

Healthy vs. Unhealthy Plant Classification

AI4ALL Group 3



Introduction

Our group and our problem of choice



Data Augmentation

How we increased our training data



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Choosing the optimal hyperparameters



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Choosing and comparing different activation functions

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01

Introduction



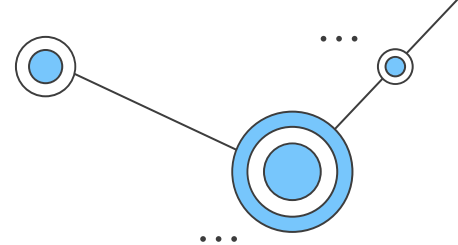
Our Group



Group Mentor: Chuer Pan

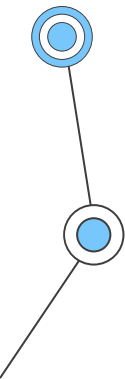
Group Members: Ariana Devito, Kenan Erol, Maigan Lafontant,
and Luis Pabon

What Problem did we Address?



According to a UN report, the World must sustainably produce 70% more food by the middle of the century

- In an effort to mitigate this problem, our group decided to make an AI that distinguishes between healthy and unhealthy plants.
- This early detection of plant diseases can prevent plant loss; therefore, contributing to the optimization of agricultural procedures.





02

Data Augmentation



What happens when we do not have enough Training Data?

- Inaccurate Results
- Biases
- Model is less prepared for Test Data



Data Augmentation: the solution to your problems!

- Data Augmentation grows data
- Creates new images based on the present data set
- Various techniques to make unique images



Data Augmentation



Original Image



De-texturized



De-colored



Edge Enhanced

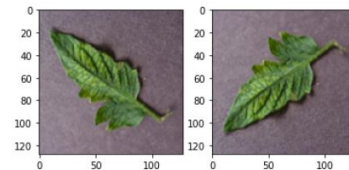
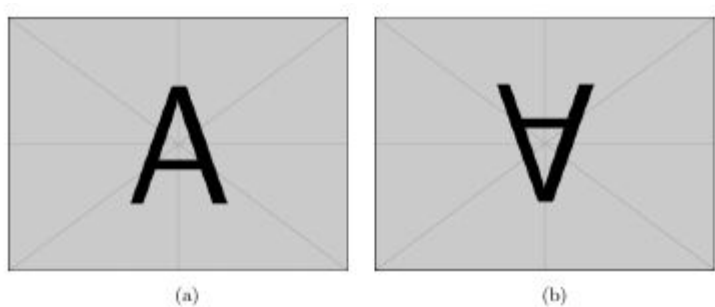


Salient Edge Map



Flip/Rotate

Image Flip

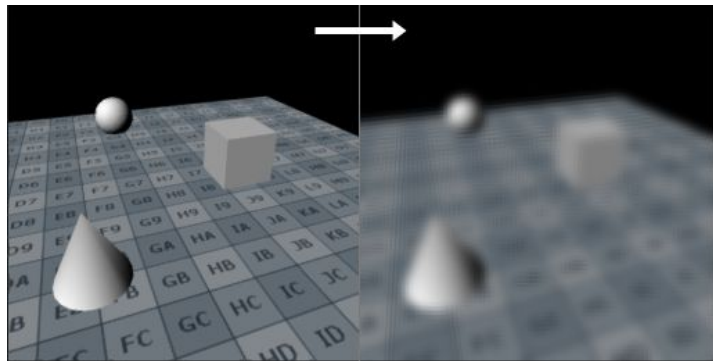
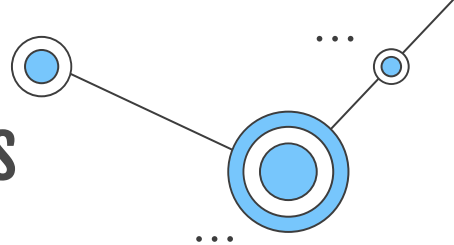


Vertical Flip

Horizontal Flip

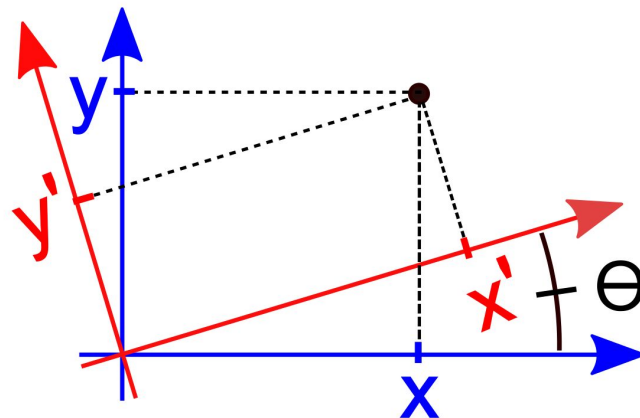


More Data Augmentation Techniques

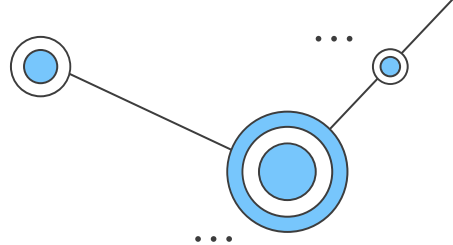


Blur

Rotation



Google Colaboratory: Limitations



- Our use of Data Augmentation for more training data
- Randomized options
- Adding new images and matching labels
- RAM and Google Colab Limitations

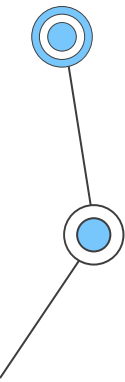
```
options = [0, 1, 2, 3, 4]
version = np.random.choice(options,2)
final_images.append(image)
final_labels.append(label)
if 1 in version:
    #flip image vertically
    flipped_image = np.flip(image, axis=0)
    final_images.append(flipped_image)
    final_labels.append(label)
if 2 in version:
    #flip image horizontally
    flipped_image = np.flip(image, axis=1)
    final_images.append(flipped_image)
    final_labels.append(label)
if 3 in version:
    #blur image
    blurred_image = gaussian_filter(image, sigma=0.5)
    final_images.append(blurred_image)
    final_labels.append(label)
if 4 in version:
    #rotate image
    angle = np.random.rand() * 30
    rotated_image = rotate(image, angle, mode='nearest')
    rotated_image_resized = cv2.resize(np.array(rotated_image), image.shape[:2])
    final_images.append(rotated_image_resized)
    final_labels.append(label)
```

Runtime disconnected

The connection to the runtime has timed out.

CLOSE

RECONNECT





03

Hyperparameter Tuning



Baseline Values

Number of Epochs: 4

Batch Size (BS): 16

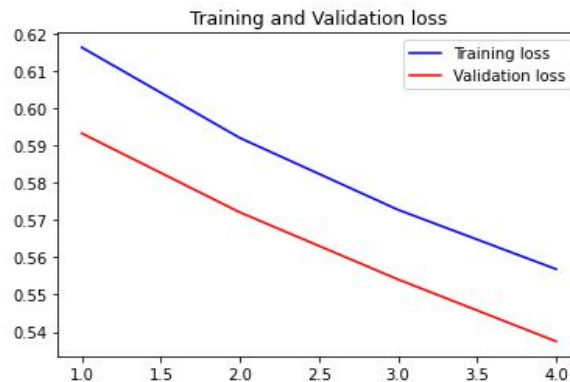
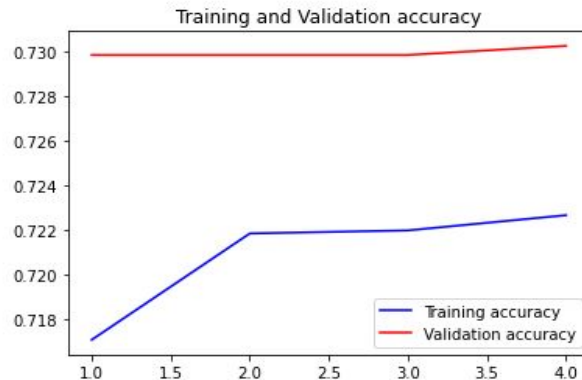
Dimensions: 128 x 128

Depth: 3

Learning Rate: $1e-6$

Test Accuracy:

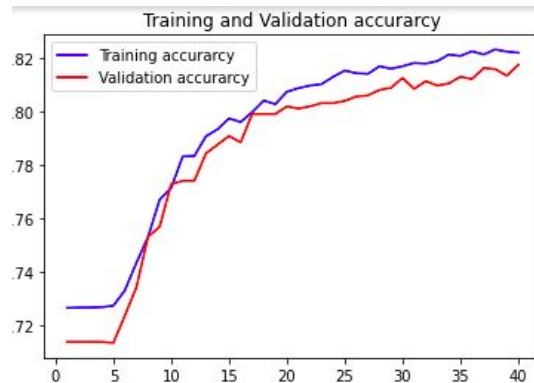
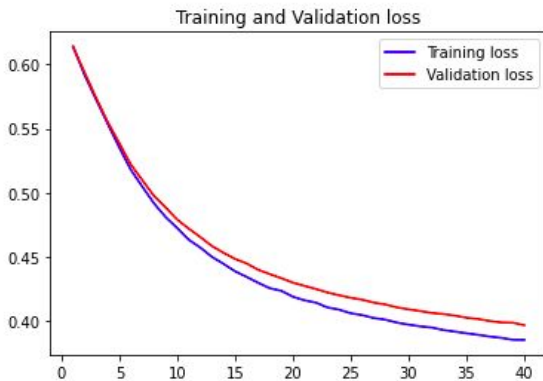
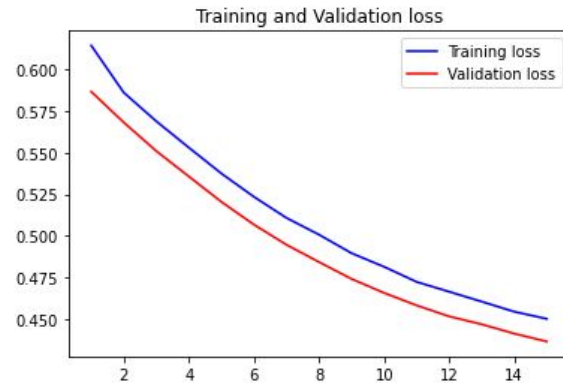
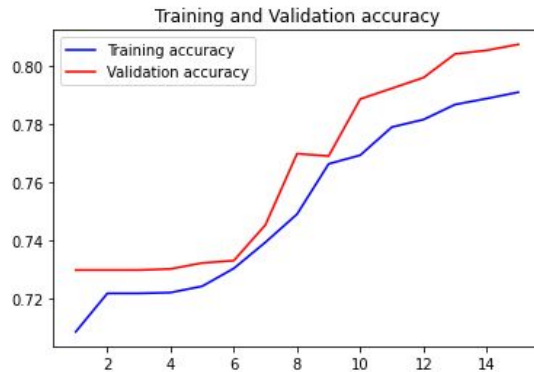
73.02497029304504



Increasing Number of Epochs

Number of Epochs: 4 → 15

Test Accuracy: 80.7613

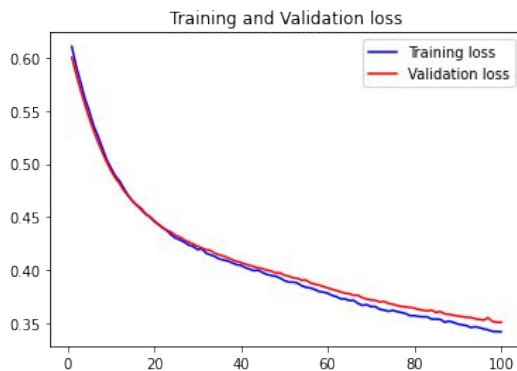
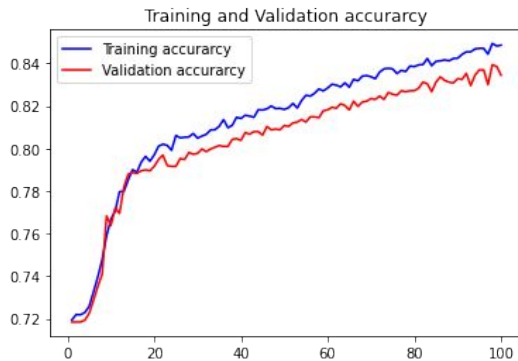
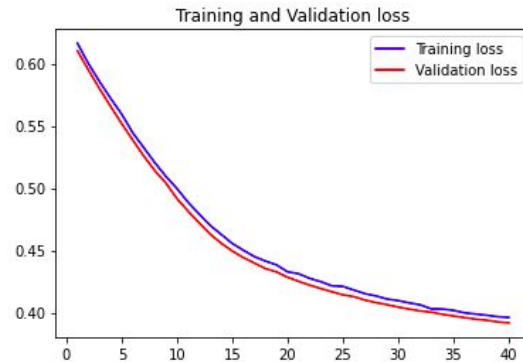
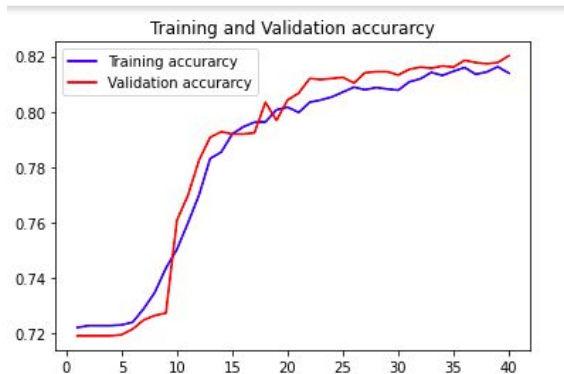


Number of Epochs: 15 → 30

Test Accuracy: 80.6636

Number of Epochs: 30 → 40

Test Accuracy: 82.0187



Number of Epochs: 40 → 100

Test Accuracy: 83.44911

Epoch Summary

Epochs	Test Accuracy
4	73.02%
15	80.76%
30	80.66%
40	82.01%
100	83.44%

Increasing Batch Size

Number of Epochs: 4

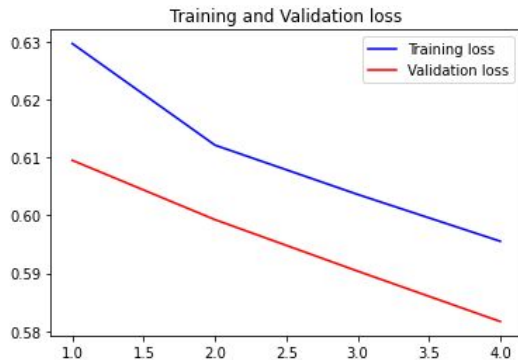
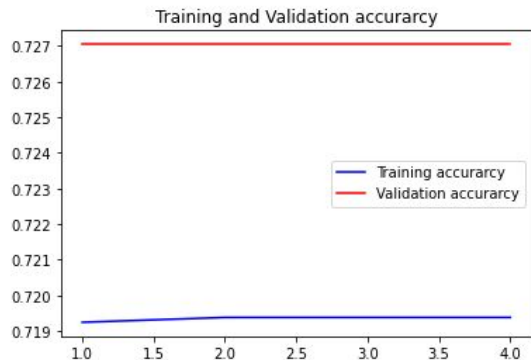
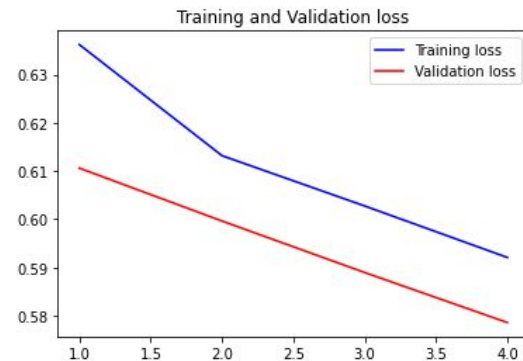
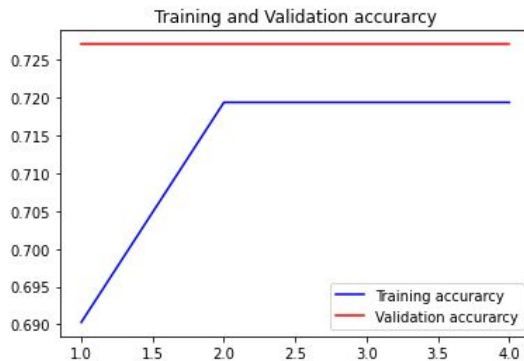
Batch Size (BS): 16 → 32

Dimensions: 128 × 128

Depth: 3

Learning Rate: 1e-6

Test Accuracy: 72.7049



Number of Epochs: 4

Batch Size (BS): 32 → 64

Dimensions: 128 × 128

Depth: 3

Learning Rate: 1e-6

Test Accuracy: 72.7049

Increasing Batch Size (cont.)

Number of Epochs: 4

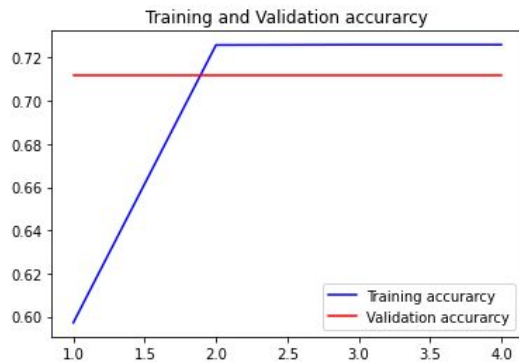
Batch Size (BS): 64 → 128

Dimensions: 128 × 128

Depth: 3

Learning Rate: 1e-6

Test Accuracy: 71.1961



EPOCHS = 4

BS = 256

width=128

height=128

depth=3

INIT_LR = 1e-6

EPOCHS = 4

BS = 512

width=128

height=128

depth=3

INIT_LR = 1e-6

Your session crashed after using all available RAM. If you are interested in access to high-RAM runtimes, you may want to check out [Colab Pro](#).

[View runtime logs](#)

Batch Size Summary

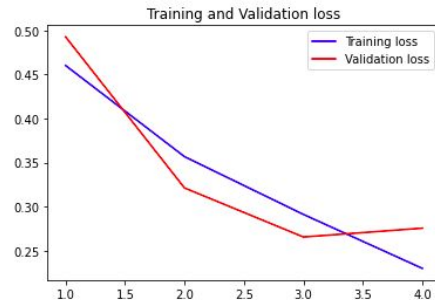
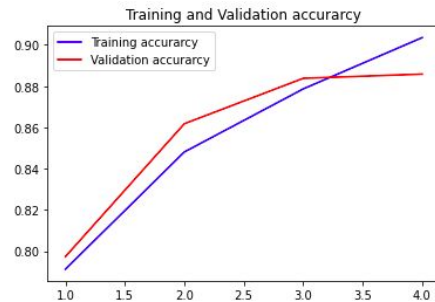
Batch Size	Test Accuracy
16	73.02%
32	72.70%
64	72.70%
128	71.20%
256	ERROR
512	ERROR

Adjusting Learning Rate

Learning Rate:

$1e-3$

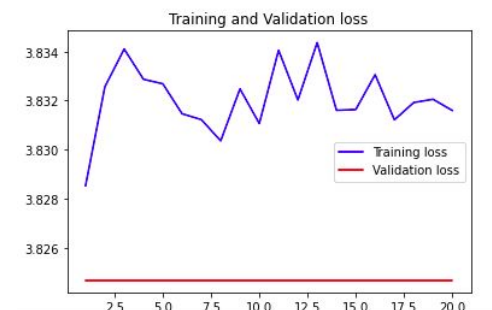
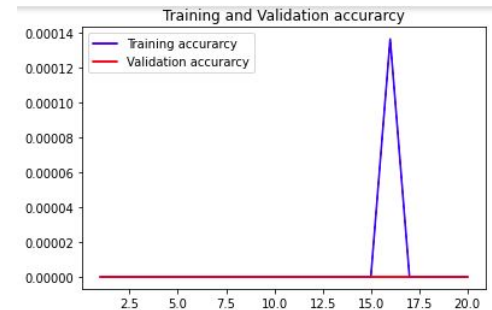
Test Accuracy:
88.5854



Learning

Rate: $1e-15$

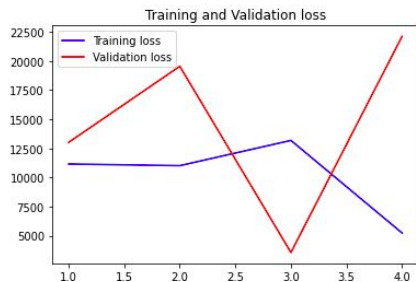
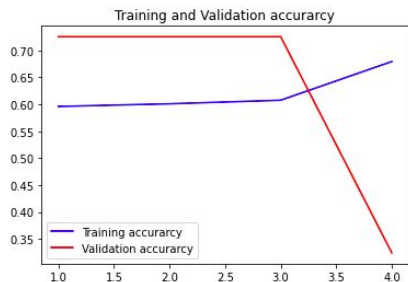
Test Accuracy:
0.0



Adjusting Learning Rate (cont.)

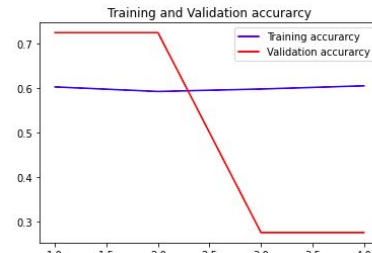
Learning Rate: 1

Test Accuracy:
32.4093



Learning Rate: 10

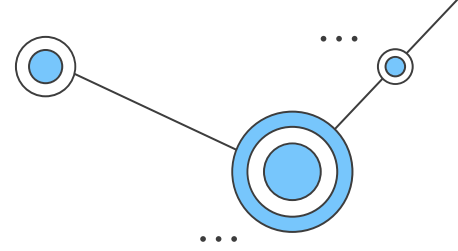
Test Accuracy:
27.4358



Learning Rate Summary

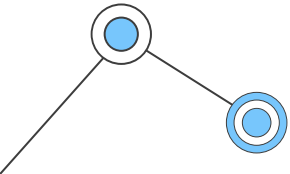
Learning Rate	Test Accuracy
10	27.44%
1	32.41%
1e-3	88.59%
1e-6	73.02%
1e-15	0.0%

Observations



Number of Epochs

Increasing the number of epochs increases the accuracy because we are training the model for longer. Yet, too many epochs would lead to a divergence in optimization and overfitting.



Batch Size

Increasing the batch size increases the test accuracy and speeds up training. However, if the batch size is too large, it can have the opposite effect.

Learning Rate

Increasing the learning rate increases the accuracy and decreases the training time. Again, when the value is either too small or too large, that accuracy will be compromised.

04

Activation Functions

Adjusting the Activation Functions

EPOCHS = 4

BS = 16

width=128

height=128

depth=3

INIT_LR = 1e-6

```
model = Sequential()
```

```
inputShape = (height, width, depth)
```

```
chanDim = -1
```

```
model.add(Conv2D(64, (3, 3), padding="same", input_shape=inputShape))
```

```
model.add(Activation("relu"))
```

```
model.add(MaxPooling2D(pool_size=(3, 3)))
```

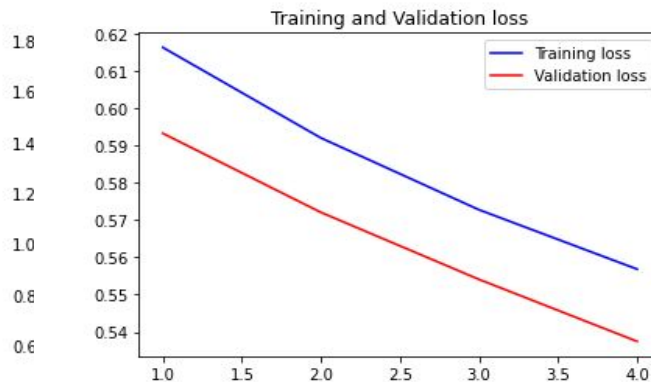
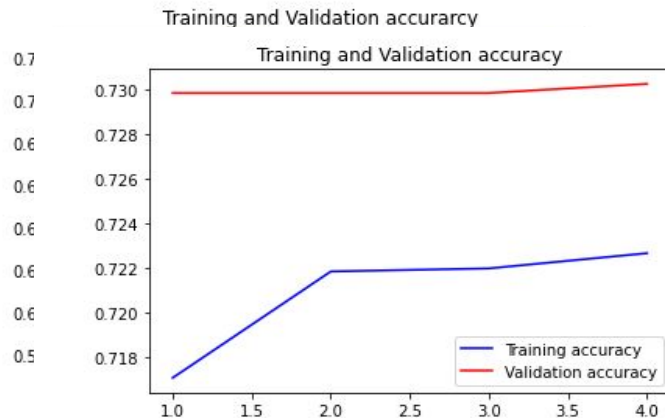
```
model.add(Dropout(0.25))
```

```
model.add(Flatten())
```

```
model.add(Dense(n_classes))
```

```
model.add(Activation("softmax"))
```

Test Accuracy: 73.02497029304504



Adjusting the Activation Functions

EPOCHS = 4
BS = 16
width=128
height=128
depth=3
INIT_LR = 1e-6

```
model = Sequential()  
inputShape = (height, width, depth)  
chanDim = -1
```

```
model.add(Conv2D(64, (3, 3), padding="same", input_shape=inputShape))
```

```
model.add(Activation("sigmoid"))
```

```
model.add(MaxPooling2D(pool_size=(3, 3)))
```

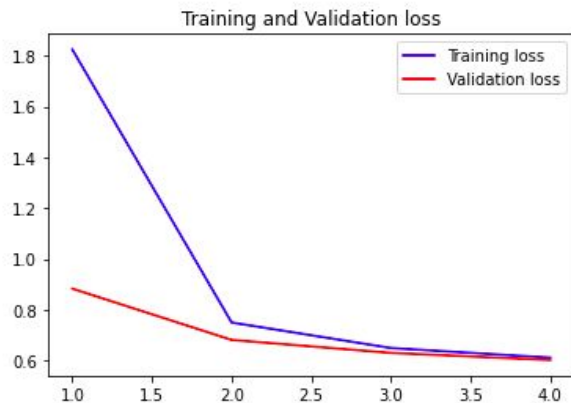
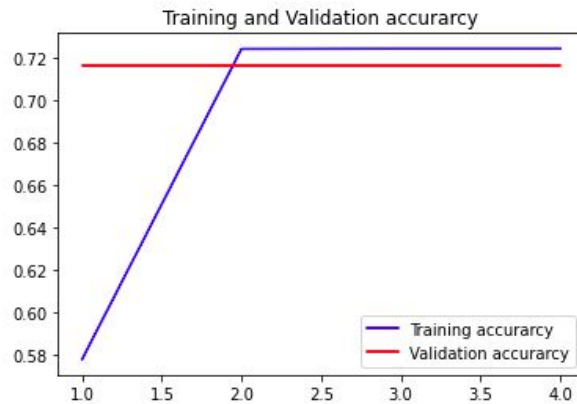
```
model.add(Dropout(0.25))
```

```
model.add(Flatten())
```

```
model.add(Dense(n_classes))
```

```
model.add(Activation("softmax"))
```

Test Accuracy: 71.63206934928894



Adjusting the Activation Functions

EPOCHS = 4

BS = 16

width=128

height=128

depth=3

INIT_LR = 1e-6

```
model = Sequential()
```

```
inputShape = (height, width, depth)
```

```
chanDim = -1
```

```
model.add(Conv2D(64, (3, 3), padding="same",
```

```
input_shape=inputShape))
```

```
model.add(Activation("tanh"))
```

```
model.add(MaxPooling2D(pool_size=(3, 3)))
```

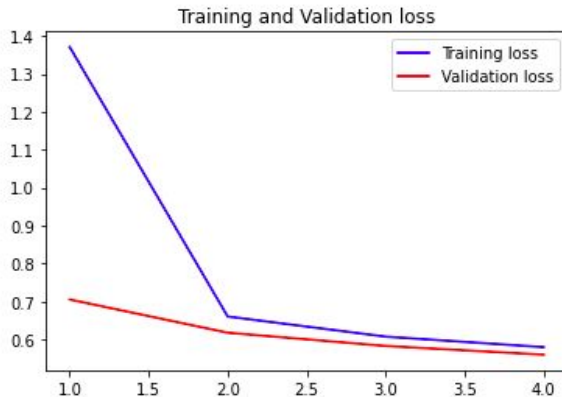
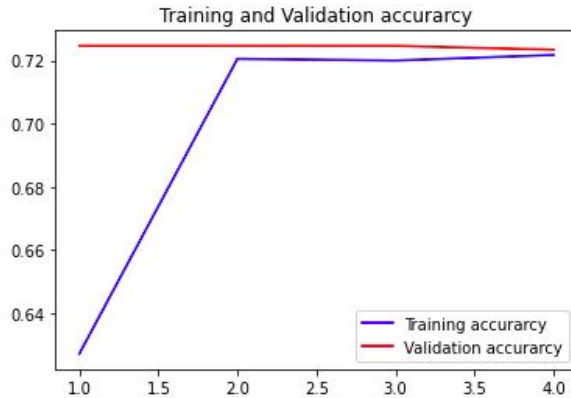
```
model.add(Dropout(0.25))
```

```
model.add(Flatten())
```

```
model.add(Dense(n_classes))
```

```
model.add(Activation("softmax"))
```

Test Accuracy: 72.33782410621643





05

Transfer Learning



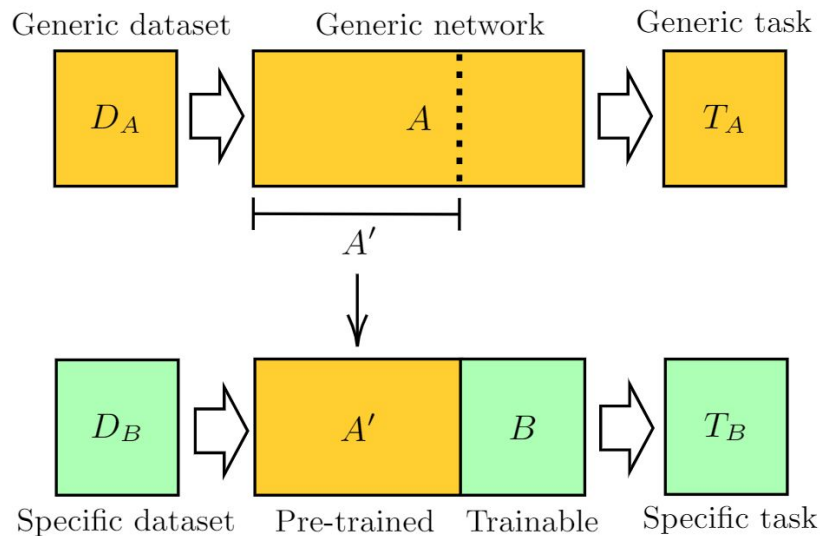
What is Transfer Learning?

Transfer Learning is a method that allows us to reuse developed models.

- This increases our accuracy
- Better performance
- We can utilize big pre-existing data pools

How did we do it?

- We loaded ResNet50 Pre-Trained Model pretrained on imagenet
- Added layers and retrained data



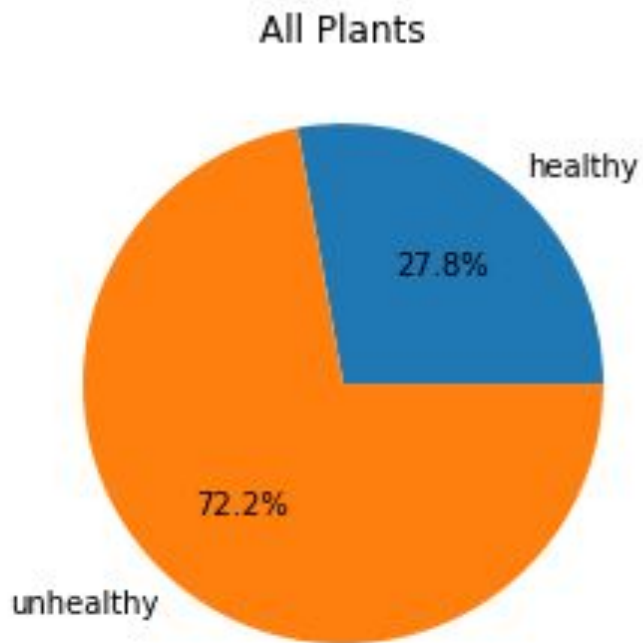


06

Displaying Results



Healthy vs Unhealthy Plants: Pie Chart



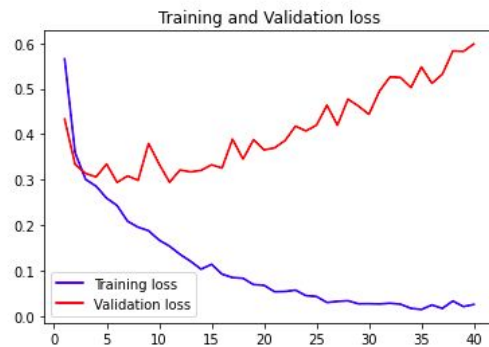
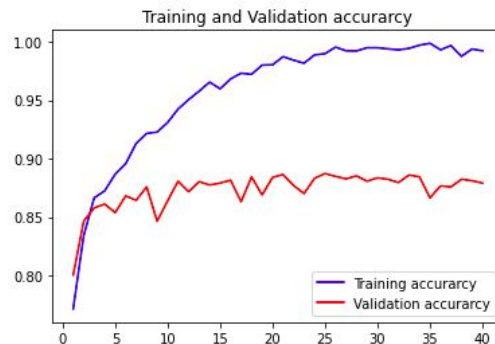
Results with Best Tuned Parameters:

BASELINE MODEL

- Combining all of the best parameters led to overfitting
- Decreasing the number of epochs solved this problem

Best Tuned Parameters (Baseline Model):

```
EPOCHS = 20  
BS = 64  
width=128  
height=128  
depth=3  
INIT_LR = 1e-2
```



Transfer Learning Tuning

TRANSFER LEARNING MODEL

- Using a large learning rate with the transfer learning model led to a lower accuracy (73.11)
- High number of epochs led to overfitting
- To solve this, we used a smaller learning rate and a lower number of epochs

Best Tuned Parameters (Transfer Learning):

EPOCHS = 20

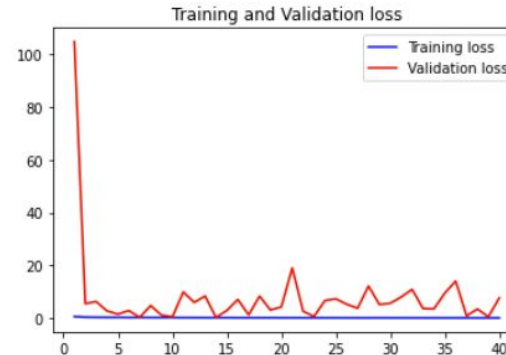
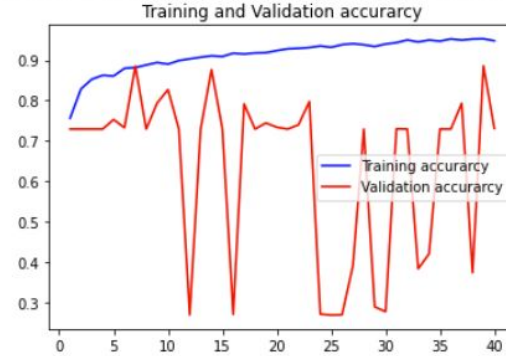
BS = 64

width=128

height=128

depth=3

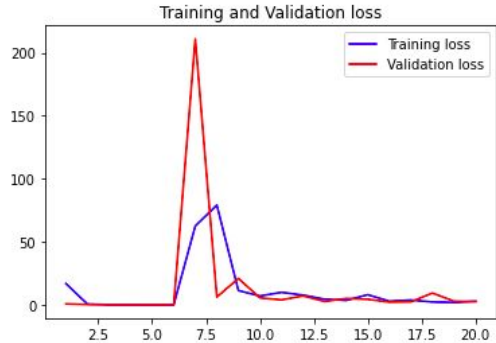
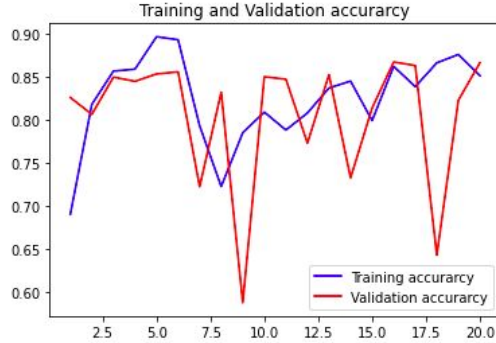
INIT_LR = 1e-6



[INFO] Calculating model accuracy
104/104 [=====] - 5s 44ms/
Test Accuracy: 73.11534881591797

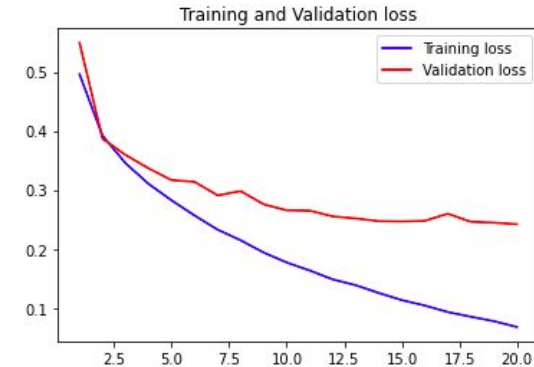
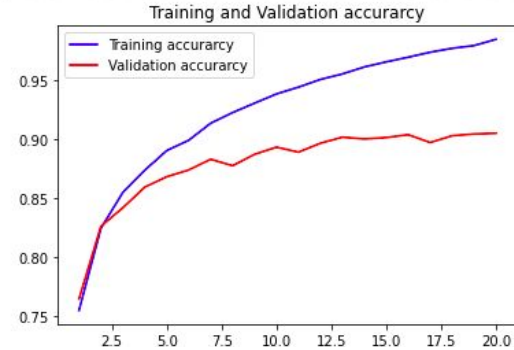
Results with Best Tuned Parameters:

Baseline Model



Test Accuracy: 86.6775631904602

Transfer Learning Model



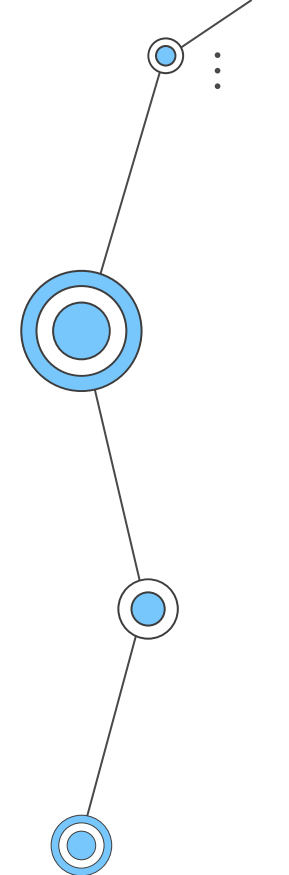
Test Accuracy: 90.0272011756897



Thanks!

Do you have any questions?

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Works Cited

Brownlee, J. (2019, September 16). *A Gentle Introduction to Transfer Learning for Deep Learning*. Machine Learning Mastery.

<https://machinelearningmastery.com/transfer-learning-for-deep-learning>

Brownlee, J. (2020, August 18). Transfer Learning in Keras with Computer Vision Models. Machine Learning Mastery.

<https://machinelearningmastery.com/how-to-use-transfer-learning-when-developing-convolutional-neural-network-models/>

Jordan, J. (2020, August 29). Setting the learning rate of your neural network. Jeremy Jordan. <https://www.jeremyjordan.me/nn-learning-rate/>

United Nations. (n.d.). *Feeding the World Sustainably*. <https://www.un.org/en/chronicle/article/feeding-world-sustainably>