```
drive.mount('/content/drive')
      Mounted at /content/drive
In [2]: !nvidia-smi
      Sun Mar 19 17:12:21 2023
      |-----
      | GPU Name | Persistence-M| Bus-Id | Disp.A | Volatile Uncorr. ECC |
      | Fan Temp Perf Pwr:Usage/Cap| Memory-Usage | GPU-Util Compute M. | | MIG M. |
      |=======+|======+|======|
      0 Tesla T4 Off | 00000000:00:04.0 Off |
      | N/A 68C PO 30W / 70W | OMiB / 15360MiB |
                                                          Default |
                                          N/A |
                          +----+
      | Processes:
                                                        GPU Memory |
      | GPU GI CI
                      PID Type Process name
           ID ID
                                                        Usage |
      |-----|
      | No running processes found
      Transfer Learning VGG 16 and 19 using keras
      from tensorflow.keras.layers import Input, Lambda, Dense, Flatten
      from tensorflow.keras.models import Model
      from tensorflow.keras.applications.resnet50 import ResNet50
      from tensorflow.keras.applications.resnet50 import preprocess input
      from tensorflow.keras.preprocessing import image
      from tensorflow.keras.preprocessing.image import ImageDataGenerator, load img
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.applications.vgg16 import VGG16
      import numpy as np
      from glob import glob
In [4]: # re_size the image
      IMAGE SIZE = [224,224]
      train path = '/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train'
      val path = '/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/val'
In [5]: # iporting the vgg16 library as show below and add preprocessing layer
      vgg16 = VGG16(input shape=IMAGE SIZE + [3], weights='imagenet', include top=False)
      Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg1
      6/vgg16 weights tf dim ordering tf kernels notop.h5
      58889256/58889256 [============== ] - 0s Ous/step
In [6]: for layer in vgg16.layers:
      layer.trainable = False
```

from google.colab import drive

In [7]: for layer in vgg16.layers:

print(layer.name , layer.trainable)

input_1 False block1 conv1 False block1 conv2 False block1 pool False block2_conv1 False block2 conv2 False block2 pool False block3_conv1 False block3 conv2 False block3 conv3 False block3 pool False block4_conv1 False block4 conv2 False block4 conv3 False block4 pool False block5_conv1 False block5 conv2 False block5 conv3 False block5 pool False

In [8]: vgg16.summary()

Model: "vgg16"

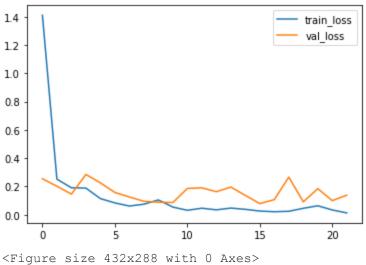
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0

Total params: 14,714,688

```
Trainable params: 0
        Non-trainable params: 14,714,688
In [9]: | folders = glob('/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train/
In [10]: folders
        ['/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train/diseased cotto
Out[10]:
         '/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train/fresh cotton l
         '/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train/diseased cotto
        n plant',
         '/content/drive/MyDrive/Deep Learning/Cotton disease Analysis/data/train/fresh cotton p
        lant']
In [11]: len(folders)
Out[11]:
In [12]: | model = Sequential()
        model.add(vgg16)
        model.add(Flatten())
        model.add(Dense(256,activation = "relu"))
        model.add(Dense(4,activation = "softmax"))
In [13]: model.summary()
        Model: "sequential"
        Layer (type)
                                   Output Shape
                                                           Param #
        ______
         vgg16 (Functional)
                                  (None, 7, 7, 512)
                                                          14714688
         flatten (Flatten)
                                  (None, 25088)
         dense (Dense)
                                  (None, 256)
                                                          6422784
         dense 1 (Dense)
                                   (None, 4)
                                                           1028
        ______
        Total params: 21,138,500
        Trainable params: 6,423,812
        Non-trainable params: 14,714,688
In [14]: # Intialization of the cost function and the optimizer
        model.compile(
           loss = "categorical crossentropy",
            optimizer = "adam",
           metrics = ["accuracy"]
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
In [15]:
In [16]: train datagen = ImageDataGenerator(rescale = 1./255,
                                         shear range = 0.2,
                                         zoom range = 0.2,
                                         horizontal flip = True)
        test datagen = ImageDataGenerator(rescale = 1./255)
```

```
In [17]: training set = train datagen.flow from directory('/content/drive/MyDrive/Deep Learning/C
                                                    target size = (224, 224),
                                                    batch size = 32,
                                                    class mode = 'categorical'
       Found 1961 images belonging to 4 classes.
In [18]: test set = test datagen.flow from directory('/content/drive/MyDrive/Deep Learning/Cotton
                                               target size = (224, 224),
                                               batch size = 32,
                                               class_mode = 'categorical')
       Found 324 images belonging to 4 classes.
In [19]: # fit the model
        r = model.fit(
           training set,
           validation data = test set,
           epochs = 22,
           steps per epoch = len(training set),
           validation steps = len(test set)
       Epoch 1/22
       62/62 [============= ] - 473s 7s/step - loss: 1.4109 - accuracy: 0.7149
       - val loss: 0.2549 - val accuracy: 0.9043
       Epoch 2/22
       62/62 [============== ] - 41s 662ms/step - loss: 0.2520 - accuracy: 0.906
       7 - val loss: 0.2020 - val accuracy: 0.9259
       Epoch 3/22
       62/62 [============ ] - 41s 663ms/step - loss: 0.1910 - accuracy: 0.931
       2 - val loss: 0.1462 - val accuracy: 0.9414
       Epoch 4/22
       62/62 [============= ] - 41s 661ms/step - loss: 0.1889 - accuracy: 0.928
       1 - val loss: 0.2852 - val accuracy: 0.8858
       Epoch 5/22
        62/62 [============== ] - 41s 662ms/step - loss: 0.1143 - accuracy: 0.957
       7 - val loss: 0.2258 - val accuracy: 0.9136
       Epoch 6/22
       62/62 [============= ] - 41s 665ms/step - loss: 0.0840 - accuracy: 0.969
       9 - val loss: 0.1580 - val accuracy: 0.9352
       Epoch 7/22
        62/62 [================= ] - 41s 661ms/step - loss: 0.0618 - accuracy: 0.980
       1 - val loss: 0.1260 - val accuracy: 0.9537
       Epoch 8/22
        62/62 [================== ] - 41s 656ms/step - loss: 0.0748 - accuracy: 0.974
       5 - val loss: 0.0954 - val accuracy: 0.9660
       Epoch 9/22
       62/62 [============== ] - 41s 660ms/step - loss: 0.1051 - accuracy: 0.958
       7 - val loss: 0.0888 - val accuracy: 0.9691
       Epoch 10/22
       62/62 [============= ] - 41s 657ms/step - loss: 0.0545 - accuracy: 0.983
       2 - val loss: 0.0865 - val accuracy: 0.9691
       Epoch 11/22
       8 - val loss: 0.1861 - val accuracy: 0.9290
       Epoch 12/22
        62/62 [================= ] - 41s 656ms/step - loss: 0.0464 - accuracy: 0.985
       7 - val loss: 0.1906 - val accuracy: 0.9228
       Epoch 13/22
       62/62 [============= ] - 41s 659ms/step - loss: 0.0350 - accuracy: 0.990
       3 - val loss: 0.1632 - val accuracy: 0.9290
       Epoch 14/22
```

```
7 - val loss: 0.1957 - val accuracy: 0.9167
       Epoch 15/22
       62/62 [============= ] - 41s 666ms/step - loss: 0.0385 - accuracy: 0.985
       7 - val loss: 0.1370 - val accuracy: 0.9475
       Epoch 16/22
        62/62 [================== ] - 41s 656ms/step - loss: 0.0262 - accuracy: 0.992
       9 - val loss: 0.0790 - val accuracy: 0.9630
       Epoch 17/22
        62/62 [==================== ] - 41s 656ms/step - loss: 0.0216 - accuracy: 0.992
       4 - val loss: 0.1073 - val accuracy: 0.9599
       Epoch 18/22
       62/62 [============== ] - 41s 655ms/step - loss: 0.0247 - accuracy: 0.990
       8 - val loss: 0.2664 - val accuracy: 0.9012
       Epoch 19/22
        62/62 [================== ] - 40s 651ms/step - loss: 0.0458 - accuracy: 0.984
       7 - val loss: 0.0917 - val accuracy: 0.9691
       Epoch 20/22
        62/62 [============== ] - 39s 636ms/step - loss: 0.0636 - accuracy: 0.979
       1 - val loss: 0.1848 - val accuracy: 0.9352
       Epoch 21/22
       62/62 [============== ] - 40s 643ms/step - loss: 0.0341 - accuracy: 0.989
       3 - val loss: 0.1000 - val accuracy: 0.9660
       Epoch 22/22
       62/62 [============== ] - 42s 671ms/step - loss: 0.0132 - accuracy: 0.995
        9 - val loss: 0.1387 - val accuracy: 0.9599
In [20]: import matplotlib.pyplot as plt
In [21]: # pllotting the loss
       plt.plot(r.history['loss'], label = 'train loss')
       plt.plot(r.history['val loss'], label = 'val loss')
       plt.legend()
        plt.show()
       plt.savefig('lossvall loss')
        1.4
                                          train loss
                                          val loss
        1.2
```



```
In [22]: # plotting the accuracy
plt.plot(r.history['accuracy'],label = 'train_acc')
plt.plot(r.history['val_accuracy'],label = 'val_acc')
plt.legend()
plt.show()
plt.savefig('accuracyfig')
```



img

In [31]:

Out[31]:



```
x=image.img to array(img)
In [32]:
         array([[[133., 208.,
                                90.],
Out[32]:
                 [123., 198.,
                                80.],
                 [132., 207., 89.],
                 [ 82., 105., 63.],
                 [117., 138., 105.],
                 [124., 145., 112.]],
                [[131., 205., 90.],
                 [138., 212., 97.],
                 [141., 215., 100.],
                 . . . ,
                 [ 95., 118.,
                               89.],
                 [108., 129.,
                               96.],
                 [ 75., 96.,
                               63.]],
                [[122., 196., 85.],
                 [143., 217., 106.],
                 [141., 215., 104.],
                 . . . ,
                 [ 73., 98., 79.],
                 [ 98., 119., 86.],
                 [ 96., 117., 84.]],
                . . . ,
                [[162., 219., 150.],
                 [164., 221., 152.],
                 [161., 218., 149.],
                 . . . ,
                 [122., 108.,
                               81.],
                 [115., 98.,
                               70.],
                 [119., 102.,
                               74.]],
                [[162., 215., 147.],
                 [166., 219., 151.],
                 [164., 217., 149.],
                 . . . ,
                 [135., 120.,
                               99.],
                 [130., 112.,
                               92.],
                 [126., 108., 88.]],
                [[159., 212., 144.],
                 [166., 219., 151.],
                 [166., 219., 151.],
                 [125., 110., 89.],
```

```
[118., 100., 80.]]], dtype=float32)
In [33]:
        x.shape
         (224, 224, 3)
Out[33]:
In [34]:
        x=x/255
        from keras.applications.vgg16 import preprocess input
In [35]:
        import numpy as np
        x=np.expand dims(x,axis=0)
        img data=preprocess input(x)
        img data.shape
        (1, 224, 224, 3)
Out[35]:
        model.predict(img data)
In [36]:
        1/1 [======] - 1s 809ms/step
        array([[9.99999881e-01, 1.27123811e-09, 1.15762395e-08, 8.03981095e-08]],
Out[36]:
              dtype=float32)
        a=np.argmax(model.predict(img data), axis=1)
In [37]:
        1/1 [======= ] - Os 21ms/step
In [38]:
        array([0])
Out[38]:
        cotton disease = ["diseased cotton leaf", "fresh cotton leaf", "diseased cotton plant", "fr
In [39]:
        cotton disease[a[0]]
In [40]:
         'diseased cotton leaf'
Out[40]:
```

[120., 102., 82.],

In []: