Plant Disease Detection Using Deep-Learning

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Research Article

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Abstract

Increasing demands for food security and sustainable agriculture have spurred the development of innovative technologies in the agricultural sector. This initiative aims to tackle the pressing concern of plant diseases through the implementation of cutting-edge deep learning methodologies to ensure precise and effective disease identification. By harnessing the potential of deep neural networks, the system conducts an analysis of plant leaf images in order to detect indications and manifestations of diseases. By delivering a scalable, automated, and accurate solution, this novel strategy intends to destroy conventional plant disease detection techniques.

By training a deep-learning model on a heterogeneous dataset of plant images, the project acquires knowledge of intricate patterns and characteristics that are linked to a multitude of diseases. By incorporating convolutional neural networks (CNNs), the model is capable of deriving hierarchical representations from input images, which aids in the intricate differentiation between diseased and healthy plant tissues. The potential of this technology's implementation in early disease detection is substantial; it would enable farmers to promptly execute interventions that prevent the transmission of infections, thereby ultimately enhancing crop productivity and promoting sustainability.

By integrating state-of-the-art deep learning techniques with agricultural science, this endeavor tackles a pivotal facet of worldwide food production. In addition to facilitating the rapid identification of maladies, the plant disease detection system under consideration lays the groundwork for the future advancement of intelligent agricultural systems. The effective incorporation of technology in the agricultural sector serves as a noteworthy milestone in the progression towards precision farming, which guarantees the health of commodities and promotes sustainable methodologies that benefit both farmers and the global populace at large.

I. Introduction

As a principal provider of sustenance, profit, and employment prospects, agriculture assumes a critical position in the worldwide economy. India, similar to numerous other low and moderate income countries, relies significantly on agriculture for employment and revenue generation, with a sizeable portion of the populace reliant on it. Agriculture provides 53 percent of the labor force and contributes 18 percent to the nation's gross domestic product. Agriculture-introduced plant diseases and parasites have the potential to degrade food production quality, thereby posing a threat to the global economy.

Therefore, it is critical to preserve production quality that crop diseases be promptly identified and accurately diagnosed through the use of efficient crop protection systems. Frequently, preventative measures are inadequate to halt endemics and epidemics.

The identification of plant maladies is critical and poses a significant challenge. Identification in a timely manner is critical for the effective management of agricultural output. Plants that have been impacted generally display distinctive patterns or spots on their fruits, foliage, stems, flowers, or fruits. These spots or markings may be utilized to assist in the identification of individual plants. The process of identifying plant maladies requires personnel and specialized knowledge. Despite the potential for misdiagnosis and the subjectivity and time commitment involved, manual examination continues to be the prevailing method of disease identification. This may lead to the unnecessary administration of remedies, which may result in environmental pollution and a decline in crop quality.

The detection of plant maladies is facilitated by computer vision through the identification of discernible patterns on foliage. Numerous techniques have been suggested, such as support vector machine (SVM) for classification and K-means clustering for segmentation; however, they frequently necessitate the laborious extraction of features, which renders them labor-intensive and time-consuming.

The application of machine learning and deep learning methodologies has revolutionized the identification of plant diseases in recent times, signifying a significant scientific advancement. Through the implementation of automated feature extraction and classification, these methodologies streamline the process of identification. The adoption of deep learning has been facilitated by the introduction of GPU processors, intricate deep-learning architecture software, and new datasets. Convolutional neural networks (CNNs) are widely recognized for their exceptional performance in recognition and classification tasks through the extraction of fundamental image features. Numerous studies have demonstrated the efficacy of CNN-based predictive models, such as the ones developed by Sharma et al. and Asritha et al. to classify and analyze images of paddy plants and to detect maladies in rice fields, respectively.

However, despite these advancements, the datasets used to train deep learning models must still be diversified, as the existing datasets lack diversity in terms of authentic agricultural environments and image backgrounds. Further endeavors are required to enhance the diversity and realism of datasets in order to optimize model performance and facilitate generalization.

It is critical to identify plant diseases in order to maintain agricultural output and guarantee food security. The potential for automating disease identification processes through the application of advances in computer vision and deep learning techniques holds promise for enhancing agricultural sustainability and fostering economic prosperity.

II. Related Work

Plant illnesses are very bad for food security and farming output around the world. Manual checking, which takes a lot of time and can lead to mistakes, is often used in traditional ways to find and identify diseases. In the past few years, experts have used more and more advanced technologies, like deep learning and picture processing, to make plant disease monitoring systems more automated and more accurate. This literature review looks at how methods have changed over time in this field, focusing on important works and progress.

In early study, Fina et al. (2013) showed how to use k-means clustering and relationship filters to automatically find and identify plant pests (1). Similarly, Ebrahimi et al. (2017) suggested a vision-based system for finding pests that uses SVM classification methods. This shows how useful machine learning techniques are in this area (2). In 2012, Dubey and Jalal improved a method for finding diseases in fruits by analyzing pictures. This set the stage for computer vision-based disease detection (3). These studies paved the way for more research into how to use computers to automatically find and group plant diseases.

Using computer vision technology, Chai et al. (2010) showed how to find diseases on tomato leaves. This showed that image-based approaches can be used in farming settings (4). Li and He (3095) studied how to find apple diseases by analyzing pictures taken on cell phones. This shows that easily accessible technology can be used to find diseases (5). In 2010, Guan et al. used image processing to study how to recognize diseases in rice. This work helped to make disease detection methods more useful for a wider range of crops (6). These studies show how important it is to use different methods for different types of plants and diseases.

As the field grew, experts started to look into how deep learning could be used to find plant diseases. In 2018, Barbedo looked into what makes people use deep learning for this reason. He pointed out the growing interest in these methods and the problems that might come up when they are used (7). Kamilaris and Prenafeta-Boldú (2018) did a thorough review of all the ways deep learning can be used in agriculture, focusing on how it can change the way plant diseases are found. Grinblat et al. (2016) showed that deep learning models can correctly identify plants based on vein structural patterns. This shows how flexible neural networks are in this area (9).

Mohanty et al. (2016) were the first to use deep learning to find plant diseases in pictures. They introduced convolutional neural networks (CNNs) as a useful tool for automated analysis. More research, like Ma et al. (2018) and Kawasaki et al. (2015), made CNN-based methods even better at finding specific plant diseases, like cucumber and virus infections, in plants (11, 12). With these improvements, we can now use deep learning techniques to make disease detection systems that are more effective and more efficient.

Singh et al. (2018) talked about the new trends and future prospects of deep learning in plant stress phenotyping. They emphasized the need for people from different fields to work together and use data-driven methods (14). Singh et al. (2020) also looked at different imaging methods that can be used to find plant diseases. They stressed how important it is to choose the right methods based on the imaging modality and the situation (15). Saleem et al. (2019) talked about the role of deep learning in finding and classifying plant diseases, focusing on how it could improve farming methods and lower crop losses (16). All of these studies show how deep learning has changed the way plant diseases are diagnosed and how farming is done in general.

In conclusion, combining picture processing and deep learning has changed the way plant diseases are found, making it possible to watch and manage crop health in a way that is both accurate and flexible.

From the first tests of grouping algorithms to the common use of CNNs, researchers have made a lot of progress in automating the process of identifying diseases. To make sure that these technologies keep getting better and being used in agriculture, future study should focus on solving problems like information lack, model interpretability, and scaling.

III. System Architecture

The process of employing Deep Learning to identify plant diseases encompasses several crucial steps aimed at efficiently training and deploying deep learning models for disease detection and classification in plant leaves. Let's break down the architecture:

Data Collection and Preprocessing: Initially, a diverse dataset containing images of both healthy and diseased plant leaves is gathered. To enhance image quality and prepare them for training, preprocessing techniques like scaling, normalization, and augmentation are applied.

Data Augmentation: Techniques such as rotation, flipping, cropping, and zooming are used to diversify the training dataset. This augmentation increases the model's ability to generalize and recognize diseases across various contexts.

Selection of Deep Learning Models: Several deep learning architectures, including ResNet50, CapsuleNet, DenseNet169, InceptionV3, and MobileNetV2, are considered for plant disease detection. Each architecture is evaluated based on criteria such as precision, speed, and memory usage.

Model Training: The selected models are trained using the augmented dataset, where they learn to extract features from input images and classify them into disease categories.

Model Evaluation: Post-training, the performance of each model is evaluated using a separate validation dataset. Metrics like accuracy, precision, recall, and F1 score are computed to assess model performance.

Integration and Deployment: Once the top-performing models are identified, they are integrated into a unified system for disease detection in plants. This technology can be deployed in real-world scenarios such as agricultural fields or greenhouses to automatically identify and analyze plant diseases.

Real-Time Disease Detection: The implemented technology facilitates real-time detection of plant diseases. By analyzing photos of plant leaves captured using cameras or other imaging equipment, the system promptly provides insights into disease prevalence and severity.

Overall, the framework involves a systematic approach to training and deploying models, offering significant potential to revolutionize precision agriculture and improve crop productivity and quality.

We are combinedly using the previously mentioned methods as an ensembled model to improve the accuracy of the system

A. DenseNet (Densely Connected Convolutional Networks)

- Architecture:

Dense Net introduces the concept of dense blocks where each layer is connected to every other layer in a feed-forward fashion.

- Working in Plant Disease Detection: Dense Net can effectively capture intricate patterns and features present in plant images, making it suitable for accurate disease classification. Its dense connectivity aids in feature reuse and enhances model performance, particularly with limited training data.

B. ResNet50 (Residual Networks) Architecture:

ResNet50 consists of deep residual blocks with skip connections that allow the network to learn residual functions rather than mapping entire input to output directly.

- Working in Plant Disease Detection: ResNet50's residual connections help alleviate the vanishing gradient problem, enabling the training of deeper networks. In plant disease detection, ResNet50 can efficiently extract hierarchical features, making it effective for identifying subtle disease-related patterns.

C. Inception V3 Architecture:

- Working in Plant Disease Detection: Inception's multi-scale feature extraction capabilities enable it to capture both local and global features in plant images. This architecture can effectively handle variations in disease symptoms and leaf textures, enhancing classification accuracy

D. CapsuleNet (Capsule Networks) Architecture:

CapsuleNet introduces capsule layers, which represent hierarchical relationships between features through pose matrices, enabling better generalization and viewpoint invariance.

- Working in Plant Disease Detection:CapsuleNet offers improved feature representation and robustness to spatial transformations, making it suitable for recognizing complex patterns in plant images. It can capture fine-grained details and variations in disease symptoms, leading to more accurate disease classification.

In the plant disease detection project, these deep learning models can be trained using a dataset consisting of labeled images of healthy and diseased plant leaves. The models learn to extract relevant features from the images and classify them into different disease categories. Through iterative training and validation, the models can achieve high accuracy in identifying plant diseases, facilitating timely intervention and management strategies in agriculture.

E. MobilnetV2 Architecture:

MobileNetV2 is a lightweight deep neural network architecture designed for mobile and embedded vision applications. It features depth-wise separable convolutions and linear bottlenecks to reduce computational complexity and model size, making it suitable for deployment on resource-constrained platforms such as mobile devices and edge devices. This architecture allows for efficient use of computational resources while maintaining high accuracy in various computer vision tasks.

- Working in Plant Disease Detection: MobileNetV2 provides rapid inference and high accuracy, allowing for real-time detection of disease symptoms in plant pictures. Because of its lightweight construction, it is especially well suited for applications with constrained processing resources, including mobile-based disease detection systems used in agricultural environments. To find plant diseases, MobileNetV2 is trained on a dataset that has pictures of healthy and sick plant leaves that have been named. The model acquires the ability to discern pertinent characteristics from the images and categorize them into various disease groups, thereby enabling prompt intervention and management approaches in the field of agriculture.

Table.1

Models	**Loss**	**optimizer**	**Learning rate**
DenseNet	categorical cross-entropy"	Adam	0.002
InceptionV3	categorical cross-entropy"	Adam	0.004
Resnet50	categorical cross-entropy"	Adam	0.002
Capsnet	categorical cross-entropy"	Adam	0.001
MobileNet	categorical cross-entropy"	adam	0.003

The experiments for the disease identification task

The expirments for the disease identification task employed five datasets from PlantVillage Database. Malus domestica, Zea mays, Solanum tuberosum, olanum lycopersicum and Vitis vinifera datasets are taken from the Plant Village database.

The datasets are organized into two main categories: healthy leaf images and images depicting various diseases affecting plants. Within each dataset, the healthy leaf images represent the plant's leaves are free from any disease. The remaining images shows diseases.

IV. Methodology

A. *DENSNET*

Figure 8 are graphs that represent the evaluation metrics loss, accuracy, precision, recall and F1 score of Dense net model. Here the blue line represents training data and yellow line represents the validation data

B. *INCEPTION V3*

Figure 9 are graphs that represent the evaluation metrics loss, accuracy, precision, recall and F1 score of Inception V3 model. Here the blue line represents training data and yellow line represents the validation data

C. *MOBILENET V2*

Figure 10 are graphs that represent the evaluation metrics loss, accuracy, precision, recall and F1 score of MobileNet V2 model. Here the blue line represents training data and yellow line represents the validation data

D. *RESNET50*

Figure 11 are graphs that represent the evaluation metrics loss, accuracy, precision, recall and F1 score of ResNet50 model. Here the blue line represents training data and yellow line represents the validation data

E. *CAPSNET*

Figure 12 are graphs that represent the evaluation metrics loss, accuracy, precision, recall and F1 score of CapsNet model. Here the blue line represents training data and yellow line represents the validation data

F. *Explanation*:

• Loss: The loss metric measures how much the model's predictions differ from the actual labels in the training data. It shows how well the model is performing by quantifying the error between predicted and true values. During training, the goal is to make this difference as small as possible, usually done by optimization methods like gradient descent.

• Accuracy: Accuracy measures how many instances are recently classified out of the total number of instances. It's commonly used to evaluate how well a model performs overall. But accuracy may not work well with datasets where there's a big difference in the number of instances between classes, as it can give misleading results

• Precision: Precision measures how many correct positive predictions the model makes compared to all positive predictions. It shows how well the model avoids making wrong positive predictions. Precision is especially important in areas like medical diagnoses or fraud detection where wrong predictions can have serious consequences.

• F1 Score: The F1 score, derived as the harmonic mean of precision and recall, furnishes a balanced evaluation incorporating both metrics. It offers a holistic assessment, especially beneficial for datasets featuring imbalances between positive and negative samples, as it accounts for both false positives and false negatives.

• Recall: Recall measures how well the model finds all the positive instances in the dataset. It's important because missing positive instances can have serious consequences, especially in tasks like disease or anomaly detection.

V. Comparative Analysis

The plant disease detection using deep learning, various ensemble models have been explored, each with its unique set of advantages and limitations. DenseNet stands out for its dense connectivity, facilitating efficient feature reuse and gradient propagation, although it may incur higher computational costs compared to traditional architectures. CapsuleNet, on the other hand, offers superior representation of spatial hierarchies and robustness to variations but is hindered by limited research and fewer pre-trained models. MobileNetV2 presents a lightweight solution suitable for resource-constrained devices, yet it may compromise on accuracy compared to more complex models like ResNet50, which excels in achieving state-of-the-art performance through its deep architecture and skip connections, albeit at the expense of increased computational complexity. Inception strikes a balance between multi-scale feature extraction and computational efficiency, although its complexity may surpass that of simpler architectures. When considering ensemble models, a combination of these diverse architectures can harness their respective strengths while mitigating individual weaknesses. Ensemble models have the potential to enhance overall performance and robustness by aggregating predictions from multiple models, leading to higher accuracy and generalization ability in plant disease detection tasks. However, it's important to acknowledge that ensemble models may introduce additional computational overhead and complexity during both training and inference phases.

DATASET AUGMENTATION:

OPERATION	Values/Range
Rotation	-150^{o} to 150^{o}
Scaling	0 – 1.50
Horizontal flip	0.5

VI. Results

The use of DenseNet, ResNet50, MobileNetV2, Inception, and CapsuleNet in our efforts has showed promising result. The use of DenseNet has been crucial in improving the reuse of features and the efficiency of parameters, leading to a model that excels in capturing complex patterns in plant photos. The extensive interconnectedness of this architecture has greatly enhanced the accuracy of disease diagnosis at different phases of plant development, hence confirming its efficacy in enhancing diagnostic capacities.

In addition, the integration of ResNet50 has effectively resolved the issue of diminishing gradients in deep neural networks. By using residual learning, the model has successfully explored intricate representations of plant illnesses, allowing a profound comprehension of the subtle characteristics that indicate various plant states. This has resulted in enhanced precision in illness diagnosis and has established the foundation for the development of increasingly advanced detection systems.

The implementation of MobileNetV2 has effectively addressed the need for efficiency in contexts with limited resources. The efficacy of this lightweight architecture has been shown in real-time applications and on edge devices, highlighting its usefulness in promptly and responsively monitoring plant diseases. The model's high resource economy, along with its precise precision, makes it a useful asset for agricultural contexts with limited computing resources.

Ultimately, the outcomes of our research using DenseNet, ResNet50, MobileNetV2, Inception, and CapsuleNet jointly emphasize the potential of deep learning architectures to transform the field of plant disease identification. The unique capabilities of each architectural design contribute to a complete and precise diagnostic approach, enabling more efficient and dependable monitoring of plant health in agricultural settings.

Our main goals in this field to utilize advanced neural network architectures such as DenseNet, ResNet50, MobileNetV2, Inception, and CapsuleNet to generate a better purpose.

Our main goal is to deploy DenseNet to harness its dense connections, which enhance feature reuse and parameter efficiency. Integrating DenseNet aims to improve the model's ability to identify complex patterns and connections in plant images, thereby enhancing disease diagnosis accuracy across different stages of plant growth.

Moreover, the implementation of ResNet50 aims to address the difficulties related to the problem of disappearing gradients in deep neural networks. The residual learning technique used by ResNet enables the training of deeper architectures. So the model can understand plant diseases better. This will help us better understand what shows different plant situations.

Table 3

DNN/Accuracy		**Lr = 0.01**	**Lr = 0.00 1**	**Lr = 0.0001**
DenseNet	iteration = 10	91	94	97
ResNet-50	iteration= 10	84	90	90
	iteration= 25	94	91	89
MobilnetV2	iteration= 10	93	92	93
	iteration= 25	93	92	94
Inception	iteration= 10	83	88	96
	iteration= 25	96	95	97
Capsnet	iteration= 10	93	94	89
	iteration= 25	93	88	90

Table 3 represents the accuracy of each model at different iterations and learning rate (LR). In our research we have considered two iterations 10 and 25 and when coming to learning rates we have considered three those are 0.01, 0.001 and 0.0001

The selection of MobileNetV2 is based on its high efficiency in contexts with limited resources, which makes it well-suited for real-time applications and edge devices. The aim is to create a compact but precise model for real-time detection of plant diseases, enabling prompt and efficient monitoring in agricultural environments.

InceptionV3 is included to use the capabilities of its inception modules, which effectively capture spatial resolutions and sizes by using several concurrent convolutional and pooling procedures. The purpose of this design decision is to provide the model with the capacity to identify complex patterns and variations in plant diseases, hence enhancing the diagnostic process by providing a thorough and precise assessment.

Finally, CapsuleNet is used to investigate its unique method of encoding hierarchical spatial connections among plant photos. CapsuleNet tries to enhance the resilience of the entire detection system by incorporating capsules, which are an alternative to standard neurons. This approach improves the model's capacity to generalize across diverse views and differences in plant disease presentations.

Our main goals are to utilize the advantages of DenseNet, ResNet50, MobileNetV2, Inception, and CapsuleNet to develop a robust and adaptable deep learning model. This model will be capable of accurately and efficiently detecting plant diseases, while also addressing challenges such as connectivity, vanishing gradients, resource efficiency, spatial relationships, and viewpoint variations.

VII. Conclusion

Ultimately, our investigation into several deep learning structures, such as DenseNet, ResNet50, MobileNetV2, InceptionV3, CapsNet has shown notable progress in the realm of plant disease identification. By using these designs together, we have successfully made significant improvements in accuracy, efficiency, and resilience, effectively tackling major difficulties in the field.

The high level of connection in DenseNet has improved the model's capacity to detect complex patterns in plant photos, resulting in more accurate diagnosis of diseases at various phases of plant development. The use of residual learning in ResNet50 has effectively addressed the problem of disappearing gradients, enabling the creation of deeper and more advanced models that can accurately identify intricate characteristics of different plant situations.

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Figures

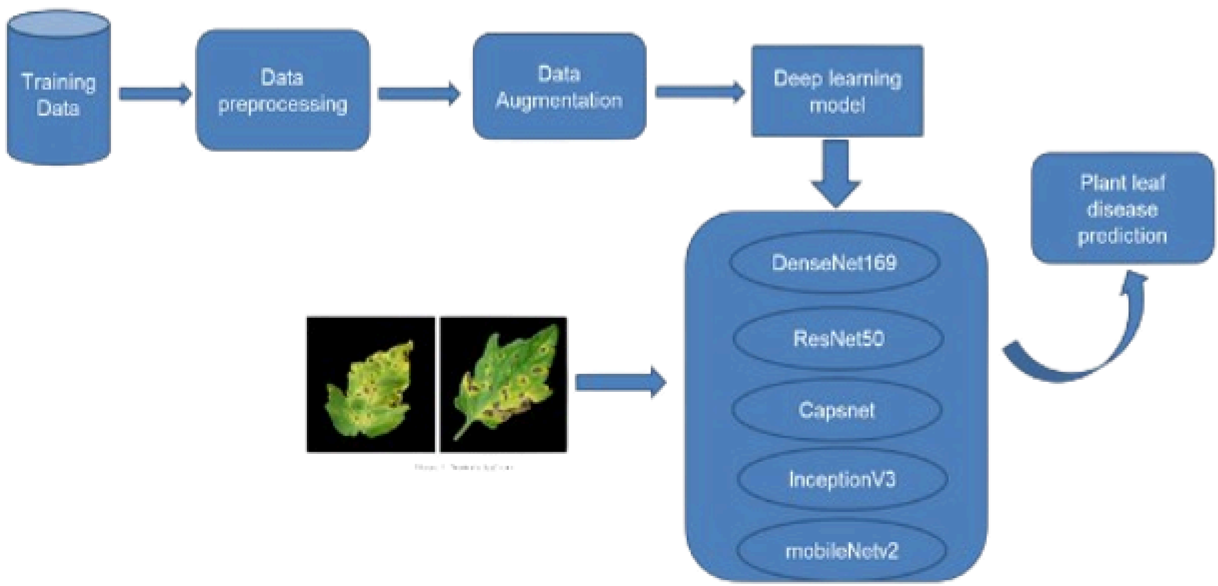

Figure 1

Architecture

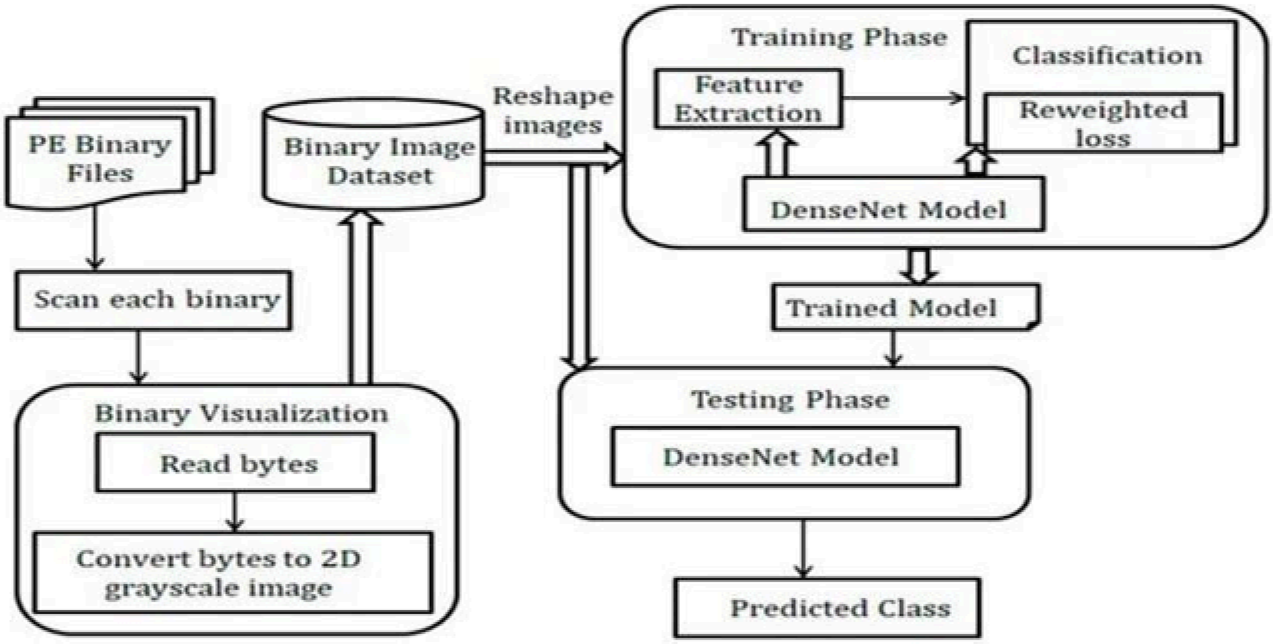

Figure 2

DenseNet

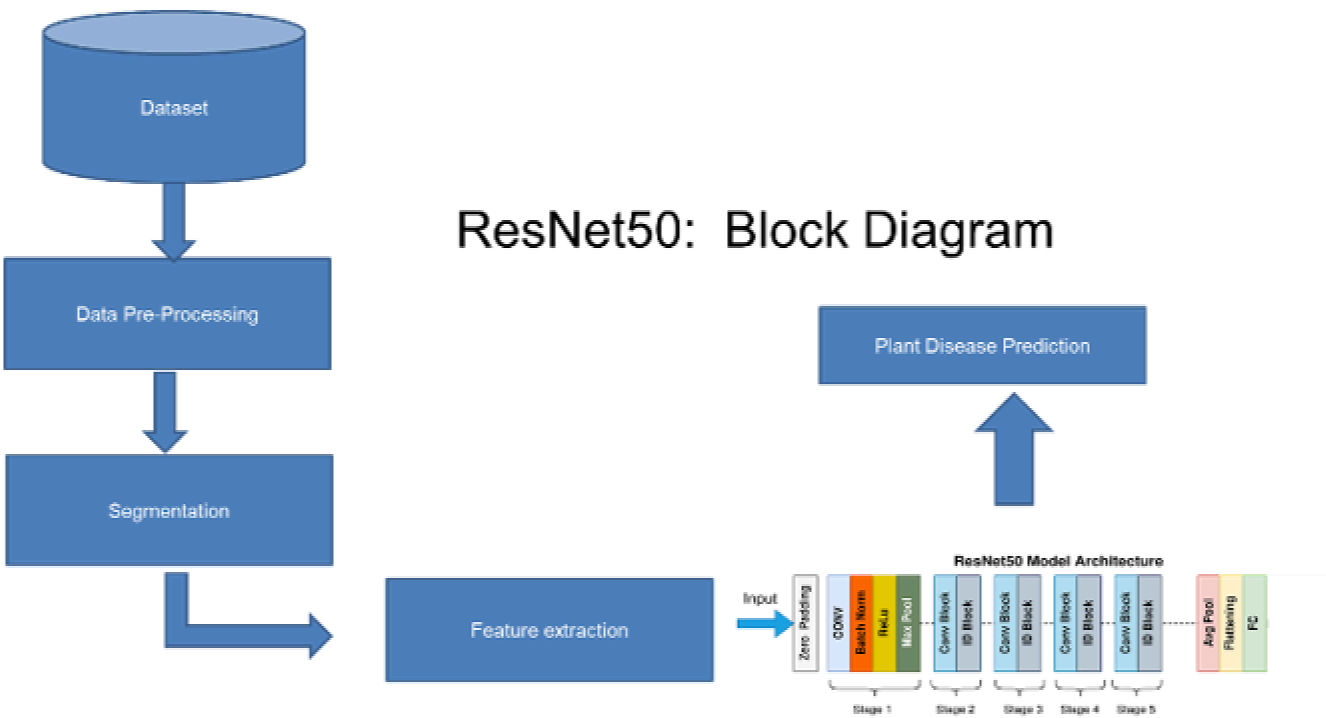

Figure 3

ResNet50

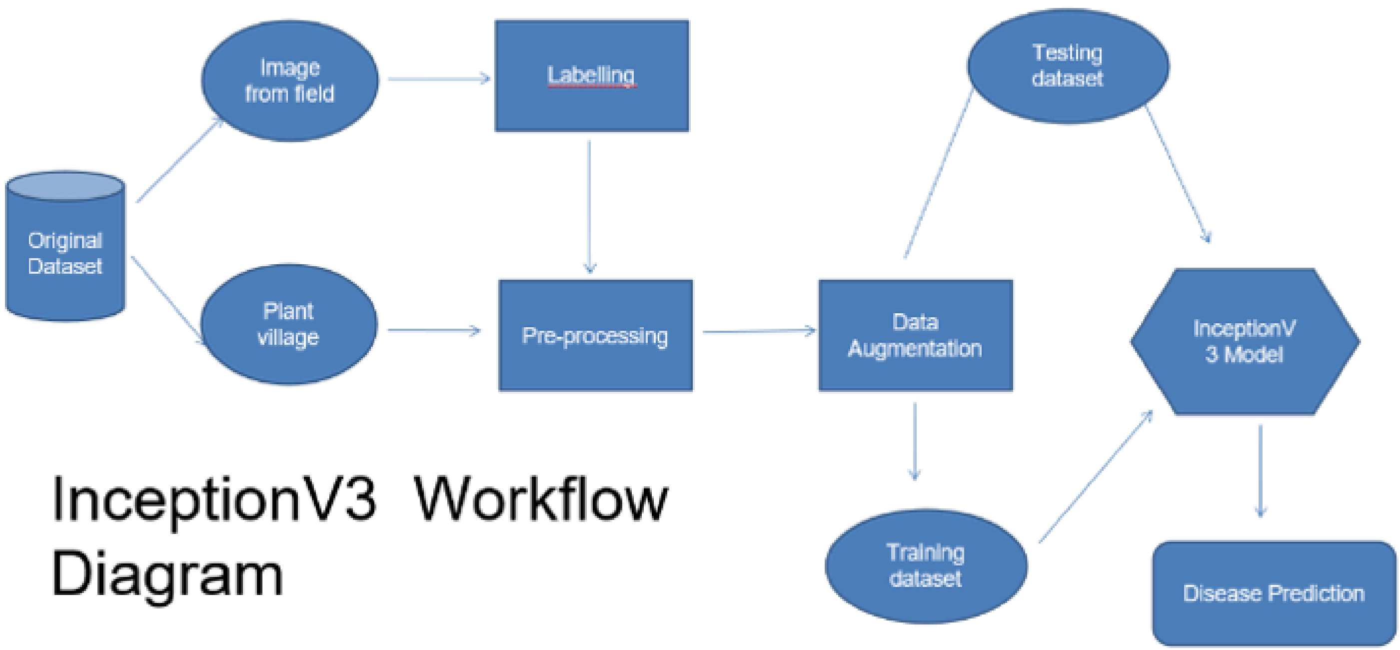

Figure 4

Inception V3

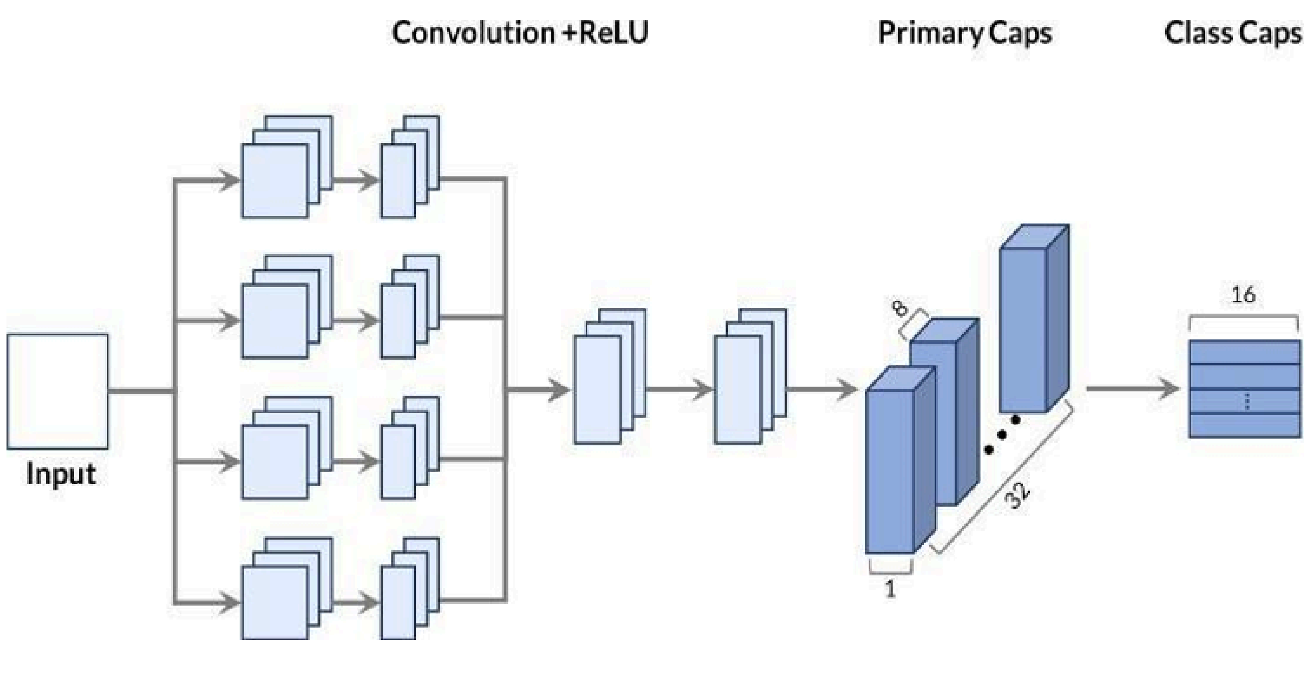

Figure 5

CapsuleNet

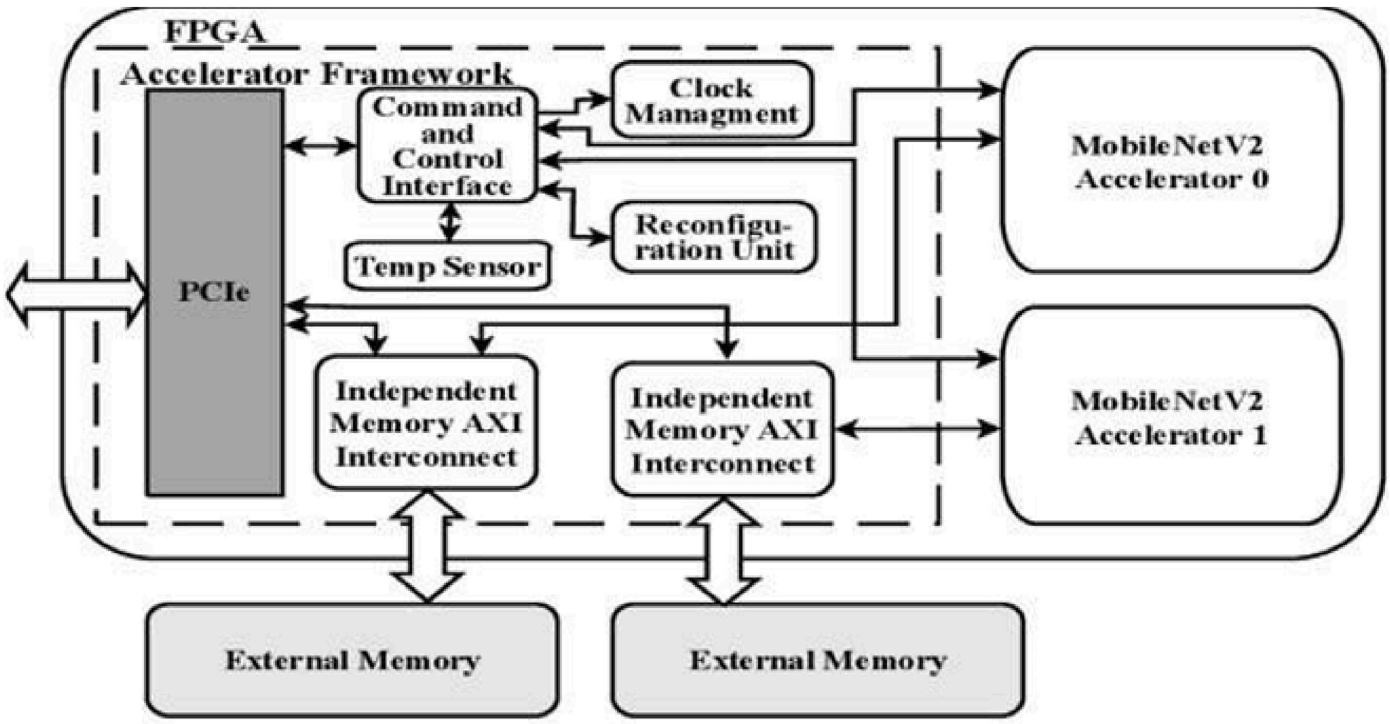

Figure 6

Mobilenetv2

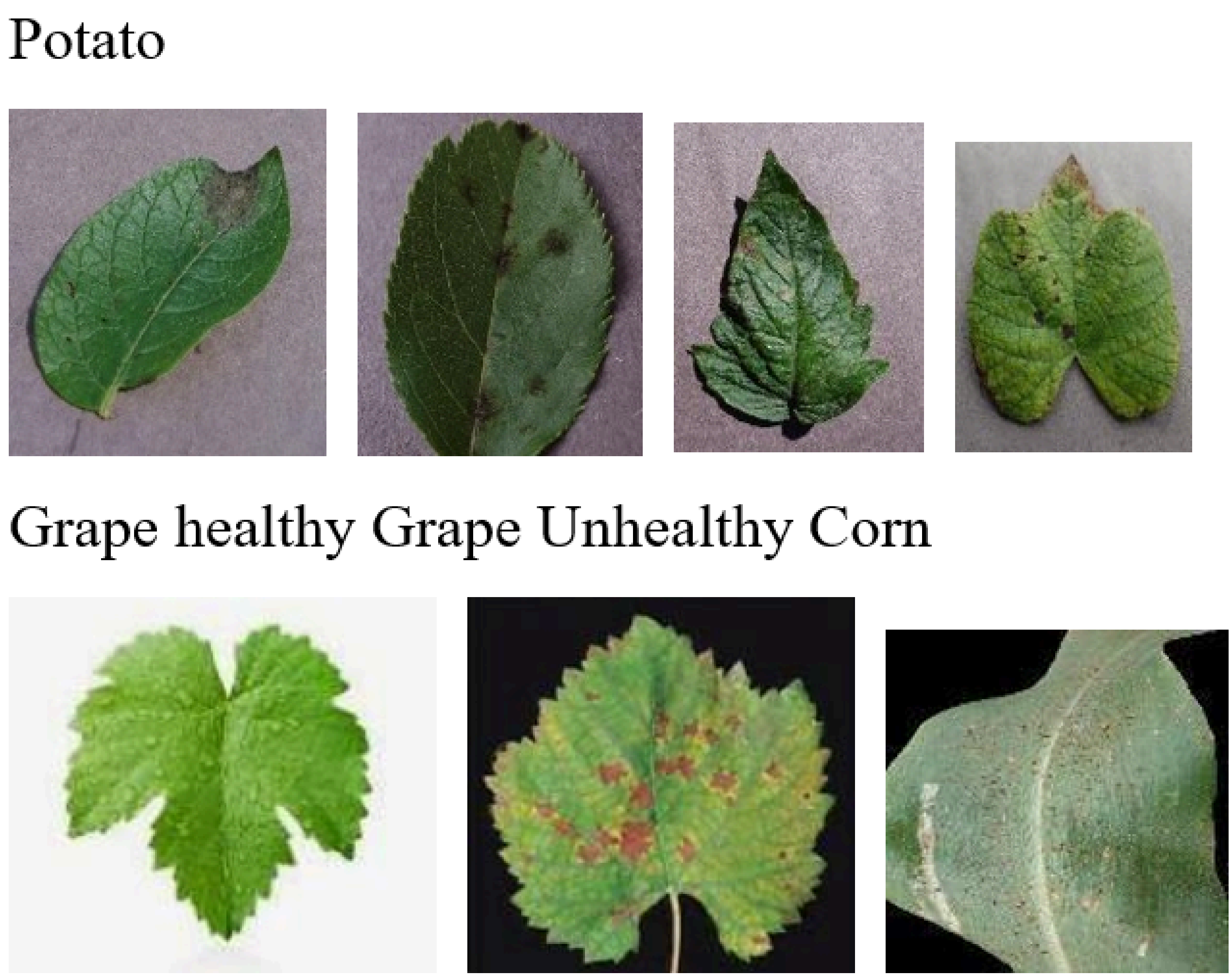

Figure 7

Data set

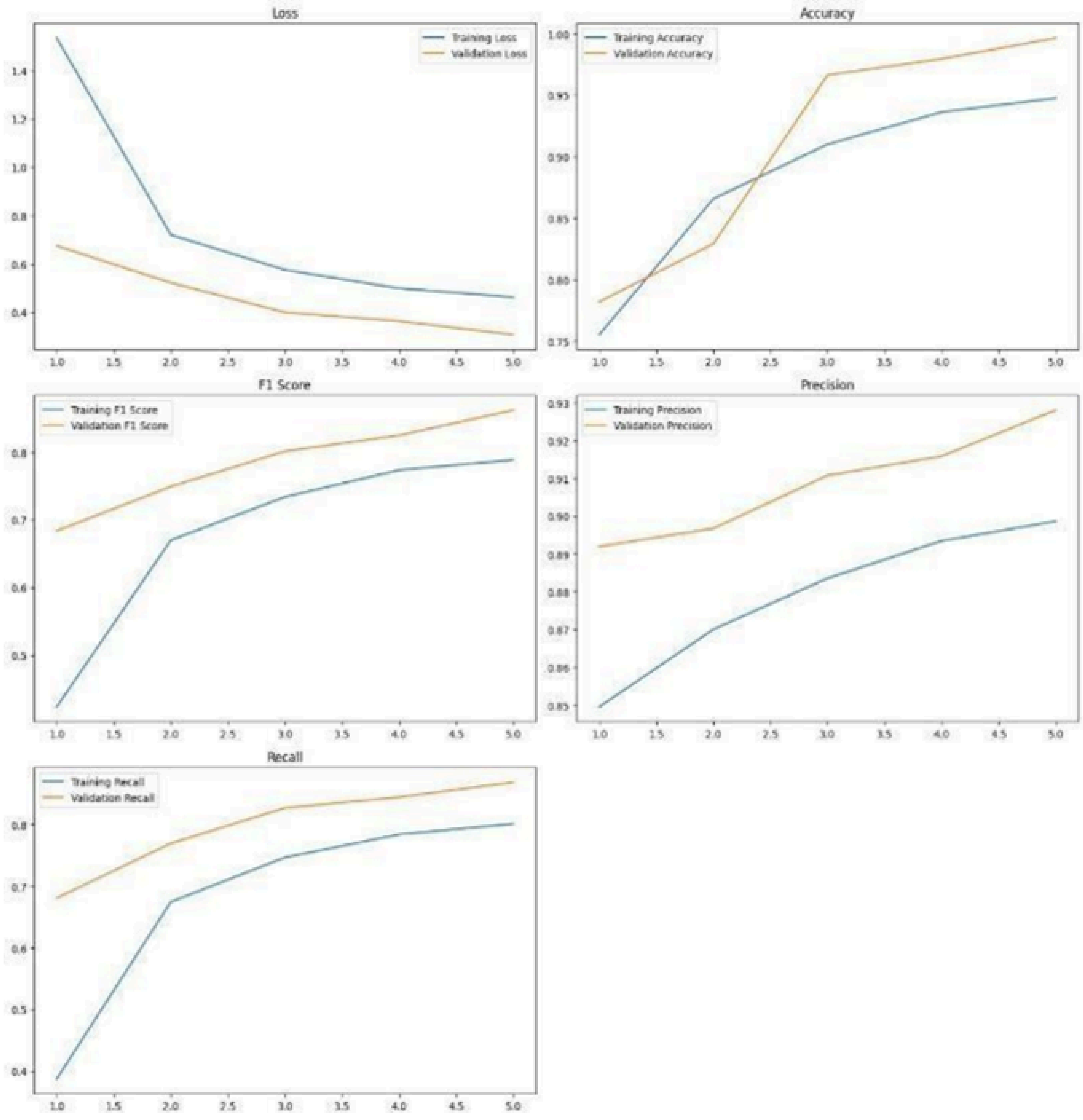

Figure 8

Densenet metrics

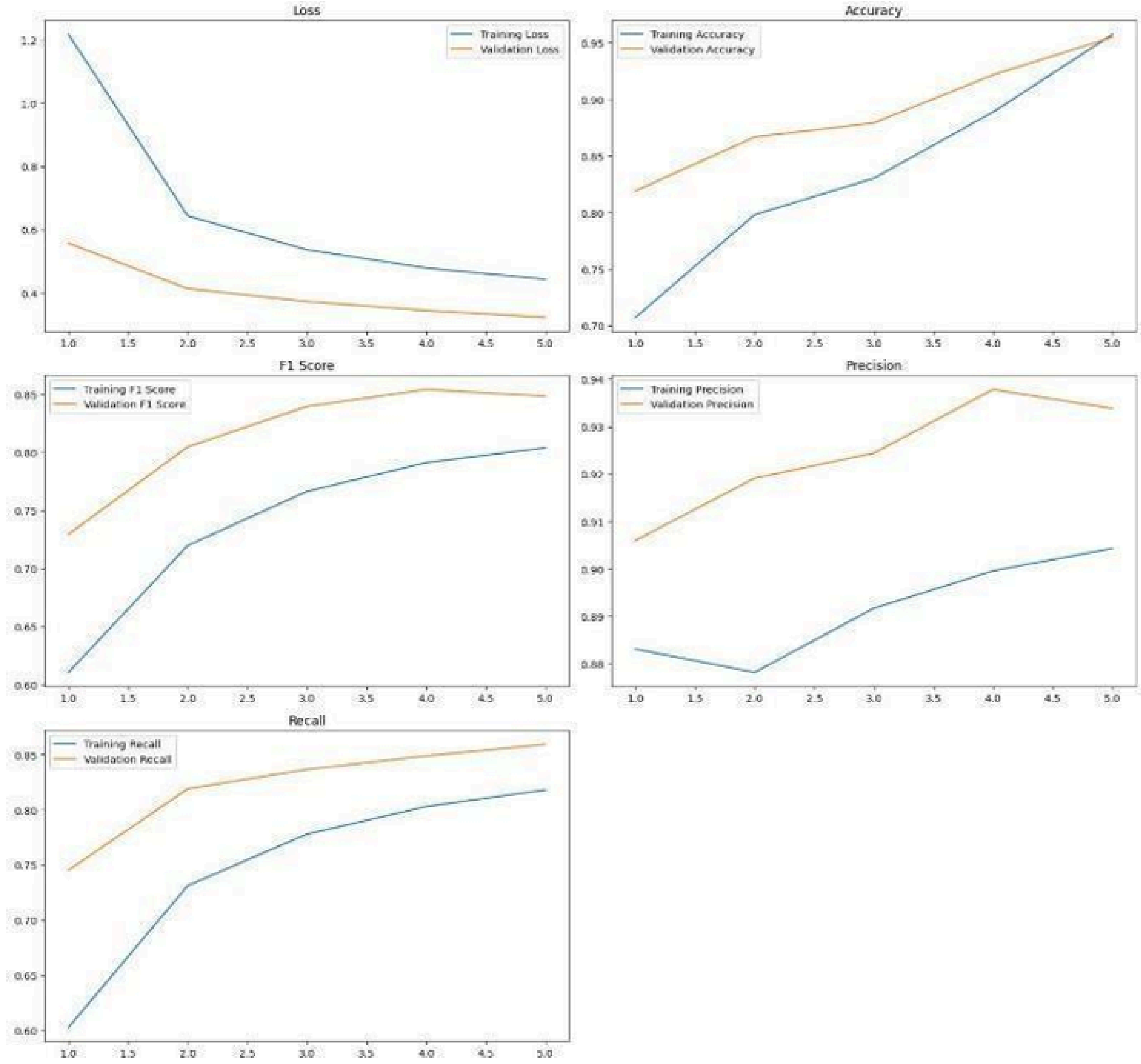

Figure 9

InceptionV3 metrics

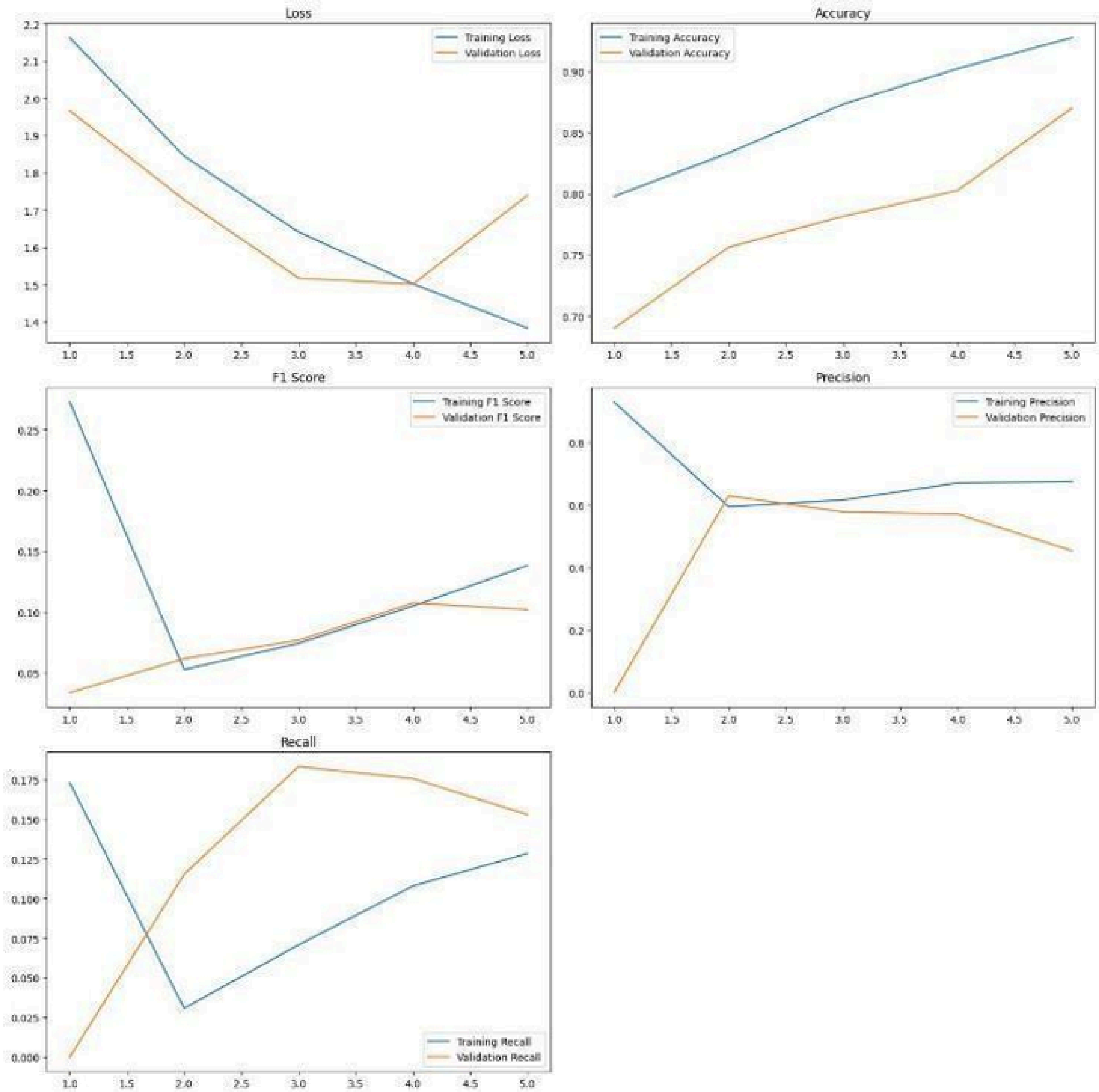

Figure 10

MobileNet V2 metrics

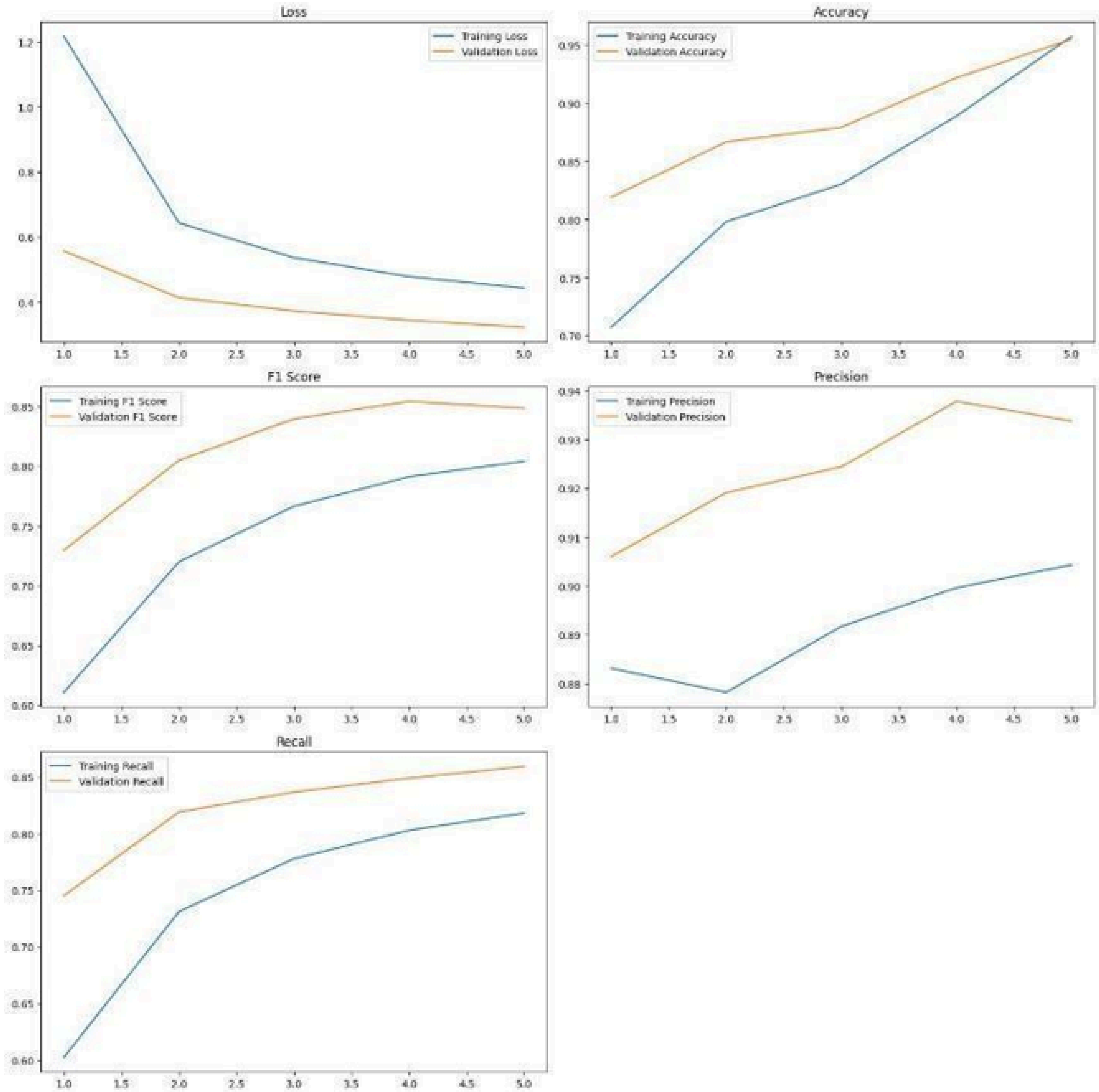

Figure 11

ResNet50 metrics

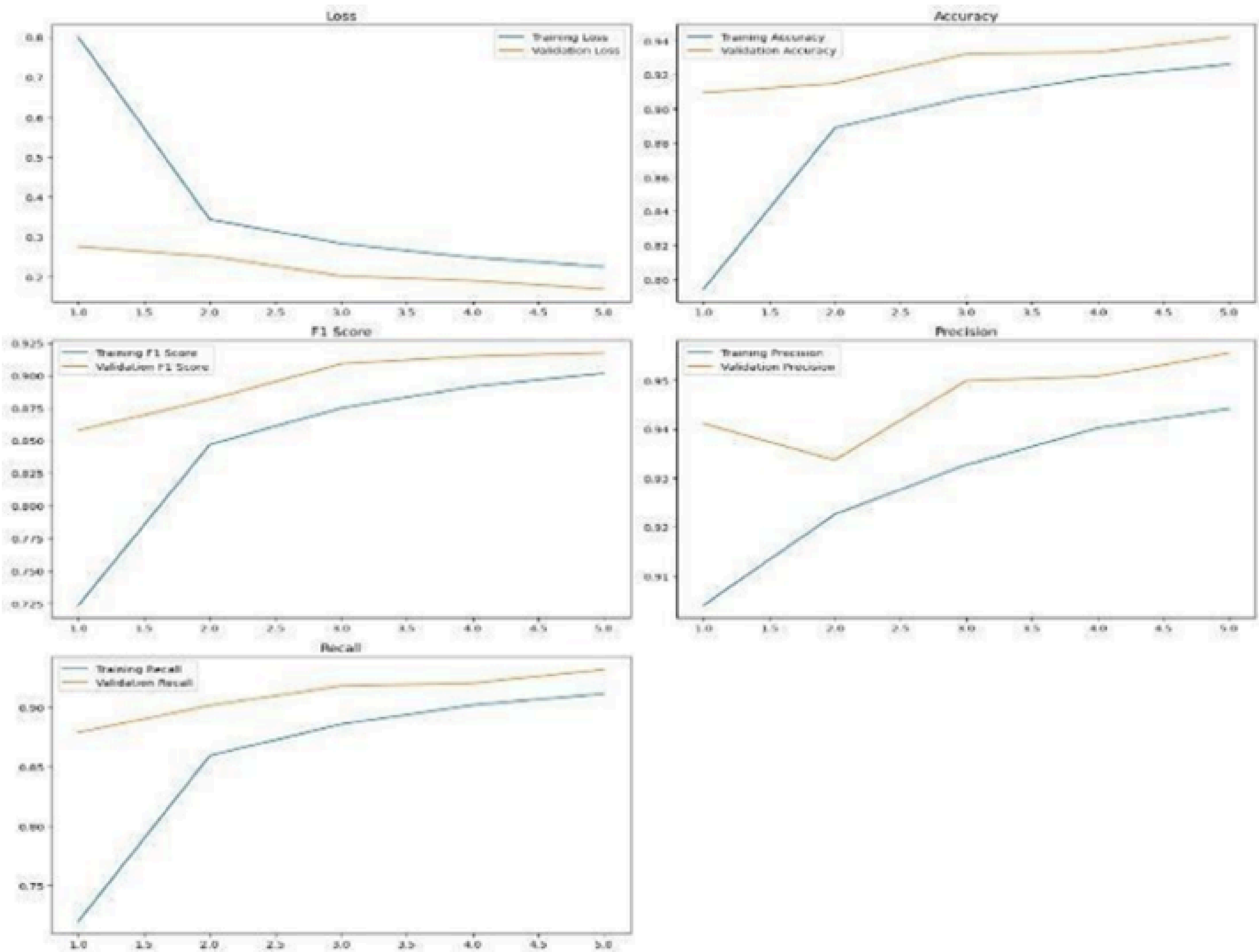

Figure 12

CapsNet metrics

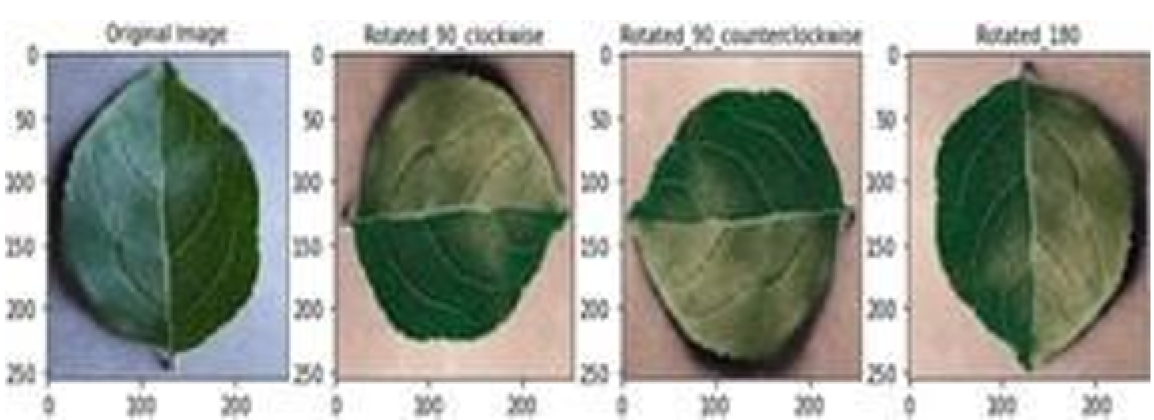

Figure 13

Rotation

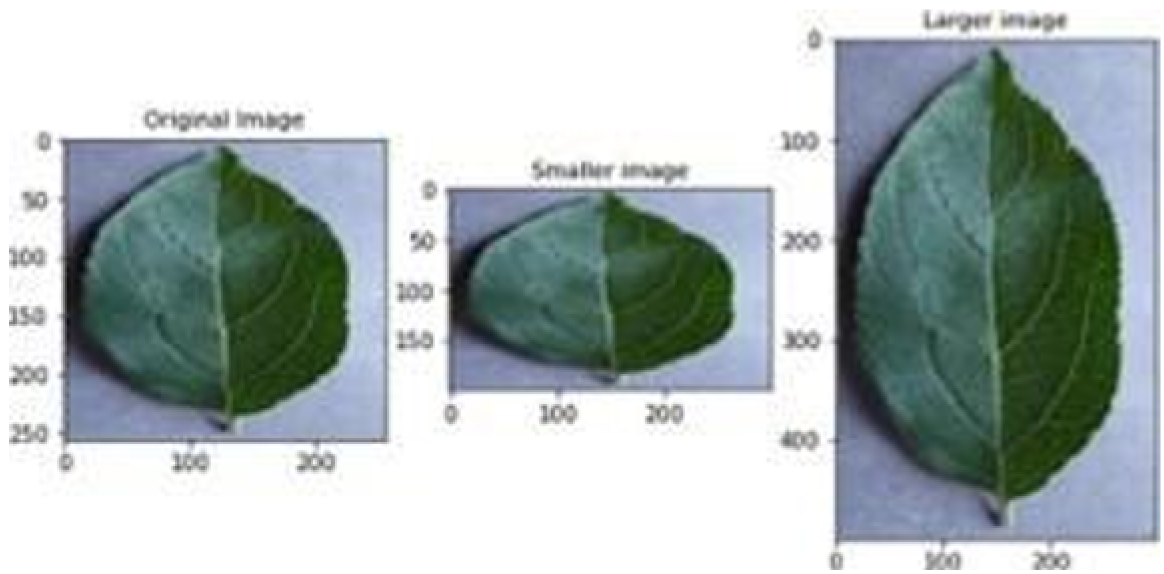

Figure 14

Scaling

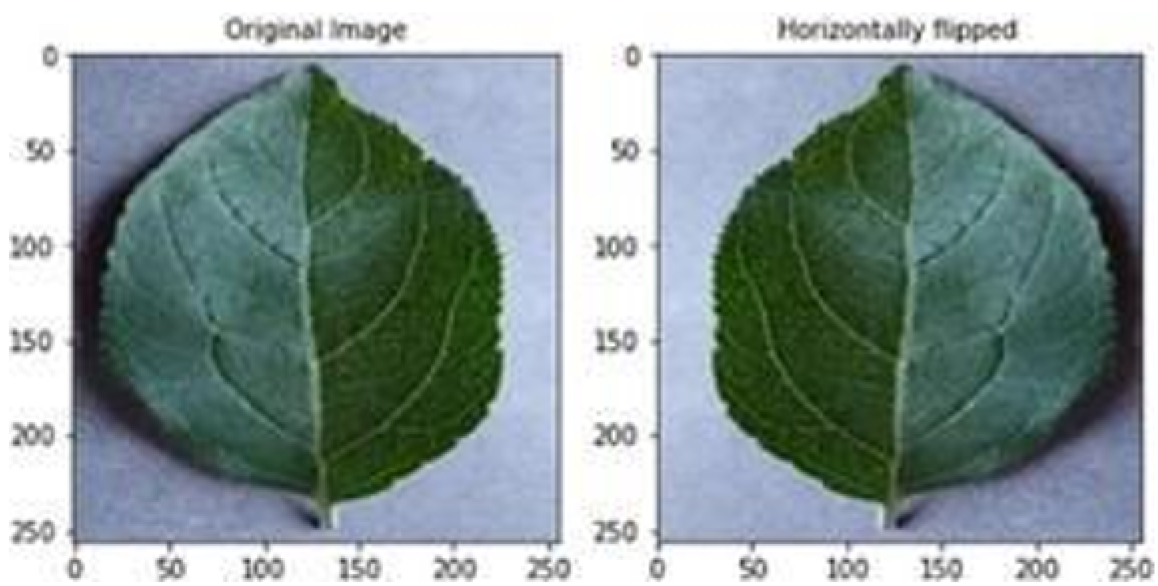

Figure 15

Flipping