# A Plant Disease Classification with Residual Convolutional Neural Network

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Prototype Video

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## 1. Introduction

Among many Convolutional Neural Networks, Residual Network (ResNet) has been used as the base model for most models that have achieved high recognition accuracy in recent studies [1]. The aim of the project is to train an image classification model for plant diseases with plant leave images using ResNet to prototype a mobile app. The challenge is to develop a practical classifier that can deliver high classification accuracy in recognition of 26 different diseases on the image dataset. Fig. 1 shows the configuration of ResNet50 [2].

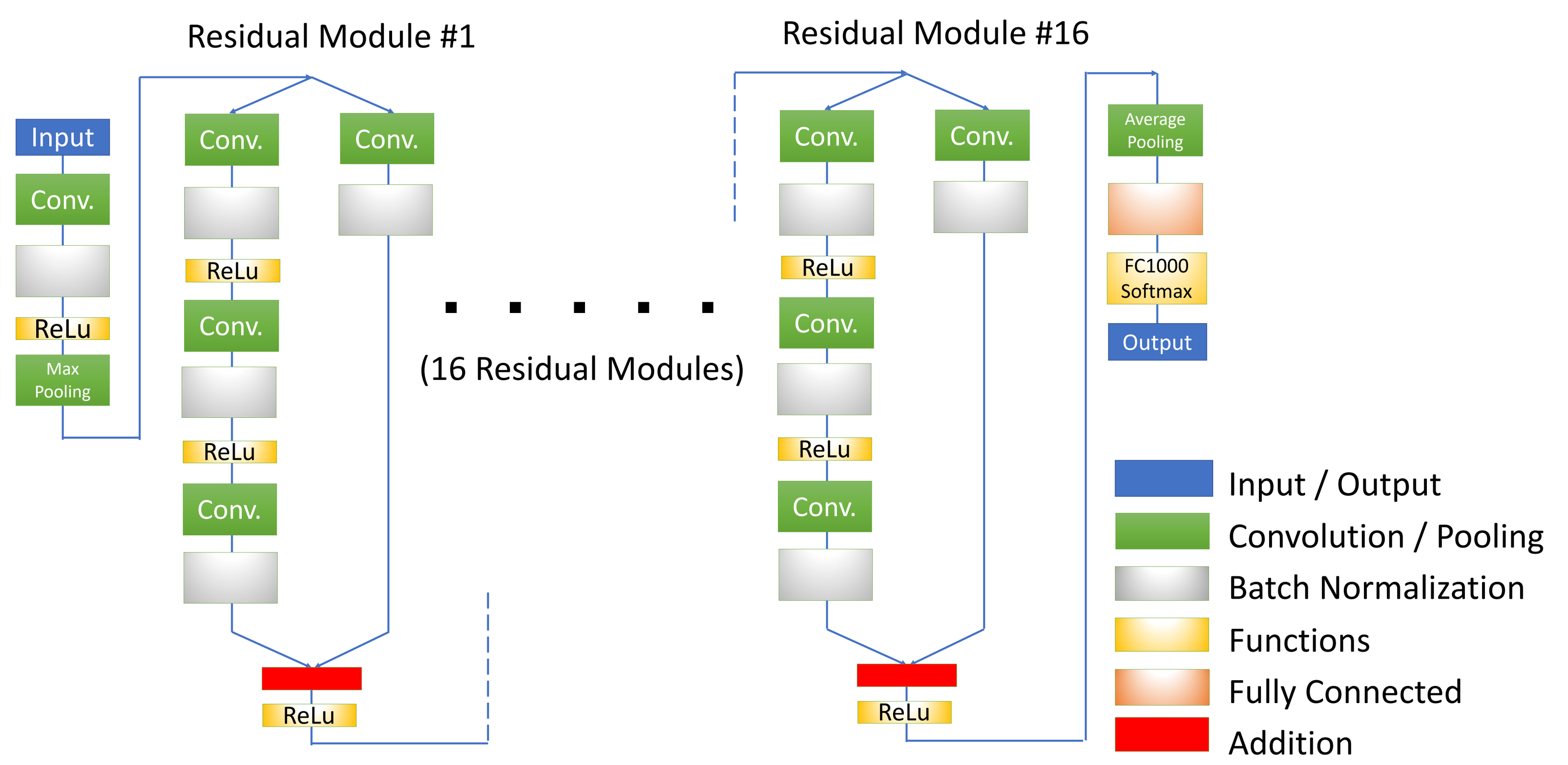


Fig.1: Concept of ResNet50

## 2. Method

The PlantVillage dataset is used for training the ResNet50. It includes 26 diseases and 12 healthy classes on 14 crops (Table 1) [3].

| Crops | Diseases | Crops | Diseases |
|---|---|---|---|
| Apple | Healthy | Potato | Healthy |
| | Black Rot | | Early Blight |
| | Cedar Apple Rust | | Late Blight |
| | Apple Scab | Raspberry | Healthy |
| Blueberry | Healthy | Soybean | Healthy |
| Cerry | Healthy | Squash | Powdery Mildew |
| | Powdery Mildew | Strawberry | Healthy |
| Corn | Healthy | | Leaf Scorch |
| | Cercospora Leaf Spot | Tomato | Healthy |
| | Common Rust | | Bacterial Spot |
| | Northern Leaf Blight | | Early Blight |
| Grape | Healthy | | Late Blight |
| | Black Rot | | Leaf Mold |
| | Esca Black Measles | | Mosaic Virus |
| | Leaf Blight Isariopsis Leaf Spot | | Septorial Leaf Spot |
| Peach | Healthy | | Spider Mites |
| | Bacterial Spot | | Target Spot |
| Pepper Bell | Healthy | | Yellow Leaf Curl Virus |
| | Bacterial Spot | Orange | Citrus Greening |

Table 1. PlantVillage Dataset Contents

Dataset images for each disease class are bulked up by Image Rotation method (Fig. 2) [3]. 1,000 images for each class are randomly selected, then these are divided into 800 and 200 images for the Training and the Testing, respectively.

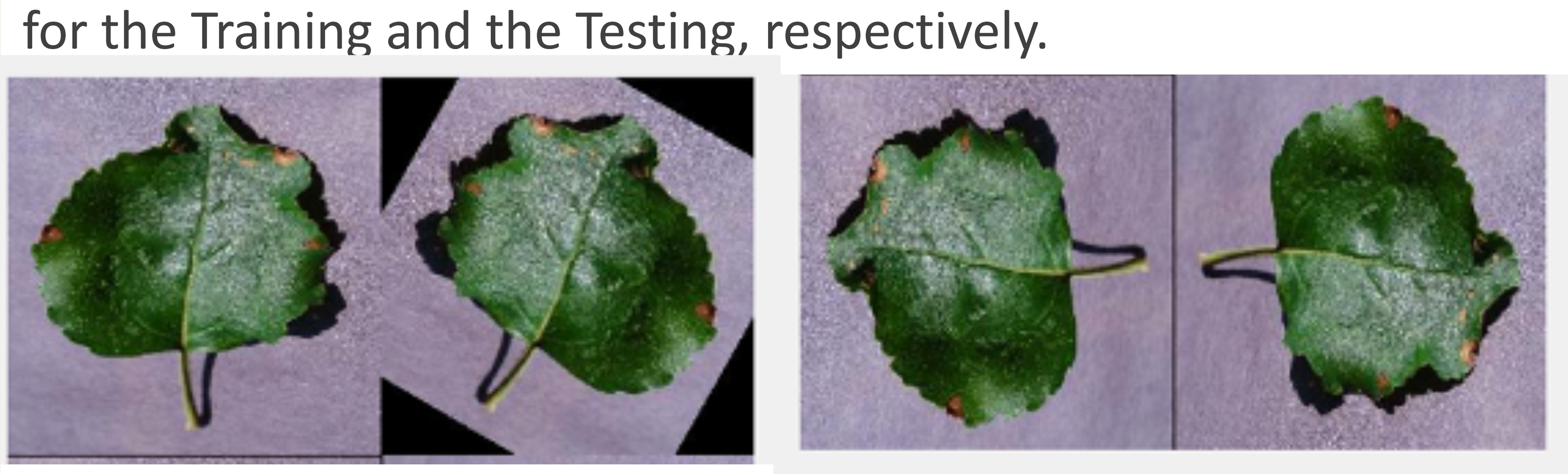

Fig 2. Image Rotation Method

The Reflection, Transition, and Scaling are randomly applied for each image before the training to further augment the dataset. Data augmenting, Training and Testing algorithms are implemented by MATLAB Deep Learning Toolbox [4]. To validate the model accuracy, 100 images per class are randomly selected from the non-augmented dataset that is not used for the Training and Testing.

## 3. Results

**An Overall Accuracy: 99.50% for 26 Disease & 12 Healthy Classes**

An overall accuracy is 99.5%, and a 100% accuracy is achieved for 22 classes (Table 2).

| | Disease Class | Accuracy | | Disease Class | Accuracy |
|---|---|---|---|---|---|
| 1 | AppleBlackRot | 100.00% | 20 | PepperBellHealthy | 100.00% |
| 2 | AppleCedarAppleRust | 100.00% | 21 | PotatoEarlyBlight | 100.00% |
| 3 | AppleHealthy | 98.00% | 22 | PotatoHealthy | 100.00% |
| 4 | AppleScab | 99.50% | 23 | PotatoLateBlight | 99.50% |
| 5 | BlueberryHealthy | 100.00% | 24 | RaspberryHealthy | 100.00% |
| 6 | CherryHealthy | 100.00% | 25 | SoybeanHealthy | 100.00% |
| 7 | CherryPowderyMildew | 99.00% | 26 | SquashPowderyMildew | 100.00% |
| 8 | CornCercosporaLeafSpotGrayLeafSpot | 98.00% | 27 | StrawberryHealthy | 100.00% |
| 9 | CornCommonRust | 100.00% | 28 | StrawberryLeafScorch | 99.50% |
| 10 | CornHealthy | 100.00% | 29 | TomatoBacterialSpot | 99.50% |
| 11 | CornNorthernLeafBlight | 98.00% | 30 | TomatoEarlyBlight | 99.00% |
| 12 | GrapeBlackRot | 99.50% | 31 | TomatoHealthy | 99.50% |
| 13 | GrapeEscaBlackMeasles | 100.00% | 32 | TomatoLateBlight | 99.50% |
| 14 | GrapeHealthy | 100.00% | 33 | TomatoLeafMold | 99.00% |
| 15 | GrapeLeafBlightIsariopsisLeafSpot | 100.00% | 34 | TomatoMosaicVirus | 99.50% |
| 16 | OrangeHaunglongbingCitrusGreening | 100.00% | 35 | TomatoSeptoriaLeafSpot | 100.00% |
| 17 | PeachBacterialSpot | 100.00% | 36 | TomatoSpiderMitesTwoSpottedSpiderMite | 100.00% |
| 18 | PeachHealthy | 100.00% | 37 | TomatoTargetSpot | 95.50% |
| 19 | PepperBellBacterialSpot | 100.00% | 38 | TomatoYellowLeafCurlVirus | 98.50% |

Table 2. Accuracy for 26 Disease Classes and 12 Healthy Classes

The training is performed with following configurations:

- Number of Epochs: 6
- Iterations per Epoch: 3,040
- Learning Rate: 0.0003

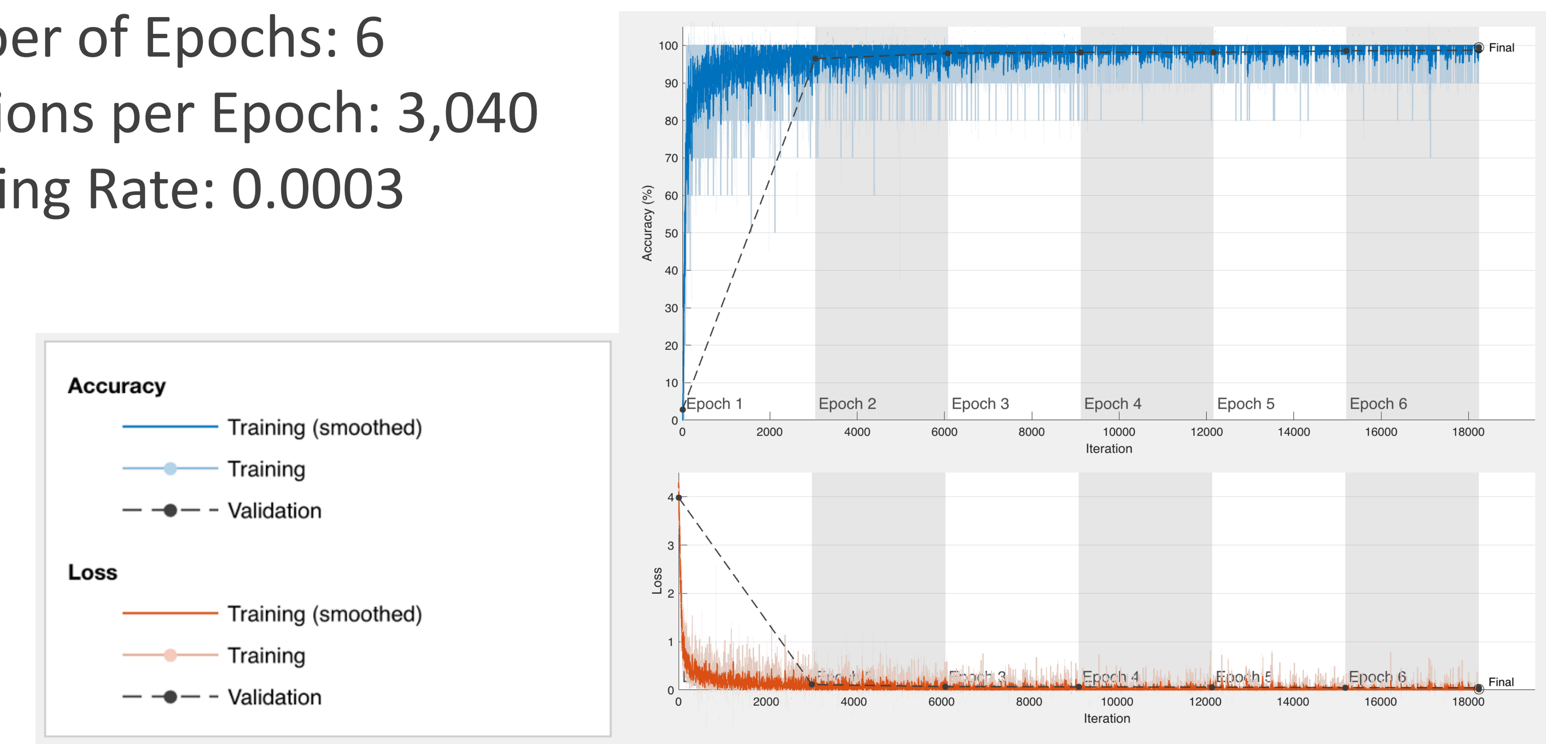


Fig 3. Training Progress with Accuracy and Loss

## 4. Conclusions & Discussions

- The trained model with a 99.5% accuracy has been implemented on iPhone 7 Plus using MATLAB Mobile as Fig 4 shows below.

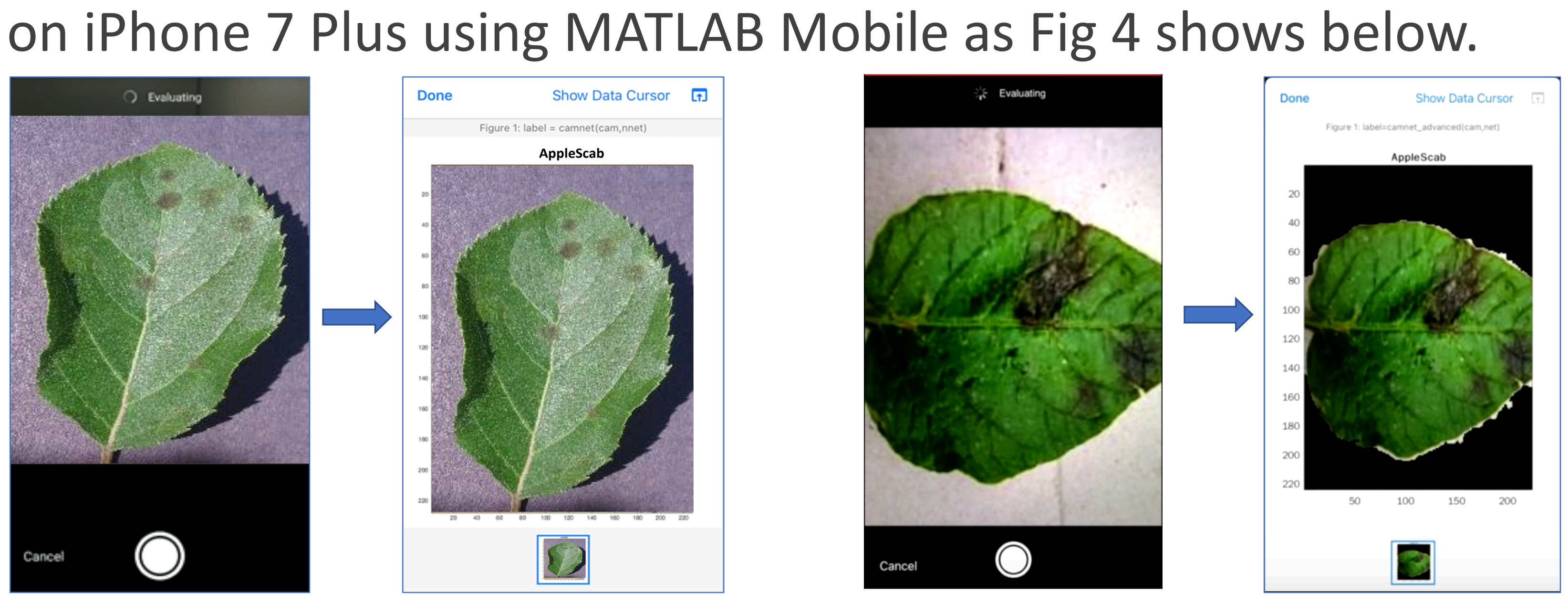

Fig 4. Basic Classifier (Left) and Automatic Leaf Boundary Extraction (Right)

- An extra experiment performed on the unknown dataset with 3 plants including 9 disease classes shows a lower accuracy, 83.7%, indicating that images with different backgrounds or other leaves may adversely affect on the accuracy. The Automatic Leaf Boundary Extraction (Fig 4., Right) might improve this issue.

## References

[1] Zhai, J., Shen, W., Singh, I., Wanyama, T. & Gao, Z. 2020, "A Review of the Evolution of Deep Learning Architectures and Comparison of their Performances for Histopathologic Cancer Detection", *Procedia Manufacturing,* vol. 46, pp. 683-689.

[2] He, K., Zhang, X., Ren, S. & Sun, J. 2015, *Deep Residual Learning for Image Recognition*

[3] J, A.P. & GOPAL, G. 2019, 18 Apr-last update, *Data for: Identification of Plant Leaf Diseases Using a 9-layer Deep Convolutional Neural Network*. Available: doi: 10.17632/tywbtsjrjv.1.

[4] MathWorks b, , *Train Deep Learning Network to Classify New Images*. Available: https://uk.mathworks.com/help/deeplearning/ug/train-deep-learning-network-to- classify-new-images.html.