Enhanced Disease Detection for Potato Crop using CNN with Transfer Learning

Harsh Mishra (harshmishraandheri@gmail.com)
Thakur College of Engineering & Technology
Vishal Pandey
Thakur College of Engineering & Technology
Deep Kothari
Thakur College of Engineering & Technology
Mihir Gharat
Thakur College of Engineering & Technology
Loukik Salvi
Thakur College of Engineering & Technology

Article

Keywords: Transfer Learning, Ensemble Technique, CNN, Deep Learning, Crop Disease

Posted Date: April 5th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2731420/v1

Abstract

Potatoes are ubiquitous and the fourth most consumed staple food in the world. Moreover, the demand is growing daily as a result of the global market. Diseases such as late blight and early blight greatly affect the quality and quantity of potatoes. Interpreting these diseases manually is cumbersome, making it more difficult to identify which potato leaves are infected with one of the diseases. Fortunately, the diseases of the potato leaves can be determined based on the leaf conditions. Using heavy architectures for convolutional neural networks, like GoogleNet, Resnet15, VGG16, and Xception, this suggested study introduces a method that uses deep learning to categorize the two varieties of illnesses and produces a precise classifier. In the first 40 CNN epochs, we were able to attain 97% accuracy, proving the viability of the deep neural network strategy.Also, a deeper analysis of various model building techniques like transfer learning, ensemble, and non-transfer techniques are done and by comparing their accuracy scores the better technique suited for this problem statement is justified.

I. Introduction

Agriculture is the most common occupation, despite the fact that there are many other types as well. The heavily agriculturalized Indian economy also reflects this. Since potatoes make up around 28.9% of all agricultural output in India, they are the country's most versatile crop. After corn, wheat, and rice, potatoes are the fourth-largest crop in the world. India produces 48.5 million tonnes of potatoes yearly, ranking as the second-largest producer in the world [1]. According to the Agricultural and Processed Food Products Export Development Authority (APEDA), Uttar Pradesh is responsible for more than 30.33 percent of total Indian potato production. In the textile industry, potato starch (farina) is used to scale cotton and worsted.

Potatoes are a rich source of fibre, vitamins (especially C and B6), and potassium.. It aids in the treatment of illnesses including high blood pressure, heart disease, and cancer by reducing total blood cholesterol levels. Diseases affect plant and agricultural areas. These illnesses are brought on by microorganisms, genetic disorders, and infectious substances including bacteria, fungus, and viruses. Fungi and bacteria are the main causes of potato leaf diseases. Soft rot and common scab are bacterial illnesses, but late and early blight is a fungal disease [2].Therefore, in this proposed literature, an automated technique was developed that might improve crop production, raise farmer profit, and significantly boost the nation's economy by identifying and diagnosing these diseases on such important plants. Many computers vision and image processing experts had previously suggested employing classic image processing methods like K-means clustering [3] and LBP To discover these leaf diseases, use [4]. Deep learning models generate better features because they perform mapping tasks more successfully. In order to diagnose potato leaf infections, a deep-learning model that makes use of several classifiers was built in this study. The categorization and detection of healthy and sick leaf states utilising the Deep Learning technique are the main goals of the suggested study methodology. VGG16, a Convolutional Neural Network architectural model with a VGG Network Group,, is the architecture employed in this study. Additionally, other CNN designs, including ResNet50 and GoogleNet, are utilized in this work. From the conventional method, transfer learning and ensemble learning techniques were also applied and contrasted.

Ii. Literature Survey

L. Li et al. [5] found that research in the field of crop leaf disease detection has 3 major categories. First is using classic well-known deep learning architecture, second is using that architecture pre-trained on large datasets and third is using new/modified dl architectures.

1. Classic well-known deep learning architecture:

Because each disease location has distinct characteristics, Barbedo [6] and Lee et al. [7] investigated the utilisation of individual lesions and spots rather from taking into account the entire leaf. This method's benefits include the capacity to recognise the presence of many diseases on the same leaf and the ability to enhance the data by breaking down the leaf picture into various sub-images.

In a diverse field setting and in an experimental setting, publication [8] employed the GoogLeNet model to detect 79 illnesses in 14 plant species. Compared to the full picture (82%), isolated lesions and spots had a better overall accuracy of 94%.Through experiments, Lee et al. [7] showed that model training using common diseases was more universal, regardless of culture, and did not see new data or cultures obtained especially in different fields. This fresh approach to detection emphasised on the disease's common name rather than its crop-target category to identify illnesses.

Liang et al. [9] compiled a collection of 2906 positive samples and 2902 negative samples to identify rice blasts. The experiment's findings also demonstrated that, in terms of identification and effectiveness, senior features produced by CNN beat traditional manual techniques like the wavelet transform (Haar-WT) and local binary pattern histogram (LBPH).

Qiu et al. [10] employed Mask-RCNN, whose feature extraction network is either ResNet50 or ResNet101, to identify wheat disease-affected regions. The test data set's average accuracy was 92.01%.

Li et al. reported that the accuracy for the lab dataset was 98.44% and for the field dataset it was 92.19%. [11] used it to determine the various levels of ginkgo biloba. The accuracy of the Inception V3 model was 92.3% and 93.2% respectively.

2. Transfer Learning:

Ahmad et al. [12] used four different pretraining convolution neural networks, including VGG19, VGG16, ResNet, and Inception V3, and the models were trained by adjusting parameters. The experimental results showed that Inception V3 performed the best on the two datasets (the laboratory dataset and the field dataset). Additionally, the average performance on the laboratory dataset was 10–15% better than the field dataset.

Xu et al. [13] suggested a convolutional neural network model (VGG16) based on transfer learning to accomplish maize leaf disease picture identification (healthy, leaf blight, and rust) in complicated outdoor backdrops with constrained samples. After being trained on ImageNet, the VGG16 model's weight parameters were added to the model, and the average recognition accuracy was 95.33%.

The ResNet50 network, previously trained on ImageNet, was used to analyse four distinct apple leaf diseases in the Plant Pathology 2020 Challenge dataset. Overall test accuracy for the model was 97%. However, excluding the group of complicated illness patterns, the identification accuracy was just 51% [14]. (the mixture of numerous disease symptoms). AlexNet was used for two different types of training by Long et al. [15] to identify illness on camellia leaves. training from scratch while incorporating ImageNet knowledge (4 diseases and health). The findings shown that transfer learning may substantially increase the model's convergence rate and classification capability, with classification accuracy reaching 96.53%.

Improved Deep Learning Architecture:

To analyze high-resolution photos of corn disease, Dechant et al. [16] used many CNN classifiers. According to the experimental findings, the accuracy rate was 90.8% if only one CNN classifier was applied, 95.9% when two first-level classifiers were employed, and 97.8% when three first-level classifiers were used.

In order to extract the specifics of the symptoms of the wheat disease, Picon et al. [17] substituted the first 7 x 7 convolutional layer of the ResNet50 network with two 3 x 3 convolutions and used the sigmoid activation function in lieu of the softmax layer. and identified the first three wheat diseases with 96% accuracy on the balanced dataset using the improved ResNet50 network (septoria, tan spot, and rust).

Fan et al. [18] added a batch standardisation layer to the convolutional layer of the Faster R-CNN model to produce a mixed-cost function. To enhance the training model, they also used a stochastic gradient descent method.

They selected nine distinct varieties of maize leaf diseases with complex field histories as their research topic. Under identical testing settings, the upgraded technique outperformed the SSD approach with an average accuracy increase of 4.25% and a single picture detection time decrease of 0.018 s. The improved technique also improved accuracy on average by 8.86%.

Guo et al. [19] modified the fully connected layers of the AlexNet network, removed the local response normalisation layer, and set a multi-scale convolution kernel as the feature extraction mechanism in order to create a multi-receptive field recognition model based on AlexNet known as Multi-Scale AlexNet. The PlantVillage dataset and the self-collected dataset of seven different tomato-damaged leaf kinds serve as the study objectives. The model reduced the memory needs of the original AlexNet by 95.4% while increasing the average recognition accuracy of tomato leaf illnesses and each disease in its early, middle, and late phases to up to 92.7%.

Chen et al. [20] introduced an improved VGG model (INC-VGGN) based on the VGG model framework by adding two Inception modules, a pooling layer, and altering the activation function. Furthermore, an average of 92% of leaf diseases in maize plants could be correctly recognised..Additionally, 92% of corn plant leaf diseases could be accurately identified on average.

In Table 1, we have summarized all the above mentioned research works about the implementation of deep learning in plant disease detection. In this table, detailed analysis of the studies have been highlighted with the model types, dataset, sample size and evaluation metric.

Table 1
Summary of recent research works about the application of DL framework directly and improvement of DL in plant disease detection.

Reference	Object	DL frame	Dataset	Sample Size	Data Enhancement	Metric
[7], 2020	Plant	VGG16, Inception V3, GoogleNet	PlantVillage, IPM, Bing	54305	Random Cropping and Mirroring	Top-1
[12], 2020	Tomato	VGG-16, VGG-19, ResNet, Inception V3	Self-acquired in field and LAB	2681–15216		Average Accuracy
[9], 2019	Rice	CNN	Self-acquired in field and LAB	5808	None	Accuracy, ROC, and AUC
[10], 2019	Wheat	Mask RCNN	Self-acquired in field and LAB	20-2809	Chunking + traditional enhancement	Average Accuracy
[11], 2020	Ginkgo biloba	VGG, Inception V3	Self-acquired in field and LAB	3730–15670	Rotate, Flip	Average Accuracy
[8], 2020	Apple	ResNet152, inception V3, MobileNet	Self-acquired in field	334–2004	Random Rotation for cutting and grayscale	Average Accuracy, Processing time of each image
[13],2020	Corn	VGG-16	Self-acquired in field	600–5400	Rotate, Flip	Average Accuracy
[18], 2020	Corn		China Science Data Network, Digipathos Network and self-acquired in field	1150–1150*8	Flip, Brightness Adjustment, Saturation Adjustment, and add Gausian Noise	Average Accuracy, Average Recall, F1-score, Overall average accuracy
[19], 2019	Tomato		PlantVillage + Self-acquired in field	5766–8349	Random Cropping, Flip, Rotation, Color dithering, Add noise	Average Accuracy
[20], 2020	Rice, Corn		Self-acquired in field	966–4000	Rotate, Flip, Scale transformations	Accuracy, Sensitivity, Specificity

Iii. Conceptual Work

This section gives an overview of some of the main concepts and methods employed in the suggested model.

3.1 Convolutional Neural Network:

CNN is one of several deep learning algorithms that evaluate visual data [21]. Convolution is utilised to extract various properties from the photos. The image is then shrunk to a smaller size so that it may be processed more quickly without losing many of its original qualities. Low-level spatial attributes that are often connected to edges, borders, or the fundamental properties of the objects are learned in the earliest layers of a CNN. At the same time, the deeper layers pick up more sophisticated, complex feA. The two primary components of CNN are feature extraction and classification, which are illustrated in Fig. 1. Features like complicated forms and object orientations are examples of these.

3.2 Classification Process:

In this section, the extracted feature maps are used to determine a mapping between the desired yield classes, which typically include totally related layers, and the characteristics. All of the contributions from one layer are linked to each enactment unit of the subsequent layer in absolutely related layers. They are used as a classifier at the organization's tail, where a layer with various neurons is used to coordinate the number of yield classifications. The SoftMax initiating work is used in multi-class ordering problems to standardise the yield into decimal quality for the likelihood that the contribution belongs to a certain class. The aim predicted class for the contributions is then determined to be the one with the highest possibility. For a classification problem with K classes, the SoftMax activation function can be formulated mathematically as in (1).

$$\sigma\left(Z\right) = \frac{e^{zi}}{\sum_{i=1}^{k} e^{zi}}$$

1

where (Z)i is the likelihood that the input belongs to the ith class, xi is the I th dimension output, and I is a class number from 1 to K.

Transfer Learning:

A model that was created and trained for one job may be used again for another task with the help of the potent approach known as transfer learning [22]. In Fig. 2, intuitive examples of transfer learning are depicted. On contemporary hardware, this can cut the amount of training time needed for such models and save days or even weeks. There are two methods for putting transfer learning into practise: Creating a model approach and retraining an existing model approach are the first two steps. The picking a task that is similar to the work at hand, with lots of data, and generating a source model are steps in the developing a model technique. The model may be utilised as a jumping off point for the second job after it fits the data and performs satisfactorily. The pre-trained model strategy entails choosing a pre-trained model that already exists.For instance, pre-trained weights from the ImageNet dataset [23] are frequently utilised in tasks involving images and are used as a foundation for training a model on another existing dataset. Transfer learning often employs the model's pre-learned weights as a feature extractor by removing the top fully connected layer that was in charge of categorising the dataset it was trained on. The model is then given a classification layer to learn the mapping between the output classes of the new dataset and the feature extractor. Pre-trained CNNs Resnet50, VGG16, and Xception were employed in this investigation.

3.3 Ensemble Learning:

In the context of machine learning, an ensemble is a system made up of a number of independent models operating concurrently, the output of which is integrated using decision fusion techniques to generate a single solution to a given issue. has a broad definition [26]. Figure 3 shows pictorial representation of ensemble learning.

Iv. Proposed Work

4.1 Dataset:

300 photos are utilised for validation in the proposed study, whereas 900 images are used to train the model.

The dataset was obtained from Kaggle and is available at: https://www.kaggle.com/abdallahalidev/plantvillagedataset. Images from classifications like Early blight, Late blight, and Healthy may be found in the dataset. Figure 4 is a snapshot of the dataset.

4.2 Data Preprocessing

Simply put, data augmentation is adding more data. To artificially enhance the size of the training data set, data augmentation is the practise of creating several plausible versions of each training sample. Overfitting is lessened as a result. Each image in the training set is gently rotated, shifted, and resized by various percentages during data augmentation, and all of the resultant images are then added to the training set. As a result, the model is more accommodating to variations in the orientation, location, and size of visual objects. Your photographs' contrast and lighting settings are editable. The photos may be rotated both vertically and horizontally. The size of the training set is subsequently increased by combining all the alterations. Then, batches of 32-pixel-wide pictures are produced, each of which has three channels.

4.3 Workflow

The workflow is shown in Fig. 5.

4.4 Architecture:

The architecture of the proposed model is shown in Fig. 6.

4.5 Model Building

1. Non-Transfer Learning: CNN, Googlenet, Resnet,vgg16

A. Classical CNN

Max Pooling and Conv layers are used to build a CNN neural network. The output layer uses a softmax activation function, whereas the hidden layers employ the Relu, a non-linear activation function. Results of CNN architecture are shown in Fig. 7 and Fig. 8.

B. Googlenet

Improved network computing resource utilisation is a major component of this system. This was made possible by a thoroughly thought-out architecture that allowed us to expand the depth and breadth of our network while maintaining the same processing budget. The Hebbian principle and the multi-scale processing intuition were the foundations for the architectural choices made to maximise quality [25]. GoogLeNet, a 22-layer deep convolutional neural network, is a modification of Google researchers' deep convolutional neural network Inception Network. The GooLeNet architecture handled computer vision tasks including picture categorization and object detection when it was demonstrated at the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). Instead of utilising the pre-trained model, Googlenet is trained in this study using the suggested dataset. Results of Googlenet architecture are shown in Fig. 9 and Fig. 10.

C. Resnet50:

Training increasingly complex neural networks is more challenging. We offer a residual learning approach that makes it easier to train networks that are significantly deeper than those previously employed [24]. This design introduced the idea of a residual block to address the gradient vanishing/exploding problem. A method termed skip connections is applied in this network. A jump connection connects the activations of one layer to another by skipping over intervening levels. This creates a leftover block. These leftover blocks are stacked to create resnets. Instead of utilising a pre-trained model that has been trained on Imagenet data, Resnet is trained on the suggested dataset in this work. Figure 11 shows the residual block of the resnet50 model. Results of resnet50 architecture are shown in Fig. 12 and Fig. 13.

D. VGG 16

The 16-layer deep convolutional neural network VGG-16 has 16 layers. From the ImageNet database, you may load a pretrained version of a network that has been trained on more than 1 million pictures. Images may be categorised into 1000 different item categories using a pre-trained network, including keyboards, mouse, pencils, and several animals. Instead of utilising a pre-trained model that has been trained on Imagenet data, VGG is trained on the suggested dataset in this work. Results of VGG architecture are shown in Fig. 14 and Fig. 15.

2. Transfer Learning- Resnet, VGG16, Xception:

Here, pre-trained CNN architectures are used, that is, training is not done on the proposed dataset but rather use it as it is. Results are shown in Fig. 16, Fig. 17, and Fig. 18.

3. Ensemble technique:

Ensembling is a quite popular practice that involves aggregating multiple CNN models into one.

Here, two variations have been studied and analyzed.

A. Non-Transfer Learning: Here,all member models are not pre-trained but rather trained on the proposed dataset and then collaborated. Here, in the proposed literature two ensemble models are created. Results are shown in Fig. 19.:

B. Transfer Learning: Here, some or all member models are pre-trained. In the proposed work two ensemble models are created:

Resnet + Googlenet: Here, only Resnet is pre-trained.

Xception + Googlenet + Resnet: Here, only Xception and Resnet are pre-trained. Results are shown in Fig. 20 and Fig. 21.

V. Result & Discussion

Classic CNN Architectures:

Table 2
Classic CNN Architectures

DL model	Validation Accuracy				
	CNN	GoogleNet	Resnet50	VGG16	Xception
Non-Transfer Learning	98.67	88.33	37.67	33.33	-
Transfer Learning	-	-	72.00	96.67	96.00

Table 2 shows the comparison of validation accuracy of all the classic CNN architectures implemented.

Evaluation of Models trained on training data:

- The CNN architecture proposed in this work performed the best having around 99% accuracy on the testing data also GoogleNet performed better having an accuracy of more than 88%.
- Deep Convolutional Neural Networks like Resnet15 and VGG16 underperformed with only 37.67% and 33% of accuracy respectively.

Evaluation of Models pre-trained on ImageNet dataset:

- This study employed three pre-trained models: ResNet15, VGG16, and Xception.Resnet's accuracy was just 72% but comparing it with the one not pre-trained, it is double.

- VGG16 has an accuracy of 96.67% and it is near to triple that of not pre-trained.
- The Xception model also had an accuracy greater than 95%.

Ensemble Technique

Table 3
Ensemble Technique

DL model	**Validation Accuracy**	
	Resnet + GoogleNet	**Resnet + GoogleNet + Xception**
Non-Transfer Learning	80.00	88.33
Transfer Learning	33.00	97.00

Table 3 shows the comparison of validation accuracy of all the ensemble architectures implemented.

Evaluation of Models trained on training data:

- The first model is a combination of Resnet and GoogleNet model and it gives an accuracy of 80%.

- This second model, which is a composite of three models, is improved by the addition of the Xception model and has an accuracy of 88.33%.Evaluation of Models pre-trained on ImageNet dataset:

- The first model is the combination of ResNet and GoogleNet where the ResNet model was pre-trained on Imagnet dataset. The accuracy of this ensemble model was the worst i.e.just 33%.
- However, adding a pre-trained Xception model made it the best with 97% accuracy on the testing data.

Vi. Conclusion

The findings of the research in this study allow us to draw the conclusion that the transfer-learning technique used on algorithms having many convolutional layers on small image datasets increases classification accuracy for potato plant diseases. Based on the comparative analysis, we may draw the conclusion that the methodology based on the transfer-learning technique for ensemble learning, which produced a classification accuracy score of 97.00%, performs better in comparison to the accuracy scores reported in the non-transfer learning technique for ensemble learning. Additionally, when transfer learning was applied on classic CNN architectures like VGG16, and Resnet50, a huge improvement in the classification accuracy was noted.

Vii. Future Scope

The similar method may be utilised in further study to recognise other potato and other plant-related illnesses from digital photos. Furthermore, several augmentation methods and CNN combinations for feature extraction may be evaluated. Furthermore, by utilising various feature extractors and fusion techniques with any dataset, the findings of this study may be investigated in other situations.

Abbreviations

CNN, Convolutional Neural Network; VGG, Visual Geometric Group; R-CNN, Region-based Convolutional Neural Network; LBP, Local Binary Patterns; SSD, Single Shot Detector.

Declarations

Authors' contributions:

HM carried out experiments and data analysis. VP designed, coordinated this research and drafted the manuscript. MG and DK conceived of the study, and participated in research coordination. LS guided and mentored the entire study. The authors read and approved the final manuscript.

Availability of data and materials:

All datasets used for supporting the conclusions of this article are available from the public data repository at the website of https://www.kaggle.com/abdallahalidev/plantvillagedataset.

Additional Information:

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable.

Ethics approval and consent to participate

Not applicable.

Funding

Not applicable.

References

1. List of countries by potato production, https://en.wikipedia.org/wiki/List_of_countrie s_by_potato_product
2. List of potato diseases, https://en.wikipedia.org/wiki/List_of_potato_diseases
3. Li, Youguo & Wu, Haiyan. (2012). A Clustering Method Based on K-Means Algorithm. Physics Procedia. 25. 1104-1109. 10.1016/j.phpro.2012.03.206.
4. Huang, di & Shan, Caifeng & Ardabilian, Mohsen & Chen, Liming. (2011). Local Binary Patterns and Its Application to Facial Image Analysis: A Survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C. 41. 765-781. 10.1109/TSMCC.2011.2118750.
5. L. Li, S. Zhang , and B. Wang, “Plant Disease Detection and Classification by Deep Learning—A Review,” *IEEE Access*, vol. 9, pp. 56683–56698, 2021.
6. J. G. A. Barbedo, “Plant disease identification from individual lesions and spots using deep learning,” Biosyst. Eng., vol. 180, pp. 96–107, Apr. 2019.
7. S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, “New perspectives on plant disease characterization based on deep learning,” Comput. Electron. Agricult., vol. 170, Mar. 2020, Art. no. 105220.
8. C. Bi, J. Wang, Y. Duan, B. Fu, J.-R. Kang, and Y. Shi, “MobileNet based apple leaf diseases identification,” Mobile Netw. Appl., vol. 10, pp. 1–9, Aug. 2020, doi: 10.1007/s11036-020-01640-1.
9. W.-J. Liang, H. Zhang, G.-F. Zhang, and H.-X. Cao, “Rice blast disease recognition using a deep convolutional neural network,” Sci. Rep., vol. 9, no. 1, pp. 1–10, Feb. 2019.
10. R. Qiu, C. Yang, A. Moghimi, M. Zhang, B. J. Steffenson, and C. D. Hirsch, “Detection of fusarium head blight in wheat using a deep neural network and color imaging,” Remote Sens., vol. 11, no. 22, Nov. 2019, Art. no. 2658.
11. K.-Z. Li, J.-H. Lin, J.-R. Liu, and Y.-D. Zhao, “Using deep learning for image-based different degrees of ginkgo leaf disease classification,” Information, vol. 11, no. 2, pp. 95–104, Feb. 2020.
12. I. Ahmad, M. Hamid, S. Yousaf, S. T. Shah, and M. O. Ahmad, “Optimizing pretrained convolutional neural networks for tomato leaf disease detection,” Complexity, vol. 2020, pp. 1–6, Sep. 2020, doi: 10.1155/2020/8812019
13. J.-H. Xu, M.-Y. Shao, Y.-C. Wang, and W.-T. Han, “Recognition of corn leaf spot and rust based on transfer learning with a convolutional neural network,” Trans. Chin. Soc. Agricult. Mach., vol. 51, no. 2, pp. 230–236, Feb. 2020.
14. R. Thapa, N. Snavely, S. Belongie, and A. Khan, “The plant pathology 2020 challenge dataset to classify foliar disease of apples,” Comput. Sci., vol. 3, Feb. 2020, Art. no. 11958.

15. M.-S. Long, C.-J. OuYang, H. Liu, and Q. Fu, “Image recognition of camellia oleifera diseases based on convolutional neural network & transfer learning,” Trans. Chin. Soc. Agricult. Eng., vol. 34, no. 18, pp. 194–201, Sep. 2018.
16. C. DeChant, T. Wiesner-Hanks, S. Chen, E. L. Stewart, J. Yosinski, M. A. Gore, R. J. Nelson, and H. Lipson, “Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning,” Phytopathology, vol. 107, no. 11, pp. 1426–1432, Nov. 2017.
17. A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, “Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild,” Comput. Electron. Agricult., vol. 161, pp. 280–290, Jun. 2019.
18. X.-P. Fan, J.-P. Zhou, and Y. Xu, “Recognition of field maize leaf diseases based on improved regional convolutional neural network,” J. South China Agricult. Univ., vol. 41, no. 6, pp. 82–91, Jun. 2020.
19. X. Q. Guo, T. J. Fan, and X. Shu, “Tomato leaf diseases recognition based on improved multi-scale AlexNet,” Trans. Chin. Soc. Agricult. Eng., vol. 35, no. 13, pp. 162–169, Jul. 2019.
20. J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, “Using deep transfer learning for image-based plant disease identification,” Comput. Electron. Agricult., vol. 173, Jun. 2020, Art. no. 105393.
21. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradientbased learning applied to document recognition,” Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.
22. L. Torrey and J. Shavlik, “Transfer learning,” in Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques. Hershey, PA, USA: IGI Global, 2010, pp. 242–264.
23. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A large-scale hierarchical image database,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 248–255
24. He, K., Zhang, X., Ren, S., & Sun, J. (2015). “Deep Residual Learning” for Image Recognition. *ArXiv*. https://doi.org/10.48550/arXiv.1512.03385
25. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2014). Going Deeper with Convolutions. *ArXiv*. https://doi.org/10.48550/arXiv.1409.4842
26. F. Huang, G. Xie and R. Xiao, "Research on Ensemble Learning," 2009 International Conference on Artificial Intelligence and Computational Intelligence, Shanghai, China, 2009, pp. 249-252, doi: 10.1109/AICI.2009.235.
27. D.N. Perkins and G. Salomon, Transfer of Learning. Oxford, England: Pergamon, 1992.
28. S.J. Pan and Q. Yang, “A survey on transfer learning,” IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, pp. 1345–1359, Oct. 2010.
29. Z. Wang, Z. Dai, B. Poczos, and J. Carbonell, “Characterizing and ´ avoiding negative transfer,” in Proc. IEEE Conference on Computer Vision and Pattern Recognition, Long Beach, Jun. 2019, pp. 11293– 11302.
30. K. Weiss, T.M. Khoshgoftaar, and D. Wang, “A survey of transfer learning,” J. Big Data, vol. 3, no. 1, Dec. 2016.

Figures

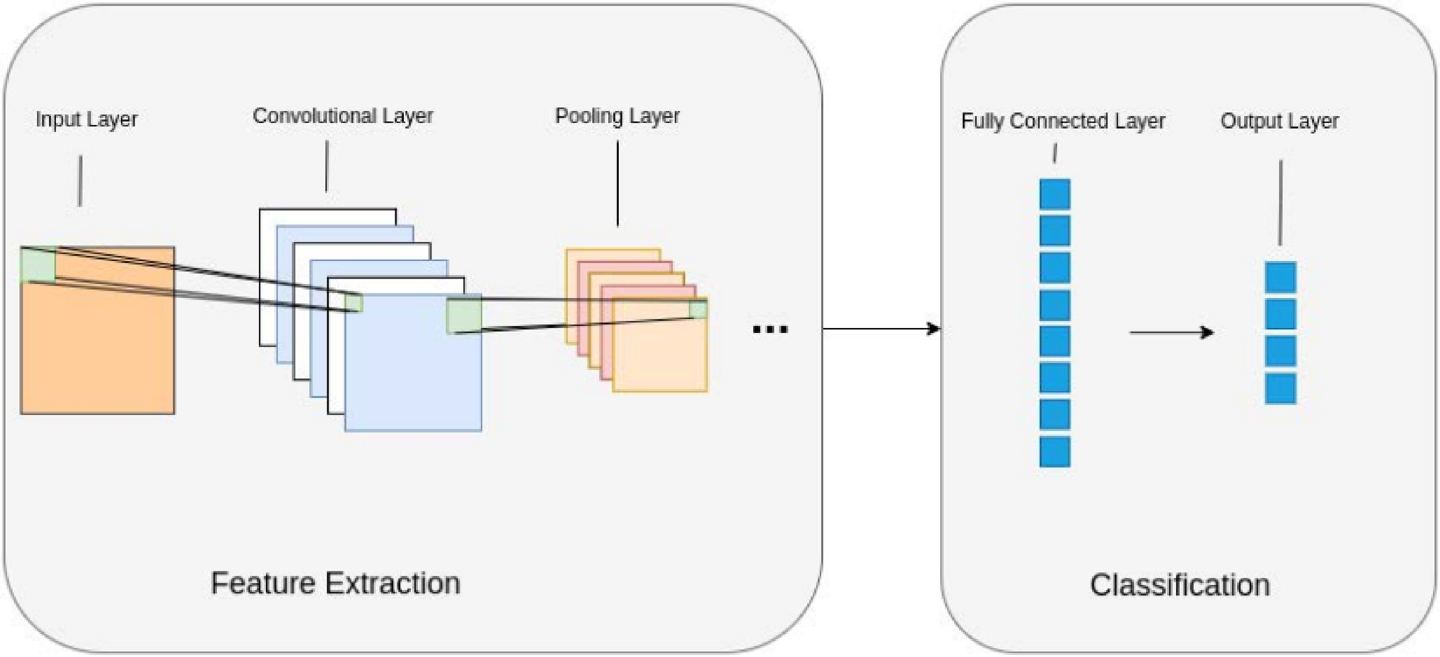

Figure 1

The convolutional neural network structure. It consists of two main building blocks: feature extraction and classification.

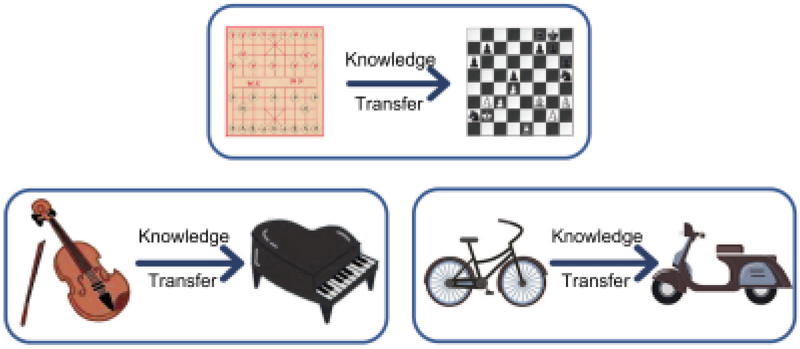

Figure 2

Intuitive examples about transfer learning.

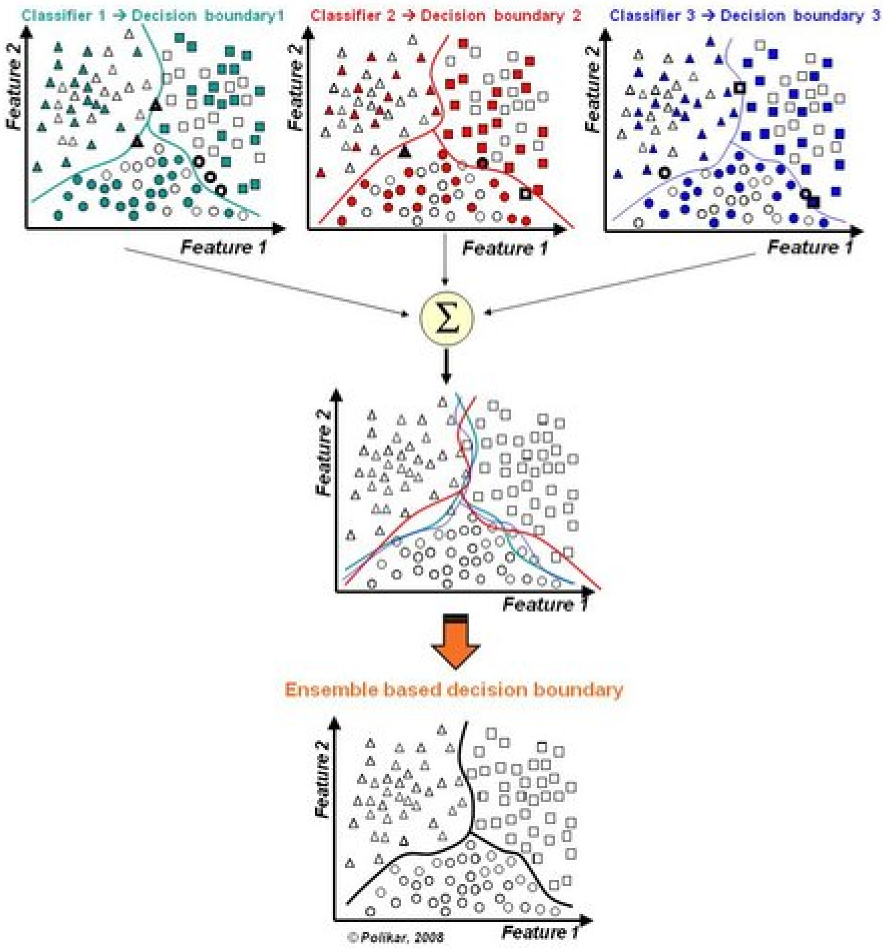

Figure 3

Combining an ensemble of classifiers for reducing classification error and/or model selection.

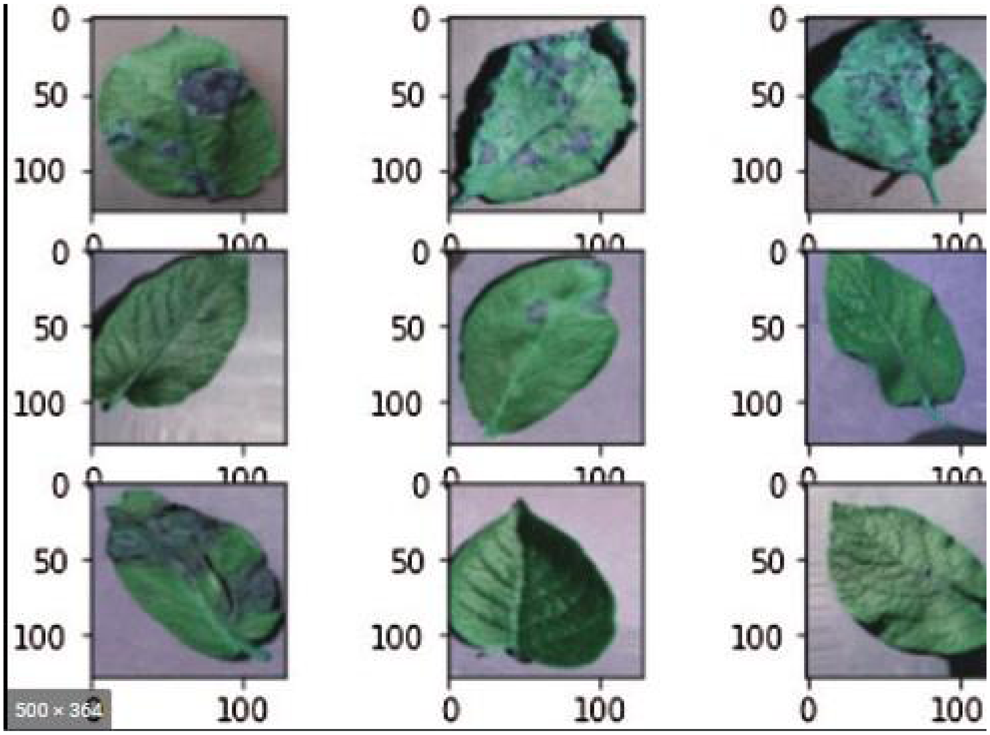

Figure 4

Dataset

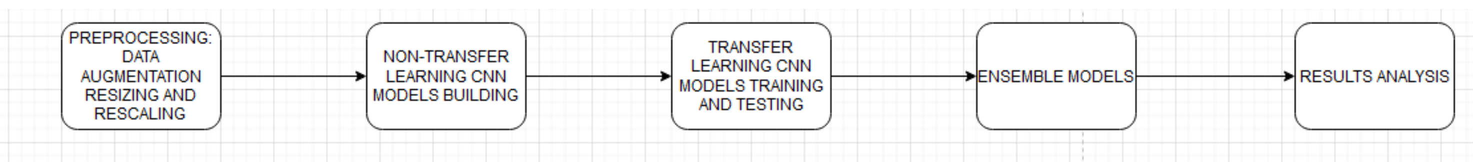

Figure 5

Workflow

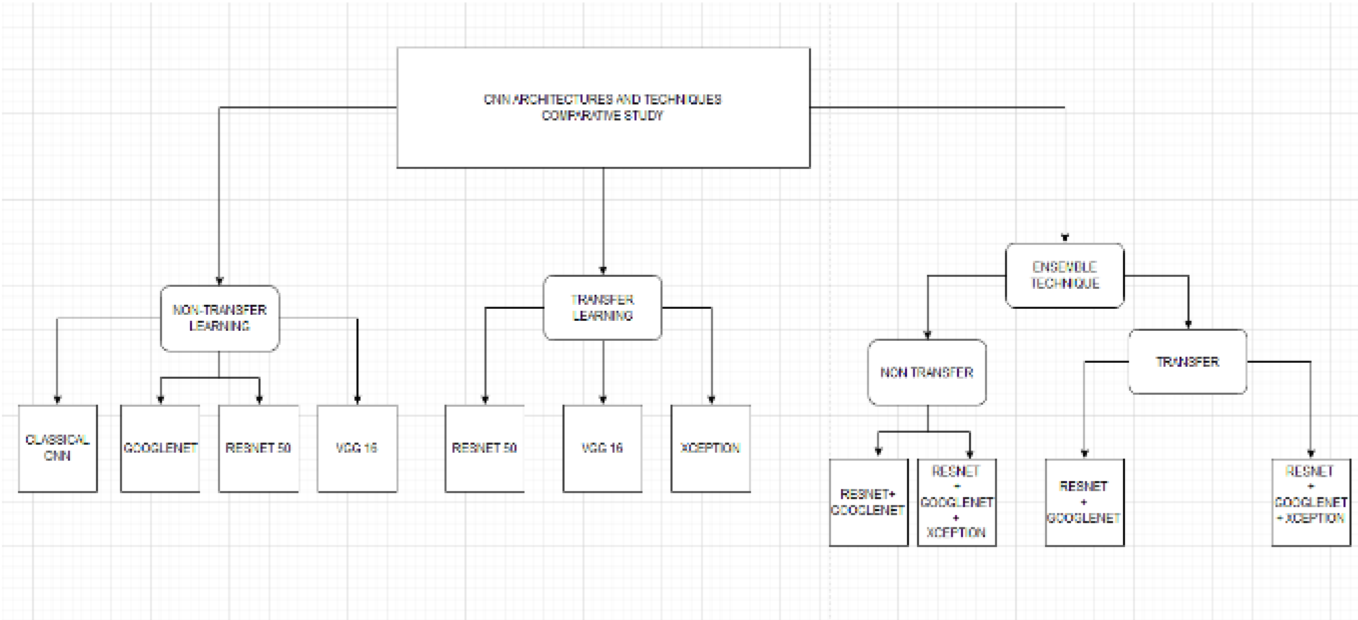

Figure 6

Architecture

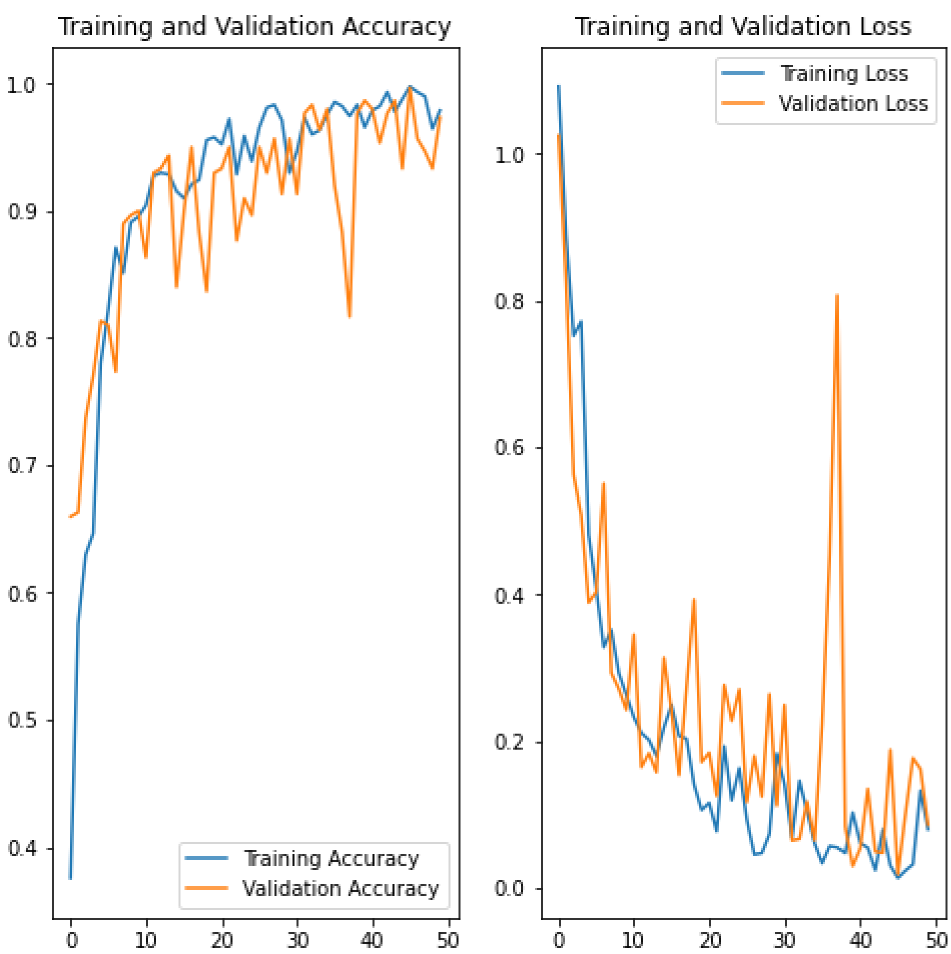

Figure 7

CNN architecture result on proposed dataset

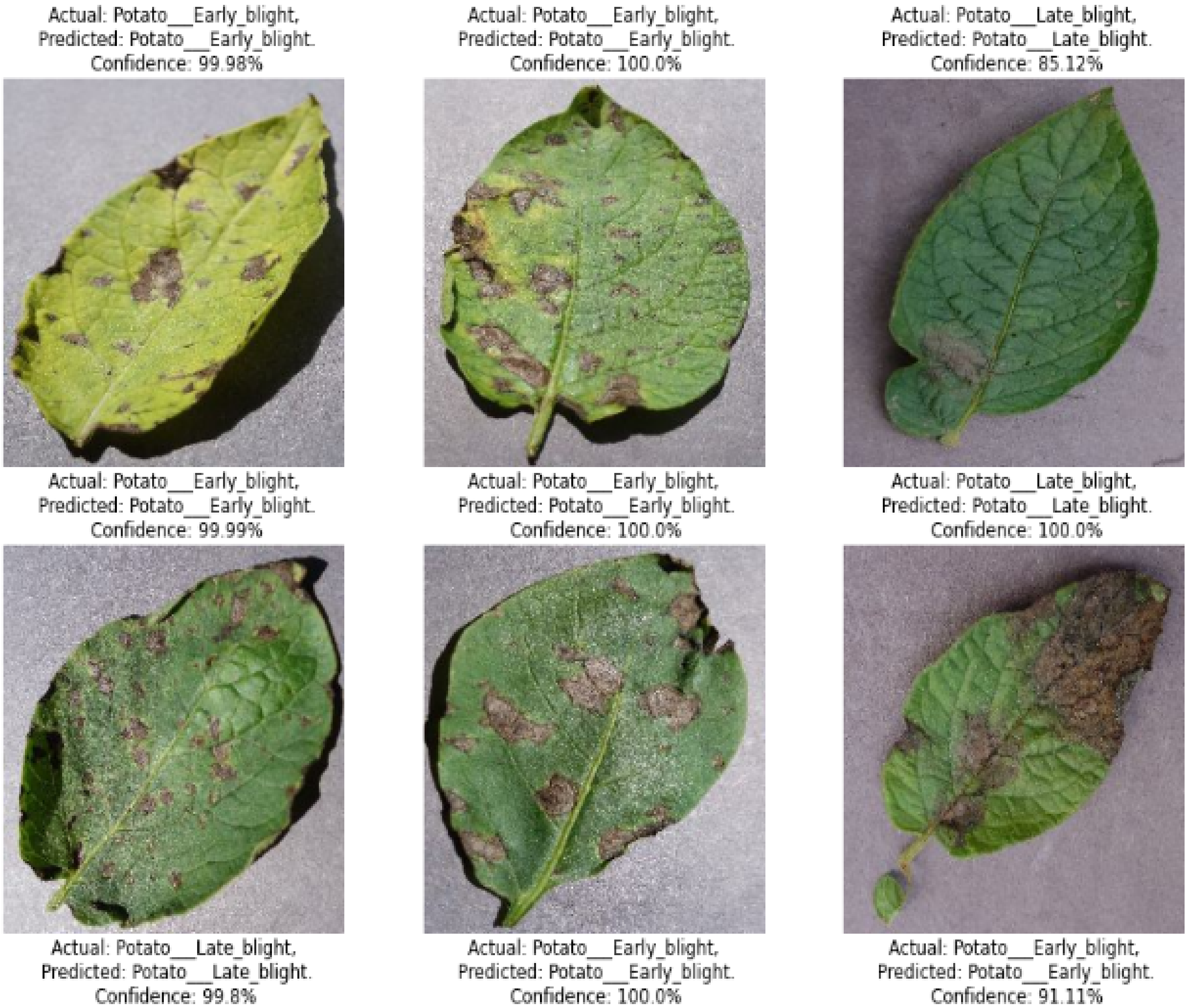

Figure 8

Visualization of CNN architecture result on proposed dataset

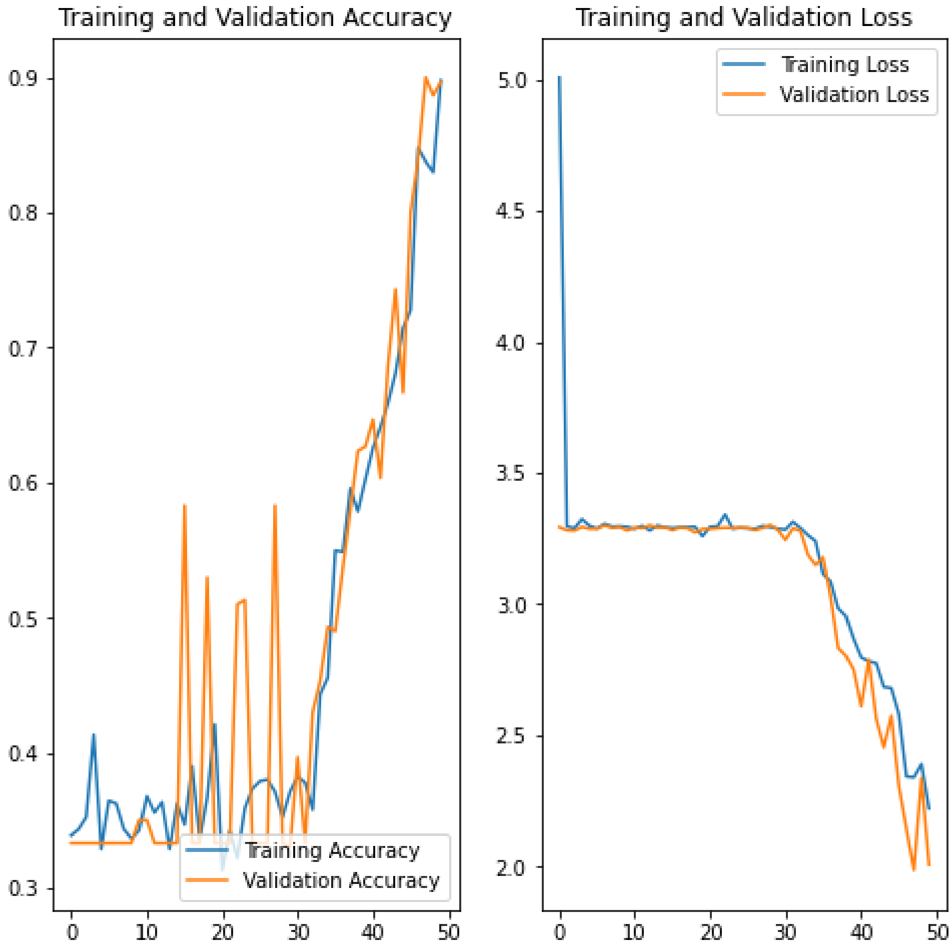

Figure 9

Googlenet result on proposed dataset

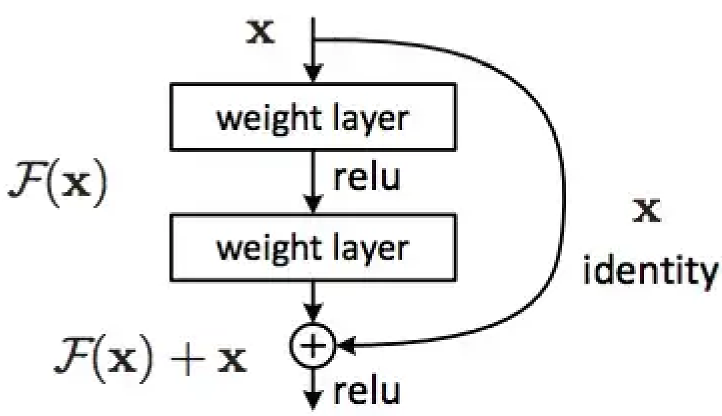

Figure 11

Residual learning: a building block. [24]

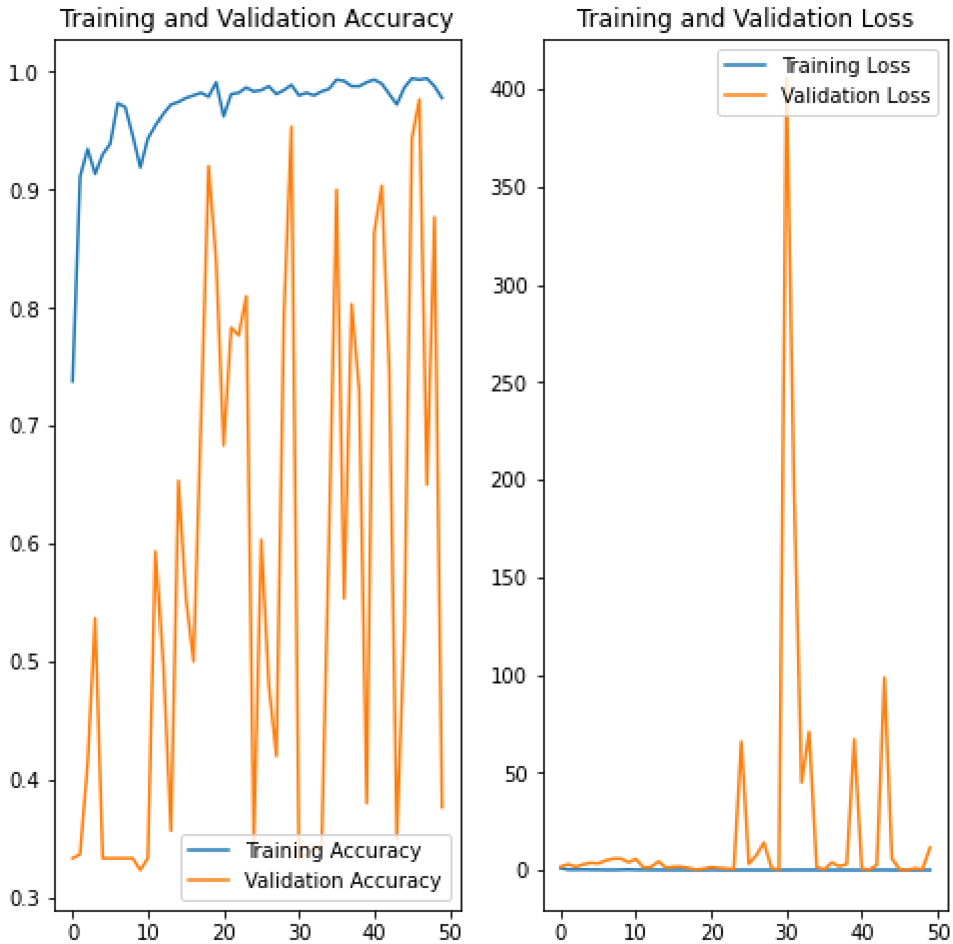

Figure 12

Resnet50 result on proposed dataset

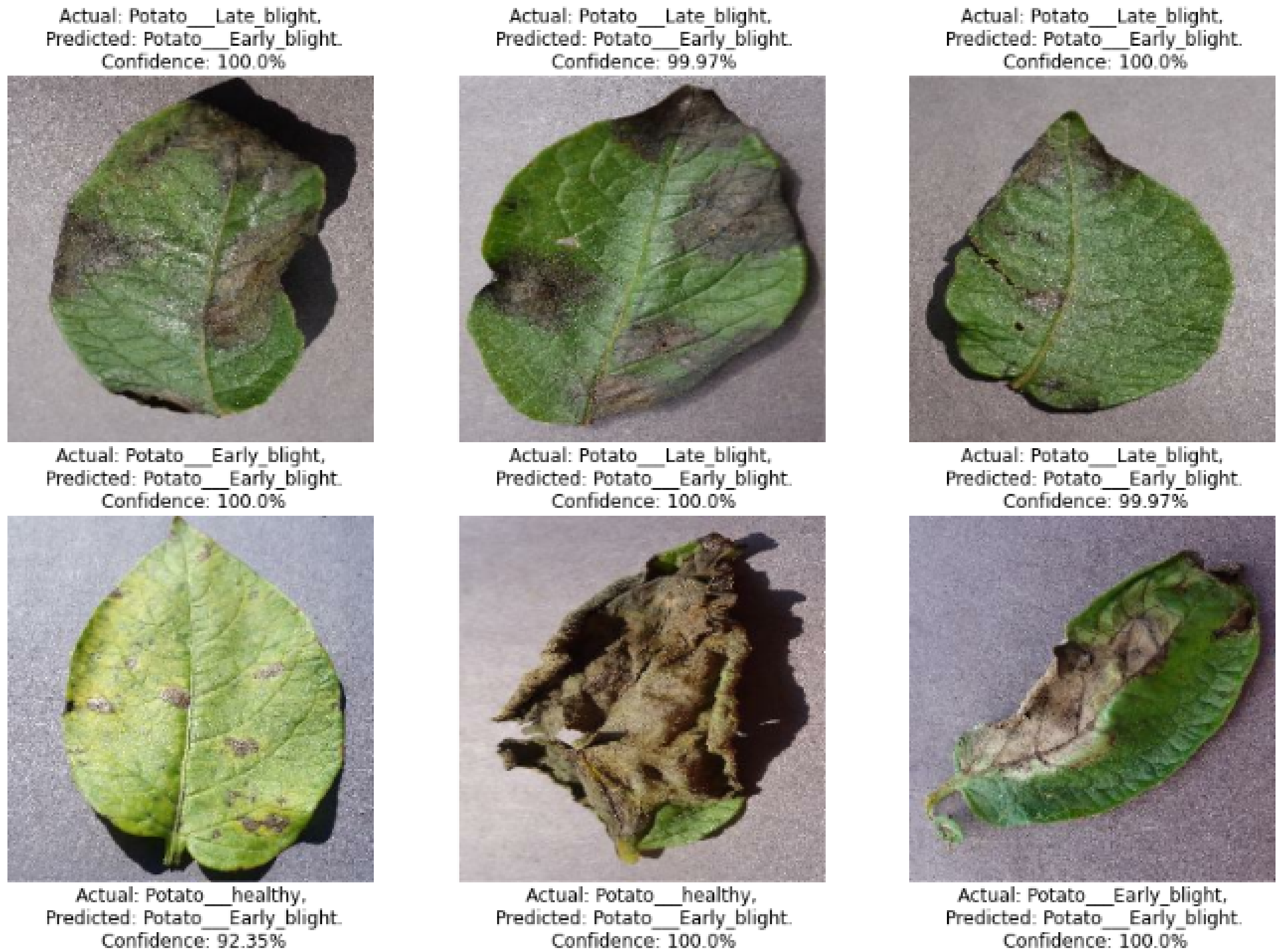

Figure 13

Visualization of Resnet50 result on proposed dataset

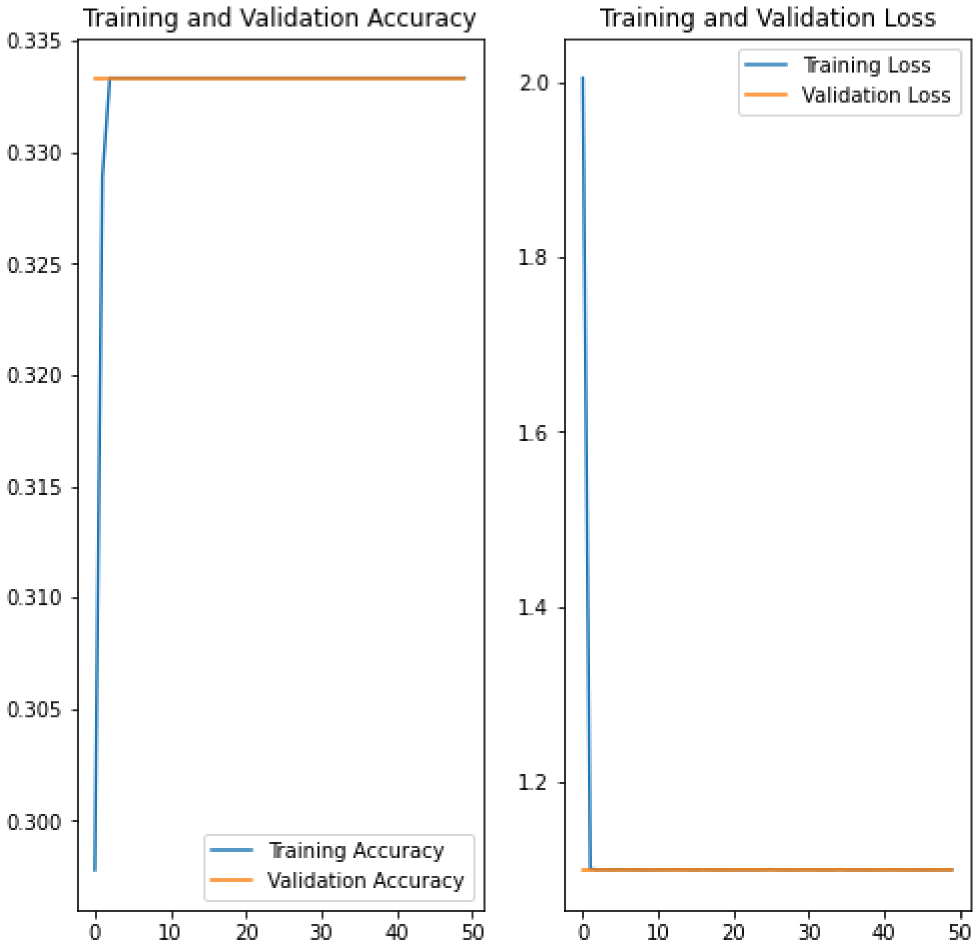

Figure 14

VGG16 result on proposed dataset

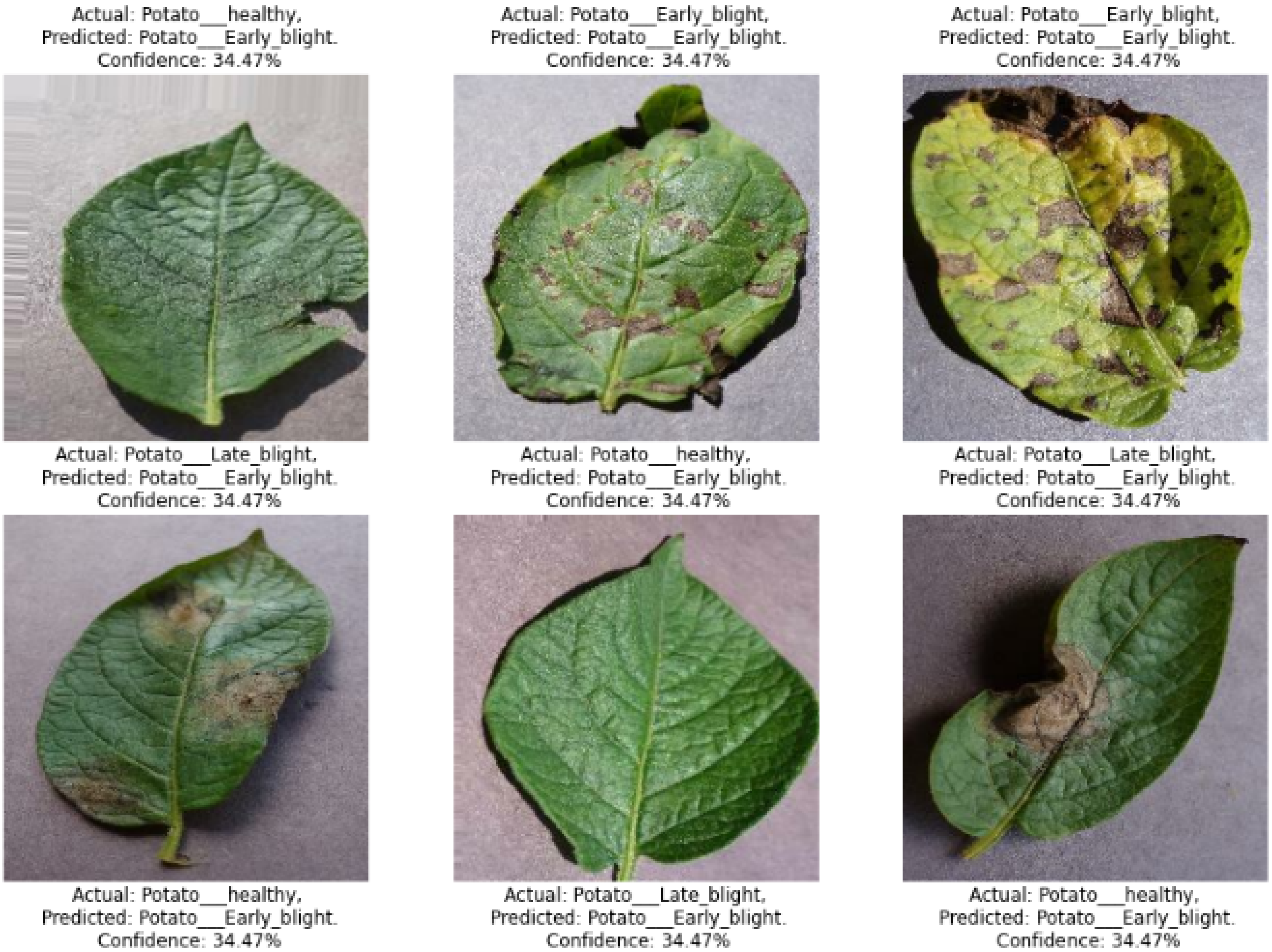

Figure 15

Visualization of VGG16 result on proposed dataset

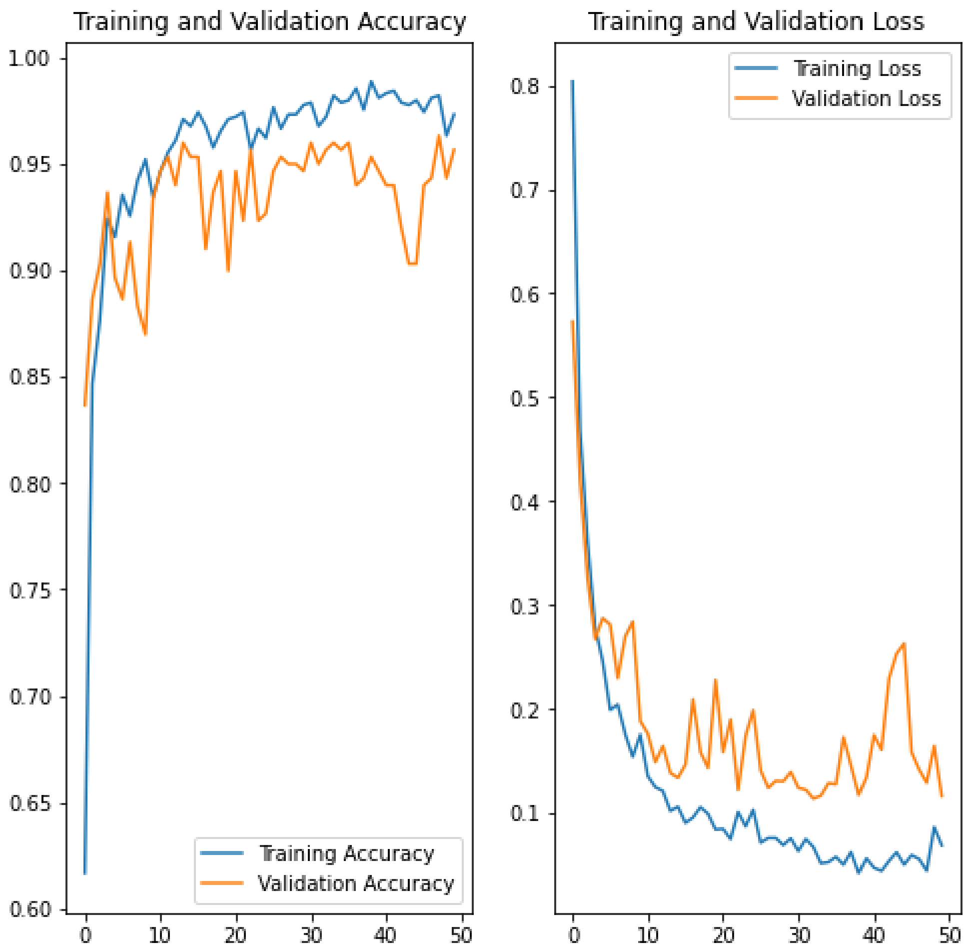

Figure 17

VGG-16 Performance Analysis (pre-trained model)

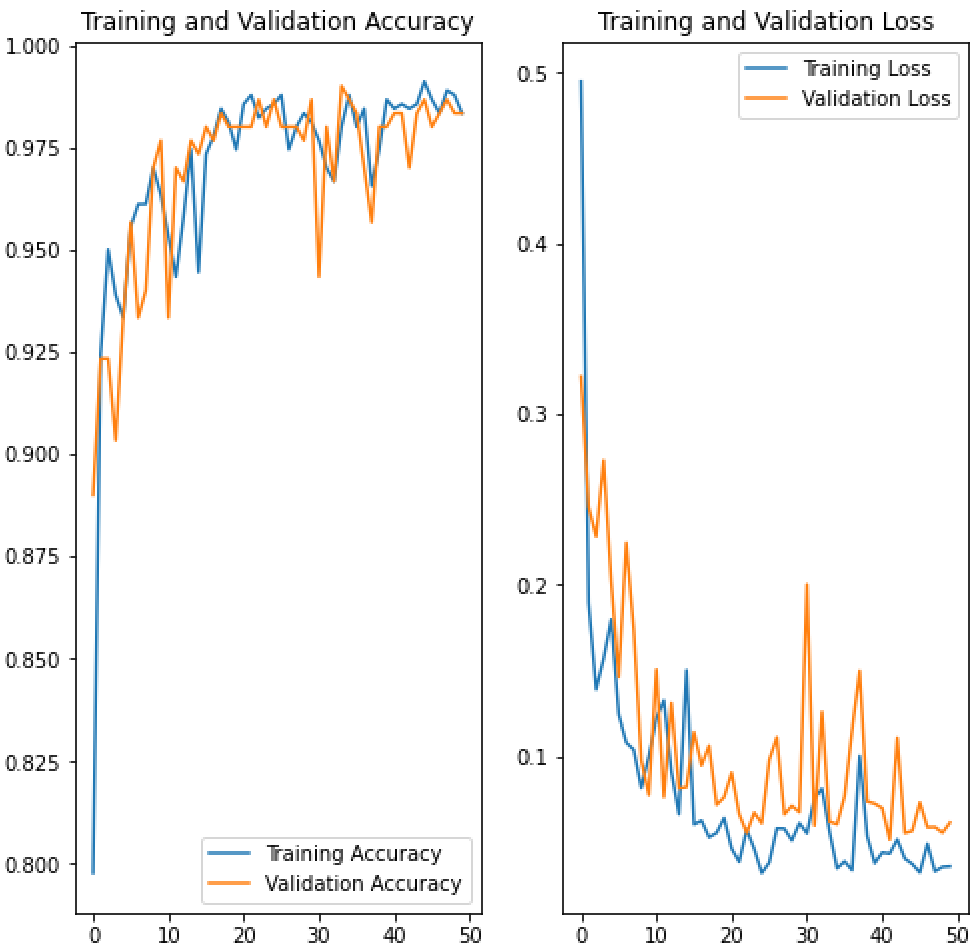

Figure 18

Xception Performance Analysis (pre-trained model)

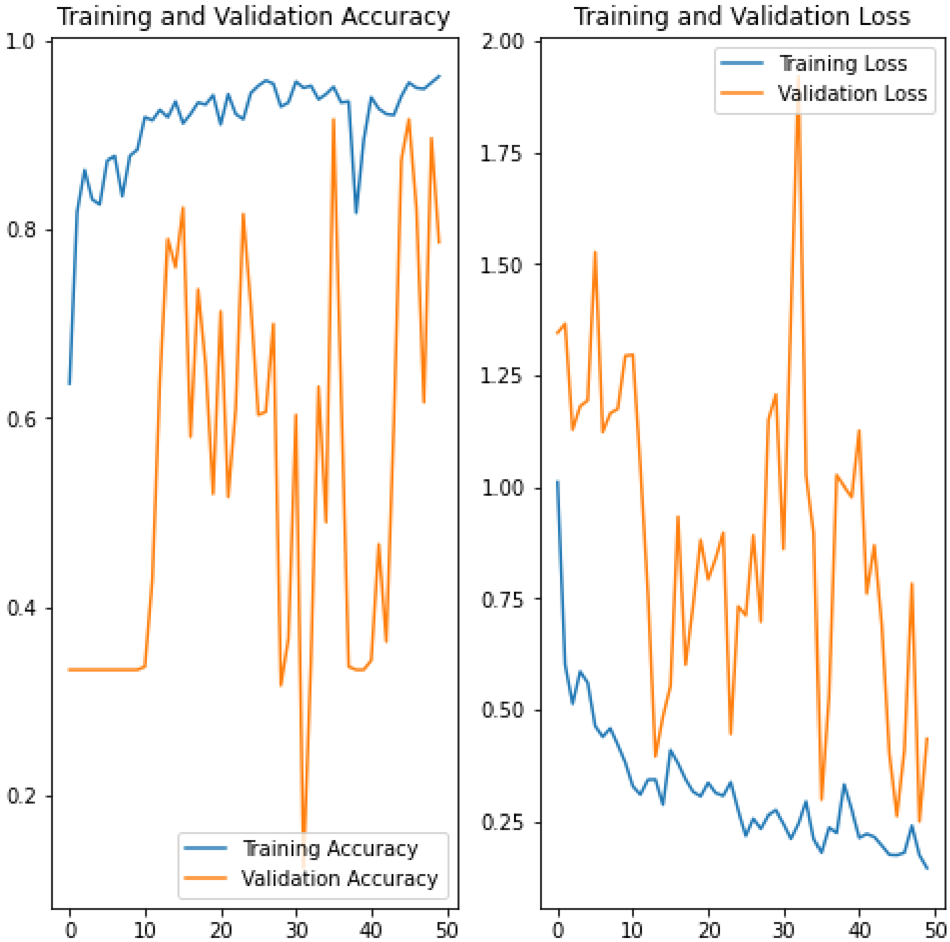

Figure 19

Resnet+GoogleNet

Figure 20

Resnet+Googlenet+Xception

Figure 21

Resnet + Googlenet