but do not offer a strategy for taking preventative action[7]. Due to this, the system suggested in this research uses a graphical user interface to both detect disorders and offer a preventive action[8].

## II. LITERATURE SURVEY

**Falaschetti 2022 et al.** To perform a real-time categorization of plant disease, offer an image detector including a resource-constrained convolutional neural networks (CNN) built in the OpenMV Cam H7 Plus platform. The resulting CNN network was trained on two distinct datasets for plant disease detection, the ESCA-dataset as well as the PlantVillage-augmented dataset, & implemented in such a low-power, low-cost Python configurable computer vision webcam for real-time image acquiring and classification. The camera is equipped with an LCD display that shows the user the classification result in real-time. The results of the experiments demonstrate that this Convolution neural image detector can be successfully implemented on the selected constrained-resource system, accomplishing an accuracy of around 98.10%/95.24% with a very low memory expense (718.961 KB/735.727 KB) & inference time (122.969 ms/125.630 ms) checked on board for such ESCA as well as the PlantVillage-augmented datasets, respectively. This paves the way for the creation of a portable embedded system[1].

**Albattah 2022 et al.** created a solid classification system for plant diseases using a Custom CenterNet architecture with the DenseNet-77 base network. The method that is being given has three steps. Annotations are created in the initial phase to identify the area of interest. Second, a better CenterNet is presented, and DenseNet-77 is suggested for the extraction of deep keypoints. Finally, a number of plant illnesses are identified and categorised using the one-stage detector CenterNet. The PlantVillage Kaggle dataset, which serves as the standard data for plant illnesses and problems in terms of intensity changes, colour changes, and discrepancies identified in the sizes and shapes of leaves, was utilised to conduct this performance analysis. The provided strategy is more proficient and dependable than other recent approaches at identifying and classifying plant diseases, according to both qualitative and quantitative analyses[9].

**Nishant 2022 et al.** to develop a disease recognition system that is aided by classification of leaf images. We are using image processing with such a neural network convolution to identify plant illnesses (CNN). Convolutional neural networks (CNNs) are a type of neural network used in image recognition that are designed primarily to process pixel input[10].

**Al-gaashani 2022 et al**. By utilising transfer learning & features concatenation, suggest a classification approach for tomato leaf disease. Utilizing pre-trained kernels (weights) of MobileNetV2 and NASNetMobile, the authors extract features. They then combine & reduce the dimensionality of the these features using kernels principal component analysis. They then integrate this information into a typical learning algorithm. The findings of the experiment support the hypothesis that concatenated features improve classifier performance. The three most prominent traditional machine learning classifiers, randomized forest, supports vector machine, & multinomial logistic regression, were examined by the authors. Of these, multinomial logistic regression performed the best, with an average accuracy of 97%[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 tested on a GAN augmented dataset. With out GAN augmentation, the model also is compared on 3 other datasets, establishing benchmark score of 98.38% average accuracy[12].

## III. PROPOSED METHODLOGY

The Guava image dataset is the source of the dataset under inquiry. After gathering the image data, numerous preprocessing techniques were used. Initial feature extraction relied heavily on training datasets, which were then meticulously cleaned. The goal of this cleaning operation was to get rid of duplicate photos and to throw away any that didn't meet the requirements. These data processing procedures culminated in the creation of graphs, which enabled additional analytical insights.Following that, set out to build two deep neural network models, called VGG-19 and DenseNet121. The input data was smoothly incorporated into these models, opening the door for exhaustive training cycles. After the training phase, the models underwent a thorough testing phase that included a variety of situations to thoroughly evaluate their performance and robustness. This rigorous testing method is a crucial step in the evaluation process because it enables us to determine the efficacy and suitability of these models for the jobs they are intended to do.[14].

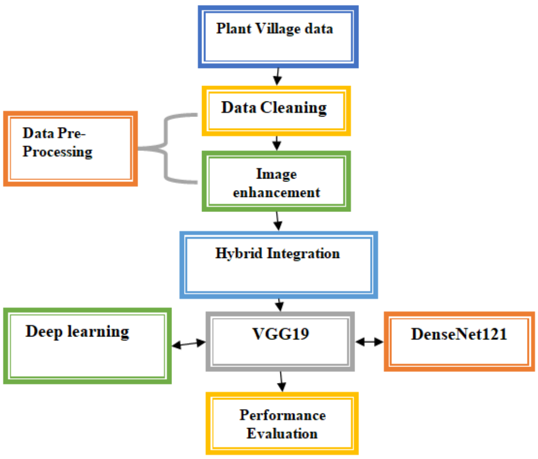



Figure 1. Proposed Methodology Flow Chart

### *A. Data image collection*

The dataset consists of a collection of pictures of guava leaves and fruits, including both diseased and healthy samples. This dataset is an important resource for the creation of automated tools that will help scientists foretell diseases in guava plants. It contains occurrences of Phytopthora, Red Rust, Scab, and Styler and Root, four different Guava diseases. The dataset also contains pictures of Guava leaves that are not infected, in addition to the diseased specimens.The original collection has 527 photos in total. The dataset's images all comply to the same standard size of 512x512 pixels. To aid with machine learning and computer vision tasks, such as the classification and diagnosis of diseases, these photographs have been painstakingly sorted and structured.By enabling the creation and assessment of algorithms and models intended to diagnose and categorize illnesses affecting Guava plants, this dataset holds significant potential for enhancing agricultural research. This dataset can be used by academics and industry professionals in the agricultural sector to improve disease diagnosis and management techniques, thereby improving crop health and output..

*B. VGG-19*

VGG-19 has an architecture of a deep convolutional neural network with 19 weight layers, 16 convolutional layers, and 3 fully connected layers. The 3x3 convolutional filters and 2x2 max-pooling layers used throughout the VGG-19, which is notable for its uniform structure, make it easier to extract features from pictures. The VGG-19 has a high computational cost because of its numerous parameters, despite the fact that its simplicity makes it easier to comprehend and use. It has been extensively utilized in image classification, object identification, and feature extraction applications and is frequently pretrained on ImageNet, while more recent architectures have addressed efficiency and performance issues[18].

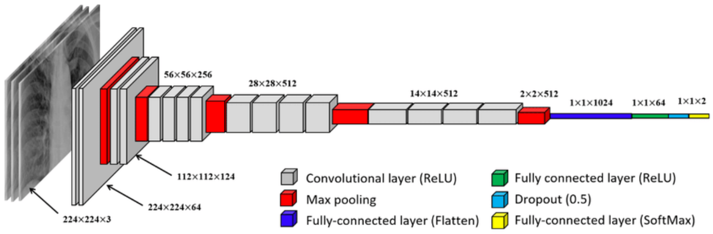



*Figure 1 VGG 19 architecture*

*C. DenseNet-121*

Convolutional neural network architecture known as DenseNet-121 is well known for its dense connection pattern and effectiveness in deep learning tasks. It has a total of 121 layers and offers the innovative idea of tightly connected blocks, where each layer receives direct inputs from all preceding layers, encouraging feature reuse and gradient flow. With this approach, the vanishing gradient problem is much diminished and extremely deep networks can be trained. Concatenating feature maps in each dense block makes it easier to create complex hierarchical representations.Additionally, DenseNet-121 uses transition layers that apply compression methods, lowering the number of feature maps and limiting model expansion. This architecture not only performs admirably in image classification, but also in transfer learning and a number of other computer vision tasks. Due to its parameter efficiency and capacity to produce cutting-edge performance with fewer parameters as compared to other designs, DenseNet-121 has grown in popularity.It is suitable for applications with limited data availability due to its compactness and capacity to keep fine-grained properties. DenseNet-121 is a versatile option in the deep learning environment since it has also proved helpful in tackling issues with model interpretability, feature visualization, and neural architecture search.[20].

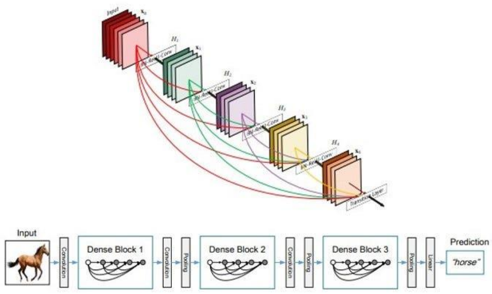



Figure 3. DenseNet-121 Architecture

## IV. Experimental Analysis

### *A. Perform EDA*

Exploratory data analysis is the first step (EDA). The use of features like class or size distribution makes it simple to summarise and analyse large datasets. Study results are frequently represented visually. Figure 4 shows a plant image illustrating how frequently each Species kind occurs. The distribution of diseases in the Guava picture collection is shown graphically in a frequency histogram, as shown in Figure 2.

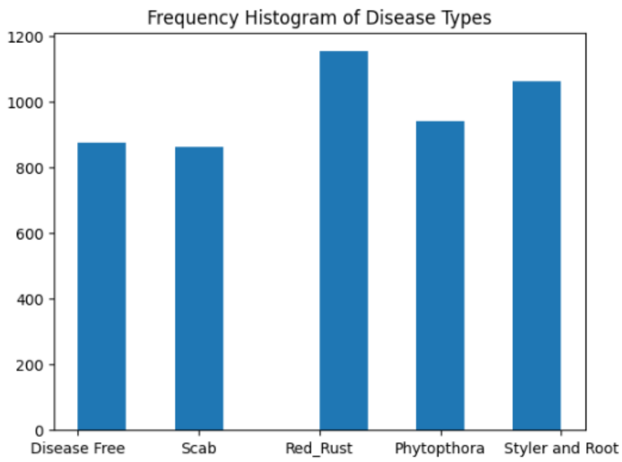



*Figure 2 frequency histogram of disease types*

Figure 3 showcases disease-free images within this dataset, encompassing instances of four distinct Guava diseases, namely Phytopthora, Red Rust, Scab, Styler, and Root, in addition to the diseased specimens.

*Figure 3 disease free images*

Figure 4 displays photos of Phytopthora from this collection, which also includes incidences of four other Guava diseases (Red Rust, Scab, Styler, and Root).

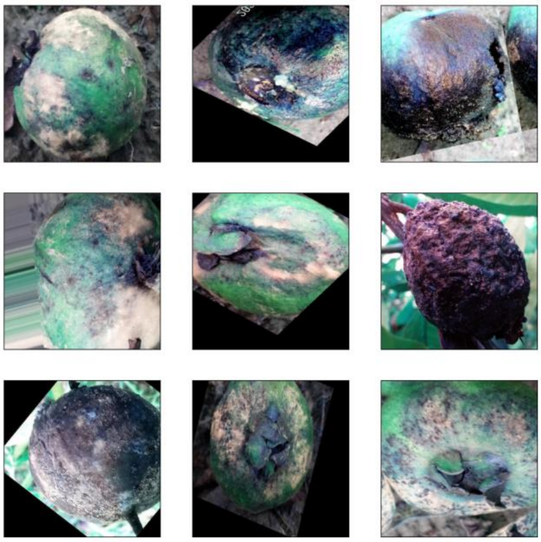


*Figure 4 Phytopthora disease images*

Figure 5 displays Red Rust photos from this dataset that also include examples of the affected specimens for four different guava diseases, including Phytopthora, Red Rust, Scab, Styler, and Root.

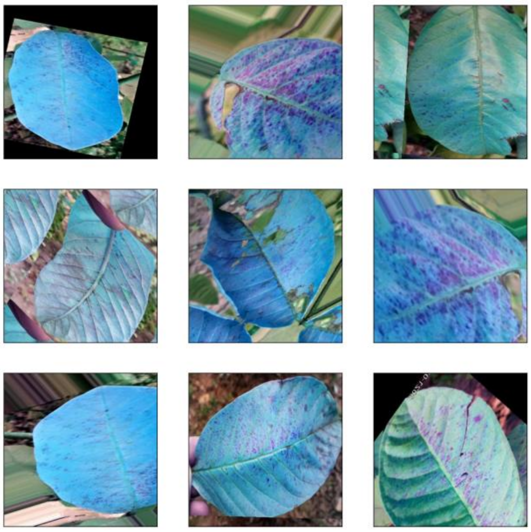


*Figure 5 Red rust disease images*

Figure 6 displays photos of the Scab disease found in this dataset, which also includes photographs of the affected specimens and four different Guava illnesses, including Phytopthora, Red Rust, Scab, Styler, and Root.

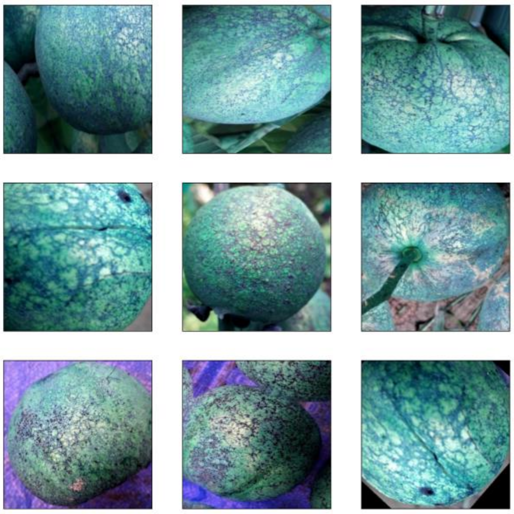


*Figure 6 scab disease images*

Figure 7 displays photos of the Styler and Root diseases found in this dataset together with examples of the affected specimens. These photographs include four different guava diseases, including Phytopthora, Red Rust, Scab, Styler, and Root.

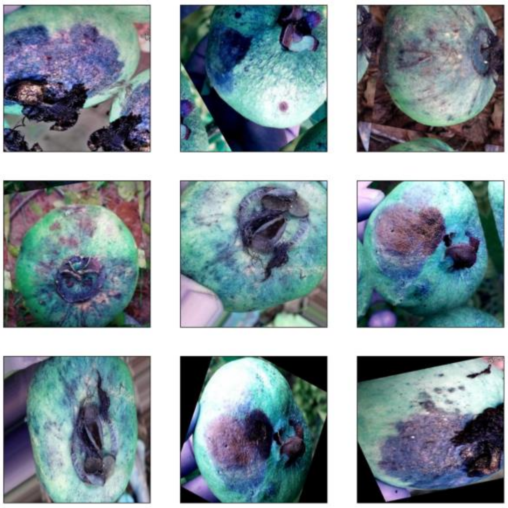


*Figure 7 Styler and Root disease images*

*B. Data preprocessing*

Pre-processing methods are essential for a number of applications, such as noise reduction, highlighting important visual cues for recognition, and improving the efficiency of deep learning (DL) training. Adjusting the height and breadth of an image while keeping its existing aspect ratio is a frequent pre-processing requirement. This procedure of shrinking the input photographs helps to reduce their file sizes, making them easier to handle for later processing processes.A crucial step in the workflow for data mining and analysis is data pretreatment. Its main goal is to convert unstructured data into a structured format that computers and machine learning algorithms can understand and analyze. Unprocessed real-world data, such as text, image, and video data, frequently displays a lack of structure, consistency, and organization. Additionally, this unprocessed data could be riddled with mistakes, abnormalities, or inconsistencies that make it difficult to do efficient analysis and modeling.In essence, data preparation serves as a vital link between unstructured, raw data and the advanced modeling and analytical methods used in machine learning. It makes it possible for chaotic and diverse data to be transformed into a well-structured and cleansed format, permitting precise and valuable insights from the data..

*C. Data Augmentation*

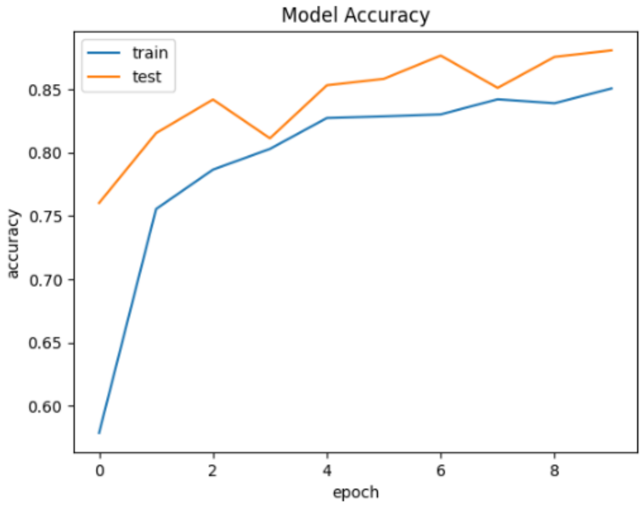
Data augmentation for the Guava image dataset involves the application of various techniques to diversify the dataset. These techniques include random rotations, horizontal and vertical flips, scaling, resizing, cropping, brightness and contrast adjustments, noise injection, color transformations, shearing, and translation. By systematically applying these transformations to the original images, we can create a more extensive and diverse dataset, enabling machine learning models to generalize better and improve their performance in tasks related to guava disease detection and plant health assessment.

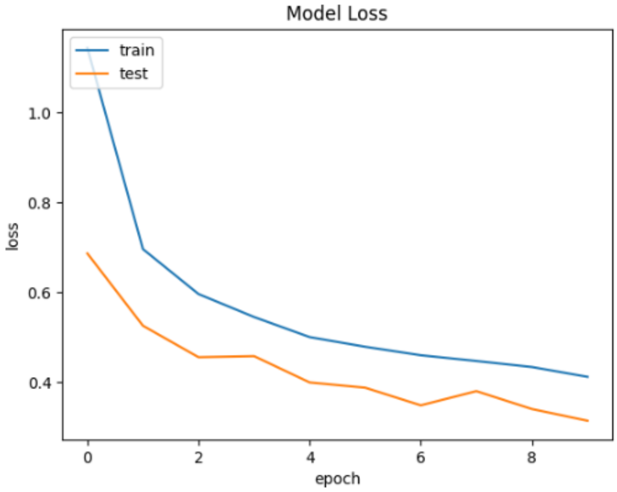
*D. Data splitting*

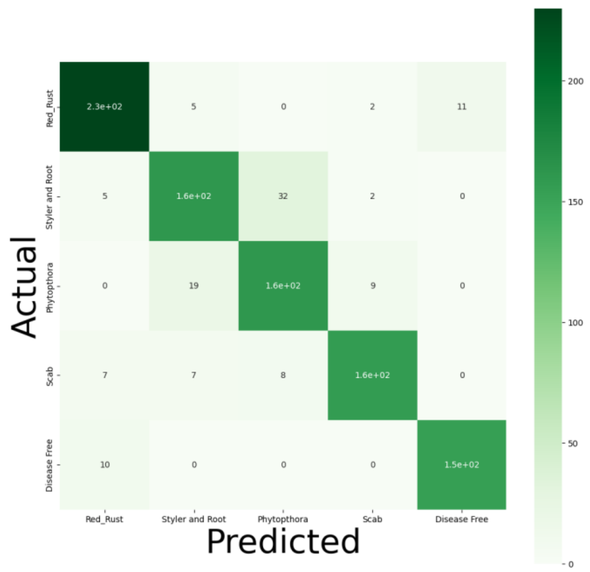
This technique divides the dataset into two parts, each having portion of the data. Once everything was order, I split the data in half, allocating 80% to the training set and 20% to the test set. The training set is utilized to train and create models in a simple two-part data split. Training sets are frequently used to estimate various parameters or to assess the effectiveness of various models. After the training has been complete, the test data set is used. To ensure that the final models operate properly, the training & test sets of data are compared. Data is frequently divided into three or even more sets when it comes to machine learning.

*E. Training and Testing*

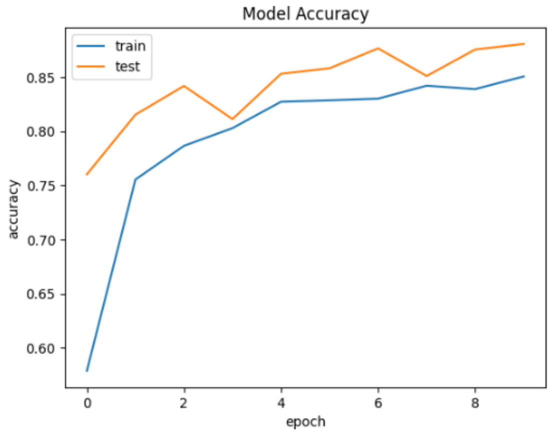
Models built with the Sequential architecture and easily merged with pretrained models like VGG19, ResNet50, or DenseNet169 in order to improve model performance through transfer learning were able to make use of the Guava image dataset. In particular, VGG19, ResNet50, and DenseNet169 were chosen because of their track records of success in the broader FCN (Fully Convolutional Network) framework for disease detection in photos of Guava plants. The Guava image dataset was crucial here; it includes pictures of Guava leaves and fruits with and without illnesses like Phytopthora, Red Rust, Scab, Styler, and Root. Method begins with disease discovery, which is then segmented utilizing a series of FC (Fully Connected) layers to ensure accurate classification. The deep learning capabilities of Convolutional Neural Networks (CNNs), also known as ConvNets, make them indispensable for image processing. Notably, by utilizing a multi-perspective design, they drastically cut down on preprocessing time. The suggested approach takes advantage of the wealth of the Guava picture dataset for thorough illness identification, and it comprises data collecting and preprocessing, which includes deleting extraneous data.To efficiently discover meaningful connections and patterns in the Guava picture dataset, For identification and classification, we use Convolutional Neural Networks and models like DenseNet121 and VGG19. Graph of VGG19 Results and Confusion Matrix are displayed below.




These two accuracy and loss graphs provide a comprehensive visualization of the performance of the DenseNet121 model.



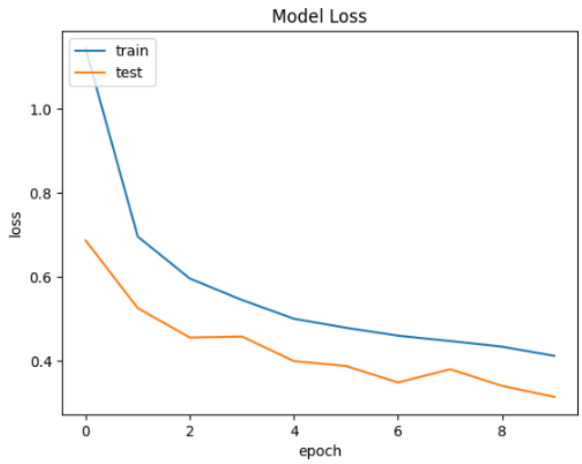




Table -1 The VGG19 and DenseNet121 models' performance evaluation results are shown in Table 1. For each of the two models, the table contains metrics like training accuracy (Train Acc), training loss (Train Loss), validation accuracy (Val Acc), and validation loss (Val Loss). The performance metrics of two different models, VGG19 and DenseNet121, are visible enter the supplied numbers into the table. While obtaining a validation accuracy of 88.06% with a loss of 31.44, VGG19's training accuracy of 85.06% is accompanied with a loss of 41.20. Comparatively, DenseNet121 has a significantly reduced training loss of 6.21 and a training accuracy that is 97.57% greater. With a validation loss of 2.24 and a remarkable validation accuracy of 99.29%, it is quite accurate. With the help of these measures, you can get a complete picture of how well the models performed during training and validation, showing their individual advantages and applicability for various tasks and datasets.

| Model | Train Acc | Train Loss | Val Acc | Val Loss |
|---|---|---|---|---|
| VGG19 | 85.06 | 41.20 | 88.06 | 31.44 |
| DenseNet121 | 97.57 | 06.21 | 99.29 | 02.24 |

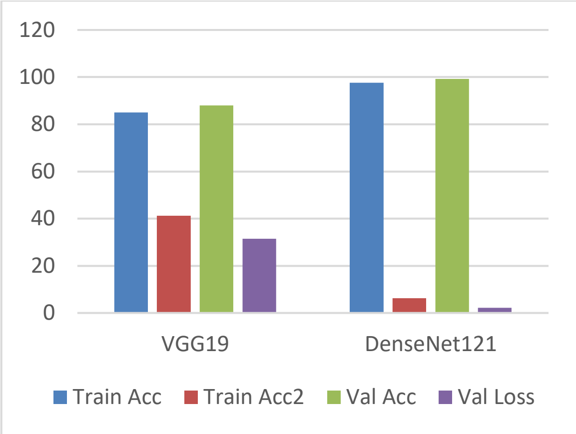



Figure 11. Performance Evaluation of Models.

## V. Conclusion

Significant differences in the performance of plant disease detection models, notably VGG19 and DenseNet121, are found in the examination. The validation accuracy of 88.06% achieved by VGG19 is commendable, however the validation loss is significantly greater at 31.44, while the training accuracy is only 85.06% with a loss of 41.20. DenseNet121, in comparison, stands out with superior outcomes. It not only maintains a remarkable training loss of 6.21 while maintaining an excellent training accuracy of 97.57%, which is significantly greater than VGG19. The validation performance of DenseNet121 is also exceptional, with a validation accuracy of 99.29% and a validation loss of just 2.24. These results illustrate DenseNet121's greater accuracy and effectiveness, making it an appealing option for tasks involving plant disease identification. Its potential to make a significant contribution to the study of plant health assessment and agricultural disease management is highlighted by its ability to identify disease patterns with such accuracy.

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